Response to Referee#1 egusphere-2024-3956

The Tibetan Plateau hosts the world's most extensive high-altitude permafrost areas, covering approximately 40% of the region. Over the past few decades, widespread permafrost degradation on the Plateau has been primarily driven by climate warming. However, the harsh environmental conditions and logistical challenges have severely limited the establishment of observational sites.

To better understand the evolution of the permafrost thermal regime over recent decades, Zhao et al. present a modeling approach—the Moving-Grid Permafrost Model. This model is forced by remote sensing data that have been corrected using a machine learning technique, thereby enabling the reconstruction of the historical permafrost thermal regime in West Kunlun. Furthermore, to enhance the spatial resolution of the simulations, the study employs clustering techniques and parallel computing methods to accelerate model runs. Consequently, the model demonstrated improved performance relative to available observational data and provided valuable insights into the spatiotemporal evolution of permafrost thermal regimes in West Kunlun.

Overall, this work merits attention from The Cryosphere, provide that the author adequately addresses the review comments and incorporate additional information.

Response:

Thanks a lot for your comments on our paper, which have helped us improve the quality of the manuscript. Below is our detailed response to these comments, describing how we have addressed them in our revised manuscript according to the Referee's comments. 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.

General Comments:

1. In terms of the transient numerical model, First, I would like to understand the distinct advantages of the Moving-Grid Permafrost Model (MVPM) compared to existing models, like GIPL, Noah-MP, CLM, and CryoGrid. The authors state that the MVPM accounts for the thermal properties between frozen and thawed soil, unfrozen water content in frozen soil, ground ice distribution, thaw settlement of the ground surface, and geothermal heat flux to address model deficiencies. However, these physical processes and parameterization schemes are also implemented in other land surface models. Could the authors clarify what specific improvements or innovations MVPM provides over these existing models? Second, how dose the MVPM model deal with the water balance in the soil domain? Which scheme does it use for dynamics of soil water contents? No flow (constant water plus ice contents)? Bucket scheme?

Richards equation? Third, although the snow cover on the Tibetan Plateau is relatively thin, it can significantly affect the hydrothermal state of the permafrost beneath it. dose the MVPM model consider the insulation and cooling effect of snow cover? Fourth, dose this study activate the ground subsidence module of MVPM? This means that does this study consider the existence of excess ice?

Response:

Currently, permafrost degradation on the Qinghai-Tibetan Plateau (QTP) has been recognized, but scholars struggle to reach consensus on quantitative assessments of permafrost changes in response to climate change. Drastic discrepancies exist in the timing, rate, and magnitude of permafrost degradation among modeling results, driven by differences in datasets, model structures and parameterization scheme (Hu et al., 2023). In general, Land surface models (LSMs) have advanced obviously over the past decades, evolving from simple schemes that produce lower boundary conditions for the atmosphere to complex models incorporating several key physical processes crucial to understanding permafrost dynamics, yet, a number of challenges persist (Matthes et al., 2025). Here, the challenges arise from:

Firstly, there are issues related to the structure of model soil columns. A key example is the subsurface grid structure and maximum depth, which remains generally fixed in LSMs coupled with ESMs due to computational constraints (Matthes et al., 2025). LSMs have primarily focused on optimizing parameterization schemes for near-surface hydrothermal processes, typically constrained to the active layer within the upper 2–3 m (Sun et al., 2019). While some models have attempted to extend the soil column simulation depth (e.g., the new version of CLM), they have inadequately accounted for the effects of ground ice and the thermal state of deep permafrost. Refining the stratification of deep soil columns and fully considering the vertical heterogeneity of ground ice distribution in deep permafrost is essential. Without these considerations, simulations may fail to accurately capture changes in the thermal state of areas with thicker, colder permafrost, whereas simulations extending to greater depths more effectively represent the thermal response of permafrost to warming (Alexeev et al., 2007; Sun et al., 2019).

Secondly, concerning of the model's lower boundary conditions, i.e. a geothermal steady heat flow at depths greater than 40 m is a fundamental prerequisite for accurately capturing long-term permafrost thermal dynamics (Mendoza et al., 2020; Sun et al., 2021). However, models such as Noah-MP and CLM often ignore geothermal heat flux by setting zero flux or constant temperature as the bottom boundary condition (Wu et al., 2010; Xiao et al., 2013, Guo et al., 2012). Consequently, this simulation can't accurately simulate permafrost thermal dynamics on the QTP.

Third, issues related to the treatment of soil freezing and thawing arise from model limitations. LSMs, such as CLM, typically assume that phase transition occurs at a specific temperature point (generally 0°C). However, observations from heat-water dynamics monitoring sites in the QTP confirm that the ice-water phase transition in the active layer occurs over a temperature interval, rather than as an abrupt change at a specific temperature point. This suggests that the apparent heat capacity method, which assumes phase change occurs over a temperature interval, more accurately represents the actual freezing and thawing processes (Sun et al., 2021).

Fourth, in addition to process representation aforementioned, horizontal resolution is a critical feature for capturing the high landscape heterogeneity of mountainous permafrost areas. Currently, LSMs in ESMs remain relatively coarse in horizontal resolution, e.g., with the approximately 140 km in the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Chen et al., 2021).

By comparison, permafrost models typically involve modeling a soil column depth greater than 20 m to describe the annual ground temperature cycle and evaluate long-term permafrost evolution, with a primary focus on heat transfer processes in permafrost (Buteau et al., 2004; Riseborough et al., 2009; Burn et al., 2009). Numerous studies have demonstrated that permafrost models can effectively capture the sluggish nature and attenuation of heat transfer in deep permafrost, with simulation results closely matching long-term observational data (Wu et al., 2010; Etzelmüller et al., 2011; Hipp et al., 2012; Zhao et al, 2022). Moreover, unlike LSMs in ESMs, permafrost models can be driven by near-surface meteorological variables (e.g., air temperature, land surface temperature) from diverse sources (Westermann et al., 2017). These forcing data are static and not influenced by the state of the land surface. Furthermore, such models face fewer runtime constraints, enabling high-resolution spatial analysis at scales ranging from meters to hundreds of meters with high computational efficiency, focusing on specific regions of interest and allowing simulations across centennial to millennial timescales (Matthes et al., 2025).

One-dimensional numerical models of ground heat conduction incorporating phase change effects serve as crucial and reliable tools for understanding complex permafrost dynamics (Riseborough et al., 2009). The Move-Grid Permafrost Model (MVPM) is a numerical framework used to infer time series of ground temperature with the land surface as the model's upper boundary (Sun et al., 2019). Its model physics is similar to other widely employed models, such as GIPL2.0 (Dmitry et al., 2017) and CryoGrid2.0 (Westermann et al., 2013): the change of internal energy and temperature in the ground is entirely determined by Fourier's law of heat conduction, and the latent heat generated or consumed by soil freezing and thawing. Movement of water or water vapor in the ground is not included, so the soil water content can only change over time due to freezing processes.

The differences lie in how soil thermophysical properties (e.g., soil heat capacity and soil thermal conductivity) are estimated. The GIPL and CryoGrid models used parameterization schemes based on soil texture derived from de Vries (1963) or modified after this scheme. It is evident that an accurate description of soil property data is essential for modeling. However, most of the soil data are from within the seasonally frozen areas, while data coverage is extremely poor in permafrost regions on the QTP (Li et al., 2015; Shangguan et al., 2013). Moreover, a comprehensive comparison by He et al. (2021) demonstrated that all of the analyzed 39 approaches to calculate soil thermal conductivity in frozen soils performed inadequately. No parameterization scheme is suitable for the permafrost on the QTP, which suggests that new parameterizations are needed (Chen et al., 2019).

In MVPM, the soil heat capacity and soil thermal conductivity under frozen and thawed stages were estimated by a piecewise function:

$$\mathrm{C_{eff}}(T) = \begin{cases} c_f & , \ T \leq T_1 \\ \dfrac{L(\theta - \theta_u)}{T_2 - T_1} + \dfrac{c_f + c_u}{2} & , \ T_1 < T < T_2 \\ c_u & , \ T \geq T_2 \end{cases}$$

$$\mathrm{C_{eff}}(T) = \begin{cases} c_f & , \ T \leq T_1 \\ \dfrac{L(\theta - \theta_u)}{T_2 - T_1} + \dfrac{c_f + c_u}{2} & , \ T_1 < T < T_2 \\ c_u & , \ T \geq T_2 \end{cases}$$

Where the subscripts f and u represent the frozen and thawed states of soil, respectively. θ and θ_u represent the total volumetric water content and volumetric unfrozen water content in frozen soil, respectively. L = 334.54 MJ/m^3 is the volumetric latent heat from the ice-water phase transition.

We utilized our established permafrost monitoring network and large-scale field investigations in the WKL survey region. Soil samples were collected from 15 borehole cores (depths 15–59 m) across various geomorphic classes. Thermophysical properties (e.g., stratigraphies, soil texture, dry bulk density, and ground ice content) of soil layers were assessed through laboratory measurements.

The apparent heat capacity (C_{eff} (z,T)) (J/(m^3·°C)) was to handle the phase change latent heat of unfrozen water within a specified temperature range of −0.3 to 0 °C based on observations. The slope of the unfrozen water-temperature curve $k = \frac{(\theta - \theta_u)}{T_2 - T_1}$ can be determined by the hydrothermal measurement from borehole core. As for thermophysical parameters (e.g., thermal conductivity and heat capacity), based on soil texture, we pre-selected plausible values from Principles of Geocryology (Yershov, 2016), and then refined these during model calibration by manual stepwise optimization procedures recommended by Hipp et al. (2012). The well-calibrated ground thermal properties upscaled using WKL geomorphological classification map. Our simulation results were carefully validated against soil temperature monitoring, ALT, and permafrost maps from different periods between 1996 and 2016 across the WKL permafrost survey region. Similar simulations were conducted before at several borehole sites and limited regions along the QTP (Zhao J. et al., 2022; Sun et al., 2022, 2023). These studies consistently demonstrate that the MVPM has high performance in modeling long-term permafrost thermal dynamics on the QTP.

Second, how does the MVPM model deal with the water balance in the soil domain? Which scheme does it use for dynamics of soil water contents? No flow (constant water plus ice contents)? Bucket scheme? Richards equation?

We set no-flow conditions in the model soil columns, and the soil water content can only change over time due to soil freezing processes. Related description, please refer to the answer to the first sub-question above.

Third, although the snow cover on the Tibetan Plateau is relatively thin, it can significantly affect the hydrothermal state of the permafrost beneath it. dose the MVPM model consider the insulation and cooling effect of snow cover?

In our current simulation time scale, the MVPM model does not explicitly consider the effect of snow cover. While we acknowledge that snow cover can influence the hydrothermal state of permafrost, we believe this omission is justified for several reasons:

Firstly, the near-surface ground temperature is greatly affected by seasonal variations of air temperature and surface conditions (e.g., snow cover, vegetation conditions), characterized by frequent fluctuations and complex patterns of variation (Lunardini et al., 1995). However, the ground acts as a natural low-pass filter for short-term meteorological signals, with the amplitude of the seasonal cycle progressively decreasing with depth. At the depth of Zero Annual Amplitude (ZAA), temperature variations become undetectable (Jin et al., 2011; Dobiński et al., 2022). The variation trend of mean annual ground temperature at ZAA generally aligns with the long-term air temperature trend (Smith and Riseborough, 1983; Buteau et al., 2004; Jin et al., 2011).

Secondly, snow cover distribution is spatially variable over the QTP, with persistently snowcovered areas primarily occurring in the southeastern QTP and in alpine regions with elevations higher than 6000m (Qin et al., 2006; Pu et al., 2007; Yan et al., 2022). In the vast permafrost zone of the QTP, due to strong solar radiation and wind, snow cover is rare, thin (approximately 3cm) with short duration that mostly lasts less than 1 day for a single snow event (Che et al., 2008; Zou et al., 2017).

Thirdly, the subsurface thermal model MVPM, using land surface temperature as model forcing at the upper model boundary, applied a modified clear-sky LST product from MODIS developed by Zou et al. (2017). This product partially accounts for the influence of surface processes, including snow cover effects on LST by incorporating automatic weather station (AWS) observations from a typical permafrost region in the central QTP. These observations, which reflect the actual climate conditions at satellite overpass times, were included in the model training datasets. Moreover, our model simulations reasonably reproduce the vertical ground temperature profile, and the simulated active layer thickness is in good agreement with observations. 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.

Fourth, dose this study activate the ground subsidence module of MVPM? This means that does this study consider the existence of excess ice?

No, in this study, we did not activate the ground subsidence module of the MVPM model. Our focus in this work was primarily on the permafrost thermal regime evolution under climate change. Additionally, turn off the ground subsidence module helped improve modeling computational cost. Therefore, the existence of excess ice and its potential effects on ground subsidence were not considered in the present study.

Reference:

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Sun, Z., Zhao, L., Hu, G., Zhou, H., Liu, S., Qiao, Y., Du, E., Zou, D., and Xie, C.: Numerical simulation of thaw settlement and permafrost changes at three sites along the Qinghai-Tibet 1145 Engineering Corridor in a warming climate, Geophys. Res. Lett., 49, e2021GL097334, https://doi.org/10.1029/2021GL097334, 2022.

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Zhao, J., Zhao, L., Sun, Z., Niu, F., Hu, G., Zou, D., Liu, G., Du, E., Wang, C., Wang, L., Qiao, Y., Shi, J., Zhang, Y., Gao, J., Wang, Y., Li, Y., Yu, W., Zhou, H., Xing, Z., Xiao, M., Yin, L., and Wang, S.: Simulating the current and future northern limit of permafrost on the Qinghai–Tibet Plateau, The Cryosphere, 16, 4823–4846, https://doi.org/10.5194/tc-16-4823-2022, 2022.

Zou, D., Zhao, L., Sheng, Y., Chen, J., Hu, G., Wu, T., Wu, J., Xie, C., Wu, X., Pang, Q., Wang, W., Du, E., Li, W., Liu, G., Li, J., Qin, Y., Qiao, Y.,Wang, Z., Shi, J., and Cheng, G.: A new map of permafrost distribution on the Tibetan Plateau, The Cryosphere, 11, 2527–2542, https://doi.org/10.5194/tc-11-2527-2017, 2017.

2. Aiming at model forcing, as the only model forcing variable, this study adopted three statistical and machine-learning approaches to extent the land surface temperature from Zou et al (2014, 2017). I was wondering why the authors selected these eight specific input variables—surface air temperature, precipitation, skin temperature, soil temperature, fractional cold over, surface radiation budget, leaf area index, and digital elevation model—for the statistical and machine learning approaches. Could the authors clarify whether including more (or fewer) variables

might help to avoid issues of model underfitting or overfitting? Besides, furthermore, what it is the basis for selecting the particular datasets used for these variables? For example, the study utilizes the uppermost soil temperature from CFSR, while skin temperature is taken from ERA5-land. Given that ERA5-land also provides uppermost soil temperature data at a higher spatiotemporal resolution compared to CFSR.

Response:

We selected these eight specific input variables based on physical relevance, expert knowledge, and a thorough review of related published literature (Wang et al., 2022; Xu et al., 2018; Janatian et al., 2017; Yang et al., 2023), which guided us to select variables having close relationships with LST as input. Moreover, data quality and availability on QTP were even more important considerations. We selected variables that had consistent, long-term records that satisfied the requirements of our study.

Regarding model complexity and model underfitting or overfitting, we conducted preliminary experiments and for each machine learning approach, we tested both training and validation errors across different variable combinations. For example, models using only air temperature, as shown in our previous work (Xing et al., 2023), demonstrated signs of underfitting with systematic errors. However, adding related variables significantly improved model performance according to our cross-validation tests. However, adding related variables significantly improved model performance according to our cross-validation tests. Thus, we believe the eight-variable configuration that closely represents LST dynamics provided the optimal balance between model performance and parsimony, performing better than simpler models with fewer variables. Conversely, whether adding additional parameters, such as wind speed, humidity, soil moisture, and snow cover, would lead to model overfitting is unknown at present. These additional data products exhibit considerable variability in quality across the permafrost zone of the QTP. Investigating their potential integration will be the focus of future work.

As for soil temperature selection, our choices were primarily driven by data quality assessments. While ERA5-land is a good choice that provides soil temperature at different depths at a higher spatiotemporal resolution than CFSR, we selected CFSR soil temperature data based on its better performance in preliminary validation against our long-term continuous observations in the permafrost zone on the QTP. The validation results suggested CFSR soil temperature products were closer to the observations at different depths in the permafrost zone on the QTP despite its coarser resolution (Hu et al., 2018). This explains our use of different sources for shallow soil temperature and skin temperature. This mixed-source approach allowed us to leverage the strengths of each dataset while compensating for their respective limitations in our specific study area.

In any way, we will try to do more work on the issues raised by the reviewers.

Reference:

Wang, X., Zhong, L., Ma, Y.: Estimation of 30 m land surface temperatures over the entire Tibetan Plateau based on Landsat-7 ETM+ data and machine learning methods. International Journal of Digital Earth,15(1), 1038-1055, 2022.

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Hu, G., Zhao, L., Li, R., Wu, X., Wu, T., Xie, C., Zhu, X., and Su, Y.: Variations in soil temperature from 1980 to 2015 in permafrost regions on the Qinghai-Tibetan Plateau based on observed and reanalysis products, Geoderma, 337, 893-905, https://doi.org/10.1016/j.geoderma.2018.10.044, 2019.

Specific comments:

1. Line 40: Smith et al 2022? Maybe it is a wrong reference?

Response:

Yeah, it was indeed a typo. The correct reference should be **Smith et al., 2022**, referring to: "Smith, S., O'Neill, H., Isaksen, K., Noetzli, J., and Romanovsky, V.: The changing thermal state of permafrost, Nat. Rev. Earth Environ., 3, 10–23, https://doi.org/10.1038/s43017-021-00240-1, 2022." We have corrected this in the revised manuscript.

2. Line 49: the reference (Zhao et al., 2019) seemed missing?

Response:

Here should be cited as Zhao et al., 2019a, referring to the following reference: "Zhao, L., Hu, G., Zou, D., Wu, X., Ma, L., Sun, Z., Yuan, L., Zhou, H., and Liu, S.: Permafrost Changes and Its Effects on Hydrological Processes on the Qinghai-Tibet Plateau, Bull. Chin. Acad. Sci., 34, 1233–1246, DOI: 10.16418/j.issn.1000-3045.2019.11.006, 2019a."

Thank you for pointing this out. In the revised manuscript, we have carefully checked and made the necessary technical corrections throughout the text.

3. Line 51: should the Qinghai-Tibet Highway and Railway be abbreviated as QTH? Not sure.

Response:

Exactly, the Qinghai-Tibet Highway and Railway should not be abbreviated as QTH. After reviewing the related literature, we found that QTH is a commonly recognized abbreviation for the Qinghai-Tibet Highway, while the Qinghai-Tibet Railway is widely abbreviated as QTR. In the revised manuscript, we use separate abbreviations (QTH and QTR) to avoid confusion.

Reference:

Ma, W., Cheng, G., Wu, Q.: Construction on permafrost foundations: lessons learned from the Qinghai–Tibet railroad. Cold regions science and technology,59(1), 3-11, doi: 10.1016/j.coldregions.2009.07.007, 2009.

Gu, W., Yu, Q., Qian, J., Jin, H., Zhang, J.: Qinghai-Tibet expressway experimental research. Sci. Cold Arid Reg, 2(5), 396-404, DOI: 10.3724/ SP.J.1226.2010.00396, 2010.

Jin, H., Luo, D., Wang, S., Lü, L., Wu, J.: Spatiotemporal variability of permafrost degradation on the Qinghai-Tibet Plateau. Sciences in Cold and Arid Regions, 3(4), 281-305, DOI: 10.3724/SP.J.1226.2011.00281, 2011.

Lin, Z., Niu, F., Luo, J., Lu, J., Liu, H.: Changes in permafrost environments caused by construction and maintenance of Qinghai-Tibet Highway, Journal of Central South University, 18(5), 1454-1464. DOI: 10.1007/s11771−011−0861−9, 2011.

4. Line 84: "ALT" should be given tis full name, this is the first time it has been abbreviated. And "refreezing" of what?

Response:

Here, I want to express that, based on our previous simulations, the MVPM can provide sufficient accuracy to capture the annual dynamics of active layer thawing and refreezing, but it seems that 'thawing' was missing. In the revised manuscript, we have corrected this in revised manuscript.

5. Line 161: dose this study activates the settlement module?

Response:

No, in this study, we did not activate the ground subsidence module of the MVPM model. Please refer to the answer to the first question.

6. Line 183: what is the surface radiation budget? Net radiation? Net shortwave radiation? Or net longwave radiation? It is not clear.

Response:

Net radiation, and we have corrected this in revised manuscript.

7. Line 189: the resolution of all input data is not daily.

Response:

Exactly, we have corrected in revised manuscript. The text there reads as:

"Monthly averages were then calculated from the available data (which varied in temporal resolution across datasets), and missing values were filled by interpolating from nearby data."

8. Line 271: how to deal with initial water/ice content?

Response:

Initial water/ice content was determined using moisture content measurements from representative borehole cores of various Quaternary sedimentary types (fluvioglacial, lacustrine, alluvial, and aeolian sediments) collected during field investigations. These initial values were subsequently fine-tuned during model calibration to optimize performance. Volumetric ice content is highest in fluvioglacial sediments, followed by lacustrine sediments and weathered residual slide rock. In the vertical profile, ground ice is concentrated at the permafrost table on the plateau, where the ALT typically ranges from 2-3 m. Ice content increases with depth from 3 to 10 m and then remains relatively stable below 10 m.

9. Line 274: "approximately"? it should be an exact number for the grid cell to be simulated.

Response:

I agree, this was not an appropriate expression and has been corrected in the revised manuscript. The text there reads as:

"Excluding lake and glacier grids, 47,284 grid cell were used for computation in this study area."

10. Line 300: "filed investigation and borehole monitoring datasets"? I guess it is "Field".

Response:

Yes, exactly, we made a typo. Thank you so much for pointing it out. We have also carefully checked and corrected similar typographical errors throughout the text.

11. Line 430: "Grey Shading"? only saw the grey line.

Response:

Yes, it should be 'grey line' instead of 'Grey Shading.' This has been corrected.

12. Section 4.2.4: the author states, "permafrost area in the West Kunlun kept stable from 1980 to 1999, decrease in the 2000s, while increase between 2010 and 2022." However, the MVPM model is just forced by land surface temperature, while showed an increasing trend between 1980 and 2022 (Figure 4). Could the author explain why permafrost area increase between 2010 and 2022?

Response:

Thank you for this insightful question. This apparent contradiction can be explained by two key factors:

Firstly, while the regional average land surface temperature indeed shows an overall increasing trend from 1980 to 2022, considerable interannual and spatial variability exists within the study area. When analyzed across different periods, some localized areas experienced cooling periods within the overall warming trend. We think these periodic cooling events contributed to new permafrost formation and expansion in those specific areas.

Secondly, the thermal response times of different soil layers to changes in surface temperature vary significantly and include substantial time lags, especially in deeper soil layers. This delayed response is heavily influenced by the presence of ground ice and specific soil properties within the permafrost. The thermal inertia of ice-rich permafrost can delay warming responses by years or even decades. Therefore, the simulated permafrost coverage showing a slight increase between 2010-

2022 may partially reflect the complex delayed response to earlier climate conditions rather than simply the contemporaneous surface temperature trends. These results highlight the complex, non-linear, and slow delaying processes in the response of the permafrost thermal regime in WKL to a warming climate.

13. Line 601-609: so how about the reanalysis data (like Chinese meteorological forcing datasets, ERA5 land)? Compared with the forcing data from ESMs, the spatiotemporal resolution of them is better.

Response:

Exactly, reanalysis or assimilated data products indeed offer spatiotemporal resolution than ESM outputs, but their accuracy in permafrost regions on QTP remains problematic due to limited observational constraints (Jiao et al., 2023). Hu et al. (2018) evaluated soil temperature products derived from reanalysis products and found that GLDAS-NOAH and ERA-Interim showed poor performance in the permafrost region of the QTP when compared with soil temperature observations. Similarly, Yang et al. (2020) reported that widely used reanalysis products, such as CFSv2, ERA-Interim, GLDAS-Noah, and ERA5, can capture temporal dynamics of soil temperature but drastically underestimate soil temperature during the thawing period. Regarding Chinese reanalysis datasets specifically, Hu et al. (2024) found that the China Meteorological Administration Land Data Assimilation System (CLDAS) land surface temperature dataset performs well in most regions of China. However, due to the lack of measurement data in the permafrost region of the QTP and insufficient consideration of the unique underlying surface characteristics of permafrost, CLDAS showed significant errors (bias=2.09°C, MAE=3.64°C, RMSE=4.67°C), primarily overestimating temperatures compared to observations. While reanalysis products indeed offer better spatiotemporal resolution than ESM outputs, their accuracy in permafrost regions on QTP remains problematic.

In the revised manuscript, we have supplemented information about current reanalysis or assimilated soil temperature products and their application in the permafrost region of the QTP. The text there reads as: Most previous evaluations indicated that soil temperature products derived from atmospheric circulation models or ESMs, which typically have coarse resolutions (~300 km), show larger uncertainties over the QTP, particularly in the permafrost region (Hu et al., 2019; Xi et al., 2023). While reanalysis products or assimilated soil temperature datasets indeed offer better spatiotemporal resolution than ESM outputs, their accuracy in permafrost regions remains problematic due to limited observational constraints (Jiao et al., 2023; Hu et al., 2024; Yang et al., 2020).

Reference:

Yang, S., Li, R., Wu, T., Hu, G., Xiao, Y., Du, Y., Qiao, Y.: Evaluation of reanalysis soil temperature and soil moisture products in permafrost regions on the Qinghai-Tibetan Plateau. Geoderma, 377, 114583, 2020.

Hu, J., Zhao, L., Wang, C., Hu, G., Zou, D., Xing, Z., Jiao, M., Qiao, Y., Liu, G., Du, E.: Applicability evaluation and correction of CLDAS surface temperature products in permafrost region of Qinghai-Tibet Plateau, Climate Change Research, 20 (1): 10-25, 2024.

Hu, G., Zhao, L., Li, R., Wu, X., Wu, T., Xie, C., Zhu, X., and Su, Y.: Variations in soil temperature from 1980 to 2015 in permafrost regions on the Qinghai-Tibetan Plateau based on observed and reanalysis products, Geoderma, 337, 893-905, https://doi.org/10.1016/j.geoderma.2018.10.044, 2019.

Jiao, M., Zhao, L., Wang, C., Hu, G., Li, Y., Zhao, J., Zou, D., Xing, Z., Qiao, Y., Liu, G.: Spatiotemporal Variations of Soil Temperature at 10 and 50 cm Depths in Permafrost Regions along the Qinghai-Tibet Engineering Corridor. Remote Sens. 2023, 15, 455. https://doi.org/10.3390/rs15020455, 2023.

Xing, Z., Zhao, L., Fan, L., Hu, G., Zou, D., Wang, C., Liu, S., Du, E., Xiao, Y., Li, R., Liu, G., Qiao, Y., and Shi, J.: Changes in the ground surface temperature in permafrost regions along the Qinghai–Tibet engineering corridor from 1900 to 2014: a modified assessment of CMIP6, Adv. Clim. Chang. Res.,14(1), 85-96, https://doi.org/10.1016/j.accre.2023.01.007, 2023.

14. Could the author explain how this study can be extended to be the future projections? Due to its inability to obtain the land surface temperature with higher resolution from remote sensing data in the future, how to diagnose the future condition of permafrost in West Kunlun.

Response:

Near-surface ground temperature responds to seasonal variations in air temperature (AT), but these fluctuations gradually diminish with depth until becoming negligible at the zero annual amplitude (ZAA) depth, typically 10–20m in the permafrost zone of the QTP (Lunardini et al., 1995; Jin et al., 2011; Dobiński et al., 2022). At the ZAA, seasonal signals are absent, and long-term climate trends dominate, causing ground temperatures to reflect persistent changes in air temperature rather than short-term variability (Smith and Riseborough, 1983; Buteau et al., 2004). This relationship forms a robust basis for projecting permafrost responses to climate change, even in the absence of high-resolution remote sensing data. In particular, the thermal response of permafrost under various future climate scenarios can be investigated by modeling ground temperature profiles driven by a linearly increasing air temperature. For example, the Sixth Assessment Report of the Intergovernmental Panel on Climate Change Working Group I (IPCC

WG1 AR6) (IPCC, 2021) has evaluated and projected climate change over the QTP during the 21st century (https://interactive-atlas.ipcc.ch, last access: April 1, 2025). The model estimated warming between 1995–2014 and 2081–2100 of the mean annual AT in the QTP under three RCP scenarios as 0.013°C a^{-1} (RCP2.6, low concentration of emissions), 0.028°C a^{-1} (RCP4.5, stable concentration of emissions), and 0.060°C a^{-1} (RCP8.5, high concentration of emissions) calculated from the multi-model ensemble median (21–29 model outputs) of CMIP5. The mean warming rate is 0.017°C a^{-1} (SSP1-2.6, strong climate change mitigation), 0.032°C a^{-1} (SSP2-4.5, moderate mitigation), and 0.064°C a^{-1} (SSP5-8.5, no mitigation), estimated from the CMIP6 ensemble median of 31–34 model outputs. A similar projection can be found in our following published literature: Hu et al. (2015), Li et al. (1999), Sun et al. (2020), and Zhao et al. (2022).

Reference:

Smith, M., Riseborough, D.: Permafrost sensitivity to climatic change. In Proceedings, 4th International Conference on Permafrost, Vol. 1. Fairbanks, Alaska, National Academy Press: Washington, DC; 1178–1183, 1983.

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Lunardini, V.: Permafrost Formation Time. CRREL Report 95-8, US Army Corps of Engineers, Cold Regions Research and Engineering Laboratory, 1995.

Jin, H., Luo, D., Wang, S., Lü, L., and Wu, J.: Spatiotemporal variability of permafrost degradation on the Qinghai-Tibet Plateau, Sci. Cold Arid Reg., 3, 281–305, DOI: 10.3724/SP.J.1226.2011.00281, 2011.

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10.3389/feart.2022.802157, 2022.

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