

Spatiotemporal Variation of NDVI and Its Driving Forces in the Northwestern Arid Eco-Geographic Region (Postprint)

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Abstract

The Normalized Difference Vegetation Index (NDVI) is an important indicator for assessing ecological environmental stability. The Northwest Arid Eco-geographical Region of China has a fragile ecological environment, and analyzing the spatiotemporal variation of its NDVI and its driving forces is of great significance for ecological vegetation restoration in this region. Based on multi-source datasets including temperature, precipitation, potential evapotranspiration, elevation, soil, and nighttime light index, and using methods such as coefficient of variation, Theil-Sen median trend analysis, Mann-Kendall significance test, Geographical Detector, and Mixed Geographically Weighted Regression (MGWR) model, this study investigated the spatiotemporal variation characteristics of NDVI and its driving factors in the Northwest Arid Eco-geographical Region of China from 2003 to 2022. The results show that: (1) From 2003 to 2022, NDVI showed an overall increasing trend, with variation ranging between 0.1974 and 0.2464. The minimum NDVI value occurred in 2009, and the maximum NDVI value occurred in 2018. (2) In the Northwest Arid Eco-geographical Region, NDVI in most areas is at a relatively low level, showing an overall spatial distribution pattern of “high in the east and west, low in the middle.” (3) In most areas of the Northwest Arid Eco-geographical Region, the degree of NDVI change is concentrated in low stability, with strong stability in the central part and weak stability in the eastern and western parts overall. (4) NDVI in most areas of the Northwest Arid Eco-geographical Region shows an increasing trend, with only a small portion showing a decreasing trend. (5) The spatiotemporal variation of NDVI in the Northwest Arid Eco-geographical Region is comprehensively affected by natural and anthropogenic factors, with soil type being the main driving factor. The interaction of various factors affects this region. The MGWR model analysis results further verify that soil type has the strongest

effect on NDVI, temperature and potential evapotranspiration show negative effects, while precipitation and nighttime light index show positive effects.

Full Text

Spatio-temporal Variation Characteristics and Driving Forces of NDVI in the Arid and Semi-arid Region of Northwest China

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Abstract

The normalized difference vegetation index (NDVI) is a crucial indicator for assessing ecological environment stability. The ecological environment in north-west China's arid and semi-arid regions is fragile, and analyzing the spatio-temporal changes and driving forces of NDVI is critical for effective vegetation restoration in this area. Based on multi-source datasets including temperature, precipitation, potential evapotranspiration, elevation, soil type, and nighttime light index, this study employs the coefficient of variation, Theil-Sen median trend analysis, Mann-Kendall significance test, geographic detector, and multi-scale geographically weighted regression (MGWR) model to explore the spatio-temporal variation characteristics and driving factors of NDVI from 2003 to 2022. The results show that: (1) NDVI exhibited an overall increasing trend, with values ranging from 0.1974 to 0.2464. The minimum value occurred in 2009, while the maximum appeared in 2018. (2) In most areas of the region, NDVI remains at relatively low levels, displaying a spatial distribution pattern of "high in the east and west, low in the middle." (3) The stability of NDVI changes is generally low, with strong stability in the central region and weak stability in the eastern and western parts. (4) Most areas show an increasing trend in NDVI, with only a few regions exhibiting decreasing trends. (5) The spatio-temporal variation of NDVI is influenced by both natural and human factors, with soil type serving as the primary driving factor. The interaction among various factors also significantly impacts the region. MGWR model analysis further confirms that soil type has the strongest effect on NDVI, with temperature

and potential evapotranspiration exerting negative effects, while precipitation and nighttime light index have positive effects.

Keywords: NDVI; trend analysis; MGWR; driving force; arid and semi-arid region of northwest China

1 Study Area Overview

The arid and semi-arid region of northwest China is located deep in the interior, spanning from $31^{\circ}53'48.23''N$ to $53^{\circ}32'58.48''N$ and $67^{\circ}03'57.51''E$ to $124^{\circ}20'5.81''E$. The region is characterized by low precipitation and an arid climate, covering a total area of $2,264,327.51 \text{ km}^2$.

Administratively, it includes most of Xinjiang, Gansu, Inner Mongolia, and Ningxia, as well as parts of Shaanxi, Hebei, Qinghai, and Shanxi, accounting for 24.53% of China's total land area. The main vegetation types are desert and desert steppe. From east to west, the climate gradually transitions from sub-arid to arid, with vegetation distribution following the sequence of typical dry steppe, desert steppe, and finally desert zones. Soils are rich in saline and alkaline content, often forming salt and gypsum crusts, with low organic matter content dominated by brown desert soil, brown calcic soil, and chestnut soil, showing alkaline to strongly alkaline reactions. The water system is poorly developed, with most areas being endorheic regions where lakes are predominantly saline or salt lakes.

This region encompasses most of China's "Three North" Shelterbelt Forest Program area and represents an ecologically vulnerable zone. Considering the vast territory of China and its diverse degraded ecosystems, this study focuses on vegetation changes in the arid and semi-arid region of northwest China. Following the classification method of Liu et al. [Figure 1: see original paper], the study area boundary was derived from the Global Change Research Data Repository (<https://www.geodoi.ac.cn/>) using the Chinese Comprehensive Geographical Regionalization Four Major Eco-geographic Regions Boundary Dataset with a spatial resolution of 0.017° . County-level administrative boundary vector data were obtained from the Geospatial Data Cloud (<https://www.gscloud.cn/>). For data processing convenience, the Xin Barag Right Banner area of Hulunbuir City in Inner Mongolia was excluded, and the larger portion was adopted as the study area.

2 Data and Methods

2.1 Data Sources and Processing

The digital elevation model (DEM) data were obtained from the National Cryosphere Desert Data Center (<https://poles.tpcd.ac.cn/en/>) as the China Digital Elevation Map with a spatial resolution of 1 km. NDVI data were derived from the MODIS MOD13A2 dataset, an L3-level product. Temperature and precipitation data were obtained from the National Earth System Science Data

Center (<http://www.resdc.cn/>) as annual average temperature data (2000-2022, 1 km resolution) and annual precipitation data (2000-2022, 1 km resolution). Potential evapotranspiration data were also sourced from the National Earth System Science Data Center (<https://www.geodata.cn/>). Nighttime light data were obtained from the Harvard Dataverse (<https://doi.org/10.7910/DVN/GI>). Soil type data were sourced from the Resource and Environmental Science Data Center. All spatial data were resampled to a unified spatial resolution using ArcGIS (FIGURE:2).

2.2 Methods

2.2.1 Maximum Value Composite Annual NDVI data were synthesized from monthly NDVI values using the maximum value composite (MVC) method, which effectively reduces atmospheric interference and enhances data quality. The calculation formula is:

$$NDVI_i = \text{Max}(NDVI_t)$$

where $NDVI_i$ represents the NDVI value for year i , and $NDVI_t$ represents the NDVI value for month t .

2.2.2 Coefficient of Variation The coefficient of variation reflects the absolute value of data dispersion. Its magnitude is influenced not only by the degree of dispersion but also by the average level of the variable values. The calculation formula is:

$$v = \frac{\sigma}{\mu}$$

where v is the coefficient of variation, σ is the standard deviation of 20-year NDVI values, and μ is the mean of 20-year NDVI values.

2.2.3 Theil-Sen Median Trend Analysis This trend analysis method is a non-parametric statistical trend analysis technique that uses median values, making it resistant to outliers and not requiring normally distributed data, thus avoiding errors caused by anomalies. The calculation formula is:

$$\beta = \text{median} \left(\frac{x_j - x_i}{j - i} \right)$$

where β represents the interannual change trend; x_j and x_i are sequential data values representing different years; i and j are time series indices; and median is the median function.

2.2.4 Mann-Kendall Significance Test The Mann-Kendall test is a non-parametric method commonly used to analyze trends in climatological and hydrological time series. The calculation formula is:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i)$$

where x_j and x_i are time series data; n is the number of data points; and sgn is the sign function. When $n \geq 10$, the statistic S approximately follows a normal distribution, so the standardized test statistic Z is defined. When $|Z| > 1.96$, the trend passes the 95% significance test.

2.2.5 Geographic Detector The geographic detector is a novel statistical method for detecting spatial stratified heterogeneity and revealing underlying driving factors. It measures spatial differentiation by calculating explanatory power (q) to detect explanatory factors and analyze interactions between variables, with applications in multiple natural and social science fields. The single-factor detector measures the influence of independent variable X on dependent variable Y using q values. Higher q values indicate stronger influence, while lower values indicate weaker influence. The calculation formula is:

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

where L is the stratification of independent variable X ; N_h and N are the number of units in layer h and the entire region, respectively; σ_h^2 is the variance of layer h ; and σ^2 is the variance of the entire region.

Factor interaction detection identifies whether the interaction between single-factor q values and dual-factor X enhances or weakens the influence on dependent variable Y . By comparing the q values of individual factor X with those after interaction, we can determine whether the combined effect strengthens or weakens the influence on Y .

2.2.6 MGWR Model Multiscale geographically weighted regression (MGWR) allows regression coefficients to vary across different spatial scales, better reflecting spatial heterogeneity. The calculation formula is:

$$y_i = \beta_{0i} + \sum_{j=1}^k \beta_{bwj}(v_i, u_i) x_{ij} + \varepsilon_i$$

where y_i is the dependent variable; β_{0i} is the intercept; (v_i, u_i) are the geographic coordinates of observation point i ; $\beta_{bwj}(v_i, u_i)$ is the regression coefficient cor-

rected by the effective bandwidth of the j th independent variable; x_{ij} is the j th independent variable at observation point i ; and ε_i is the random error term.

3 Results and Analysis

3.1 Temporal Variation Characteristics of NDVI

Using Python and ArcGIS, we extracted the maximum NDVI value for each year from 2003 to 2022 and plotted the temporal variation (FIGURE:3). The results show that NDVI increased overall, ranging from 0.1974 to 0.2464. The minimum value occurred in 2009, while the maximum appeared in 2018. Linear fitting yielded the equation $y = 0.0018x + 0.6241$ with $R^2 = 0.6241$, indicating a significant positive correlation between NDVI and time, reflecting effective ecological restoration in the region.

3.2 Spatial Variation Characteristics of NDVI

The spatial distribution of mean NDVI from 2003 to 2022 was obtained by averaging across the spatial domain (FIGURE:4). Following the Soil Erosion Classification and Grading Standard (GB/SL190-2007), vegetation coverage was classified into five levels: low (< 0.20), *medium-low* (0.20–0.40), *medium* (0.40–0.60), *medium-high* (0.60–0.80), and *high* (> 0.80). Results show that most areas have relatively low NDVI, displaying a spatial pattern of “high in the east and west, low in the middle.” This pattern primarily relates to environmental conditions: high elevation, extremely low annual precipitation, very arid climate, and poor soil quality, which are unsuitable for vegetation growth, resulting in relatively low NDVI values.

3.3 Variation Characteristics of NDVI

Based on the coefficient of variation formula, we calculated NDVI variability using Python’s `arcpy` module (FIGURE:5). The coefficient of variation image reveals that most areas exhibit low stability, with variation concentrated in low stability zones, showing higher variability in the east and west and lower variability in the center. Reclassification based on variation coefficient values divides stability into five levels: high stability ($v \leq 0.05$), relatively low fluctuation ($0.05 < v \leq 0.10$), medium fluctuation ($0.10 < v \leq 0.15$), relatively high fluctuation ($0.15 < v \leq 0.20$), and high fluctuation ($v > 0.20$). The high stability class accounts for only 16.49%, while the low stability class accounts for 23.21%. Overall, areas with $v > 0.1$ comprise 62.74%, reflecting that most vegetation in the region exhibits instability, likely due to large-scale ecological projects such as the “Three North” Shelterbelt Program and Grain for Green Project.

3.4 Change Trend of NDVI

Using Python's `arcpy` module, we performed Theil-Sen median trend analysis on NDVI from 2003 to 2022 and conducted Mann-Kendall significance testing. Referencing trend classification standards, we reclassified and overlaid the results (FIGURE:6). The trend map shows that most areas display increasing trends, with only a few showing decreasing trends. Areas with extremely significant decreasing trends account for only 1.05%, distributed mainly in the central-western part of the region. Areas with non-significant increasing trends account for the largest proportion at 49.30%, followed by extremely significant increasing trends at 15.56% and significant increasing trends at 10.45%. Overall, 75.31% of the region shows increasing trends, significantly greater than the 24.69% showing decreasing trends. These increasing trend areas are concentrated in the middle section of the "Three North" Shelterbelt Program.

3.5 Analysis of Driving Factors

3.5.1 Key Driving Factors of NDVI We selected six independent variables: temperature, precipitation, potential evapotranspiration, elevation, soil type, and nighttime light index. Continuous variables (temperature, precipitation, potential evapotranspiration, elevation, nighttime light index) were discretized using the natural breaks method into nine categories. Geographic detector analysis revealed the influence (q values) of each factor on NDVI spatial differentiation (FIGURE:7). The q values ranked as: soil type (0.42) > precipitation (0.38) > potential evapotranspiration (0.31) > temperature (0.29) > elevation (0.21) > nighttime light index (0.08). Soil type is the dominant factor influencing NDVI spatial differentiation, followed by precipitation and potential evapotranspiration. Nighttime light index has the weakest influence at only 0.08.

Interaction factor detection reveals that the strongest interaction is between soil type and precipitation, with explanatory power reaching 0.62, while the weakest is between nighttime light index and elevation at 0.31. This indicates that the influence of factors on NDVI spatial differentiation is not independent or simply additive, but rather a mutually reinforcing process.

3.5.2 Spatial Heterogeneity of Driving Factors The MGWR model was used to analyze spatial heterogeneity between NDVI and its driving factors. Model parameters show $R^2 = 0.81$ and adjusted $R^2 = 0.78$, indicating high overall goodness-of-fit. To further analyze scale differences in driving factors, we plotted histogram kernel density curves of regression coefficients for different factors (FIGURE:9). Overall, the intensity and direction of each factor's influence on NDVI vary. Elevation and soil type show both positive and negative effects, precipitation and nighttime light index show positive effects, while temperature and potential evapotranspiration show negative effects. The kernel density curves reveal that temperature, potential evapotranspiration, and elevation exhibit two distinct peaks, indicating multimodal distribution with

concentrated driving factors. The other three factors show single peaks, indicating significant differences in driving factors affecting NDVI, with strong variability across all six factors. In terms of absolute regression coefficient values, soil type has the strongest influence on NDVI, followed by precipitation. Overall, natural factors dominate in this region.

Spatial visualization of MGWR regression coefficients at the county scale (FIGURE:10) shows that temperature and potential evapotranspiration have negative effects on NDVI, with intensity decreasing from east to west, and high-value areas concentrated in central Xinjiang. Precipitation has positive effects, with intensity showing a low-east-west, high-middle pattern, strongest in eastern Xinjiang, western Gansu, and western Inner Mongolia. Potential evapotranspiration shows negative effects with an east-west high, middle-low pattern, with high-value areas in western Xinjiang. Elevation has negative effects with low intensity in the east and west and high intensity in the middle, concentrated in the Ordos Basin where Shaanxi, Ningxia, and Inner Mongolia meet. Soil type has the strongest positive effects, with highest intensity in southern Xinjiang and central Inner Mongolia. Nighttime light index has positive effects, decreasing in intensity from west to east, most pronounced in eastern Xinjiang and western Gansu.

4 Discussion

NDVI is an important indicator reflecting vegetation growth status and coverage, with significant implications for regional ecological monitoring, agricultural management, and environmental change. With the development of big data and artificial intelligence, there is an urgent need to re-examine geographical regionalization issues. Liu et al. [Figure 1: see original paper] reclassified China's eco-geographic regions, with the northwest arid eco-geographic region being one of the four basic geographical units. However, few studies have examined this region as a basic unit.

This study combined geographic detector with MGWR model to explore the main driving forces affecting NDVI in the region, quantitatively analyzing spatial differences across different driving factors at various scales, focusing on climate, terrain, soil, and human activity indicators. Human activities were primarily represented by nighttime light index, whose relationship with NDVI has been verified in relevant literature [Figure 1: see original paper]. Geographic detector results show that this trend is mainly driven by soil type, followed by precipitation and temperature, with natural variation explaining more than human factors. The northwest arid eco-geographic region accounts for 24.53% of China's land area, with nighttime light activities concentrated in 44.69% of the region, mainly along the Yellow River basins in Xinjiang, Ningxia, and Shanxi, with scattered distribution in most central areas. These findings align with reality.

In terms of spatial change trends, 75.31% of the region's vegetation has improved,

with 15.56% showing extremely significant increasing trends, likely benefiting from ecological measures implemented since the 21st century, such as the “Three North” Shelterbelt Program and Grain for Green Project, which have effectively promoted ecological construction and alleviated desertification.

The MGWR model, as a linear regression method, offers significant advantages in analyzing relationships between NDVI and climate factors. Han et al. [Figure 1: see original paper] analyzed the relationship between NDVI and climate factors in China using geographically weighted regression. However, GWR may produce false regression results when applied, requiring MGWR model improvement. Specifically, MGWR is superior to GWR in analyzing factor relationships, primarily due to its flexible bandwidth processing, allowing each independent variable to select optimal bandwidth based on spatial characteristics. This more accurately captures local relationships, fully considers scale dependence, and improves model explanatory power, making results better reflect the true spatial heterogeneity and non-stationarity characteristics of NDVI changes.

However, limited by few previous studies on this region, this study did not conduct accuracy validation, resulting in few comparable references and potentially lower credibility. Future research should further analyze this eco-geographic region. Additionally, due to data continuity and availability limitations, the representativeness of selected indicators needs clarification, particularly regarding the modifiable areal unit problem (MAUP) [Figure 1: see original paper]. This study only considered county scale in MGWR spatial heterogeneity analysis; relationships between NDVI and different spatial scales require further investigation.

5 Conclusions

- 1) **Temporal characteristics:** NDVI showed an overall increasing trend from 2003 to 2022, ranging from 0.1974 to 0.2464. The minimum occurred in 2009 and the maximum in 2018. Linear fitting and trend distribution revealed a significant positive correlation between NDVI and time, indicating effective ecological restoration.
- 2) **Spatial characteristics:** Most areas have relatively low NDVI levels, displaying a “high in east and west, low in middle” spatial pattern. This relates to environmental conditions: high elevation, low precipitation, extreme aridity, and poor soils unsuitable for vegetation growth.
- 3) **Variation characteristics:** Most areas show low stability in NDVI changes, with higher variability in the east and west and lower variability in the center. Areas with coefficient of variation $v > 0.1$ account for 62.74%, reflecting vegetation instability across most of the region, likely due to large-scale ecological projects causing extensive changes.
- 4) **Change trend:** Most regions show increasing trends, with only a few decreasing. Areas with extremely significant decreasing trends account for

only 1.05% in the central-western region. Non-significant increasing trends account for 49.30%, extremely significant increasing trends for 15.56%, and significant increasing trends for 10.45%. Overall, 75.31% of the region shows increasing trends, concentrated in the middle section of the “Three North” Shelterbelt Program.

- 5) **Driving forces:** Soil type is the dominant factor influencing NDVI spatial differentiation, followed by precipitation and potential evapotranspiration; nighttime light index has the weakest influence. The strongest interaction is between soil type and precipitation (explanatory power 0.62), while the weakest is between nighttime light index and elevation (0.31). MGWR analysis confirms soil type has the strongest effect, with temperature and potential evapotranspiration showing negative effects, precipitation and nighttime light index showing positive effects, and significant scale differences among factors. The influence of driving factors is not independent or simply additive but mutually reinforcing.

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