

Article

Response of Vegetation Coverage to Climate Drivers in the Min-Jiang River Basin along the Eastern Margin of the Tibetan Plateau, 2000–2022

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Abstract: Ecological zonation research is typically conducted in the eastern margin of the Tibetan Plateau. In order to enhance the structure and function of regional ecosystems and monitor their quality, it is crucial to investigate shifts in the coverage of vegetation and the factors that contribute to these shifts. The goal of this study is to assess the spatial and temporal variations in vegetation covering and the partitioning of its drivers in the Minjiang River Basin on the eastern edge of the Tibetan Plateau between 2000 and 2022. The Mann-Kendall test, Hurst index, Theil-Sen median trend analysis, and other techniques were used to look at the features of temporal and geographical changes in regional vegetation coverage as well as potential development trends. The climatic influences leading to the spatial differentiation of vegetation NDVI (Normalized Difference Vegetation Index) were quantified through partial and complex correlation analyses of NDVI with temperature and precipitation. The results of the study showed that (1) the NDVI of the watershed performed well with a stable upward trend, indicating that the vegetation growth was generally good; (2) the spatial analysis showed that the coefficient of variation of the NDVI reached 0.092, which highlighted the stability of the vegetation change in the region; (3) the future development trend of the vegetation coverage in the watershed is low, and there is a certain degree of ecological risk; and (4) the main driver of the vegetation coverage is the non-climate factor, distributed in most parts of the watershed; (5) the climate driver shows localized influence, especially concentrated in the southwest, downstream and part of the upstream areas of the watershed.

Keywords: NDVI; vegetation coverage; correlation analysis; driving factors



Citation: Liu, S.; Gu, Y.; Wang, H.; Lin, J.; Zhuo, P.; Ao, T. Response of Vegetation Coverage to Climate Drivers in the Min-Jiang River Basin along the Eastern Margin of the Tibetan Plateau, 2000–2022. *Forests* **2024**, *15*, 1093. <https://doi.org/10.3390/f15071093>

Academic Editors: Nadezhda Tchebakova and Nikolay S. Strigul

Received: 9 May 2024

Revised: 16 June 2024

Accepted: 20 June 2024

Published: 24 June 2024



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1. Introduction

Vegetation influences the global carbon cycle and biodiversity as well as the hydrological cycle system through the storage and release of organic matter, provision of habitat, and transpiration. Thus, as a key component of terrestrial ecosystems, vegetation plays an important role in maintaining ecological stability, soil conservation, and regulation of the hydrological cycle [1–4]. The NDVI (Normalized Difference Vegetation Index) data can reveal the changes in terrestrial vegetation ecosystems in the global changes and can also be used as a monitoring factor to reflect the regional vegetation growth status and monitor the extent of vegetation coverage [5,6]. It is also widely used as a prioritized indicator for crop growth detection, ecological monitoring, and ecological risk assessment in the region, with the advantages of high sensitivity, clear physical significance, simplicity of computation, wide coverage, and long time series, but it may also be affected by non-vegetative factors such as cloud cover, atmospheric conditions, and sensors [7,8]. The NDVI has shown an increasing trend in various degrees under the trend of global warming in many distinct places [9]. Vegetation changes have been impacted by both natural settings and human

activity, which has partially resulted in spatial variation in vegetation changes [10]. Since the 1980s, the NDVI in China has been increasing significantly, especially in the Tibetan Plateau region. Since 2000, this trend has gradually slowed down [11].

Due to few human influences, one of the primary causes of the vegetation change on the Tibetan Plateau is climate change [12,13]. The capacity of climate to modify soil moisture, organic carbon content, and plant metabolism, either directly or indirectly, is the primary indicator of how vegetation grows [14,15]. As the highest plateau on Earth, the Tibetan Plateau is extremely vulnerable to changes in the global climate. Variations in world temperature and precipitation have also caused notable fluctuations in the amount of vegetation [16–18]. From a temperature perspective, this has been largely accompanied by a significant lengthening of the vegetation growing season [19]. Nonetheless, the rise in temperature also caused plants to transpire more quickly, which had an impact on the rate and efficiency of the plants' use of water, ultimately impeding their growth to some degree [20,21]. On the other hand, vegetation growth is strongly influenced by precipitation, especially in the arid regions of the Southern Hemisphere, where precipitation not only provides necessary water for plants but also helps to regulate surface temperatures and slows down the process of evapotranspiration and heat dissipation in soil and vegetation [22–24].

The study of NDVI and its drivers still has methodological flaws despite notable advancements. For example, while traditional methods for vegetation coverage research, such as spatio-temporal analysis and geostatistical methods, have been widely adopted, they also have certain limitations. The implementation of these methods is limited by topography and other natural conditions, resulting in difficult data acquisition, high time cost, and low efficiency [25–27]. In recent years, there have been fast advancements in remote sensing technology, and the Google Earth Engine platform (GEE) has given researchers a strong tool for quickly accessing, processing, and analyzing data on vegetation coverage worldwide. As a result, a significant area of current vegetation coverage research is the analysis of extensive, long-term vegetation databases based on the GEE platform [28,29]. Vegetation indices are used in this study method to examine the growth and coverage of vegetation [30]. The application of vegetation indices has significant advantages in large-scale vegetation studies and provides theoretical support for ecological restoration and vegetation management. The NDVI-based study has been widely used as the main vegetation assessment index, which is important for revealing the changes in vegetation coverage on the Tibetan Plateau and globally [31,32]. By calculating how plants absorb and reflect light, these indices offer a numerical evaluation of the development and health of the vegetation. Researchers can see dynamic changes in vegetation coverage through the use of NDVI, which allows them to monitor and analyze changes in vegetation coverage over the course of the study area [33,34]. Currently, China is focusing on large-scale areas such as the Huanghuaihai Basin [35], the Loess Plateau [36], and the Yangtze River Basin [37] in terms of NDVI research. However, at smaller watershed scales, less research has been conducted on the eastern boundary, and more research has concentrated on the Sanjiangyuan and Qiangtang regions, particularly on the Tibetan Plateau [38,39]. Consequently, in order to uncover the pattern of change and underlying causes more thoroughly, it is imperative to intensify the study of the vegetation cover on the eastern edge of the Tibetan Plateau.

The Minjiang River Basin is a crucial region on the eastern side of the Tibetan Plateau, with significant ecological and water resource protection implications [36]. The water volume of the basin is gradually decreasing due to environmental changes, which makes water resources scarce and the surrounding ecosystem deteriorated. As a result, there is considerable uncertainty regarding the ecological security of the basin. Secondly, irrational land use and over-exploitation have triggered soil erosion, grassland degradation, and biodiversity loss [40]. Along the eastern edge of the Tibetan Plateau, the spatial variability in vegetative coverage is influenced by numerous natural and anthropogenic factors [41,42]. As a crucial indicator for evaluating regional ecosystem quality and advancements in ecosystem structure and function, dynamic changes based on NDVI are employed. Understanding the vegetation changes in the watersheds along the eastern edge of the Tibetan

Plateau was the goal of this study, which also examined and assessed the various elements that contribute to vegetation changes. The regional and temporal variations in vegetation cover, as well as the trends in these changes, were examined using the MK test, Hurst index, and correlation analysis. Compounded and partial correlation analyses were also used to quantify the impact of climate conditions on the spatial variance of the NDVI. The present study hypothesized that the primary determinants of the vegetation growth patterns along the eastern border of the Tibetan Plateau are climate-related variables, particularly temperature and precipitation data. The creation of adaptive management techniques to preserve and improve ecosystem services and resilience in the area is theoretically supported by this theory, which also offers a scientific foundation for a greater knowledge of how vegetation responds to climate change.

2. Materials and Methods

2.1. Study Area

The Minjiang River Basin is located at latitude $28^{\circ}6' - 33^{\circ}23'$ north, longitude $99^{\circ}43' - 104^{\circ}21'$ east; the total length of the main stream is 711 km, with a watershed area of 135,900 km², an average drop of 4.84‰, and a total drop of 3560 m [36]. It belongs to the eastern edge of the Tibetan Plateau and is the bordering zone between the Tibetan Plateau and the Sichuan Basin. The upper part of the Minjiang River Basin, especially the subalpine zone, is one of the areas where forest resources are concentrated along the eastern margin of the Qinghai-Tibetan Plateau, and the vegetation types are mainly subtropical evergreen broad-leaved forests and coniferous forests, with a unique vertical zone climate and rich biodiversity. The Minjiang River's main stream splits into inner and outward streams near Dujiangyan. It then joins the Dadu and Qingyi rivers on Leshan's right bank before joining the Yangtze River at Yibin (Figure 1a). The Minjiang River Basin has a complex topography and a variety of landform types. Above Dujiangyan and Luding are the upper reaches, the main stream Dujiangyan and the tributary Dadu River from Luding to Leshan are the middle reaches, and Leshan to the mouth of the Yangtze River is the lower reaches. The relative height difference of the basin is large, and the upper reaches flow through areas with many high mountains and gorges, with great topographic relief and complex geological conditions, which is a high incidence area for natural disasters such as landslides and mudslides, while the middle and lower reaches flow through the plains, which is on the western edge of the Sichuan Plateau and has a simple geologic structure and a gentle stratigraphic layer (Figure 1b). The average annual temperature of the Minjiang River Basin is around 11 °C; the annual precipitation is roughly 500–700 mm, with large inter-annual variations, and forests, grasslands, and farmlands are the most important land-use types in the basin, of which forests are distributed in most of the basin, grasslands are distributed in the upstream areas of the basin, and farmlands are mainly distributed in the plains (Figure 1c).

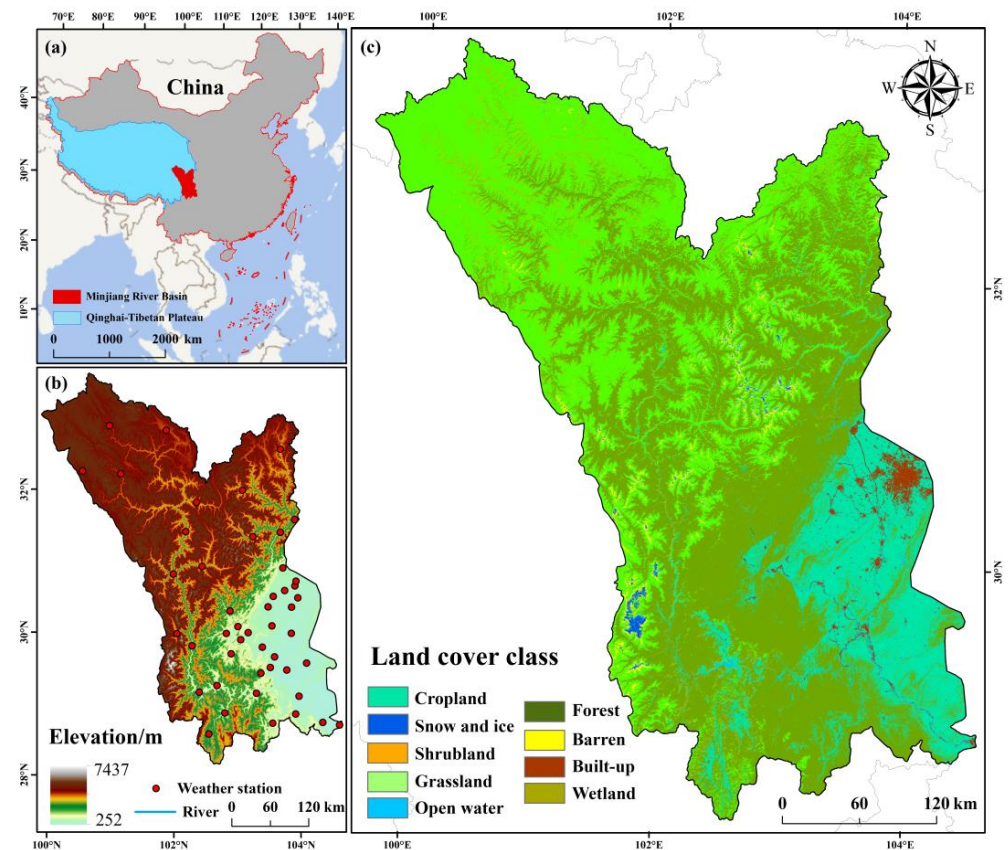


Figure 1. Study region on the eastern edge of the Tibetan Plateau; (a) its geographical position; (b) elevation; and (c) categories of land use.

2.2. Datasets

Mod13A1 data product (<https://lpdaac.usgs.gov/products/mod13a1v006/> (accessed on 20 August 2023)) provided the NDVI data, and the track numbers were h25v05, h25v06, h26v05, and h26v06 [43]. The NDVI data were computed pixel by pixel by the GEE platform, and a total of 23 time periods were obtained from 2000 to 2022. Meteorological data were obtained from the National Center for Meteorological Information (<http://data.cma.cn/> (accessed on 20 July 2023)), and the day-by-day meteorological data from 46 meteorological stations in the watershed and the surrounding areas for the period of 2000–2022 were selected [44]. The meteorological data were resampled to produce raster data with the same resolution as the NDVI data. DEM data were downloaded from the Geospatial Data Cloud (<http://www.gscloud.cn/> (accessed on 20 August 2023)) for the SRTM30m DEM data product and cropped to the extent of the study area. The China Land Cover Dataset (CLCD) (<https://doi.org/10.5281/zenodo.4417810> (accessed on 20 June 2023)) contains a 30-m land cover classification dataset. The CLCD uses a standardized classification system to define and differentiate different land use types, which facilitates comparisons between different studies and data consistency and is mostly used in ecological monitoring and climate change research.

2.3. Methods

The GEE platform was utilized to build an NDVI dataset of the Tibetan Plateau's eastern edge watershed. We quantitatively analyzed the climatic drivers of vegetation coverage in the basin using partial and complex correlation analysis, as well as the Hurst index, to predict future trends in the region. Theil-Sen median trend analysis and the Mann-Kendall test were utilized to investigate the spatial and temporal variations of regional NDVI. The coefficient of variation was employed to assess the volatility of vegetation

changes. The results offer a theoretical foundation for sustainable development in the Minjiang River Basin.

2.3.1. Trend Analysis

The difference in reflectance between the red and near-infrared light bands is analyzed using remote sensing techniques to calculate the NDVI index. The index has a range of values from -1 to 1 , where positive values typically denote the existence of vegetation cover and negative values are either negligible or absent [45]. In order to analyze trends, this study employed Theil-Sen slope analysis, a reliable nonparametric statistical technique [46,47]. Theil-Sen slope can show how the NDVI changed between 2000 and 2022. It is computed as follows:

$$Slope = Median\left(\frac{NDVI_j - NDVI_i}{j - i}\right), 2000 \leq i < j \leq 2022 \quad (1)$$

where NDVI shows an increasing trend with time when $Slope > 0$ and the opposite when $Slope < 0$. $NDVI_i$ and $NDVI_j$ are the values of NDVI in year i and year j .

With the benefit that the sample does not have to follow a certain distribution, the Mann-Kendall significance test is a nonparametric test that is often used in hydrology and meteorology [48]. In recent years, it has been used in the study of vegetation variability [49]. This is how the MK statistic S is computed:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(NDVI_j - NDVI_i) \quad (2)$$

$$\text{sgn}(NDVI_j - NDVI_i) = \begin{cases} 1, NDVI_j - NDVI_i > 0 \\ 0, NDVI_j - NDVI_i = 0 \\ -1, NDVI_j - NDVI_i < 0 \end{cases} \quad (3)$$

S exhibits variation and a normal distribution:

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \quad (4)$$

S is standardized as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, S < 0 \end{cases} \quad (5)$$

Z is a statistic in the range of open paren minus infinity, plus infinity, and $(-\infty, +\infty)$ that has been normalized by MK. We chose $\alpha = 0.05$, which indicates the significance of the calculated NDVI trend for the watershed from 2000–2022 at the 0.05 confidence level.

2.3.2. Coefficient of Variation

A statistical measure used to characterize the level of variability in time series data is the coefficient of variation [50]. Among other things, lower values of CV indicate lower volatility of vegetation change, while the opposite is true for higher values of CV.

$$CV_{NDVI} = \frac{\sigma_{NDVI}}{NDVI_m} \quad (6)$$

where $NDVI_m$ is the average NDVI value from 2000 to 2022, CV_{NDVI} is the coefficient of variation of NDVI data and σ_{NDVI} is the standard deviation of NDVI values.

2.3.3. Hurst Index

Based on the range of adjustment (R/S) analysis, the Hurst index is a useful tool for predicting the future trend of a time series [51]. It can also be used to distinguish

the sustainability of the time series data and quantitatively characterize the long-term dependence of the time series [52].

Calculate the average series of the time series:

$$NDVI_m = \frac{1}{m} \sum_{i=1}^m NDVI_i, m = 1, 2, \dots, n \quad (7)$$

Cumulative deviation:

$$X(t) = \sum_{i=1}^m (NDVI_i - NDVI_m), 1 \leq t \leq m \quad (8)$$

Range:

$$R(m) = \max_{1 \leq t \leq \tau} X(t) - \min_{1 \leq t \leq \tau} X(t), m = 1, 2, \dots, n \quad (9)$$

Standard deviation:

$$S(m) = \sqrt{\frac{1}{m} \sum_{i=1}^m (NDVI_i - NDVI_m)^2}, m = 1, 2, \dots, n \quad (10)$$

An arbitrary sequence devoid of sustainability is shown by a $H = 0.5$ NDVI. An unknown future trend in the NDVI is indicated when $0 < H < 0.5$. A sustainable NDVI is seen for $0.5 < H < 1$.

2.3.4. NDVI Driving Force Analysis

When examining the factors that influence vegetation cover, one of the most common analytical techniques is correlation analysis. In this work, we examined the degrees of association between vegetation indices and climate variables in the watersheds around the eastern margin of the Tibetan Plateau using partial correlation analysis. The degree to which climatic factors influence changes in vegetation can be measured using the partial correlation coefficient (PCC), and the significance of the results was examined using the t -test. Compound correlation analysis was used to investigate the combined effects of temperature and precipitation on NDVI. By measuring the complex correlation coefficient (CCC), the association between the NDVI and temperature and precipitation was assessed, and the F-test was used to determine the significance [53].

Regionalization and summarization of the spatial distribution of climate drivers of vegetation change in the watershed were conducted using the findings of the PCC and CCC significance tests in conjunction with t -tests and F-tests. We eliminated pixels that were significant according to the F-test for climate-driven regionalization and presumed that other pixel regions were impacted by non-climatic causes in order to guarantee spatial non-repetition and regional continuity for each categorization. In addition, based on the results of t -tests between NDVI and each climate parameter, we classified climate drivers into three groups. Studies on the factors that influence vegetation coverage have made extensive use of this split [54]. The basis of the classification is shown in Table 1.

Table 1. Guidelines for partitioning the drivers of NDVI change.

Driving Factors of NDVI Change	Driving Partitioning Criteria		
	R_{NDVI-P}	R_{NDVI-T}	$R_{NDVI-T-P}$
Driven by precipitation	$ t > t_{0.05}$		$F > F_{0.05}$
Driven by temperature		$ t > t_{0.05}$	$F > F_{0.05}$
Driven by temperature and precipitation	$ t < t_{0.05}$	$ t < t_{0.05}$	$F < F_{0.05}$
Driven by non-climate factors			$F < F_{0.05}$

3. Results

3.1. Features of the NDVI in Terms of Space and Time

3.1.1. Characteristics of the Spatial Distribution of Vegetation Coverage

Using the NDVI data downloaded from the GEE platform, we calculated the average values of NDVI in different seasons for 23 years and showed its spatial distribution (Figure 2). In comparison to other seasons, the eastern margin of the Tibetan Plateau watershed displayed the highest NDVI coverage in the summer, the lowest vegetation coverage in the winter, and the lowest vegetation coverage in the fall. Analyzed from the perspective of spatial distribution, NDVI was higher in the central and southwestern part of the basin during the full growing season (March–October), generally higher than that in the northwestern part of the basin and the central mountainous area, with an overall NDVI in the range of 0.6–0.8, and the higher elevations of the middle and upper reaches of the basin in the summer showed very high levels of vegetation cover. With an overall NDVI of 0.2–0.4, the western portion of the Sichuan Basin, which is impacted by the Tibetan Plateau, had an average level of plant cover, whereas the southwest portion of the watershed had the lowest amount of vegetation coverage, with an NDVI of only 0–0.2.

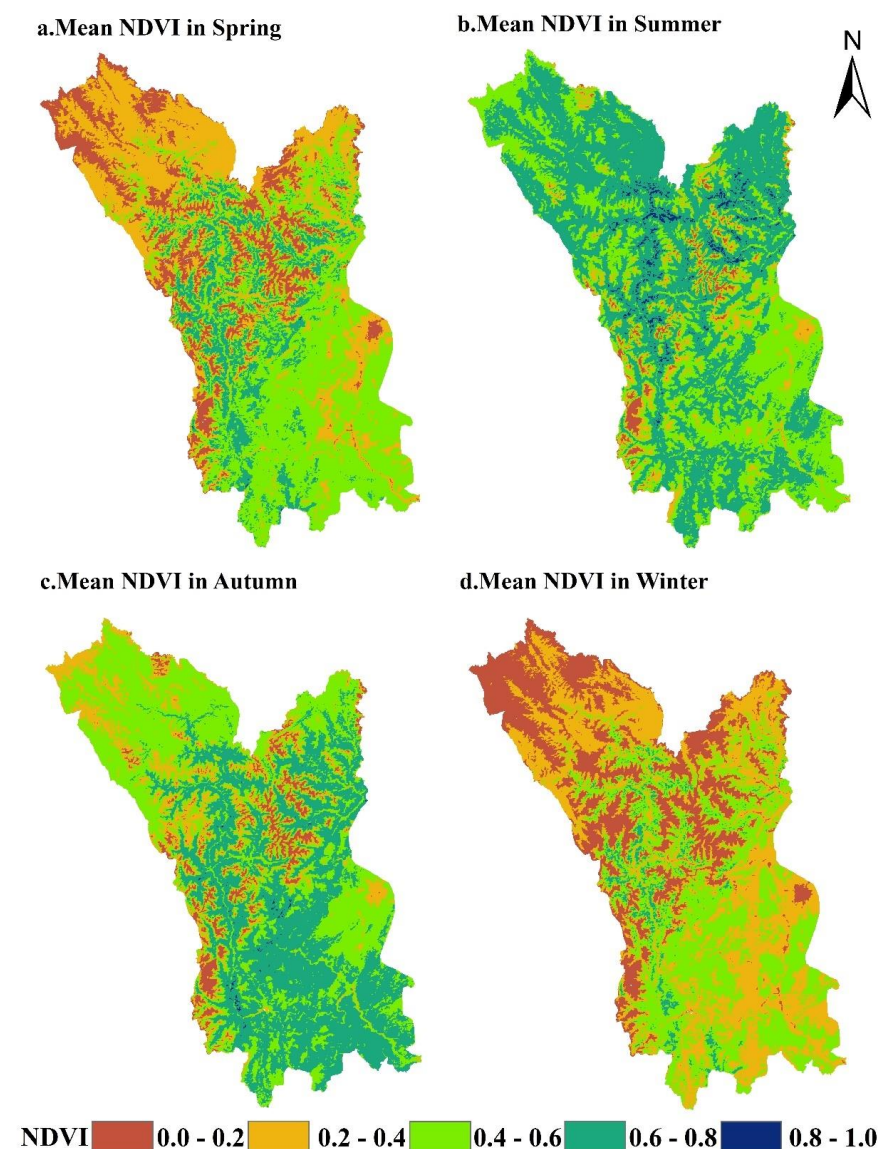


Figure 2. Spatial distribution of mean NDVI in watersheds along the eastern edge of the Tibetan Plateau from 2000 to 2022.

3.1.2. Characteristics of Temporal Changes in the Extent of Vegetation Coverage

We utilized the multi-year median values to reflect the overall changes in the vegetation cover index from 2000 to 2022 in order to explore the geographical and temporal aspects of NDVI in the water-sheds along the eastern margin of the Tibetan Plateau (Figure 3a). The results show that the multi-year distribution of NDVI values is characterized by a range from 0.32 to 0.61. The line graph illustrates the inter-annual variation of the watershed median over the 23 years, which fluctuated between 0.45 and 0.52. The lowest value was in 2001, while the highest value was in 2016. We counted the number of pixels (Figure 3b), which showed that the number of pixels with NDVI values between 0.4 and 0.5 decreased over time. From 2012 to 2016, the percentage of pixels falling between 0.5 and 0.85 made up over 47% of all pixels. The percentage of pixels above 0.5 also increased, peaking at 56% in 2016.

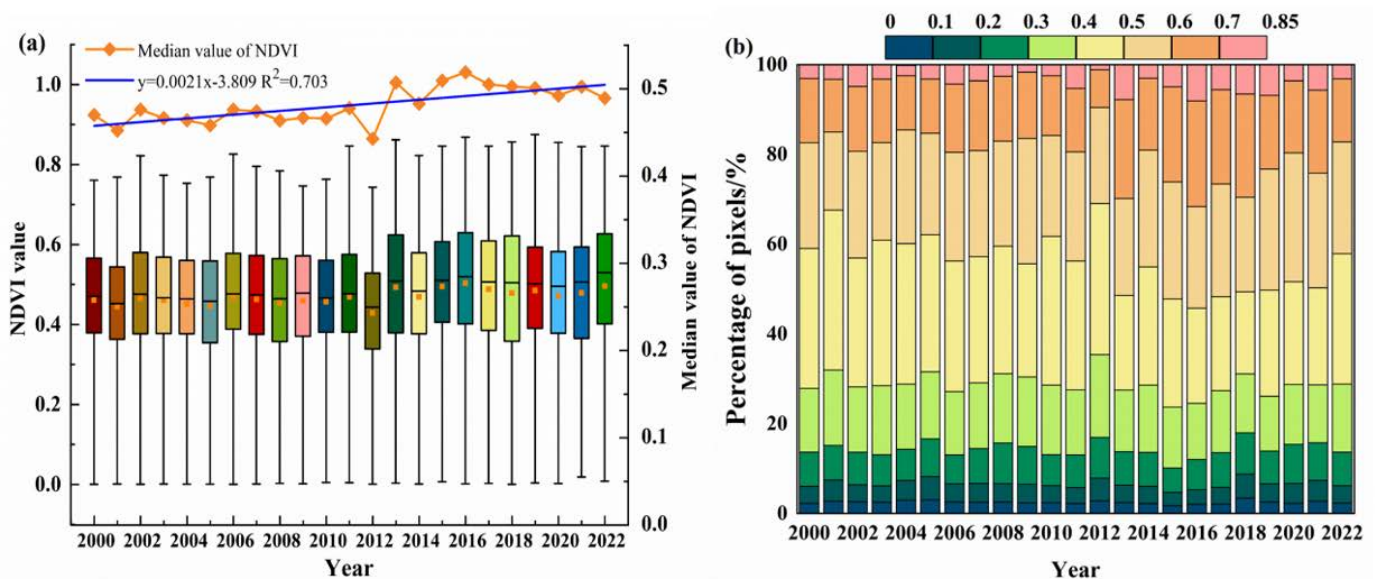


Figure 3. 2000–2022 interannual trends in NDVI in the watersheds along the eastern margin of the Tibetan Plateau, including median NDVI (a) and interannual changes in the coverage of NDVI elements (b).

3.1.3. Trend Analysis of Changes in Vegetation Coverage

Combining the pixel-by-pixel Theil-Sen slope analysis (Figure 4a) and the MK significance test (Figure 4b) in the watersheds along the eastern edge of the Tibetan Plateau, we obtained the trend data of NDVI changes at the image scale and categorized the results into five types of changes (Table 2). The areas with increased vegetation cover accounted for 67.07% of the total area covered by vegetation, the areas with stable and unchanged vegetation cover-age accounted for 17.82%, and the areas with degraded vegetation coverage accounted for just 15.11%, according to the stratified results of the Theil-Sen trend analysis and MK test superimposed.

Table 2. 2000–2022 NDVI Trend Classification.

S_{NDVI}	Z	NDVI Change Trend	Area Percentage/%
≥ 0.0005	$ Z > 1.96$	Significant improvement	30.93%
≥ 0.0005	$-1.96 \leq Z \leq 1.96$	Slight improvement	36.14%
$-0.0005-0.0005$	$-1.96 \leq Z \leq 1.96$	Stable and unchanging	17.82%
≤ -0.0005	$-1.96 \leq Z \leq 1.96$	Slight degradation	12.73%
≤ -0.0005	$ Z < -1.96$	Significant degradation	2.38%

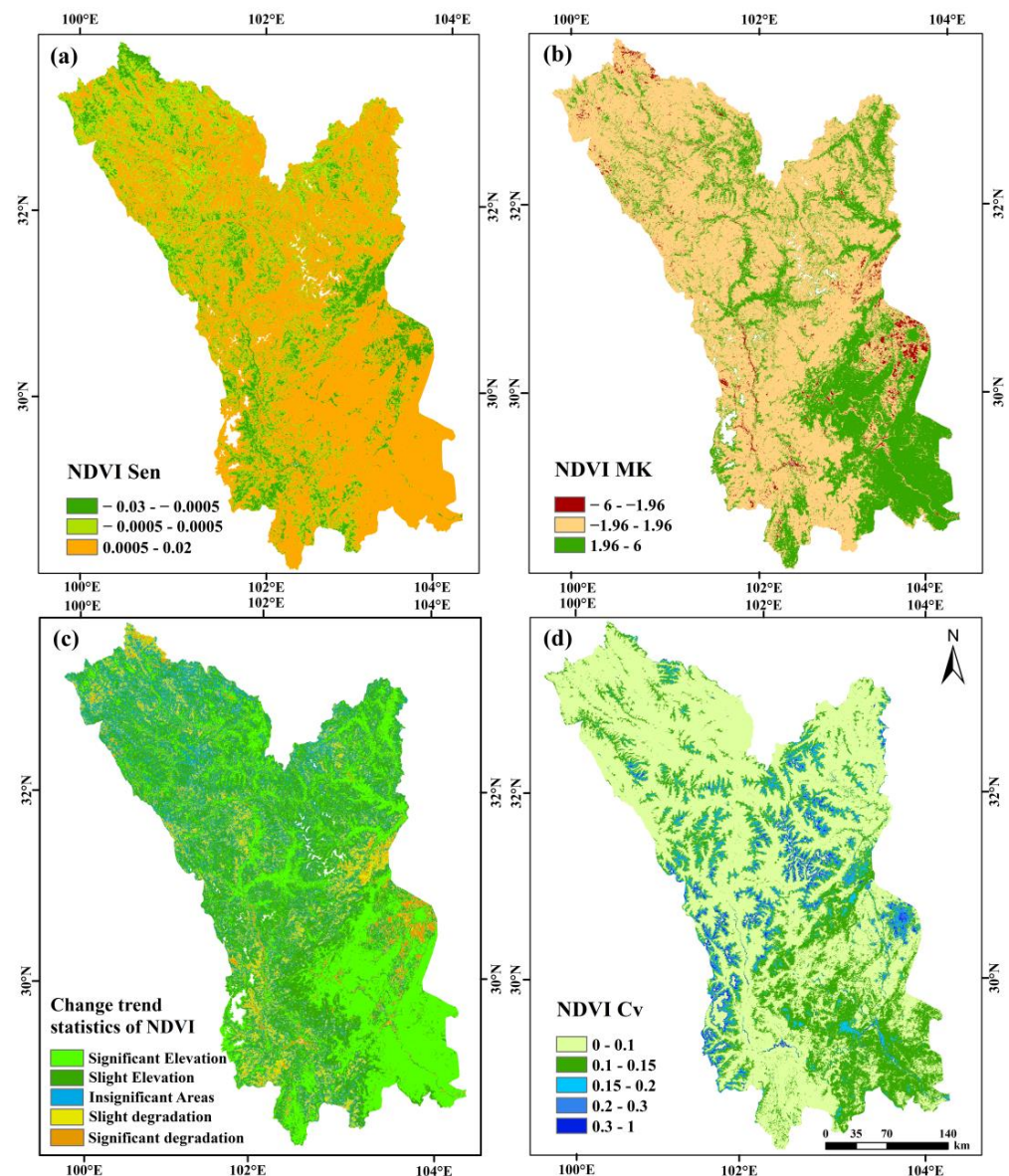


Figure 4. Theil-Sen slope analysis (a), MK trend test (b), inter-annual trend of NDVI (c), and coefficient of variation of NDVI (d) are characteristics of the spatial variation of NDVI at the eastern fringe of the Tibetan plateau from 2000 to 2022.

The spatial distribution of NDVI trends in the watershed showed obvious heterogeneity (Figure 4c). The portions of the basin with enhanced surface vegetation are significantly greater than those with degraded vegetation, it is important to note. To be more precise, the places with minor improvements were mostly found in the northwest, southwest, and certain sections of the middle portion of the basin, whilst the areas with significant improvements were primarily found in the eastern Sichuan plain and lower portions of the basin. On the contrary, stable and unchanged areas showed a scattered distribution in the basin, while slightly degraded and severely degraded areas were mainly located in areas with high urbanization as well as rapid elevation increase. In response to the results of the NDVI variability calculations for each image element of the watershed for 23 years and the actual situation, we classified the variability into five classes (Figure 4d). The findings demonstrated that the watershed's mean NDVI coefficient of variation was 0.092, suggesting that its plant growth state was comparatively steady (<0.15). The percentage of low fluctuation (0–0.1) reached 66.37%. Of these, the plains in the lower portion of the watershed accounted for the majority (24.75%), with the lowest fluctuation change (0.1–0.15). Higher fluctuation changes (0.15–0.2) and high fluctuation changes (>0.2) accounted

for only 8.88% of the whole watershed and were concentrated in Chengdu City and some areas in the central part of the watershed, which indicated that the growth of vegetation was more fragile compared with other areas.

3.1.4. Future Trends in Vegetation Coverage

The mean value of the Hurst index for NDVI in the eastern margin of the Tibetan Plateau is 0.42 (Figure 5a). The area that was less than 0.5 made up 78.57% of the total area, while the area that was higher than 0.5 made up 21.43%. According to this finding, its vegetation has a weakly positive NDVI.

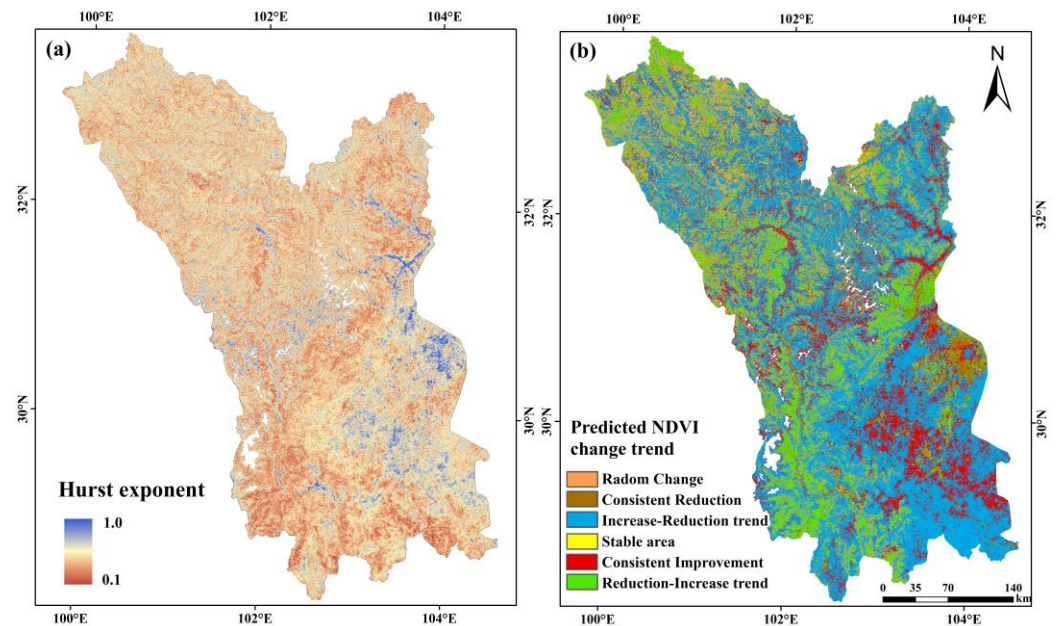


Figure 5. Hurst index spatial distribution and distribution of future trends in vegetation cover: (a) Hurst index spatial distribution and (b) future trends in NDVI.

In order to ascertain the direction and duration of the vegetation change, we merged the Hurst index with the NDVI trend data to derive the coupling information between the trend and persistence (Figure 5b). According to the classification of the coupling results (Table 3), we found that the area from degradation to improvement was 11.68%. The southern regions of Ya'an City, the eastern portion of Ganzi Prefecture, and the southern counties of Aba Prefecture were the primary centers of this trend. The Chengdu area accounted for the majority of the trend's 15.06% area of persistent improvement. In contrast, the area that remained unchanged accounted for a relatively small proportion of 2.98%. In addition, the percentage of area from improving to degrading reached 52%, which was widely distributed in the whole basin. The amount of 3.37% of the region was still degrading, with the majority of that area being in and around Chengdu City and the southern portion of Aba Prefecture. Furthermore, 14.82% of the area had an unknown future change tendency, which was primarily found in the intersection of the two distribution areas from improvement to degradation and degradation to improvement. When considered together, the region ranging from improving to degrading has the highest share, suggesting that future plant cover deterioration may be a possibility and that the watershed's natural environment should be better protected.

Table 3. Classification table for the persistence of NDVI changes.

S_{NDVI}	Hurst Index	Persistence of NDVI Changes	Area Ratio/%
≤ -0.0005	0~0.5	From degradation to improvement	11.68%
≥ 0.0005	0.5~1	Continuous improvement	15.06%
$-0.0005 \sim 0.0005$	0.5~1	Persistent	2.98%
≥ 0.0005	0~0.5	From improvement to degradation	52%
≤ -0.0005	0.5~1	Continuous degradation	3.37%
$-0.0005 \sim 0.0005$	0~0.5	Random variation	14.82%

3.2. Meteorological Drivers of Vegetation Coverage

3.2.1. Characteristics of Spatial and Temporal Variability of Meteorological Factors

We selected the mean annual air temperature and mean annual precipitation as the primary research objects to assess their effects on the NDVI of the corresponding years during the study of the spatial and temporal variations of climate factors in the Minjiang River Basin at the eastern edge of the Tibetan Plateau during the period of 2000–2022. In the meantime, we represented the geographical distribution features of the basin's climate elements using the mean temperature and precipitation. As shown in Figure 6a,b, the temperature and precipitation in the basin show a fluctuating upward trend, with the annual mean temperature increasing by about 0.026 °C/a, while the multi-year mean precipitation increases by 15.7 mm/a. This indicates that the Minjiang River basin as a whole is moving towards a warmer and wetter direction. We conducted a geographical interpolation study, the results of which are displayed in Figure 6c,d, in order to clearly illustrate the spatial distribution characteristics of temperature and precipitation. With a moderate increasing tendency from north to south, the temperature ranges from 1.31 °C to 18.51 °C. The precipitation ranges from 473.91 mm to 1671.03 mm and also shows a gradual increasing trend from north to south.

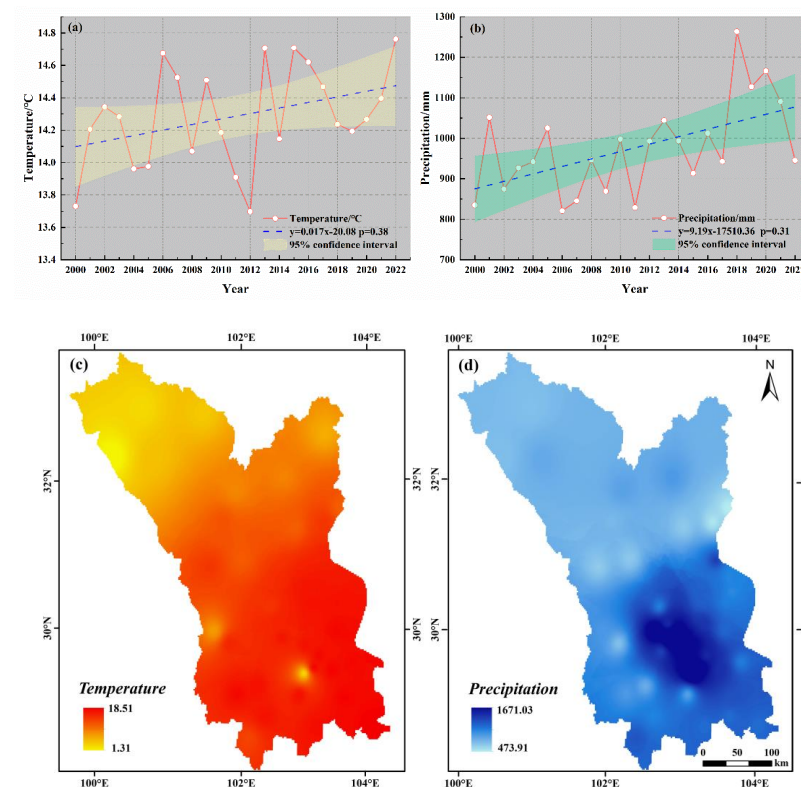


Figure 6. Temperature and precipitation trends and their spatial distribution in the basin along the eastern margin of the Tibetan Plateau, 2000–2022: trend of average temperature (a), trend of total precipitation (b), trend of precipitation distribution (c), and trend of temperature (d).

3.2.2. Seasonal Correlation Analysis of Climate Factors with NDVI

In the Minjiang River Basin, on the eastern point of the Tibetan Plateau, the findings of a correlation study between the quarterly NDVI and air temperature and precipitation are displayed in Figure 7. In different seasons, the correlation coefficients between quarterly NDVI and precipitation were in the order of autumn (0.37) > summer (0.31) > winter (0.24) > spring (0.23); while the correlation coefficients between seasonal NDVI and temperature were in the order of spring (0.47) > summer (0.43) > autumn (0.13) > winter (0.11). Summer and autumn precipitation in the watershed had a greater significant impact on NDVI, as seen by the higher correlation coefficients between NDVI and precipitation in these seasons compared to the other two. With the increase of precipitation, the NDVI values increased accordingly. The suitable temperature was shown to be crucial for the growth of vegetation, as evidenced by the much greater correlation coefficients between NDVI and temperature in the spring and summer compared to autumn and winter. The correlation coefficients of NDVI with air temperature and precipitation were lower in autumn and winter, and the correlation of precipitation was higher than that of air temperature, indicating that in these two seasons, the changes of NDVI were also affected by the growth cycle of the vegetation, light time and evaporation. The summertime showed the largest link between NDVI and temperature and precipitation, suggesting that these two factors were crucial for the growth of plants during this time of year. While in winter, the correlation of precipitation and temperature to NDVI was lower, indicating that the correlation between NDVI and precipitation and temperature was weak in this season.

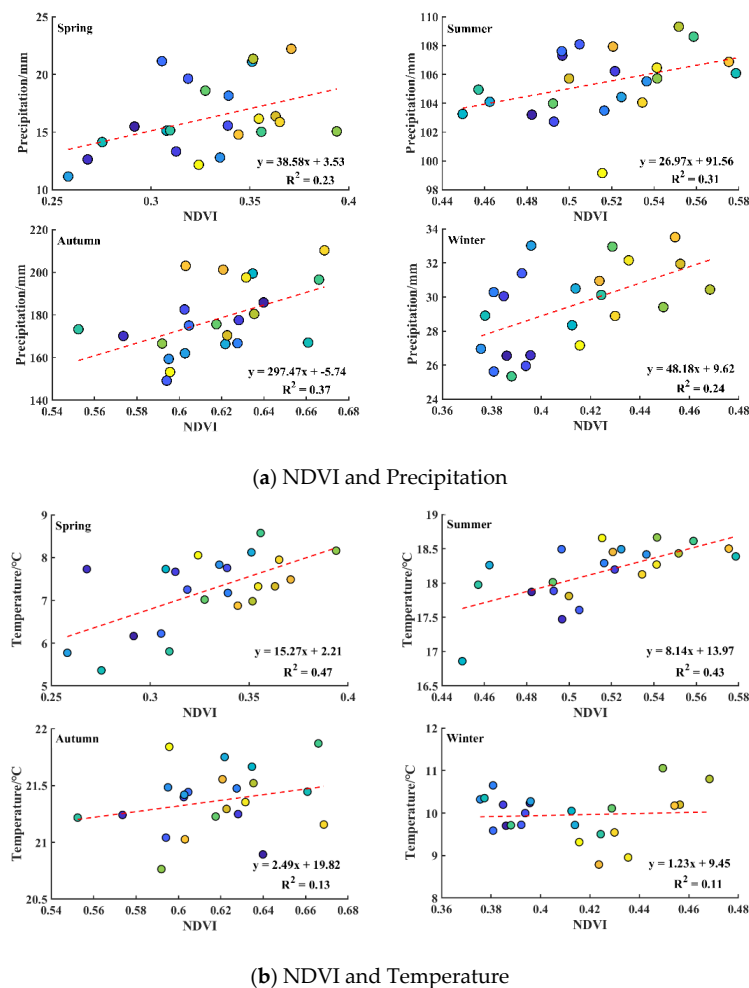


Figure 7. Correlation of seasonal NDVI with precipitation (a) and air temperature (b) in the watershed along the eastern margin of the Tibetan Plateau from 2000 to 2022.

3.2.3. Partial Correlation Analysis between NDVI and Climatic Factors

By using classification, the regional distribution of the partial correlation coefficients between the NDVI and climate parameters in the watersheds was examined. With a mean value of 0.12 (Figure 8a), the partial correlation coefficients between the NDVI and precipitation varied between -1 and 1 , indicating a generally positive correlation. Positive correlation pixel values (56.52%) were more common than negative correlation pixel values (43.48%), while “significant positive correlation” and “significant negative correlation” pixels accounted for 47.69% and 41.93%, respectively (Figure 8b). The spatial distribution of NDVI and precipitation is obviously spatially heterogeneous. The lower and upper portions of the basins were where the positive association was most prevalent. Significant positive correlations were mainly distributed in the central and downstream parts of the basin. While the negative correlations were dispersed more discretely, the significant negative correlations were primarily centered in the southwestern portion of the basin and much of the central portion of the upper basin.

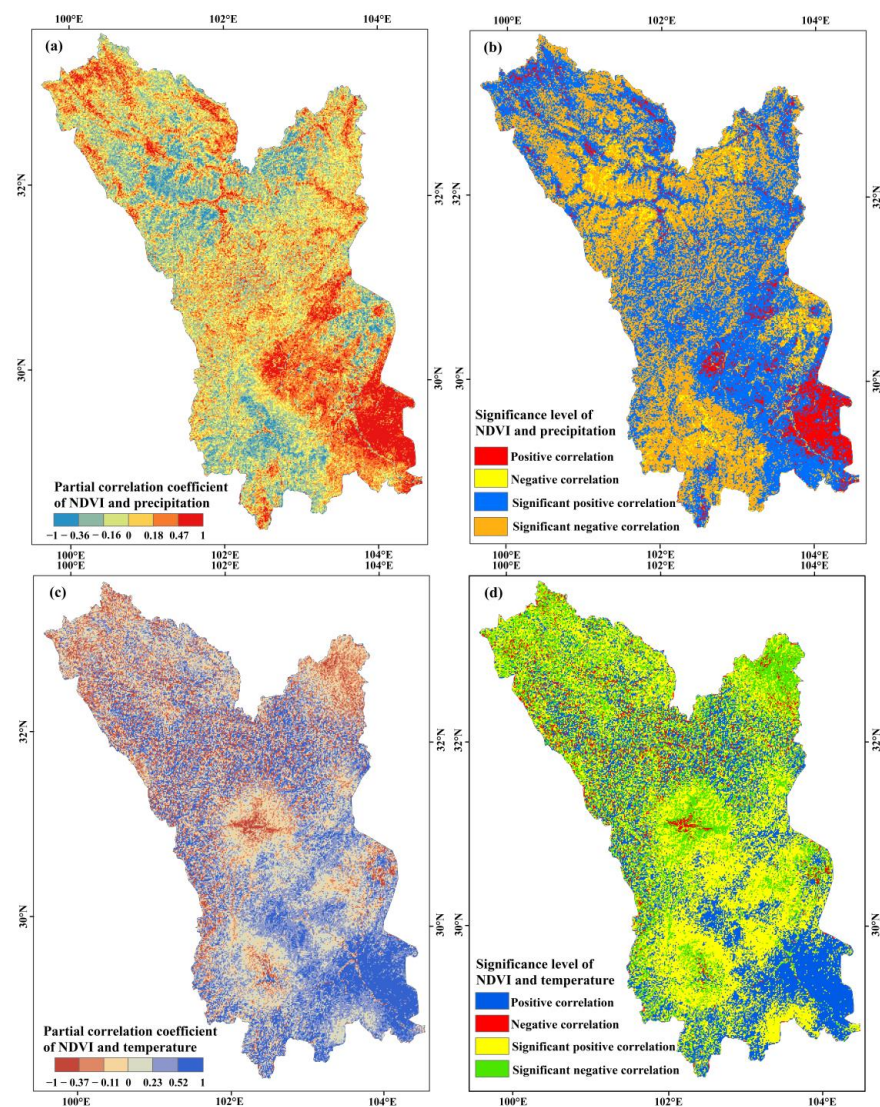


Figure 8. The partial correlation coefficient of NDVI with precipitation (a), the significance of the coefficient of partial correlation between NDVI and precipitation (b), the partial correlation coefficient between NDVI and precipitation (c), and the significance of the coefficient of partial correlation between NDVI and precipitation (d) are the spatial distribution of the coefficient of partial correlation and the level of significance of NDVI with climatic factors.

An analysis was conducted on the partial correlation coefficients between temperature and NDVI, which had a mean value of 0.2 and varied from -1 to 1 . The proportions of positive and negative correlations differed greatly, with 73.04% of positively correlated areas and 26.96% of negatively correlated areas, indicating that the temperature was positively correlated with NDVI as a whole. The spatial distribution of temperature bias correlation showed obvious heterogeneity, which was more significant compared with the correlation of precipitation (Figure 8d). Both the significant and positive correlation areas were mostly found in the central region of the basin, with the positive correlation area being mostly located in the southeast of the lower basin. Significant negative correlation areas are primarily found in the middle and northeastern regions of the basin, whereas negative correlation areas are more widely distributed.

3.2.4. Analysis of Watershed NDVI Drivers

The spatial distribution of the complex correlation coefficients between NDVI and climatic factors in the watersheds along the eastern edge of the Tibetan Plateau is shown in Figure 9a, which ranges from 0 to 1, with a mean value of 0.32. Through the test of significance at 0.05, it was found that the complex correlation between NDVI and climatic factors in the basin was significant (Figure 9b), and the complex correlation was significant in most areas of the basin. In contrast, the areas with weak complex correlations were mainly located in the southeast and northwest, accounting for 19.4% of the total watershed area.

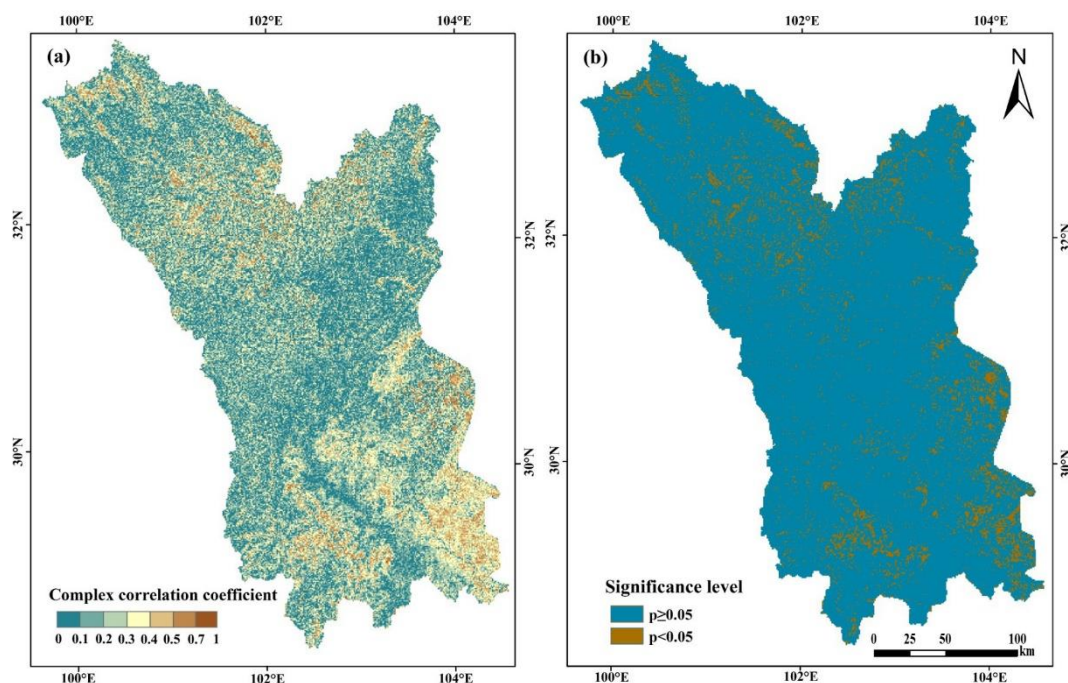


Figure 9. The NDVI driver analysis consists of two parts: (a) the complex correlation coefficients' spatial distribution between NDVI and climatic parameters and (b) the complex correlation coefficients' significant level.

Based on the identified driver criteria, the driver analysis of climate factors in the watershed (Figure 10) revealed a strong spatial heterogeneity in the driver partitioning of climate factors. In the study area, NDVI changes were mainly influenced by temperature-driven (I), precipitation-driven (II), precipitation and temperature-co-driven (III), and other factor-driven types (IV). At the watershed scale, only 19.4% of the vegetation was driven by climatic factors, while 80.6% of the area was driven by non-climatic factors. Precipitation-driven areas (II) accounted for 3.1% of the watershed area, meaning that precipitation-driven is not significantly expressed in the watershed. This type is mainly distributed

in the higher-elevation plateau zone in the upper part of the watershed, indicating that precipitation in the plateau area is one of the main drivers of NDVI changes. This is due to the fact that mountainous areas have a wide variety of vegetation types, more dense vegetation coverage, and a more sensitive response to precipitation. The area share of the precipitation and temperature co-driven type is 7.2%, which is mainly distributed in the plains in the lower part of the basin. The temperature-driven area accounted for 9.1% of the total area, which was widely distributed, especially in the upper basin, Chengdu City, and the southwest part of the basin.

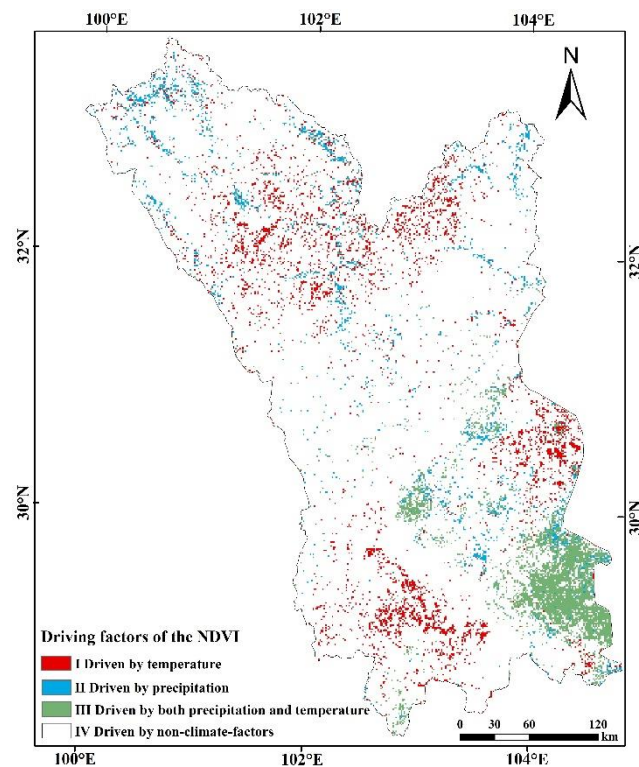


Figure 10. Driver partitioning of NDVI in watersheds along the eastern margin of the Tibetan Plateau, 2000–2022.

4. Discussion

4.1. Features of the Temporal and Spatial Dynamics of the Vegetation Coverage

Utilizing NDVI information spanning from 2000 to 2022, we examined the geographical and temporal variations in NDVI within the Minjiang River basin, situated near the eastern edge of the Tibetan Plateau. During the growth season, the central and southern regions of the basin had higher levels of vegetation coverage, as indicated by the spatial distribution of NDVI (Figure 2a). This was mainly due to favorable temperature and precipitation and relatively low elevation, as in Chengdu and Leshan, where the vegetation types consisted mainly of broadleaf forests, shrubs, and crops. It was discovered that the northwest has little vegetation cover and is ecologically sensitive. Large diurnal temperature variations, high altitudes, and limited precipitation are some of the environmental factors that limit the growth of large-scale vegetation in these places [55]. The average NDVI values of different years and vegetation types are shown in Figure 11, in which the average NDVI values of various vegetation types reached the highest in 2015. Forest had the highest mean NDVI value of 0.59, followed by cropland with 0.54, and the smallest was grassland with 0.38. From 2015 to 2022, there was a decreasing trend in the NDVI values of forests, shrubs, grassland, and cropland. This could be related to the regional drought caused by the decrease in precipitation and increase in temperature in the watershed in recent years.

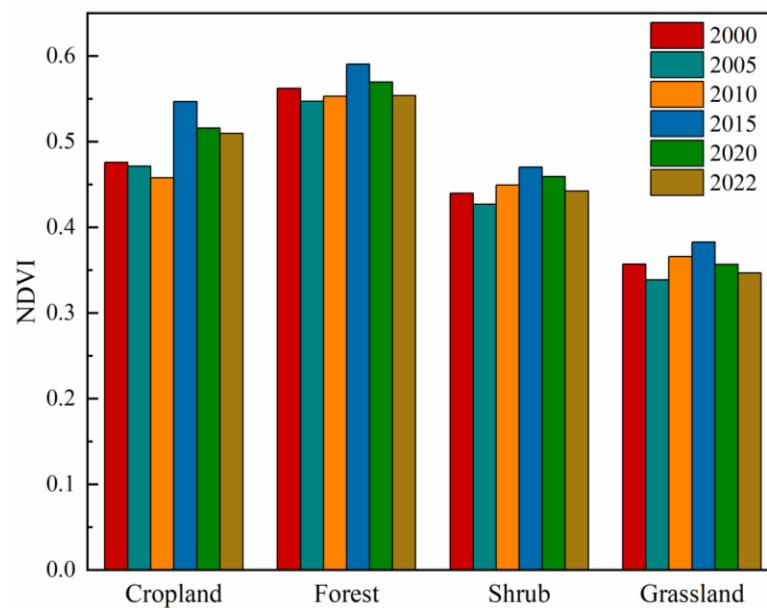


Figure 11. The mean NDVI values of different vegetation types.

As a whole, the NDVI of the watershed increased steadily (Figure 3a), and a bigger increase was observed in the percentage of high-value locations with an NDVI of more than 0.5. Since 2001, the environmental quality of the watershed has significantly improved due to the implementation of several forestry and ecological projects such as ecological protection forests, farmland reforestation, and grassland projects (Figure 3b) [56]. In the classification of NDVI trends, the highest proportion of vegetation coverage was found in “significant improvement” and “obvious improvement” (Figure 4c). Vegetation coverage categorized from “continuous improvement” and “degradation to improvement” also accounted for a certain proportion of the future trend (Figure 5b), which is consistent with the results of a study [41]. However, the future trend showed a higher proportion of vegetation coverage in the “increasing to decreasing” category, indicating the risk of decreasing NDVI in the watershed. The rapid expansion of construction land in the region, along with the effects of climate change, has exacerbated changes in land use types. This is a result of the development of urbanization and the ongoing population growth in the Chengdu Plain. The decline in vegetation coverage and the decrease in vegetation stability have serious negative impacts on the future trend of NDVI [49,57]. In addition, some areas show a trend of “continuous degradation” and “stochastic change,” where climate and human activities have caused significant negative impacts on the vegetation coverage in these areas. Because of their high altitude, the higher parts of the watershed experience severe seasonal changes and low temperatures, which are adverse to the growth of vegetation and limit the cycle of growth and biomass accumulation of vegetation [58]. Therefore, government departments should strengthen vegetation management in the upper watershed, develop measures to cope with human activities and climate change and enhance financial support for ecological conservation to promote ecological restoration [59].

4.2. Factors Influencing the Temporal and Geographical Development of Vegetation Cover

Climate change has been found to be a major factor in fostering vegetation growth in the watershed, according to a study of the NDVI drivers. This conclusion is in line with earlier research conducted on the Tibetan plateau by Sun et al. [60]. Climate warming extends the growing season of vegetation and accelerates the rate of photosynthesis in plants, which in turn affects the climatic events of vegetation [61]. In addition, climate warming also causes an increase in precipitation, which increases soil moisture and also provides more water and nutrients for plants, which is favorable for plant growth [62]. Higher altitudes with more undulating terrain usually have lower temperatures, not high

enough in the summer and even colder in the winter. This cold environment makes the growth of plants slower and the growing season relatively shorter [63]. In addition, the relatively low precipitation at high altitudes, coupled with the high rate of water evaporation from the terrain, results in increased soil aridity and inadequate water supply, limiting vegetation growth [64].

Despite the dominance of non-climatic factors in the influence of vegetation cover in watersheds, the dominant factors that lead to changes in NDVI vary in different regions. Research has indicated that climate and human activity are the main determinants of vegetation covering [65]. Through the selected six periods of land use (Figure 12), we can conclude that over the past 23 years, the area of forests, shrubs, water bodies, unutilized land, and urban built-up land has increased to 2288.11 km², 801.92 km², 208.17 km², 719.34 km², and 1062.77 km² as compared to the year 2000. The increase in the area of unutilized land and water bodies was mainly by the conversion of grassland and cropland, while urban construction land was converted from cropland. Cultivated land and grassland decreased by 984.72 km² and 147.29 km², which negatively affected the NDVI in the declining area. Meteorological variables are the primary source of changes in plant cover in locations where human activity is less prevalent [66]. Significant regional variation is seen in the distribution of climatic variables in the watersheds along the eastern margin of the Tibetan Plateau with respect to the driving spatial distribution. Since these topographic parameters affected heat and water fluxes, which in turn affected climatic features and land cover types, they had a significant impact on the spatial distribution of vegetation. The majority of the precipitation-driven regions were found at high altitudes with little precipitation [67]. Temperature-driven regions are mainly concentrated in areas with higher temperatures, such as the Chengdu Plain, where temperature changes affect other environmental factors such as humidity and precipitation, thus significantly influencing vegetation growth and development [68]. However, areas driven by a combination of precipitation and temperature are in the lower reaches of the watershed that are prone to drought events, resulting in a severe lack of moisture in the soil and the inability of plant roots to adequately absorb the water they need, thus directly affecting the extent of vegetation coverage [69]. Changes in climatic conditions enhance the impact of other factors on vegetation coverage in the research region, and vegetation development is determined by the interaction of natural and other causes. Plant development can be aided or hindered by other factors. Previous research has focused on the relationship between altitude soil moisture content and fertility [70], as well as the positive link between temperature precipitation and NDVI [71]. The interaction of these factors significantly improves the ability to explain the spatial variation of NDVI. Therefore, the government should comprehensively consider the cumulative effects of NDVI when formulating vegetation restoration policies. Finally, the selection of suitable ecological management methods for the watershed can provide the necessary guarantee for the healthy development of the watershed.

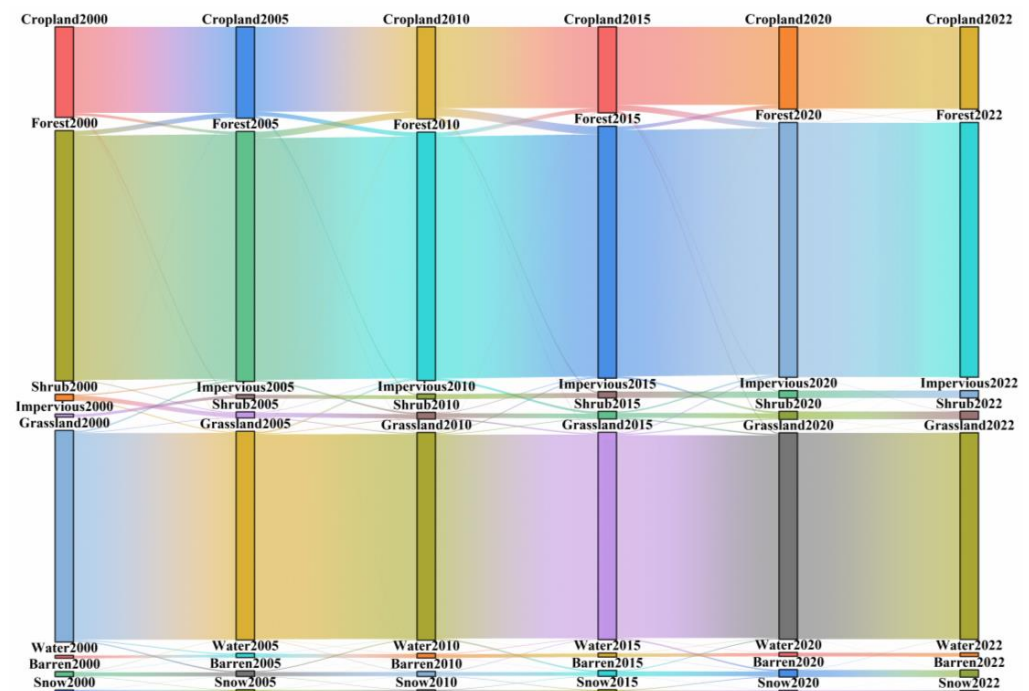


Figure 12. Mulberry patch of land use change from 2000 to 2022 in the Minjiang River Basin, on the eastern side of the Qinghai Tibet Plateau.

4.3. Shortcomings and Future Work

In order to forecast the sustainability of NDVI dynamics and its geographical distribution influenced by climatic conditions, the current study explores the spatial heterogeneity of NDVI in the watershed and thoroughly examines its changes. These results might offer a theoretical foundation for managing and conserving the vegetation in watersheds along the Tibetan Plateau's eastern edge. In contrast to previous studies, this study derives the response relationship between climatic factors and NDVI in the Eastern Marginal Basin by overlaying NDVI trend analysis and the Hurst Index and applying partial and complex correlation analyses to delineate the driving contribution regions. However, the study has some limitations, especially the Hurst index, which cannot accurately predict the duration of sustainability of vegetation dynamics. Therefore, future studies need to take a step toward determining the spatial and temporal extent of trends. In addition, regarding the trend of vegetation cover change, we only considered the linear trend, while there are also studies that show that there is a nonlinear trend of vegetation cover, so the nonlinear trend change of vegetation cover should be considered in the future [72]. In our study, we selected only temperature and precipitation as climate-driven parameters for vegetation cover. Although vegetation growth is important by climatic conditions, it is also influenced by topographic factors such as altitude and slope [73], as well as other natural factors such as soil factors, biological factors, and water resources [74]. Future studies should take into account the effects of other natural factors in this study as much as possible.

5. Conclusions

This study hypothesized that temperature and precipitation are the primary drivers of vegetation changes in the watershed in order to meet the goal of quantitative analysis of spatial and temporal changes in vegetation and its drivers in the study region. The characteristics of vegetation cover changes in the Minjiang River basin at the eastern edge of the Tibetan Plateau were examined using the coefficient of variation, Theil-Sen trend analysis, Mann-Kendall test, and Hurst exponential technique. Furthermore, partial correlation and complex correlation analysis were used to examine how the plant cover responded to genesis and climate.

(1) During the growing season of 2000–2022, the basin on the eastern edge of the Tibetan Plateau saw a steady increase in NDVI, with a multi-year mean of 0.47. In comparison to the tie value of the study area, which included 43.33% of the study area, the NDVI in the central and western mountainous areas was comparatively low during this era. Additionally, its NDVI coefficient of variation was 0.092, indicating that the vegetation state remained stable.

(2) The NDVI trend analysis in the watershed, when combined with MK and Theil-Sen, revealed that 67.07% of the watershed's total area exhibited a statistically significant upward trend in NDVI, while approximately 15.11% of the study area displayed a downward trend in NDVI, particularly in the watershed's southern and densely populated metropolitan areas. The study's rising trend was evident in the watershed overall NDVI.

(3) Through the Hurst index analysis, the future NDVI trend changes showed that 29.72% of the vegetation cover was sustainable, 55.37% of the vegetation cover showed a degradation trend, and 14.91% of the vegetation cover showed an unpredictable future trend. This indicates that there is a risk of a decline in NDVI in the watershed in the future.

(4) There is a general rising tendency in both temperature and precipitation, with a steady increase from the northwest to the southeast. Furthermore, there is a degree of association between NDVI and temperature as well. In spring and summer, temperature and NDVI have the strongest correlation, reaching 0.47 and 0.43, while the highest correlation between precipitation and NDVI is only 0.37 and 0.31. Temperature is more likely to affect NDVI variations on the eastern edge of the Tibetan Plateau.

(5) Non-climatic causes account for 80.6% of the vegetation cover in the central basin and most of the remaining portion, whereas climatic variables account for 19.4% of the vegetation cover. In the meantime, the northwest, southeast, and portions of the southwest are the regions of the basin that are more strongly influenced by temperature and precipitation. As a result, the majority of the basin is not affected by climate.

Author Contributions: Writing—original draft, S.L. and P.Z.; Writing—review and editing, S.L., Y.G., H.W., J.L. and T.A.; Project administration, P.Z. and H.W.; Funding acquisition, H.W. and J.L.; Conceptualization, H.W.; Methodology, S.L.; Software, S.L.; Formal analysis, S.L.; Data curation, S.L. and Y.G. After reading the published version of the manuscript, all writers have given their approval. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key R&D Program of China (2022YFC3002902).

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ding, M.; Zhang, Y.; Sun, X.; Liu, L.; Wang, Z.; Bai, W. Spatiotemporal variation in alpine grassland phenology in the Qinghai-Tibetan Plateau from 1999 to 2009. *Chin. Sci. Bull.* **2013**, *58*, 396–405. [\[CrossRef\]](#)
2. Gil, J.D.; Daioglou, V.; van Ittersum, M.; Reidsma, P.; Doelman, J.C.; van Middelaar, C.E.; van Vuuren, D.P. Reconciling global sustainability targets and local action for food production and climate change mitigation. *Glob. Environ. Chang.* **2019**, *59*, 101983. [\[CrossRef\]](#)
3. Jeong, S.J.; HO, C.H.; GIM, H.J.; Brown, M.E. Phenology shifts at start vs. end of growing season in temperate vegetation over the Northern Hemisphere for the period 1982–2008. *Glob. Chang. Biol.* **2011**, *17*, 2385–2399. [\[CrossRef\]](#)
4. Liu, S.; Wang, L.; Lin, J.; Wang, H.; Li, X.; Ao, T. Evaluation of Water-Energy-Food-Ecology System Development in Beijing-Tianjin-Hebei Region from a Symbiotic Perspective and Analysis of Influencing Factors. *Sustainability* **2023**, *15*, 5138. [\[CrossRef\]](#)
5. Chen, C.; Park, T.; Wang, X.; Piao, S.; Xu, B.; Chaturvedi, R.K.; Fuchs, R.; Brovkin, V.; Ciais, P.; Fensholt, R.; et al. China and India lead in greening of the world through land-use management. *Nat. Sustain.* **2019**, *2*, 122–129. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Chu, H.; Venevsky, S.; Wu, C.; Wang, M. NDVI-based vegetation dynamics and its response to climate changes at Amur-Heilongjiang River Basin from 1982 to 2015. *Sci. Total Environ.* **2019**, *650*, 2051–2062. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Du, J.; Shu, J.; Zhao, C.; Ahati, J.; Wang, L.; Xiang, B.; Fang, G.; Liu, W.; He, P. Comparison of GIMMS NDVI3g and GIMMS NDVIg for monitoring vegetation activity and its responses to climate changes in Xinjiang during 1982–2006. *Acta Ecol. Sin.* **2016**, *36*, 6738–6749.
8. Nemani, R.R.; Keeling, C.D.; Hashimoto, H.; Jolly, W.M.; Piper, S.C.; Tucker, C.J.; Myneni, R.B.; Running, S.W. Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science* **2003**, *300*, 1560–1563. [\[CrossRef\]](#) [\[PubMed\]](#)

9. Wu, D.; Wu, H.; Zhao, X.; Zhou, T.; Tang, B.; Zhao, W.; Jia, K. Evaluation of spatiotemporal variations of global fractional vegetation cover based on GIMMS NDVI data from 1982 to 2011. *Remote Sens.* **2014**, *6*, 4217–4239. [\[CrossRef\]](#)
10. Li, J.; Liu, H.; Li, C.; Li, L. Changes of green-up day of vegetation growing season based on GIMMS 3g NDVI in northern China in recent 30 years. *Sci. Geogr. Sin* **2017**, *37*, 620–629.
11. Pang, G.; Wang, X.; Yang, M. Using the NDVI to identify variations in, and responses of, vegetation to climate change on the Tibetan Plateau from 1982 to 2012. *Quat. Int.* **2017**, *444*, 87–96. [\[CrossRef\]](#)
12. Wang, T.; Yang, M.; Yan, S.; Geng, G.; Li, Q.; Wang, F. Temporal and Spatial Vegetation Index Variability and Response to Temperature and Precipitation in the Qinghai-Tibet Plateau Using GIMMS NDVI. *Pol. J. Environ. Stud.* **2020**, *29*, 4385–4395. [\[CrossRef\]](#)
13. Ziyu, S.; Junbang, W. The 30m-NDVI-based alpine grassland changes and climate impacts in the Three-River headwaters region on the Qinghai-Tibet Plateau from 1990 to 2018. *J. Resour. Ecol.* **2022**, *13*, 186–195. [\[CrossRef\]](#)
14. Alvarado, R.; Tillaguango, B.; Dagar, V.; Ahmad, M.; Işık, C.; Méndez, P.; Toledo, E. Ecological footprint, economic complexity and natural resources rents in Latin America: Empirical evidence using quantile regressions. *J. Clean. Prod.* **2021**, *318*, 128585. [\[CrossRef\]](#)
15. Rehman, A.; Ma, H.; Ozturk, I.; Murshed, M.; Dagar, V. The dynamic impacts of CO2 emissions from different sources on Pakistan's economic progress: A roadmap to sustainable development. *Environ. Dev. Sustain.* **2021**, *23*, 17857–17880. [\[CrossRef\]](#)
16. Enebish, B.; Dashkhuu, D.; Renchin, M.; Russell, M.; Singh, P. Impact of Climate on the NDVI of Northern Mongolia. *J. Indian Soc. Remote Sens.* **2020**, *48*, 333–340. [\[CrossRef\]](#)
17. Zhang, R.; Qi, J.; Leng, S.; Wang, Q. Long-term vegetation phenology changes and responses to pre-season temperature and precipitation in Northern China. *Remote Sens.* **2022**, *14*, 1396. [\[CrossRef\]](#)
18. Zhang, L.; Shen, M.; Yang, Z.; Wang, Y.; Chen, J. Spatial variations in the difference in elevational shifts between greenness and temperature isolines across the Tibetan Plateau grasslands under warming. *Sci. Total Environ.* **2024**, *906*, 167715. [\[CrossRef\]](#)
19. Chen, T.; Dai, J.; Chen, X.; Liang, C.; Shi, T.; Lyu, Y.; Zhao, F.; Wu, X.; Gao, M.; Huang, J.; et al. Agricultural land management extends the duration of the impacts of extreme climate events on vegetation in double-cropping systems in the Yangtze-Huai plain China. *Ecol. Indic.* **2024**, *158*, 111488. [\[CrossRef\]](#)
20. Lian, X.; Peñuelas, J.; Ryu, Y.; Piao, S.; Keenan, T.F.; Fang, J.; Yu, K.; Chen, A.; Zhang, Y.; Gentile, P. Diminishing carryover benefits of earlier spring vegetation growth. *Nat. Ecol. Evol.* **2024**, *8*, 218–228. [\[CrossRef\]](#)
21. Myers-Smith, I.H.; Kerby, J.T.; Phoenix, G.K.; Bjerke, J.W.; Epstein, H.E.; Assmann, J.J.; John, C.; Andreu-Hayles, L.; Angers-Blondin, S.; Beck, P.S.; et al. Complexity revealed in the greening of the Arctic. *Nat. Clim. Chang.* **2020**, *10*, 106–117. [\[CrossRef\]](#)
22. Jiang, H.; Xu, X.; Guan, M.; Wang, L.; Huang, Y.; Jiang, Y. Determining the contributions of climate change and human activities to vegetation dynamics in agro-pastoral transitional zone of northern China from 2000 to 2015. *Sci. Total Environ.* **2020**, *718*, 134871. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Zhang, H.; Li, L.; Zhao, X.; Chen, F.; Wei, J.; Feng, Z.; Hou, T.; Chen, Y.; Yue, W.; Shang, H.; et al. Changes in Vegetation NDVI and Its Response to Climate Change and Human Activities in the Ferghana Basin from 1982 to 2015. *Remote Sens.* **2024**, *16*, 1296. [\[CrossRef\]](#)
24. Tuoku, L.; Wu, Z.; Men, B. Impacts of climate factors and human activities on NDVI change in China. *Ecol. Inform.* **2024**, *81*, 102555. [\[CrossRef\]](#)
25. Niwa, H.; Kamada, M.; Morisada, S.; Ogawa, M. Assessing the impact of storm surge flooding on coastal pine forests using a vegetation index. *Landsc. Ecol. Eng.* **2023**, *19*, 151–159. [\[CrossRef\]](#)
26. Ivits, E.; Horion, S.; Fensholt, R.; Cherlet, M. Drought footprint on European ecosystems between 1999 and 2010 assessed by remotely sensed vegetation phenology and productivity. *Glob. Chang. Biol.* **2014**, *20*, 581–593. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Tangen, B.A.; Bansal, S.; Jones, S.; Dixon, C.S.; Nahlik, A.M.; DeKeyser, E.S.; Hargiss, C.L.; Mushet, D.M. Using a vegetation index to assess wetland condition in the Prairie Pothole Region of North America. *Front. Environ. Sci.* **2022**, *10*, 889170. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Liao, W.; Nie, X.; Zhang, Z. Interval association of remote sensing ecological index in China based on concept lattice. *Environ. Sci. Pollut. Res.* **2022**, *29*, 34194–34208. [\[CrossRef\]](#)
29. Guo, W.; Zhou, H.; Jiao, X.; Huang, L.; Wang, H. Analysis of alterations of the hydrological situation and causes of river runoff in the Min River, China. *Water* **2022**, *14*, 1093. [\[CrossRef\]](#)
30. Faour, G.; Mhawej, M.; Nasrallah, A. Global trends analysis of the main vegetation types throughout the past four decades. *Appl. Geogr.* **2018**, *97*, 184–195. [\[CrossRef\]](#)
31. Shammi, S.A.; Meng, Q. Use time series NDVI and EVI to develop dynamic crop growth metrics for yield modeling. *Ecol. Indic.* **2021**, *121*, 107124. [\[CrossRef\]](#)
32. Liu, C.; Li, W.; Wang, W.; Zhou, H.; Liang, T.; Hou, F.; Xu, J.; Xue, P. 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* **2021**, *206*, 105500. [\[CrossRef\]](#)
33. Jin, H.; Chen, X.; Wang, Y.; Zhong, R.; Zhao, T.; Liu, Z.; Tu, X. Spatio-temporal distribution of NDVI and its influencing factors in China. *J. Hydrol.* **2021**, *603*, 127129. [\[CrossRef\]](#)
34. Xiong, Y.; Wang, H. Spatial relationships between NDVI and topographic factors at multiple scales in a watershed of the Minjiang River, China. *Ecol. Inform.* **2022**, *69*, 101617. [\[CrossRef\]](#)

35. Wu, H.; Zhang, J.; Bao, Z.; Wang, G.; Wang, W.; Yang, Y.; Wang, J.; Kan, G. The impacts of natural and anthropogenic factors on vegetation change in the Yellow-Huai-Hai River Basin. *Front. Earth Sci.* **2022**, *10*, 959403. [\[CrossRef\]](#)
36. Liu, L.; Ao, T.; Zhou, L.; Takeuchi, K.; Gusev, M.; Zhang, X.; Wang, W.; Ren, Y. Comprehensive evaluation of parameter importance and optimization based on the integrated sensitivity analysis system: A case study of the BTOP model in the upper Min River Basin, China. *J. Hydrol.* **2022**, *610*, 127819. [\[CrossRef\]](#)
37. Qu, S.; Wang, L.; Lin, A.; Zhu, H.; Yuan, M. What drives the vegetation restoration in Yangtze River basin, China: Climate change or anthropogenic factors? *Ecol. Indic.* **2018**, *90*, 438–450. [\[CrossRef\]](#)
38. Zhu, P.; Liu, G.; He, J. Spatio-temporal variation and impacting factors of NPP from 2001 to 2020 in Sanjiangyuan region, China: A deep neural network-based quantitative estimation approach. *Ecol. Inform.* **2023**, *78*, 102345. [\[CrossRef\]](#)
39. Zhu, X.; Xiao, G.; Zhang, D.; Guo, L. Mapping abandoned farmland in China using time series MODIS NDVI. *Sci. Total Environ.* **2021**, *755*, 142651. [\[CrossRef\]](#)
40. Hu, J.; Ma, J.; Nie, C.; Xue, L.; Zhang, Y.; Ni, F.; Deng, Y.; Liu, J.; Zhou, D.; Li, L.; et al. Attribution Analysis of Runoff change in Min-tuo River Basin based on SWAT model simulations, china. *Sci. Rep.* **2020**, *10*, 2900. [\[CrossRef\]](#)
41. Wang, J.; Fan, Y.; Yang, Y.; Zhang, L.; Zhang, Y.; Li, S.; Wei, Y. Spatial-temporal evolution characteristics and driving force analysis of NDVI in the Minjiang River Basin, China, from 2001 to 2020. *Water* **2022**, *14*, 2923. [\[CrossRef\]](#)
42. Wang, Y.; Shen, X.; Jiang, M.; Tong, S.; Lu, X. Spatiotemporal change of aboveground biomass and its response to climate change in marshes of the Tibetan Plateau. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102385. [\[CrossRef\]](#)
43. Liu, Z.; Chen, Y.; Chen, C. Analysis of the Spatiotemporal Characteristics and Influencing Factors of the NDVI Based on the GEE Cloud Platform and Landsat Images. *Remote Sens.* **2023**, *15*, 4980. [\[CrossRef\]](#)
44. Wang, Z.; Wang, Y.; Liu, Y.; Wang, F.; Deng, W.; Rao, P. Spatiotemporal characteristics and natural forces of grassland NDVI changes in Qilian Mountains from a sub-basin perspective. *Ecol. Indic.* **2023**, *157*, 111186. [\[CrossRef\]](#)
45. De La Iglesia Martinez, A.; Labib, S. Demystifying normalized difference vegetation index (NDVI) for greenness exposure assessments and policy interventions in urban greening. *Environ. Res.* **2023**, *220*, 115155. [\[CrossRef\]](#) [\[PubMed\]](#)
46. Wang, Q.; Qi, J.; Li, J.; Cole, J.; Waldhoff, S.T.; Zhang, X. Nitrate loading projection is sensitive to freeze-thaw cycle representation. *Water Res.* **2020**, *186*, 116355. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Wang, Q.; Qi, J.; Qiu, H.; Li, J.; Cole, J.; Waldhoff, S.; Zhang, X. Pronounced increases in future soil erosion and sediment deposition as influenced by Freeze–Thaw Cycles in the Upper Mississippi River Basin. *Environ. Sci. Technol.* **2021**, *55*, 9905–9915. [\[CrossRef\]](#)
48. Dastigerdi, M.; Nadi, M.; Sarjaz, M.R.; Kiapasha, K. Trend analysis of MODIS NDVI time series and its relationship to temperature and precipitation in Northeastern of Iran. *Environ. Monit. Assess.* **2024**, *196*, 346. [\[CrossRef\]](#)
49. Wang, X.; Fang, S.; Li, Y.; Dong, C.; Sun, L. Spatiotemporal Variability of Vegetation NDVI in the Huaihe River Basin, China: Driving Force Analysis and Ecological Implications. *Preprints* **2024**, 2024012006. [\[CrossRef\]](#)
50. Alharbi, S.; Raun, W.R.; Arnall, D.B.; Zhang, H. Prediction of maize (*Zea mays* L.) population using normalized-difference vegetative index (NDVI) and coefficient of variation (CV). *J. Plant Nutr.* **2019**, *42*, 673–679. [\[CrossRef\]](#)
51. De Oliveira, H.F.E.; de Castro, L.E.V.; Sousa, C.M.; Alves Júnior, L.R.; Mesquita, M.; Silva, J.A.O.S.; Faria, L.C.; da Silva, M.V.; Giongo, P.R.; de Oliveira Júnior, J.F.; et al. Geotechnologies in Biophysical Analysis through the Applicability of the UAV and Sentinel-2A/MSI in Irrigated Area of Common Beans: Accuracy and Spatial Dynamics. *Remote Sens.* **2024**, *16*, 1254. [\[CrossRef\]](#)
52. Zuo, Y.; Li, Y.; He, K.; Wen, Y. Temporal and spatial variation characteristics of vegetation coverage and quantitative analysis of its potential driving forces in the Qilian Mountains, China, 2000–2020. *Ecol. Indic.* **2022**, *143*, 109429. [\[CrossRef\]](#)
53. Zhu, Y.; Zhang, S.; Luo, P.; Su, F.; Sun, B.; Guo, J.; Yang, R. Assessing ecohydrological factors variations and their relationships at different spatio-temporal scales in semiarid area, northwestern China. *Adv. Space Res.* **2021**, *67*, 2368–2381. [\[CrossRef\]](#)
54. Li, M.; Yin, L.; Zhang, Y.; Su, X.; Liu, G.; Wang, X.; Au, Y.; Wu, X. Spatio-temporal dynamics of fractional vegetation coverage based on MODIS-EVI and its driving factors in Southwest China. *Acta Ecol. Sin* **2021**, *41*, 1138–1147. [\[CrossRef\]](#)
55. He, N.; Guo, W.; Lan, J.; Yu, Z.; Wang, H. The impact of human activities and climate change on the eco-hydrological processes in the Yangtze River basin. *J. Hydrol. Reg. Stud.* **2024**, *53*, 101753. [\[CrossRef\]](#)
56. Yang, Y.; Wang, Y.; Cong, N.; Wang, N.; Yao, W. Impacts of the Three Gorges Dam on riparian vegetation in the Yangtze River Basin under climate change. *Sci. Total Environ.* **2024**, *912*, 169415. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Chen, T.; Ao, T.; Zhang, X.; Li, X.; Yang, K. Climate change characteristics of extreme temperature in the Minjiang River Basin. *Adv. Meteorol.* **2019**, *2019*, 1935719. [\[CrossRef\]](#)
58. Yu, H.; Yang, Q.; Jiang, S.; Zhan, B.; Zhan, C. Detection and Attribution of Vegetation Dynamics in the Yellow River Basin Based on Long-Term Kernel NDVI Data. *Remote Sens.* **2024**, *16*, 1280. [\[CrossRef\]](#)
59. He, W.; Wang, F.; Feng, N. Research on the characteristics and influencing factors of the spatial correlation network of cultivated land utilization ecological efficiency in the upper reaches of the Yangtze River, China. *PLoS ONE* **2024**, *19*, e0297933. [\[CrossRef\]](#)
60. Sun, H.; Wang, X.; Fan, D.; Sun, O.J. Contrasting vegetation response to climate change between two monsoon regions in Southwest China: The roles of climate condition and vegetation height. *Sci. Total Environ.* **2022**, *802*, 149643. [\[CrossRef\]](#)
61. Chen, S.; Wen, Z.; Zhang, S.; Huang, P.; Ma, M.; Zhou, X.; Liao, T.; Wu, S. Effects of long-term and large-scale ecology projects on forest dynamics in Yangtze River Basin, China. *For. Ecol. Manag.* **2021**, *496*, 119463. [\[CrossRef\]](#)
62. Xu, X.; Riley, W.J.; Koven, C.D.; Jia, G.; Zhang, X. Earlier leaf-out warms air in the north. *Nat. Clim. Chang.* **2020**, *10*, 370–375. [\[CrossRef\]](#)

63. Tao, S.; Kuang, T.; Peng, W.; Wang, G. Analyzing the spatio-temporal variation and drivers of NDVI in upper reaches of the Yangtze River from 2000 to 2015: A case study of Yibin City. *Acta Ecol. Sin* **2020**, *40*, 5029–5043.
64. Dai, T.; Dai, X.; Lu, H.; He, T.; Li, W.; Li, C.; Huang, S.; Huang, Y.; Tong, C.; Qu, G.; et al. The impact of climate change and human activities on the change in the net primary productivity of vegetation—Taking Sichuan Province as an example. *Environ. Sci. Pollut. Res.* **2024**, *31*, 7514–7532. [[CrossRef](#)] [[PubMed](#)]
65. Liang, Y.; Su, Z.; Liu, L. Assessing the contribution of ecological restoration projects to ecosystem services values in the Chinese loess plateau. *GeoJournal* **2024**, *89*, 23. [[CrossRef](#)]
66. MengHan, T.; Wang, M.; Gao, Y. Spatio-temporal distribution and response relationship of NDVI based on GeoDetector in the arid regions in Northwest China. *Res. Sq. preprints*. **2024**. [[CrossRef](#)]
67. Peng, W.; Kuang, T.; Tao, S. Quantifying influences of natural factors on vegetation NDVI changes based on geographical detector in Sichuan, western China. *J. Clean. Prod.* **2019**, *233*, 353–367. [[CrossRef](#)]
68. Peng, W.; Zhang, D.; Luo, Y.; Tao, S.; Xu, X. Influence of natural factors on vegetation NDVI using geographical detection in Sichuan Province. *Acta Geogr. Sin* **2019**, *74*, 1758–1776.
69. Xu, Y.; Dai, Q.-Y.; Lu, Y.-G.; Zhao, C.; Huang, W.-T.; Xu, M.; Feng, Y.-X. Identification of ecologically sensitive zones affected by climate change and anthropogenic activities in Southwest China through a NDVI-based spatial-temporal model. *Ecol. Indic.* **2024**, *158*, 111482. [[CrossRef](#)]
70. Baumgertel, A.; Lukić, S.; Caković, M.; Lazić, I.; Tošić, M.; Momirović, N.; Pandey, S.; Bezdan, A.; Blagojević, B.; Djurdjević, V. Spatio-Temporal Analysis of Vegetation Response to Climate Change, Case Study: Republic of Serbia. *Int. J. Environ. Res.* **2024**, *18*, 21. [[CrossRef](#)]
71. Visscher, A.M.; Vanek, S.; Huaraca, J.; Mendoza, J.; Ccanto, R.; Meza, K.; Olivera, E.; Scurrah, M.; Wellstein, C.; Bonari, G.; et al. Traditional soil fertility management ameliorates climate change impacts on traditional Andean crops within smallholder farming systems. *Sci. Total Environ.* **2024**, *912*, 168725. [[CrossRef](#)] [[PubMed](#)]
72. Ghorbanian, A.; Mohammadzadeh, A.; Jamali, S. Linear and non-linear vegetation trend analysis throughout Iran using two decades of MODIS NDVI imagery. *Remote Sens.* **2022**, *14*, 3683. [[CrossRef](#)]
73. Liu, Y.; Xie, Y.; Guo, Z.; Xi, G. Effects of Climate Variability and Human Activities on Vegetation Dynamics across the Qinghai–Tibet Plateau from 1982 to 2020. *Remote Sens.* **2023**, *15*, 4988. [[CrossRef](#)]
74. Wang, H.; Zhang, Q.-w.; Wang, J. Spatial variation in soil water on a hillslope with ephemeral gullies restored by different vegetation restoration modes on the Loess Plateau. *Catena* **2023**, *224*, 107001. [[CrossRef](#)]

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