Quantitative Analysis of Climate Change and Human Activities on NDVI Changes in the Mu Us Sandy Land: Postprint

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Abstract

Climate change and human activities are the two key driving factors of vegetation dynamic changes. The Normalized Difference Vegetation Index (NDVI) is an effective indicator for assessing vegetation dynamic changes and can reasonably evaluate ecosystem changes and their sustainability. Based on SPOT/VEG ETATION NDVI time series data, meteorological data, and land cover data, and using methods such as GIS spatial analysis, correlation analysis, and residual analysis, this study explored the spatiotemporal evolution characteristics and driving mechanisms of NDVI in the Mu Us Sandy Land from 1998 to 2019, and determined the relative contribution rates of the two driving factors—climate change and human activities—to NDVI changes in the Mu Us Sandy Land. The results show that: (1) From 1998 to 2019, NDVI in the Mu Us Sandy Land increased at an overall rate of 0.0067 · a-1, with the spatial distribution exhibiting a gradually increasing trend from northwest to southeast. However, the overall persistence of NDVI growth was weak, and fluctuations may occur in the future. (2) Climate change and human activities jointly drove the NDVI increase in the Mu Us Sandy Land. Specifically, NDVI changes were significantly positively correlated with precipitation, but showed weaker correlation with temperature. The coupled driving of large-scale ecological engineering project implementation and climate factors contributed to 86.30% of vegetation improvement in the Mu Us Sandy Land, which is consistent with existing research conclusions on ecological construction project effectiveness. (3) Attribution analysis results indicate that human activities contributed to 83.20% of NDVI growth in the Mu Us Sandy Land, while precipitation drove 73.14% of NDVI growth, and the coupling effect between precipitation and human activities had a more significant impact on NDVI.

Full Text

Preamble

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Quantitative Analysis of NDVI Changes in Mu Us Sandy Land Driven by Climate Change and Human Activities

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Abstract: Climate change and human activities are the two key factors driving vegetation dynamics. The Normalized Difference Vegetation Index (NDVI) is an effective indicator for assessing vegetation dynamics, enabling reasonable evaluation of ecosystem changes and their sustainability. Based on SPOT/VEGETATION NDVI time series data, meteorological data, and land cover data, this study employs GIS spatial analysis, correlation analysis, and residual analysis to investigate the spatiotemporal evolution characteristics and driving mechanisms of NDVI in the Mu Us Sandy Land from 1998 to 2019, and quantifies the relative contribution rates of climate change and human activities to NDVI changes. The results show that: (1) From 1998 to 2019, NDVI in the Mu Us Sandy Land increased significantly at a rate of $0.0067 \cdot a^{-1}$, with a spatial distribution pattern gradually increasing from northwest to southeast. However, the overall sustainability of this growth was weak, indicating potential future fluctuations. (2) Both climate change and human activities jointly drove NDVI growth. NDVI changes showed significant positive correlation with precipitation, while correlation with temperature was weak. The implementation of large-scale ecological projects and their coupling with climatic factors drove vegetation improvement in 86.30% of the area, consistent with existing research conclusions on ecological project effectiveness. (3) Attribution analysis revealed that human activities contributed to 83.20% of NDVI growth, while precipitation contributed to 73.14%. The coupling effect of precipitation and human activities had a more significant impact on NDVI changes.

Keywords: Mu Us Sandy Land; vegetation NDVI; climate change; human activities; relative contribution rate

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1. Introduction

The Mu Us Sandy Land is a critical zone in China' s northern sand prevention belt, located in the transition zone between the North China warm-dry trend belt and the Northwest-Qinghai-Tibet Plateau warm-wet trend belt. Since the mid-20th century, excessive grazing, fuelwood collection, and other human disturbances have caused land degradation and desertification. In recent years, intensified climate change and extreme weather events have exacerbated these problems, reducing ecosystem services and biodiversity while severely impacting the natural environment, agricultural activities, and regional economic development. As vegetation degradation and land desertification have become severe in the Mu Us Sandy Land, grassland productivity has declined and the conflict between forage and livestock has become increasingly prominent.

Since 2000, China has gradually implemented a series of ecological projects including grazing withdrawal, returning farmland to forest, and grassland ecological compensation policies to reduce grazing pressure on natural grasslands and promote vegetation restoration. Monitoring vegetation dynamics not only provides accurate, timely, and comprehensive information on desertification land changes but also enables evaluation and prediction of ecological project effectiveness. Vegetation exhibits significant interannual and seasonal variations, and under land-atmosphere interactions, it can represent surface land cover changes to a certain extent, serving as an "indicator" of global change. Therefore, monitoring vegetation dynamics to some extent reflects climate change trends.

Commonly used monitoring indicators for vegetation dynamics include NDVI, Net Primary Productivity (NPP), and Fractional Vegetation Cover (FVC). Among these, NDVI effectively characterizes vegetation coverage and growth status and is widely used as a proxy for aboveground vegetation productivity. Due to its wide coverage, high monitoring sensitivity, low noise, and broad data sources, NDVI is considered the most accurate indicator for reflecting vegetation dynamics. Climate change and human activities are the two primary factors driving vegetation dynamics. The implementation of returning farmland to forest and grazing withdrawal projects has significantly improved NDVI in the Mu Us Sandy Land, with human activities becoming the main factor influencing NDVI changes. The eastward expansion of the "warm-wet" climate pattern in Northwest China has enhanced the effectiveness of ecological projects and promoted vegetation restoration. Human activities can also determine vegetation dynamics in specific regions.

Distinguishing the contribution rates of human activities and climate change to ecological project effectiveness is important not only for monitoring and evaluating ecological project outcomes but also for further clarifying carbon source-sink change mechanisms. Therefore, this study uses 1998 as the baseline year before ecological restoration project implementation. Through remote sensing image analysis, it examines the spatiotemporal distribution of vegetation NDVI before and after ecological project implementation, analyzes vegetation responses to climate change based on temperature and precipitation data, and employs trend analysis and residual analysis to examine vegetation change trends and relative contribution rates. The aim is to clarify the driving mechanisms of climate change and human activities on vegetation growth in the Mu Us Sandy

Land, providing scientific basis for evaluating ecological project effectiveness and formulating ecological environment restoration measures.

1.1 Study Area Overview

The Mu Us Sandy Land (107°20 -111°30 E, 37°27.5 -39°22.5 N) is one of China's four major sandy lands, located in the central part of the northern China agro-pastoral ecotone, in the transition zone between the Ordos Plateau and the Loess Plateau. It serves as an important ecological barrier in northern China, with an overall topography sloping from northwest to southeast at elevations ranging from 255–1948 m and covering an area of 4.22$\times10^{4}$ km^{2}. The region belongs to a typical continental monsoon climate with annual precipitation of 150–500 mm (higher in the southeast than northwest) and mean annual temperature of 6.5–10.3°C (decreasing from southeast to northwest). According to the 1:1,000,000 China Vegetation Atlas, local vegetation types can be divided into nine categories: grassland, cultivated vegetation, swamp, shrubland, broadleaf forest, steppe, meadow, desert, and others. The southern and southeastern parts of the Mu Us Sandy Land are dominated by loess hilly terrain with complex and diverse climate conditions, primarily covered by broadleaf forest with significantly better vegetation growth than other areas. The central and eastern parts belong to dry steppe, while the northern edge belongs to desert steppe, where shrubland and cultivated vegetation are distributed. Scarce precipitation severely affects regional vegetation growth conditions.

Note: Based on the standard map from the Ministry of Natural Resources Standard Map Service website (Approval No. GS(2022)1873), with no modifications to base map boundaries. The same applies below.

[Figure 1: see original paper] Distribution of vegetation types in Mu Us Sandy Land

1.2 Data Sources

Remote sensing data were obtained from SPOT VEGETATION NDVI images in the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/), with a spatial resolution of 1 km. The Maximum Value Composite (MVC) method was used to generate annual NDVI data to eliminate interference from aerosols, clouds, shadows, and solar elevation angles.

Meteorological data were obtained from the National Meteorological Science Data Center (http://data.cma.cn/), including monthly precipitation and temperature data from meteorological stations in and around the Mu Us Sandy Land, with a temporal resolution of 1 year. To ensure data completeness, meteorological data from 25 national meteorological stations within and adjacent to the Mu Us Sandy Land were selected. Kriging interpolation was performed in ArcGIS to obtain meteorological data for missing stations, generating precipitation and temperature raster data with the same spatial resolution as NDVI data.

1.3 Methods

1.3.1 Trend Analysis Linear regression is widely used to analyze spatial change trends in vegetation cover. A unary linear regression formula was used to fit the slope (S) of NDVI for each pixel over n years, obtaining the spatial change trend of NDVI pixels over n years. The calculation formula is:

$$S = \frac{n\sum_{i=1}^{n} i \times NDVI_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} NDVI_i}{n\sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where $NDVI_i$ is the annual average NDVI in year i, and n is the study period length. F-test was used for significance testing. The calculation formula is:

$$F = \frac{\sum_{i=1}^{n} (\widehat{y_i} - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \widehat{y_i})^2/(n-2)}$$

where y_i is the NDVI in year i, $\widehat{y_i}$ is the linear regression value, and $\bar{y}$ is the average NDVI during the study period. t-test was selected for significance testing, with results categorized as: extremely significant decrease (S < 0, P < 0.01), significant decrease (S < 0, 0.01 < P < 0.05), extremely significant increase (S > 0, P < 0.01), significant increase (S > 0, 0.01 < P < 0.05), and non-significant change (P > 0.05).

The change magnitude (E) represents the NDVI change direction over time. When E > 0, it indicates an increasing trend, with larger values indicating faster increase; conversely, it indicates decrease. The calculation formula is:

$$E = S \times n$$

1.3.2 Hurst Index The Hurst index is an effective method for quantitatively describing long-term dependence in time series. The calculation formula is:

$$R(t)/S(t) = Ct^H$$

where for any positive integer t (t ≤ n), the time series NDVI_i defines the mean sequence as $N(t)_m = \frac{1}{t}\sum_{i=1}^{t} NDVI_i$, the cumulative deviation as $X(t)_i = \sum_{i=1}^{t}(NDVI_i - N(t)_m)$, the range as $R(t) = \max_{1\le i\le t} X(t)_i - \min_{1\le i\le t} X(t)_i$, and the standard deviation as $S(t) = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(NDVI_i - N(t)_m)^2}$. The difference sequence is $\Delta N_i = NDVI_i - NDVI_{i-1}$. If $R(t)/S(t) \propto t^H$, the time series NDVI_i exhibits Hurst phenomenon. When H > 0.5, the time series has persistence; when H < 0.5, it has anti-persistence.

1.3.3 Partial Correlation Analysis Partial correlation analysis examines the correlation between two factors while eliminating the influence of other variables. This study used partial correlation analysis to analyze the relationship between NDVI and precipitation and temperature in the Mu Us Sandy Land. The calculation formula is:

$$r_{xy,z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}}$$

where $r_{xy,z}$ is the partial correlation coefficient between x and y controlling for z; r_{xy}, r_{xz}, and r_{yz} are linear correlation coefficients between x and y, x and z, and y and z, respectively. Results were categorized as: non-significant positive correlation ($r > 0$, $P > 0.05$), non-significant negative correlation ($r < 0$, $P > 0.05$), significant positive correlation ($r > 0$, $P < 0.05$), and significant negative correlation ($r < 0$, $P < 0.05$).

1.3.4 Multiple Regression Residual Analysis Residual trend analysis is the most representative method for quantitatively distinguishing the relative contributions of human activities and climate change to vegetation changes. It can effectively clarify their relative contributions and is suitable for long-term sequence analysis. This method assumes that vegetation growth is determined by climate change. First, ordinary least squares regression is used to establish the relationship between NDVI and climate factors. The equation residuals are considered ecosystem productivity changes caused by human activities. Positive residuals indicate that human factors (such as ecological projects) drive vegetation improvement, while negative residuals indicate that human activities cause vegetation degradation. The specific calculation formula is:

$$NDVI_{pred} = aT + bP + c$$

$$NDVI_{res} = NDVI_{obs} - NDVI_{pred}$$

where $NDVI_{pred}$, $NDVI_{obs}$, and $NDVI_{res}$ are the predicted, observed, and residual NDVI values, respectively; a, b, and c are regression coefficients for mean annual temperature, annual precipitation, and constant term, respectively; T is mean annual temperature (°C); and P is annual precipitation (mm).

To better measure the impacts of climate change and human activities on NDVI changes, based on the change trends of NDVI affected by climate change and human activities, the driving factors were divided into six categories: climate change and human activities both promoting NDVI increase, climate change promoting and human activities inhibiting, climate change inhibiting and human activities promoting, both inhibiting, and basically no impact. Additionally, based on distinguishing vegetation driving factors, the relative contribution rates of each driving factor to NDVI changes were calculated through residual analysis (Table 1).

Determination of the driving factors of climate change and human activities on NDVI vegetation in Mu Us Sandy Land and the calculation method of contribution rate

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2 Results

2.1 Spatiotemporal Variation Characteristics and Trend Analysis of NDVI in Mu Us Sandy Land

From 1998 to 2019, NDVI in the Mu Us Sandy Land showed an overall increasing trend with interannual fluctuations. F-test results indicated that NDVI increased extremely significantly at a rate of $0.0067 \cdot a^{-1}$. Using 1998 as the evaluation baseline year, vegetation growth conditions were relatively poor, while conditions were relatively good in 2019, with the best growth occurring in 2018. Interannual trend analysis showed that NDVI in the Mu Us Sandy Land tended to improve, increasing significantly at a rate of $0.0067 \cdot a^{-1}$ (Fig. 2).

[Figure 2: see original paper] Interannual change trend of average NDVI in Mu Us Sandy Land from 1998 to 2019

The spatial distribution map of NDVI (Fig. 3) shows that NDVI in the Mu Us Sandy Land generally increased. However, due to differences in hydrothermal conditions and vegetation types across locations, NDVI showed significant spatial differentiation, gradually increasing from northwest to southeast. High-value areas were concentrated in the southern Mu Us Sandy Land (Jingbian County, Dingbian County, Shenmu City, and Hengshan District), while low-value areas were distributed in the central and northwestern parts (Otog Banner, Uxin Banner, and Otog Front Banner). The spatial distribution of NDVI change trend types (Fig. 4) shows that areas with increasing trends accounted for 95.25% of the total area, mainly distributed in the eastern Mu Us Sandy Land. Areas with decreasing trends accounted for a relatively small proportion of 4.75%, primarily showing non-significant decreases and distributed in the northwestern Mu Us Sandy Land. Areas with severe vegetation degradation were minimal and scattered, accounting for only 0.86% and distributed as scattered points in central Yuyang District, northwestern Otog Banner, central Otog Front Banner, western Shenmu City, and central Jingbian County.

From the perspective of vegetation types, significant differences existed in average NDVI among different vegetation types, specifically 表现为 grassland (0.34), cultivated vegetation (0.40), shrubland (0.35), and broadleaf forest (0.48). Statistical results of area proportion changes for each vegetation type (Table 2) show that steppe had the largest area proportion at 43.88%, followed by cultivated vegetation at 16.38%. This is mainly related to the implementation of large-scale ecological projects in the Mu Us Sandy Land in recent years.

Area proportions of NDVI changes of each vegetation type in Mu Us Sandy Land

Hurst index analysis results (Fig. 5) show that 30.09% of the Mu Us Sandy Land exhibited anti-persistence, while 63.99% showed persistence, indicating that the sustainability of NDVI change trends was stronger than anti-persistence. From the spatial distribution proportion of Hurst index, areas with potential degradation trends were larger than those with continuous improvement. Coupling and overlaying NDVI change magnitude with Hurst index can analyze the sustainability of change trends. Areas where change magnitude showed increasing trends while Hurst index indicated anti-persistence accounted for 63.99%, suggesting that although these areas still showed increasing trends, they were opposite to past trends, meaning future changes would have no correlation with past trends. Areas with continuous improvement accounted for 30.09%. Areas with continuous degradation and anti-persistent degradation accounted for 1.18% and 4.74%, respectively. The Mu Us Sandy Land had weak and relatively weak persistence accounting for 94.38% of the area, indicating an overall weak continuous improvement trend.

Area proportions of persistence regions of NDVI change trends in Mu Us Sandy Land

[Figure 3: see original paper] Spatial distributions of NDVI in Mu Us Sandy Land in 1998, 2009 and 2019

[Figure 4: see original paper] Spatial distribution of NDVI change trends in Mu Us Sandy Land from 1998 to 2019

[Figure 5: see original paper] Spatial distribution of NDVI Hurst index in Mu Us Sand Land

[Figure 6: see original paper] Spatial distribution of persistence regions of NDVI change trends in Mu Us Sand Land

2.2 Driving Mechanism Analysis of NDVI Changes in Mu Us Sandy Land

NDVI in the Mu Us Sandy Land was positively correlated with precipitation and negatively correlated with temperature ($P < 0.05$). Among these, areas with significant positive correlation with precipitation were mainly concentrated in Shenmu City, Yuyang District, Hengshan District, Jingbian County, and Yijinhuoluo Banner, accounting for 73.14% of the total area. Areas with significant negative correlation with precipitation were sporadically distributed in central-southern Yuyang District, northern Hengshan District, eastern Uxin Banner, and northern Otog Banner, accounting for only 0.61% of the area.

Partial correlation analysis results (Fig. 7) show that areas where human activities promoted NDVI increase accounted for 83.20% of the total area, mainly distributed in Yijinhuoluo Banner, Shenmu City, Yuyang District, Hengshan

District, Uxin Banner, Jingbian County, Dingbian County, and Yanchi County. In these areas, the implementation of ecological projects and implementation of ecological protection policies promoted vegetation growth. The area proportion where human activities had negative effects on NDVI was only 9.53%, mainly distributed in western Otog Banner (Fig. 8). Referring to the desertification land control zoning in the Mu Us Sandy Land, western Otog Banner has functions of mineral exploitation, agriculture and animal husbandry development, and desertified grassland ecological construction. In some areas such as Qipanjing mining area, rich natural gas, oil, coal, and clay resources have led to functions of coal mining and building material processing. Intense human development activities have caused desertification and weakened vegetation stability.

Area proportion of partial correlation regions of NDVI with precipitation and temperature in Mu Us Sandy Land

[Figure 7: see original paper] Spatial distributions of partial correlation regions of NDVI with precipitation and temperature in Mu Us Sandy Land

Overall, NDVI in the Mu Us Sandy Land showed non-significant negative correlation with temperature. Among these, areas with significant positive correlation with temperature were distributed as points in the central Mu Us Sandy Land, sporadically in northern Dingbian and Jingbian counties, southern Otog Front Banner, and southern and central Uxin Banner, as well as western Yuyang District, accounting for only 0.72% of the area. Areas with significant negative correlation with temperature were mainly distributed in eastern Shenmu City, accounting for 7.69% of the area.

As shown in Fig. 8, NDVI increase in the Mu Us Sandy Land was driven by the combined effects of climate change and human activities in 86.3% of the area, while NDVI decrease driven by both factors accounted for 10.82% of the area, mainly distributed in western Otog Banner and Otog Front Banner. Areas driven solely by climate change to increase NDVI accounted for 0.31%, distributed sporadically; areas driven solely by human activities to increase NDVI accounted for 0.81%, distributed as points in central Mu Us Sandy Land. Areas driven solely by climate change to decrease NDVI accounted for 0.10%, distributed dispersedly; areas driven solely by human activities to decrease NDVI accounted for 2.46%, mainly distributed in Otog Banner and Otog Front Banner. Overall, the combined effects of climate change and human activities dominated vegetation improvement in the Mu Us Sandy Land.

Area proportions of NDVI change regions effected by climate changes and human activities in Mu Us Sandy Land

[Figure 8: see original paper] Spatial distributions of NDVI change regions effected by climate changes and human activities in Mu Us Sandy Land

2.3 Relative Contributions of Different Driving Factors to Vegetation NDVI Changes

Residual analysis can distinguish the relative contributions of climate change and human activities to NDVI changes. As shown in Fig. 9, the area where climate change contributed positively to NDVI changes accounted for 94.38% of the total area. Among these, areas with climate change contribution rates of 20%-60% accounted for 53.39% of the total area, mainly distributed in western Otog Banner and Otog Front Banner. The area where climate change contributed negatively to NDVI changes accounted for 5.62%, concentrated in northwestern Otog Banner and Otog Front Banner.

As shown in Fig. 10, the area where human activities contributed positively to NDVI changes accounted for approximately 88.09% of the total area. Among these, areas with contribution rates of 40%-60% had the largest area proportion at 48.08%, with spatial distribution similar to but relatively smaller than that of climate change.

Comparison of relative contribution rates showed that the relative contribution rate of human activities (52.67%) was significantly higher than that of climate change (47.33%).

Area proportions of driving factors of NDVI changes in Mu Us Sandy Land

Area proportions of the relative contribution rates of climate changes and human activities to NDVI changes in Mu Us Sandy Land

[Figure 9: see original paper] Spatial distribution of driving factors of NDVI changes in Mu Us Sandy Land

[Figure 10: see original paper] Spatial distributions of the relative contribution rate of climate changes and human activities on NDVI changes in Mu Us Sandy Land

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3 Discussion

3.1 Spatiotemporal Change Trends of NDVI in Mu Us Sandy Land

From 1998 to 2019, NDVI in the Mu Us Sandy Land showed an overall increasing trend with an annual growth rate of $0.0067 \cdot a^{-1}$. The spatial pattern presented as southeast-high and northwest-low, consistent with research conclusions by Wang et al. High-value areas ($\mathrm{NDVI} > 0.40$) were concentrated continuously in the southeastern Mu Us Sandy Land, showing significant consistency with the precipitation pattern. This is mainly because this region is a key implementation area for sand prevention and control, returning farmland to forest, and natural forest protection projects, which have effectively curbed the southward expansion of the Mu Us Sandy Land. Low-value areas were distributed in the central and northwestern parts. Temporally, NDVI showed a significant linear increasing trend with interannual fluctuations, possibly related to differences in ecological project implementation categories and years as well as climate fluctuations. Persistence analysis results indicated that the future evolution trend of NDVI in the Mu Us Sandy Land showed weak anti-persistence, with potential degradation risks due to continuous drought. Analysis of future NDVI changes, spatial distribution differences, and temporal variation characteristics can provide theoretical basis for major ecological restoration evaluation and future vegetation protection policy formulation, and help determine the rationality of new ecological protection policies.

3.2 Driving Mechanism Analysis of NDVI Dynamic Changes in Mu Us Sandy Land

Climate and human activities are the basic driving forces controlling and influencing vegetation spatial distribution and its changes. In this study, climate change drove NDVI increase in 93.12% of the area. Among these, precipitation had high explanatory power for spatial distribution, driving NDVI increase in 73.14% of the area. Correlation analysis between NDVI and precipitation showed that interannual NDVI fluctuations were basically consistent with precipitation fluctuations, indicating that vegetation is more sensitive to interannual precipitation changes, consistent with Zhou et al.' s conclusion about the most significant correlation between warm desert steppe NDVI and precipitation. NDVI fluctuations showed a basically negative correlation with temperature, mainly because warming intensified drought and inhibited vegetation growth, even causing withering and death of local artificial vegetation due to soil dry layers. Against the background of climate warming, drought frequency, duration, intensity, and impact range have shown significant increasing trends. However, the occurrence of drought events has not changed the increasing trend of NDVI in the Mu Us Sandy Land, possibly attributable to ecological restoration projects such as returning farmland to forest and grassland implemented since 2000.

Pixel-scale analysis revealed that human activities promoted NDVI changes in 83.20% of the area. Among these, vegetation in the southeastern Mu Us Sandy Land was significantly improved under the coupling effects of precipitation and human activities, and land desertification was controlled. With the implementation of large-scale ecological projects and grazing prohibition policies, the negative impact of human activities on NDVI in the Mu Us Sandy Land gradually weakened. In local areas such as the Qipanjing mining area in western Otog Banner, rich coal and mineral resources have led to long-term and rapid expansion of mining activities, causing serious land compression, landscape destruction, and weak vegetation stability, with land desertification and soil erosion problems. Strengthening human activity control and coordinating economic development with environmental protection are needed. Under the combined effects of climate change and human activities, NDVI in the Mu Us Sandy Land has been greatly improved.

Climate change is a key controlling factor for vegetation growth, but the implementation of ecological restoration projects has also played an important role in rapid vegetation recovery. Given the spatial heterogeneity of climate factors and human activities, their contribution rates to NDVI impacts show significant spatial differentiation. Specifically, climate change dominated vegetation improvement in 94.38% of the area, while human activities dominated vegetation improvement in 88.09% of the area. Climate factors and human activities jointly dominated vegetation improvement in 86.30% of the area. However, different vegetation types showed spatial differentiation in their response degree to climate change. Areas with significant improvement trends were mainly distributed in the southeastern region with better precipitation conditions rather than desert areas with less precipitation, consistent with Zhang et al.' s attribution analysis results of vegetation changes in Northwest China. Positive human activities such as converting farmland to forestland, water-saving irrigation, fenced grazing, grazing prohibition, returning farmland to forest, especially large-scale center-pivot sprinkler irrigation operations in agriculture, forestry, and animal husbandry, not only effectively alleviated water resource constraints on regional vegetation restoration but also promoted large-scale NDVI increase. Negative human activities such as urban expansion, mineral resource exploitation, and illegal grazing caused local NDVI degradation in the Mu Us Sandy Land.

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4 Conclusions

(1) From 1998 to 2019, NDVI in the Mu Us Sandy Land showed a significant increasing trend with an average annual growth rate of $0.0067 \cdot \mathrm{a}^{-1}$, characterized by vegetation improvement area (95.25%) far greater than vegetation degradation area (4.25%). Spatially, NDVI showed a gradually increasing trend from northwest to southeast.

(2) The coupling effect of climate change and human activities jointly drove NDVI growth in the Mu Us Sandy Land. Precipitation had a more significant impact on NDVI than temperature. The coupling of human activities and climate factors drove vegetation improvement in 86.30% of the area, consistent with existing research conclusions on ecological project effectiveness. Some negative human activities drove local vegetation degradation, but the trend has slowed.

(3) The coupling effect of climate change and human activities had a more significant impact on NDVI in the Mu Us Sandy Land. Human activities promoted NDVI growth in 83.20% of the area, while precipitation among climate factors had high explanatory power for spatial distribution, driving NDVI increase in 73.14% of the area.

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Quantitative analysis of NDVI changes in Mu Us Sandy Land by climate change and human activities

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