



Precipitation phase-partitioning schemes introduce substantial uncertainty into simulations of the permafrost thermal regime over the Tibetan Plateau

Rui Chen¹, Haoying Li¹, and Shichang Kang^{1,2}

¹Key Laboratory of Mountain Hazards and Engineering Resilience, Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu 610213, China

²University of Chinese Academy of Sciences, Beijing 100049, China

Correspondence: Rui Chen (rui.chen@imde.ac.cn) and Shichang Kang (shichang.kang@imde.ac.cn)

Abstract.

Precipitation phase-partitioning schemes determine how precipitation forcing is divided into snowfall and rainfall at each time step in land surface modelling. However, their influence on simulated permafrost thermal regimes remains poorly quantified. In this study, we use the one-dimensional transient permafrost model CryoGridLite to assess the uncertainty in permafrost simulations induced by different schemes over the Tibetan Plateau during 1951–2024. By keeping the meteorological forcing dataset, model configurations, and input parameters identical, we implemented eight commonly used schemes, including binary threshold schemes, temperature-ramp schemes, piecewise schemes, and wet-bulb/humidity-dependent schemes, allowing the effect of precipitation phase assignment to be isolated. Our simulations indicate that precipitation phase-partitioning schemes produce substantial differences in snowfall and rainfall forcing, which propagate into simulated ground thermal regimes. Across the ensemble-defined permafrost area, 83.4 % of the area shows an inter-scheme range in mean annual ground temperature at 10 m depth exceeding 0.5 °C, and 48.9 % exceeds 1.0 °C. Uncertainty in simulated thaw depth is more spatially localized than that in mean annual ground temperature, but 47.2 % and 18.3 % of the ensemble-defined permafrost area still show inter-scheme thaw depth ranges exceeding 0.25 and 0.5 m, respectively. These thermal differences further affect threshold-based permafrost diagnosis. Differences among schemes lead to measurable changes in diagnosed permafrost area, with the largest diagnostic uncertainty occurring in marginal permafrost regions where simulated ground temperatures are close to 0 °C. Although precipitation phase assignment is commonly treated as a preprocessing step in meteorological forcing preparation, our controlled experiments show that the choice of scheme can generate pronounced differences in simulated ground thermal states and permafrost area diagnostics. Phase partitioning should therefore be considered a previously underexamined forcing-related source of uncertainty in high-elevation permafrost thermal simulations.

1 Introduction

The thermal regime of permafrost is a fundamental indicator of the physical state of frozen ground and its response to climate change (Biskaborn et al., 2019; Smith et al., 2022; Noetzli et al., 2024). Because in situ observations of ground thermal condi-



tions remain sparse and unevenly distributed, numerical models are widely used to simulate permafrost thermal regimes and to project their future changes under different climate scenarios (Obu et al., 2019; Ran et al., 2022; Westermann et al., 2023). The reliability of these simulations depends on both the representation of key physical processes and the quality of meteorological forcing, which together determine how atmospheric conditions are translated into subsurface thermal states (Lu et al., 2020; Matthes et al., 2025). For precipitation forcing, the pathway from atmospheric input to ground thermal conditions depends not only on the amount and timing of precipitation, but also on its phase (Westermann et al., 2011; Jan and Painter, 2020). Although precipitation phase partitioning (PPP) is often treated as a technical step in forcing preparation or model preprocessing, it determines how total precipitation is divided into snowfall and rainfall components, thereby shaping the subsequent snow, water, and energy pathways through which precipitation affects surface and subsurface thermal conditions (Hamm et al., 2023; Damseaux et al., 2025; Zhang et al., 2026). For example, the same amount of precipitation can be represented as snowfall, promoting snow accumulation and persistence while affecting surface albedo and insulation (Zhang, 2005; Peng et al., 2024; Xiao et al., 2025), or as rainfall, adding liquid water to the surface and altering infiltration, runoff, and near-surface hydrological conditions (Douglas et al., 2020; Li et al., 2026). This issue is particularly relevant over the Tibetan Plateau (TP), which contains the largest low- and middle-latitude permafrost area in the world (Fig. 1). Recent studies have estimated that permafrost covers about $1.09 \times 10^6 \text{ km}^2$ over the TP, accounting for roughly 41 % of the plateau area (Cao et al., 2023). At the same time, permafrost over the TP has been undergoing thermal degradation, with increasing mean annual ground temperature, deepening active layer thickness, and decreasing permafrost extent (Ran et al., 2018; Zhao et al., 2021; Fu et al., 2025). Additionally, precipitation over the TP is strongly controlled by the interaction between the mid-latitude westerlies and the Asian monsoon systems, producing pronounced spatial heterogeneity and strong seasonality (MauSSION et al., 2014; Cui et al., 2021; Jiang et al., 2023). Annual precipitation is largely concentrated in the warm season (Wang et al., 2017), but precipitation during this period can still include both liquid and solid phases (Song and Liu, 2021; Li et al., 2025b). Some precipitation events occur when near-surface temperature conditions are close to the rain–snow transition, where small differences in partitioning criteria can lead to different assignments of the same precipitation as snowfall or rainfall (Hu et al., 2024; Jennings et al., 2025). These differences alter the snowfall and rainfall forcing received by the land surface and may therefore change the snow, hydrological, and surface energy balance conditions through which precipitation influences the simulated ground thermal regime. This makes precipitation phase assignment a potentially important source of uncertainty in permafrost thermal simulations.

Uncertainty in simulated permafrost thermal regimes is not only a function of external meteorological forcing (Guo et al., 2017; Cao et al., 2020), but also depends on the internal model representation of physical processes (Burke et al., 2020; Matthes et al., 2025). This has been demonstrated by modelling studies showing that estimates of ground temperature, active-layer thickness, and permafrost extent can differ substantially among forcing datasets, model structures, diagnostic methods, and process parameterizations (McGuire et al., 2016; Wang et al., 2016; Steinert et al., 2024; Matthes et al., 2025). Input forcing defines the atmospheric boundary conditions imposed on the model, including near-surface air temperature, precipitation, radiation, humidity, and wind. These variables regulate the energy and water supplied to the land surface and therefore influence the simulated surface boundary condition for ground heat transfer (Blyth et al., 2021; Westermann et al., 2023). For example, a sensitivity experiment using the same land surface model (CLM4.5) but different atmospheric forcing datasets showed that



historical pan-Arctic permafrost simulations differed by $2.3 \times 10^6 \text{ km}^2$ in simulated permafrost area, 1.29°C in ground temperature at 6 m depth, and 0.16 m in active-layer thickness (Guo et al., 2017). This model-internal component of uncertainty includes both model structure and process parameterizations. Model structure determines which processes are represented and how they are coupled, whereas parameterizations determine how individual processes are formulated within a given model framework. Multi-model intercomparison studies have shown marked model-dependent differences in diagnosed permafrost area over the TP during 1980–2000 (Wang et al., 2016). Process-level parameterization choices, such as the representation of snow processes, soil thermal and hydrological properties, and freeze–thaw dynamics, can further modify simulated ground thermal conditions and thaw-related diagnostics (Magnusson et al., 2015; Li et al., 2021; Hu et al., 2023; Tao et al., 2024; Yang et al., 2025). Furthermore, uncertainty may also be introduced at the diagnostic stage, as different criteria used to identify permafrost can produce different estimates of permafrost area or extent from the same or comparable model outputs (Wang et al., 2016; Steinert et al., 2024; Li et al., 2025a).

Within this broader uncertainty framework, PPP is a specific preprocessing step applied to precipitation forcing and determines how precipitation at each time step is partitioned into snowfall and rainfall (Westermann et al., 2023; He et al., 2023). In land surface, hydrological, and permafrost models, this partitioning is commonly represented using empirical temperature-based thresholds or more complex humidity-dependent formulations (Harpold et al., 2017; Jennings et al., 2018; Behrangi et al., 2018; Leroux et al., 2023). Consequently, different PPP formulations can produce different snowfall and rainfall forcing, especially under near-freezing conditions (Jennings et al., 2018; Behrangi et al., 2018; Jennings et al., 2025). Previous studies have shown that these differences can affect snowfall fraction, snowpack evolution, snowmelt timing, and runoff generation (Jennings and Molotch, 2019; Leroux et al., 2023; Singh et al., 2025). These studies have established PPP as an important source of uncertainty in snow hydrology and land-surface modelling, particularly in mountainous and cold-region environments where precipitation frequently occurs near the rain–snow transition (Harpold et al., 2017; Jennings and Molotch, 2019; Leroux et al., 2023; Singh et al., 2025). However, most of this work has focused on snowpack evolution and hydrological responses, whereas the consequences for permafrost thermal simulations remain insufficiently quantified. PPP-induced differences in snowfall and rainfall forcing may propagate into simulated ground temperature, thaw depth, and threshold-based permafrost diagnosis, but the magnitude, spatial pattern, and diagnostic consequences of this uncertainty remain poorly understood, especially over the TP.

Here, we use the one-dimensional numerical permafrost model CryoGridLite (Nitzbon et al., 2023; Langer et al., 2024; Chen et al., 2025) to quantify uncertainty in simulated permafrost thermal regimes over the TP introduced by different PPP schemes. To isolate the effect of precipitation phase assignment, all experiments are driven by the same meteorological forcing and use identical model configurations and input parameters, with only the PPP scheme varying among simulations. We first evaluate how different PPP schemes redistribute total precipitation into snowfall and rainfall across spatial and temporal scales. We then examine whether these forcing-level differences are reflected in the simulated thermal regime of permafrost over the TP. Finally, we diagnose the physical pathways linking PPP-induced snowfall and rainfall differences to simulated ground thermal responses. By tracing uncertainty from precipitation phase assignment to snowfall–rainfall forcing, ground thermal



diagnostics, and permafrost classification, this study provides a controlled assessment of PPP as a previously underexamined source of uncertainty in permafrost thermal simulations over the TP.

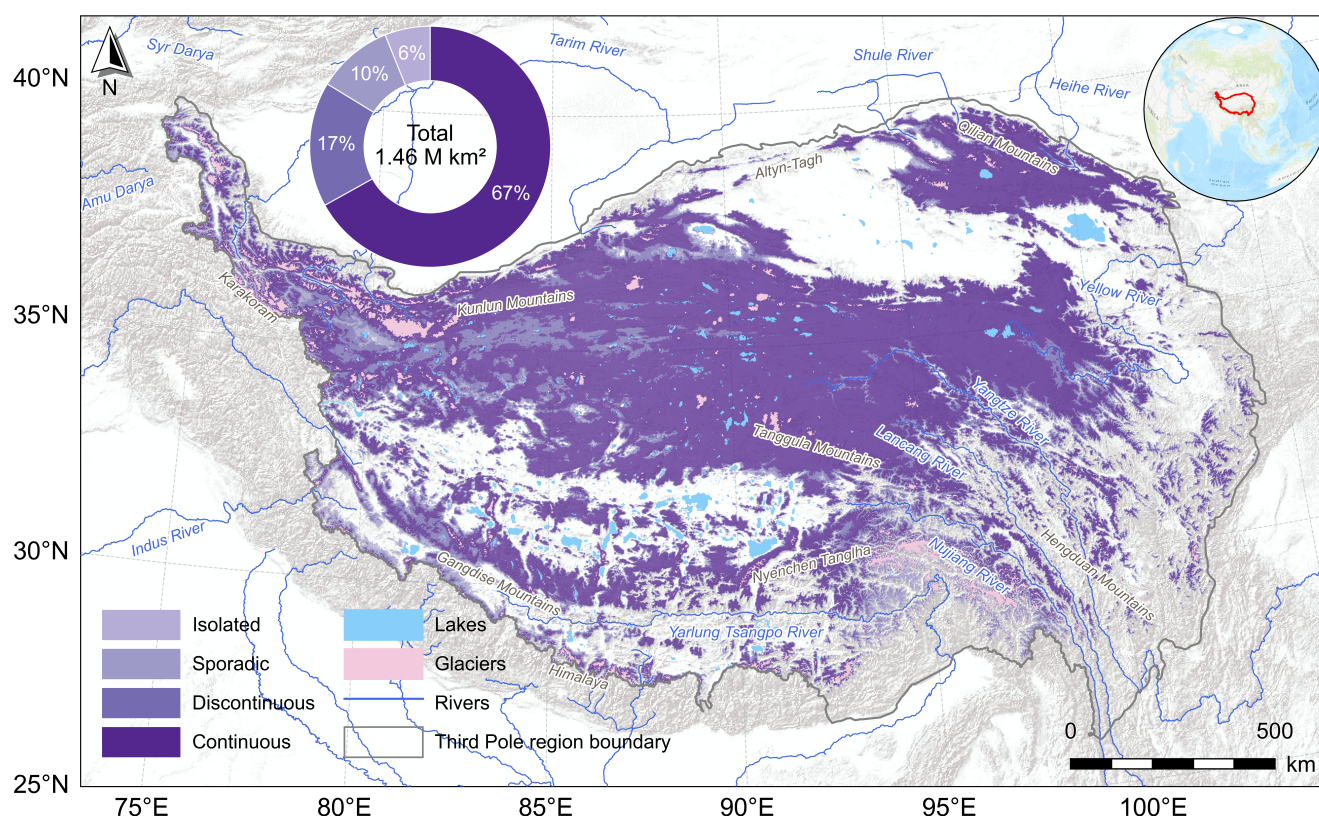


Figure 1. Map of the Tibetan Plateau showing the extent of continuous, discontinuous, sporadic, and isolated permafrost derived from the Northern Hemisphere Permafrost Map (Obu et al., 2019). The donut chart shows the percentage of permafrost area in each type. The background basemap is based on Esri World Topographic Map tiles from ArcGIS online (Esri, 2026 | Powered by Esri).

2 Methods

95 2.1 Model description

We used CryoGridLite, a one-dimensional transient numerical permafrost model (Nitzbon et al., 2023; Langer et al., 2024), to quantify the uncertainty in simulated permafrost thermal regimes over the TP during 1951–2024 arising from different PPP schemes. The surface energy balance, driven by meteorological forcing, provided the upper boundary condition (Chen et al., 2025). Subsurface heat transfer with freeze–thaw phase change was then solved using an enthalpy-based formulation, with
 100 volumetric enthalpy as the prognostic state variable. The lower boundary condition was prescribed as a constant geothermal



heat flux. Compared with the previous version of CryoGridLite, we updated the soil thermal property parameterizations of Dai et al. (2019a, b) and the Balland and Arp scheme (Balland and Arp, 2005), allowing the effect of gravel on volumetric heat capacity and thermal conductivity to be represented explicitly (see Appendix A for details and equations). Surface and subsurface hydrological processes were simulated using a simple bucket scheme (Chen et al., 2025). Liquid water from rainfall and snowmelt was allowed to infiltrate into the soil column when pore space was available, and the near-surface soil was unfrozen, whereas excess water was routed as runoff or drainage. The seasonal snowpack scheme allowed the model to simulate snow accumulation, ablation, liquid-water routing, and refreezing within the snow cover. We also replaced the prescribed constant snow density used in the previous CryoGridLite version (Chen et al., 2025) with a dynamic snow-density scheme (Dutra et al., 2010; van Kampenhout et al., 2017) that accounts for fresh snow density, mechanical compaction due to overburden pressure, thermal metamorphism, and melt-related snow density changes (see Appendix B for details and equations).

2.2 Model setup and initialization

CryoGridLite was configured for grid cell simulations over the TP, excluding lakes and glaciers. Each grid cell was simulated independently using gridded meteorological forcing and subsurface parameters. These inputs were used to define the vertical soil stratigraphy, initialize the thermal and hydrological states, and drive the coupled surface energy balance, snowpack, hydrological, and subsurface heat-transfer processes.

The model was forced with the China Meteorological Forcing Dataset version 2.0 (CMFD V2.0; time range: 1951–2024; resolution: 3 h and $0.1^\circ \times 0.1^\circ$; He et al. (2020)), including surface air temperature (K), precipitation rate ($\text{kg m}^{-2} \text{s}^{-1}$), specific humidity (kg kg^{-1}), surface pressure (Pa), downward shortwave and longwave radiation (W m^{-2}), and wind speed (m s^{-1}). The original 3-hourly forcing data were processed to an hourly time step and converted to the units required by CryoGridLite. Instantaneous variables (i.e., surface air temperature, specific humidity, surface pressure, and wind speed) were linearly interpolated to hourly values, whereas radiation and precipitation were processed as 3-hourly mean fluxes to preserve the corresponding energy and water amounts.

For each grid cell, the subsurface column extended from the soil surface (0 m) to a lower boundary at 100 m, with vertical grid spacing increasing with depth, and gridded soil property datasets were assigned to the corresponding vertical soil layers. Volumetric fractions of mineral (i.e., sum of sand, silt and clay), organic matter, gravel, and air constituted the soil stratigraphy. Meanwhile, field capacity was estimated from the van Genuchten model (van Genuchten, 1980), using porosity, residual water content, the inverse of the air-entry parameter α , and log-10 transformation shape parameter n from the soil property datasets. Bedrock depth was used to distinguish soil and bedrock layers within the subsurface column. Soil properties below the deepest available soil layer (i.e., 3.8019 m) were extended downward to the bedrock depth. Below the bedrock depth, we assumed that organic matter was set to zero, porosity was limited to a maximum of 0.1, and gravel content was increased relative to the deepest soil layer but constrained by the available solid fraction. The remaining solid fraction was assigned to mineral soil. Field capacity and residual water content were adjusted by the reduced porosity of the bedrock layer. Water-table depth was used to define the initial subsurface hydrological state. Following Langer et al. (2023), the initial water/ice content above the water table was assumed halfway between field capacity and porosity, whereas layers below the water table were initialized



as saturated. The partitioning between liquid water and ice was then determined by the initial soil temperature relative to the freezing point (0 °C). The initial soil temperature profile was interpolated from the mean annual ERA5-Land soil temperature data of four layers in 1951 (start time of the simulation). Below 2.89 m, the deepest soil layer available in ERA5-Land, the temperature profile was extrapolated downward using a one-dimensional conductive heat transfer equation with a constant geothermal heat flux. The initial temperature above the soil surface was set to the mean surface air temperature during the first decade of the forcing period. Unlike our previous study (Chen et al., 2025), which used a uniform maximum snow depth across the model domain, the snow domain in this study extended upward from the soil surface to a grid cell-specific maximum snow depth derived from a snow-depth dataset.

To obtain a quasi-equilibrium initial ground thermal regime at the start of the simulation, we performed a dynamic spin-up strategy. The model was repeatedly driven by the forcing from the first decade (i.e., 1951–1960) of the simulation period until the maximum absolute difference in monthly mean ground temperature at 15 m depth between two consecutive spin-up cycles was below 0.1 °C (Ji et al., 2022; Ross et al., 2022). For input datasets with spatial resolutions different from the simulation grid, each grid cell in the model domain was assigned the value of the nearest grid point in the corresponding source dataset. Table 1 summarizes the input datasets used for model forcing and parameterization. An overview of parameters used in this study is provided in Appendix C.

2.3 Experiments

To quantify the uncertainty in simulated permafrost thermal regimes introduced by PPP schemes, we conducted eight experiments over the TP for the period 1951–2024. The experiments differed only in the scheme used to partition total precipitation into rainfall and snowfall, while all other model settings, forcing data, and subsurface parameters were kept identical. The implemented schemes include binary threshold schemes, temperature-ramp schemes, a piecewise air-temperature scheme, and wet-bulb/humidity-dependent schemes (Table 2).

Total precipitation was partitioned into rainfall and snowfall using rainfall and snowfall fractions:

$$P_{\text{rain}} = f_{\text{rain}} P_{\text{total}}, \quad P_{\text{snow}} = f_{\text{snow}} P_{\text{total}}, \quad f_{\text{rain}} + f_{\text{snow}} = 1, \quad (1)$$

where P_{total} is total precipitation from the meteorological forcing, P_{rain} is rainfall, P_{snow} is snowfall, and f_{rain} and f_{snow} are the rainfall and snowfall fractions, respectively.

For the binary threshold schemes, precipitation was assigned entirely to snowfall or rainfall according to scheme-specific air-temperature thresholds. For the Simple0 and JULES experiments, the rainfall fraction was calculated as:

$$f_{\text{rain}} = \begin{cases} 0, & T_{\text{air}} \leq T_{\text{th}}, \\ 1, & T_{\text{air}} > T_{\text{th}}, \end{cases} \quad (2)$$

where T_{th} was set to 0 °C and 0.85 °C, respectively. For the BATS experiment, the same binary structure was used, but rainfall occurred when $T_{\text{air}} \geq 2.2$ °C.



Table 1. Overview of datasets used in this study

Datasets	Variable/parameter	Comments	Reference/source
Tibetan Plateau Boundary Dataset	Study domain	Used to define the model domain	Zhang et al. (2021)
Shapefile of lake distribution	Lake mask	Used to exclude lake-covered grid cells	Zhang et al. (2019)
Randolph Glacier Inventory version 7.0	Glacier outlines	Used to exclude glacier-covered grid cells	RGI Consortium (2023)
China Meteorological Forcing Dataset version 2.0	Meteorological forcing	1951–2024; 3-hourly; $0.1^\circ \times 0.1^\circ$	He et al. (2020)
Global High-Resolution Dataset of Soil Hydraulic and Thermal parameters	Volumetric fractions of gravel, organic matter, sand, silt, and clay; porosity; residual water content; and van Genuchten parameters	Soil stratigraphy	Dai et al. (2019a, b)
Global Depth to Bedrock Dataset	Bedrock depth	Used to constrain soil depth	Shangguan et al. (2017)
Global Water Table Depth Dataset	Water table depth	Used to initialize the soil hydrological state	Fan et al. (2013)
Terrestrial Heat Flow Dataset	Geothermal heat flux	Lower boundary conditions	Lucazeau (2019)
ERA5-Land	Four-layer soil temperature	Used to initialize the soil thermal state	Muñoz-Sabater et al. (2021)
Daily, 0.05° Snow Depth Dataset for Tibetan Plateau	Maximum snow depth	Used to define grid cell-specific maximum snow depth	Yan et al. (2022)

165 For the temperature-ramp schemes, the rainfall fraction increased linearly from 0 to 1 within a prescribed air-temperature transition interval:

$$f_{\text{rain}} = \begin{cases} 0, & T_{\text{air}} \leq T_{\text{low}}, \\ \frac{T_{\text{air}} - T_{\text{low}}}{T_{\text{high}} - T_{\text{low}}}, & T_{\text{low}} < T_{\text{air}} < T_{\text{high}}, \\ 1, & T_{\text{air}} \geq T_{\text{high}}, \end{cases} \quad (3)$$

where T_{low} and T_{high} are the lower and upper bounds of the transition interval, respectively. For the CLM experiment, $T_{\text{low}} = 0^\circ\text{C}$ and $T_{\text{high}} = 2^\circ\text{C}$. For the VIC experiment, $T_{\text{low}} = -0.5^\circ\text{C}$ and $T_{\text{high}} = 0.5^\circ\text{C}$.



Table 2. Overview of precipitation phase-partitioning experiments.

Experiment	Scheme type	Description	Reference
Simple0	Binary threshold	Partitions precipitation into rainfall or snowfall using a single air temperature threshold of 0 °C	Langer et al. (2024)
JULES	Binary threshold scheme	Same as Simple0, but using a higher air temperature threshold of 0.85 °C, following the JULES setting	Yang et al. (2020)
CLM	Temperature ramp scheme	Partitions precipitation gradually between snowfall and rainfall across a prescribed air temperature transition interval	Lawrence et al. (2019)
BATS	Binary threshold scheme	Uses the BATS-type precipitation phase treatment implemented in Noah-MP	He et al. (2023)
VIC	Temperature ramp scheme	Uses a linear surface air temperature transition between all snow and all rain conditions	Hamman et al. (2018)
Jordan	Piecewise air-temperature scheme	Uses a piecewise relationship between air temperature and snowfall fraction	Jordan (1991)
Ding	Wet-bulb/humidity-dependent scheme	Calculates snowfall fraction from wet-bulb temperature using relative humidity and elevation-dependent transition thresholds, accounting for air temperature, humidity, pressure, and elevation	Ding et al. (2014)
Wet-Bulb	Wet-bulb/humidity-dependent scheme	Calculates snowfall fraction from wet-bulb temperature, accounting for air temperature, humidity, and pressure	Wang et al. (2019)

170 For the Jordan scheme, the snowfall fraction was calculated as a piecewise function of near-surface air temperature:

$$f_{\text{snow}} = \begin{cases} 0, & T_{\text{air}} > 2.5 \text{ }^{\circ}\text{C}, \\ 0.6, & 2.0 \text{ }^{\circ}\text{C} < T_{\text{air}} \leq 2.5 \text{ }^{\circ}\text{C}, \\ 1 - [-54.632 + 0.2(T_{\text{air}} + 273.15)], & 0.5 \text{ }^{\circ}\text{C} < T_{\text{air}} \leq 2.0 \text{ }^{\circ}\text{C}, \\ 1, & T_{\text{air}} \leq 0.5 \text{ }^{\circ}\text{C}. \end{cases} \quad (4)$$

For the Ding scheme, we adopted the dynamic wet-bulb-temperature threshold parameterization originally developed by Ding et al. (2014) and applied it in a two-phase rainfall–snowfall partitioning form following Xu et al. (2024). The snowfall



fraction was calculated as

$$f_{\text{snow}} = \begin{cases} 1, & T_w \leq T_{\min}, \\ \frac{1}{1 + \exp\left[\frac{T_w - T_0}{\Delta S}\right]}, & T_{\min} < T_w < T_{\max}, \\ 0, & T_w \geq T_{\max}. \end{cases} \quad (5)$$

where T_w is the wet-bulb temperature. The dynamic transition thresholds $T_{\min}$ and $T_{\max}$ were determined from relative humidity and surface elevation through

$$\Delta T = 0.215 - 0.099RH + 1.018RH^2, \quad (6)$$

$$\Delta S = 2.374 - 1.634RH, \quad (7)$$

$$T_0 = -5.87 - 0.1042Z + 0.0885Z^2 + 16.06RH - 9.614RH^2, \quad (8)$$

where RH is relative humidity, ranging from 0 to 1, and Z is surface elevation in km. The lower and upper wet-bulb temperature thresholds were calculated as

$$T_{\min} = \begin{cases} T_0 - \Delta S \ln \left[\exp\left(\frac{\Delta T}{\Delta S}\right) - 2 \exp\left(-\frac{\Delta T}{\Delta S}\right) \right], & \frac{\Delta T}{\Delta S} > \ln 2, \\ T_0, & \frac{\Delta T}{\Delta S} \leq \ln 2, \end{cases} \quad (9)$$

and

$$T_{\max} = \begin{cases} 2T_0 - T_{\min}, & \frac{\Delta T}{\Delta S} > \ln 2, \\ T_0, & \frac{\Delta T}{\Delta S} \leq \ln 2. \end{cases} \quad (10)$$

For the Wet-Bulb scheme, the snowfall fraction was calculated from wet-bulb temperature:

$$f_{\text{snow}} = \begin{cases} 0, & T_{\text{air}} \geq 8^\circ\text{C}, \\ \frac{1}{1 + a \exp[b(T_w + c)]}, & T_{\text{air}} < 8^\circ\text{C}, \end{cases} \quad (11)$$

where T_w is the wet-bulb temperature, and $a = 6.99 \times 10^{-5}$, $b = 2.0$, and $c = 3.97$. The wet-bulb temperature was calculated from air temperature, water vapor pressure, and surface pressure following the Noah-MP Wet-Bulb formulation (Wang et al., 2019).

2.4 Diagnostics

We diagnosed the effects of PPP on the thermal regime of permafrost using three key diagnostics: mean annual ground temperature at 10 m depth ($\text{MAGT}_{10\text{m}}$; $^\circ\text{C}$), maximum annual thaw depth within the upper 10 m depth of the subsurface (TD; m), and the permafrost area (PA; km^2), following previous studies (Nitzbon et al., 2023; Langer et al., 2024; Zhao et al., 2025;



195 Brown and Gruber, 2026; Nitzbon et al., 2026). For each year, permafrost was identified where $MAGT_{10m}$ was below $0^{\circ}C$ (Obu et al., 2019; Ran et al., 2022; Steinert et al., 2024). TD was reported only for grid cells satisfying this criterion; otherwise, the grid cell was treated as non-permafrost and no thaw depth was assigned. The PA was calculated by summing the area of all grid cells identified as permafrost, using an Albers Equal Area projection for area calculation (Zhang et al., 2022). Additionally, we point out that this study focuses on quantifying the effects of PPP schemes on simulated permafrost thermal regime, rather than assessing the performance of CryoGridLite. The ability of CryoGridLite to simulate ground thermal regimes has been evaluated against observations in previous applications over both the pan-Arctic and the TP (Langer et al., 2024; Chen et al., 2025). Here, we therefore used the model outputs to compare the diagnosed permafrost thermal states across the eight phase-partitioning experiments.

3 Results

205 3.1 Precipitation phase-partitioning schemes reshape the snowfall and rainfall forcing

Different PPP schemes produced markedly different snowfall fractions within the near-freezing temperature range (Fig. 2a). Among these schemes, the binary-threshold schemes generated abrupt transitions from snowfall to rainfall, with Simple0 switching at $0.0^{\circ}C$, JULES at $0.85^{\circ}C$, and BATS retaining snowfall up to a higher temperature threshold of $2.2^{\circ}C$. By contrast, the temperature-ramp schemes described more gradual transitions over prescribed temperature intervals (T_{low} and T_{high}), with CLM and VIC following linear ramp functions and the Jordan scheme displaying a piecewise transition. The Wet-Bulb scheme was characterized by a smoother transition based on wet-bulb temperature, whereas the Ding scheme produced a range of transition curves because its snowfall fraction depends not only on wet-bulb temperature but also on relative humidity and elevation. These differences indicated that the precipitation phase assignment is most sensitive to scheme choice under near-freezing conditions.

215 The CMFD version 2.0 forcing data showed a domain-mean annual precipitation of about $585.69 \text{ mm yr}^{-1}$ over the TP during 1951–2024 (Fig. 2b). Because all schemes were applied to the same precipitation forcing, the total annual precipitation remained nearly identical among schemes; however, the partitioning schemes redistributed this total precipitation differently between rainfall and snowfall. Simple0 and VIC assigned the largest amounts of precipitation to rainfall, with mean annual rainfall of 458.58 and $458.49 \text{ mm yr}^{-1}$, respectively. JULES (24.89%), CLM (25.58%), Jordan (29.60%), and BATS (30.69%) classified progressively larger fractions of precipitation as snowfall. Wet-Bulb and Ding produced the largest snowfall amounts reaching 244.95 and $226.10 \text{ mm yr}^{-1}$, respectively, about 1.8–1.9 times the snowfall estimated by Simple0 ($127.11 \text{ mm yr}^{-1}$) and VIC ($127.20 \text{ mm yr}^{-1}$). This scheme ranking was broadly consistent with the snowfall-fraction responses in Fig. 2a, as schemes with higher snowfall fractions under near-freezing conditions also partitioned more annual precipitation into snowfall.

225 The across-scheme spread in mean annual snowfall showed clear spatial heterogeneity across the TP, generally increasing from the northwestern TP toward the southeastern TP. At the same time, local maxima occurred in mountain regions where the difference between the maximum and minimum snowfall among the eight schemes reached up to about 400 mm (Fig. 2c). This spatial pattern indicated that the effect of phase-partitioning schemes on snowfall forcing was not spatially uniform, but

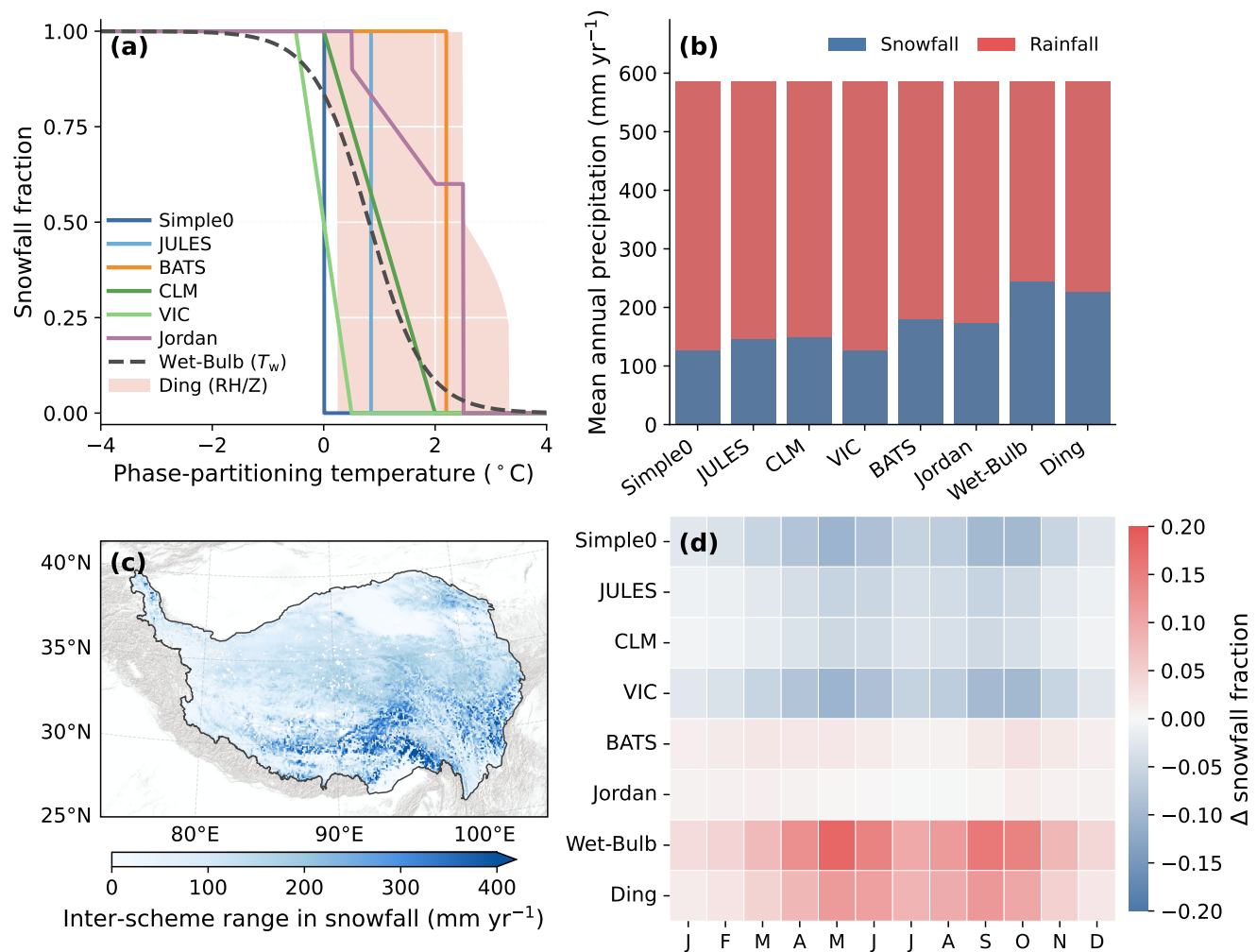


Figure 2. Scheme differences in rainfall and snowfall forcing over the Tibetan Plateau. (a) Snowfall fraction prescribed by the eight precipitation phase-partitioning schemes as a function of phase-partitioning temperature. For air-temperature-based schemes, the x-axis represents near-surface air temperature, whereas for the Wet-Bulb and Ding schemes, it represents wet-bulb temperature (T_w). The shaded range for the Ding scheme denotes the family of snowfall transfer functions generated by varying relative humidity (RH) from 0.5 to 1.0 and elevation (Z) from 3 to 5 km. (b) Domain-mean annual snowfall and rainfall amounts averaged over 1951–2024, as estimated using the eight schemes. (c) Spatial distribution of the inter-scheme range in mean annual snowfall over 1951–2024, calculated as the difference between the maximum and minimum annual snowfall amounts among the eight schemes at each grid cell. (d) Deviations of the domain-averaged monthly snowfall fraction over 1951–2024 for each scheme from the ensemble mean.



was amplified in regions where precipitation frequently occurred under near-freezing conditions. We further examined the monthly changes in domain-mean snowfall fraction relative to the ensemble mean (Fig. 2d). Simple0, JULES, CLM, and VIC showed negative deviations across the year, whereas BATS, Jordan, Wet-Bulb and Ding showed positive deviations. The largest deviations were concentrated in the warm season. In contrast, deviations were much smaller in the cold season than in the warm season, when precipitation was generally classified as snowfall. Overall, these results showed that PPP schemes substantially reshaped the snowfall and rainfall forcing, providing the forcing-level basis for subsequent differences in simulated permafrost thermal regimes.

3.2 Precipitation phase-partitioning schemes induce uncertainty in mean annual ground temperature at 10 m depth

The ensemble-mean $MAGT_{10m}$ showed a clear spatial contrast across the TP during 1951–2024 (Fig. 3a). Colder ground thermal conditions were mainly simulated in the northwestern areas of the Changtang Plateau, whereas warmer conditions occurred toward the marginal permafrost region and the Three River Sources region, where the $MAGT_{10m}$ approached 0 °C. To avoid changes in the analysis domain among schemes, we used grid cells with ensemble-mean $MAGT_{10m}$ below 0 °C as a fixed ensemble-defined permafrost mask for evaluating scheme-induced thermal uncertainty.

The inter-scheme range in $MAGT_{10m}$ showed pronounced spatial heterogeneity across the ensemble-defined permafrost region (Fig. 3b). $MAGT$ differences among schemes were distributed over a large part of the permafrost domain rather than being confined to a few isolated grid cells. Within this broad pattern, particularly large ranges were concentrated in the southern and southeastern TP, as well as in several marginal and topographically complex permafrost areas. These high-range regions broadly corresponded to areas with large inter-scheme snowfall differences (Fig. 2c), indicating that differences introduced at the PPP stage were reflected in the simulated ground thermal state.

We further analysed the area-based statistics to quantify the magnitude of this thermal uncertainty (Fig. 3c). Across the ensemble-defined PA, 91.1 % of the PA showed an inter-scheme $MAGT_{10m}$ range exceeding 0.25 °C, and 83.4 % exceeded 0.5 °C. The affected area remained substantial at higher thresholds, with 69.2 % of the PA exceeding 0.75 °C and 48.9 % exceeding 1.0 °C. Even for thresholds of 1.5 and 2.0 °C, 20.4 % and 9.2 % of the PA remained affected, respectively. These threshold-based statistics quantitatively support the spatial pattern shown in Fig. 3b, indicating that PPP-induced $MAGT_{10m}$ uncertainty was not limited to isolated grid cells, but extended over a substantial portion of the simulated PA.

Scheme-specific deviations from the ensemble mean further revealed systematic differences among the eight experiments (Fig. 3d). Simple0, JULES, CLM, and VIC generally showed positive $MAGT_{10m}$ deviations, indicating warmer-than-ensemble simulations. In contrast, Wet-Bulb and Ding were shifted toward negative deviations and exhibited pronounced cold tails, indicating that these schemes contributed most strongly to the colder end of the simulated thermal range. BATS and Jordan were closer to the ensemble mean, with BATS showing slightly negative deviations and Jordan remaining near zero. The deviation patterns were consistent with the snowfall partitioning differences shown in Fig. 2, suggesting that schemes assigning larger snowfall fractions were associated with colder simulated ground temperatures. Together, these results indicated that PPP uncertainty propagated from snowfall and rainfall forcing into the simulated permafrost thermal regime, providing the basis for subsequent differences in TD diagnostics.

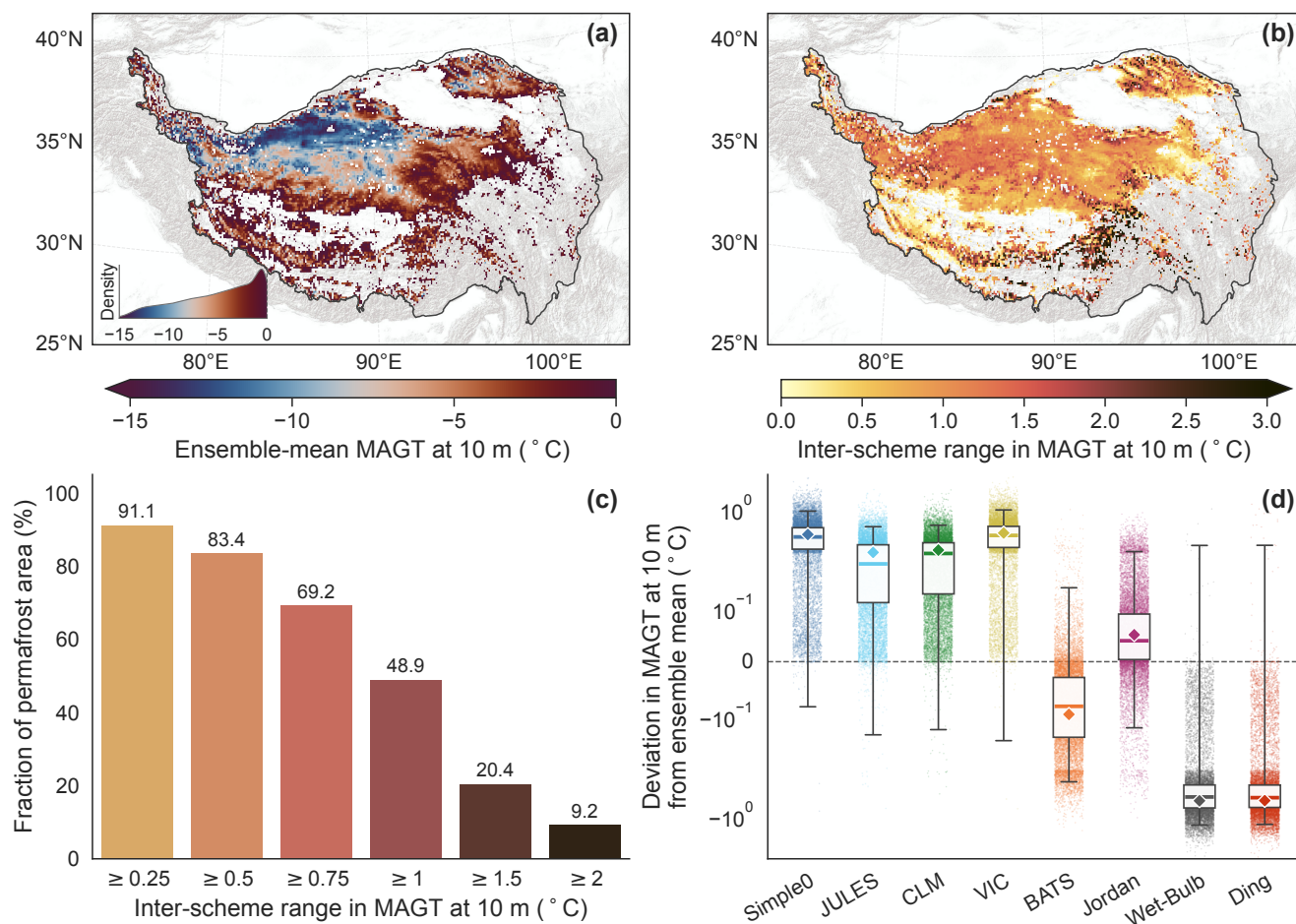


Figure 3. Scheme-induced uncertainty in simulated mean annual ground temperature at 10 m depth (MAGT_{10m}). (a) Ensemble-mean MAGT_{10m} over 1951–2024 across the eight PPP schemes. The inset shows the distribution of ensemble-mean MAGT_{10m} within the ensemble-defined permafrost area. (b) Spatial distribution of the inter-scheme MAGT_{10m} range over 1951–2024, calculated as the grid cell difference between the maximum and minimum MAGT_{10m} among the eight schemes. (c) Fraction of the ensemble-defined permafrost area where the inter-scheme MAGT_{10m} range exceeds different thresholds. (d) Grid cell distributions of scheme-specific MAGT_{10m} deviations from the ensemble mean. Boxes indicate the interquartile range, whiskers extend to 1.5 times the interquartile range, and the colored horizontal lines and diamonds indicate the median and mean, respectively. Positive values indicate warmer-than-ensemble simulations, whereas negative values indicate colder-than-ensemble simulations.

3.3 Precipitation phase-partitioning schemes induce uncertainty in maximum annual thaw depth within the upper 10 m of the ground

We next assessed whether the thermal differences among phase-partitioning schemes were reflected in the simulated TD diagnostics. The ensemble-mean TD was shallower in the colder interior permafrost regions and deeper toward warmer marginal permafrost regions (Fig. 4a). This spatial correspondence with $MAGT_{10m}$ indicated that the TD diagnostic captured the near-surface expression of the simulated ground thermal state. To make the TD comparison consistent across experiments, TD was evaluated using the same ensemble-defined permafrost mask as in the $MAGT_{10m}$ analysis.

Unlike the widespread $MAGT_{10m}$ differences, the TD response to phase-partitioning schemes was more spatially localized (Fig. 4b). Large inter-scheme differences in TD occurred mainly along marginal permafrost zones and in local mountain regions, while much of the colder interior permafrost region showed limited TD differences among schemes. This contrast suggests that the propagation from thermal state uncertainty to TD uncertainty was not uniform: some regions showed clear TD sensitivity, whereas others remained relatively insensitive despite scheme-dependent differences in snowfall forcing.

The threshold-based area statistics further highlight this localized but non-negligible TD response (Fig. 4c). An inter-scheme TD range larger than 0.25 m occurred over 47.2 % of the ensemble-defined PA, whereas 18.3 % exceeded 0.5 m. The affected area declined rapidly for larger TD differences, with 10.3 % exceeding 0.75 m and 6.3 % exceeding 1.0 m. Only 3.3 % and 2.2 % of the PA exceeded thresholds of 1.5 and 2.0 m, respectively. Thus, compared with the $MAGT_{10m}$ response, TD uncertainty was less spatially extensive, but it still reached meter-scale differences in localized areas.

At the scheme level, the TD deviations were generally more concentrated around zero than the corresponding $MAGT_{10m}$ deviations, indicating that scheme-induced thermal differences translated into thaw-depth changes only in part of the permafrost domain (Fig. 4d). Nevertheless, the direction of the deviations remained broadly consistent with the thermal response: Simple0 and VIC tended to produce deeper-than-ensemble TD, whereas Wet-Bulb and Ding more frequently produced shallower-than-ensemble TD and showed the most pronounced negative tails. JULES and CLM were clustered close to the ensemble mean, while BATS and Jordan showed weakly negative or near-zero deviations. These distributions suggest that PPP uncertainty affected TD mainly through localized shifts toward deeper or shallower seasonal thaw.

3.4 Precipitation phase-partitioning schemes affected simulated permafrost area and diagnosis

We further examined whether the scheme-induced differences in $MAGT_{10m}$ and TD propagated into diagnosed permafrost-area estimates. Diagnosed PA followed a similar temporal evolution across all eight experiments with a slight increase during the early decades, followed by a relatively stable phase and a decline after the late twentieth century (Fig. 5a). By 2024, the ensemble-mean simulated PA was $1.33 \times 10^6 \text{ km}^2$, with scheme-specific estimates ranging from $1.29 \times 10^6 \text{ km}^2$ in VIC to $1.40 \times 10^6 \text{ km}^2$ in Wet-Bulb. Given that the same meteorological forcing drove all experiments, this common temporal pattern reflected the shared forcing background and the transient response of the simulated ground thermal regime.

Despite this common temporal evolution, the area estimates differed systematically among schemes. Wet-Bulb and Ding generally diagnosed the largest PA, followed by BATS, whereas Simple0 and VIC generally diagnosed the smallest areas (Fig. 5a).

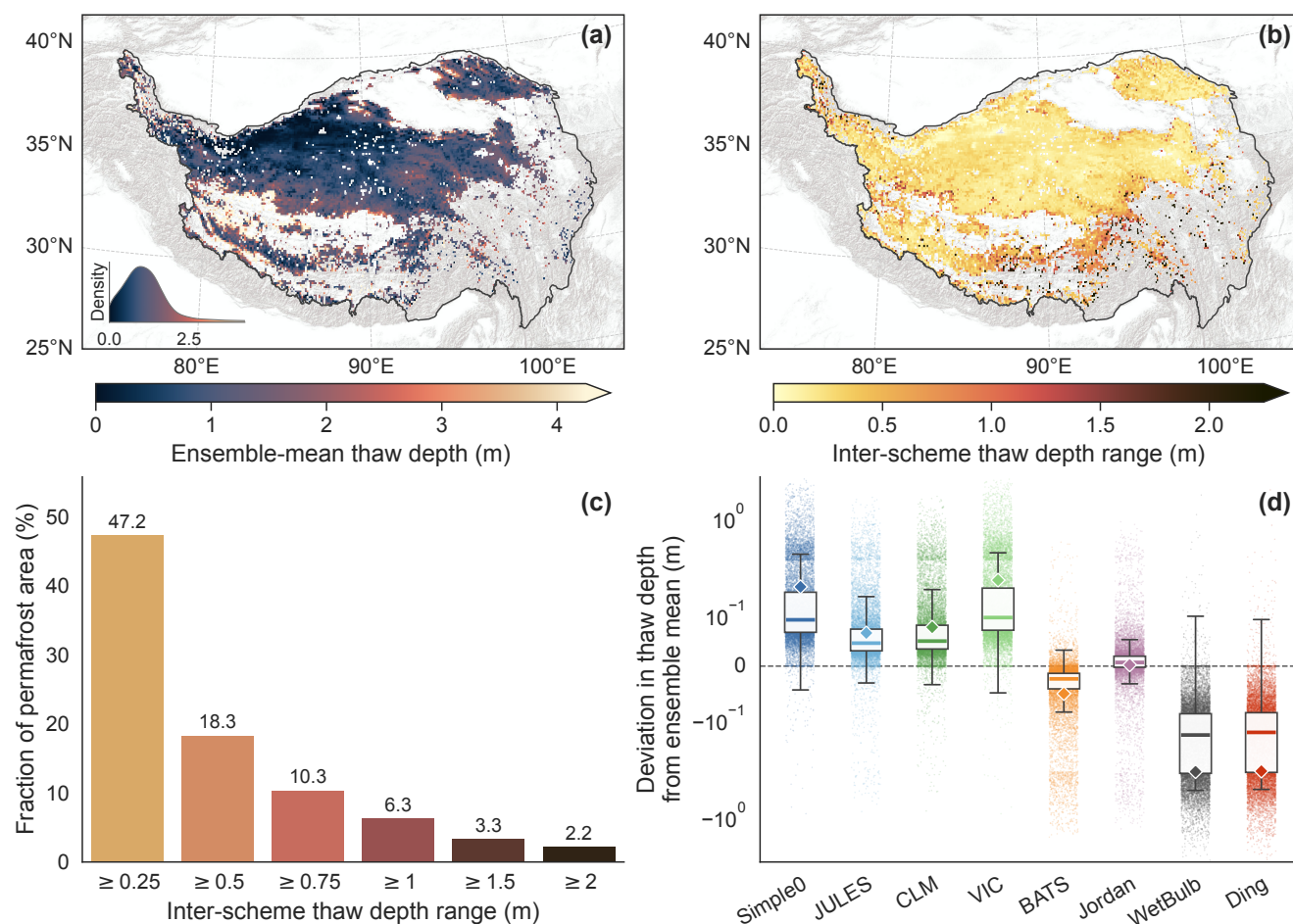


Figure 4. Scheme-induced uncertainty in simulated thaw depth within the upper 10 m of the ground (TD). (a) Ensemble-mean TD within the upper 10 m over 1951–2024 across the eight precipitation phase-partitioning schemes. The inset shows the distribution of ensemble-mean TD within the ensemble-defined permafrost area. (b) Spatial distribution of the inter-scheme TD range during 1951–2024, calculated as the grid cell difference between the maximum and minimum TD among the eight schemes. (c) Fraction of the ensemble-defined permafrost area where the inter-scheme TD range exceeds different thresholds. (d) Grid cell distributions of scheme-specific TD deviations from the ensemble mean. Boxes indicate the interquartile range, whiskers extend to 1.5 times the interquartile range, and the colored horizontal lines and diamonds indicate the median and mean, respectively. Positive values indicate deeper-than-ensemble simulations, whereas negative values indicate shallower-than-ensemble simulations.



295 This ordering was consistent with the scheme-specific thermal responses, in which colder-than-ensemble simulations retained larger PA and warmer-than-ensemble simulations diagnosed smaller areas. The spread across schemes in threshold-based area estimates persisted throughout the simulation period and tended to increase slightly toward recent decades, remaining approximately on the order of $0.09\text{--}0.11 \times 10^6 \text{ km}^2$ (Fig. 5b). This result indicated that PPP introduced a persistent uncertainty into PA estimates, and that this uncertainty may become more relevant under continued warming.

300 A comparison between the early (1951–1975) and recent (2000–2024) periods further quantified the scheme dependence in diagnosed PA (Fig. 5c). During 1951–1975, the diagnosed PA ranged from $1.36 \times 10^6 \text{ km}^2$ in VIC to $1.46 \times 10^6 \text{ km}^2$ in Wet-Bulb. During 2000–2024, the diagnosed PA decreased across all schemes, ranging from $1.32 \times 10^6 \text{ km}^2$ in VIC to $1.42 \times 10^6 \text{ km}^2$ in Wet-Bulb. The corresponding PA loss varied from $0.034 \times 10^6 \text{ km}^2$ in Ding to $0.046 \times 10^6 \text{ km}^2$ in VIC (Fig. 5d), equivalent to a relative decline of 2.33–3.36 %. These results indicated that PPP schemes affected both the diagnosed
 305 PA and the estimated magnitude of area loss, while all schemes consistently indicated an overall reduction in PA.

Beyond the temporal evolution of diagnosed PA, we further evaluated the spatial consistency of permafrost diagnosis among the eight schemes. The spatial pattern during 2000–2024 showed that most grid cells were classified consistently across the eight schemes (Fig. 6a). Robust non-permafrost, where none of the schemes diagnosed permafrost, accounted for 44.4 % of the model domain, whereas robust permafrost, where all eight schemes diagnosed permafrost, accounted for 51.1 %. In contrast,
 310 the scheme-dependent diagnostic zone, where one to seven schemes diagnosed permafrost, occupied only 4.5 % of the model domain. This result indicated that the effect of PPP on permafrost diagnosis was spatially constrained and mainly concentrated along the margins of the simulated permafrost region.

Within the scheme-dependent diagnostic zone, the degree of agreement among schemes was uneven (Fig. 6b). The largest portion occurred where two schemes diagnosed permafrost, covering $40.0 \times 10^3 \text{ km}^2$, followed by areas where three schemes
 315 diagnosed permafrost, covering $20.5 \times 10^3 \text{ km}^2$. Areas diagnosed as permafrost by one, four, and six schemes were smaller but still comparable, covering 13.6 , 14.3 , and $14.6 \times 10^3 \text{ km}^2$, respectively. By contrast, areas where five or seven schemes diagnosed permafrost were limited, covering 6.0 and $6.1 \times 10^3 \text{ km}^2$, respectively. Overall, these results showed that PPP uncertainty propagated into permafrost-area and spatial-diagnosis estimates, but its impact was more spatially constrained than its effect on $\text{MAGT}_{10\text{m}}$ and TD.

320 4 Discussion

4.1 Potential physical pathways from precipitation phase partitioning to ground thermal responses

PPP is not only a source of uncertainty in rainfall and snowfall forcing, but also alters the surface conditions through which energy and water are transferred into the ground. This uncertainty is particularly relevant under near-freezing conditions, where different threshold, ramp, piecewise, wet-bulb and humidity-dependent formulations may assign the same precipitation event
 325 to different phases. Recent studies have shown that PPP methods can differ substantially around the rain–snow transition and can affect simulated snowfall fraction, snowpack accumulation and melt, snow phenology, and hydrological states in snow, hydrological, and land surface models (Harpold et al., 2017; Jennings and Molotch, 2019; Leroux et al., 2023; Jennings et al.,

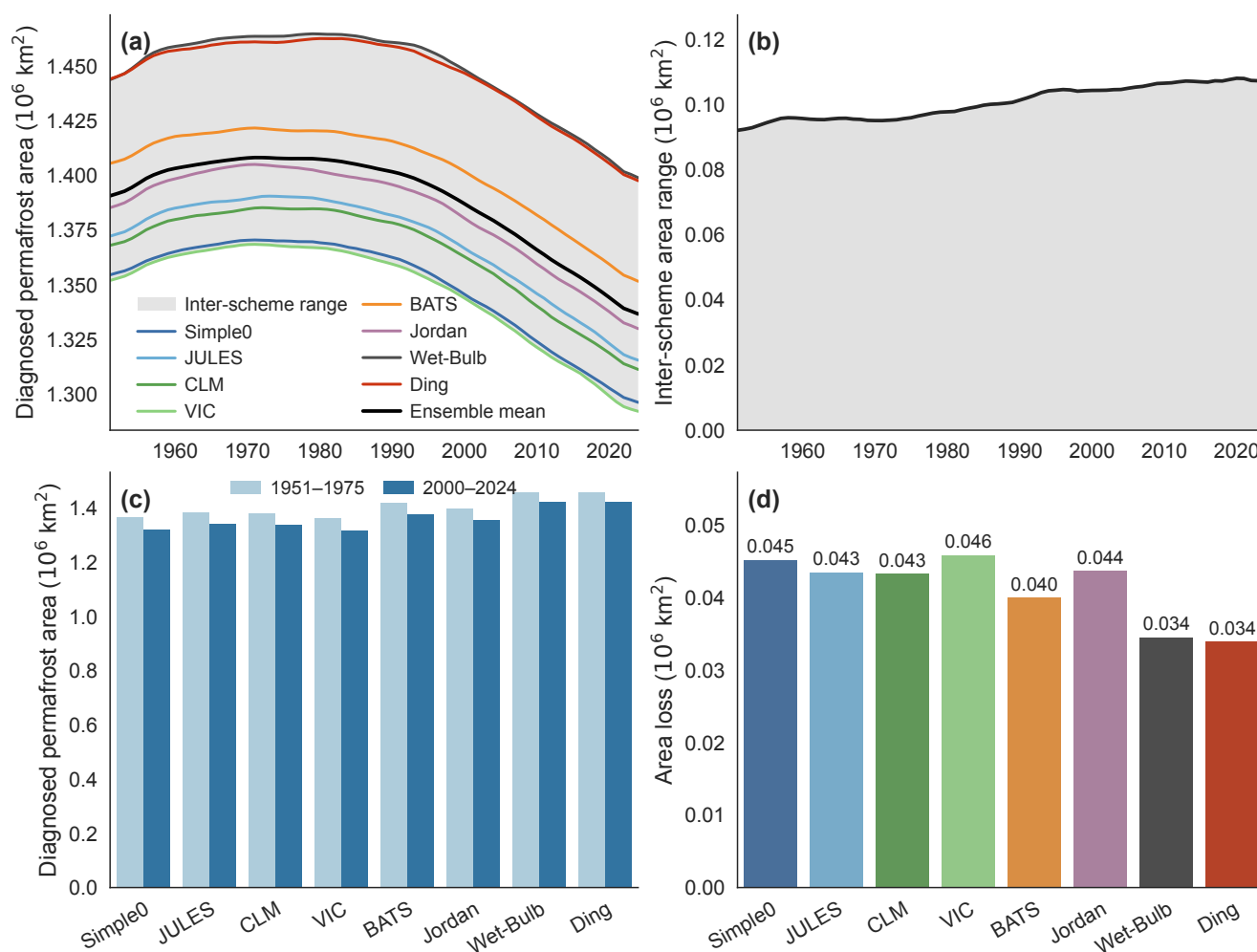


Figure 5. Impacts of precipitation phase-partitioning schemes on diagnosed permafrost area during 1951–2024. (a) Temporal evolution of diagnosed permafrost area across the eight schemes. Colored lines indicate 5-year moving averages for individual schemes, the black line indicates the ensemble mean, and the grey shading indicates the inter-scheme range. (b) Temporal evolution of the inter-scheme range in diagnosed permafrost area, shown as a 5-year moving average. (c) Mean diagnosed permafrost area during the early period (1951–1975) and recent period (2000–2024). (d) Permafrost-area loss between the early and recent periods, calculated as the early-period mean minus the recent-period mean.

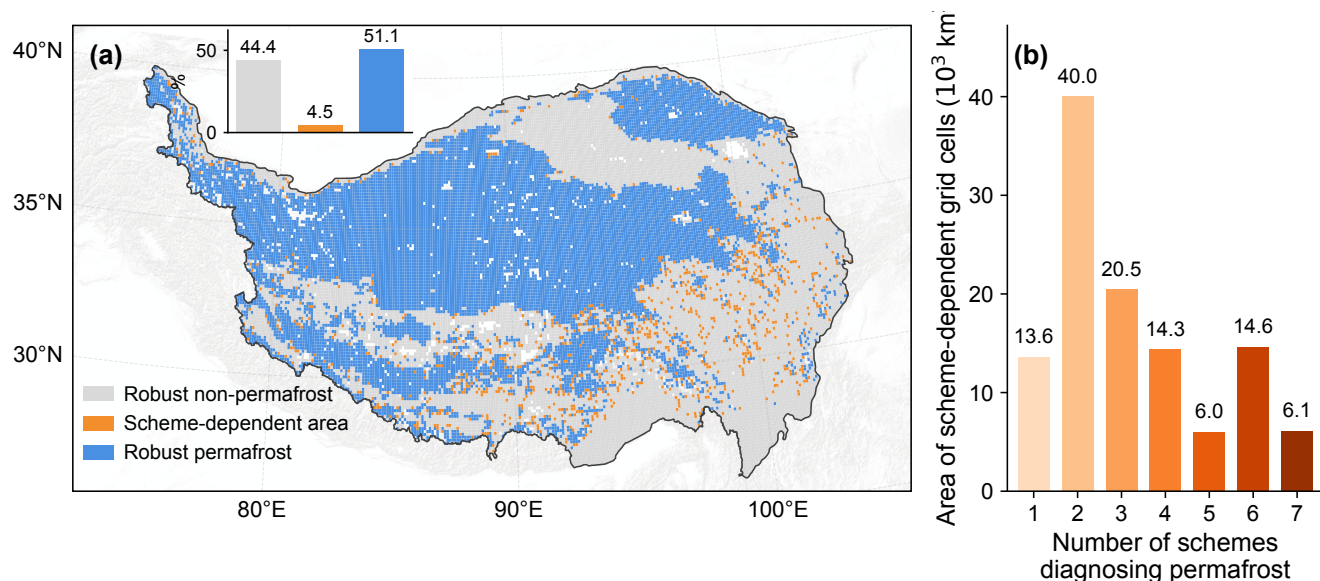


Figure 6. Spatial uncertainty in simulated permafrost diagnosis during 2000–2024. (a) Diagnostic classes derived from the number of precipitation phase-partitioning schemes diagnosing permafrost at each grid cell. Robust non-permafrost and robust permafrost indicate grid cells where none or all eight schemes diagnosed permafrost, respectively; the scheme-dependent diagnostic zone indicates grid cells where one to seven schemes diagnosed permafrost. The inset shows the area fraction of the three diagnostic classes. (b) Area distribution of the scheme-dependent diagnostic zone by the number of schemes diagnosing permafrost. Permafrost was diagnosed based on whether the 2000–2024 mean $MAGT_{10m}$ was below 0 °C.

2025; Liu et al., 2025; Singh et al., 2025). Here, we extend this framework to examine its effects on permafrost thermal simulations over the TP. By holding the total precipitation, meteorological forcing, model configuration, and subsurface parameters constant across experiments, our design isolates the consequences of phase assignment itself. The resulting scheme differences therefore reflect not different amounts of water input, but different seasonal pathways through which the same precipitation is expressed as snowfall or rainfall and subsequently modifies snowpack conditions, radiative exchange, and ground thermal states.

Based on the annual and seasonal rainfall–snowfall fractions under near-freezing conditions, Wet-Bulb and Ding can be interpreted as high-snowfall, low-rainfall partitioning schemes, whereas Simple0 and VIC represent low-snowfall, high-rainfall schemes (Fig. 2a, b). In our simulations, the high-snowfall, low-rainfall schemes produced colder $MAGT_{10m}$, shallower TD, and larger diagnosed PA than the low-snowfall, high-rainfall schemes (Figs. 3–5). These results demonstrate that phase-partitioning uncertainty propagates beyond the forcing level and produces coherent shifts in simulated permafrost thermal conditions. We further conducted seasonal mechanism diagnostics by comparing snow depth, surface albedo, upward short-wave radiation, and ground surface temperature between the two scheme groups for the warm season (April–October) and cold season (November–March), with each diagnostic averaged over the ensemble-defined permafrost area and across the simulated



period (1951–2024). The results suggested that this difference was primarily attributable to warm-season snow persistence and surface radiative effects. Compared with the low-snowfall, high-rainfall schemes, the high-snowfall, low-rainfall schemes maintained greater snow depth during the warm season, accompanied by higher albedo and greater upward shortwave radiation (Fig. 7a–c). Because incoming shortwave radiation was identical across the experiments, stronger upward shortwave radiation indicates reduced net shortwave radiation at the surface. This interpretation is consistent with recent snow model and snow energy balance studies showing that snow cover and snowmelt strongly affect albedo and surface net shortwave radiation, and that absorbed solar radiation controlled by snow albedo is a key component of the snow surface energy balance (Liu and Ma, 2024; Meyer et al., 2024). Thus, the relevant effect of the high-snowfall schemes is not simply that they produce more snow, but that they allow snow to persist into a season when shortwave radiative controls on surface energy uptake are important.

The ground surface temperature response further supports this pathway. High-snowfall, low-rainfall schemes simulated lower ground surface temperatures than the low-snowfall, high-rainfall schemes, with a much larger high-minus-low difference during the warm season than during the cold season (Fig. 7d). This seasonal asymmetry explains why schemes that diagnose more snowfall can produce colder, rather than warmer, simulated ground conditions: the dominant scheme-induced signal is not enhanced winter snow-insulation warming, but warm-season snow persistence that increases surface reflection, reduces net shortwave radiation at the surface, and cools the ground surface. Other rainfall- and snowfall-related processes, including liquid-water input, rain-on-snow events, infiltration or runoff, soil moisture changes, and seasonal ground heat storage, may further modulate local responses. However, the clearest pathway resolved by our diagnostics links PPP to ground thermal responses through warm-season snow persistence and surface shortwave radiation.

4.2 Different sensitivities of mean annual ground temperature, thaw depth, and diagnosed permafrost area to precipitation phase partitioning

The different responses of $MAGT_{10m}$, TD, and PA arise because these diagnostics summarize different components of the simulated permafrost system. $MAGT_{10m}$ and TD are commonly used to describe permafrost thermal conditions, but they emphasize different aspects of permafrost change and are not expected to respond identically to the same perturbation (Brown and Gruber, 2026). In our simulations, $MAGT_{10m}$ shows the broadest sensitivity to PPP because it is a continuous measure of the subsurface thermal state and can therefore record thermal offsets among schemes over large areas. By contrast, TD represents the seasonal propagation of surface and near-surface thermal perturbations into upper ground. Its response is more strongly conditioned by local soil hydrothermal properties, water–ice phase change, latent heat effects, and the depth at which thaw is diagnosed (Clayton et al., 2021; Uxa et al., 2026). PA differs from both because it is a threshold-based diagnostic rather than a continuous thermal variable. It may show limited sensitivity where permafrost is either clearly stable or clearly absent, but small thermal differences among schemes can lead to appreciable area differences in marginal permafrost regions. This is consistent with previous studies showing that estimates of PA depend strongly on the chosen diagnostic definition (Steinert et al., 2024). Thus, the three diagnostics show different forms of sensitivity rather than a single linear ranking: $MAGT_{10m}$ records broad thermal offsets, TD responds where these offsets propagate into seasonal thaw dynamics, and PA translates small thermal differences into diagnostic differences mainly near threshold conditions.

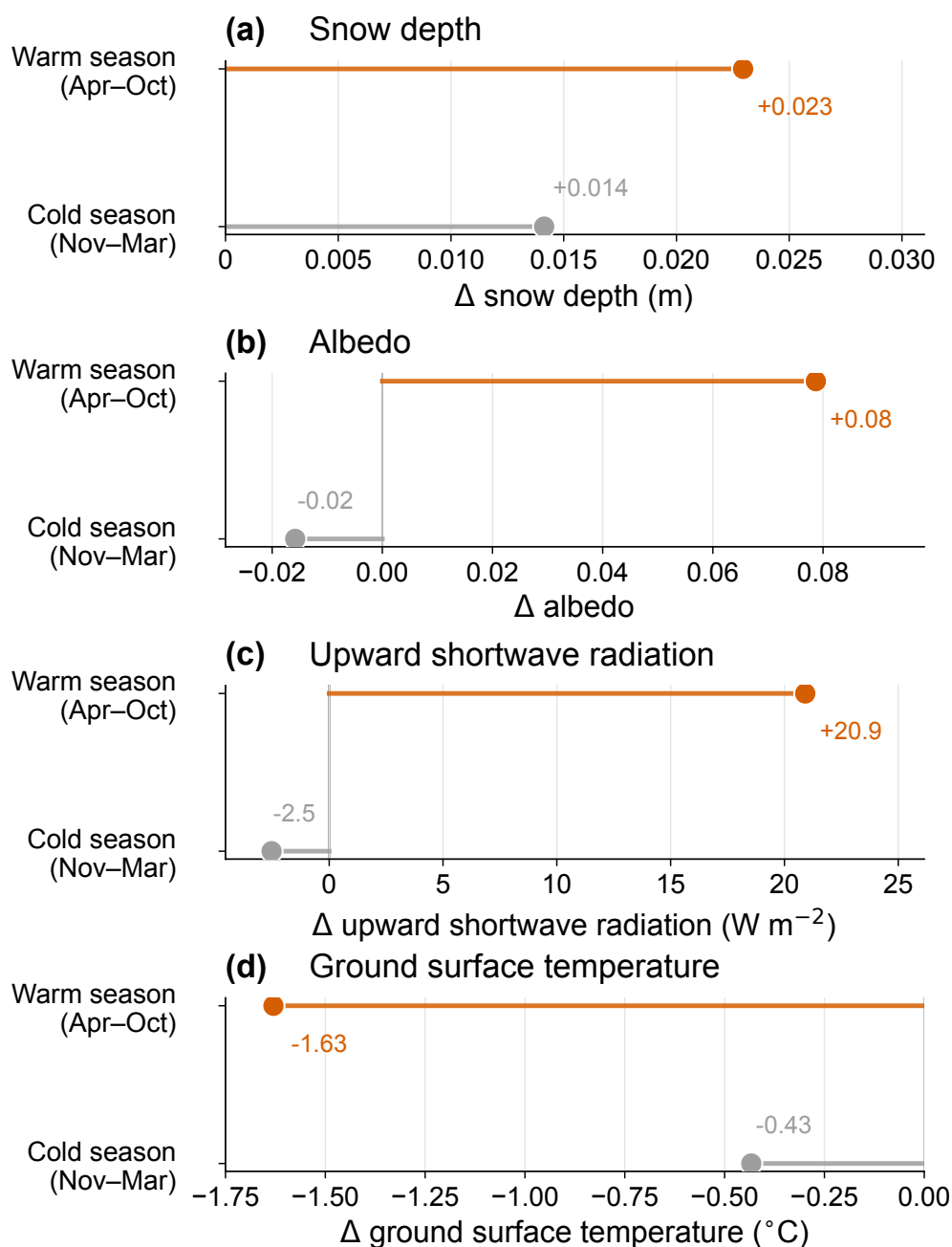


Figure 7. Seasonal differences in modelled (a) snow depth, (b) albedo, (c) upward shortwave radiation, and (d) ground surface temperature between high-snow schemes (Wet-Bulb and Ding) and low-snow schemes (Simple0 and VIC) averaged over the ensemble-defined permafrost area across 1951–2024. Values indicate high-snow schemes minus low-snow schemes.



4.3 Implications for permafrost simulations under continued warming

Although this study does not include future climate projections, the historical simulations provide useful implications for interpreting permafrost simulations under continued warming. Previous studies have projected that continued warming will alter precipitation phase regimes over the TP by reducing snowfall fractions and shifting a larger share of precipitation from snow to rain (Wang et al., 2023; Gao et al., 2025; Li et al., 2025b). In this context, uncertainty associated with rainfall–snowfall partitioning is likely to become increasingly relevant for permafrost simulations. In our simulations, the diagnosed PA follows a broadly similar temporal trajectory across all phase-partitioning schemes, suggesting that the first-order evolution is controlled by the common meteorological forcing (Fig. 5a). However, the spread across schemes in diagnosed PA increases over time (Fig. 5b), indicating that differences among phase-partitioning schemes become more apparent in area-based permafrost diagnostics as the system evolves under warming.

This increasing range does not imply that PPP would overturn the overall expectation of permafrost degradation under sustained warming (Burke et al., 2020; García-Pereira et al., 2025). Rather, it suggests that different rainfall–snowfall assumptions can shift the simulated thermal state from which thaw and degradation proceed, thereby affecting the magnitude and timing of diagnosed permafrost loss. This is particularly relevant for threshold-based quantities such as PA, for which small differences in simulated ground temperature or diagnostic definitions can alter whether marginal grid cells are classified as permafrost or non-permafrost (Slater and Lawrence, 2013; Steinert et al., 2024). Thus, PPP may contribute more strongly to uncertainty during transitional stages of permafrost degradation than under clearly stable or clearly degraded conditions.

These findings imply that PPP should be treated as a structural source of uncertainty in large-scale permafrost simulations, rather than only as a technical step in meteorological forcing preparation. Changes in snowfall and snowpack conditions can affect ground thermal trajectories and permafrost-related feedbacks (Pongracz et al., 2024; García-Pereira et al., 2025), and our results show that different phase-partitioning schemes can systematically shift simulated permafrost thermal states and diagnosed PA. For future permafrost assessments, uncertainty in rainfall–snowfall partitioning should therefore be considered when interpreting projected permafrost extent, degradation timing, and other threshold-based diagnostics, especially in high-elevation regions where small differences in snow accumulation, rainfall input, and ground thermal conditions can translate into appreciable differences in diagnosed permafrost extent.

4.4 Limitations and outlook

Our simulations were designed to isolate the effect of PPP on permafrost thermal conditions by keeping the meteorological forcing, model structure, parameter settings, and snow depth constraint identical across all experiments, while varying only the phase partitioning scheme. This implementation allows the inter-scheme differences in $MAGT_{10m}$, TD, and PA diagnostics to be attributed primarily to the choice of PPP scheme. It should be noted, however, that the results quantify the sensitivity of simulated permafrost thermal states to phase partitioning assumptions within a fixed modelling framework, rather than the full uncertainty range of TP permafrost simulations.



This advantage of the experimental design also defines its main limitation. Because the forcing data, model structure, parameter settings, and snow depth constraint were held fixed, we did not test whether the magnitude and spatial pattern of the phase partitioning effect would change under alternative forcing datasets (Guo et al., 2017; Lu et al., 2020) or model parameterizations (Li et al., 2021; von Kaenel and Margulis, 2024). The diagnosed rainfall–snowfall fraction depends on near-surface air temperature, humidity, and precipitation amount, especially when conditions fluctuate around 0 °C (Jennings et al., 2018; Wang et al., 2019; Jennings et al., 2025). Biases in these forcing variables may therefore affect both simulated snowfall and rainfall amounts (Appendix D1). Changes in snowfall influence snow accumulation, snow depth evolution, and snow insulation, whereas changes in rainfall can affect liquid-water input, rain-on-snow processes, infiltration or runoff, soil moisture, and near-surface heat transfer (Westermann et al., 2011; Dutch et al., 2022; Zhang et al., 2026). The resulting ground thermal response also depends on how the model represents snow density evolution, liquid water retention, surface energy exchange, and soil heat transfer (Dutch et al., 2022; Tao et al., 2024; Damseaux et al., 2025; Yang et al., 2025). The magnitude and spatial pattern of the inter-scheme differences may therefore differ if alternative forcing datasets, snow parameterizations, hydrological parameterizations, or soil thermal parameterizations are used.

A further limitation concerns the model representation of the processes that mediate the response of the ground thermal regime to changes in rainfall and snowfall. CryoGridLite has been evaluated for simulating permafrost thermal regimes across the pan-Arctic (Nitzbon et al., 2023; Langer et al., 2024) and the TP (Chen et al., 2025), and several model components were further developed in this study to improve the representation of snow and subsurface thermal processes. These developments included soil thermal conductivity and heat capacity schemes that account for gravel content (Appendix A), a dynamic snow-density scheme representing snow compaction, snow metamorphism, liquid-water retention, and rain-on-snow processes (Appendix B), together with an additional constraint on maximum snow depth using a fine-resolution snow-depth dataset (Yan et al., 2022). Nevertheless, as a computationally efficient one-dimensional permafrost model, CryoGridLite still overlooks or simplifies some surface and subsurface processes through which precipitation-phase differences are translated into soil temperature and thaw diagnostics (Langer et al., 2024; Chen et al., 2025). Three aspects are particularly relevant here.

First, CryoGridLite treats soil freezing and thawing using a free-water enthalpy–temperature formulation rather than soil-specific freezing characteristic curves (Devoie et al., 2022; Wang et al., 2025). This simplification may overestimate the latent heat required for thaw-front progression in clay- and silt-rich soils, where matric and adsorptive forces allow part of the pore water to remain unfrozen below 0 °C. It may therefore contribute to an underestimation of active layer thickness in fine-textured soils.

Second, vegetation is not explicitly represented in the current model setup. The simulated surface types are limited to bare ground, snow, ice, and water, and therefore do not account for vegetation-mediated controls on the ground thermal regime. Vegetation regulates the ground thermal regime by modifying radiative and turbulent fluxes, moisture exchange and surface insulation through canopy shading, aerodynamic roughness, evapotranspiration, precipitation interception, snow redistribution and near-surface organic matter accumulation (Loranty et al., 2018; Zwieback et al., 2019; Grünberg et al., 2020; Stuenzi et al., 2021a, b; Heijmans et al., 2022; Yuan et al., 2025; Travers-Smith et al., 2025; Stuenzi et al., 2026).



Third, each grid cell in the model domain is represented by an independent one-dimensional soil column that resolves vertical processes but cannot capture lateral subsurface heat and water transfer and snow redistribution arising from subgrid-scale heterogeneity. Multi-dimensional modelling studies have shown that these processes can significantly influence the transient evolution of permafrost, especially in complex terrain (Noetzli and Gruber, 2009; Aas et al., 2019; Nitzbon et al., 2021; Sun et al., 2023). This limitation is particularly relevant to the TP, where pronounced within-grid variations in elevation, slope, and aspect make simulated ground thermal states particularly sensitive to the omission of lateral processes, potentially affecting both their spatial patterns and magnitudes.

These structural simplifications may influence the simulated permafrost thermal state and the magnitude of thaw-related responses, although the controlled experimental design still allows the relative inter-scheme differences to be attributed primarily to PPP. Future work should therefore focus on whether the inter-scheme differences identified in this study remain consistent across different meteorological forcing and model configurations. Simulations driven by multiple forcing products would allow the sensitivity of these differences to uncertainties in near-surface air temperature, humidity, and precipitation to be quantified. Additionally, experiments with alternative representations of snowpack physics, near-surface hydrology, and soil thermal properties would further indicate how strongly the reported spread depends on specific process parameterizations. Incorporating soil freezing characteristic curves, explicitly representing permafrost–vegetation interactions, and accounting for lateral subsurface heat and water transfer as well as snow redistribution would also help assess how these processes modify the simulated response to rainfall–snowfall partitioning. Such experiments would place the present single configuration sensitivity analysis within a broader modelling uncertainty framework.

5 Conclusions

This study quantified how PPP schemes affect simulated permafrost thermal conditions over the TP using a CryoGridLite modelling framework tailored for controlled PPP sensitivity experiments. Meteorological forcing, model configuration, and subsurface parameters were held constant across experiments, allowing the effect of rainfall–snowfall phase assignment itself to be isolated. The results show that PPP can lead to systematic differences in simulated snowfall and rainfall fractions, snow conditions, surface energy exchange, and permafrost thermal diagnostics.

The largest contrasts occurred between the high-snowfall schemes, represented by Wet-Bulb and Ding, and the low-snowfall schemes, represented by Simple0 and VIC. The former produced colder $MAGT_{10m}$, shallower TD, and larger diagnosed permafrost area than the latter. Seasonal diagnostics suggest that this cooling response was linked mainly to warm-season snow persistence and associated radiative effects. In the high-snowfall simulations, greater snow depth during April–October increased surface albedo and upward shortwave radiation, thereby reducing shortwave radiation absorbed at the surface and cooling the near-surface ground.

These findings indicate that PPP should be treated as an explicit forcing-related source of uncertainty in permafrost simulations, rather than only as a preprocessing step for meteorological forcing. Its influence is particularly relevant in high-elevation regions such as the TP, where near-freezing conditions make rainfall–snowfall assignment sensitive to the chosen empirical



475 formulation. Future permafrost assessments and projections should therefore consider phase-partitioning uncertainty when interpreting simulated ground thermal states in a changing climate.

Appendix A: Description of thermal conductivity and heat capacity schemes incorporating gravel

Gravel is a substantial component of the soil across the TP (Yi et al., 2018; Zhao et al., 2018), and its presence can significantly alter the hydrothermal properties of subground (Liu et al., 2021; Yuan et al., 2021). Therefore, compared with the previous
 480 CryoGridLite version, we implemented a new soil thermal conductivity and heat capacity scheme (Dai et al., 2019a, b; Yang et al., 2021; Langer et al., 2024) that account for the effect of gravel. Following Dai et al. (2019b), volumetric heat capacity (C_v) was calculated as a weighted arithmetic mean based on the volumetric fractions of the soil components as

$$C_v = \theta_g c_g + \theta_i c_i + \theta_m c_m + \theta_o c_o + \theta_w c_w, \quad (A1)$$

where θ_g , θ_i , θ_m , θ_o , and θ_w are the volumetric fractions of gravel, ice, mineral, organic matter, and water, respectively; and
 485 c_g , c_i , c_m , c_o , and c_w are the volumetric heat capacities of gravel, ice, mineral, organic matter, and water, respectively. Among them, θ_m is the sum of the volumetric fractions of sand (θ_{sand}), silt (θ_{silt}), and clay (θ_{clay}). For thermal conductivity (k), we adopted the Balland and Arp (Balland and Arp, 2005) scheme, which shows suitable performance for use in the numerical permafrost model (Dai et al., 2019a; Yang et al., 2021). The soil thermal conductivity was estimated as a Kersten-number-weighted combination of the thermal conductivity of dry soil (k_{dry}) and that of saturated soil (k_{sat}):

$$490 \quad k = (k_{sat} - k_{dry}) K_e + k_{dry} \quad (A2)$$

where K_e is the dimensionless Kersten number, expressed as a function of the degree of soil saturation (S_r). The degree of soil saturation is defined as:

$$S_r = \frac{\theta_w + \theta_i}{\phi} \quad (A3)$$

where θ_w and θ_i are the volumetric liquid-water and ice contents, respectively, and ϕ is the soil porosity. The Kersten number
 495 was parameterized for unfrozen and frozen soils as follows:

$$K_e = \begin{cases} S_r^{0.5(1+\theta_o-\alpha\theta_{sand}-\theta_g)} \left[\left(\frac{1}{1+e^{-\beta S_r}} \right)^3 - \left(\frac{1-S_r}{2} \right)^3 \right]^{1-\theta_o}, & \text{for unfrozen soils,} \\ S_r^{1+\theta_o}, & \text{for frozen soils.} \end{cases} \quad (A4)$$

where α (0.24) and β (18.1) are empirical parameters.

Similar to the volumetric heat capacity, the thermal conductivity of dry soil was depicted as a weighted arithmetic mean of the thermal conductivities of the soil components:

$$500 \quad \begin{aligned} k_{dry} &= f_g k_g + f_m k_{m,dry} + f_o k_{o,dry}, \\ f_j &= \frac{\theta_j}{\phi_{solid}}, \quad j \in \{g, m, o\}. \end{aligned} \quad (A5)$$



Here, f_j denotes the volume fraction of each component within the solid soil matrix, $\phi_{\text{solid}} = 1 - \phi$ is the total solid fraction. k_g , $k_{m, \text{dry}}$, and $k_{o, \text{dry}}$ are the corresponding thermal conductivities of gravel, mineral, and organic matter under dry conditions, respectively,

$$k_g = 0.039 \phi^{-2.2} \quad (\text{A6})$$

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$$k_{m, \text{dry}} = \frac{0.135 \rho_d + 0.0647}{2.7 - 0.947 \rho_d} \quad (\text{A7})$$

$$k_{o, \text{dry}} = 0.05 \quad (\text{A8})$$

where ρ_d is the dry bulk density of mineral.

510 The thermal conductivity of saturated soil was approximated using a volumetric weighted geometric mean of the thermal conductivities of the soil components:

$$k_{\text{sat}} = k_g^{\theta_g} k_{m, \text{sat}}^{\theta_m} k_{o, \text{sat}}^{\theta_o} k_w^{\theta_w} k_i^{\theta_i} \quad (\text{A9})$$

Here, k_g , $k_{m, \text{sat}}$, and $k_{o, \text{sat}}$ are the corresponding thermal conductivities of gravel, mineral, and organic matter under saturated conditions, respectively. Among them, k_g is the same as that under dry conditions, while $k_{m, \text{sat}}$ and $k_{o, \text{sat}}$ are given by

$$515 \quad k_{m, \text{sat}} = k_q^{v_q} k_{\text{other}}^{1-v_q} \quad (\text{A10})$$

where v_q is the volume fraction of quartz within the mineral component. The thermal conductivity of quartz, k_q , is set to $7.7 \text{ W m}^{-1} \text{ K}^{-1}$, and that of other minerals, k_{other} , is set to $2.0 \text{ W m}^{-1} \text{ K}^{-1}$ for $v_q < 0.2$ and $3.0 \text{ W m}^{-1} \text{ K}^{-1}$ otherwise.

Appendix B: Description of the dynamic snow density scheme

520 The previous version of CryoGridLite prescribed snow density as a constant parameter (Chen et al., 2025), following a simplified snow treatment used in some permafrost modeling studies (Ekici et al., 2014; Westermann et al., 2016, 2023; Sun and Cao, 2026). However, snow density can vary substantially in space and time, affecting the snow thermal properties and, consequently, the ground thermal regime (Zhang, 2005; Dutch et al., 2022). We therefore introduced a dynamic snow density scheme into CryoGridLite, following the approaches of Dutra et al. (2010) and van Kampenhout et al. (2017).

525 The fresh snow density ($\rho_{\text{snow, fresh}}$) was calculated from the sum of the wind-dependent term ($\rho_{\text{snow, wind}}$) and the temperature-dependent term ($\rho_{\text{snow, temp}}$) as:

$$\rho_{\text{snow, fresh}} = \rho_{\text{snow, wind}} + \rho_{\text{snow, temp}} \quad (\text{B1})$$



The wind-dependent term was given by:

$$\rho_{\text{snow, wind}} = 266.861 \left[\frac{1 + \tanh(U/5)}{2} \right]^{8.8} \quad (\text{B2})$$

where U is the 10 m wind speed from the meteorological forcing dataset. The temperature-dependent term was parameterized
 530 as a piecewise function of surface air temperature (T_{air} , °C):

$$\rho_{\text{snow, temp}} = \begin{cases} 50 + 1.7(17)^{3/2}, & T_{\text{air}} > 2^\circ\text{C}, \\ 50 + 1.7(T_{\text{air}} + 15)^{3/2}, & -15^\circ\text{C} < T_{\text{air}} \leq 2^\circ\text{C}, \\ -3.8328T_{\text{air}} - 0.0333T_{\text{air}}^2, & T_{\text{air}} \leq -15^\circ\text{C} \end{cases} \quad (\text{B3})$$

Once snowfall filled a snow cell in the snow domain, the bulk snow density was initialized as the fresh snow density for snowfall over bare ground. For snowfall over an existing snowpack, the bulk snow density was updated by conserving snow water equivalent and corresponding snow volume:

$$535 \quad \rho_{\text{snow, bulk}} = \begin{cases} \rho_{\text{snow, fresh}}, & S_{\text{old}} = 0, \\ \frac{S_{\text{old}} + S_{\text{new}}}{S_{\text{old}}/\rho_{\text{snow, old}} + S_{\text{new}}/\rho_{\text{snow, fresh}}}, & S_{\text{old}} > 0, \end{cases} \quad (\text{B4})$$

where S_{old} and S_{new} are the existing and newly added snow water equivalent, respectively; $\rho_{\text{snow, old}}$ is the snow density from the previous time step; $\rho_{\text{snow, fresh}}$ is the fresh snow density; and $\rho_{\text{snow, bulk}}$ is the bulk snow density after snowfall addition. The subsequent evolution of bulk snow density arose from three processes:

$$\frac{1}{\rho_{\text{snow, bulk}}} \frac{\partial \rho_{\text{snow, bulk}}}{\partial t} = \frac{\sigma_{\text{snow}}}{\eta_{\text{snow}}} + \xi_{\text{snow}} + \mathcal{M}_{\text{melt}}, \quad (\text{B5})$$

540 where t denotes time; σ_{snow} and η_{snow} are the overburden pressure and snow viscosity, respectively; ξ_{snow} is the thermal metamorphism term, and $\mathcal{M}_{\text{melt}}$ denotes the melt-related changes. The first two terms on the right-hand side were explicitly calculated following Dutra et al. (2010), whereas melt-related changes were represented through the original CryoGridLite snow-layer update (Langer et al., 2024):

$$\begin{aligned} \sigma_{\text{snow}} &= \frac{1}{2} Sg, \\ \eta_{\text{snow}} &= \eta_0 \exp[a_\eta(273.15 - T_{\text{snow}}) + b_\eta \rho_{\text{snow, bulk}}], \\ \xi_{\text{snow}} &= a_\xi \exp[-b_\xi(273.15 - T_{\text{snow}}) - c_\xi \max(0, \rho_{\text{snow, bulk}} - \rho_\xi)]. \end{aligned} \quad (\text{B6})$$

545 where S is the snow water equivalent expressed as snow mass per unit area, g is gravitational acceleration, and T_{snow} is the snow temperature. In CryoGridLite, T_{snow} was approximated by the near-surface air temperature. The empirical parameters were set to $\eta_0 = 3.7 \times 10^7$ Pa s, $a_\eta = 8.1 \times 10^{-2}$ K⁻¹, $b_\eta = 1.8 \times 10^{-2}$ m³ kg⁻¹, $a_\xi = 2.8 \times 10^{-6}$ s⁻¹, $b_\xi = 4.2 \times 10^{-2}$ K⁻¹, $c_\xi = 460$ m³ kg⁻¹, and $\rho_\xi = 150$ kg m⁻³.



Appendix C: Parameter overview

Table C1. Overview of the natural constants

Parameter	Symbol	Value	Unit	Reference
Atmospheric pressure at sea level	P_0	1.005×10^5	Pa	—
Gravitational acceleration	g	9.81	m s^{-2}	—
von Kármán constant	κ	0.4	—	—
Stefan–Boltzmann constant	σ	5.6704×10^{-8}	$\text{W m}^{-2} \text{K}^{-4}$	—
Specific gas constant for dry air	R_d	287.058	$\text{J kg}^{-1} \text{K}^{-1}$	—

Table C2. Overview of the surface properties

Parameter	Symbol	Value	Unit	Reference
Albedo of fresh snow	$\alpha_{\text{snow, max}}$	0.85	—	Westermann et al. (2016)
Albedo of old snow	$\alpha_{\text{snow, min}}$	0.50	—	Westermann et al. (2016)
Albedo of bare ground	α_{soil}	0.20	—	Westermann et al. (2016)
Albedo of water	α_{water}	0.07	—	Westermann et al. (2016)
Albedo of ice	α_{ice}	0.20	—	Westermann et al. (2016)
Emissivity of snow	ϵ_{snow}	0.99	—	Westermann et al. (2016)
Emissivity of bare ground	ϵ_{soil}	0.97	—	Westermann et al. (2016)
Emissivity of water	ϵ_{water}	0.99	—	Westermann et al. (2016)
Emissivity of ice	ϵ_{ice}	0.98	—	Westermann et al. (2016)
Roughness length of snow	$z_{0, \text{snow}}$	5.0×10^{-4}	m	Westermann et al. (2016)
Roughness length of bare ground	$z_{0, \text{soil}}$	1.0×10^{-3}	m	Westermann et al. (2016)
Roughness length of water	$z_{0, \text{water}}$	5.0×10^{-4}	m	Westermann et al. (2016)
Roughness length of ice	$z_{0, \text{ice}}$	5.0×10^{-4}	m	Westermann et al. (2016)
Surface resistance of snow	r_{snow}	0.0	s m^{-1}	Westermann et al. (2016)
Surface resistance of bare ground	r_{soil}	50.0	s m^{-1}	Westermann et al. (2016)
Surface resistance of frozen bare ground	$r_{\text{frozen soil}}$	100.0	s m^{-1}	Chen et al. (2025)
Surface resistance of water	r_{water}	0.0	s m^{-1}	Westermann et al. (2016)
Surface resistance of ice	r_{ice}	0.0	s m^{-1}	Westermann et al. (2016)



Table C3. Overview of the material properties

Parameter	Symbol	Value	Unit	Reference
Density of air	ρ_a	1.293	kg m^{-3}	—
Density of water	ρ_w	1000	kg m^{-3}	—
Density of ice	ρ_i	1000	kg m^{-3}	—
Evaporation depth	d_{evap}	0.1	m	Chen et al. (2025)
Latent heat of fusion	L_{sl}	3.34×10^5	J kg^{-1}	—
Latent heat of vaporization	L_{lg}	2.501×10^6	J kg^{-1}	—
Particle density of soil organic matter	$\rho_{\text{soil, org}}$	1300.0	kg m^{-3}	Langer et al. (2024)
Particle density of mineral soil	$\rho_{\text{soil, min}}$	2700.0	kg m^{-3}	Dai et al. (2019a)
Thermal conductivity of air	k_a	0.025	$\text{W m}^{-1} \text{K}^{-1}$	Langer et al. (2024)
Thermal conductivity of dry organic matter	$k_{\text{o, dry}}$	0.05	$\text{W m}^{-1} \text{K}^{-1}$	Dai et al. (2019a)
Thermal conductivity of ice	k_i	2.29	$\text{W m}^{-1} \text{K}^{-1}$	Dai et al. (2019a)
Thermal conductivity of quartz	k_q	7.7	$\text{W m}^{-1} \text{K}^{-1}$	Dai et al. (2019a)
Thermal conductivity of saturated organic matter	$k_{\text{o, sat}}$	0.25	$\text{W m}^{-1} \text{K}^{-1}$	Dai et al. (2019a)
Thermal conductivity of water	k_w	0.57	$\text{W m}^{-1} \text{K}^{-1}$	Dai et al. (2019a)
Volumetric heat capacity of air	c_a	1300.37	$\text{J m}^{-3} \text{K}^{-1}$	—
Volumetric heat capacity of gravel	c_g	2.2×10^6	$\text{J m}^{-3} \text{K}^{-1}$	Liu et al. (2021)
Volumetric heat capacity of ice	c_i	1.9×10^6	$\text{J m}^{-3} \text{K}^{-1}$	Langer et al. (2024)
Volumetric heat capacity of mineral soil	c_m	2.0×10^6	$\text{J m}^{-3} \text{K}^{-1}$	Langer et al. (2024)
Volumetric heat capacity of organic matter	c_o	2.5×10^6	$\text{J m}^{-3} \text{K}^{-1}$	Langer et al. (2024)
Volumetric heat capacity of water	c_w	4.2×10^6	$\text{J m}^{-3} \text{K}^{-1}$	Langer et al. (2024)



550 **Appendix D: Comparison of near-surface air temperature and precipitation among three meteorological forcing datasets**

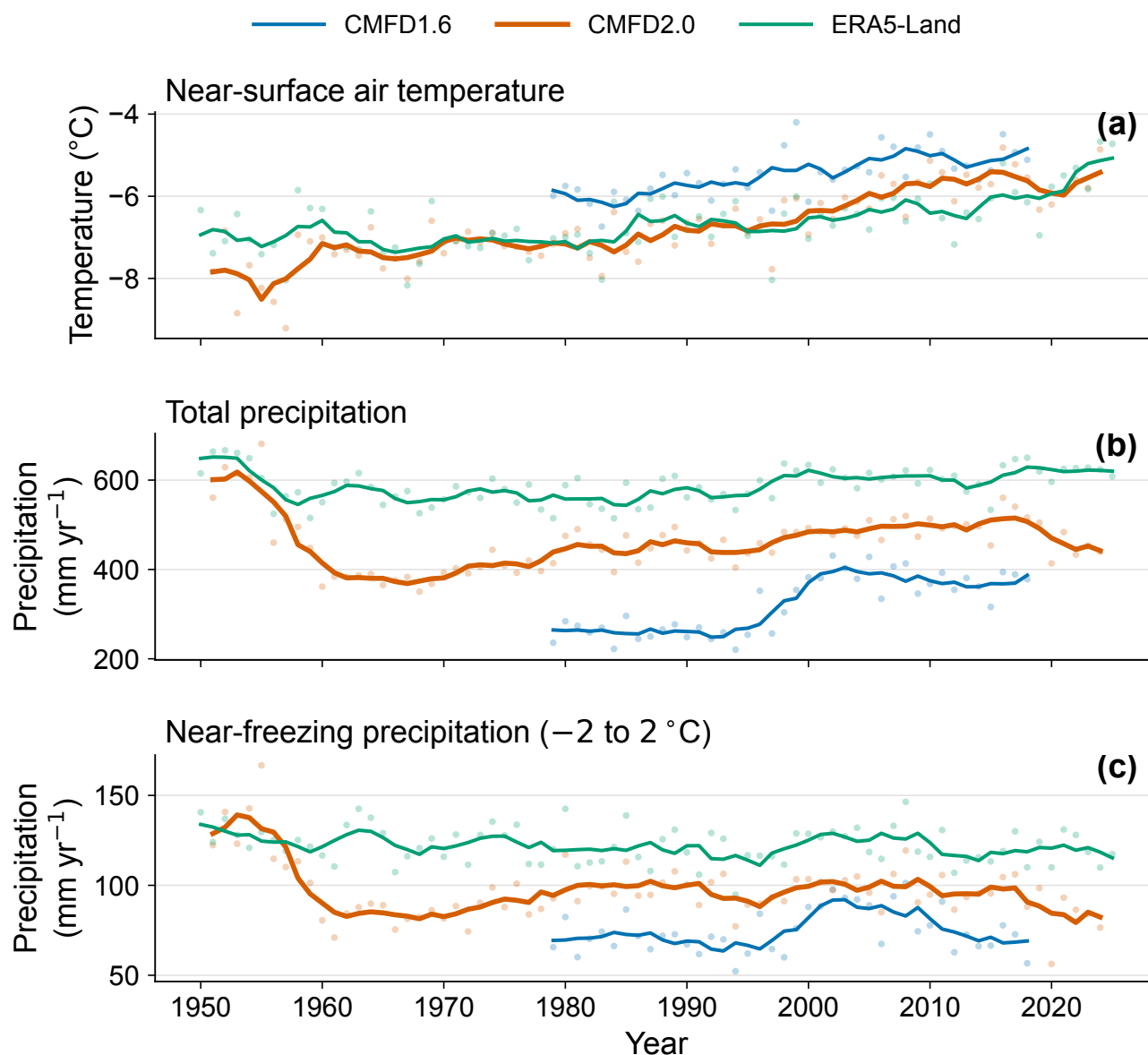


Figure D1. Temporal evolution of meteorological forcing datasets over the simulated permafrost region across the Tibetan Plateau. Annual near-surface air temperature, annual total precipitation, and annual precipitation occurring under near-freezing conditions ($-2^{\circ}\text{C} \leq T_{\text{air}} \leq 2^{\circ}\text{C}$) were calculated as area-weighted means over grid cells included in the ensemble-defined permafrost mask. Points indicate annual values, and thick lines indicate 5-year moving average. Different temporal coverage reflects data availability for each forcing dataset.



Code and data availability. The model source code, reproducibility settings, and post-processing and visualization scripts used in this study have been archived in Zenodo (10.5281/zenodo.20637282). Numerical experiments were conducted using Julia 1.12.6. Data analysis and visualization were performed using Python (3.13.0) with numpy (2.4.0), pandas (2.3.3), geopandas (1.1.2), matplotlib (3.10.8), seaborn (0.13.2), cartopy (0.25.0), xarray (2025.12.0), rioxarray (0.20.0), contextily (1.7.0), and colormaps (0.4.2). The China Meteorological Forcing Dataset version 2.0 is available at <https://data.tpdc.ac.cn/en/data/e60dfd96-5fd8-493f-beae-e8e5d24dece4>. The shapefiles of the Tibetan Plateau boundary and lakes on the Tibetan Plateau are available at <https://data.tpdc.ac.cn/en/data/61701a2b-31e5-41bf-b0a3-607c2a9bd3b3> and <https://data.tpdc.ac.cn/en/data/7fee8675-d4ab-4f97-8bbf-269e20b7ac16>, respectively. Glacier shapefiles for the Tibetan Plateau are available at <https://nsidc.org/data/nsidc-0770/versions/7>. The soil stratigraphy and bedrock depth data for each grid cell of the model domain are available at <http://globalchange.bnu.edu.cn/research/soil5.jsp> and <http://globalchange.bnu.edu.cn/research/dtb.jsp>. The terrestrial heat flow dataset is available at <https://doi.org/10.1029/2019GC008389>. The global water-table depth dataset is available at <http://thredds-gfml.usc.es/thredds/catalog/GLOBALWTDFTP/annualmeans/catalog.html>. The snow depth dataset for Tibetan Plateau is available at <https://data.tpdc.ac.cn/en/data/0515ce19-5a69-4f86-822b-330aa11e2a28>. The initial soil temperature fields for 1951 were derived from ERA5-Land, available at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means?tab=overview>.

Author contributions. RC conceived the study, developed and implemented the numerical model, carried out the simulations and analysed the results, prepared the figures, and led the paper preparation. HL interpreted the simulation results. SK supervised the study and was responsible for funding acquisition. All authors contributed to editing and revising the manuscript.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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