The Minimum Temperature Outweighed the Maximum Temperature in Determining Plant Growth over the Tibetan Plateau from 1982 to 2017

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Abstract: The Tibetan Plateau (TP) plays a crucial role in the climate change of China as well as global climate change. It is therefore of great practical significance to study vegetation and its dynamic changes for regional ecological protection. The combination of a dry climate and notable temperature disparities can lead to intricate effects on the region’s vegetation. However, there are few studies exploring the complex effects of diurnal temperature variations on vegetation growth that differ from the effects of mean temperature on the TP, especially under different frozen ground types. Based on the long-time series maximum temperature ($T_{\text{max}}$), minimum temperature ($T_{\text{min}}$), and Normalized Difference Vegetation Index (NDVI) of the TP, we conducted a comparative study of the warming effects on plant growth under different frozen types. The results exhibit that it warms up faster at night ($0.223^\circ\text{C} \text{de}^{-1}; p < 0.01$) than during the day ($0.06^\circ\text{C} \text{de}^{-1}; p < 0.01$), resulting in a significant decrease in the temperature difference between day and night ($-0.078^\circ\text{C} \text{de}^{-1}; p < 0.01$) in the past few decades. The principal finding of this paper is that $T_{\text{min}}$ is the dominant temperature indicator for vegetation growth on the TP, which dominates 63.3% of the area for NDVI and 61.4% of the area for GPP, respectively. The results further identify a stronger correlation between air temperature and vegetation growth in seasonal frozen grounds ($R = 0.68, p < 0.01$) and permafrost regions ($R = 0.7, p < 0.01$) compared to unfrozen grounds ($R = 0.58, p < 0.01$). Moreover, the physiological mechanism underlying the asymmetric influence of $T_{\text{min}}$ and $T_{\text{max}}$ on vegetation growth is further elucidated in this study. Given that future climate changes are expected to exacerbate these changes, it is imperative to explore additional avenues in pursuit of potential mechanisms that can offer adaptive strategies for safeguarding the ecology of the TP.

Keywords: plant growth; Tibetan Plateau; air temperature indices; frozen ground types; the growing season

1. Introduction

The Tibetan Plateau (TP) is the largest and highest plateau in the world, and it contains almost all of the key elements of the entire system of the Earth, including the interconnected lithosphere, atmosphere, cryosphere, biosphere, and anthroposphere [1–3]. The average annual temperature at lower elevations of the TP is about $-15^\circ\text{C}$, while temperatures at higher elevations can reach $10^\circ\text{C}$ [4]. In recent decades, the TP has undergone a significant warming [5,6], with a warming rate more than twice as fast as the global average over the past 50 years [7]. This rapid warming trend could have a significant impact on the thawing...
processes of the permafrost and the seasonally frozen soil, and this would further affect the vegetation dynamics and the ecosystem stability of the TP [8]. There is an ongoing debate about how vegetation growth responds to climate warming, largely due to our limited understanding of the physical mechanisms that underlie this process. To understand the warming impact on vegetation growth, most studies select mean air temperature as the proxy variable of climate warming [9–13]. However, as the use of mean temperature smooths out the dynamic response of vegetation growth to climate warming, several studies suggest the use of maximum temperature ($T_{\text{max}}$) and minimum temperature ($T_{\text{min}}$) as alternative proxy variables for climate warming. The asymmetrical increase in $T_{\text{max}}$ or $T_{\text{min}}$ could play different roles on vegetation growth from mean air temperature [14]. Therefore, understanding the driving mechanisms of the $T_{\text{min}}$ and $T_{\text{max}}$ effect rather than the mean air temperature on the TP is crucial for developing adaptation strategies that will protect its fragile ecosystems and also for better understanding vegetation growth changes across the TP.

Currently, an increasing number of studies investigate how maximum and minimum temperatures impact vegetation growth. A recent study has revealed that marsh vegetation exhibited asymmetric responses to nighttime minimum and daytime maximum temperatures on the Songnen Plain of China [15]. The impact of asymmetric warming between day and night on the NDVI of different vegetation types varies across different regions: it has been found to promote NDVI growth in the grasslands of Inner Mongolia, for example [16]. However, the dependence of plant growth on the daily maximum or minimum temperatures may differ on the TP due to its higher elevations and its colder and drier conditions. Recent studies have reported that a rise in the minimum temperature could alleviate the negative impacts of frost damage, while an increase in the maximum temperature in the arid regions could exacerbate the detrimental effects of drought. Both of these factors have the potential to influence plant growth [17]. In addition, many studies have shown the necessity of plants tolerating cold environments during dormancy [18,19]. The nighttime warming may have a stronger impact on the ecosystems of the TP [17]. The latest study has indicated that the annual marsh net primary productivity (NPP) on the TP significantly increased with the rising minimum temperatures during winter and spring [20]. However, there is limited research that compares the impact of diurnal and nocturnal warming on vegetation growth across the TP [21]. Considering the asymmetric rise in daytime and nighttime temperatures worldwide, it is imperative to investigate how changes in these temperatures can impact plant growth on the TP, especially on different types of frozen soils.

The aim of this study is to examine the intricate response of vegetation growth on the TP to various temperature driving factors, particularly in the context of asymmetric warming between day and night. Here, based upon the satellite-measured normalized difference vegetation index (NDVI), monthly maximum temperature ($T_{\text{max}}$), monthly minimum temperature ($T_{\text{min}}$), and the temperature difference ($T_\Delta$) in the growing season (April to September), we investigated the spatiotemporal changes in plant growth using various temperature indices over the TP. A comprehensive attribution framework was then applied in order to systematically explore the functions of different temperature indices on plant growth. On top of this, the spatial heterogeneity of the effects of temperature indices on plant growth in various frozen grounds is further explored. The findings of this study will contribute to the conservation of the natural environment across the TP and promote its sustainable utilization. It is of great significance to understand the carbon cycle of plateau ecosystems and to thereby guide regional ecological environment construction.

2. Materials and Methods

2.1. Normalized Difference Vegetation Index (NDVI)

The 25-km Normalized Difference Vegetation Index (NDVI) data were used to examine the long-term (1982–2017) changes in plant growth over the TP. To obtain the NDVI product, we merged the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI, the Univer-
The frozen soil distribution dataset was made on the basis of the modified Moderate Resolution Imaging Spectroradiometer (MODIS) Surface Temperature 1 km clear sky MOD11A2 (Terra MODIS) and MYD11A2 (Aqua MODIS) products from 2003 to 2012. The frozen soil dataset was simulated by the freeze-thaw indices and the top frozen soil temperature factors influencing vegetation growth. This framework incorporates three categories: seasonally frozen ground, permafrost, and unfrozen ground. Further details of data fusion and its evaluation are provided by Zhang et al. [22] The data range excludes urban regions and non-vegetated regions, and all datasets were resampled to the 25 km spatial resolution using bilinear interpolation.

2.2. Total Ecosystem Primary Productivity (GPP)

Total ecosystem primary productivity (GPP) datasets were acquired from the National TP Data Center (http://data.tpdc.ac.cn/ (accessed on 7 November 2022)). This dataset contains a long time series of GPP data from 1982 to 2017 based on 40 years of the Advanced Very High Resolution Radiometer (AVHRR) data and observations from hundreds of flux sites around the world. This dataset has been widely used for global and regional climate change [23]. For a detailed description of the GPP data, a reference is made to Wang et al. [24].

2.3. Air Temperature Data

This dataset was published by WorldClim through the Delta spatial downscaling scheme in China [25,26]. Monthly Maximum temperature (T_max) and Monthly Minimum temperature (T_min) are the maximum values of the daily maximum temperature and the minimum daily minimum temperature observed during a given month, respectively. The difference between T_max and T_min is expressed as the temperature difference (TD). More information on the air temperature data can be found in National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/ (accessed on 20 November 2022)).

2.4. Frozen Soil Distribution Data

The frozen soil distribution dataset was made on the basis of the modified Moderate Resolution Imaging Spectroradiometer (MODIS) Surface Temperature 1 km clear sky MOD11A2 (Terra MODIS) and MYD11A2 (Aqua MODIS) products from 2003 to 2012. The frozen soil dataset was simulated by the freeze-thaw indices and the top frozen soil temperature (TTOP) model, as shown in Figure 1. The ground type was divided into three categories: seasonally frozen ground, permafrost, and unfrozen ground. Further descriptions of this dataset can be found in Zou et al. [27]

![Figure 1](image-url)
2.5. Trend Analysis

Theil-Sen estimation method was used to reveal the temporal and spatial variations of vegetation and air temperature indices over the TP. Theil-Sen Median selects the median of all line slopes of a pair of points for linear fitting that is not sensitive to outliers, especially for data with large variance. Compared with the robust linear regression fitting method, its accuracy is significantly improved. A positive value of T-Sen illustrates an increase in the variable of interest and vice versa [28].

The coefficient of variation (CV), also known as the dispersion coefficient, is a mathematical indicator to measure the degree of dispersion between observed values and unit mean value [29]:

\[
CV = \frac{1}{\text{NDVI}} \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\text{NDVI}_i - \bar{\text{NDVI}})^2},
\]

where \( \text{NDVI}_i \) is the NDVI of year \( i \) and \( \bar{\text{NDVI}} \) is the inter-annual average value from 1982 to 2017. The larger the CV value, the more dispersed the data and the greater the interannual variation of plant growth.

2.6. Attribution Analysis Methods

In this study, a comprehensive analytical framework was employed to investigate air temperature factors influencing vegetation growth. This framework incorporates three attribution methods to circumvent the limitations of using any individual method. Firstly, a partial correlation analysis method was utilized to examine the positive or negative impacts of each air temperature indice on plant growth while controlling other variables. Subsequently, standardized multivariate linear regression was employed to identify the driving factors behind vegetation growth. The explanatory power of factors was used to assess the explanatory power of different air temperature factors on vegetation growth based on the GeoDetector. These methods enable a more comprehensive and nuanced understanding of the factors that contribute to plant growth.

Partial correlation analysis, also known as net correlation analysis, analyzes the relationship between two variables when excluding the influence of other variables [30]. Before the analysis, we detrended the dataset to eliminate the influence of the trend [31]. The influences of a specified factor excluding other factors related to vegetation growth was found using the following formula:

\[
\rho_{l,k,m} = \frac{\rho_{lk} - \rho_{lm} \rho_{km}}{\sqrt{(1 - \rho_{lm}^2)(1 - \rho_{km}^2)}},
\]

where \( \rho_{l,k,m} \) represents the partial correlation coefficient between \( l \) and \( k \), excluding the influence of \( m \).

The Geographical Detector method is a relatively new statistical approach for detecting spatial heterogeneity. A Geographical Detector includes four detectors: a risk detector, a factor detector, an ecosystem detector, and an interaction detector [32]. Based on the factor detector, \( Y \) was employed as the vegetation indicator, and \( X \) was employed as each air temperature factor. The \( q \) value represented the level of explanatory power that factor \( X \) has on the spatial heterogeneity of factor \( Y \):

\[
q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N^2} = 1 - \frac{SSW}{SST}
\]

\[
SSW = \sum_{h=1}^{L} N_h \sigma_h^2, \quad SST = N \sigma^2
\]

In the equation, \( h = 1, \ldots, L \) represents the stratification of variable \( Y \) or factor \( X \), that is, classification or zoning; \( N_h \) and \( N \) are the number of units in layer \( h \) and the entire region, respectively; and \( \sigma_h^2 \) and \( \sigma^2 \) are the variances of \( Y \) in layer \( h \) and the entire region,
respectively. SSW and SST are the sums of the within-layer variances and the total variance of the entire region, respectively. The value of $q$ ranges from 0 to 1. The larger $q$ illustrates the stronger influence of temperature determinants on vegetation and the more distinct spatial heterogeneity. A larger value of $q$ indicates that the independent variable $X$ has a stronger explanatory power for the attribute $Y$ when the stratification is generated by $X$. A $q$ value of 1 means that $X$ dominates the spatial and temporal variations of $Y$, and $100 \times q\%$ illustrates the extent to which $X$ explains $Y$. Its significance can be tested in the calculation process [32].

Standardized multiple linear regression was utilized to explore the dominant regions where air temperature factors significantly influence vegetation growth. In the standardized multiple linear regression (SMLR) model, the coefficient before each variable denotes its significance in dividing the SMLR model. Prior to analysis, the variance inflation factor (VIF) between influencing factors was computed to detect multicollinearity. The SMLR model can be expressed as follows:

$$\frac{W - \overline{W}}{\sigma_W} = \gamma_0 + \gamma_1 \frac{IP_1 - \overline{IP_1}}{\sigma_1} + \ldots + \gamma_n \frac{IP_n - \overline{IP_n}}{\sigma_n}$$

(5)

$IP_i$ represents temperature factors; $\overline{W}$ and $\overline{IP_i}$ are mean values of NDVI (or GPP) and temperature variables; $\sigma_W$ and $\sigma_i$ are standard deviations of NDVI (or GPP) and other variables; and $\gamma_1, \gamma_2, \ldots, \gamma_i$ are regression coefficients. The greater the coefficient, the greater the contribution of the variable to plant growth.

3. Results

3.1. Interannual Variation of Plant Growth and Air Temperature Indices in the Growing Season over the TP

Figure 2a illustrated the spatial distribution of trends in the NDVI over the TP during the last four decades. As shown, NDVI has predominantly increased (94.9%, Figure 2a) over the TP, with 62.7% of the increase reaching statistical significance ($p < 0.05$). This implies that vegetation growth over the TP region is significantly responsive (with an average of increasing rate of 0.001 year$^{-1}$) to climate change, and this aligns with prior findings [33,34]. Additionally, we found that the upward trend of NDVI declines from the southeastern to the northwestern regions, and this could be possibly due to the notable dissimilarities in climate conditions and elevations [33]. Figure 2b displayed the stability of NDVI on the TP region over the past 40 years. We observed a coexistence of high and low fluctuations, with noted regional variability over the TP region. The low fluctuation with a coefficient of variation (CV) between 0 and 0.02 occupied only 5.7% of the TP. In comparison, the high fluctuation area ($0.06 < CV < 0.1$) characterized 36.3% of the area and exhibited a zonal distribution, mainly concentrated in the northern and western boundaries of the TP. It has been suggested that there is a greater variability of NDVI in seasonally frozen areas and permafrost compared to unfrozen areas, and it has been revealed that plant growth in regions with relatively lower altitudes and humid conditions has tended to be more stable.

Figure 3 exhibited the spatial distribution of annual means of $T_{\text{min}}$, $T_{\text{max}}$, and $T_D$ in the growing season over the TP. $T_{\text{min}}$ displayed significant spatial heterogeneity, with over 71.41% of the regions experiencing a $T_{\text{min}}$ below 0 °C, while the temperature in the southern edges was larger than 10 °C (Figure 3a). The $T_{\text{max}}$ in 99.2% of the TP was above 0 °C, which confirms the presence of a significant diurnal temperature range over the region [35]. Figure 3c illustrated the spatial distribution of $T_D$, revealing that the $T_D$ in the unfrozen regions is the lowest. In contrast, the $T_D$ in the seasonally frozen regions surpassed 10 °C and even exceeded 15 °C in certain parts of the permafrost grounds.
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Figure 2. (a) Spatial trend pattern of NDVI from 1982 to 2017. (b) Coefficient of variation of NDVI from 1982 to 2017. The bottom left inset shows the relative frequency (%) of values in the corresponding range indicated by the color bars. Areas marked by dots indicate the trends that are statistically significant ($p < 0.05$).

Figure 3. Spatial distributions of multi-year mean of (a) $T_{\text{min}}$, (b) $T_{\text{max}}$, and (c) $T_D$ from 1982 to 2017. The bottom left inset shows the relative frequency (%) of values in the corresponding range indicated by the color bars.

As depicted in Figure 4a, there was a significant increasing trend in $T_{\text{min}}$ during the growing season of the TP. Specifically, 96% of the regions displayed a significant increasing trend ($p < 0.05$) in $T_{\text{min}}$. It is interesting to note that in contrast to NDVI, the spatial distribution of $T_{\text{min}}$ exhibited a gradual increase from southeast to northwest. Overall, the growth trend of $T_{\text{max}}$ was found to be smaller than that of $T_{\text{min}}$. A significant growth trend ($p < 0.05$) was observed in 80.4% of the TP in $T_{\text{max}}$. Under the combined effect of day and night temperatures, $T_D$ exhibited a decreasing trend in 69.5% of the areas, of which 63.7% were statistically significant ($p < 0.05$). A comparison of the findings with those of other studies confirms that the diurnal temperature over the past 60 years has declined, which can be primarily attributed to the pronounced increase in $T_{\text{min}}$ in relation to $T_{\text{max}}$ [36]. We also observe that 30.5% of TP displayed an increasing trend in $T_D$, which is mainly distributed in unfrozen and seasonal frozen grounds. This suggests that $T_D$ is symmetrically distributed on the TP, rather than exhibiting a unimodal distribution.

Figure 4. Spatial distribution of long-term (1982–2017) trend of (a) $T_{\text{min}}$, (b) $T_{\text{max}}$, and (c) $T_D$. The color bars on the bottom left are the percentage (%) of the values in the corresponding color range. Areas marked by dots indicate the trends are statistically significant ($p < 0.05$).

We further investigated how the trends of the three temperature indices differ across different frozen grounds. Figure 5 demonstrates that the $T_{\text{max}}$ and $T_{\text{min}}$ of the unfrozen region have almost all exceeded 10 °C over the last 40 years. The trend of $T_{\text{min}}$ in the permafrost region was the most pronounced, with a slope of 0.0406 °C year$^{-1}$, and with
Additionally, in order to mitigate the potential influence of a single data source, partial correlation analysis of GPP and temperature indices were also examined. The above results indicated that temperature factors have demonstrated complex variations during the past decades. The interaction of arid weather conditions and significant temperature discrepancies can have intricate effects on plant growth. To explore the connection between plant growth and air temperature indicators while removing potential confounding effects between the two variables, a partial correlation analysis was conducted. Additionally, in order to mitigate the potential influence of a single data source, partial correlation analysis of GPP and temperature indices were also examined.

On the whole, $T_{\text{min}}$ and NDVI illustrated a positive relationship in 86.7% of the TP, and 21% of this was significant ($p < 0.05$) (Figure 6a), which was mostly concentrated in the central and southwest boundaries, whilst only 13.3% of the regions were negatively subject to $T_{\text{min}}$. With regards to the $T_{\text{max}}$ during the growing season (as displayed in Figure 6b), it is worth noting that over 61.8% of the regions exhibited significant positive correlations, and the strongest correlations were found to be concentrated in the eastern regions under conditions without water stress. In comparison, the western region illustrated a significant negative correlation (12.60%), which is basically in line with Shen et al. [17] The spatial partial correlation between GPP and air temperature exhibited a similar pattern to that of NDVI. Specifically, 65.24% of the TP for $T_{\text{min}}$ displayed a positive association with GPP, and 7.38% of the correlation was found to be significant ($p < 0.05$). As for $T_{\text{max}}$ and GPP, most of the western regions showed a negative correlation (51.59%), while 48.41% displayed a positive correlation, and 4.3% was significant ($p < 0.05$). The correlation between $T_{\text{min}}$ and vegetation growth was generally stronger than that between $T_{\text{max}}$ and vegetation.

Overall, $T_{\text{min}}$ had a relatively stronger explanatory significance to the variations of both NDVI and GPP. These results are in accord with recent studies, which have indicated that the vegetation index has exhibited a strong positive partial correlation with $T_{\text{min}}$ during the summer season [17]. In contrast, the relationship between $T_{\text{max}}$ and vegetation growth was spatially heterogeneous. A positive correlation was found across the eastern region, while $T_{\text{max}}$ had a negative impact on plant growth in high-altitude arid regions of the western TP. This negative correlation between $T_{\text{max}}$ and plant growth may be related to the increased water stress that is caused by warming-induced soil moisture depletion [37].

Additionaly, we investigated the interannual correlations among $T_{\text{max}}$, $T_{\text{min}}$, and NDVI across three frozen soil grounds (Figure 7). Our findings indicated that the correlation between $T_{\text{min}}$ and vegetation growth was strongest in the permafrost ground ($R = 0.7$, $p < 0.01$) (Figure 7c). The correlation was lowest in the unfrozen region ($R = 0.58$, $p < 0.01$) (Figure 7a). In the seasonally frozen soil region, we observed a significant correlation between $T_{\text{max}}$ and vegetation growth ($p = 0.67$, $R < 0.01$). This was followed by the permafrost region ($p = 0.62$, $R < 0.01$), as illustrated in Figure 7f. By contrast, in the unfrozen regions, the correlations between $T_{\text{max}}$, $T_{\text{min}}$, and NDVI were all the lowest. What stands out in Figure 7 is that the correlation between $T_{\text{min}}$ and plant growth was found to be stronger than that between $T_{\text{max}}$ and plant growth across all of the frozen types, which confirms that $T_{\text{min}}$ has a greater impact on plant growth. Vegetation growth is likely constrained by low $T_{\text{min}}$ [17]. The strong impact of air temperature on plant growth in higher altitudes with arid conditions has also been emphasized.

![Figure 6](image6.png)

**Figure 6.** Spatial patterns of long-term (1982–2017) partial correlation coefficients between (a) $T_{\text{min}}$, (b) $T_{\text{max}}$, and NDVI, and spatial distributions of long-term (1982–2017) correlation coefficients between (c) $T_{\text{min}}$, (d) $T_{\text{max}}$ and GPP. The color bars on the bottom left are the percentage (%) of the values in the corresponding color range. The areas marked by dots indicate that the trends are statistically significant ($p < 0.05$).

![Figure 7](image7.png)

**Figure 7.** The correlation between $T_{\text{min}}$ and NDVI in (a) unfrozen ground, (b) seasonally frozen ground, and (c) permafrost, and the correlation between $T_{\text{max}}$ and NDVI in (d) unfrozen ground, (e) seasonally frozen ground, and (f) permafrost.
3.3. Temperature Determinants to Plant Growth

Finally, standardized multivariate linear regression and GeoDetector were applied to capture (generally) the driving force for plant growth. The results of VIF demonstrated that all of the values were less than 1, which indicates that there was no multicollinearity among the air temperature factors. Figure 8 illustrated that T$_{\text{min}}$ had a more significant influence on both NDVI and GPP than T$_{\text{max}}$ across the entire region, with contributions of 63.3% and 61.6%, respectively. In contrast, T$_{\text{max}}$ dominated 36.7% of the area for NDVI and 38.4% of the area for GPP, respectively. It could thereby be concluded that T$_{\text{min}}$ was the dominant temperature indicator for vegetation growth and productivity on the TP. What is interesting in Figure 7 is that T$_{\text{min}}$ primarily regulates NDVI in dry and cold conditions at higher elevations. By contrast, T$_{\text{max}}$ has a greater influence on vegetation growth over the eastern TP, which has lower elevations and higher air temperatures (Figure 3).

![Figure 8](image)

**Figure 8.** The frequency distributions of the corresponding contributions of which the values were indicated by the map legend on (a) NDVI and (b) GPP based on the Standardized Multivariate Linear Regression (SMLR) method.

The results from the GeoDetector further revealed that the $q$ value of T$_{\text{min}}$ was the largest for all frozen types, especially in the seasonally frozen soils, which confirmed that T$_{\text{min}}$ dominates greenness across the TP (Table 1). Additionally, in the areas with seasonally frozen soil, the $q$ values for the T$_{\text{min}}$ and the T$_{\text{max}}$ were the highest compared to the other ground types, with $q$ values of 0.56 and 0.49 for NDVI and 0.44 and 0.35 for GPP, respectively. On the contrary, the $q$ values of NDVI (or GPP) and the T$_{\text{min}}$ (or the T$_{\text{max}}$) in the unfrozen region were the smallest among the three ground types. These results were also statistically tested, and were found to be significant ($p < 0.05$).

<table>
<thead>
<tr>
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<th>Seasonal Frozen Ground</th>
<th>Permafrost</th>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI</td>
<td>0.48 **</td>
<td>0.56 **</td>
<td>0.53 **</td>
</tr>
<tr>
<td>GPP</td>
<td>0.21 *</td>
<td>0.44 **</td>
<td>0.36 **</td>
</tr>
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<td>T$_{\text{max}}$</td>
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<td>0.49 **</td>
<td>0.40 **</td>
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<tr>
<td>GPP</td>
<td>0.16</td>
<td>0.35 **</td>
<td>0.34 **</td>
</tr>
</tbody>
</table>

Table 1. Temperature determinants affect the spatial patterns of NDVI and GPP in different frozen regions, determined by the $q$ value. The $q$ value less than 0.05 represents significance (95% confidence is denoted by *, 99% confidence is denoted by **).

4. Discussion

4.1. Possible Reasons for T$_{\text{min}}$ in Determining Plant Growth over the TP

The TP is a sensitive and early-warning area of global warming. Numerous studies have shown that climate warming has resulted in the overall growth in vegetation on the TP as well as the earlier start of the growing season for the vegetation during the
past decades [38,39], and have also unequivocally shown that temperature is the primary driving force of vegetation growth on the TP [40]. The results of this study demonstrate a significant growth trend in NDVI over the past 40 years, as well as a significant rising trend in both $T_{\text{min}}$ and $T_{\text{max}}$ during the growing season. These trends have resulted in a significant decrease in $T_D$, which is well in line with the findings of previous studies [41]. The reduction in the diurnal temperature range is caused by the fact that temperature varies more rapidly at night than during the day. Previous studies have revealed that the growth rate of $T_{\text{min}}$ is significantly faster than that of $T_{\text{max}}$ [42]. Moreover, since photosynthesis in most plants primarily occurs during the day while respiration continues throughout the day and night, this asymmetrical warming will inevitably impact the carbon uptake and consumption of vegetation [43].

A comparison of the findings with those of other studies confirms that $T_{\text{min}}$ has a stronger effect on plant growth than $T_{\text{max}}$ [17]. There could be several reasons for this, including the fact that higher $T_{\text{min}}$ may help to reduce frost damage, as suggested by Kim et al. [44] To be more specific, during the growing season, $T_{\text{min}}$ is typically below 0 °C, except in unfrozen regions on the TP (Figures 3a and 5), which may limit the growth processes of the plants [45]. To reduce the risk of freezing damage, plants may slow or postpone their growth [46]. Faster growing nighttime temperatures enable plants to consume more carbohydrates at night, which stimulates an increase in photosynthesis over the next few days [16,47]. Therefore, rising nighttime temperatures could potentially alleviate these limitations and reduce the risk of freezing injury, which may promote vegetation and leaf development during the growing season. Additionally, the absorption of soil water is heavily dependent on the thawing of the soil during early spring on the TP. The vegetation of the TP is mainly dominated by alpine meadows and alpine grasslands. The growth of this vegetation during spring is limited by low water utilization efficiency [48]. Minimum soil temperature controls the amount of spring soil water available [49–51]. Moreover, nighttime warming stimulates carbon sequestration, enhancing the community’s resistance to drought and potentially promoting ecosystem sustainability [52]. However, $T_{\text{min}}$ also has inhibitory effects on vegetation growth around 13% of the TP, mainly located in the northern and southern edges. One potential explanation is that an elevation in $T_{\text{min}}$ may lead to a decrease in the volume of endosperm cells during the vegetation’s mature stage [53], and the accelerated rate of vegetation autotrophic respiration [54] may lead to a shortened grain-filling period for the vegetation [55].

In addition, this study reveals a stronger correlation between air temperature and vegetation growth in seasonal frozen grounds and permafrost regions compared to unfrozen grounds (Figure 7 and Table 1). This is in good agreement with Huang et al. [56], who reported that temperature at high altitude (>3500 m) has a stronger influence on NDVI than at lower altitudes. The results of the GeoDetector further confirmed that the explanation of air temperature on vegetation growth is highest in seasonal frozen regions, followed by permafrost. One possible explanation for this may be related to the fact that in seasonal frozen soil regions and in permafrost regions, the increasing rates of $T_{\text{min}}$ and $T_{\text{max}}$ are higher than in unfrozen regions (Figure 5). Additionally, the unfrozen region of the vegetation area typically receives sufficient precipitation and light. In contrast, the seasonal frozen grounds and permafrost regions are located at relatively higher altitudes, which experience colder and drier climates, and which undergo surface soil freeze-thaw cycles [57–59]. The rise in air temperature has led to an earlier timing of seasonal thaw during the past decades, and the relative increase in plant-available moisture will further promote vegetation growth [60].

Finally, an interesting finding of this study is the asymmetric influence of $T_{\text{min}}$ and $T_{\text{max}}$ on vegetation growth. Specifically, the results show that $T_{\text{min}}$ is the dominant factor influencing plant growth in the western TP, while vegetation in the eastern area is predominantly affected by $T_{\text{max}}$. The restricted soil freeze-thaw conditions in the western alpine region make it mainly controlled by $T_{\text{min}}$, as reported by Kim et al. [44] By contrast, $T_{\text{max}}$ is significantly negatively correlated with NDVI and GPP in part of the western TP (Figure 6b). This result may be explained by the fact that in regions with less precipitation, daytime warming can cause higher evapotranspiration and lower soil water content, and
higher $T_{\text{max}}$ can exacerbate the effects of drought. Therefore, the arid climate, especially the water deficit due to the high $T_{\text{max}}$, will lead to a weak correlation between $T_{\text{max}}$ and plant growth [57], and it will even restrict the growth of vegetation. Additionally, a decrease in NDVI can lower latent heat and increase sensible heat, leading to further warming [61].

With increasing temperatures, significant changes in soil moisture within the root zone adversely impact vegetation photosynthesis in relatively arid regions [62]. Peng et al. [63] have also proposed that an increase in daytime temperature is beneficial for plant growth and its ecosystem carbon sequestration function in most humid regions, but that it is not favorable for plant growth in arid regions. Moreover, ecological processes are also considered as critical factors influencing the differential effects of $T_{\text{min}}$ and $T_{\text{max}}$ on plant growth. The increases in $T_{\text{max}}$ and $T_{\text{min}}$ affect different plant species, and each displays unique adaptability. For plant species in different frozen soil regions, there are variations in the timing of leaf unfolding and senescence adjustments to adapt to seasonal changes [64], and this adaptation allows them to optimize carbon uptake and minimize water loss, thereby ensuring their survival and resilience in response to changing environmental conditions [65].

4.2. Possible Uncertainty Sources and Future Work

It should be acknowledged that this paper may entail some uncertainty. This study has utilized long-time series of NDVI, GPP, $T_{\text{min}}$, and $T_{\text{max}}$ data, and it has employed three attribution analysis methods to explore the impact of air temperature factors on vegetation growth. However, variations exist among statistical methods regarding the exploration of this relationship. Moreover, statistical analyses can have uncertainties, as correlation does not necessarily imply causation [66]. Vegetation growth may also display nonlinear responses to environmental factors, and interactions among various factors could also exist. Moreover, statistical methods would presume a temperature-dominated influence on plant growth while potentially neglecting plant feedback on temperature [67]. Therefore, future research should focus on investigating the non-linear effects of various climatic factors on vegetation growth. Utilizing other approaches, such as physical process models, machine learning models, or hybrid models, will enable the estimation of the non-linear contributions of different driving factors and further validation of the results of statistical analysis. This would provide a more comprehensive and accurate understanding of the complex relationships among air temperature factors that impact vegetation growth. The dominant function of $T_{\text{min}}$ warming implies that the effect of $T_{\text{min}}$ on the TP may persist and, thus, may be more significant than that of $T_{\text{max}}$ in the future. Consequently, exploring the mechanisms behind the asymmetric effects of minimum and maximum temperature on vegetation growth should be a focus of future research. Other factors, such as changes in cloud cover, solar radiation, and vegetation growth activity, may also contribute to this decrease in diurnal temperature range, and these factors also warrant further investigation in the future. Moreover, in addition to temperature, precipitation, wind speed, humidity, and snowmelt also have an impact on vegetation dynamics [21,68], although the mechanisms underlying the joint influence of air temperature and these other factors on vegetation growth are not yet fully understood. Given the spatial heterogeneity of climatic conditions, it is crucial to conduct comprehensive attribution analyses that link spatiotemporal changes in vegetation growth on the TP with multiple climatic variables. Such analyses are essential in order to fully capture the complexity of plant growth in the region and to facilitate better predictions for the future.

5. Conclusions

In this study, we investigated the spatiotemporal patterns of vegetation growth, $T_{\text{min}}$, $T_{\text{max}}$, and $T_{D}$ during the growing season between 1982 and 2017. Additionally, we probed the spatial heterogeneity of vegetation response to air temperature in different frozen soil types using multiple attribution analysis methods.

The findings clearly indicate that $T_{\text{min}}$ increases more significantly ($0.223 \degree \text{C de}^{-1}; p < 0.01$) than $T_{\text{max}}$ ($0.145 \degree \text{C de}^{-1}; p < 0.01$), which has resulted in a significant decrease
in the temperature difference between day and night (−0.078 °C day⁻¹; p < 0.01) over the past few decades. The principal conclusion of this study is that Tₘᵟᵢₙ emerges as the predominant temperature indicator influencing vegetation growth across the TP, effectively reducing the high risk of freezing injury and actively promoting the development of both vegetation and leaf growth throughout the growing season, and it also exerts significant influence on vegetation growth with significant elevation effect on the eastern TP. This has an inhibitory effect on vegetation growth in drier and colder conditions at higher elevations, whereas Tₘᵞᵢᵝ has a greater influence on vegetation growth over the eastern TP. Our study provides evidence of the varying impacts of diurnal warming on vegetation, with different types of frozen ground exhibiting distinct responses. These findings could enhance our comprehension and explanation of the TP's unique ecosystem.

**Author Contributions:** X.L. (Xi Li): Conceptualization, methodology, data curation, writing—original draft preparation, visualization, investigation. K.Z.: supervision, writing—reviewing and editing. X.L. (Xin Li): supervision, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

**Funding:** This study was supported by the Fundamental Research Funds for the Central Universities (B220204014 and B220203051).

**Data Availability Statement:** Only public data duly referenced are used in the present study.

**Acknowledgments:** The author warmly thanks the reviewers for their help and dedication.

**Conflicts of Interest:** The author declares no conflict of interest.

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