Response of vegetation to climate change along the elevation gradient in High Mountain Asia (Postprint)

Authors: HE Bing, LI Ying, GAO Fan, XU Hailiang, WU Bin, YANG Pengnian, BAN Jingya, LIU Zeyi, LIU Kun, HAN Fanghong, MA Zhenghu, Lu Wang, GAO Fan

Date: 2025-09-22T11:48:31+00:00

Abstract

Climate change in High Mountain Asia (HMA) is characterized by elevation dependence, which results in vertical zoning of vegetation distribution. However, few studies have been conducted on the distribution patterns of vegetation, the response of vegetation to climate change, and the key climatic control factors of vegetation along the elevation gradient in this region. In this study, based on the Normalized Difference Vegetation index (NDVI), we investigated the evolution pattern of vegetation in HMA during 2001–2020 using linear trend and Bayesian Estimator of Abrupt change, Seasonality, and Trend (BEAST) methods. Pearson correlation analysis and partial correlation analysis were used to explore the response relationship between vegetation and climatic factors along the elevation gradient. Path analysis was employed to quantitatively reveal the dominant climatic factors affecting vegetation distribution along the elevation gradient. The results showed that NDVI in HMA increased at a rate of 0.011/10a from 2001 to 2020, and the rate of increase abruptly slowed down after 2017. NDVI showed a fluctuating increase at elevation zones 1-2 (<2500 m) and then decreased at elevation zones 3–9 (2500–6000 m) with the increase of elevation. NDVI was most sensitive to precipitation and temperature at a 1-month lag. With the increase of elevation, the positive response relationship of NDVI with precipitation gradually weakened, while that of NDVI with temperature was the opposite. The total effect coefficient of precipitation (0.95) on vegetation was larger than that of temperature (0.87), indicating that precipitation is the dominant control factor affecting vegetation growth. Spacially, vegetation growth is jointly influenced by precipitation and temperature, but the influence of precipitation on vegetation growth is dominant at each elevation zone. The results of this study contribute to understanding how the elevation gradient effect influences the response of vegetation to climate change in alpine ecosystems.

Full Text

Preamble

Response of vegetation to climate change along the elevation gradient in High Mountain Asia

HE Bing[1,2,3], LI Ying[1,2], GAO Fan[1,2*], XU Hailiang[4], WU Bin[1,2], YANG Pengnian[1,2], BAN Jingya[1,2], LIU Zeyi[3], LIU Kun[1,2], HAN Fanghong[1,2], MA Zhenghu[1,2], WANG Lu[5]

[1] College of Hydraulic and Civil Engineering, Xinjiang Agricultural University, Urumqi 830052, China
[2] Xinjiang Key Laboratory of Hydraulic Engineering Security and Water Disasters Prevention, Urumqi 830052, China
[3] Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China
[4] State Key Laboratory of Eco-hydraulics in Northwest Arid Region of China, Xi' an University of Technology, Xi' an 710048, China

Abstract: Climate change in High Mountain Asia (HMA) is characterized by elevation dependence, which results in vertical zoning of vegetation distribution. However, few studies have examined the distribution patterns of vegetation, the response of vegetation to climate change, and the key climatic control factors of vegetation along the elevation gradient in this region. In this study, based on the Normalized Difference Vegetation Index (NDVI), we investigated the evolution pattern of vegetation in HMA during 2001–2020 using linear trend and Bayesian Estimator of Abrupt Change, Seasonality, and Trend (BEAST) methods. Pearson correlation analysis and partial correlation analysis were used to explore the response relationship between vegetation and climatic factors along the elevation gradient. Path analysis was employed to quantitatively reveal the dominant climatic factors affecting vegetation distribution along the elevation gradient. The results showed that NDVI in HMA increased at a rate of 0.011/10a from 2001 to 2020, with the rate of increase abruptly slowing down after 2017. NDVI exhibited a fluctuating increase at elevation zones 1–2 (<2500 m) and then decreased at elevation zones 3–9 (2500–6000 m) with increasing elevation. NDVI was most sensitive to precipitation and temperature at a 1-month lag. With increasing elevation, the positive response relationship of NDVI with precipitation gradually weakened, while that of NDVI with temperature showed the opposite pattern. The total effect coefficient of precipitation (0.95) on vegetation was larger than that of temperature (0.87), indicating that precipitation is the dominant control factor affecting vegetation growth. Spatially, vegetation growth is jointly influenced by precipitation and temperature, but the influence of precipitation on vegetation growth is dominant at each elevation zone. These results contribute to understanding how the elevation gradient effect influences the response of vegetation to climate change in alpine ecosystems.

Keywords: vegetation growth; climate change; elevation gradient; Normalized

Difference Vegetation Index (NDVI); path analysis; High Mountain Asia

1 Introduction

Vegetation, as a critical component of terrestrial ecosystems, participates in ecological processes such as material cycling and energy transformation while significantly impacting the water cycle and climate change (Tai et al., 2020). Simultaneously, climatic factors including precipitation, temperature, and solar radiation influence vegetation phenology and growth processes, which in turn affect plant distribution patterns (Linscheid et al., 2020). Climate change, particularly global warming, has resulted in increased frequency of high temperatures, droughts, floods, and other extreme events in recent years, causing serious harm to global and regional ecosystems (Zhou et al., 2014). Warming and humidification of high-elevation climates will affect vegetation growth over time (Palazzi et al., 2017). Consequently, investigating vegetation dynamics and the driving role of climatic factors has become a hotspot and key issue in current global change research, which is critical for evaluating regional vegetation growth status.

To quantify dynamics in vegetation cover, many studies have employed the Normalized Difference Vegetation Index (NDVI), derived from satellite remote sensing data, which can quantitatively and intuitively reflect vegetation growth dynamics and is widely used in studies examining relationships between vegetation and climatic factors (Piao et al., 2006; Wen et al., 2017; Zhuang et al., 2020; Yang et al., 2024). Based on NDVI data, studies have concluded that global vegetation growth is improving, particularly in the middle and high latitudes of the Northern Hemisphere (Myneni et al., 1997), and that vegetation greenness is increasing on the Qinghai–Xizang Plateau and in other areas (Meng et al., 2018).

Temperature and precipitation are the two main climatic factors influencing surface vegetation dynamics, though their relative importance differs across regions (Satti et al., 2024). Interannual variation in vegetation cover is more sensitive to precipitation in arid areas, as insufficient precipitation may limit vegetation growth (Xu et al., 2008; Cao et al., 2014). However, Li and Tao (2000) demonstrated that temperature has a greater influence on vegetation than precipitation in most parts of China. Cui et al. (2013) found that vegetation in the high-elevation areas of the Qinling Mountains is primarily controlled by temperature changes. Liu et al. (2021b) studied the alpine region in Asia and discovered that vegetation greening in High Mountain Asia (HMA) is mainly influenced by the dual effects of precipitation and temperature.

Vegetation growth processes and snow distribution are related not only to precipitation and temperature but also to elevation, which plays an indispensable role in shaping mountain vegetation and snow distribution patterns (Li et al., 2015). For example, climate change-induced shifts in vegetation boundaries are intrinsically linked to elevation gradients (Verdhen et al., 2016). In alpine ecosystems, elevational differences critically modulate regional hydrothermal conditions, snow-ice melt dynamics, and soil moisture availability, collectively governing vegetation growth patterns (Li et al., 2017; Wang et al., 2021b). Studies indicate that warming rates are generally amplified at higher elevations compared to lower elevations (Liu et al., 2019). Concurrently, temperature-driven precipitation increases in mountainous areas exhibit distinct elevation-dependent characteristics (Li et al., 2015; Li et al., 2017). These altitudinally stratified climate trends drive heterogeneous vegetation responses along the elevation gradient, often yielding contradictory and elevation-dependent patterns (Morán-Tejeda et al., 2017). For instance, while the sensitivity of vegetation greenness to temperature increases with elevation, absolute greenness values decline at higher elevations (Wang et al., 2021a; Zhang et al., 2024). Consequently, elevation serves not only as a key determinant of vegetation distribution but also as a critical variable in vegetation dynamic studies (Liu et al., 2022). Although the regulatory role of elevation in vegetation growth has been established (Shen et al., 2014), the mechanisms underlying vegetation-climate feedbacks along the elevation gradient remain poorly resolved, particularly regarding the interplay between vegetation evolutionary traits and variability in climatic factors (Li et al., 2015).

As the Earth’ s third pole, HMA has a distinct geographical location and climate system. Meanwhile, HMA is an alpine ecosystem where climate change is elevation-dependent and vegetation is extremely vulnerable to climate change (Shen et al., 2016; Li et al., 2017). As a result, scientific attention has shifted to studying the impact of climate change on NDVI in HMA. For example, Liu et al. (2021b) and Rani and Mal (2022) examined vegetation dynamics and their climate-driven mechanisms in HMA using NDVI data. Furthermore, NDVI variability and its drivers have been studied in some regions of HMA, particularly on the Qinghai–Xizang Plateau (Mishra and Mainali, 2017; Tai et al., 2020; Liu et al., 2021a). However, the distribution patterns of vegetation along the elevation gradient in HMA and the underlying mechanisms regulating these patterns remain poorly understood. Addressing this issue is critical for understanding and forecasting vegetation change in HMA under global climate change.

In recent years, researchers have typically employed Pearson correlation analysis (Sun et al., 2022; Li et al., 2024), partial correlation analysis (Ma et al., 2022), and multiple linear regression (Gao et al., 2019) to investigate relationships between vegetation cover and climate change. However, interactions between climatic factors cause them to have indirect effects on vegetation growth, which are rarely quantified. Although studies have used geographic probes to explore the multiple effects of factor interactions on the study population, the accuracy of this method depends on a large sample size (Peng et al., 2019; Shao et al., 2022). Path analysis, as an effective method for exploring multivariate interactive systems, can visually demonstrate the complex network of relationships between variables. Path analysis, with the premise of limited samples, can deal not only with multiple dependent and mediating variables between path variables but also with the direct and indirect effects of multiple factors interacting with each other on the study object (Fang et al., 2018). Consequently, path analysis was used in this study to quantify the impact of climatic factors on NDVI.

Based on this background, the scientific problem to be solved in this study is to analyze the evolution pattern of vegetation distribution along the elevation gradient in HMA and quantitatively reveal the dominant control factors affecting vegetation growth. To accomplish these objectives, this study will: (1) analyze the spatial and temporal evolution of NDVI in HMA; (2) investigate the distribution patterns of NDVI during the growing season along the elevation gradient; (3) detect the response relationships between NDVI and climatic factors along the elevation gradient; and (4) quantify the impacts of the main climatic control factors affecting NDVI along the elevation gradient. The findings can provide a basic reference for vegetation growth and ecosystem evolution in alpine regions.

2.1 Study Area

The HMA (Fig. 1 [Figure 1: see original paper]), with a geographic range of 25°–51°N and 64°-106°E, describes the high-elevation region of Asia centered on the Qinghai–Xizang Plateau. HMA has a land area of approximately 2.90×10^{6} km^{2} and consists of the Himalaya Mountains, Hindu Kush, Kunlun Mountains, Pamir Plateau, and other mountain ranges and plateaus, with an average elevation exceeding 4000 m. The main terrestrial ecosystems in the region are alpine grasslands, alpine meadows, and deciduous broad-leaved forests, among which alpine grasslands cover an area exceeding 1.50×10^{6} km^{2}. HMA is considered the water tower of Asia and has the largest snow and ice reserves outside the polar regions, with a glacier area of approximately 9.76×10^{4} km^{2} (Brun et al., 2017; Furian et al., 2021). The region receives approximately 400 mm of annual precipitation, more than 40.0% of which is snowfall (Sun et al., 2022), and serves as a water source for major rivers in East and South Asia, including the Indus River, Ganges River, Yangtze River, and Brahmaputra River.

2.2.1 Digital Elevation Model (DEM) Data

The DEM data were downloaded from the Geospatial Data Cloud (http://www.gscloud.cn/) at a spatial resolution of 90 m. Considering that the spatial resolution of NDVI data is 500 m, we divided HMA into 14 elevation zones with intervals of 500 m to form an elevation gradient (Fig. 1).

2.2.2 Normalized Difference Vegetation Index (NDVI) Dataset

The MOD13Q1 product, which can be downloaded from Earthdata Search (https://earthdata.nasa.gov), was used to obtain NDVI data from 2001 to 2020. The product has a temporal scale of 16 days and a spatial resolution of 250 m.

For projection, stitching, and other conversions, we used the Moderate Resolution Imaging Spectroradiometer (MODIS) Reprojection Tool (MRT) software. The maximum value composite method was then used to synthesize monthly NDVI data (Holben, 1986).

2.2.3 Meteorological Data

Precipitation and temperature data were selected from the fifth generation of European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalyses of the global climate (ERA5) data (http://apps.ecmwf.int/datasets/). The ERA5 data have significantly superior ability to reproduce weather and climate evolution compared to earlier ERA-Interim products. The spatial resolution of the ERA5 monthly data used in this study is 0.1°$×$0.1°. The data were formatted and synthesized annually using MATLAB 2024b software. The projection coordinates were then converted and resampled using ArcGIS 10.4 software to achieve the same spatial resolution as the NDVI data. Figure 2 [Figure 2: see original paper] shows that in HMA, both precipitation and temperature exhibit elevation-dependent characteristics, i.e., both decrease with elevation.

2.2.4 Vegetation Type Data

The vegetation type data for this study were obtained from the European Space Agency (ESA) (https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover). The total accuracy of this dataset is 75.4%, and the accuracy of many vegetation types, such as broadleaf forest, cropland, wetland, and other categories that can reflect the distribution and vertical zonality of vegetation in HMA, can exceed 80.0%. This study collected vegetation type data in HMA for 2001 and 2020 and identified 11 vegetation types (Fig. 3 [Figure 3: see original paper]).

2.3 Methods

In this study, we examined the evolution pattern of NDVI using linear trend and Bayesian Estimator of Abrupt Change, Seasonality, and Trend (BEAST) methods, investigated the response of NDVI to climatic factors using correlation and partial correlation methods, and detected the main climatic control factors affecting NDVI using path analysis. The flowchart of the research method is shown in Figure 4 [Figure 4: see original paper].

2.3.1 BEAST Method

The BEAST algorithm decomposes time series data into three components: trend, seasonality, and abrupt changes (Zhao et al., 2019). This method employs Bayesian statistical principles to reduce uncertainties, mitigate overfitting, and minimize modeling errors during decomposition. In cases where seasonal signals are absent, BEAST can be applied exclusively for trend analysis and abrupt change detection. It has been widely adopted to identify nonlinear trends and change points in NDVI time series (Zhao et al., 2019; Cai et al., 2020; Mardian et al., 2021). Specifically, BEAST decomposes a time series Y into:

$$Y_t = T_t + S_t + \varepsilon$$

where T , S , and   are the trend signal, seasonal signal, and residual signal of time series Y , respectively. The trend component T is a piecewise linear model with m breakpoints and m+1 linear models, where abrupt changes are found at the breakpoints τ (i=1, 2, ···, m) and gradual changes are given by the linear model:

$$T_t = \alpha + \beta_i(t - \tau_i), \quad \tau_i < t < \tau_{i+1}$$

where α is the intercept and β is the slope of the linear segment. The seasonal component S can be expressed as:

$$S_t = \sum_{k=1}^{K} \gamma_k \sin(2\pi f t + \delta_k)$$

where K represents the total number of segments in the time series; γ and δ are the amplitude and phase in the kth segment; and f is the frequency.

In this study, the BEAST method was used for mutation point analysis of the NDVI time series. For this purpose, we used the BEAST program package in MATLAB 2024b, which can be downloaded at https://www.mathworks.com/matlabcentral/fileexchange/26546-approximate-entropy.

2.3.2 Correlation Analysis

Pearson correlation analysis is a method to study correlations between elements. By calculating the correlation coefficient between NDVI and temperature as well as between NDVI and precipitation, we can intuitively and effectively observe the response degree of NDVI to temperature and precipitation, respectively. The calculation formula is as follows:

$$r = \frac{\sum_{j=1}^{n}(x_j - \bar{x})(y_j - \bar{y})}{\sqrt{\sum_{j=1}^{n}(x_j - \bar{x})^2 \sum_{j=1}^{n}(y_j - \bar{y})^2}}$$

where r is the correlation coefficient; x and y are the NDVI and precipitation (or temperature) in the jth year, respectively; and x̄ and ȳ are the average values of NDVI and precipitation (or temperature), respectively. The closer the correlation coefficient is to 1.0 or -1.0, the stronger the correlation. The closer the correlation coefficient is to zero, the weaker the correlation. The validity of the Pearson correlation coefficient is controlled by a two-tailed significance test, and a significance level of $P<0.01$ indicates that the correlation between the two variables is significant.

In this study, correlation coefficients between monthly-scale NDVI and climatic factors (precipitation and temperature) at various time scales (1-month, 3-month, 6-month, 9-month, and 12-month) were calculated to explain the time-lag effect of vegetation response to climatic factors. The time scales with the highest correlation coefficients were defined as the lag times of vegetation response to precipitation and temperature.

2.3.3 Partial Correlation Analysis

Partial correlation analysis describes the relationship between two variables while removing the influence of other variables (Yan, 2003). The partial correlation coefficient is calculated as follows:

$$r_{XY,Z} = \frac{r_{XY} - r_{XZ}r_{YZ}}{\sqrt{(1-r_{XZ}^2)(1-r_{YZ}^2)}}$$

where r , represents the partial correlation coefficient of variables X and Y, with Z as the control variable; and r , r , and r represent Pearson correlation coefficients between X and Y, X and Z, and Y and Z, respectively.

2.3.4 Path Analysis

In this study, path analysis was used to analyze the degree of influence of major climatic factors (precipitation and temperature) on vegetation cover in HMA. The core idea of path analysis is to translate the relative importance of each factor on the results by decomposing correlation coefficients into direct and indirect effects based on multiple regression analysis (Feng et al., 2021). The specific formula is as follows:

$$V = a_0 + a_{1v}1 + a_{2v}2 + \cdots + a_{nv}n$$

where V is the dependent variable; v_1-v are the independent variables; n is the number of independent variables; a_0 is the constant term; and a_1-a are the partial regression coefficients.

Equation 6 can be mathematically transformed to the following normal equation of moments by substituting the actual observations into it and solving the system of equations using least squares. The specific formulas are as follows:

$$\begin{cases} r_{v_{1V}} = P_{v_{1V}} + r_{v_{1v}2}P_{v_{2V}} + \cdots + r_{v_{1v}n}P_{v_{nV}} \\ r_{v_{2V}} = r_{v_{2v}1}P_{v_{1V}} + P_{v_{2V}} + \cdots + r_{v_{2v}n}P_{v_{nV}} \\ \vdots \\ r_{v_{nV}} = r_{v_{nv}1}P_{v_{1V}} + r_{v_{nv}2}P_{v_{2V}} + \cdots + P_{v_{nV}} \end{cases}$$

where r $_{1\ 2}$ and r $_{1}$ are the correlation coefficients between v_1 and v_2 and between v_1 and V, respectively; P is the direct path coefficient of variable v , which represents the direct effect of variable v on V; a is the partial regression coefficient of v to V; and σ and σ are the standard deviations of v and V, respectively. The indirect path coefficient of variable v via variable v can be defined as P = r P , which represents the indirect influence of variable v on V via variable v . The total effect of v equals the direct effect of variable v on V plus the indirect effect of variable v on V via all independent variables except v .

In this study, the effects of precipitation and temperature on NDVI during the growing season were calculated using path analysis from both time series and spatial pixel-by-pixel perspectives. The time series perspective was calculated using SPSS 27.0 software, and the spatial pixel-by-pixel perspective was calculated using MATLAB 2024b (the code extraction is available at https://pan.baidu.com/s/1PZM_{3wQO7XkVGA2HikLrzA}?pwd=7ml9).

3.1.1 Temporal Variations of NDVI

The NDVI began to increase in January, reached its peak in July and August, then declined to its lowest point in September (Fig. 5a [Figure 5: see original paper]). From 2001 to 2020, the growing season (April-October) consistently had the highest NDVI values, while all other months had the lowest NDVI values. The NDVI data from April to October were thus used in this study to reflect vegetation change in HMA during the growing season. All subsequent analyses of NDVI referred to the NDVI during the growing season.

Figure 5b shows the interannual variation of NDVI from 2001 to 2020. The NDVI in HMA demonstrated a general trend of fluctuating increase, but the rate of increase was only 0.011/10a. This study used the BEAST method to detect NDVI mutation points to more clearly reveal the mutation characteristics of the interannual trend (Fig. 5c). The NDVI time series had a mutation in 2017. The increasing trend of NDVI was evident from 2001 to 2017, while from 2017 to 2020, NDVI exhibited a slow fluctuating increase. HMA exhibited an overall trend of vegetation improvement during 2001-2020.

3.1.2 Spatial Variations of NDVI

Figure 6a [Figure 6: see original paper] shows the spatial distribution of multi-year average NDVI during 2001-2020. NDVI was high in the northwestern, southeastern, and southern marginal zones, and low in the center of HMA. Areas with NDVI greater than 0.40 accounted for approximately 28.4% of the study area and were mainly distributed around the southeastern region and southern borders of HMA.

Figures 6b and 6c show the spatial linear trends of NDVI before and after the breakpoint in 2017. Before 2017, 77.0% of HMA showed an increasing trend in NDVI and only 23.0% showed a decreasing trend. After 2017, only 53.0% of HMA showed an increasing trend in NDVI, and the decreasing areas (47.0% of HMA) were mainly located in the northern and central parts of HMA. This indicated that the increasing trend of vegetation during the growing season has slowed down since 2017.

3.2 NDVI Variations Along the Elevation Gradient in HMA

NDVI fluctuated upward and then downward with increasing elevation, showing specific elevation-dependent characteristics (Fig. 7a [Figure 7: see original paper]). Specifically, NDVI showed an increasing trend as elevation increased and was relatively high at elevation zones 1–2 (with NDVI greater than 0.30), whereas it tended to drop as elevation continued to rise from elevation zone 2 onward. NDVI values were negative from elevation zone 10 onward, mainly because glacial snow is mostly distributed in these areas. Therefore, in the following study, we only examined NDVI variation characteristics at elevation zones 1–9.

From 2001 to 2020, NDVI along the elevation gradient exhibited fluctuating increases and decreases (Fig. 7b). Elevation zones 1–6 had higher NDVI values, where elevation zone 2 had the largest NDVI value, indicating the best vegetation condition at this elevation zone. Elevation zones 6–9 had relatively small NDVI values, indicating relatively poor vegetation cover in these elevation ranges.

NDVI at elevation zones 1–8 before the breakpoint in 2017 was dominated by an increasing trend (the proportions of NDVI-increasing pixels at these elevation zones were all greater than 60.0%), indicating that vegetation in these elevation ranges entered a rapid growth phase before 2017 (Fig. 7c). The proportion of NDVI-increasing pixels declined at all elevation zones after 2017, suggesting that vegetation growth rates slowed down after the mutation (Fig. 7d). As elevation increased, the proportion of NDVI-increasing pixels gradually decreased, and at elevation zone 9, the proportion of NDVI-increasing pixels (40.6%) was less than the proportion of NDVI-decreasing pixels (59.4%).

3.3.1 Time-Lag Effect of NDVI Response to Climatic Factors

Figure 8 [Figure 8: see original paper] shows that the time-lag effect of NDVI to climate elements varies across elevation zones. The correlation coefficients between precipitation and NDVI at time scales of 1-month, 3-month, 6-month, and 12-month were almost all positive, while the correlation coefficients between NDVI and precipitation at the 9-month time scale were negative. The correlation coefficients between NDVI and temperature at time scales of 1-month, 3-month, and 12-month were all positive, while at 6-month and 9-month time scales they were negative. The absolute value of the correlation coefficient was highest when NDVI lagged precipitation or temperature by one month, indicating that climate element changes in the previous month had the most obvious influence on NDVI.

3.3.2 Response Relationship Between NDVI and Climatic Factors

Partial correlation coefficients of NDVI with temperature and precipitation were calculated considering the best time-lag effect to reveal the response relationship between NDVI and one climatic factor while removing the influence of the other climatic factor. The partial correlation coefficients of NDVI with precipitation and temperature were typically positive, but spatial differences were significant.

By calculating the area proportions of positive and negative partial correlation coefficients between NDVI and precipitation (Fig. 9a [Figure 9: see original paper]) as well as between NDVI and temperature (Fig. 9b) along the elevation gradient in HMA, we found that vegetation was affected by both precipitation and temperature along the elevation gradient, but the degree of influence differed. Along the elevation gradient, the positive response relationship of NDVI with precipitation showed a fluctuating weakening trend, while the positive response relationship of NDVI with temperature showed the opposite pattern—a fluctuating increasing trend—indicating that as elevation increases, the promotion effect of precipitation on vegetation is weakened, while the opposite is true for temperature.

3.4 Dominant Control Factors Affecting NDVI

The path analysis method can quantitatively reveal the degree of influence of different climatic factors on vegetation cover. From the time series perspective (Fig. 10a [Figure 10: see original paper]), the direct effect coefficient of precipitation on NDVI (0.88) was significantly higher than that of temperature on vegetation (0.79) when only a single factor was considered. This result indicated that the effect of a single temperature change on vegetation is smaller than the effect of a single precipitation change on vegetation. The correlation coefficient between precipitation and temperature was large (0.9), indicating a clear interaction between precipitation and temperature. When considering the interaction between precipitation and temperature, their total effect coefficients were 0.95 and 0.87, respectively, indicating that the total effect of precipitation on vegetation is more significant and precipitation is the dominant control factor affecting vegetation growth, though the effect of temperature on vegetation should not be neglected.

The total effects of precipitation and temperature on NDVI along the elevation gradient showed a similar trend, exhibiting fluctuating increasing and decreasing states (Fig. 10b). The difference was that the total effects of precipitation at elevation zones 1-6 and elevation zone 9 were greater than those of temperature, indicating that precipitation is the dominant control factor affecting vegetation growth in these elevation ranges. The total effects of temperature at elevation zones 7 and 8 were greater than those of precipitation, indicating that temperature is the dominant control factor affecting vegetation growth in these elevation ranges.

The spatial distribution of the dominant control factors affecting NDVI also indicated that NDVI is jointly influenced by precipitation and temperature (Fig. 10c). However, 60.9% of the study area showed that precipitation was the dominant control factor affecting NDVI, whereas only 39.2% of areas showed that temperature was the dominant control factor, and these areas were mostly distributed at high elevations. At each elevation zone, the proportion of pixels with precipitation as the dominant control factor was larger than that with temperature as the dominant control factor (Fig. 10d), indicating that precipitation is the dominant control factor affecting vegetation distribution along the elevation gradient.

4.1 Spatial and Temporal Evolution Characteristics of NDVI in HMA

Extensive studies have utilized NDVI data to investigate vegetation dynamics at global and regional scales (e.g., Chen et al., 2014; Zhao et al., 2018). Specifically in HMA, research by Liu et al. (2022) and Maina et al. (2022) identified a persistent greening trend in alpine vegetation. This finding aligns with our analysis, which revealed a significant greening trend across HMA from 2001 to 2020, with an NDVI increase rate of 0.011/10a ($P<0.05$).

The spatial distribution characteristics of NDVI are closely related to vegetation types (Ma et al., 2022). By analyzing vegetation type transfer (Table 1), we found that area increases in broad-leaved forest, needle-leaf forest, and cropland were 3708.54, 9884.34, and 4473.99 km^2, respectively, and the area decline in bare area (3832.47 km^2) may contribute to vegetation greening in HMA. The vegetation type transfer process showed that reduced grassland was primarily converted to needle-leaf forest, cropland, shrubland, and broad-leaved forest, with transformed areas of 11,626.47, 12,567.42, 2299.05, and 2760.84 km^2, respectively (Fig. 11a [Figure 11: see original paper]).

4.2 Distribution Characteristics of NDVI Along the Elevation Gradient

The spatial distribution of NDVI is closely related to vegetation type distribution, but elevation is also an important influencing factor (Piao et al., 2006; Ma et al., 2022). NDVI in HMA tended to increase at elevation zones 1–2 and then decrease at elevation zones 6–9 with increasing elevation (Fig. 6a). This finding is similar to that of Gao et al. (2019), where vegetation greenness decreased at higher elevations. The decrease in vegetation greenness with increasing elevation may be related to low temperatures at higher elevations, i.e., vegetation growth at higher elevations is susceptible to low-temperature limitation (Tao et al., 2018; Gao et al., 2019). Additionally, variation in vegetation type is associated with changes in NDVI along the elevation gradient. Each elevation zone showed a trend of increasing and then decreasing proportions of grassland, broad-leaved forest, needle-leaf forest, and shrubland (Fig. 11b and 11c).

4.3 Dominant Control Factors Affecting Vegetation Distribution Along the Elevation Gradient

Temperature and precipitation constitute the primary climatic drivers of vegetation growth, though their effects are modulated by complex interactions between these factors. Precipitation enhances vegetation greenness by directly increasing soil moisture availability (Wang et al., 2021a). However, elevated precipitation may indirectly suppress vegetation growth by reducing surface temperatures—a cooling effect that constrains thermal conditions for plant metabolism. Temperature regulates key physiological processes of plants such as photosynthesis and respiration rates (Ma et al., 2016). When temperatures remain below species-specific optima, warming improves vegetation growth through enhanced snowmelt-derived water supply and extended growing seasons. Conversely, temperatures exceeding physiological thresholds exacerbate soil moisture depletion via evapotranspiration, thereby inhibiting vegetation productivity (Xie et al., 2020).

We found that precipitation is the dominant control factor influencing vegetation growth in HMA at each elevation zone. However, as elevation increases, precipitation gradually decreases, and the direct effect of precipitation on vegetation growth would be reduced. In contrast, as elevation increases, temperature drops and becomes lower than the range suitable for vegetation growth; at this point, temperature increase would have a certain promotion effect on vegetation growth. Thus, this suggests that vegetation growth in HMA is influenced by a combination of climatic factors.

Vegetation types with high cover density, such as broad-leaved forest, needle-leaf forest, shrubland, and grassland, are primarily distributed at elevation zones 1–6 (Fig. 11b and 11c), suggesting that the distribution of these vegetation types impacts the overall change of vegetation in HMA. Precipitation was also the dominant control factor of vegetation for each vegetation type, according to statistical analysis of the proportions of dominant control factors for various vegetation types (Fig. 12 [Figure 12: see original paper]). This matches the findings of Liu et al. (2021b) and Zhang et al. (2021).

4.4 Limitations and Future Work

Despite the comprehensive analyses conducted in this study, several limitations warrant acknowledgment and future exploration. The 500 m elevation interval used here may oversimplify altitudinal zonation patterns. Future studies could employ finer elevation intervals to better resolve NDVI evolution mechanisms along the elevation gradient. While ERA5 provides continuous spatiotemporal coverage, its reliability in HMA remains partially constrained by sparse ground meteorological stations and short observational records (<20 a). Subsequent work should integrate in-situ station measurements or higher-resolution datasets to quantify ERA5 biases in complex terrains. Furthermore, relying solely on MODIS NDVI and two climatic variables (precipitation and temperature) overlooks key biophysical drivers such as vapor pressure deficit, solar radiation, and evapotranspiration. A multi-sensor approach incorporating Sentinel-2 (10 m resolution) and eddy covariance flux data could enhance mechanistic understanding of vegetation-climate interactions.

To address these shortcomings, future research could establish an integrated monitoring network (ground sensors/unmanned aerial vehicles/satellites) for tracking long-term vegetation changes through continuous remote sensing monitoring and data collection, which would help more comprehensively understand long-term evolution patterns of vegetation cover. Simultaneously, more accurate artificial intelligence algorithms could be considered to quantify the coupling relationship between drivers and vegetation changes by combining field surveys and validation, to accurately quantify vegetation evolution mechanisms and improve result credibility. Since it is difficult to estimate future trends of human activities, more consideration should be given to the role of anthropogenic factors, such as agricultural management and grazing, in influencing vegetation change in future studies.

5 Conclusions

This study analyzed the evolution characteristics of NDVI along the elevation gradient in HMA from 2000 to 2020, investigated the response of vegetation to climate change, and quantitatively revealed the dominant climatic factors affecting vegetation growth. The average NDVI during the growing season showed an overall increasing trend from 2001 to 2020. After the mutation (2017), only 53.0% of HMA showed an increasing trend in NDVI, and 47.0% showed a decreasing trend. NDVI showed a fluctuating increase at elevation zones 1–2 and then decreased at elevation zones 3–9 with increasing elevation. After the mutation, the proportion of pixels with a greening trend spatially decreased with increasing elevation. Changes in precipitation and temperature in the previous month had the most significant effect on NDVI. The response of NDVI to climatic factors varied with elevation. As elevation increased, the positive response relationship of NDVI with precipitation gradually weakened, while that of NDVI with temperature showed the opposite pattern. Path analysis indicated that precipitation is the dominant control factor affecting vegetation distribution along the elevation gradient, but the effect of temperature on vegetation cannot be ignored. Future research should focus on exploring the adaptation mechanisms of vegetation in alpine regions under the background of climate warming and permafrost degradation.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was supported by the Xinjiang Uygur Autonomous Region Major Scientific and Technological Special Project: Research and Demonstration on the Development Model of Ecological Agriculture and Efficient Utilization of Soil and Water Resources in Modern Irrigation Areas (2023A02002-1).

Author Contributions

Conceptualization: HE Bing, GAO Fan, WANG Lu; Data curation: LI Ying, LIU Kun; Formal analysis: HE Bing, LI Ying, WANG Lu; Funding acquisition: HE Bing; Investigation: HE Bing, XU Hailiang, WU Bin; Methodology: LIU Zeyi, HAN Fanghong, MA Zhenghu; Resources: YANG Pengnian, BAN Jingya; Software: HE Bing, LIU Kun; Validation: GAO Fan, WANG Lu; Visualization: WANG Lu; Writing - original draft: HE Bing, WANG Lu; Writing - review & editing: HE Bing, WANG Lu. All authors approved the manuscript.

References

Brun F, Berthier E, Wagnon P, et al. 2017. A spatially resolved estimate of High Mountain Asia glacier mass balances from 2000 to 2016. *Nature Geoscience*, 10(9): 668–673.

Cai Y T, Liu S T, Lin H. 2020. Monitoring the vegetation dynamics in the Dongting Lake wetland from 2000 to 2019 using the BEAST algorithm based on dense Landsat time series. *Applied Sciences*, 10(12): 4209, doi: 10.3390/app10124209.

Cao R, Jiang W G, Yuan L H, et al. 2014. Inter-annual variations in vegetation and their response to climatic factors in the upper catchments of the Yellow River from 2000 to 2010. *Journal of Geographical Sciences*, 24(6): 963–979.

Chen B Z, Xu G, Coops N C, et al. 2014. Changes in vegetation photosynthetic activity trends across the Asia-Pacific region over the last three decades. *Remote Sensing of Environment*, 144: 28–41.

Cui X L, Bai H Y, Wang T. 2013. Difference in NDVI with altitudinal gradient and temperature in Qinling area. *Resources Science*, 35(3): 618–626. (in Chinese)

Fang X Q, Zhu Q A, Ren L L, et al. 2018. Large-scale detection of vegetation dynamics and their potential drivers using MODIS images and BFAST: A case study in Quebec, Canada. *Remote Sensing of Environment*, 206: 391–402.

Feng K, Wang T, Liu S L, et al. 2021. Path analysis model to identify and analyse the causes of aeolian desertification in Mu Us Sandy Land, China. *Ecological Indicators*, 124: 107386, doi: 10.1016/j.ecolind.2021.107386.

Furian W, Loibl D, Schneider C. 2021. Future glacial lakes in High Mountain Asia: an inventory and assessment of hazard potential from surrounding slopes. *Journal of Glaciology*, 67(264): 653–670.

Gao M D, Piao S L, Chen A P, et al. 2019. Divergent changes in the elevational gradient of vegetation activities over the last 30 years. *Nature Communications*, 10(1): 2970, doi: 10.1038/s41467-019-11035-w.

Holben B N. 1986. Characteristics of maximum-value composite images from temporal AVHRR data. *International Journal of Remote Sensing*, 7(11): 1417–1434.

Li B G, Tao S. 2000. Correlation between AVHRR NDVI and climate factors. *Acta Ecologica Sinica*, 20(5): 898–902. (in Chinese)

Li H D, Li Y K, Shen W S, et al. 2015. Elevation-dependent vegetation greening of the Yarlungzangbo River basin in the southern Tibetan Plateau, 1999–2013. *Remote Sensing*, 7(12): 16672–16687.

Li N, Zhan P, Pan Y Z, et al. 2024. Quantifying uncertainty: The benefits of removing snow cover from remote sensing time series on the extraction of climate-influenced grassland phenology on the Qinghai–Tibet Plateau. *Agricultural and Forest Meteorology*, 345: 109862, doi: 10.1016/j.agrformet.2023.109862.

Li X P, Wang L, Guo X Y, et al. 2017. Does summer precipitation trend over and around the Tibetan Plateau depend on elevation? *International Journal of Climatology*, 37(Supp1.): 1278–1284.

Linscheid N, Estupinan-Suarez L M, Brenning A, et al. 2020. Towards a global understanding of vegetation–climate dynamics at multiple timescales. *Biogeosciences*, 17(4): 945–962.

Liu C L, Li W L, Wang W Y, et al. 2021a. Quantitative spatial analysis of vegetation dynamics and potential driving factors in a typical alpine region on the northeastern Tibetan Plateau using the Google Earth Engine. *CATENA*, 206: 105500, doi: 10.1016/j.catena.2021.105500.

Liu L B, Wang Y, Wang Z, et al. 2019. Elevation-dependent decline in vegetation greening rate driven by increasing dryness based on three satellite NDVI datasets on the Tibetan Plateau. *Ecological Indicators*, 107: 105569, doi: 10.1016/j.ecolind.2019.105569.

Liu Y C, Li Z, Chen Y N. 2021b. Continuous warming shift greening towards browning in the Southeast and Northwest High Mountain Asia. *Scientific Reports*, 11(1): 17920, doi: 10.1038/s41598-021-97240-4.

Liu Y C, Li Z, Chen Y N, et al. 2022. Evaluation of consistency among three NDVI products applied to High Mountain Asia in 2000–2015. *Remote Sensing of Environment*, 269: 112821, doi: 10.1016/j.rse.2021.112821.

Ma L, Wang J R, Liu T X, et al. 2016. Response relationship between vegetation and climate factors in Horqin sandy land from 2000 to 2012. *Transactions of the Chinese Society for Agricultural Machinery*, 47(4): 162–172. (in Chinese)

Ma Y R, Guan Q Y, Sun Y F, et al. 2022. Three-dimensional dynamic characteristics of vegetation and its response to climatic factors in the Qilian Mountains. *CATENA*, 208: 105694, doi: 10.1016/j.catena.2021.105694.

Maina F Z, Kumar S V, Albergel C, et al. 2022. Warming, increase in precipitation, and irrigation enhance greening in High Mountain Asia. *Communications Earth & Environment*, 3: 43, doi: 10.1038/s43247-022-00374-0.

Mardian J, Berg A, Daneshfar B. 2021. Evaluating the temporal accuracy of grassland to cropland change detection using multitemporal image analysis. *Remote Sensing of Environment*, 255: 112292, doi: 10.1016/j.rse.2021.112292.

Meng M, Niu Z, Ma C, et al. 2018. Variation trend of NDVI and response to climate change in Tibetan Plateau. *Research of Soil and Water Conservation*, 25(3): 360–365, 372. (in Chinese)

Mishra N B, Mainali K P. 2017. Greening and browning of the Himalaya: Spatial patterns and the role of climatic change and human drivers. *Science of the Total Environment*, 587–588: 326–339.

Morán-Tejeda E, López-Moreno J I, Sanmiguel-Vallelado A. 2017. Changes in climate, snow and water resources in the Spanish Pyrenees: observations and projections in a warming climate. In: Catalan J, Ninot J M, Aniz M M. *High Mountain Conservation in a Changing World*. Cham: Springer, 305–323.

Myneni R B, Keeling C D, Tucker C J, et al. 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature*, 386(6626): 698–702.

Palazzi E, Filippi L, von Hardenberg J. 2017. Insights into elevation-dependent warming in the Tibetan Plateau-Himalayas from CMIP5 model simulations. *Climate Dynamics*, 48(11): 3991–4008.

Peng W F, Kuang T T, Tao S. 2019. Quantifying influences of natural factors on vegetation NDVI changes based on geographical detector in Sichuan, western China. *Journal of Cleaner Production*, 233: 353–367.

Piao S L, Fang J Y, Zhou L M, et al. 2006. Variations in satellite-derived phenology in China' s temperate vegetation. *Global Change Biology*, 12(4): 672-685.

Rani S, Mal S. 2022. Trends in land surface temperature and its drivers over the High Mountain Asia. *The Egyptian Journal of Remote Sensing and Space Science*, 25(3): 717-729.

Satti Z, Naveed M, Shafeeque M, et al. 2024. Investigating the impact of climate change on trend shifts of vegetation growth in Gilgit Baltistan. *Global and Planetary Change*, 232: 104341, doi: 10.1016/j.gloplacha.2023.104341.

Shao W Y, Wang Q Z, Guan Q Y, et al. 2022. Distribution of soil available nutrients and their response to environmental factors based on path analysis model in arid and semi-arid area of northwest China. *Science of the Total Environment*, 827: 154254, doi: 10.1016/j.scitotenv.2022.154254.

Shen M G, Zhang G X, Cong N, et al. 2014. Increasing altitudinal gradient of spring vegetation phenology during the last decade on the Qinghai–Tibetan Plateau. *Agricultural and Forest Meteorology*, 189–190: 71–80.

Shen M G, Piao S L, Chen X Q, et al. 2016. Strong impacts of daily minimum temperature on the green-up date and summer greenness of the Tibetan Plateau. *Global Change Biology*, 22(9): 3057–3066.

Sun F, Chen Y N, Li Y P, et al. 2022. Incorporating relative humidity improves the accuracy of precipitation phase discrimination in High Mountain Asia. *Atmospheric Research*, 271: 106094, doi: 10.1016/j.atmosres.2022.106094.

Tai X L, Epstein H E, Li B. 2020. Elevation and climate effects on vegetation greenness in an arid mountain-basin system of Central Asia. *Remote Sensing*, 12(10): 1665, doi: 10.3390/rs12101665.

Tao J, Xu T Q, Dong J W, et al. 2018. Elevation-dependent effects of climate change on vegetation greenness in the high mountains of southwest China during 1982–2013. *International Journal of Climatology*, 38(4): 2029–2038.

Verdhen A, Chahar B R, Ganju A, et al. 2016. Modeling snow line altitudes in the Himalayan Watershed. *Journal of Hydrologic Engineering*, 21(1): 04015056, doi: 10.1061/(ASCE)HE.1943-5584.0001255.

Wang Y J, Fu B J, Liu Y X, et al. 2021a. Response of vegetation to drought in the Tibetan Plateau: Elevation differentiation and the dominant factors. *Agricultural and Forest Meteorology*, 306: 108468, doi: 10.1016/j.agrformet.2021.108468.

Wang Y J, Shen X J, Jiang M, et al. 2021b. Spatiotemporal change of aboveground biomass and its response to climate change in marshes of the Tibetan Plateau. *International Journal of Applied Earth Observation and Geoinformation*, 102: 102385, doi: 10.1016/j.jag.2021.102385.

Wen Z F, Wu S J, Chen J L, et al. 2017. NDVI indicated long-term interannual changes in vegetation activities and their responses to climatic and anthropogenic factors in the Three Gorges Reservoir Region, China. *Science of the Total Environment*, 574: 947-959.

Xie S D, Mo X G, Hu S, et al. 2020. Responses of vegetation greenness to temperature and precipitation in the Three-North Shelter Forest Program. *Geographical Research*, 39(1): 152-165. (in Chinese)

Xu X K, Chen H, Levy J K. 2008. Spatiotemporal vegetation cover variations in the Qinghai-Tibet Plateau under global climate change. *Science Bulletin*, 53(6): 915-922.

Yan L K. 2003. Application of correlation coefficient and biased correlation coefficient in related analysis. *Journal of Yunnan University of Finance and Economics*, 19(3): 78-80. (in Chinese)

Yang X L, Ding W K, Zhou H, et al. 2024. Normalized difference vegetation index change and its driving factors in Shiyang River Basin. *Arid Land Geography*, 47(10): 1735-1744. (in Chinese)

Zhang L, Shen M G, Yang Z Y, et al. 2024. Spatial variations in the difference in elevational shifts between greenness and temperature isolines across the Tibetan Plateau grasslands under warming. *Science of the Total Environment*, 906: 167715, doi: 10.1016/j.scitotenv.2023.167715.

Zhang Y, Feng X M, Fu B J, et al. 2021. Satellite-observed global terrestrial vegetation production in response to water availability. *Journal of Hydrology*, 13(7): 1289, doi: 10.3390/rs13071289.

Zhao K G, Wulder M A, Hu T X, et al. 2019. Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm. *Remote Sensing of Environment*, 232: 111181, doi: 10.1016/j.rse.2019.04.034.

Zhao L, Dai A G, Dong B. 2018. Changes in global vegetation activity and its driving factors during 1982-2013. *Agricultural and Forest Meteorology*, 249: 198-209.

Zhou L M, Tian Y H, Myneni R B, et al. 2014. Widespread decline of Congo rainforest greenness in the past decade. *Nature*, 509(7498): 86-90.

Zhuang Q W, Wu S X, Feng X Y, et al. 2020. Analysis and prediction of vegetation dynamics under the background of climate change in Xinjiang, China. *PeerJ*, 8: e8282, doi: 10.7717/peerj.8282.

Note: Figure translations are in progress. See original paper for figures.