

Article

Climate Warming Controls Vegetation Growth with Increasing Importance of Permafrost Degradation in the Northern Hemisphere During 1982–2022

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Abstract: In permafrost regions, vegetation growth is influenced by both climate conditions and the effects of permafrost degradation. Climate factors affect multiple aspects of the environment, while permafrost degradation has a significant impact on soil moisture and nutrient availability, both of which are crucial for ecosystem health and vegetation growth. However, the quantitative analysis of climate and permafrost remains largely unknown, hindering our ability to predict future vegetation changes in permafrost regions. Here, we used statistical methods to analyze the NDVI change in the permafrost region from 1982 to 2022. We employed correlation analysis, multiple regression residual analysis and partial least squares structural equation modeling (PLS-SEM) methods to examine the impacts of different environmental factors on NDVI changes. The results show that the average NDVI in the study area from 1982 to 2022 is 0.39, with NDVI values in 80% of the area remaining stable or exhibiting an increasing trend. NDVI had the highest correlation with air temperature, averaging 0.32, with active layer thickness coming in second at 0.25. Climate change plays a dominant role in NDVI variations, with a relative contribution rate of 89.6%. The changes in NDVI are positively influenced by air temperature, with correlation coefficients of 0.92. Although the active layer thickness accounted for only 7% of the NDVI changes, its influence demonstrated an increasing trend from 1982 to 2022. Overall, our results suggest that temperature is the primary factor influencing NDVI variations in this region.

Keywords: climate change; permafrost degradation; NDVI; multiple regression residual analysis; partial least squares structural equation modeling; Northern Hemisphere



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1. Introduction

Permafrost serves as an essential and extensive element of the cryosphere, playing an integral role in maintaining the stability of cold-region ecosystems and influencing global climate patterns [1,2]. This unique layer of frozen ground acts as a crucial buffer against climate change, helping to regulate temperature and moisture levels in these

sensitive environments. It has a notable presence across the terrestrial landscape of high-latitude regions [3], spanning large stretches of elevated and northern terrains in cold and mountainous environments [4,5]. Originating from frigid environments, permafrost is particularly responsive to climatic shifts, potentially resulting in considerable changes to its characteristics and coverage [6]. In recent years, global warming has led to varying degrees of permafrost degradation, evident in rising permafrost temperatures, increased active layer thickness, and a shrinking permafrost area [7]. Thickening of the active layer alters surface moisture conditions, which can impact vegetation growth and development in the Northern Hemisphere's permafrost regions.

In permafrost regions, common vegetation types include tundra and boreal forest ecosystems, with high-latitude areas mainly dominated by cold-adapted species such as mosses, lichens, shrubs, and dwarf trees [8,9]. These regions are often classified as temperature-limited ecosystems. Over the past decades, climate warming has significantly promoted vegetation growth in Arctic ecosystems, leading to an overall "greening" trend, typically reflected in increased shrub density and decreased plant species diversity [10–12]. While previous studies have explored the direct effects of rising temperatures and shifting precipitation patterns on plant growth, phenology, and species distribution [13], as well as the indirect impacts of permafrost degradation on soil temperature, moisture, and nutrient availability [14,15], the relative contributions of climate change and human activities to vegetation changes in permafrost regions remain insufficiently quantified. Earlier studies emphasized the direct influence of climate change on NDVI across various regions characterized by colder climates [16,17], while the combined impacts of permafrost degradation and human interventions on vegetation growth are still poorly understood. This study is innovative in quantifying the relative contributions of climate change and human activities to NDVI changes across the permafrost regions of the Northern Hemisphere. For the first time, the partial least squares structural equation modeling (PLS-SEM) approach was applied to quantify the influence pathways and coefficients of various environmental factors on NDVI, providing critical insights into the complex mechanisms driving vegetation changes. The significance of this study lies in addressing a critical research gap regarding the drivers of vegetation changes in permafrost regions. It systematically unveils the combined effects of climate change and human activities on permafrost ecosystems, offering a new perspective for understanding ecosystem responses and serving as a valuable reference for developing strategies for ecological protection and management.

The exploration of long-term changes in vegetation patterns occurs through the examination of temporal data associated with spectral vegetation indices, which provide a detailed view of vegetation changes over extended periods. Currently, numerous indicators are utilized to analyze vegetation growth. These indicators offer crucial insights into vegetation health, density, distribution, and change trends by employing various algorithms and measurement methods from multiple perspectives and across different time scales [18]. NDVI, which is strongly linked to vegetation's physical properties, stands as the most extensively utilized vegetation index [19]. Moreover, due to its simplicity in calculation and abundance of data, NDVI can effectively reflect vegetation coverage and is widely applied in research. The traditional regression methods can indeed identify linear relationships between vegetation dynamics and influencing factors [20,21]. However, they often fail to account for the spatial and temporal dependencies between variables. Recently, residual trend analysis based on multiple regression residuals has been extensively used to discern the varying influences of climatic elements and anthropogenic factors on changes in vegetation dynamics, and it is regarded as a reliable method [22]. Furthermore, the PLS-SEM method, compared to traditional correlation analysis, can provide the pathways and coefficients of various environmental factors affecting vegetation dynamics [23–25].

To quantitatively evaluate the varying impacts of permafrost degradation and human activities on changes in NDVI, we analyzed NDVI variations and their relationships with environmental factors from 1982 to 2022. This study aims to achieve the following key objectives: (1) Assess the spatiotemporal changes in NDVI throughout the growing season in permafrost areas from 1982 to 2022 by employing a range of statistical techniques. (2) Explore the main environmental factors affecting NDVI changes through correlation analysis. Building on these insights, a multiple regression residual analysis was performed to quantitatively assess the influences of climate variations and human interventions on NDVI changes. (3) Employ PLS-SEM to quantitatively analyze the influence of pathways and relationships between climate variations, soil changes, human influences, and changes in permafrost on NDVI.

2. Materials and Methods

2.1. Study Area

The permafrost zone in the Northern Hemisphere is extensively distributed across high latitudes and altitudes [3]. This region encompasses various geographical areas, including Siberia, northern Canada, Alaska, northern Europe, and the Qinghai–Tibet Plateau, forming the largest frozen region on Earth. The climate in this permafrost zone is characterized by cold, dry conditions, with average annual temperatures typically below 0 °C. Winters are long and harsh, while summers are short and cool. Precipitation levels are generally low, consisting mostly of solid precipitation. Based on their continuity and distribution characteristics, permafrost can be grouped into different categories based on its extent and distribution characteristics, reflecting variations in its presence and density across different regions (Figure 1).

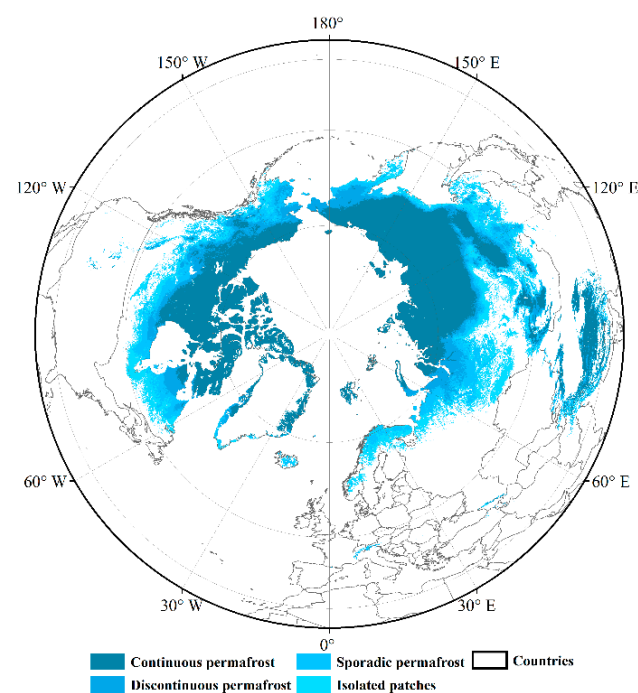


Figure 1. Overview of the study area (spatial distribution of Northern Hemisphere permafrost regions based on [3]).

2.2. Data Source

2.2.1. Vegetation Data

We used the new generation GMMIS NDVI 3g+ dataset to represent vegetation change. The GMMIS NDVI 3g+ dataset features a spatial resolution of 0.0833° and a temporal

resolution of 16 days, extending from 1981 to 2022 (<https://doi.org/10.3334/ORNLDAAAC/2187>, accessed on 12 December 2023). Compared to other NDVI datasets, the GMMIS NDVI 3g+ offers several notable advantages, including enhanced spatial and temporal resolution, which provides more detailed and frequent observations of vegetation dynamics. Moreover, the GMMIS NDVI 3g+ data have undergone rigorous quality control, particularly in high-latitude areas affected by snow cover, using Bayesian calibration and spline interpolation to improve data quality. These high-resolution data allow for a more accurate assessment of vegetation changes and trends, particularly in remote and challenging permafrost regions. Additionally, the extended temporal coverage of the dataset enables a comprehensive analysis of long-term vegetation trends, offering valuable insights into the impacts of climate change over several decades. In this study, we calculated the annual NDVI values for the growing season (June–September) from 1982 to 2022 using the mean values during this period and analyzed the trends in these values.

2.2.2. Environment Data

The environmental factor data used in this study include temperature, precipitation, active layer thickness (ALT), volume of water in the soil layer (SWVL), soil temperature (ST) and Human Footprint (HF). The temperature, precipitation, ST, and SWVL, sourced from the ECMWF Reanalysis v5 (ERA5), cover a time series from 1982 to 2022 with a spatial resolution of $0.1^\circ \times 0.1^\circ$ (<https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means?tab=download>). The ALT data, primarily obtained using the TTOP model, cover the period from 1997 to 2019 with a resolution of 0.0833° . The Human Footprint dataset, which quantifies the influence of human activities on vegetation, is characterized by eight variables that capture various dimensions of human impact. This dataset is provided at a spatial resolution of 1 km. The description of specific environmental factors is shown in Table 1.

Table 1. Environmental data and sources.

Variable	Description	Period	Resolution	Source
ALT	Active layer thickness	1997–2019	1 km	[3]
ST	Soil temperature at (0–7 cm)	1982–2022	0.1°	ERA5-Land
Precipitation	Precipitation	1982–2022	0.1°	ERA5-Land
SWVL	Volume of water in soil layer (0–7 cm)	1982–2022	0.1°	ERA5-Land
Temperature	2 m Air temperature	1982–2022	0.1°	ERA5-Land
HF	Human Footprint	2000–2020	1 km	[26]

2.3. Methods

2.3.1. Correlation Analysis and Partial Correlation Analysis

In this research, the Pearson correlation coefficient was utilized to investigate the relationships among various factors, including temperature, precipitation, ALT, ST, SWVL, HF, and NDVI. Additionally, we utilized partial correlation analysis to assess the strength of the correlation between key environmental variables and NDVI values, allowing us to account for the influences of other variables and gain a clearer understanding of their specific impacts on vegetation dynamics.

2.3.2. Theil–Sen Median Trend Analysis and Mann–Kendall Test

The Theil–Sen Median method is an effective regression analysis technique [27]. This method is particularly valued for its ability to handle outliers and provide a more accurate

estimate of the slope in trend analysis compared to traditional parametric methods. The formula is as follows:

$$\beta = \text{median}\left(\frac{X_i - X_j}{i - j}\right), 1 < i < j < n$$

In the formula, β represents the NDVI trend; $\text{median}()$ denotes the median function; X_i and X_j are the NDVI values for year i and year j , respectively. When $\beta > 0$, NDVI shows an increasing trend, and vice versa.

The Mann–Kendall (M-K) test serves as a non-parametric statistical approach designed to detect trends within temporal datasets [28]. This technique is valued for its ability to detect monotonic trends without making assumptions about the data's distribution, thereby providing a robust analysis of temporal changes [29]. The formula is as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(X_j - X_i)$$

$$\text{sign}(X_j - X_i) = \begin{cases} 1, & (X_j - X_i > 0) \\ 0, & (X_j - X_i = 0) \\ -1, & (X_j - X_i < 0) \end{cases}$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & (S > 0) \\ 0 & (S = 0) \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & (S < 0) \end{cases}$$

In the equation, S represents the test statistic, Z is the standardized test statistic, n is the length of the dataset, and X_j and X_i are the sample time series data. When $n \geq 8$, S approximately follows a normal distribution, and the formula for variance is as follows:

$$\text{Var}(S) = \frac{n(n-1)(2n+5)}{18}$$

The Z statistic follows a standard normal distribution. When $Z > 0$, it indicates an increasing trend, while $Z < 0$, it indicates a decreasing trend. For a given significance level α , if $|Z| \geq Z_{1-\alpha/2}$, the time series demonstrates a significant upward or downward trend. In our analysis, we adopted a threshold of $|Z| \geq 1.96$, which corresponds to a significance level of $\alpha = 0.05$ (95% confidence level). This implies that the time series has passed the test for a statistically significant trend at the 95% confidence level.

The Theil–Sen median analysis was applied due to its robustness to outliers and its ability to estimate linear trends reliably in non-parametric or non-normally distributed datasets, which aligns with the characteristics of the NDVI time series analyzed in this study. Therefore, this study uses a combination of Theil–Sen median analysis and the Mann–Kendall (M-K) test to examine the interannual trends of NDVI and assess their statistical significance. The results are categorized into five distinct groups, which are detailed in Table 2.

Table 2. Sen + Mann–Kendall level of trend change.

β	Z	Trend Characteristics
$\beta > 0$	$Z > 1.96$	significantly increase increase
	$Z < 1.96$	
$\beta = 0$	$Z = 0$	stable
$\beta < 0$	$Z > -1.96$	decrease significantly decrease
	$Z < -1.96$	

2.3.3. Multiple Regression Residual Analysis

Numerous studies indicate that climate factors are the primary influences on vegetation growth; however, the impact of human activities on vegetation changes should not be overlooked. Research indicates that employing multiple regression residual analysis methods can effectively assess the impact of human activities on vegetation changes at a spatial scale [30,31]. By analyzing the residuals from the regression model, this approach facilitates a comprehensive understanding of how each factor independently affects the dependent variables. It effectively isolates their impacts, allowing for a clearer distinction of each factor's individual influence. It is assumed that, throughout the study period, variations in NDVI are exclusively driven by climate fluctuations and human activities. This model enables us to quantify the relative impacts of these two factors on vegetation changes throughout the study period.

The multiple regression residual analysis involves selecting the growing-season NDVI as the dependent variable and temperature and precipitation as independent variables to establish a bivariate linear regression model, from which the model parameters are calculated. Using the temperature and precipitation data along with the model parameters, the predicted NDVI values ($NDVI_{CC}$) are calculated to represent the impact of climate on NDVI. The residuals are then obtained by calculating the difference between the observed NDVI values and the predicted $NDVI_{CC}$, resulting in the NDVI residuals ($NDVI_{HA}$), which reflect the impact of human activities on NDVI. The specific calculation formulas are shown as follows:

$$NDVI_{CC} = a \times T + b \times P + c$$

$$NDVI_{HA} = NDVI_{obs} - NDVI_{CC}$$

In the formula, a , b , and c are the regression model parameters; T and P represent the mean temperature and cumulative precipitation, respectively.

2.3.4. Partial Least Squares Structural Equation Modeling (PLS-SEM) Analysis

The PLS-SEM approach is a powerful data analysis tool suitable for modeling and interpreting potential relationships in multivariate datasets [32,33]. Additionally, PLS-SEM can capture both straightforward and complex interactions among variables [34–36]. On the R platform, PLS-SEM results can be achieved using the ‘plssem’ package [37–39]. The PLS-SEM model comprises both the structural path model and the variable structure. PLS-SEM was chosen due to its ability to model complex relationships between multiple independent and dependent variables, especially when dealing with non-normally distributed data. This method is particularly suited for our study, as it allows for the exploration of the direct and indirect effects of various environmental factors on NDVI. In this study, environmental factors affecting NDVI changes are categorized as soil change, climate change, human activity change, and permafrost change. The four types of environmental factors include one or more observable variables. For soil changes, they include ST and SWVL. The climate includes temperature and precipitation. The human activity is represented by Human Footprint, and permafrost change is represented by ALT.

3. Results

3.1. NDVI Changes in Permafrost Areas

The spatial distribution of the average NDVI during the growing season (June–September) in the study area from 1982 to 2022 is shown in Figure 2a. Research shows that there is significant heterogeneity in the spatial distribution of NDVI. High NDVI values are mainly distributed in the high-latitude areas of Siberia and Alaska, while low NDVI values are primarily found in northeastern Canada, the periphery of Greenland,

and the high-altitude Qinghai–Tibet Plateau (Figure 2a). Statistics indicate that areas with NDVI values ranging from 0.0 to 0.1 constitute 4% of the region, while areas with NDVI values between 0.0 and 0.5 make up 55%. From 1982 to 2022, the average NDVI during the growing season has shown a notable upward trend, increasing from 0.37 to 0.43, with a rate of change of 0.01 per decade (Figure 2b).

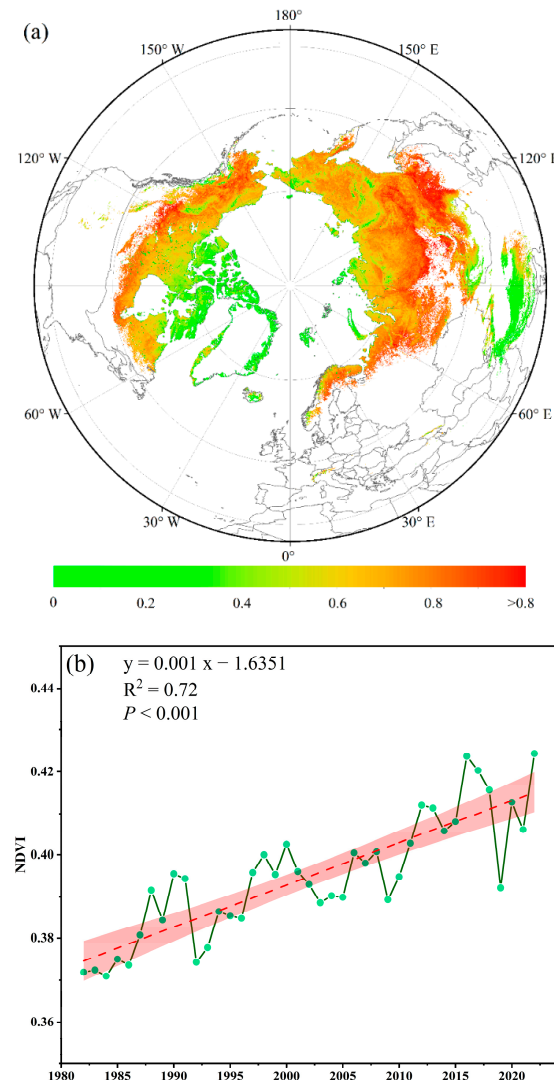


Figure 2. Spatial and temporal distribution of the average NDVI during the growing season in permafrost regions from 1982 to 2022. (a) Spatial distribution of mean NDVI from 1982 to 2022; (b) Temporal variation of NDVI from 1982 to 2022. The green dots represent the annual average NDVI values, the green line shows the interannual fluctuation trend of NDVI, the red dashed line represents the fitted long-term trend line of NDVI, and the shaded area indicates the 95% confidence interval.

Research indicates that the growing-season NDVI in the permafrost regions has been increasing or significantly increasing from 1982 to 2022, mainly in North America and northern Eurasia. Areas with decreasing or significantly decreasing NDVI are relatively small and are concentrated in the Qinghai–Tibet Plateau and northeastern Canada (Figure 3a). The regions exhibiting a significant increase make up the largest share at 49%, followed by areas with increasing trends of 19%. The areas with stable NDVI values account for about 11%, and areas with a decrease and significant decrease account for approximately 13% and 8%, respectively (Figure 3b).

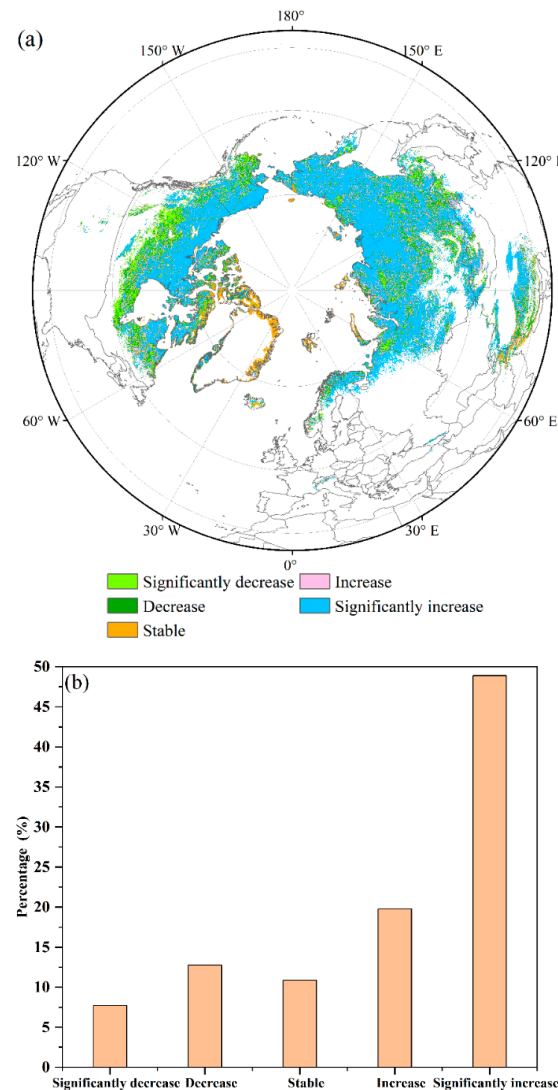


Figure 3. Sen–MK trend changes and area proportions in the Northern Hemisphere permafrost regions from 1982 to 2022. (a) Represents the spatial distribution of NDVI change trends from 1982 to 2022; (b) Indicates the percentage of pixels of various types.

3.2. Correlation and Partial Correlation Analysis

From a spatial distribution perspective, the correlations between these factors and NDVI exhibit significant spatial variability in the Northern Hemisphere (Figure 4). Temperature shows a significant positive correlation with NDVI in high-latitude terrestrial regions such as Siberia, Alaska, and northern Canada (Figure 4a). The correlation between precipitation and NDVI demonstrates notable spatial heterogeneity (Figure 4b). Active layer thickness is significantly positively correlated with NDVI in Siberia and northern North America (Figure 4c). The positive correlation between soil temperature and NDVI resembles that of temperature, concentrated in Siberia and other high-latitude regions of North America (Figure 4d). The correlation between soil water content and NDVI varies regionally (Figure 4e). The Human Footprint shows a significant positive correlation with NDVI in some areas of Siberia and North America, but the majority of regions exhibit a negative correlation (Figure 4f). Among the factors analyzed, the average correlation coefficient between NDVI and air temperature stands out as the highest at 0.32 (Figure 4a). The average correlation coefficients between NDVI and the active layer thickness and soil temperature are 0.25 and 0.22, respectively. The average correlation coefficients between NDVI and soil water contents and human activities are -0.08 and -0.18 , respectively. In

addition, the average correlation coefficient for NDVI in relation to precipitation is 0.01. The findings indicate that, overall, the variation in NDVI is primarily associated with temperature, ALT, and ST.

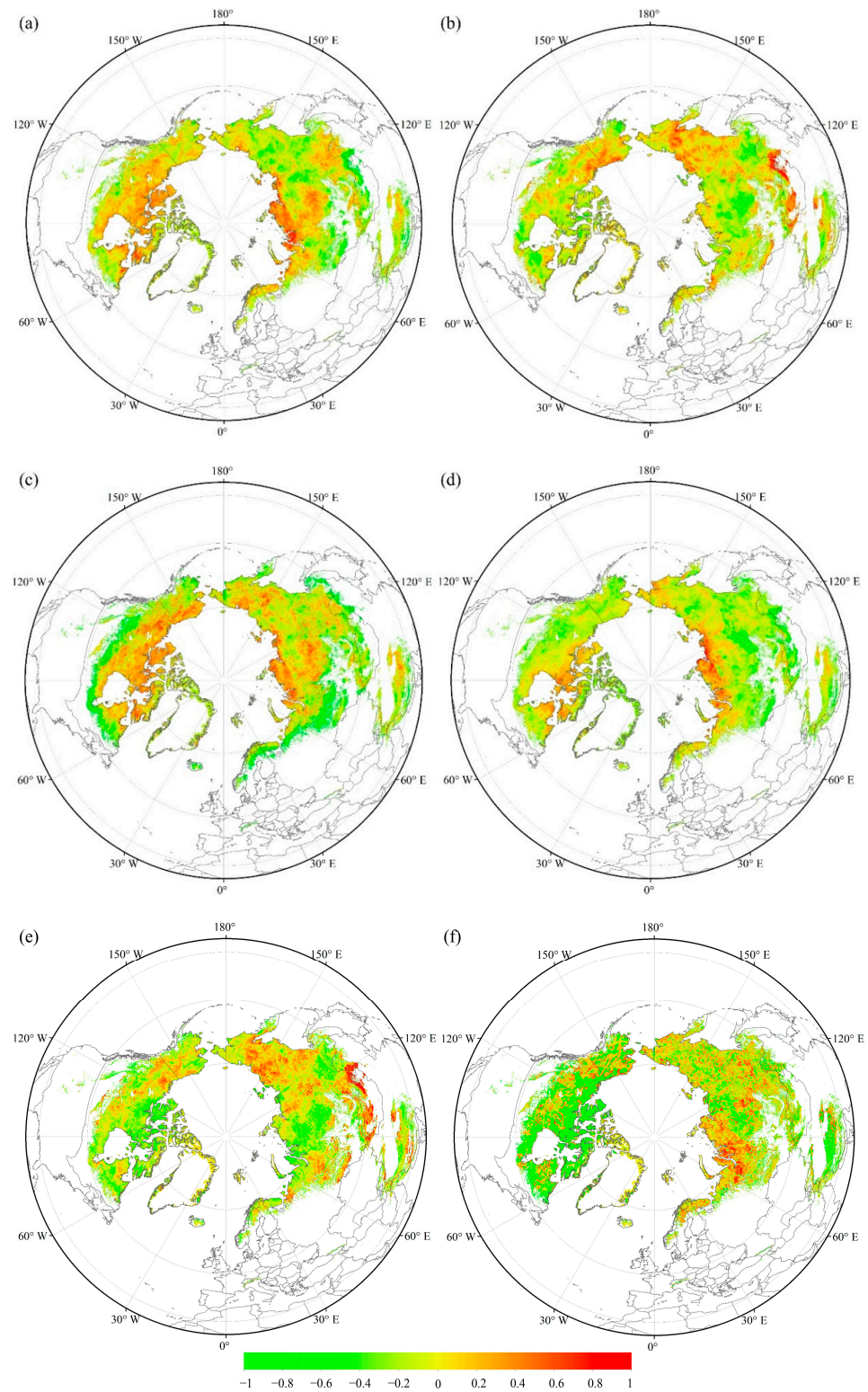


Figure 4. Correlation between NDVI and different environmental factors: (a) temperature, (b) precipitation, (c) ALT, (d) ST, (e) SWVL, (f) HF.

We performed a second-order partial correlation analysis focusing on temperature, ALT, and ST. This analysis was conducted to explore the relationships between NDVI and

each variable, while accounting for the influence of other factors. Specifically, when both ALT and ST were held constant, the average partial correlation coefficient between NDVI and temperature was 0.07 (Figure 5a). The partial correlation between temperature and NDVI exhibits significant spatial heterogeneity, showing a strong positive correlation in high-latitude regions such as Siberia, Alaska, and northern Canada. Conversely, when temperature and ST were controlled, the average partial correlation coefficient between NDVI and ALT increased to 0.13 (Figure 5b). In terms of spatial distribution, the partial correlation between ALT and NDVI shows a positive correlation in parts of Siberia and North America, although there are some areas with a weak negative correlation. In contrast, when temperature and ALT were kept constant, the average partial correlation coefficient between NDVI and ST was recorded at -0.04 (Figure 5c). In terms of spatial distribution, the partial correlation between ST and NDVI follows a pattern similar to that of temperature, showing a positive correlation in the high-latitude regions of Siberia and North America.

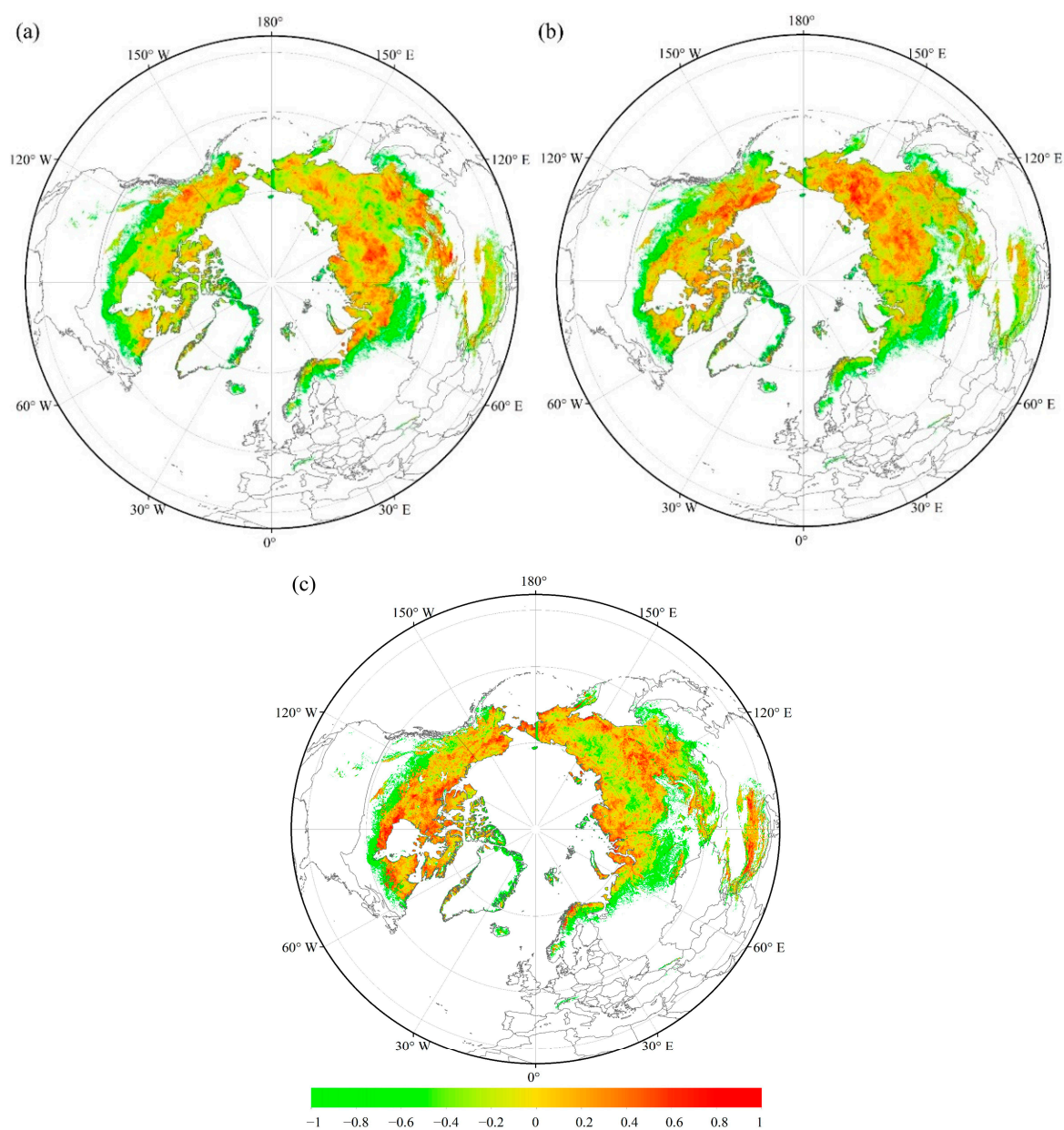


Figure 5. Partial correlations between NDVI and major environmental factors: (a) temperature, (b) ALT, (c) ST.

3.3. The Relative Contributions of Climate Change and Human Activities to Variations in NDVI

The multiple regression residual analysis reveals that the relative contribution of climate change to variations in NDVI is 89.6%, highlighting its dominant influence. Spatially, high values are primarily concentrated in the vast regions surrounding the Arctic Circle, particularly in Siberia, northern Russia, and Canada (Figure 6a). In contrast, the relative contribution of human activities is relatively low, at only 10.6%. This analysis emphasizes the dominant role of climate change in affecting NDVI. Conversely, the impact of human activities on NDVI is primarily found in proximity to populated and developed areas (Figure 6b).

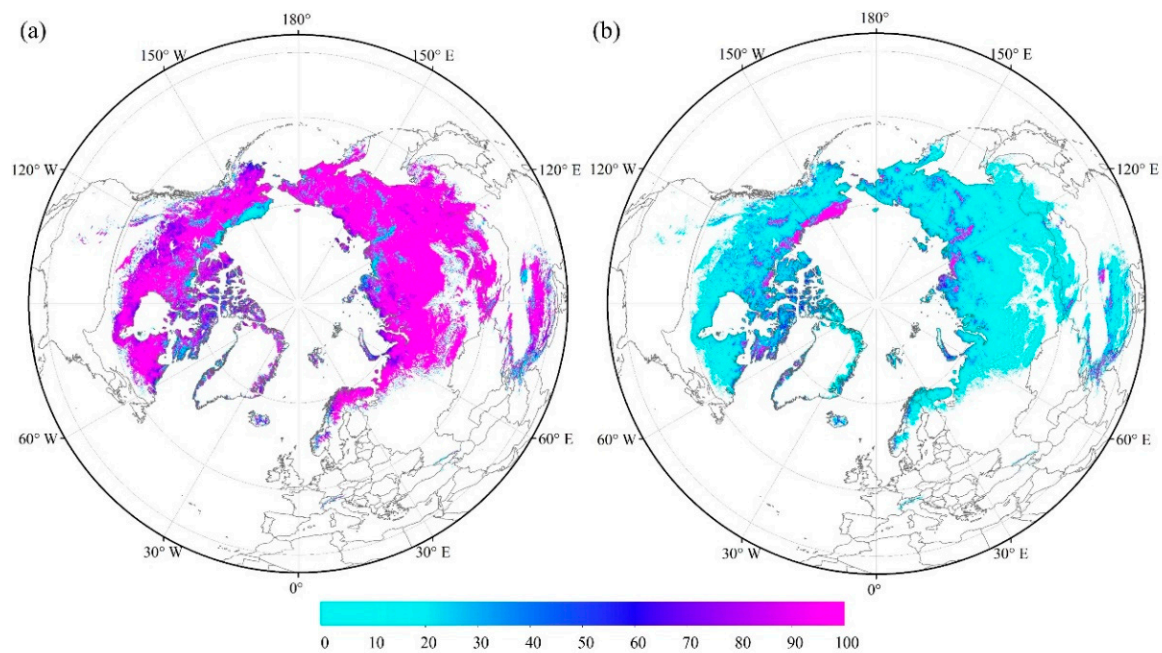


Figure 6. The spatial distribution of the relative contributions of climate change and human activities to NDVI: (a) climate change; (b) human activities.

3.4. Influencing Pathways of Environmental Factors Affecting NDVI Variations

The PLS-SEM results show that climate change and permafrost change have a positive effect on the change in NDVI, and their path coefficients are 0.92 and 0.07, respectively (Figure 7). Air temperature plays a leading role, and its path coefficient is 0.98. Soil properties and human activity have a negative effect on NDVI change, and their path coefficients are -0.24 and -0.12 , respectively (Figure 7). Additionally, climate change has a positive impact on permafrost degradation and soil changes, with correlation coefficients of 0.45 and 0.9, respectively. In contrast, human activities exert a negative impact on permafrost and soil, with correlation coefficients of -0.03 and -0.05 , respectively.

The direct effects of climate and permafrost on NDVI are more significant than their indirect effects (Figure 8a), indicating that both climate change and permafrost promote NDVI. Climate change has a greater direct and overall effect compared to permafrost change, indicating that climate change is the primary driver of growing-season NDVI variations. In addition, the direct, indirect, and total effects of soil properties and human activity on NDVI are all negative (Figure 8a). We further analyzed the direct and total effects of active layer thickness on NDVI changes over different time periods (Figure 8b). The results indicate that, over time, both the direct effect and the total effect values of ALT show an increasing trend.

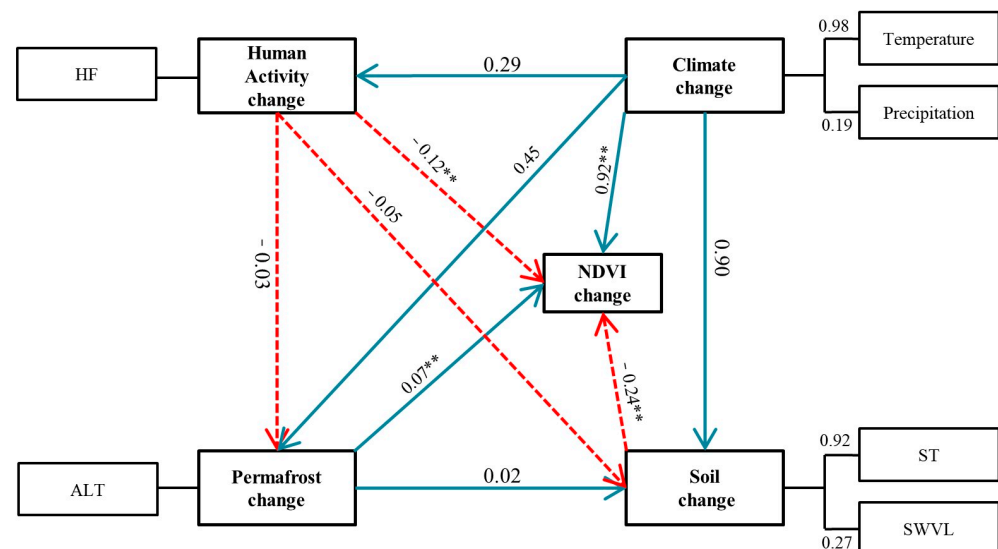


Figure 7. The impacts of climate change, human activity change, soil change and permafrost change on NDVI from 2000 to 2019 were studied using PLS-SEM. The blue solid lines indicate positive correlations, while the red dashed lines represent negative correlations. ** indicates the significance at $p < 0.01$.

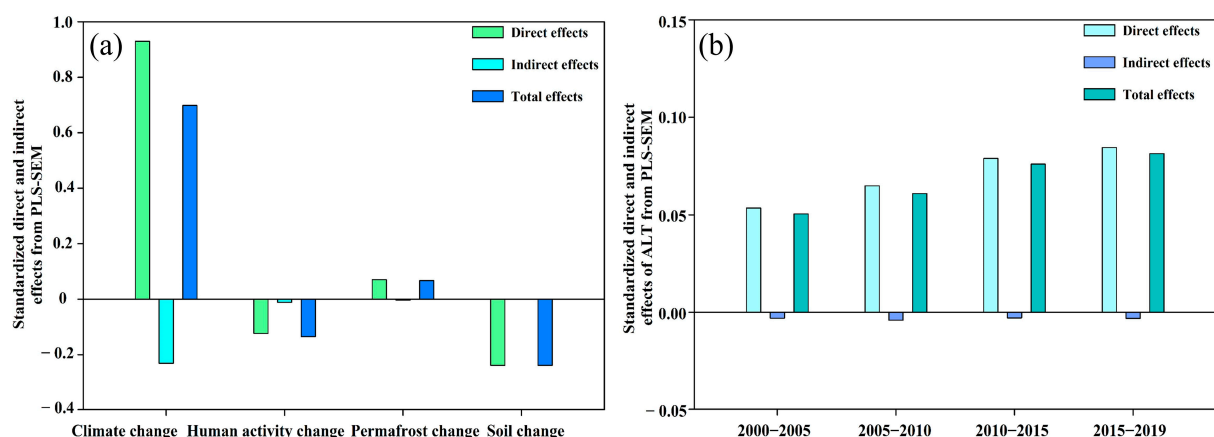


Figure 8. (a) The direct, indirect and total effects of climate change, human activity change, soil change and permafrost change on NDVI; (b) direct, indirect and total effects of ALT across different time periods.

Our research indicates that the NDVI in the NH permafrost regions has shown an overall increasing trend, with climate factors, especially temperature, playing a dominant role. Considering the impact of climate change on permafrost, we conducted a quantitative analysis of the spatiotemporal variations in ALT across the Northern Hemisphere permafrost region from 1997 to 2019 (Figure 9). The findings reveal significant spatial heterogeneity in the distribution of ALT within this region (Figure 9a). Moreover, during the study period, ALT exhibited a consistent increasing trend, with an average growth rate of 0.0086 m/a (Figure 9b).

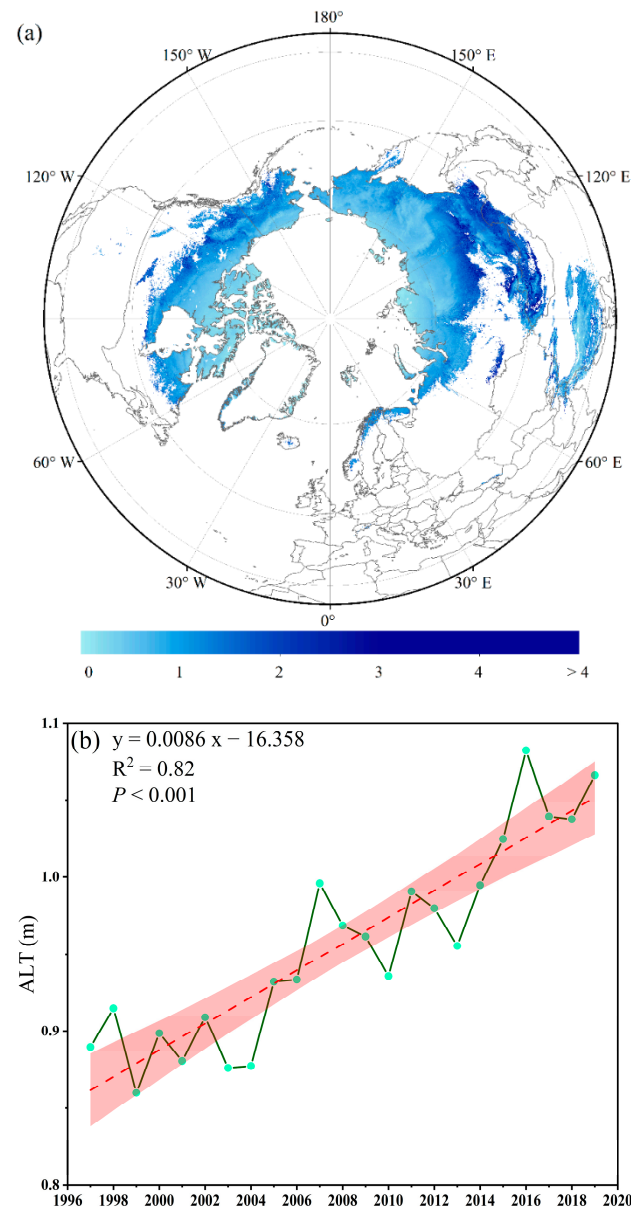


Figure 9. Spatial and temporal changes in active layer thickness in permafrost regions of the Northern Hemisphere from 1997 to 2019: (a) average active layer thickness; (b) temporal changes in active layer thickness. The green dots represent the annual average values of ALT, the green line shows the interannual fluctuation trend of ALT, the red dashed line represents the fitted long-term trend line of ALT, and the shaded area indicates the 95% confidence interval.

4. Discussion

4.1. Temporal and Spatial Distribution Characteristics of NDVI

In our study, we identified significant spatial heterogeneities in NDVI values across permafrost regions, revealing an overall increasing trend in average NDVI values. Previous scholars have studied changes in NDVI in the Northern Hemisphere using field surveys and remote sensing data. For example, ref. [40] investigated NDVI changes in 70 moist acidic tundra sites through ground surveys and found that NDVI is increasing. Ref. [41] examined the seasonality of pan-Arctic tundra vegetation from 1982 to 2015 and observed a rising trend in NDVI. Ref. [42] analyzed NDVI changes in different seasons around the Arctic using GIMMS NDVI3g data from 1982 to 2015, and their results indicated an upward trend in NDVI, aligning with our findings. These studies, despite employing

different remote sensing datasets and methodologies, consistently highlight a positive shift in vegetation growth over recent decades. The convergence of these findings reinforces the trend of increasing NDVI, supporting our results and reflecting a broader pattern of vegetation change in permafrost regions.

Our results indicate that the proportion of areas with significant increases represents approximately 50% of the overall area. As climate change intensifies, this number is projected to rise even more in the future. This indicates that under the influence of factors such as climate change and permafrost degradation, vegetation in the permafrost regions of the Northern Hemisphere has shown a significant increasing trend overall [43]. It has been observed that the pace of vegetation greening in the Arctic has intensified over the last few years, mainly driven by rising temperatures [44]. This anticipated increase underscores a broadening trend of enhanced vegetation dynamics in these regions. The observed pattern emphasizes a significant and expanding area where vegetation is responding to changing conditions, potentially driven by ongoing climatic shifts. Continued monitoring of these trends will be essential for comprehending the complete scope of future changes in vegetation throughout permafrost regions.

4.2. The Impact of Environmental Factors on NDVI

Our results indicate that air temperature was the primary factor influencing vegetation growth from 1982 to 2022. A mechanistic terrestrial carbon model showed that climate change, especially temperature change, is the main controlling factor of greening trends [45]. The association between NDVI and temperature is statistically significant, underscoring the critical role temperature plays in vegetation dynamics [46]. In cold regions, temperature acts as a limiting factor for plant growth, making its influence particularly pronounced in these environments [47]. Warmer temperatures enhance the photosynthetic capacity of plants and promote the synthesis of chlorophyll, both of which contribute to higher NDVI values by improving plant growth and health [48]. Furthermore, increased temperatures can extend the growing season for plants, allowing for a longer period of active growth and photosynthesis. Moreover, higher temperatures can speed up the breakdown of organic matter in the soil, releasing more minerals and nutrients for plant uptake [49]. This nutrient release further supports plant growth and contributes to the observed increases in NDVI. Overall, the interplay of temperature with both plant physiological processes and soil nutrient dynamics highlights its central role in shaping vegetation patterns in permafrost regions.

Our findings indicate that active layer thickness is the second most influential factor affecting NDVI changes. This underscores the critical role that permafrost plays in regulating vegetation dynamics. This finding is supported by previous research, which reported an average Pearson correlation coefficient of 0.35 between Arctic NDVI and ALT [42], which is consistent with our research results. The correlation underscores how variations in permafrost depth can impact vegetation growth and health. Rising temperature accelerates soil thawing [50,51], allowing plant roots to access more nutrients and water [52]. As the active layer thickens due to increasing temperatures, the availability of these critical resources is enhanced, thereby influencing NDVI values. Our PLS-SEM results further emphasized the impact of permafrost degradation on NDVI. The Arctic is undergoing intensified warming [53], and the implications for the region's climate and ecosystems are becoming increasingly pronounced. Careful monitoring and a thorough understanding of the impacts of these changes on permafrost are essential, as they are pivotal in shaping the dynamics and adaptability of ecosystems in Arctic areas. These insights are essential for anticipating how these ecosystems will react to the current climate transformations. The accelerated warming and consequent alterations in permafrost conditions

could have profound implications for vegetation patterns, making ongoing research and observation essential for predicting future ecological impacts and developing effective management strategies.

Research indicates that, at the spatial scale, the impact of human activities on NDVI changes in permafrost regions is relatively minor. This finding highlights that, despite the recent intensification of anthropogenic activities in the Northern Hemisphere, which have significantly affected regional ecosystems [54,55], climate factors remain the primary drivers of vegetation changes in these areas. While human activities have indeed escalated and are expected to have significant effects on vegetation dynamics at regional scales [56], our study emphasizes that climate factors continue to be the primary influence on vegetation changes in permafrost regions. This suggests that, despite the increasing presence of anthropogenic influences, the prevailing climatic conditions play a much more crucial role in shaping the environmental dynamics within these areas. This suggests that understanding the dynamics of vegetation growth in permafrost regions requires a primary focus on climatic factors, given their overwhelming influence compared to human activities.

4.3. Limitations and Prospect

In this study, we used statistical methods to explore the factors influencing vegetation growth in the permafrost regions of the Northern Hemisphere. Although we have achieved certain results, there are still some limitations. Firstly, regarding the data, although we used the quality-controlled GIMMS NDVI3g+ dataset, which has been processed through Bayesian calibration and interpolation methods and corrected for the effects of snow cover and cloud cover [57], there are still some potential limitations. For example, despite the dataset providing quality assurance flags, variations in snow cover in certain high-latitude areas may not have been fully eliminated, which could affect the NDVI trend, particularly in regions with a short growing season. Additionally, the spatial and temporal resolutions of the meteorological data are relatively low [58], which may not accurately capture the effects of local climate change on vegetation, especially in areas with complex terrain and climate conditions. In terms of methodology, although we employed statistical methods such as multiple regression residual analysis, Theil–Sen median analysis, and Mann–Kendall tests to analyze the interannual trends of NDVI and its relationship with environmental factors, these methods can reveal correlations and trends to a certain extent, but there is still room for improvement. For instance, the Pearson correlation coefficient may not fully capture non-linear relationships or outliers between variables, potentially leaving some underlying influencing factors undiscovered [59]. In future research, using rank correlation analysis (such as Spearman’s rank correlation coefficient), which is more suitable for non-linear relationships and outliers, might be more appropriate [60]. Furthermore, while this study considered the contributions of climate change and human activities to NDVI variations, due to data limitations and the complexity of the study, we were unable to fully account for other potentially important factors influencing NDVI changes, such as soil types and land use changes. These factors may have significant impacts on vegetation growth in certain regions [61]. Future research could enhance the accuracy and reliability of the study by using higher-resolution remote sensing data, longer observation periods, and more sophisticated modeling methods.

5. Conclusions

In the context of climate warming, permafrost regions are undergoing accelerated thawing, altering the regional hydrological state. This phenomenon has resulted in a significant greening trend, as the thawing generates more conducive conditions for plant growth and extends the growing season. This study employed various statistical analysis

methods to quantitatively analyze the changes in growing-season NDVI and its influencing factors in the Northern Hemisphere's permafrost region. Our study indicates that during 1982–2022, the average growing-season NDVI in the Northern Hemisphere permafrost region was 0.39, with an increasing trend at a rate of 0.001/a. We found that NDVI values in 80% of permafrost regions in the region are stable or increased from 1982 to 2022. Correlation analysis revealed that NDVI had the highest mean correlation coefficients with temperature and active layer thickness, at 0.32 and 0.25, respectively. The multiple regression residual analysis results showed that climate change played a dominant role in NDVI changes, with a relative contribution of 89.6%, while human activities had a relatively minor contribution of 10.4%. PLS-SEM further explored the pathways and coefficients of different environmental factors affecting NDVI. The results indicated that both climate and ALT exerted positive effects on NDVI, with coefficients of 0.92 and 0.07, respectively. Moreover, the direct and total effects of ALT on NDVI were calculated for different time periods, revealing that the influence of ALT on NDVI increased over time.

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