Potential vegetation changes in the permafrost areas over the Tibetan Plateau under future climate warming

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Key Points:

- By 2100, the permafrost areas will thaw at 0.23 ± 0.04 and $0.60 \pm 0.02 \times 10^{6}\,km^2$ under SSP1–2.6 and SSP5–8.5, respectively.
- By 2050, NDVI in the permafrost areas likely stay stable under SSP1–2.6 scenarios and likely show a rising trend under SSP5–8.5 scenarios.
- Surface air temperature and liquid water content at the root zone are the dominant features affecting NDVI changes in the permafrost areas.

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Abstract

Permafrost degradation on the Tibetan Plateau is well-documented and expected to continue throughout this century. However, the impact of thawing permafrost on the distribution, composition, and resilience of vegetation communities in this region is not well understood. In this study, we combined a transient numerical permafrost model with machine learning algorithms to project the near-future thermal state of permafrost and vegetation (represented by the Normalized Difference Vegetation Index [NDVI]) changes under two contrasting climate pathways (Shared Socioeconomic Pathway 1–2.6 [SSP1–2.6] and SSP5–8.5). The contribution of climatic and terrestrial variables to vegetation evolution was quantified using ridge regression. By 2100, permafrost areas were expected to decrease by $21 \pm 4\%$, and $55 \pm 2\%$ under the SSP1–2.6 and SSP5–8.5 scenarios, respectively, relative to the baseline period (2000–2018). Under the SSP1–2.6 scenarios, the mean annual ground temperature and active layer thickness were projected to fluctuate stably, while under the SSP5–8.5 scenarios, a significant increasing trend was anticipated. Satellite-based observations indicated an increasing trend of NDVI within the permafrost areas from 2000 to 2018 (0.01 per decade), mainly attributed to climatic factors. In the future, vegetation greenness was expected to possibly remain stable under SSP1–2.6 scenarios, whereas a rising trend was likely noted under SSP5–8.5 scenarios during 2019–2050, mainly controlled by the surface air temperature and liquid water content at the root zone during the growing season. Our modeling work provides a potential approach for investigating future vegetation changes and offers more possibilities to improve understanding of the interaction between soil-vegetation-atmosphere in cold regions.

Plain Language Summary

About 40% of the Tibetan Plateau is underlain by permafrost, which has undergone significant degradation and is estimated to experience substantial thawing by the end of this century. The thawing permafrost has impacted vegetation growth. To date, it has not been clear how the Normalized Difference Vegetation Index (NDVI; representing vegetation) changes with climate warming and permafrost degradation. Here, we used a land surface model and machine learning algorithms to simulate future permafrost thermal regimes and variations in the NDVI for future growing seasons and assess the most important variables influencing NDVI variability. We found that permafrost areas were projected to shrink by $21 \pm 4\%$ under the SSP1–2.6 scenarios and $55 \pm 2\%$ under the SSP5–8.5 scenarios by 2100, compared to the baseline period (2000–2018). Our results suggested that under mild climate conditions (SSP1–2.6), NDVI in the permafrost areas likely remained stable from 2019 to 2050, while NDVI in the permafrost areas likely showed an increasing trend under harsh climate conditions (SSP5–8.5), which was mainly due to increasing surface air temperature and liquid water content at the root zone on the Tibetan Plateau.

1 Introduction

The Tibetan Plateau (TP; Figure 1) hosts the world's most extensive high-altitude permafrost areas, estimated at $1.15 \times 10^6\, km^2$ (2005–2015) (Ran et al., 2021). Previous studies showed that permafrost had undergone significant degradation due to anthropogenic warming (Smith et al., 2022; X. Wang et al., 2022; Baral et al., 2023), as evidenced by increased mean annual ground temperature (MAGT) (Q. Wu & Zhang, 2008; Zhao et al., 2021), increased active layer thickness (ALT) (Q. Wu & Zhang, 2010; Qin et al., 2017), reduced permafrost thickness and areas (D. Guo & Wang, 2013; Ran et al., 2018), and altered geomorphological features (T. Gao et al., 2021; Xia et al., 2022). According to state-of-the-art Earth System Models (ESMs), the mean annual surface air temperature over the TP is projected to rise by $1.9\,^\circ C$ under the Shared Socioeconomic Pathway 1–2.6 (SSP1–2.6) and by as much as $6.3\,^\circ C$ under SSP5–8.5 by the end of the

21st century, relative to the baseline period of 1981–2010 (R. Chen, Li, et al., 2022). Such warming is expected to exacerbate the thawing and warming of the permafrost. Compared to the baseline period (2006–2015), the MAGT and ALT are estimated to increase by $0.8\,^{\circ}C$ to $2.6\,^{\circ}C$ and $0.7\,m$ to $3.0\,m$, respectively, in the period 2091–2100 under the SSP2–4.5 to SSP5–8.5 scenarios (G. Zhang et al., 2022), corresponding with a decline in permafrost areas by 44% to 71% (G. Zhang et al., 2022). This degradation is expected to cause major impacts on the carbon budget (Mu et al., 2020; T. Wang et al., 2020), hydrological dynamics (Song et al., 2022; T. Wang et al., 2023), ecosystem (Cuo et al., 2022; T. Wang et al., 2022), and infrastructure stability (Ran, Cheng, et al., 2022; R. Chen et al., 2023) on the regional scale. Vegetation covers approximately 81 % of the permafrost areas on the TP, rendering it the predominant surface characteristic (Z. Wang et al., 2016). With methodological innovations, sophisticated models, and a surge in observational data, our understanding of permafrost–vegetation interactions is improving (Heijmans et al., 2022). On the one hand, vegetation significantly influences the hydrothermal regime, carbon, and nutrient dynamics in permafrost environments. This influence is exerted through alterations in the surface energy balance (Chang et al., 2015; Stuenzi, Boike, Cable, et al., 2021), regulation of snow cover dynamics (Lawrence & Swenson, 2011; Grünberg et al., 2020), and impacts on both ecosystem carbon uptake (Ding et al., 2017; D. Wei et al., 2021) and ecosystem respiration processes (Gagnon et al., 2019; Prager et al., 2020). On the other hand, the evolution of permafrost significantly affects vegetation patterns, either promoting greening or browning (Myers-Smith et al., 2020). This is primarily mediated by its control over soil temperature and liquid water content in the root zone (Yi et al., 2014; de Vrese et al., 2023), alterations in landscape morphology (van der Kolk et al., 2016; Mu et al., 2017; Loranty et al., 2018), impacts on microbial stability (M. Wu et al., 2021), and influences on carbon and nitrogen cycling processes (Mekonnen et al., 2018; L. Liu et al., 2022; Mauclet et al., 2022).

Continuous vegetation greening and enhanced carbon uptake were also observed on the TP along with climate warming and permafrost degradation since the 1980s (Teng et al., 2021; Cuo et al., 2022; Shi et al., 2023; Z. Jin et al., 2023; Y. Wang et al., 2023). Notably, the Normalized Difference Vegetation Index (NDVI) exhibited an upward trend of 0.011 per decade from 1982 to 2015 (Teng et al., 2021). Similarly, the Enhanced Vegetation Index (EVI; which was developed to optimize the vegetation signal with improved sensitivity in high-biomass regions) increased by 0.01 per decade from 2000 to 2020 (Shi et al., 2023), and the Net Primary Productivity (NPP) demonstrated a positive trend of $0.51\,g\,C\,m^{-2}$ per decade from 1982 to 2014 (Cuo et al., 2022). While many studies have identified warming temperatures and increasing precipitation to be the main drives of greening (Teng et al., 2021; X. Li et al., 2022; T. Wang et al., 2022) and plant phenology changes (Q. Zhang et al., 2018; M. Shen et al., 2022; T. Wang et al., 2022) across the TP, vegetation greening on the global scale is thought to be mainly induced by CO_2 fertilization (Piao et al., 2020). In addition to the climatic factors, the hydrothermal conditions of the permafrost would also affect the vegetation dynamics through the permafrost-vegetation interactions (J. Wang & Liu, 2022; T. Wang et al., 2022). All of these studies have significantly improved our understanding of the characteristics and drivers of the vegetation greenness on the TP. However, it is still largely unknown how the vegetation cover will evolve under further destabilizing permafrost conditions on the TP accounting for future climate scenarios at a larger spatial scale. This uncertainty persists since the very complex vegetation physiological processes which are often tied to specific local conditions are not yet well represented in generalistic ESMs (Piao et al., 2020). With machine learning approaches increasingly being used to analyze complex spatiotemporal data and explore future environmental change (Pearson et al., 2013; Nitze et al., 2018; J. Guo et al., 2023; C. Shen et al., 2023), coupling the model-based and data-driven methods allows us to deal with the complex permafrost-vegetation interactions and quantify the vegetation dynamics and its dominant factors under different climate scenarios.

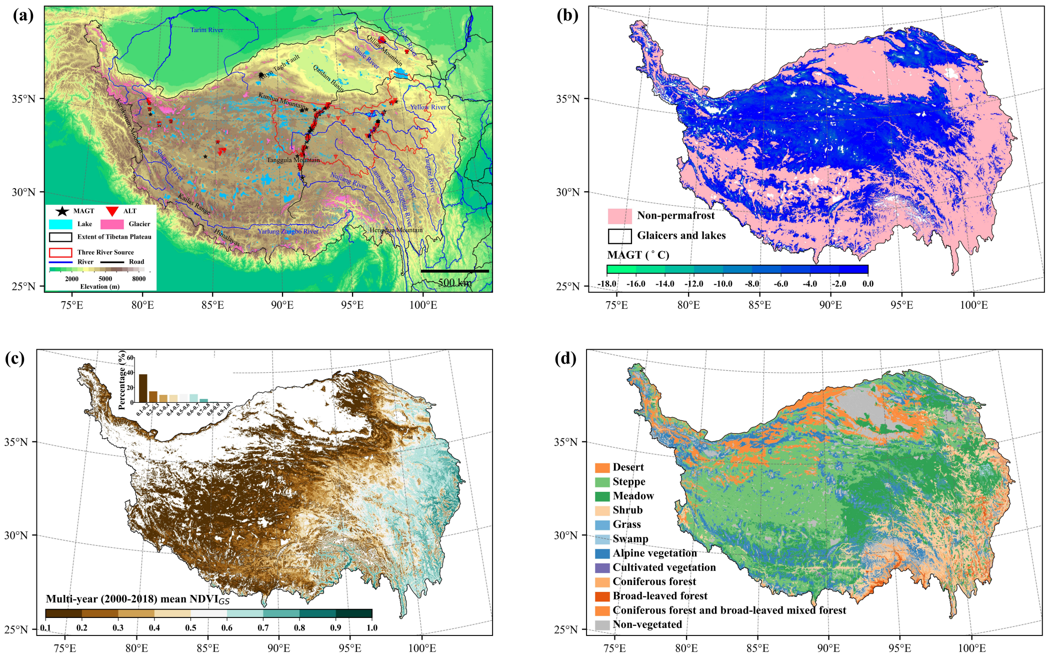

Figure 1. (a) Topography of study areas and location of observation sites over the Tibetan Plateau. Black stars and red triangles stand for the mean annual ground temperature (MAGT) and active layer thickness (ALT) of the monitoring sites, respectively. The digital elevation model, glacier, lake, river, and the boundary of the Tibetan Plateau data and the boundary of Three River Sources are obtained from the National Tibetan Plateau Data Center `https://data.tpdc.ac.cn` and are licensed under CC BY 4.0. The road data is available from the national 1:1000000 public basic geographic database of China (version 2017). (b) Spatial distributions of permafrost and non-permafrost areas on the Tibetan Plateau. Data source: (Obu et al., 2019). (c) Spatial distribution of the multi-year (2000–2018) mean of the growing season (May to September) NDVI on the Tibetan Plateau at 1km^2 scale from MODIS satellite imagery, the sub barplot represents the percentage of the number of grid cells of NDVI in each interval to the total number of grid cells. (d) Maps of vegetation types in the Tibetan Plateau adapted from the 1:1000000 vegetation map of China (Zhou et al., 2022)

In this study, we combined a physically-based permafrost model (CryoGridLite) (Langer et al., 2024) and machine-learning approaches for predicting the vegetation evolution (represented by the NDVI) over the permafrost areas on the TP. Firstly, we applied the CryoGridLite, driven by historical and future forcing datasets under the two different SSPs scenarios (SSP1–2.6 and SSP5–8.5) from two ESMs (AWI-CM-1-1-MR and MPI-ESM1-2-HR), to assess the potential shifts in permafrost distribution and its thermal state over the TP. Then, based on the output of the CryoGridLite model, we used machine-learning algorithms, which are Light Gradient Boosting Machine (LightGBM) (Ke et al., 2017) and Extreme Gradient Boosting Machine (XGBoost) (T. Chen & Guestrin, 2016), to quantify the prospective changes in NDVI within the permafrost areas of the TP. Finally, we elucidated the dominant factors influencing NDVI variations and quantified the contribution of each explanatory variable to the NDVI change.

2 Methods

2.1 CryoGridLite

We applied the one-dimensional transient permafrost model CryoGridLite (Langer et al., 2024) to simulate the trajectory of permafrost evolution over the TP. CryoGridLite was a fast version that was inherited from CryoGrid3 (Westermann et al., 2016) and the CryoGrid community model (Westermann et al., 2023), reducing computational costs and thus making it more suitable for regional (e.g., TP) to hemispherical scale (e.g., Pan-Arctic; Nitzbon et al. (2023)) permafrost modeling. In the following, we briefly describe the main aspects of CryoGridLite and provide the model setup for this work. Further detailed descriptions of model structures and physical processes can be found in Langer et al. (2024).

2.1.1 Model description

In this tailored version of CryoGridLite, we implemented the surface energy balance module, which was driven by the time series of forcing data (i.e. surface air temperature ($^\circ C$), rainfall and snowfall rate ($m\,h^{-1}$), ($kg\,kg^{-1}$), surface air pressure (Pa), incoming shortwave and longwave radiation ($W\,m^{-1}$), and wind ($m\,s^{-1}$)), to provide the upper boundary condition of the model (detailed description can be seen in Supporting Information Text S1.1). Unlike the heat condition equation implemented in CryoGrid3, the CryoGridLite used enthalpy instead of temperature as the state variable to solve the one-dimensional subsurface heat transfer:

$$\frac{\partial H}{\partial t} - \frac{\partial}{\partial z}(k(z,T)\frac{\partial T(H)}{\partial z}) = 0 \tag{1}$$

where $H\,(J\,m^{-3})$ is the volumetric enthalpy including sensible and latent heat contents of the ground, $t\,(s)$ is time, $z\,(m)$ is the vertical subsurface depth, $k\,(z,T)(W\,m^{-1}\,K^{-1})$ is the effective thermal conductivity derived from volumetric soil fractions of mineral, organic, water, ice and air in a given soil depth, and $T\,(k)$ is the ground temperature. The lower boundary condition was defined by constant geothermal heat flux. The implemented snowpack scheme allowed the model to simulate snow accumulation, ablation, melt-water routing, and refreezing within the snow cover. Once the snow had filled the first grid cell above the soil surface, the surface albedo changed from that of the soil to that of the fresh snow and decreased over time towards that of the albedo of old snow (Westermann et al., 2016). Besides, we applied a simple bucket scheme (a detailed description can be seen in Supporting Information Text S1.2) with only downward vertical water flow driven by gravity to compute the dynamics of soil water content rather than constant water contents used in (Langer et al., 2024).

2.1.2 Model setup

In this study, we synthesized the China Meteorological Forcing dataset (CMFD; selected period: 1979–2018 to represent historical climate conditions; resolution: 3 hours and $0.1^\circ \times 0.1^\circ$) (He et al. (2020); `https://www.tpdc.ac.cn`), along with two ESMs from CMIP6 (AWI-CM-1-1-MR and MPI-ESM1-2-HR; selected period: 2019–2100 to portray future climate conditions; resolution: monthly and $0.9375^\circ \times 0.9375^\circ$) (Müller et al. (2018); Semmler et al. (2020); `https://esgf-data.dkrz.de`) following the two SSP scenarios (SSP1–2.6 and SSP5–8.5) to construct the completely forcing data (period: 1979–2100; resolution: hourly and $0.1^\circ \times 0.1^\circ$). Compared with other ESMs, AWI-CM-1-1-MR, and MPI-ESM1-2-HR presented the best performance in depicting the spatiotemporal patterns of mean annual and seasonal surface air temperature on the TP in the past decades (R. Chen, Li, et al., 2022). To ensure model stability and consistency of the forcing data from 1979 to 2100, we performed a linear interpolation on the CMFD data from a 3-hour to an hourly resolution. Further, we utilized the approach from Westermann et al. (2016) by combining baseline climate data (from CMFD) with monthly climate anomalies (from ESMs) to generate the forcing data for this study. The time series of all forcing variables under the two SSPs and two ESMs for the period 1979–2100 is shown in Supporting Information Figure S1.

For the soil domain of the model, the vertical resolution of grid cells increased with thickness from the soil surface (0m) to the lower boundary of the model (100m) (0.02m in 0–2m depth; 0.05m in 2–4m depth; 0.1m in 4–10m depth; 0.2m in 10–20m depth; 1m in 20–30m depth; 5m in 30–50m depth; 10m in 50–100m depth). The soil stratigraphies were specified as mineral, organic, initial water/ice, and air volumetric fractions. The initial water/ice content according to Langer et al. (2023) was assumed halfway between field capacity and porosity for the soil layer above the water table depth, which was provided by a global groundwater table depths product (Fan et al. (2013); `https://thredds-gfnl.usc.es/thredds/catalog/GLOBALWTDFTP/catalog.html`), and saturated with the soil layer below the water table depth. The soil properties were derived from a new version of the global high-resolution dataset of soil hydraulic and thermal parameters dataset for land surface modeling (Y. Dai, Xin, et al. (2019); Y. Dai, Wei, et al. (2019); `https://globalchange.bnu.edu.cn`). The spatial resolution of this dataset was 0.00833° covering from 90°N to 90°S, 180°W to 180°E, and the vertical soil profile was provided in 8 layers (0–0.0451m, 0.0451–0.0906m, 0.0906–0.1655m, 0.1655–0.2891m, 0.2891–0.4929m, 0.4929–0.8289m, 0.8289–1.3828m and 1.3828–3.8019m). This dataset directly provided the volumetric fraction of soil organic matter and soil porosity. At the same time, mineral content and field capacity were calculated based on the approach in Y. Dai et al. (2013); Y. Dai, Xin, et al. (2019); Y. Dai, Wei, et al. (2019). Besides, we assumed the soil stratigraphy from 3.8019m to the bedrock depth Yan et al. (2020) was the same as that of the soil layer above it (i.e.1.3828–3.8019m). Below the bedrock depth, we assumed no soil organic matter existed, the soil porosity was arbitrarily set to 0.1, and the soil mineral content was set to 0.9. We utilized the geothermal gradient ($0.031\,^\circ C\,m^{-1}$; Y. Pang et al. (2022)) to interpolate the four-layer ERA5Land soil temperature (Muñoz-Sabater et al., 2021) in January 1979 to the whole soil profile as the initial ground temperature profile. The constant geothermal heat flux was extracted from the Terrestrial Heat Flow Dataset Lucazeau (2019) to describe the lower boundary condition.

To depict snowpack dynamics over time, five empty grid cells were set above the soil surface in the initial state to represent the maximum snow depth of 0.1m with a vertical resolution of 0.02m (Orsolini et al., 2019). We assumed a constant snow density (150 $\mathrm{kg\,m^{-3}}$) across the snowpack (L. Dai et al., 2018; Yin et al., 2021) and the fresh snow albedo was set to 0.82 (W. Wang et al., 2020). The parameters used in this study for model setup are summarized in the Supporting Information Table S1. We applied nearest-neighbor interpolation for all input datasets (detailed information is provided in Table 1) and further masked them with shape files of the boundary (Y. Zhang et al. (2014); `https://www.geodoi.ac.cn`), glaciers (W. Guo et al. (2015); `https://www.tpdc.ac.cn`), and lakes (G. Zhang et al. (2019); `https://www.tpdc.ac.cn`) of the TP to finalize the model setup for each grid cell in our simulations.

2.2 Machine learning model

In this study, we adopted two regression-based machine learning approaches to project the future NDVI change on the permafrost areas over the TP, which have been widely used in the prediction of future climate as well as environmental variables (Ukkonen & Mäkelä, 2019; Kondylatos et al., 2022; F. Chen et al., 2023; Veigel et al., 2023; C. Chen et al., 2024). The NDVI was collected from the Moderate Resolution Imaging Spectroradiometer (MODIS; MOD13A2; Didan (2015)) with a 1km spatial resolution from 2000–2018 to match up the period of CMFD and be regarded as the baseline period in this study. We processed the raw NDVI data to aggregate them into monthly intervals, which was the time resolution used in our machine learning approaches, using the maximum value composition approach (G. Pang et al., 2022) and further applied a Savitzky-Golay

Table 1. Overview of datasets used in this study

Datasets	Variable/Parameter	Reference/Source	Comments
China Meteorological Forcing Dataset	meteorological forcing	He et al. (2020)	Historical forcing 1979–2018
AWI-CM-1-1-MR MPI-ESM1-2-HR	meteorological forcing	Semmler et al. (2020) Müller et al. (2018)	Future forcing 2019–2100
Global high-resolution dataset of soil hydraulic and thermal parameters	Volumetric fractions of mineral, organic, porosity, and field capacity	Y. Dai, Xin, et al. (2019) Y. Dai, Wei, et al. (2019)	Soil stratigraphy
Global water-table depth dataset	Watertable depth	Fan et al. (2013)	Used to determine initial water/ice content
Terrestrial Heat Flow Dataset	Geothermal heat flux	Lucazeau (2019)	Lower boundary conditions
A Global Depth to Bedrock Dataset for Earth System Modeling	Bedrock depth	Yan et al. (2020)	Used to constrain soil depth
ERA5-Land	Four-layer soil temperature	Muñoz-Sabater et al. (2021)	Initial soil temperature
MODIS NDVI (MOD13A2, Version 6.1, 1km spatial resolution)	NDVI	Didan (2015)	Vegetation condition
Vegetation map from a digitized 1:1000000 vegetation atlas of China	Vegetation types	Zhou et al. (2022)	Analyzing NDVI changes and driving factors across various vegetation types

filter to smooth the NDVI time series (T. Wang et al., 2022). In addition, we assumed that there was no vegetation in the area with a multi-year (2000–2018) average growing season NDVI (from May to September, $NDVI_{GS}$; Teng et al. (2021)) lower than 0.1 (T. Wang et al., 2022). The spatiotemporal trend of $NDVI_{GS}$ over the TP (excluding the non-vegetation areas) from 2000 to 2018 based on the MODIS dataset is shown in the Supporting Information Figure S2. We incorporated six variables as explanatory factors in the machine-learning model based on previous studies (J. Wang & Liu, 2022; T. Wang et al., 2022; Y. Wang et al., 2023). Among them, surface air temperature (SAT), total precipitation (PRE), and incoming shortwave radiation (SIN) originated from climate-forcing data. Furthermore, the soil temperature (ST) and liquid water content (LWC) at the root zone (0–20cm; T. Wang et al. (2022)), and ALT are derived from the output of the CryoGridLite model for each grid cell. The time interval of these six variables was monthly, corresponding with the temporal resolution of the NDVI. The flow of the machine learning approach was as follows: First, the MODIS NDVI dataset and six explanatory variables that correspond with the same grid cell were divided into two groups: data from 2000 to 2014 served as the training dataset (about 80% of the data), and the remaining data (2015–2018) as the testing dataset (about 20% of the data). Then, according to the results from the CryoGridLite in the baseline period, we constructed the training and testing datasets on permafrost and non-permafrost areas (excluded ALT). For tuning the hyperparameters of each machine learning model in the training dataset in each area, we used Bayesian optimization (Python; Optuna package) with 500 iterations and set the early stopping and pruning strategy. The range of possible values for the part of hyperparameters and the final best hyperparameters can be seen in the Supporting Information Table S2. In each iteration, we used mean squared error as a scoring criterion and performed 5-fold cross-validation using the TimeSeriesSplit (Python; Scikit-learn package) approach due to there being a time dependence within the NDVI data. The optimal model parameter combinations resulting from each iteration were recorded and utilized to train the final model. Moreover, we introduced a weighting parameter for each model to enhance the model's emphasis on the growing season $NDVI_{GS}$ associated with individual grid cells. In comparison to the monthly NDVI values, our preference was for the model to exhibit superior performance when modeling the $NDVI_{GS}$ value. Similar to the hyperparameters used for each model, this weighting parameter was employed to obtain the optimal solution during the Bayesian optimization process. To evaluate the performance of each model, we employed root mean squared error (RMSE), bias (BIAS), coefficient of determination (R^2), and Kling-Gupta efficiency (KGE; Gupta et al. (2009)) as the evaluation metrics.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - O_i)^2} \tag{2}$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}(S_i - O_i) \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{4}$$

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{S}{O} - 1\right)^2 + \left(\frac{\sigma_S}{\sigma_O} - 1\right)^2} \tag{5}$$

where N is the number of validation data, S_i and $O_i (i = 1, 2, ..., N)$ are the values of simulated and observed data, respectively, S and O are the mean values of simulated and observed data, respectively, r is the Pearson correlation coefficient, σ_S, and σ_O are the standard deviations of simulated and observed data, respectively. We utilized the optimal machine learning model and future explanatory data to produce the NDVI for each grid cell within the permafrost and non-permafrost region over the TP.

2.3 Statistical analysis

We employed three indices including the MAGT ($^\circ C$), ALT (m), and permafrost areas (km^2) to quantify permafrost degradation. In this study, we obtained the MAGT from the depth of zero annual amplitude, which was typically at the 10–15m soil depth on the TP (Q. Wu & Zhang, 2010; Qin et al., 2017). We defined a grid cell as permafrost if its MAGT lies below the 0°C isotherm at the specific year (Ran, Li, et al., 2022). The ALT was quantified as the maximum thaw depth within the upper 10m of the subsurface (Langer et al., 2024) and there is no existing ALT and permafrost when the MAGT exceeds 0°C at the specific year at a grid cell. We employed the Albers Equal Area projection for area calculations to accurately represent permafrost areas. To better track the dynamics of vegetation conditions across the permafrost and non-permafrost areas on the TP, we used the annual NDVI_{GS} to represent the vegetation at individual years for each grid cell. In this study, we used ridge regression to robustly estimate the individual contributions of explanatory variables (mean or sum value at the growing season, i.e. SAT_{GS}, PRE_{GS}, SIN_{GS}, ST_{GS}, LWC_{GS}, and ALT_{GS}) to the variability in annual NDVI_{GS} across the permafrost and non-permafrost region (T. Wang et al., 2022; J. Li et al., 2023). This approach effectively mitigated the issue of multicollinearity inherent among the predictors. The incorporation of a regularization penalty term (λ) served to apportion variance across the coefficients efficiently, thereby enhancing the precision of the estimated impacts of the explanatory variables on NDVI_{GS}. Preceding the regression analysis, standardized explanatory variables and corresponding NDVI_{GS} served as inputs for the ridge regression model. The optimal regularization parameter, λ, was systematically determined through 5-fold cross-validation and the Grid Search algorithm, ensuring the most robust model performance. Variables exhibiting the largest absolute values of the regression coefficients post-regularization were interpreted as the dominant factors influencing NDVI_{GS} within the specific grid cells. A comprehensive range of the λ values explored during the model tuning phase was from $1{\times}10^{-6}$ to $1{\times}10^{6}$. Besides, trend estimations of time series in this study were based on Sen's slope, which was selected over linear regression for its robustness against outliers and its nonparametric nature (Y. Wang et al., 2023). The flowchart of this study is shown in Figure 2.

3 Results

3.1 Model evaluations

3.1.1 CryoGridLite

For this study, we synthesized observational data, including MAGT and ALT, from a range of literature and public resources across the TP to assess the effectiveness of the CryoGridLite model (Q. Wu et al., 2020; H. Chen et al., 2015; J. Chen et al., 2016; Qin et al., 2017; Luo et al., 2018; Z. Zhang et al., 2020; Zhao et al., 2021; Mu & Peng, 2022; Y. Gao et al., 2023). Ultimately, we selected a total of $n_{MAGT} = 84$ and $n_{ALT} = 66$ different grid cells comprising 151 MAGT and 86 ALT data records within various permafrost regions of the TP from 2000 to 2015 in our model domain (Detailed information see Supporting Information Table S3). Figure 1 (a) displays the geographical distribution of these sites across the TP. For MAGT, we utilized the model output at the depth closest to the measured for comparison while for ALT, we considered the annual maximum thaw depth to compare the observed. Our modeling results indicated the simulated MAGT at most sites (53.6 %) in the range of $\pm 1^\circ C$ of the observed value (Figure 3 (a)), and there was a positive correlation between simulated and observed MAGT (Pearson correlation coefficient = 0.46, $p < 0.01$). However, we noted that our model tended to underestimate observed MAGT across the TP (Bias = -0.77 $^\circ C$), which could be attributed to inaccuracies of forcing, soil stratigraphy dataset, and imitated processes representation (Langer et al., 2024) and setting for the maximum snow height (0.1m). Overall, our model displayed the ability to reproduce the MAGT in the TP permafrost

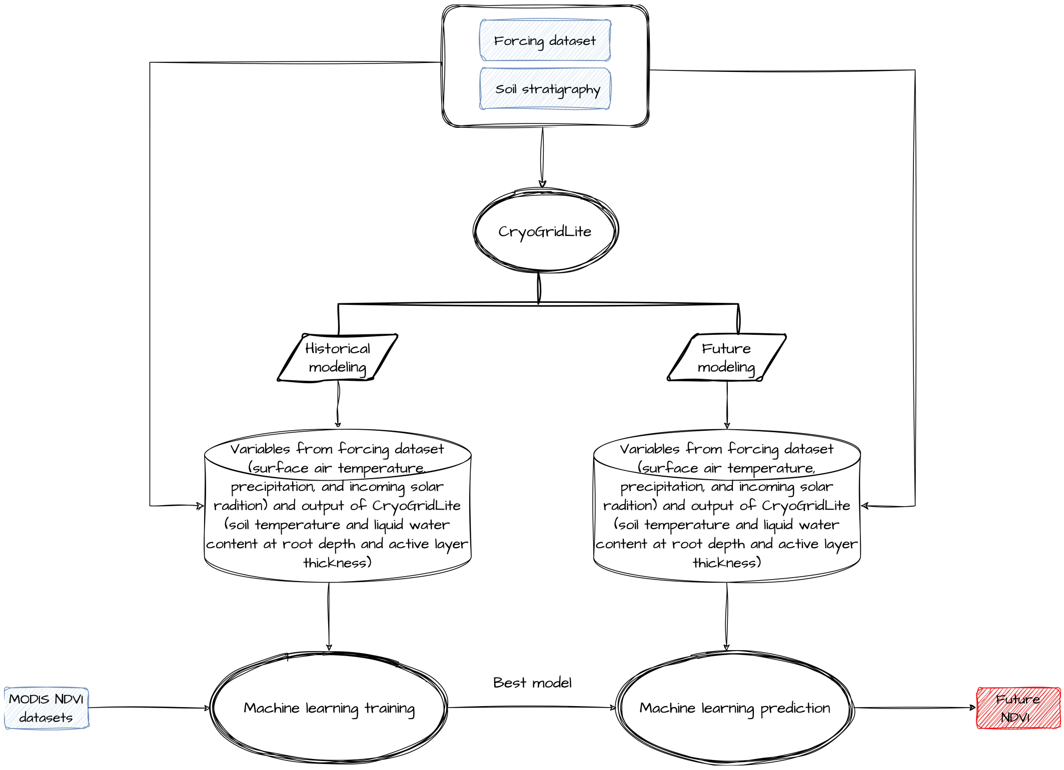

Figure 2. Flowchart of the process used to estimate the future vegetation change

areas well. Compared with the model capability on the MAGT, there was a poorer relationship between simulated and observed ALT, with a Pearson correlation coefficient of 0.17 (Figure 3 (b)). Similarly, the model exhibited a trend of underestimating the measured ALT compared to the observed values (Bias = -0.03 m), which aligns with the simulated cold bias for MAGT. The deviations between measured and modeled ALT were likely to be explained by inadequate forcing and soil dataset, shortcomings of the model (Langer et al., 2024), the cooling effect of shallow snow cover (0.1m), and high spatial heterogeneity of ALT on the TP (B. Cao et al., 2017; Ni et al., 2021). Nevertheless, our model reproduced the observed ALT on the TP, with modeled ALT deviations of $\pm 1\,m$ for most sites (59.1 %). A more detailed model evaluation was conducted for the soil temperature at upper soil depth across the TP due to the soil temperature at the root zone as an input index in machine learning (see Supporting Information Table S4 and Figure S3). In this research, CryoGridLite, driven by CMFD data, was employed to model the distribution of permafrost across the TP during the historical period (Figure 3 (c)). To demonstrate the capability of CryoGridLite to reproduce spatial permafrost occurrence, we juxtaposed our simulation results with five contemporary maps of permafrost distribution based on different approaches, thereby providing a comprehensive comparison and validation of our modeling results (Zou et al. (2017); Ran et al. (2018); Obu et al. (2019); Ni et al. (2021); Z. Cao et al. (2023); Figure 3 (d-h)). The comparison largely confirmed that the projected area of permafrost was consistent between our results and those of previous studies. Our modeling results indicated that the most likely permafrost areas on the TP were $1.10 \times 10^6\,km^2$ for the period 2000–2018 (excluding lakes and glaciers), which agreed well with other five studies ($1.04–1.28 \times 10^6\,km^2$). However, local differences were found between our results and other permafrost maps, which were most pronounced in the southern TP and along the southeast margin of the zone of continuous permafrost. It can be explained in several parts, first, spatial resolution and study period differences; lower resolutions (i.e., $0.1\,^{\circ}$) make it difficult to capture the dynamics of permafrost changes at the boundaries of permafrost zones (Ni et al., 2021) and study period leads a slight discrepancy for the modeled results. Second, simulated approach differences; our results offer a dynamic, transient modeling perspective. In contrast, other models, such as the temperature at the top of the permafrost model and the surface frost number model, while simpler and requiring less data input, are not as equipped to capture transient effects or to project the evolution of permafrost accurately (Smith et al., 2022). Besides, the permafrost-modeled results of the machine learning model have data dependence and the risk of overfitting (Ni et al., 2021). Third, the definition of permafrost differences; we diagnose the absence or presence of permafrost relying on the MAGT at the zero depth of annual amplitude. Other studies adopt different criteria to determine the permafrost exists (e.g., the MAGT at the top of permafrost or the $10\,m$ depth). In summary, despite limitations our model provides a reasonable basis for describing spatially and temporally transient conditions of permafrost on the TP as input variable for the following analysis.

3.1.2 Machine learning model

We utilized the pre-partitioned test dataset to evaluate the performance of two machine-learning algorithms in modeling the NDVI_{GS} over the permafrost and non-permafrost areas of the TP (Figure 4). A comparison analysis of the two results (Figure 4 (a-b)) revealed that each algorithm proficiently captured the satellite-derived NDVI_{GS} values on the permafrost areas. The performance metrics (with $\mathrm{R}^2 >= 0.65$, $\mathrm{BIAS} <= 0.01$, $\mathrm{RMSE} <= 0.08$, and $\mathrm{KGE} >= 0.59$) suggested each model demonstrated robust capabilities in capturing the NDVI_{GS} dynamics over the permafrost regions of the TP. In comparison, the LightGBM model has better performance. Consequently, we selected the lightGBM model for further analysis of the spatial and temporal variability of NDVI_{GS} and its underlying drivers under different future climate scenarios. Additionally, complimentary assessments conducted for NDVI_{GS} over the non-permafrost areas underscored the simulation ability of both algorithms were remarkably similar and both can well repeat the changes in NDVI_{GS} (Figure 4 (c-d)).

3.2 Spatial and temporal patterns of the permafrost dynamics on the TP

To elucidate the spatiotemporal dynamics of permafrost variability on the TP throughout this century, we executed four distinct simulations driven by the AWI-CM-1-1-MR (Figure 5) and MPI-ESM1-2-HR (Supporting Information Figure S4) models, under both the SSP1–2.6 and SSP5–8.5 scenarios. Our findings revealed that spatial variability of permafrost distribution under the AWI-CM-1-1-MR, particularly by mid-century (2041–2060), manifested as a moderate reduction relative to the baseline period (2000–2018). This reduction was predominantly observed along the northern boundary of the continuous permafrost zone, southern regions of the TP, and the Three Rivers Sources (TRS) region (the red box in Figure 1 (a)), with negligible disparities between the lower and higher emission pathways (Figure 5 (a, c, e, g)). In contrast, by the end of the century (2081–2100), the majority of the permafrost areas were projected to remain relatively intact under SSP1-2.6, while areas that experienced permafrost thaw by mid-century continued to show visible degradation (Figure 5 (b, f)). Under a scenario of intensified climate warming, substantial thawing of existing permafrost was anticipated, particularly in the southwestern and southern parts of the TP, where the MAGT at the depth of zero annual amplitude was likely to approach or even exceed $0\,^{\circ}C$ (Figure 5 (d, h)). The TRS region, in particular, was expected to undergo extensive permafrost degradation. Conversely, the northwestern areas of the Changtang Plateau and the Qilian Mountains were projected to maintain their permafrost coverage (Figure 5 (d, h)). In examining the projected changes in MAGT under the AWI-CM-1-1-MR, significant spatial heterogeneity

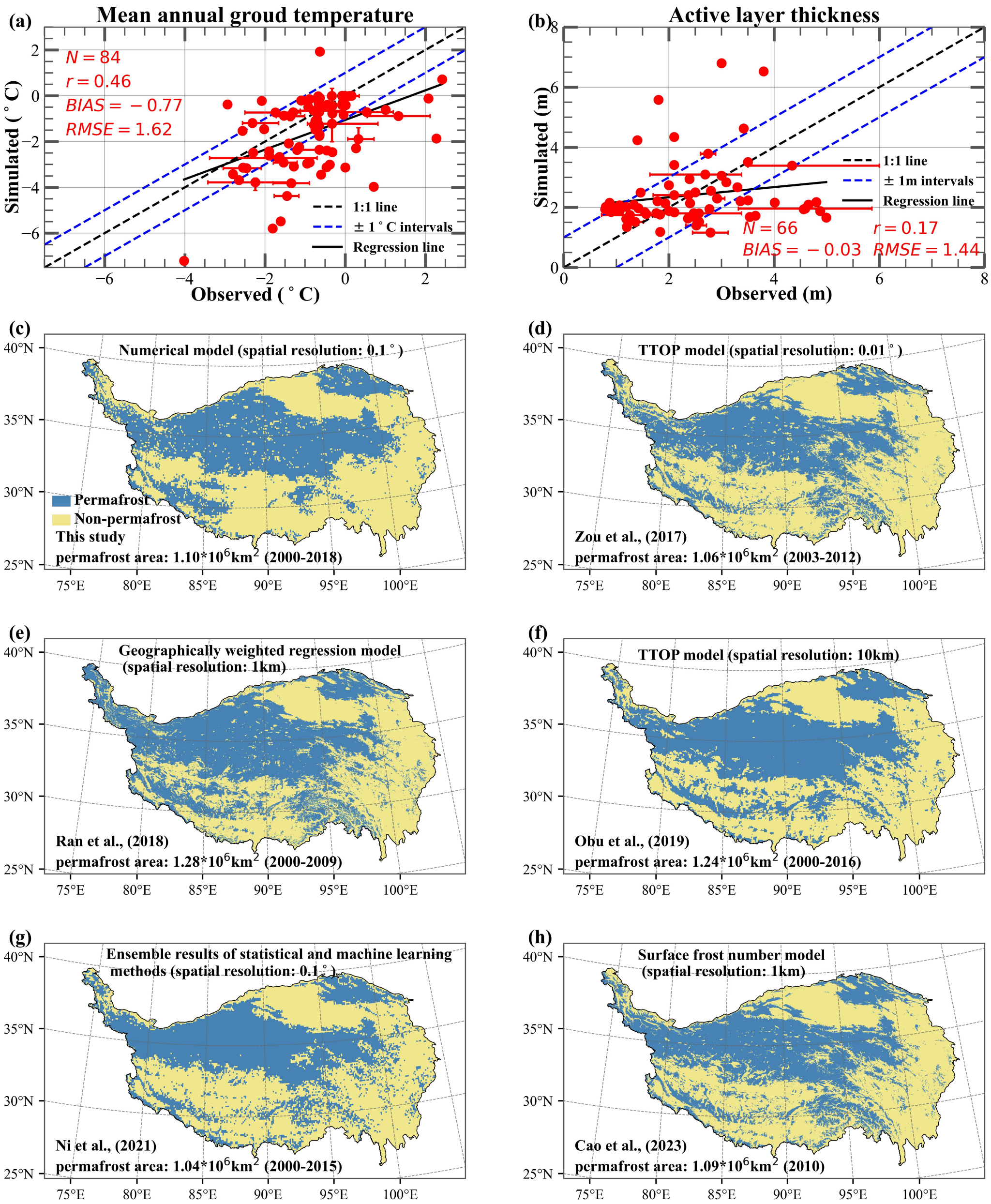

Figure 3. (a) Scatter plot illustrates the comparison results between the observed and simulated mean annual ground temperature (MAGT) for 151 records located within 84 different grid cells. (b) Scatter plot compares the observed and modeled active layer thickness (ALT) for 86 records located within 66 different grid cells. (c) Spatial distribution of permafrost during 2000–2018 over the Tibetan Plateau based on CryoGridLite model. (d-h) Spatial distribution of permafrost on the Tibetan Plateau from other studies. In (a) and (b), each point indicates the average value of observed and modeled MAGT/ALT in the same grid cell. The horizontal error bars represent the range of all observed MAGT/ALT located in the same grid cell, and vertical error bars indicate the range of simulated MAGT/ALT in the same grid cell.

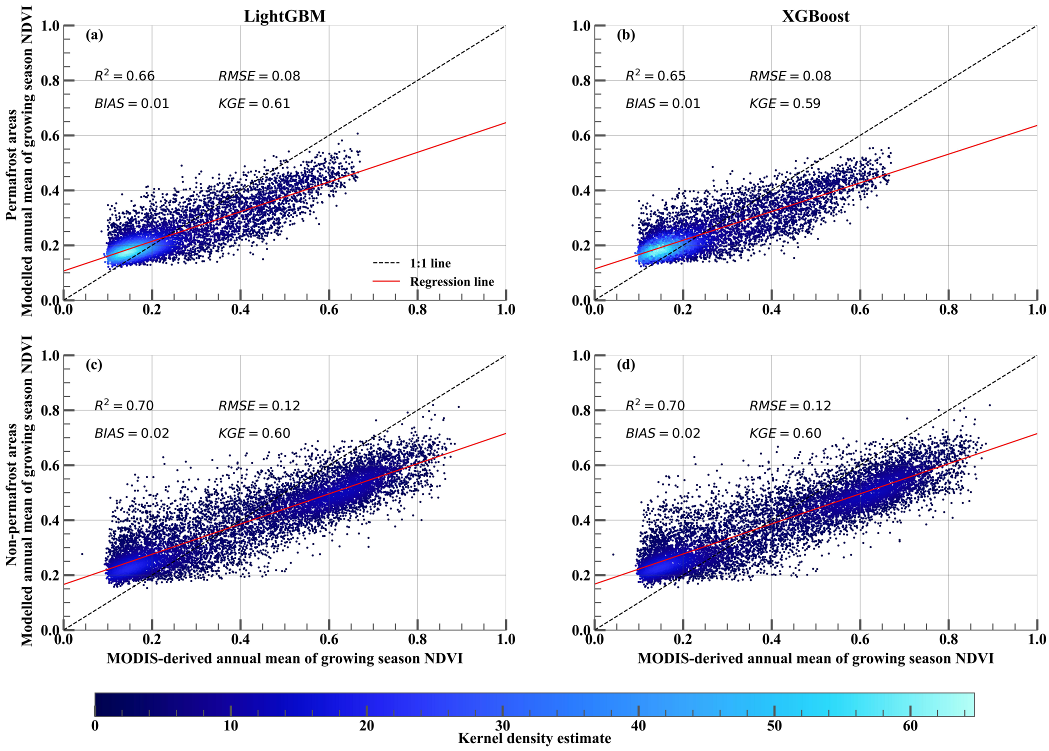

Figure 4. Density scatter plot for comparison between observed and modeled mean annual NDVI_{GS} in the permafrost and non-permafrost areas from 2015 to 2018. (a, c) LightGBM, (b, d) XGBoost. The black dashed line indicates a 1:1 line. The red line represents the regression line.

was observed across the permafrost regions. Under the SSP1–2.6 scenarios, this variability contrasted with the SSP5–8.5 scenarios; specifically, the eastern permafrost regions were trending warmer, whereas the central Changtang Plateau and the Pamir Mountains experiencing cooling trends (Figure 5 (a-b)). The future dynamics of MAGT in these permafrost areas were expected to be largely influenced by the extent of climatic warming (Figure 5 (c-d)). Figure 5 (e-h) depicts the changes in ALT across the permafrost areas on the TP under the AWI-CM-1-1-MR for both mid-century and end-century, under two contrasting scenarios, relative to the 2000–2018 baseline period. The pattern of ALT changes mirrored that of MAGT, with a notable increase in ALT observed in the TRS region and along the Qinghai-Tibet Engineering Corridor (QTEC), throughout the century under both scenarios. Therefore, additional actions are needed to maintain the stability of infrastructure in the QTEC in the future. However, in the western TP, the evolutionary trajectory of ALT was contingent upon the extent of climate warming, i.e. ALT was likely to decrease under stable climatic conditions, while it tended to increase in scenarios of ongoing climate warming. The spatial distribution of MAGT, ALT, and permafrost areas under both scenarios under the MPI-ESM1-2-HR was in correspondence with the results from AWI-CM-1-1-MR (Supporting Information Figure S4).

We further detected the time evolution of permafrost areas, MAGT, and ALT across the TP from 2019 to 2100 under SSP1–2.6 and SSP5–8.5 scenarios (Figure 5 (i-k)). The projected permafrost area consistently showed a decreasing trend across different climate scenarios; however, the rate of this decline varied. Permafrost areas decreased gradually from $1.06 \pm 0.00 \times 10^{6}\, km^2$ (mean $\pm$ standard deviation) to $0.87 \pm 0.04 \times 10^{6}\, km^2$ under SSP1-2.6 and $0.49 \pm 0.02 \times 10^{6}\, km^2$ under SSP5-8.5 during 2019–2100 at a rate of $-0.02 \pm 0.00 \times 10^{6}\, km^2$ per decade (SSP1-2.6) and $-0.07 \pm 0.00 \times 10^{6}\, km^2$ per decade (SSP5-8.5) under the lower and higher emission pathway, respectively (Figure 5 (i)). By 2100, the permafrost areas, under SSP1-2.6 and SSP5-8.5, were projected to decrease by $22 \pm 3\,\%$ and $56 \pm 2\,\%$, respectively, compared to the baseline period.

Figure 5 (j) presents the changes in MAGT during the period 2019–2100. Although projected MAGT based on AWI-CM-1-1-MR and MPI-ESM1-2-HR varies considerably under SSP1–2.6, MAGT increases slightly in the first half-century and decreases further until the end of the century, with insignificant changes in MAGT throughout the century. Under SSP5–8.5 scenarios, MAGT increased significantly to around $-1.0\,^{\circ}C$ by 2100. Relative to the mean MAGT ($-2.26 \pm 0.17\,^{\circ}C$) in the baseline period, MAGT decreased by about $-0.07 \pm 0.18\,^{\circ}C$ and $-0.26 \pm 0.15\,^{\circ}C$ under SSP1–2.6 by mid-century (2041–2060) and end-century (2081–2100), respectively, while, under SSP5–8.5, MAGT increases by about $0.28 \pm 0.03\,^{\circ}C$ and $1.20 \pm 0.05\,^{\circ}C$ by the period 2041–2060 and 2081–2100, respectively.

The time series of simulated ALT in the permafrost areas are shown in Figure 5 (k). The temporal variation of ALT was different in both climate scenarios. Under the lower emission pathway, ALT had no evident change throughout this century, while increasing to around 5.0 m by 2100 under severe climate warming. By the middle of this century, ALT in the permafrost areas of the TP increased by approximately 0.03 ± 0.17 m to 0.37 ± 0.07 m under SSP1–2.6 and SSP5–8.5 scenarios, respectively. However, ALT decreased by about 0.24 ± 0.11 m under SSP1–2.6 and increased by about 1.87 ± 0.14 m under SSP5–8.5 by the end of this century.

3.3 Spatial and temporal patterns of the vegetation in the permafrost areas on the TP

Analysis of satellite imagery data at the grid cell level (i.e. $0.1\,^{\circ}$) revealed that, during the period from 2000 to 2018, NDVI_{GS} trends in the majority of permafrost areas (67.17%) on the TP did not exhibit significant changes (p-value $>$ 0.05). A portion of the permafrost areas, constituting 31.55%, displayed an increase in NDVI_{GS} (p-value $<$

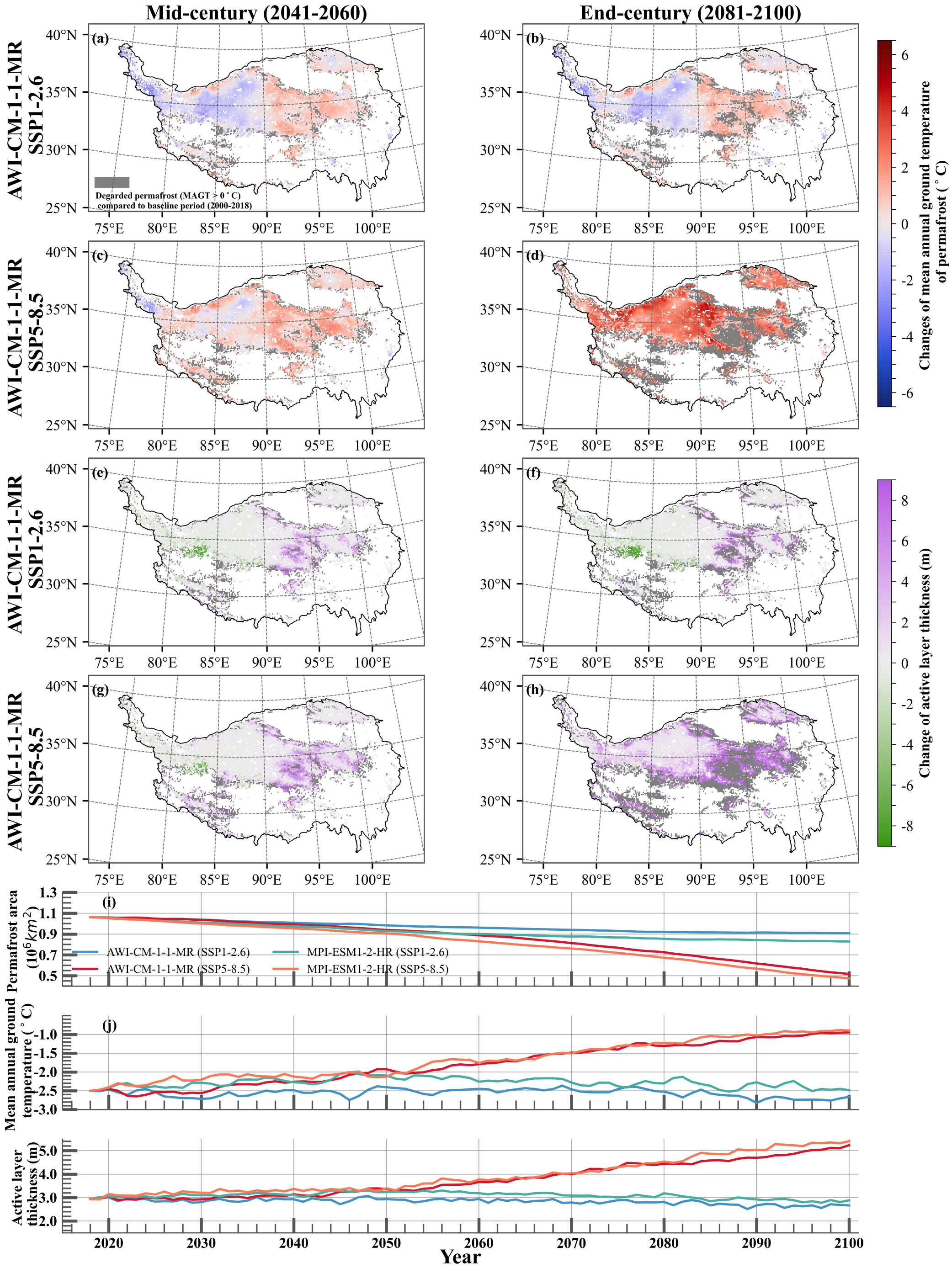

Figure 5. Spatial changes of the mean annual ground temperature (a-d) and active layer thickness (e-h) on the Tibetan Plateau by mid-century (2041–2060) and end-century(2081–2100) under SSP1–2.6 and SSP5–8.5 scenarios from AWI-CM-1-1-MR, related to the baseline period (2000–2018), respectively. (i-k) Time evolution of the changes in permafrost areas, mean annual ground temperature, and active layer thickness from 2019 to 2100 under the SSP1-2.6 and SSP5-8.5 scenarios. The grey area indicates degraded permafrost areas compared with the baseline by the mid-century (2041–2060) and end-century (2081–2100), and the blue, red, green, and orange lines represent the SSP1–2.6 and SSP5–8.5 scenarios from AWI-CM-1-1-MR and SSP1–2.6 and SSP5–8.5 scenarios from MPI-ESM1-2-HR, respectively.

0.05), whereas a minimal area, representing only 1.28% experienced a decline in $NDVI_{GS}$ (p-value < 0.05) (Figure 6 (c)). Within the non-permafrost areas, 18.96% and 2.24% proportion of the area experienced an increased and decreased $NDVI_{GS}$, respectively, during the same period (Figure 6 (d)). Although we utilized data from both permafrost and non-permafrost areas across all grid cells to construct our training dataset, the predictive accuracy for extrapolations beyond the training data range was notably constrained, especially under the high-emission SSP5–8.5 scenarios, due to the inherent data dependency in machine learning. To enhance the robustness of our future NDVI change simulations, we narrowed down our predictions to 2050. Our machine learning analysis, based on the SSP1–2.6 scenarios using two ESMs, indicated a stable $NDVI_{GS}$ (ensemble mean) across the permafrost areas, with no significant alterations anticipated from 2019 through 2050 (p-value > 0.05), maintaining an average $NDVI_{GS}$ of 0.25 ± 0.03 (Figure 6 (a); blue and green line). Spatial distribution analysis of the mean annual $NDVI_{GS}$ trend under both ESMs showed no considerable shifts in vegetation conditions over 85–97% of the permafrost regions up to the middle of the century (Figure 6 (e) and Supporting Information Figure S5 (a)), this stability likely attributable to the relatively stable climatic conditions associated with lower emission trajectories. In contrast, under the SSP5–8.5 scenarios, results from the Mann-Kendall test suggested a marginally increasing trend in the ensemble mean of the $NDVI_{GS}$ anomaly time series ($0.05 <$ p-value < 0.10), with a rate of 0.01 ± 0.00 per decade (Figure 6 (a); orange and red line). Moreover, over 7–29% of the permafrost areas exhibited increased $NDVI_{GS}$, while a significant decrease in $NDVI_{GS}$ was observed in only about 0.33–1.17% of the area under both scenarios (Figure 6 (g) and Supporting Information Figure S5 (c)). Consequently, our findings hint at a potential slightly increased $NDVI_{GS}$ within the permafrost areas over the TP, amidst the ongoing severe climate warming projected by the middle of the century. Figure 6 (b, f, h) and Supporting Information Figure S5 (b, d) outline the time series of the $NDVI_{GS}$ anomaly and spatial distribution of the mean annual $NDVI_{GS}$ trend across the non-permafrost areas. From 2019 to 2050, the ensemble mean of the time series for mean annual $NDVI_{GS}$ anomaly in the majority of non-permafrost areas was expected to remain relatively stable under SSP1–2.6 scenarios (p-value > 0.05), while a slight increase in $NDVI_{GS}$ trend, similar with the permafrost areas, is anticipated under SSP5–8.5 scenarios ($0.05 <$ p-value < 0.10). Spatially, 1.90–5.03% permafrost and 6.10–8.77% non-permafrost areas showed an increasing trend under the SSP1–2.6 and SSP5–8.5 scenarios, respectively. In summary, $NDVI_{GS}$ trends in most permafrost and non-permafrost areas were expected to remain stable under lower emission pathways till the midpoint of this century. Conversely, under higher emission pathways, $NDVI_{GS}$ was likely to exhibit an increasing trend in permafrost and non-permafrost areas. According to the vegetation types dataset of the TP Zhou et al. (2022), the alpine meadow and alpine steppe constituted the primary vegetation in the permafrost areas. We further detected the annual $NDVI_{GS}$ change for different vegetation types (alpine steppe and alpine meadow) in the permafrost areas (Supporting Information Figure S6). Our results showed that areas with increased mean annual $NDVI_{GS}$ outnumbered those with decreased mean annual $NDVI_{GS}$ for both vegetation types, although the extent of this disparity varied under the two scenarios.

3.4 Important features of spatiotemporal variability of the vegetation in the permafrost areas on the TP

The evolution of vegetation is influenced by an interplay of various climatic and terrestrial factors (Hawinkel et al., 2016; Y. Wei et al., 2022; Higgins et al., 2023). We performed ridge regression for both permafrost and non-permafrost areas to identify the absolute values of the contribution of each explanatory factor and detect the most important variables to $NDVI_{GS}$ change. For the baseline period, climate variables (i.e. SAT_{GS}, PRE_{GS}, and SIN_{GS}) contributed notably (59.34% of permafrost areas and 68.65% of non-permafrost areas) to the $NDVI_{GS}$ change, specifically, the contribution of SAT_{GS} was the largest (22.99%) in the permafrost and was the secondary important factor (21.53%)

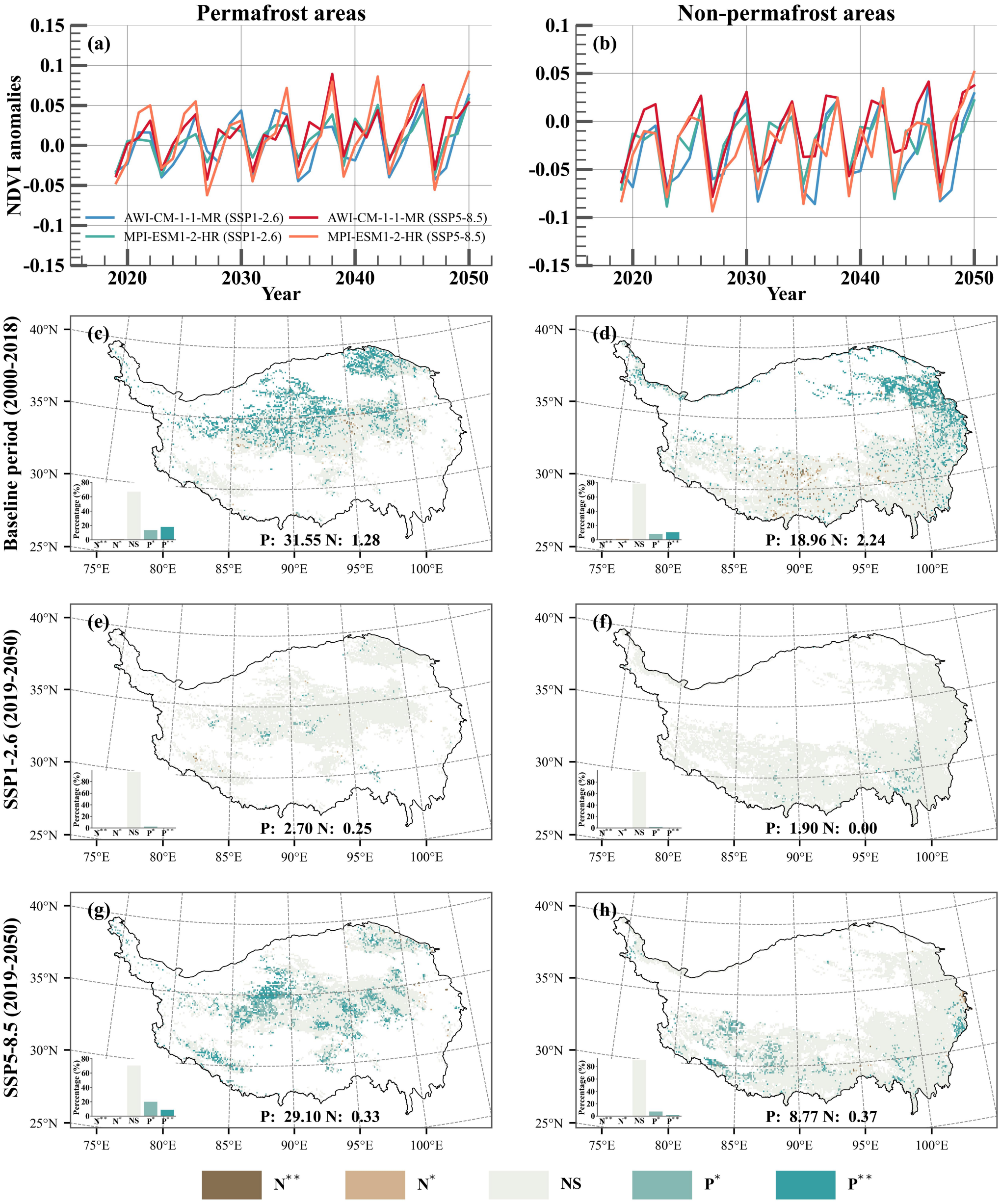

Figure 6. (a-b) Time series of mean annual NDVI$_{GS}$ anomalies (minus the mean value during 2000–2018) from 2019 to 2050 under the future climate conditions on the permafrost and non-permafrost areas over the TP. The blue, red, green, and orange lines represent SSP1–2.6 and SSP5–8.5 scenarios from AWI-CM-1-1-MR and MPI-ESM1-2-HR, respectively. (c-h) Spatial patterns of mean annual NDVI$_{GS}$ trend across the permafrost and non-permafrost areas during the baseline (2000–2018) and future periods (2019–2050) under different climate scenarios from AWI-CM-1-1-MR. N, NS, and P indicate negative, non-significant, and positive trends. * and ** represent significance at p-value $<$ 0.05 and 0.01, respectively

in the non-permafrost area of the plateau, the PRE_{GS} was identified as the third important factor and made similar contributions (17.52% and 19.67%) in the permafrost and non-permafrost areas, the SIN_{GS} had more contributions to the NDVI_{GS} change in the non-permafrost areas (27.45%) than that of in the permafrost areas (18.84%) (Figure 7 (a-d)). For the terrestrial variables (i.e. ST_{GS}, LWC_{GS}, and ALT_{GS} [excluded in non-permafrost areas]), they contributed to the NDVI_{GS} change of approximately 40% of the permafrost areas and 30% of the non-permafrost areas. We used the same method to examine the dominant factors controlling the change of annual NDVI_{GS} during 2019–2050 under different climate scenarios and different ESMs (Figure 7 (e-l) and Supporting Information Figure S7 (a-h)). The results revealed that predominant factors affecting the future NDVI_{GS} changes in permafrost and non-permafrost areas under the different scenarios remained largely consistent. That is, under the SSP1–2.6 and SSP5–8.5 scenarios, it was found that SAT_{GS} and LWC_{GS} emerged as the primary determinants of the interannual variability in NDVI_{GS} across permafrost areas, influencing between 61.24% and 76.26% of these areas. In non-permafrost areas on the TP, SIN_{GS} was identified as the predominant driver behind NDVI_{GS} interannual variability, affecting 33.38% to 45.59% of the areas under both scenarios. Supporting Information Figure S8 depicts the spatial patterns and relative importance of each explanatory variable across diverse vegetation types. The NDVI_{GS} interannual variation in both vegetation types was responsive to variations of climatic factors in the baseline period (approximately 60%). Aiming at the future periods, SAT_{GS} and LWC_{GS} explained a much larger portion of the NDVI_{GS} variations than other factors in both vegetation types (Supporting Information Figure S8 (e-l)). Overall, the interannual variability of the NDVI_{GS} tended to be predominantly controlled by the climate variables in both permafrost and non-permafrost areas from 2000 to 2018. Compared to the baseline period, our study indicated that SAT_{GS}, LWC_{GS} and SIN_{GS} were the main contributors to the NDVI_{GS} change in the permafrost and non-permafrost areas in the future periods (Figure 7 (e-l), Supporting Information Figure S7 (a-h)). Consequently, surface air temperature, liquid water content at the root zone, and incoming solar radiation played an important role in future NDVI_{GS} evolution on the TP.

4 Discussion

4.1 Comparison with previous modeling studies of the permafrost state and vegetation conditions on the TP

In this study, we utilized a computationally efficient numerical permafrost model (CryoGridLite) driven by climatic forcing data to simulate the thermal state of permafrost and ALT over the TP from 1979 to 2100. Table S5 summarizes the simulation results of the thermal state of permafrost and ALT on the TP under present and future climate conditions in the past 10 years based on different approaches. For the historical period, our results fell within the range of these studies for the permafrost state (MAGT: [-3.32° C, -1.35° C]; Permafrost areas: [$1.01 \times 10^{6}\, km^2$, $1.66 \times 10^{6}\, km^2$]) and ALT [1.24m, 3.23m]. As previously mentioned, the differences among these simulation results can be attributed to spatial resolution and study period, study approaches, and the definition of the permafrost state and ALT, etc. For the future period, although there were variations in magnitude and trends for the permafrost state and ALT between our study and others, all demonstrated that permafrost degradation over the TP would be an inevitable consequence in the 21st century under the SSP5–8.5/Representative Concentration Pathway (RCP) 8.5 scenarios. Meanwhile, under the SSP1–2.6/RCP2.6 scenarios, permafrost was anticipated to exhibit relative stability or only slight warming until the end of the century and was most likely aggradation in the northwest of the plateau due to the cooling surface air temperature under the SSP1-2.6 scenarios. In addition to the reasons mentioned above, the divergence in projections could largely be explained by the disparities among the ESMs employed in these studies. For instance, G. Zhang et al. (2022) used

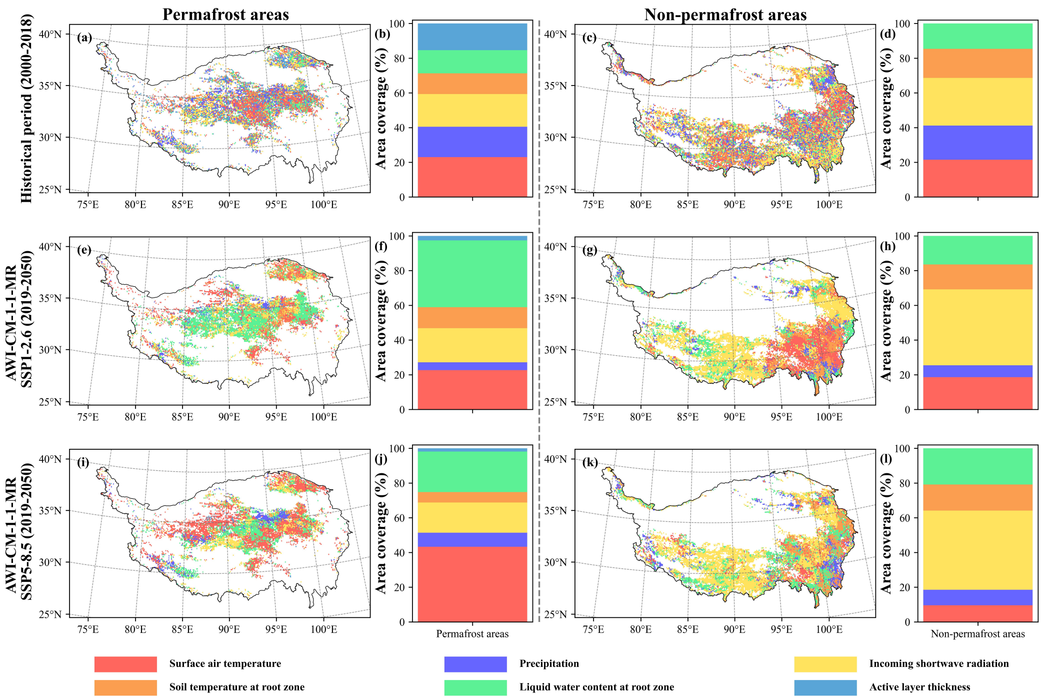

Figure 7. Spatial distribution of the dominant factors to the NDVI_{GS} changes over different periods in the permafrost and non-permafrost areas. (a, c) Baseline period (2000–2018). (e, g) Future period (SSP1–2.6; AWI-CM-1-1-MR). (i,k) Future period (SSP5–8.5; AWI-CM-1-1-MR). The barplot (b, d, f, h, j, l) represents the proportion of the contribution of each variable in the permafrost and non-permafrost areas under AWI-CM-1-1-MR.

the Noah-LSM driven by five ESMs to project permafrost stability on the TP throughout this century. Their findings revealed significant variances among the ESMs' projections under identical scenarios (e.g. under the SSP5-8.5 scenarios, simulations driven by CESM2 and EC-Earth3 suggested that permafrost was highly likely to vanish by 2100, while, projections based on MPI-ESM1-2-HR (also used in our study) indicated that approximately $0.5 \times 10^{6}\,km^2$ (similar with our results) of permafrost might persist by the end of the century).

To project the NDVI in the future on the TP, we employed statistical models trained by machine-learning algorithms under two contrasting climate scenarios in this study. For the historical period (2000–2018), MODIS imagery indicated that the NDVI_{GS} showed an increasing trend over the TP, with a rate of 0.01 per decade, and 24% proportion of the area covered by plants exhibits greening (Supporting Information Figure S2 (a-c)). In addition to the MODIS NDVI data, other ecological indicators (e.g. LAI, NPP, EVI, fractional vegetation coverage [FVC]) demonstrated that vegetation greenness increased on the TP since 2000 (Piao et al., 2020; M. Shen et al., 2022; Yang et al., 2023; X. Zhang & Li, 2023). Regarding vegetation evolution in the future, although few studies have elucidated the magnitude and trends of NDVI in the permafrost areas on the TP (H. Li et al., 2024), studies based on other vegetation factors and methods showed that under the background of future climate change, there was a potential for vegetation greening on the TP (Q. Gao et al., 2016; Mahowald et al., 2016; W. Liu et al., 2020; Cuo et al., 2022; M. Shen et al., 2022; Kong et al., 2023), which aligns with our study. For example, Q. Gao et al. (2016) and Cuo et al. (2022) applied the Lund-Potsdam-Jena dynamic global vegetation model (LPJ-DGVM) to quantify the annual NPP changes on the TP under CMIP5/CMIP6 scenarios. Their findings indicated a general increase in annual NPP, with a notable shift in the dominant vegetation, as alpine shrubs are projected to replace alpine meadows and steppes. The simulation results from ESMs (CMIP5) and regional climate models indicated a continued increasing trend of LAI by the end of the century in the northern temperate region (25–50° N: including the TP) and TP (Mahowald et al., 2016; W. Liu et al., 2020). Kong et al. (2023) constructed a framework of machine learning algorithms to predict the evolution trajectory of FVC in China under four SSP scenarios from 2019 to 2060, with FVC showing an increasing trend except for the east region of China. H. Li et al. (2024) indicated that under the various climate scenarios, along with significant permafrost degradation, the TP exhibited a greening (NDVI) trend in vegetation which persists until the end of the century. In addition to employing the vegetation indices to analyze future vegetation greenness, a recent review summarized the potential plant phenology changes on the TP in this century, which included the advanced start of the growing season and the delayed end of the growing season, causing vegetation greening on the TP (M. Shen et al., 2022). Besides, we would like to point out that there are ongoing debates regarding the continued vegetation greening phenomenon that occurs on the TP and the prospect of the TP becoming a net carbon sink in the future, especially considering carbon released by thawing permafrost and enhanced soil and plant respiration (X. Jin et al., 2021; D. Wei et al., 2021; Ehlers et al., 2022; T. Wang et al., 2022). Consequently, an enhanced focus on the vegetation conditions within the permafrost regions of the Tibetan Plateau is warranted in future studies.

4.2 Important features of vegetation greening

In our study, we used ridge regression to discern the absolute values of the contributions of the driving factors for the NDVI changes on the TP. For the baseline period, the climatic variables were the important features of NDVI_{GS} on the TP in both permafrost (approximately 60%) and non-permafrost areas (approximately 70%) (Figure 7, Supporting Information Figure S7). Piao et al. (2020) noted that dynamic global vegetation models suggested that CO_2 fertilization (a phenomenon widely acknowledged for enhancing vegetation growth) continued to be the predominant factor driving vegetative greening on a global scale. However, in northern high latitudes and the TP, it is the increasing temperatures that primarily contributed to the observed greening trends (LAI). Statistical analysis (Teng et al., 2021; X. Li et al., 2022; M. Shen et al., 2022; T. Wang et al., 2022) and sensitivity experiments (Y. Wang et al., 2023) also demonstrated that climate change played an important role in vegetation growth over the past 40 years on the TP, albeit with contributions of varying magnitudes. This variability in quantitative contributions was attributed to the differential impact of various input explanatory variables (e.g. climate variables, terrain, soil properties) and different data sources (e.g. MODIS data, Global Inventory Modeling and Mapping Studies NDVI product [GIMMS NDVI], and SPOT VEGETATION imagery [SPOT-VEG NDVI]). For the future period, our findings indicated that, compared with the baseline period, $NDVI_{GS}$ showed a potential increasing trend likely occurring in the permafrost areas under the SSP5–8.5 scenarios, mainly attributed to the change of SAT_{GS} and LWC_{GS}. Supporting Information Figure S9 and S10 indicate the spatiotemporal distribution of LWC_{GS} and SAT_{GS} in the permafrost areas from 2019 to 2050. In the vast majority of permafrost regions, both the SATGS and the LWCGS have exhibited an increasing trend. This was in agreement with the results from J. Gao et al. (2017), who combined the LPJ-DGVM with the geographical regression, and R. Cao et al. (2023), who conducted multiple sensitivity experiments based on machine learning algorithms. All indicated that temperature would more significantly affect vegetation changes over the TP. One potential explanation is that warmer temperatures extend the duration of growing seasons, enhance photosynthetic activity, and lead to greater biomass accumulation ((J. Gao et al., 2017; X. Li et al., 2022; M. Shen et al., 2022)). Additionally, our results emphasized the important role of LWC_{GS} in vegetation growing in the permafrost areas. Besides, it is important to acknowledge that in this study we only considered the impact of a few variables on $NDVI_{GS}$ change over the TP, without taking into account other factors. Future studies should synthesize more driving factors and implement more analysis methods (e.g. partial correlation analysis or structural equation model) to improve our understanding of the vegetation change on the TP.

4.3 Model limitation and uncertainty

While the CryoGridLite model capably replicates the mean state (Figure 3 (a-b), Table S4) and temporal evolution (Supporting Information Figure S3) of the permafrost thermal regime across the TP, there is a need for further development and enhancements to diminish the uncertainty of simulations. For instance, the single offline simulation driven by singular meteorological forcing data (He et al., 2020) and soil stratigraphy datasets (Y. Dai, Xin, et al., 2019; Y. Dai, Wei, et al., 2019) and a fixed maximum snow depth (i.e., 0.1 m) and snow density (i.e., $150\,kg\,m^{-3}$) for all grid cells may introduce a large degree of uncertainty for simulation (W. Wang et al., 2016; Lu et al., 2020; Langer et al., 2024). Hence, conducting ensemble parameter simulations (including forcing, soil, and snow properties datasets) should be the direction of our subsequent research endeavors (Nitzbon et al., 2023; Langer et al., 2024). This approach is crucial for a more accurate quantification of the permafrost thermal state across the TP. Furthermore, compared with Nitzbon et al. (2023) and Langer et al. (2024), in this tailored version of CryoGridLite, we implemented the surface energy balance (Supporting Information Text S1.1) and "bucket" scheme (Supporting Information Text S1.2) to calculate the dynamics of upper boundary conditions and groundwater changes, respectively. However, as pointed out by Langer et al. (2024), the model calculated the ground freezing by an enthalpy–temperature relation of free water instead of accurate soil freezing characteristic curves, and the model does not account for the interactions between permafrost and vegetation (Stuenzi, Boike, Cable, et al., 2021; Stuenzi, Boike, Gädeke, et al., 2021), subsidence processes following excess ice melting (Nitzbon et al., 2019), and sub-grid lateral fluxes (Nitzbon et al., 2021), which are known to affect permafrost thaw trajectories in complex landscapes. Further detailed descriptions of model limitation and uncertainty can be found in Langer et al. (2024). Moreover, for future permafrost simulations, we employed two ESMs (AWI-CM-

1-1-MR and MPI-ESM1-2-HR) to drive our CryoGridLite model. These ESMs have demonstrated their capability in accurately reproducing mean annual and seasonal surface air temperatures over recent decades (R. Chen, Li, et al., 2022). However, significant discrepancies were observed in their representation of precipitation changes (R. Chen, Duan, et al., 2022), introducing a notable degree of uncertainty into our permafrost projections. This is due to the permafrost's thermal state being highly sensitive not only to air temperature but also to precipitation; increased rainfall can significantly mitigate permafrost degradation on the Tibetan Plateau (TP) (G. Zhang et al., 2021; Hamm et al., 2023). Therefore, to enhance our understanding of permafrost evolution on the TP, it is imperative to conduct additional simulations using a variety of ESMs

Regarding the NDVI changes predicted by our model, we acknowledge a certain degree of uncertainty inherent in the outputs of our machine learning algorithms. Primarily, these models are challenged by their reliance on data-driven approaches, which may lack a solid physical basis, transparency, interpretability, and a heightened sensitivity to outliers, potentially leading to instability or inaccurate predictions (G. Zhang et al., 2022; C. Shen et al., 2023). Therefore, in our study, although we implemented several strategies to overcome the inherent shortcomings of machine learning algorithms, to make our results more robust, we extrapolated the predicted NDVI only to 2050. In addition, while NDVI data are extensively utilized for assessing the vegetative state of the TP (Teng et al., 2021; T. Wang et al., 2022; Yang et al., 2023), the reliability of this satellite-derived data is considerably impacted by factors such as sensor characteristics, atmospheric interference, and soil background effects (Sha et al., 2020). Therefore, it is crucial for future research to incorporate a broad spectrum of vegetation indices (e.g. LAI, EVI, NPP, soil-adjusted vegetation index) and apply more data to feed machine learning model to reduce these errors and enable a more comprehensive analysis of vegetative dynamics on the TP, particularly against the backdrop of ongoing climatic warming. Moreover, we would like to point out that NDVI_{GS} predictions in this study were based on MODIS satellite imagery. Owing to the data dependency of the machine learning model, the use of alternative NDVI products as response variables might yield divergent results. This is particularly evident in the study of Yang et al. (2023), which employed multi-source data to investigate vegetation changes on the TP since 2000, revealing significant spatiotemporal discrepancies among MODIS data, GIMMS NDVI, and SPOT-VEG NDVI (e.g. SPOT-VEG NDVI ($p < 0.001$) and MODIS NDVI ($p < 0.05$) indicated a significant increasing trend, while GIMMS NDVI data ($p < 0.534$) did not show a significant increasing trend in NDVI on the TP). Meanwhile, the selection of explanatory variables significantly influences the determination of the quantitative contributions of predominant factors. Additionally, vegetation browning events induced by abrupt permafrost thaw (Heijmans et al., 2022) and vegetation greening occurring in thermokarst-drained lake basins (Y. Chen et al., 2023) are not considered in our study, which play an important role in controlling vegetation growth. Despite several shortcomings in our permafrost model and machine learning algorithms, our results attempt to provide a framework for exploring future vegetation changes in cold regions and identified limitations give opportunities for future improvements in our modeling approach.

5 Conclusions

In this study, we combined a numerical permafrost model (CryoGridLite) with machine-learning algorithms to analyze the vegetation conditions in the permafrost areas over the TP under various climate scenarios. Our model simulations, when compared with observational data, efficiently captured the spatiotemporal patterns of permafrost across the TP during the baseline period (2000–2018), and the machine learning algorithm effectively reproduced the interannual NDVI_{GS} for the testing period (2015–2018). Forced by different climate conditions, our CryoGridLite model projected a continual decline in the permafrost areas on the TP in response to future climate warming. Under the SSP1-

2.6 scenario, mean annual ground temperature and active layer thickness appeared stable on average, but with regionally different responses i.e mean annual ground temperature and active layer thickness tended to increase in the Three River Source region and Qinghai-Tibet Engineering Corridor and decrease in the northwest of TP. However, under the SSP5-8.5 scenarios, there was a notable increase in both mean annual ground temperature and active layer thickness. Remote sensing imagery from MODIS suggested that approximately 30% of the permafrost areas on the TP showed an increasing trend in NDVI$_{GS}$ over the baseline period. The results of machine learning indicated that under the low emission scenario (SSP1–2.6), no significant change in NDVI$_{GS}$ was expected for >85% permafrost areas in the future. In contrast, under the high emission scenario, an increasing trend in NDVI$_{GS}$ in the future in about 7.31–29.10% of the permafrost areas, with less than 2% of the area experiencing a significantly decreased NDVI. Analysis of the contributory factors revealed that climatic factors during the growing season were the primary influence on NDVI alterations within the permafrost areas for the baseline period (2000–2018). For the future periods (2019–2050), it was found that the surface air temperature and liquid water content at the root zone during the growing season were anticipated to play a crucial, undeniable role in the NDVI$_{GS}$ changes within the permafrost areas. Although our approach has not yet fully accounted for the processes affecting the thermal state of permafrost and vegetation growth on the TP, the coupling of process-based and data-driven models provides a potential and meaningful pathway for detecting future vegetation evolution on the plateau. Our future research will aim to address the limitations of our methodology and deliver more accurate predictions, thereby enhancing our understanding of the carbon budget of the TP.

Open Research Section

The China Meteorological Forcing Dataset is available at `https://data.tpdc.ac.cn/zh-hans/data/8028b944-daaa-4511-8769-965612652c49`. The AWI-CM-1-1-MR and MPI-ESM1-2-HR datasets are available at `https://esgf-data.dkrz.de/search/cmip6-dkrz/`. The Vegetation types data is available at `https://www.resdc.cn/data.aspx?DATAID=122`. The shapefile of the boundary of the Tibetan Plateau is available at `https://www.geodoi.ac.cn/WebCn/doi.aspx?Id=135`. The shape file of lakes on the Tibetan Plateau is available at `https://www.tpdc.ac.cn/zh-hans/data/da4ffc9a-91fb-4ae9-8da5-c57aa92c8d2b`. The shape file of the glacier on the Tibetan Plateau is available at `https://www.tpdc.ac.cn/zh-hans/data/f92a4346-a33f-497d-9470-2b357ccb4246`. The Global high-resolution dataset of soil hydraulic and thermal parameters dataset is available at `http://globalchange.bnu.edu.cn/research/soil5.jsp`. The Global watertable depth dataset is available at `https://glowasis.deltares.nl/thredds/catalog/opendap/opendap/Equilibrium_Water_Table/catalog.html`. The Terrestrial heat flow dataset is available at `https://doi.org/10.1029/2019GC008389`. The ERA5-Land dataset is available at `https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview`. The MODIS NDVI (MOD13A2, Version 6.1) is available from Google Earth Engine at `https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD13A2`. The CryoGridLite model code, machine-learning algorithms, and ridge regression method used for the simulations and analysis in this work are archived on Zenodo (`https://doi.org/10.5281/zenodo.10928146`).

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