Spatiotemporal Variation of Vegetation NDVI and Its Response to Climate Factors on the Southeastern Margin of the Mu Us Sandy Land (Postprint)

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Abstract

Understanding the response of vegetation growth to climate change is crucial for clarifying dynamic relationships within ecosystems. Based on meteorological data and Normalized Difference Vegetation Index (NDVI) from 1990 to 2018, and using methods such as partial correlation analysis and Geographical Detector, we analyzed the changing trends of annual mean NDVI for different vegetation types during the growing season in the southeastern margin of the Mu Us Sandy Land, and investigated the impacts of annual mean temperature and annual total precipitation on various vegetation types. The results show that: (1) During the 1990-2018 growing seasons, the area with significant and highly significant increases in annual mean NDVI of vegetation in the study region reached 97.9%, indicating substantial improvement in overall ecological environmental quality. Before 2005, the annual mean NDVI increased slowly, after which it experienced an abrupt increase at a rate of $0.011 \cdot a^{-1}$, with shrub vegetation showing the largest increase in annual mean NDVI. (2) The year 2000 was the turning point for trends in annual total precipitation and annual mean temperature. Before the turning point, annual total precipitation decreased at a rate of -5.510 $mm \cdot a^{-1}$, after which it increased at a rate of 5.541 $mm \cdot a^{-1}$, primarily dependent on increases in heavy rainfall amounts. Before the turning point, annual mean maximum temperature and annual mean minimum temperature increased at rates of 0.122 $℃ \cdot a^{-1}$ and 0.230 $℃ \cdot a^{-1}$, respectively; after the turning point, annual mean maximum temperature decreased at a rate of -0.014 $℃ \cdot a^{-1}$, while annual mean minimum temperature increased at a rate of 0.022 $℃ \cdot a^{-1}$. (3) During the slow growth stage of annual mean NDVI (1990-2005), annual mean minimum temperature had a greater impact on vegetation, showing significant positive correlations with annual mean NDVI of different vegetation types. During the rapid growth stage of annual mean NDVI (2006-

2018), annual total precipitation showed significant positive correlations with annual mean NDVI of different vegetation types, and the frequent occurrence of heavy rainfall events made precipitation the dominant factor for vegetation growth. The interaction effect between annual total precipitation and annual mean temperature, particularly annual mean minimum temperature, is key to promoting vegetation growth.

Full Text

Preamble

Temporal and Spatial Variation of Vegetation NDVI and Its Response to Climatic Factors in the Southeastern Margin of Mu Us Sandy Land

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Abstract: Understanding vegetation growth responses to climate change is fundamental to clarifying ecosystem dynamics. Based on meteorological data and the Normalized Difference Vegetation Index (NDVI) from 1990 to 2018, this study analyzes the variation trends of annual NDVI for different vegetation types in the southeastern margin of Mu Us Sandy Land during the growing season using partial correlation analysis and geographic detector methods. The effects of mean annual temperature and total annual precipitation on NDVI for various vegetation types are examined. The results show that: (1) During the 1990-2018 growing seasons, vegetation NDVI increased significantly across 97.9% of the study area, indicating substantial improvement in overall ecological environmental quality. The growth rate of annual NDVI was slow before 2005, after which it increased abruptly at a rate of $0.011 \cdot a^{-1}$, with shrub vegetation showing the largest increase amplitude. (2) The year 2000 marked a turning point for both total precipitation and mean temperature trends. Before 2000, total precipitation decreased at a rate of $5.510\ mm \cdot a^{-1}$, while after 2000 it increased at $5.541\ mm \cdot a^{-1}$, primarily due to increased heavy rainfall events. Before the turning point, annual extreme daily mean temperature and annual minimum daily mean temperature increased at rates of $0.122\ ℃ \cdot a^{-1}$ and $0.230\ ℃ \cdot a^{-1}$, respectively. After 2000, extreme temperature decreased at $0.014\ ℃ \cdot a^{-1}$ while minimum temperature continued to increase at $0.022\ ℃ \cdot a^{-1}$. (3) During the slow growth stage of NDVI (1990-2005), annual minimum temperature showed significant positive correlations with NDVI for different vegetation types and exerted the greatest influence. During the rapid growth stage (2006-2018), total precipitation demonstrated significant positive correlations with NDVI for all vegetation types, with frequent heavy rainfall events making precipitation the dominant factor for vegetation growth. The interaction between total precipitation and mean temperature, especially minimum temperature, is the key factor promoting vegetation growth.

Keywords: Mu Us Sandy Land; climatic factor; Normalized Difference Vegetation Index (NDVI); geographic detector; Extreme-Point Symmetric Mode Decomposition (ESMD)

Introduction

Under the background of global warming, regional water cycles and dry-wet conditions have undergone significant changes, profoundly affecting vegetation growth and development worldwide. The Normalized Difference Vegetation Index (NDVI) has been widely applied in studying vegetation responses to climatic factors because it effectively reflects changes in vegetation and ecosystem parameters and sensitively indicates variations in meteorological factors. Among climatic factors, precipitation and temperature most prominently influence vegetation. Previous studies have shown complex relationships between precipitation, temperature, and vegetation, possibly related to study area or temporal scale, or due to failure to separate various factors within the study region, leading to biased results.

Recent research has demonstrated the mechanisms through which precipitation and temperature affect vegetation growth from different perspectives. For instance, studies have shown that both the amount and frequency of rainfall events determine the biomass and biodiversity of annual vegetation in the Horqin Sandy Land. In southern Shaanxi Province, increasing daily minimum temperatures promotes vegetation growth and development. In the Mu Us Sandy Land, an important ecological barrier in northern China with scarce water resources and a fragile ecological environment, vegetation dynamics are highly sensitive to climate change. Although previous studies have examined vegetation responses to temperature and precipitation in arid regions, most have analyzed mean precipitation and temperature values without further separating the effects of individual climatic factors on vegetation growth in the Mu Us Sandy Land, and have lacked quantification of the degree of influence of each factor.

Therefore, this study, based on vegetation remote sensing data and meteorological data from 1990 to 2018 for 25 stations in the southeastern margin of Mu Us Sandy Land, analyzes the effects of annual extreme daily mean temperature, annual minimum daily mean temperature, and total annual precipitation on NDVI trends for different vegetation types during the growing season. The research aims to separate relevant factors, clarify the variation patterns of temperature and precipitation and their influence mechanisms on vegetation growth, and use the geographic detector model to quantify the role and contribution of each factor to vegetation growth changes. This provides an important basis for rational ecological planning and understanding vegetation responses to climate change.

1 Study Area Overview

The southeastern margin of Mu Us Sandy Land (107°15 -110°55 E, 36°49 - 39°27 N) covers an area of approximately 3.1$×10^{4}$ km^2, encompassing seven administrative regions in Yulin City, Shaanxi Province: Dingbian County, Jingbian County, Hengshan District, Yuyang District, Shenmu City, and others [Figure 1: see original paper]. Located in the farming-pastoral ecotone of northern China, this region is a typical ecologically fragile zone characterized by frequent droughts, strong winds, land desertification, and dust storms. It has a temperate semi-arid continental monsoon climate with an average annual temperature of about 9.7 ℃ and average annual precipitation of approximately 393 mm.

2.1 Data Sources

Meteorological data were obtained from the daily dataset of surface climate data from the China Meteorological Data Center (http://data.com.cn/site/index.html) for the period 1990-2018. The data included daily maximum and minimum temperatures and precipitation at 25 meteorological stations. Annual extreme daily mean temperature was defined as the annual average of daily maximum temperatures, while annual minimum daily mean temperature was defined as the annual average of daily minimum temperatures. The growing season was defined as May to September. According to national meteorological standards, precipitation intensity was classified as light rain (0.1-9.9 mm), moderate rain (10.0-24.9 mm), heavy rain (25.0-49.9 mm), and torrential rain ($ $50.0 mm). Only effective rainfall events above 0.5 mm were retained to assess vegetation impacts.

Vegetation type data were derived from the 1:1,000,000 China Vegetation Atlas compiled by the "Environmental and Ecological Science Data Center for West China" of the National Natural Science Foundation of China, and from the GIMMS 3g v1 NDVI dataset released by the Chinese Academy of Sciences Resource and Environmental Science Data Center (http://www.resdc.cn/). The GIMMS 3g v1 dataset spans 1990–2018 with a spatial resolution of 1/12°, while the China Vegetation Atlas data for 2018 have a spatial resolution of 30 m. Data preprocessing included format conversion, coordinate system unification, projection, and clipping using GIS 10.6. The 30 m resolution vegetation map was resampled and masked to match the 1/12° resolution dataset for integration.

Based on the vegetation atlas, vegetation types in the study area include, in descending order of area: cultivated vegetation (corn, potatoes, etc., mainly in Dingbian and Jingbian counties), grassland vegetation (Artemisia, bunchgrass, etc., mainly in Yuyang District and Shenmu City), shrub vegetation (Caragana, Salix, etc., scattered distribution), meadow vegetation (Achnatherum, etc., mainly in northern Dingbian County), broadleaf forest vegetation (poplar, willow, elm), herbaceous vegetation (Bothriochloa), desert vegetation (Ephedra, Halocnemum), and marsh vegetation (Phragmites). Kriging interpolation was applied to meteorological data from the 25 stations, and ArcGIS 10.6 was used to extract NDVI, temperature, and precipitation data for each vegetation type to analyze relationships between vegetation and meteorological factors.

2.2.1 Extreme-Point Symmetric Mode Decomposition (ESMD)

The ESMD method offers significant advantages in climate analysis. This study utilized its mode decomposition component to extract residual variables from time series, thereby isolating the overall trends of annual NDVI, annual extreme temperature, annual minimum temperature, and total precipitation across temporal scales.

2.2.2 Mann-Kendall Trend Test

The Mann-Kendall test analyzes time series trends. For a time series Xi (i = 1, 2, ···, n) with sample distribution function Fi, the null hypothesis states that the n variables are independent and identically distributed, while the alternative hypothesis is a two-tailed test suggesting different distributions. The test statistic S is calculated as:

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

where sgn is the sign function. The variance is given by:

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

The standardized test statistic Z is:

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

A positive Z indicates an increasing trend, while a negative Z indicates a decreasing trend. At significance levels of $\alpha = 0.05$ and $\alpha = 0.01$, the critical values are $±$1.96 and $±$2.58, respectively. These significance levels categorize the trend magnitude of NDVI, temperature, and precipitation across the study area.

2.2.3 Trend Analysis

Trend analysis reflects spatiotemporal variation patterns of annual NDVI, extreme temperature, minimum temperature, and total precipitation during the growing season:

$$\text{slope} = \frac{n\sum_{i=1}^{n} i \cdot I_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} I_i}{n\sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where slope represents the trend rate; i is the year index; n is the total number of years; and Ii is the annual value of NDVI, extreme temperature, minimum temperature, or total precipitation.

2.2.4 Partial Correlation Analysis

Partial correlation analysis explores relationships between vegetation growth and individual climatic factors while controlling for other factors:

$$r_{xy,mz} = \frac{r_{xy} - r_{xm} r_{ym}}{\sqrt{(1 - r_{xm}^2)(1 - r_{ym}^2)}}$$

where x is annual NDVI; y is annual extreme temperature; z is annual minimum temperature; m is total precipitation; rxy,mz is the partial correlation coefficient between extreme temperature and NDVI controlling for precipitation and minimum temperature; and other partial correlation coefficients are calculated similarly. Positive r values indicate positive correlations, negative values indicate negative correlations, and values near zero indicate no linear correlation.

2.2.5 Geographic Detector Model

The geographic detector model identifies spatial heterogeneity and reveals mechanisms of how independent variables affect dependent variables through statistical methods. This study employed the optimal parameter geographic detector, calculating the contribution rate of each continuous factor under different classification methods and break numbers using R software. Classification methods included equal interval, natural breaks, quantile, geometric interval, and standard deviation, with 3–10 classes tested. The parameter combination yielding the highest q-value was selected.

Differentiation and Factor Detector: This assesses spatial heterogeneity of NDVI for different vegetation types and the influence magnitude of each factor X on NDVI changes, measured by q-value:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where L is the number of strata; Nh and N are sample numbers in stratum h and the entire region; σh^2 and σ^2 are variances of NDVI in stratum h and the entire region. The q-value ranges [0,1], where 1 indicates complete contribution of the factor to NDVI spatial distribution and 0 indicates no relationship.

Interaction Detector: This identifies whether interactions between factors enhance or weaken explanatory power for NDVI. By comparing individual q-values (q(X1), q(X2)) with their interaction q-value (q(X1 X2)), interactions are classified into five types: nonlinear weakening, single-factor nonlinear weakening, independent, double-factor enhancement, and nonlinear enhancement .

3.1 Changes in Temperature and Precipitation

For total precipitation, 2000 was identified as the mutation point. Before 2000, precipitation decreased significantly at 5.510 $\mathrm{mm \cdot a^{-1}}$, while after 2000 it increased significantly at 5.541 $\mathrm{mm \cdot a^{-1}}$ [Figure 2: see original paper]. Regarding rainfall intensity, after 2000, although light rain accounted for the largest proportion of average rainfall, its share declined at $0.003 \cdot \mathrm{a^{-1}}$, while heavy rain proportion increased at $0.005 \cdot \mathrm{a^{-1}}$—the largest increase among all intensities—indicating that precipitation increases depended mainly on frequent heavy rainfall events [Figure 4: see original paper].

Spatially, during 1990–2018, multi-year mean extreme temperature ranged 26.33–27.62 ℃, with trends of -0.01 to 0.03 $℃ \cdot \mathrm{a^{-1}}$; 19.3% of the area passed significance tests. Minimum temperature ranged 13.92–15.13 ℃, with trends of 0.01–0.08 $℃ \cdot \mathrm{a^{-1}}$; 79.7% of the area passed significance tests. Precipitation ranged 386.12–511.17 mm, with trends of -0.72 to 4.95 $\mathrm{mm \cdot a^{-1}}$, but only 3.96% passed significance tests, indicating large, unstable precipitation changes [Figure 5: see original paper].

3.2 NDVI Changes

Temporally, during 1990–2018, 2000 was the turning point for both extreme and minimum temperatures [Figure 2: see original paper]. Before 2000, extreme temperature increased at 0.122 $℃ \cdot \mathrm{a^{-1}}$ and minimum temperature at 0.230 $℃ \cdot \mathrm{a^{-1}}$. After 2000, extreme temperature decreased at 0.014 $℃ \cdot \mathrm{a^{-1}}$ while minimum temperature continued increasing at 0.022 $℃ \cdot \mathrm{a^{-1}}$.

All vegetation types showed significant increasing NDVI trends, with shrub vegetation showing the largest increase amplitude [Figure 3: see original paper]. The annual NDVI for the entire region increased abruptly in 2000, though this mutation was inconsistent with temperature and precipitation changes, possibly due to ecological restoration policies such as the Grain-for-Green program that artificially improved vegetation conditions [Figure 6: see original paper]. Spatially, mean NDVI ranged 0.14–0.64, with high values in eastern Dingbian and western Jingbian counties and low values in the sandy interior of northern Yuyang and western Shenmu. During the study period, significantly and extremely significantly increasing NDVI areas accounted for 97.9% of the region, while decreasing areas comprised only 2.1%, mainly in central Yuyang, western Shenmu, and central Jingbian [Figure 6: see original paper].

3.3 Relationships Between NDVI and Temperature/Precipitation

To effectively investigate vegetation responses, analysis focused on cultivated vegetation, grassland, shrub, and meadow types, which dominate the area. Partial correlation analysis revealed significant differences in how extreme temperature, minimum temperature, and precipitation affected NDVI across vegetation types .

During 1990–2005, controlling for minimum temperature and precipitation, extreme temperature showed significant negative correlation with shrub NDVI. Controlling for extreme temperature and precipitation, minimum temperature showed significant positive correlations with cultivated, grassland, and shrub NDVI. Controlling for both temperature factors, precipitation showed extremely significant positive correlations with all vegetation types.

During 2006–2018, controlling for temperature factors, precipitation maintained extremely significant positive correlations with all vegetation types. Although minimum temperature showed no significant partial correlations with NDVI when controlling for precipitation and extreme temperature, it significantly promoted biomass of cultivated, shrub, and grassland vegetation. This indicates that during the slow NDVI growth stage (1990–2005), minimum temperature dominated vegetation growth, while during the rapid growth stage (2006–2018), precipitation became the dominant factor, jointly promoting vegetation growth with minimum temperature.

Geographic detector results showed that climatic factors' contributions to NDVI varied by period and vegetation type . Overall, precipitation contributed most ($q = 0.713$ for grassland, 0.390 for shrub), followed by minimum temperature ($q = 0.356$ for meadow). Extreme temperature contributed least, with non-significant effects on meadow vegetation. Interaction detector results showed that interactions between precipitation and temperature (especially minimum temperature) consistently produced double-factor enhancement effects, with interaction q-values exceeding individual factor contributions . This confirms that in arid regions, increased rainfall intensity enhances vegetation productivity, and the interaction between minimum temperature and precipitation most strongly promotes vegetation growth.

4 Discussion

Both partial correlation analysis and geographic detectors revealed that minimum temperature, extreme temperature, and precipitation are closely related to vegetation growth. During 1990–2005, despite decreasing precipitation, increasing temperatures—especially minimum temperature—ensured continued NDVI growth, demonstrating the importance of temperature changes for vegetation.

At low temperatures, plant survival rates, leaf elongation rates, chlorophyll content, and aboveground net primary productivity are minimized. Low temperature stress severely limits seedling emergence and delays phenology, while increased freeze-thaw cycles reduce perennial vegetation survival. Therefore, in the mid-high latitude Mu Us Sandy Land, temperature increases—particularly minimum temperature increases—improve vegetation physiological performance and biomass.

Shrub vegetation showed the fastest NDVI growth rate, with large variations in temperature and precipitation in its distribution areas. Geographic detector results showed strong interactive effects of precipitation with both temperature measures on shrub vegetation, indicating that shrubs adapt well to climate changes while maintaining high biomass. This suggests that artificial restoration measures should increase shrub coverage in the sandy interior to sustain vegetation recovery.

5 Conclusions

Based on NDVI, temperature, and precipitation data from 1990–2018 for 25 meteorological stations, this study used ESMD, partial correlation analysis, and geographic detectors to clarify trends in extreme temperature, minimum temperature, total precipitation, and NDVI during the growing season, and to elucidate how different vegetation types respond to meteorological factors. The main conclusions are:

1. From 1990–2018, regional mean NDVI increased significantly, with significantly and extremely significantly increasing areas accounting for 97.9% of the region, while decreasing areas comprised only 2.1%, located mainly in central Yuyang, western Shenmu, and central Jingbian. Overall ecological environmental quality improved substantially. NDVI growth was slow before 2005, then increased abruptly at $0.011 \cdot a^{-1}$, with shrub vegetation showing the largest increase amplitude.

2. The year 2000 was the turning point for precipitation and temperature trends. Before 2000, precipitation decreased at $5.510\ mm \cdot a^{-1}$, then increased at $5.541\ mm \cdot a^{-1}$, depending mainly on increased heavy rainfall. Before 2000, extreme and minimum temperatures increased at $0.122\ ℃ \cdot a^{-1}$ and $0.230\ ℃ \cdot a^{-1}$, respectively. After 2000, extreme temperature decreased at $0.014\ ℃ \cdot a^{-1}$ while minimum temperature increased at $0.022\ ℃ \cdot a^{-1}$.

3. Separating climatic factors reveals their relative effects on vegetation growth. All vegetation types responded sensitively to climate change, showing that hydrothermal conditions affect and constrain vegetation activity. Minimum temperature showed significant positive correlations with NDVI, especially during the slow growth stage (1990–2005). Precipitation showed significant positive correlations with NDVI, becoming dominant during the rapid growth stage (2006–2018). After 2000, fre-

quent heavy rainfall events drove the upward precipitation trend, making precipitation the dominant factor for vegetation growth. Throughout the study period, the interaction between precipitation and mean temperature—especially minimum temperature—was key to promoting vegetation growth.

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