Response to Referee#2 egusphere-2024-3956

This study investigates permafrost dynamics in the West Kunlun region of the Qinghai-Tibet Plateau (QTP) using a high-resolution permafrost modelling approach. The authors employ the previously developed Moving-Grid Permafrost Model (MVPM) to reconstruct permafrost thermal conditions over the past four decades, integrating remote sensing data from a previously published dataset, machine learning techniques, and filed observations. The study provides valuable insights into the effects of climate change on permafrost, demonstrating a significant warming trend in land surface temperature (LST) while indicating a relatively stable permafrost extent. The methodology is reasonably innovative and well-structured, offering an improvement over previous large-scale permafrost models by considering detailed processes at depth. While the study is well-executed and contributes to our understanding of permafrost changes in this region, there are areas that require further clarification and refinement as detailed below:

Response:

We greatly appreciate your detailed comments, revisions, and suggestions, which have helped us improve the quality of the manuscript. We provide our responses to each comment individually. The original reviewer comments are in black font, while our responses appear in blue font. The corresponding edits in the manuscript are highlighted in red font.

Major Comments:

1. Model validation and uncertainties

The authors report high model accuracy (±0.25 °C for ground temperature and ±0.25 m for active layer thickness). However, the discussion of model uncertainties could be expanded. Key areas for improvement include:

* a sensitivity analysis of key model parameter such as soil thermal properties and initial boundary conditions to assess their impact on the results.

* a deeper discussion on the limitations of the forcing datasets, particularly the machine-learning-based reconstruction of LST prior to 2003 and impact of the cold bias of 0.8degC (Compared to in situ measurements, we found a slight cold bias in our reconstructed LST series, averaging approximately -0.80°C)

Response:

To quantitatively assess model uncertainties, we conducted a one-at-a-time sensitivity analysis

(Figure 1) using three representative boreholes that span different types of frozen ground—stable permafrost, unstable permafrost, and seasonally frozen ground (see Table 1 for details). Key model parameters, including soil thermal conductivity, heat capacity, water/ice content, initial temperature profile, and upper boundary temperature, were systematically perturbed by ±10% to evaluate their relative influence on the simulated mean annual ground temperature (MAGT, at 15 m depth) and active layer thickness (ALT).

Our results show that upper boundary temperature (e.g., model forcing) has the strongest influence on MAGT across all ground types. However, the magnitude of its impact remains relatively small: around ±0.5 °C in seasonally frozen ground and ≤ ±0.1 °C in both stable and unstable permafrost. ALT exhibits similarly modest sensitivity, with variations of approximately ±0.1 m in stable permafrost and ±0.05 m in unstable permafrost. Soil thermal conductivity and water/ice content have a more pronounced effect on ALT, particularly in unstable permafrost, where a 10% change in these parameters can lead to a 0.05–0.1 m variation. In contrast, heat capacity has minimal influence on both MAGT and ALT. Initial ground temperature shows a moderate effect in seasonally frozen ground (~±0.12 °C), but exerts negligible influence in permafrost areas. These findings suggest that the model achieves thermal stability over the simulation period and that uncertainties in individual parameters exert only limited influence on overall model performance.

We acknowledge that the machine-learning-based reconstruction of LST, particularly before 2003, introduces uncertainty, most notably an average cold bias of approximately -0.8 °C relative to in situ measurements. While this bias may affect the absolute values of the upper boundary forcing, our sensitivity analysis suggests that the model is relatively robust to such small shifts in LST, especially in permafrost regions. Nonetheless, we recognize this cold bias as a key source of systematic uncertainty and will expand the discussion in the revised manuscript.

Table 1. Information on three representative borehole sites used for one-at-a-time sensitivity analysis

Borehole	Description
ZK30	The borehole reaches a depth of 15 m, with the ground primarily composed of fine sand and silty sand. The MAGT is -1.66 °C, and the ALT is 2.4 m, classifying the site as stable permafrost.
ZK12	The borehole has a drilling depth of 13.5 m, with a vegetation-free surface. The core consists primarily of Fluvial sand and sand. Frozen soil was first encountered at a depth of 4.9 m, where small ice crystals are evenly distributed within a granular soil structure. Below 5.5 m, the frozen layer disappears, accompanied by a noticeable increase in ground temperature. The 4.9–5.5 m interval represents a transition zone, and the site is classified as unstable permafrost.

ZK13	No frozen soil was encountered during the drilling process, and the site is classified as seasonally frozen ground

Note: This information is compiled from Li et al. (2012) and Zhao et al. (2019).

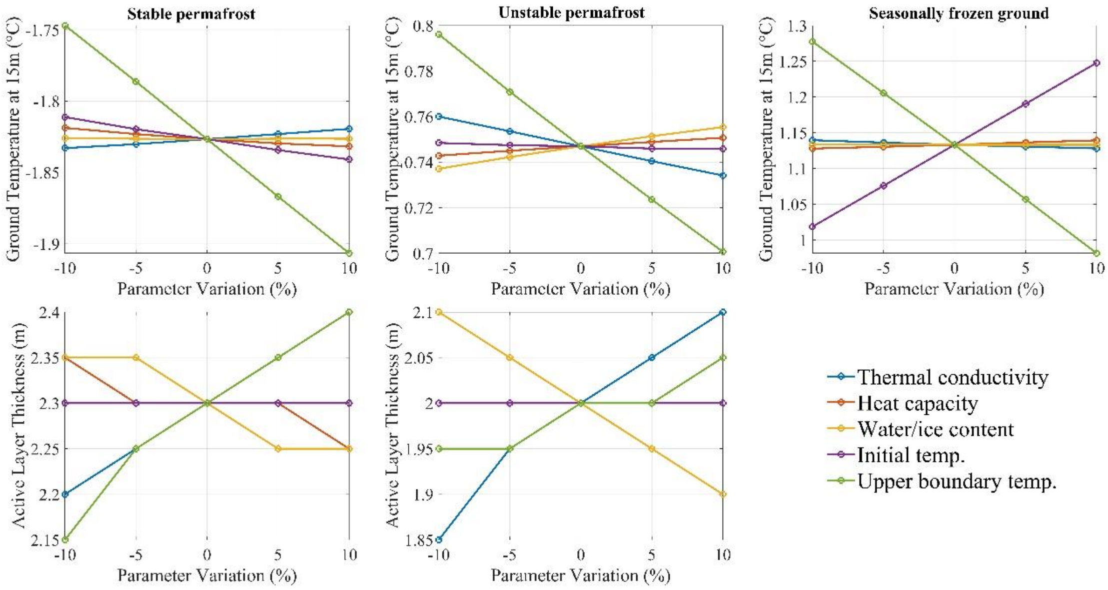

Figure 1. One-at-a-time sensitivity analysis showing the effects of ±10% variation in individual model parameters, e.g., soil thermal conductivity, heat capacity, water/ice content, initial temperature, and upper boundary temperature—on (top row) mean annual ground temperature (MAGT) at 15 m depth and (bottom row) active layer thickness (ALT), across three ground conditions: stable permafrost (left), unstable permafrost (middle), and seasonally frozen ground (right).

Reference:

Li, K., Chen, J., Zhao, L., Zhang, X., Pang, Q., Fang, H., Liu, G.: Permafrost distribution in typical area of west Kunlun Mountains derived from a comprehensive survey (in Chines with English abstract), J. GLACIOL.,2012.

Zhao L, Sheng Y. Permafrost and environment changes on the Qinghai-Tibetan Plateau. Beijing, China: Science Press.; 2019.

* The effect of snow cover on LST reconstruction and subsurface thermal dynamics is not sufficiently addressed. How are snow-insulated period accounted for? Is there any bias introduced by could-covered or snow-covered days in the satellite-derived LST? (linked to point 2)

Response:

Firstly, in the vast permafrost zone of the QTP, strong solar radiation and wind result in rare, thin (~3cm) snow cover that typically lasts less than one day per snow event (Wu and Zhang, 2008;

Che et al., 2008; Zou et al., 2017; Yan et al., 2022). Vegetation in the alpine ecosystem of the permafrost region consists of grassland characterized by dwarf and sparsely distributed plants, with vegetation cover below 10% in the western QTP (Wang et al., 2016). Given the specific conditions of snow cover and vegetation in the permafrost zone of the QTP, the average thermal offset between GST and LST is minimal (Hachem et al., 2012).

Secondly, the subsurface thermal model MVPM, which uses land surface temperature as the upper boundary forcing, employed a modified LST product from MODIS developed by Zou et al. (2017). This product partially accounts for the influence of surface conditions including the effects of snow cover, vegetation and cloud cover on LST through a cloud gap filling algorithm, as well as incorporating automatic weather station (AWS) observations from representative permafrost regions in the central QTP. These AWS observations, which reflect climate conditions at satellite overpass times, were used to calibrated MODIS LST and calculate mean daily LST values at those times and included in the model training dataset.

Moreover, our model simulations reasonably reproduce the mean annual ground temperature, and the simulated active layer thickness is in good agreement with observations as well as permafrost distribution in different periods. While thin snow cover might have a cooling effect on ground surface temperature due to the high albedo of fresh snow and rapid snowmelt processes (Zhang et al., 2005), we believe this cooling effect is of short duration and has minimal impact at our simulation time scales. On the contrary, snow cover effects would be more significant for centennial to millennial time scale simulations rather than the decadal scale used in our study (**please see response to the second question about 'use of MODIS LST as forcing data'**).

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https://doi.org/10.5194/tc-11-2527-2017, 2017.

2. Use of MODIS LST as forcing data

While MODIS LST provides high spatial resolution and extensive temporal coverage, it poses several challenges when used to force model models:

* MODIS measures skin temperature rather than subsurface ground temperature, which can differ significantly—especially under snow cover or vegetation (vegetation is acknowledged in this study)

* Snow cover introduces thermal insulation, decoupling surface LST from the subsurface thermal regime (Albeit often nonexistent or thin snow cover). However, wind driven snow drift can be significant and give spatial heterogeneity at high model resolutions. The significance of these effects needs to be addressed in this study region.

* Cloud cover causes data gaps, which can lead to temporal inconsistencies or biases if gap-filling methods are not robust—particularly problematic in winter months?

* MODIS LST captures only clear-sky conditions, potentially biasing the dataset toward colder nighttime or warmer daytime extremes, depending on retrieval timing.

The paper should better articulate how these limitations are mitigated in the LST reconstruction, and what implications they have for subsurface heat fluxes and permafrost thermal state. A comparison with measured air-temperature or reanalysis-based forcing would also help.

Response:

Surface (i.e., skin) temperature serves as model forcing at the upper model boundary in our study, where we applied machine learning techniques to reconstruct remote-sensing-based LST. We acknowledge the limitations highlighted by the reviewer: MODIS LST is skin temperature e.g., vegetation canopy, snow rather than ground surface temperature. Snow cover introduces thermal insulation effects; cloud cover causes data gaps; and MODIS LST captures only clear-sky conditions. We implemented several preprocessing procedures to mitigate these uncertainties:

Firstly, we employed a modified Moderate Resolution Imaging Spectroradiometer land surface temperature (MODIS LST) product provided by Zou et al. (2017), available since 2003. This product was derived from the clear-sky MOD11A2 (Terra MODIS) and MYD11A2 (Aqua MODIS) datasets (Collection 6), which provide two observations per day (daytime and nighttime) for the same pixel. Prior to analysis, irregularly spaced time series caused by cloud cover or other factors were identified, and data gaps were filled using the Harmonic Analysis of Time Series (HANTS) algorithm (Xu et al., 2013; Zou et al., 2017). This method has proven effective for filling gaps in MODIS LST data over the QTP (Xu et al., 2013) and helps mitigate the cold bias associated with clear-sky temporal averages.

Secondly, to estimate daily mean LST values from Aqua and Terra instantaneous daytime and nighttime observations, multi-stepwise statistical model were established using ground-based ground surface temperature (GST) data from AWS in typical permafrost regions of the central QTP. These relationships, which reflect actual climate conditions at satellite overpass times, were developed by Zou et al. (2014, 2017). The resulting empirical correction model was then applied across the entire QTP permafrost zone to upscale and estimate reliable LST values. Previous validation by Zou et al. (2014) at three typical permafrost monitoring sites with different land cover types—alpine steppe (Xidatan), alpine meadow (Tangula), and alpine desert (Wudaoliang)—demonstrated strong model performance, with coefficients of determination (R^2) ranging from 0.91 to 0.93, mean errors between –0.21°C and 1°C, mean absolute errors (MAE) from 2.28°C to 2.42°C, and root mean square errors (RMSE) between 2.96°C and 3.05°C. In the West Kunlun permafrost zone, we further evaluation using monthly in situ data from the TSH AWS (81.4°E, 36.0°N, 5019 m a.s.l.) for the period 2016–2018 also showed strong agreement, with R^2 exceeding 0.90, MAE of 1.62°C, RMSE of 2.09°C. These results confirm that the empirical model reliably captures the spatial patterns of LST across the QTP.

Third, in this study, the modified LST product from Zou et al. (2017) was further refined to reconstruct historical LST data prior to 2003—extending back to 1980—using machine learning techniques that integrate eight specific variables derived from ground-based observations, satellite data, reanalysis datasets, and other sources. The reconstructed LST was evaluated against monthly in situ observations from the TSH AWS for the period 2016–2018, showing strong correlations above 0.95, with RMSE values from 1.62°C to 1.91°C and MAE ranging from 1.29°C to 1.50°C. The validation results show that the reconstructed LST performs slightly better than the satellite-derived LST_Zou, with a particularly notable improvement over reanalysis product ERA5-Land (Figure 2)

Fourth, while direct validation of pre-2003 LST is not possible due to the lack of satellite or ground observations in the West Kunlun region, we employed an indirect validation approach. Specifically, the reconstructed LST was used to force the MVPM to simulate permafrost thermal dynamics from 1980 onward. The simulation results were then evaluated against existing permafrost monitoring network data and previously published permafrost distribution maps from different periods, i.e., the 1980s (Li et al., 1996), the 2000s (Wang et al., 2006), 2010 (Cao et al., 2023), and after 2010 (Zou et al., 2017). The strong agreement between the MVPM outputs and these independent data sources supports the reliability of the pre-2003 LST reconstruction. Furthermore, our analysis showed that the West Kunlun permafrost survey area has experienced pronounced LST warming since the mid-1980s, with an accelerated warming trend in the last decade. This pattern aligns well with the documented warming trends on the QTP in recent studies (Jin et al., 2011; You et al., 2021; Yao et al., 2019; Li et al., 2024), indirectly validating the accuracy of our reconstructed LST data. These multi-faceted validation approach provides reasonable confidence in our LST dataset, despite the absence of direct observations for the earlier period. While we acknowledge this limitation, we believe the methodology offers the most robust solution given the data constraints in this remote and observational challenging region.

The above comparisons demonstrate that the reconstructed LST time series closely align with in situ measurements and provide sufficient accuracy for ground thermal modeling in our study. However, a systematic cold bias is evident in the mean annual cycle of LST, particularly during the summer months of July, August, and September (Figure 2). Compared to LST_Zou, the reconstructed monthly LST reduce this bias to varying degrees. Nevertheless, a residual cold bias remains noticeable in the reconstructed LST during these months. This bias likely contributes to the underestimation of shallow soil temperatures, which in turn affects the simulation of active layer thickness or thaw depth. Near-surface ground temperature is highly sensitive to seasonal variations in model forcing, which are often marked by frequent fluctuations and complex patterns (Lunardini et al., 1995). This may help explain the underestimation of active layer thickness or melt depth observed in our simulations. Similarly, Westermann et al. (2015) reported that inaccuracies in summer LST forcing can directly impact the accuracy of thaw depth simulations; with an LST uncertainty of ±2 °C, the resulting thaw depth is reproduced with an uncertainty of approximately ±3 cm. However, in permafrost regions, the seasonal signal becomes increasingly attenuated with depth due to the complex coupling among environmental conditions, thermal properties, phase change, ground ice, and cryoturbation. At the depth of Zero Annual Amplitude (ZAA) temperature fluctuations become undetectable (Jin et al., 2011; Dobiński et al., 2022). The trend in mean annual ground temperature at the ZAA generally mirrors long-term air temperature trends (Smith and Riseborough, 1983; Buteau et al., 2004; Jin et al., 2011). Our sensitivity analysis also demonstrated that the model is relatively robust to such small shifts in LST, especially in permafrost regions. We therefore believe that the existing cold bias, as a limitation of our LST reconstruction approach, is seasonal and transient, and has minimal influence on the long-term permafrost thermal status within the time scale of our simulations.

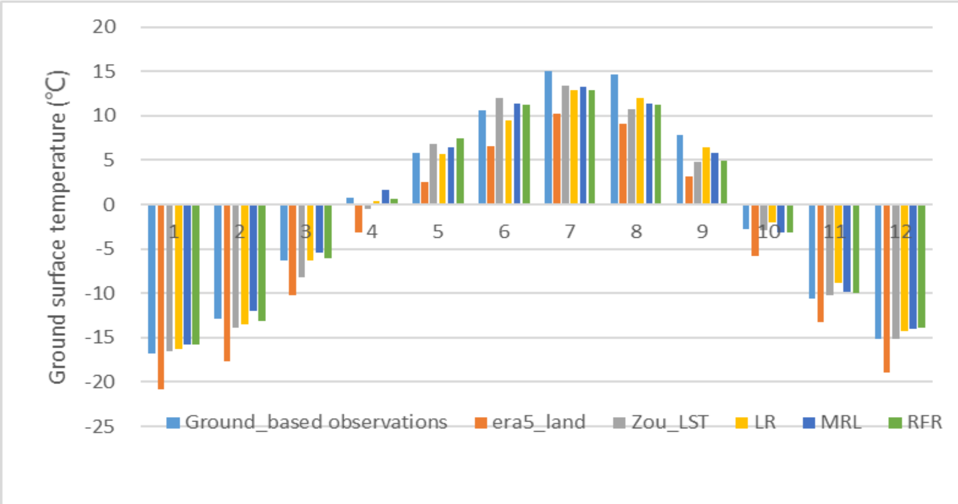

Figure 2. Monthly average LST at the TSH AWS from 2016 to 2018, including reanalysis-derived LST (ERA5-Land), modified satellite-derived LST (LST_Zou), estimates from three machine learning models (LR, MLR, and RFR), and in situ observations.

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3. Representation of soil stratigraphy

The study highlights variations in permafrost responses based on soil stratigraphy, but further clarity is needed regarding:

* The specific role of soil moisture and ice content in modulating permafrost temperature trends.

* Potential biases in stratigraphic classification and how these might affect regional variability in permafrost degradation.

* The extent to which subsurface heterogeneity is accounted for in the model.

Response:

In our modeling framework, we incorporated detailed thermophysical characterization of the subsurface based on measurements from 15 boreholes distributed across the WKL permafrost survey area, with depths ranging from 15 to 59 m. Core sampling, field observations, and borehole descriptions (Li et al., 2012; Zhao et al., 2019) indicate that ground ice content varies between 5% and 50% in WKL, depending on Quaternary sediment type. Higher ice contents are observed in fine-grained glarosional and lacustrine sediments due to enhanced segregation ice formation, while lower values are typical of coarse-grained alluvial and colluvial deposits. Vertically, ice-rich layers are consistently present near the upper boundary of permafrost, where generally ranges from 2 to 3 m. Ice content tends to slight increase with depth between 3 and 10 m and remains relatively stable below 10 m (Zhao et al., 2010). The site-level stratigraphic and thermophysical data were spatially upscaled using vector-based geomorphological classification maps of western China. The five stratigraphic classes commonly found in the West Kunlun region are glarosional, alluvial plain, aeolian, colluvial valley, and lacustrine deposits

Our simulation results highlight the critical role of ground ice content in shaping permafrost thermal dynamics. Modeled ALT varies remarkable change across stratigraphic classes, with the greatest ALT found in alluvial sediments and the shallowest ALT in glarosional sediments. While some uncertainty in stratigraphic classification and spatial representation is inevitable, our approach is grounded in field observations and measured thermal properties. Furthermore, sensitivity analysis shows that the model outputs are relatively robust to variations in key input parameters related to soil stratigraphy. That said, considerable small-scale heterogeneity in ground properties exists beyond what can be captured at the 1 km modeling resolution, especially complex mountainous. Variability within each sediment class may also lead to biases in local model estimates. Despite these limitations, we are confident that our model captures the essential thermal characteristics of each sediment class, which are central to simulating permafrost thermal regime response to climate change. Continued improvements in soil property datasets particularly in permafrost regions will be vital for refining future model performance.

Reference:

Li, K., Chen, J., Zhao, L., Zhang, X., Pang, Q., Fang, H., Liu, G.: Permafrost distribution in typical area of west Kunlun Mountains derived from a comprehensive survey (in Chines with English abstract), J. GLACIOL.,2012.

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4. Permafrost stability and warming trends

The study concludes that despite significant warming trends in LST, permafrost extent remains stable. While plausible given the thermal inertia of deep permafrost, the paper could be benefit from:

* A clearer discussion on why this stability is observed and how it compares with degradation rates reported in other high-altitude or Arctic regions.

* Consideration of potential threshold effect (e.g., rapid degradation once a critical warming threshold is exceeded)

* More discussion on subsurface processes such as latent heat effects and talik formation, which may delay degradation despite rising surface temperatures.

* The observed increase in permafrost area despite a warming trend of 0.4°C per decade is surprising and warrants closer examination and justification.

Response:

Permafrost thermal degradation is a complex process characterized by a time lag in response to climate warming and is further modulated by local environmental factors such as soil type, ground ice content, geothermal heat flux, and the initial thermal state of the permafrost (Zhao et al., 2020; 2024; Hu et al., 2023). In response to climate change, permafrost gradually adjusts its thermal regime across multiple timescales—ranging from years to centuries or even millennia. Based on their classification of ground temperature profiles, Wu et al. (2010) suggested that the current diversity in permafrost thermal conditions across the QTP may reflect different stages of degradation (e.g., warming stage, zero geothermal gradient stage, talik development stage, and complete disappearance) dating back to the cold climatic conditions of the Last Glacial Maximum (LGM).

Our study found that approximately 70.98% of the permafrost in the Western Kunlun region is in the temperature-rising stage, characterized by an initial MAGT below –2.0 °C and an ALT of less than 1.5m. This type predominantly occurs in high-elevation areas (above 4800 m a.s.l.). Additionally, 17.58% of the permafrost is transitioning from the temperature-rising stage to the zero geothermal gradient stage. Only 11.44% is either in the zero geothermal gradient stage or transitioning toward the talik development stage, and may be facing degradation. This type of permafrost is typically located in lower-elevation areas (below 4800 m a.s.l.) and is characterized by a relatively high MAGT (above –1 °C).

Permafrost is a state variable that forms when heat loss at the ground surface exceeds heat gain over a prolonged period under a severely cold climate (Wu et al., 2010). Under a warming climate, sustained increases in ground surface temperature disrupt the thermal equilibrium established under historical climate conditions. Consequently, the active layer begins to accumulate more heat each year than it can release, leading to progressive ground warming from the surface downward and a reduced temperature gradient within the permafrost. However, during the early phase of warming, permafrost temperatures rise more readily than ground thaw occurs, since most of the incoming energy is used to warm the frozen soil to its thawing point. This explains why the areal extent of permafrost in the Western Kunlun region remained relatively unchanged during our simulation period, despite the pronounced warming trend.

Moreover, although the regional average LST shows an overall increasing trend from 1980 to 2022, considerable interannual and spatial variability exists within the study area. We suggest that periodic cooling events contributed to the formation and expansion of new permafrost in specific areas through a complex, delayed response. This is supported by our simulated permafrost coverage, which shows a slight increase between 2010 and 2022 despite the pronounced warming trend during this period.

Under future climate warming scenarios, MAGT will continue to rise. As heat penetrates deeper, the thermal gradient at the permafrost base becomes smaller than the geothermal gradient, causing heat to flow upward from the underlying unfrozen ground. This initiates basal thawing, resulting in a gradual upward retreat of the permafrost base and overall thinning of the permafrost layer. Compared to Arctic and sub-Arctic regions, the QTP has a relatively high geothermal gradient, which contributes to a longer permafrost response time to atmospheric warming (Jin et al., 2011). As a result, the rate of ground temperature increase is noticeably lower in the QTP than in circumpolar regions (Zou et al., 2017).

When permafrost temperatures approach 0°C, ground ice near the permafrost table begins to melt, consuming large amounts of latent heat, a phenomenon known as the "zero curtain effect." This process significantly slows or even temporarily halts further warming for a much longer period than observed in unfrozen soil, and substantially reduces seasonal temperature variations within the shallow permafrost. Simultaneously, geothermal heat from below is almost entirely used for thawing permafrost from the bottom up.

The zero geothermal gradient stage represents a critical transitional state in permafrost degradation. At this stage, nearly all available heat from the surface is consumed by ice melt, leading to a rapid downward shift in the permafrost table. When the maximum seasonal freezing depth no longer reaches the permafrost table, a talik (unfrozen ground within permafrost) forms and expands. Numerical simulations conducted by Sun et al. (2019) indicated that talik formation coincides with accelerated permafrost thaw and marks the onset of irreversible degradation that continues until complete permafrost loss.

The revised manuscript will include an expanded discussion on permafrost stability.

Reference:

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5. Implications for future projections

While the paper effectively documents historical changes, it lacks a forward-looking component. While I realize this is beyond the scope of the paper perhaps some additional point could be added to the discussion to enhance its relevance, such as:

* Discussion how the observed trends might evolve under different climate scenarios.

* Assess the potential for abrupt future permafrost degradation/non-linearly of the system and its implications for infrastructure and carbon release.

* Offer suggestions for integrating MVPM outputs into Earth System Models to improve global climate projections.

Response:

Thank you for this thoughtful and constructive suggestion. Understanding the current status of permafrost in the context of its historical evolution is essential for projecting future changes, and we agree that incorporating a forward-looking component enhances the relevance of the paper.

In fact, in our previous work (Sun et al., 2019; Zhao et al., 2022), we used MVPM to simulate and assess permafrost thermal dynamics under various future climate change scenarios. Our modeling results indicated that permafrost degradation, particularly in terms of areal extent, does not follow a linear trajectory, and the response of permafrost temperature to climate warming is not as rapid as projected in many published reports (Guo et al., 2012; Ni et al., 2021). Even under the most extreme warming scenario (RCP8.5), the permafrost table was projected to deepen only gradually. By 2050, permafrost would still remain at a depth of 40 m at both Wudaoliang and Tanggula, two borehole sites located in the continuous permafrost zone characterized by cold ground temperatures and thick permafrost layers. In contrast, at Xidatan, a site located at the lower boundary of the permafrost zone, with warmer ground and a thinner permafrost layer of about 32m, the permafrost base is projected to move upward significantly. Nevertheless, permafrost is still expected to persist at this site through 2100 based on projected changes in the deep permafrost ground temperature, ground ice, and thermal gradients.

Similarly, along the northern margin of the permafrost zone on the QTP, MVPM simulation results (Zhao et al., 2022) showed that MAGT would continue to rise under gradual warming scenarios. The warming rate was projected to be slightly higher under Shared Socioeconomic Pathway (SSP) scenarios compared to Representative Concentration Pathway (RCP) scenarios.

However, no significant differences were modeled in the projected areal extent of permafrost between the SSP and RCP scenarios. These results indicate that although permafrost temperatures on the QTP are rising rapidly under climate warming, the rate of permafrost loss, particularly in terms of areal extent is relatively slow, which have important implications for simulating the magnitude and timing of permafrost carbon feedback and associated hydrological processes.

It is worth noting that the slow response of the permafrost thermal regime to future climate warming may exhibit substantial variability in ice-rich permafrost zones (e.g., those containing excess ground ice), largely due to the melting of massive ground ice and the vertical movement of water. These processes exert a strong influence on permafrost thaw trajectories, often leading to landscape changes such as thermokarst pond formation and surface subsidence (Westermann et al., 2016). The associated hydrological dynamics can either accelerate or delay permafrost degradation. Specifically, when meltwater from thawed ice-rich layers drains effectively, both ground subsidence and talik formation are delayed (Westermann et al., 2016). In contrast, if meltwater accumulates at the surface, it can form ponds that enhance heat transfer into the ground, thereby accelerating talik development and intensifying permafrost thaw (Jan et al., 2020). This process holds substantial potential to unlock vast stores of currently frozen organic carbon, particularly greenhouse gases like CO_2 and CH_4 stored in cold, ice-rich lowlands. As such, thermokarst-related permafrost degradation in a warming climate could significantly amplify the global permafrost carbon–climate feedback (Turetsky et al., 2015).

We agree that integrating MVPM outputs into Earth System Models (ESMs) is essential for improving global climate projections. Based on our findings and previous modeling experience, we offer the following suggestions for improving land surface models (LSMs) within ESMs:

First, enhancing lower boundary conditions is critical for accurately simulating long-term permafrost thermal dynamics. Many existing LSMs use shallow soil profiles (e.g., less than 10 m) and simplified zero-flux lower boundaries, which are inadequate for capturing deep ground thermal processes. We recommend implementing deeper soil configurations (e.g., 50–100 m) combined with geothermal heat flux boundary conditions to better represent the ground thermal regime over decadal to centennial timescales.

Second, accurately simulating permafrost degradation requires high vertical resolution and robust model initialization. This involves resolving both seasonal and long-term thermal changes across deep soil profiles with sufficient layering, and accounting for the extended thermal memory in permafrost systems (Razavi et al., 2015). We recommend increasing the number of soil layers to improve vertical resolution and carefully initializing (longer spin up) deep soil thermal and moisture states, ideally informed by long spin-up runs or in situ observations.

Third, improving the representation of ground ice is vital. Ground ice plays a key role in controlling the thermal and hydrological regimes of permafrost regions by affecting soil thermal conductivity, heat capacity, and moisture content (Hu et al., 2023). It also significantly affects permafrost thaw trajectories, causes surface subsidence or thermokarst pond (Lee et al., 2014; Westermann et al., 2016; Sun et al., 2022). However, current LSMs often apply overly simplistic ground ice parameterizations, typically limited to near-surface layers and lacking representations of excess and segregated ice and their formation mechanisms (Lu et al., 2017). We suggest incorporating sub-grid scale representations of ground ice distribution, modeling the dynamic formation and melt of excess and segregated ice, and explicitly including thaw-induced ground subsidence and thermokarst pond processes.

Finally, MVPM outputs, which provide high-resolution, observation-constrained simulations of ground thermal dynamics, can serve as benchmarks for evaluating and calibrating LSMs across diverse regions of the QTP. Furthermore, integrating satellite remote sensing products parameter optimization can significantly improve model realism and reduce uncertainties.

The revised manuscript will include an expanded discussion on implication for future projections.

Reference:

Guo, D., Wang, H., and Li, D.: A projection of permafrost degradation on the Tibetan Plateau during the 21st century, 117, D05106, J. Geophys. Res.-Atmos., 117, D05106, https://doi.org/10.1029/2011JD016545, 2012

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6. Spatial resolution

The use of 1km spatial resolution may not adequately capture topographic effects (e.g., slope, aspect), which can critically influence local permafrost dynamics. The paper should be further justifying the adequacy of this resolution, particularly in complex mountainous terrain and variables snow cover (controlled by wind redistribution, slope, aspect)

Response:

We appreciate the reviewer's insightful comment regarding the potential limitations of using a 1 km spatial resolution in capturing fine-scale topographic effects on permafrost thermal regime.

Compared with large-scale studies employing coarser resolutions (e.g., 10 km in Zhang et al., 2022; ~62km in Guo et al., 2012) or point-scale simulations (e.g., Sun et al., 2019, 2022), our use of a 1 km resolution represents a meaningful improvement in balancing spatial coverage with topographic sensitivity. Specifically, our simulations at this resolution successfully capture two important characteristics of the regional permafrost thermal regime in the West Kunlun region: (a) the differentiation of ALT among various soil stratigraphic units (i.e., glarosion, aeolian, lacustrine, colluvial), and (b) the elevation-dependent spatial variability of ground temperatures.

Nonetheless, we fully acknowledge that in complex mountainous terrain, a grid cell size of 1 km is insufficient to resolve micro-topographic features such as slope, aspect, and wind-driven snow redistribution—factors that significantly influence local permafrost hydrothermal conditions. As such, our modeling scheme should be regarded as providing a first-order approximation of permafrost thermal distribution in mountainous areas, rather than capturing detailed topographic controls necessary for slope-scale permafrost assessments.

Despite this limitation, we believe our simulations effectively capture the broader spatial patterns of the permafrost thermal regime across the West Kunlun region. This conclusion is supported by a multi-faceted validation approach, which combines in situ measurements from the regional permafrost monitoring network with previously published permafrost distribution maps. These validations lend reasonable confidence to our simulation results. More importantly, although our current model resolution is limited by the available satellite-derived LST products, the approach produces promising results for the permafrost thermal state and ALT distribution in the West Kunlun region. It provides valuable insights into the regional permafrost thermal regime in remote and data-sparse areas of the western QTP, where observations are difficult. Future improvements will depend on incorporating higher-resolution remote sensing data that better capture topographic and snow cover variability.

The revised manuscript will include an expanded discussion on limitations of model resolution in complex mountainous terrain.

Reference:

Guo, D., Wang, H., and Li, D.: A projection of permafrost degradation on the Tibetan Plateau during the 21st century, 117, D05106, J. Geophys. Res.-Atmos., 117, D05106, https://doi.org/10.1029/2011JD016545, 2012

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7. Figure 5 and Figure 10

These figures display a gridded pattern at approximately 25km resolution, which appears inconsistent with the stated 1km model resolution. the source of this pattern should be clarified and discussed. Is it an artefact of the clustering used? This deserves explanation, especially given the emphasis on fine-scale modelling.

Response:

We believe the gridded pattern occurred in the figures, particularly Figure 5 is not a result of the clustering approaches used in our modeling. Figure 5 presents maps of decadal anomalous LST patterns over the West Kunlun permafrost region, derived from our reconstructed LST dataset spanning 1980 to 2022. Notably, no clustering algorithms were applied in this part of the analysis. The spatial distribution maps in Figures 6, 7, and 9 were indeed produced using clustering algorithms, but the gridded pattern does not appear, further suggesting that it is not an inherent artifact of the clustering process.

The apparent gridded artifacts are primarily due to uncertainties introduced during the resampling process of input datasets used for LST reconstruction. Specifically, several key input variables fed into the machine learning models， such as skin temperature (ST, 0.312° × 0.312°), fractional cold cover (CFC, 0.25° × 0.25°), surface net radiation budget (SRB, 0.25° × 0.25°), and leaf area index (LAI, 0.05° × 0.05°) have coarser spatial resolutions than the 1 km target resolution of our model. To match the modeling grid, we resampled all input variables to a 1 km × 1 km resolution using the nearest neighbor method. This resampling process—from coarse-scale model data to higher resolution is subject to uncertainties. In particular, the coarse resolution of inputs like surface temperature (ST), which is approximately 25–30 km at this latitude, introduced visible gridded patterns in the outputs, even though the resampling enabled analysis at our target 1 km resolution. We acknowledge this as a limitation and have added a discussion to the revised manuscript to clarify this issue during model forcing reconstruction.

Minor Comments

* Line 283: Typo: “account for only 28.02% of the total model grid cells, **remarkable** reducing computation time”

Response:

Yes, we have corrected this typo in the revised manuscript. The revised sentence now reads: “account for only 28.02% of the total model grid cells, remarkably reducing computation time.”

* Line 300: Typo: Section title should read “3.3 Filed investigation and borehole monitoring datasets”

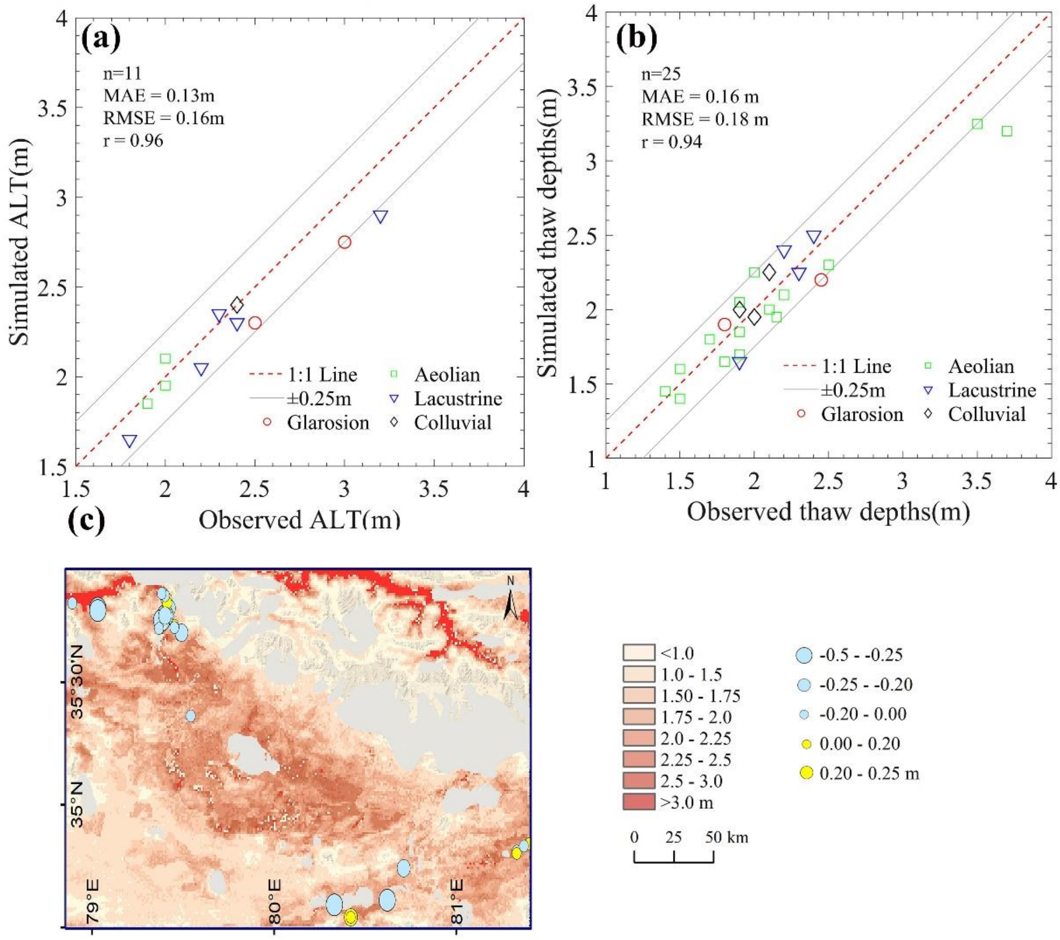
Response:

Yeah, thanks, we have made the revision. We have also carefully checked and corrected similar typos throughout the text.

*Figure 7: Missing units on the lagend: overall presentation could be improved.

Response:

In the revised manuscript, we have added the units to the legend in Figure 7



*Line 538: Add space in “with 74.20%” to read “with 74.20%”

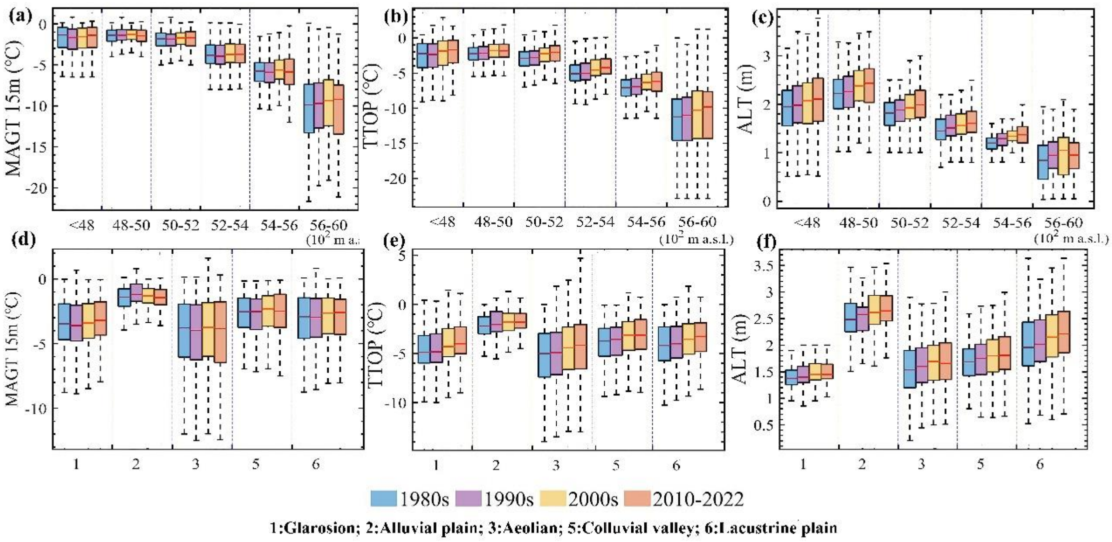
Response:

We have added space in the revised manuscript.

* Figure 11: Legend and labelling could be enhanced for readability.

Response:

We have revised Figure 11 to enhance readability by improving the resolution of the legend and increasing the font size of the labels for better clarity. We hope these improvements make the figure easier to interpret.



* Line 600: Discussion: “Most previous evaluations indicated that soil temperature products derived from atmospheric circulation model or ESMs, which typically have coarse resolutions (~300km) …” Consider replacing “ESMs” with “GCMs” for clarity. Or revise to more moderate number typical of historical forcing datasets such as ERA5 (25km) or ERA5-Land (9km) as you do not use GCMs in this study.

Response:

Yeah, exactly. We agree that "GCMs" would be a more accurate term than "ESMs" in this context and have revised the sentence accordingly. The revised sentence now reads:

“Most previous evaluations indicated that soil temperature products derived from atmospheric reanalysis datasets such as ERA5 (~25 km) or ERA5-Land (~9 km), which typically have coarser spatial resolutions”

* Line 613: Clarify what is mean by “compared to in situ measurements, we found a slight cold bias in our reconstructed LST series, averaging approximately -0.80°C”-is this computed over the entire period? Please specify the period.

Response:

The reconstructed LST was evaluated against monthly in situ observations from the TSH AWS for the period 2016–2018. The average bias across all months during this period was approximately –0.80°C. A systematic cold bias is evident in the mean annual cycle of LST, particularly during the summer months of July, August, and September, as shown in Figure 1.

* Line 858: Typo: “experiencing recover or degradation” should be revised to “experiencing recovery or degradation.”

Response:

The revision has been made in the revised manuscript.

* Line 185: How and what in situ measurement integrated? Please add additional clarification here. (this dataset was created by integrating in situ observations with satellite-based LST from the Moderate Resolution Imaging Spectroradiometer (MODIS).)

Response:

To estimate daily mean LST values from Aqua and Terra's instantaneous daytime and nighttime observations, Zou et al. (2014, 2017) developed a multi-stepwise statistical model based on GST data from AWS located in typical permafrost regions of the central QTP. These relationships capture actual climate conditions corresponding to satellite overpass times. The resulting empirical correction model was then applied across the entire QTP permafrost zone to upscale and generate reliable LST estimates. We therefore believe that the modified MODIS LST dataset developed by Zou et al. (2017) partially accounts for the influence of surface conditions—including snow cover, vegetation, and cloud cover—through the use of a cloud-gap filling algorithm and the incorporation of AWS observations from representative permafrost regions in the central QTP. Please see details in response of secondary question “Use of MODIS LST as forcing data”