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From Barrenness to Lushness: Vegetation Greening of the Loess Plateau as Seen from Satellite Images and Its Implications for Urban Ecological Resilience

Mingrun Wang, Xin Yang*

School of Architecture and Art, North China University of Technology, Beijing 100144, China

***Corresponding author:** Xin Yang, bjyangxin@126.com

Abstract: Understanding vegetation dynamics in ecologically fragile regions is crucial for assessing the impacts of climate change. This study employed the kernel Normalized Difference Vegetation Index (kNDVI) to characterize the vegetation changes on the Loess Plateau from 2001 to 2022, analyzing its spatiotemporal trends, stability, and persistence, and quantitatively evaluating the environmental driving factors using the Geodetector method. The results showed a significant increasing trend in kNDVI, reflecting an improvement in vegetation coverage. The coefficient of variation (0.03–4.41) revealed significant spatial heterogeneity and low vegetation stability, while the Hurst exponent (0.21–0.77, with an average of 0.67) indicated strong persistence in vegetation changes. Climatic factors, especially the mean annual precipitation (MAP) and the aridity index, were the dominant drivers of kNDVI changes. There were significant interactions between climatic factors and biophysical and anthropogenic factors, particularly the interaction between MAP and vegetation type, topography, and land use change, which explained over 60% of the variation. These findings deepen the understanding of nonlinear vegetation-environment interactions and provide key insights for optimizing ecological policies on the Loess Plateau.

Keywords: Climate change; kNDVI; Vegetation dynamics; GeoDetector; Loess Plateau

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1. Introduction

Global climate change has had a profound impact on terrestrial ecosystems, making continuous vegetation monitoring crucial [1–2]. As a key component of the terrestrial system, vegetation is highly sensitive to climate change [3–4]. Therefore, understanding its spatiotemporal dynamics and driving factors has become a priority in ecology and environmental science [5–6].

The Loess Plateau is one of the most ecologically fragile regions in the world, with severe soil erosion, and is a sensitive indicator of climate change. Over the past two decades, large-scale ecological restoration projects, especially the "Grain for Green" program, have significantly increased vegetation coverage [7–8]. However, due to ongoing aridification and the decline in soil water retention capacity, its sustainability remains a challenge, which requires further quantitative analysis of the driving factors.

Satellite remote sensing provides a powerful tool for large-scale vegetation studies. Although the Normalized Difference Vegetation Index (NDVI) is widely used, it shows saturation in high-biomass areas and is sensitive to atmospheric and soil noise [9–10]. The Kernel Normalized Difference Vegetation Index (kNDVI), as a nonlinear extension of NDVI, enhances the sensitivity to vegetation changes and reduces saturation effects [11–13]. Despite these advantages, most studies on the Loess Plateau still rely on linear methods, which cannot fully capture the nonlinear interactions among driving factors [14]. The Geodetector, as a spatial heterogeneity analysis tool, overcomes this limitation by detecting dominant factors and their interactions [15]. Therefore, this study applies kNDVI and the Geodetector to: (1) analyze vegetation trends using Theil-Sen and Mann-Kendall methods; (2) assess stability and persistence through the coefficient of variation and Hurst exponent; (3) quantify natural and anthropogenic driving factors and their nonlinear interactions.

2. Materials and methods

2.1. Study area

The Loess Plateau (33°41′–41°16′N, 100°52′–114°33′E) covers ~640,000 km². The region shows a northwest–southeast gradient: wind-eroded landforms in the northwest and water-eroded gullies in the southeast. Annual precipitation declines from 650 mm to 250 mm, with an aridity index of 1.5–3.0. Six sub-regions are analyzed, as classified by Fu and Li [16].

2.2. Data sources

MODIS NDVI (MOD13Q1, 250m, 16-day) from 2001–2022 was processed on Google Earth Engine using the Maximum Value Composite method and Savitzky-Golay filtering. Driving factors include: climate variables (mean annual temperature [MAT], mean annual precipitation [MAP], aridity index [AI], mean annual potential evapotranspiration [MAPET]), vegetation type, landform, soil type, topography (elevation, slope, aspect), and anthropogenic factors (population density, PM2.5, land use/cover). Data were resampled to 1 km, and 99,375 random sampling points were generated after outlier removal.

2.3. Methods

kNDVI was computed as kNDVI = $\tanh(NDVI^2)$ [11]. Trend analysis used the Theil-Sen slope estimator and Mann-Kendall significance test. Vegetation stability was assessed by the coefficient of variation (CV), and persistence by the Hurst exponent (H) from rescaled range (R/S) analysis ($H>0.5$: persistence; $H<0.5$: anti-persistence). Geodetector's factor detection and interaction detection modules were applied, with q-statistic measuring explanatory power and interaction types classified as bivariate-enhanced or nonlinear-enhanced.

3. Results

3.1. kNDVI Dynamics

Compared to NDVI, kNDVI exhibited more pronounced spatial heterogeneity and effectively mitigated saturation in densely vegetated areas. The multi-year average kNDVI displayed a distinct southeast–high and northwest–low pattern. Low values (0–0.1) clustered in the Sandy Land region, while high values occurred in the Ziwuling and Qinling areas. From 2001 to 2022, kNDVI slopes ranged from -0.028 to 0.018; rapid increase areas covered 83.93% of the plateau, slow increase 13.26%, while rapid and slow decrease occupied 1.39% and 1.38%, mainly in irrigation and river valley plains. Annual mean kNDVI rose from 0.091 (2001) to 0.156 (2021), and all six sub-regions showed significant upward trends ($P<0.001$), with the Loess Hilly and Gully region exhibiting the fastest growth.

3.2. Stability and persistence

The vegetation coverage (CV) values range from 0.02 to 4.41, indicating a relatively low overall vegetation stability. Among them, the variability is relatively large in sandy areas, irrigated areas, and hilly and gully areas. The stable areas are mainly concentrated in the river valley plains and the mountainous areas with soil and rocks. The average Hurst index is 0.67 (ranging from 0.21 to 0.77); most of the plateaus show persistence ($H > 0.5$), indicating continuous greening, while anti-persistence is limited only to the northwest edge. Future predictions suggest that the key restoration areas will continue to grow, while small scattered areas in the irrigated areas and river valley plains may decline.

3.3. Driving forces

Factor detection in 2001, 2005, 2010, 2015, and 2020 indicated that all factors significantly affected kNDVI ($P < 0.01$). The average q value ranking was: annual average precipitation (0.498) > climate aridity index (0.399) > vegetation type (0.326) > topography (0.325) > soil type (0.286) > land use/land cover (0.281) > slope > annual average potential evapotranspiration > annual average temperature > PM2.5 > altitude > population density > aspect. In 2001, topography and vegetation type were dominant, but from 2005, annual average precipitation and climate aridity index became the dominant factors, which might be due to the gradual maturation of vegetation restoration. Interaction detection showed a continuous enhancement effect. The strongest interactions from 2005 to 2020 were between annual average precipitation and land use/land cover, annual average precipitation and vegetation type, annual average precipitation and topography, annual average precipitation and soil type, annual average precipitation and potential evapotranspiration, and annual average precipitation and altitude. Each interaction explained more than 60% of the variance in the normalized vegetation index (kNDVI), confirming significant nonlinear synergy (**Figure 1**).

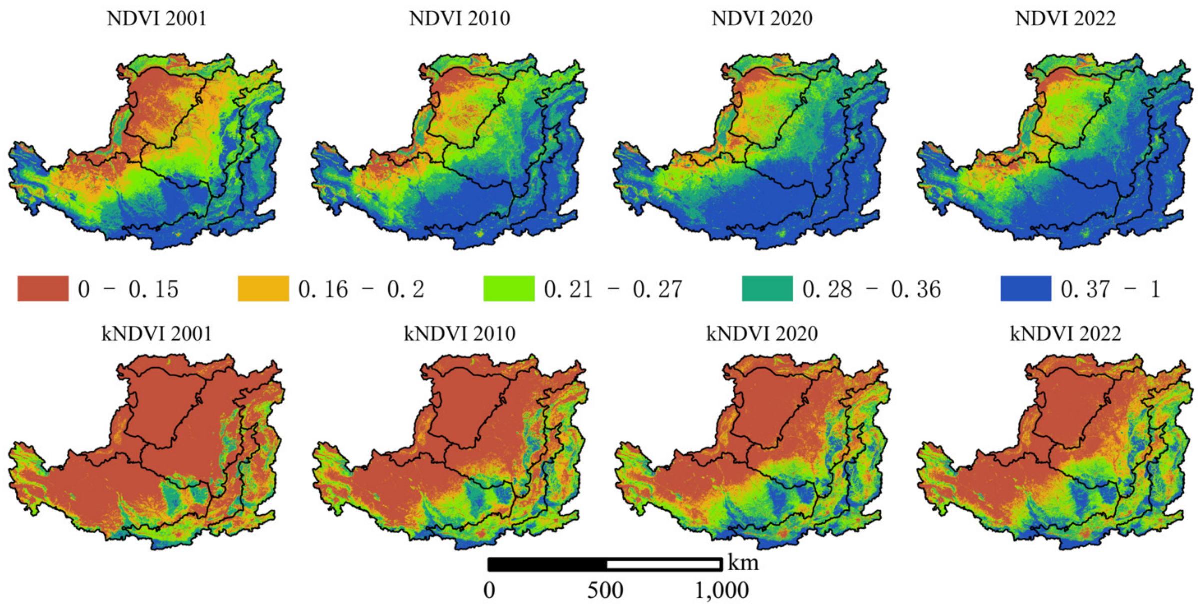

Figure 1. Spatial distribution of NDVl and kNDVl in 2001, 2010, 2020, and 2022

4. Discussion

The gradient of the normalized vegetation index (kNDVI) from northwest to southeast is consistent with the water and heat regime: the moist southeast has denser vegetation, while the arid northwest restricts vegetation growth. The extensive greening phenomenon observed in over 83% of the area aligns with the focus areas of national restoration projects, validating the effectiveness of these initiatives. The average annual precipitation (MAP) and aridity index, as the primary drivers, are in line with previous research findings [17–18]. Notably, the shift from terrain/vegetation dominance (2001) to climate dominance (after 2005) indicates that as vegetation communities mature, water and heat limitations become crucial. This highlights the necessity of climate-adaptive restoration strategies. Interaction analysis reveals that vegetation changes are caused by the combined effects of multiple factors; particularly, the persistent strong interaction between MAP and land use/land cover (LULC) suggests the interweaving of climate and human impacts [19]. Therefore, policy optimization should consider this coupling rather than isolated interventions. Limitations include the neglect of the effects of carbon dioxide fertilization and nitrogen deposition, as well as the potential shortness of the time series to capture long-term responses. Future research should integrate longer records and more biogeochemical variables [20].

5. Conclusions

This study demonstrates that kNDVI can effectively capture the dynamic changes of vegetation greening in the Loess Plateau from 2001 to 2022, and it is more sensitive. The main findings include: (1) A clear southeast-to-northwest gradient is presented, with rapid vegetation increase in 83.93% of the plateau area; (2) The overall vegetation stability is relatively low (with a coefficient of variation as high as 4.41), but the persistence is strong (with an average H value of 0.67); (3) Annual average precipitation and the aridity index are the main driving factors, explaining approximately 50% and 40% of the changes, respectively; (4) There is a significant nonlinear interaction between climatic factors and surface/human-induced variables, with an explanatory power exceeding 60%. These insights provide a scientific basis for climate-adaptive ecological restoration and sustainable land management in vulnerable regions.

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Disclosure statement

The authors declare no conflict of interest.

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