Impacts of Climate Change and Human Activities on Vegetation Net Primary Productivity in Yanchi County (Postprint)

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Abstract

To quantitatively distinguish the relative contributions of climate change and human activities to vegetation dynamics in the typical agro-pastoral ecotone of northern China under the context of the Grain for Green Program, this study examined vegetation changes in Yanchi County, Ningxia from 2000 to 2020. Based on MODIS13Q1-NDVI data, land cover data, and meteorological data, the Thornthwaite Memorial Model and the CASA (Carnegie-Ames-Stanford Approach) model were employed to estimate annual Potential Net Primary Productivity (PNPP) and Actual Net Primary Productivity (ANPP), respectively. Comprehensive trend analysis, correlation analysis, and difference comparison methods were utilized to analyze the spatiotemporal variation characteristics of Net Primary Productivity (NPP) and its driving forces in Yanchi County from 2000 to 2020, and to quantitatively determine the relative contributions of climatic factors and human activities to vegetation changes in Yanchi County. The results indicate that: (1) From 2000 to 2020, NPP in Yanchi County exhibited an overall increasing trend, but with significant spatial heterogeneity, primarily manifested as the area of vegetation NPP improvement being substantially greater than that of NPP degradation, and the degree of improvement or degradation also showing significant spatial differentiation. Vegetation improvement areas were mainly distributed in desert, desert steppe, and other regions under the Grain for Green Program and irrigation districts, while vegetation degradation areas were located at the edges of desert and desert steppe. (2) Attribution analysis of vegetation changes revealed that in vegetation improvement areas, both climate change and human activities jointly drove vegetation improvement, but the relative contribution of climate change (59.77%) was greater than that of human activities (40.23%). In contrast, in vegetation degradation areas, the relative contribution of human activities (91.77%) was significantly higher than that of climate change (8.23%). (3) Driving force analysis indicated that vegetation NPP changes in the study area were significantly positively correlated with precipitation, but weakly correlated with temperature. Human activities were the primary cause driving NPP decline in vegetation degradation areas, although their negative influence has weakened. Overall, climate change was the main driving force in vegetation improvement areas, while human activities were the main driving factor in vegetation degradation areas, and their combined effects led to the overall improvement of the ecological environment in Yanchi County.

Full Text

Effects of Climate Change and Human Activities on Vegetation Net Primary Productivity in Yanchi County

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Abstract: This study aims to quantitatively differentiate the relative contributions of climate change and human activities to vegetation dynamics in the typical agricultural-pastoral ecotone of northern China under the context of the Grain-for-Green Program. Taking Yanchi County in Ningxia as the study area, we simulated annual potential net primary productivity (PNPP) and actual net primary productivity (ANPP) from 2000 to 2020 using MODIS13Q1-NDVI data, land cover data, and meteorological data, employing the Thornthwaite Memorial and Carnegie-Ames-Stanford Approach (CASA) models. We analyzed the spatiotemporal variation characteristics of net primary productivity (NPP) and its driving forces using trend analysis, correlation analysis, and difference comparison methods, and quantitatively determined the relative contribution rates of climatic factors and human activities to vegetation changes in Yanchi County. The results indicate that: (1) NPP in Yanchi County showed an overall increasing trend from 2000 to 2020, but with significant spatial heterogeneity. The area of vegetation improvement far exceeded that of degradation, though both exhibited substantial spatial differentiation. Improved vegetation was primarily distributed in desert and desert steppe areas under the Grain-for-Green Program and in irrigation districts, while degraded vegetation occurred mainly at the margins of desert and desert steppe zones. (2) Attribution analysis revealed that in vegetation-improved areas, climate change contributed 59.77% while human activities contributed 40.23%. In contrast, in vegetation-degraded areas, human activities accounted for 91.77% of the relative contribution, significantly exceeding climate change' s 8.23%. (3) Driving force analysis showed that vegetation NPP was significantly positively correlated with precipitation but weakly correlated with temperature. Human activities were the primary driver of vegetation degradation, though their negative impact has weakened.

Overall, climate change is the main driving force for vegetation improvement, while human activities dominate vegetation degradation, with their combined effects leading to overall ecological environment improvement in Yanchi County.

Keywords: net primary productivity (NPP); desert steppe; vegetation change; driving force; Yanchi County

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1 Study Area Overview

Yanchi County is located in eastern Ningxia (37°04 -38°10 N, 106°30 -107°47 E), covering a land area of 6,749 km^2 (10.16% of Ningxia' s total area). Geomorphologically, it lies in the transition zone from the Ordos Plateau to the Loess Plateau. Climatically, it represents a transition from arid to semi-arid regions and from steppe to desert, characterized by a mid-temperate continental climate with perennial drought, low rainfall, strong winds, and abundant sand. The county receives 250–350 mm of annual precipitation (primarily concentrated in July–September), has an annual mean temperature of 8.1°C, and experiences annual evaporation of 2,200 mm. Prevailing winds are westerly and northwesterly. The zonal soils are primarily sierozem and aeolian sandy soils with loose structure and low fertility, susceptible to wind and water erosion. Based on the 1:1,000,000 Vegetation Atlas of China, local vegetation can be classified into six types: typical steppe, desert steppe, desert, grain and economic crops, deciduous shrubland, and meadow (Figure 1).

2.1 Data Sources

2.1.1 NDVI Data We used the Normalized Difference Vegetation Index (NDVI) as a key indicator to analyze spatiotemporal dynamics of grassland vegetation in the study area. NDVI data were obtained from the Level-1 and Atmosphere Archive & Distribution System Distributed Active Archive Center (LAADS DAAC). Specifically, we used the MOD13Q1 dataset (250 m spatial resolution, 16-day temporal resolution) for 2000–2020. Monthly maximum NDVI composites were generated using the Maximum Value Composition (MVC) method. For validation, we used the MOD17A3HGF dataset (500 m spatial resolution) from the same time series to verify the accuracy of NPP simulations.

2.1.2 Meteorological Data Meteorological data were obtained from the China Meteorological Data Network (http://data.cma.cn/). We selected data from four meteorological stations in and around Yanchi County, including monthly precipitation, mean temperature, sunshine percentage, and geographic coordinates for 2000–2020. Using the Kriging interpolation method in ArcGIS

10.2 Geostatistical Analyst, we interpolated meteorological data based on station coordinates.

2.1.3 Land Cover Data Land cover data were derived from the GlobeLand30 dataset, a key product of China's National High-Tech Research and Development Program (863 Program) for global land cover mapping. The dataset has a 30 m spatial resolution and covers 2000–2020. All input parameters for the models were transformed to the WGS 84 Albers equal-area conic projection coordinate system, resampled to match the spatial resolution of the NDVI data, and clipped to the study area boundaries.

2.2 Methods

2.2.1 Actual Net Primary Productivity (ANPP) We estimated ANPP using the improved CASA model developed by Zhu Wenquan et al. This light use efficiency model, driven by vegetation cover type and meteorological data, has been widely applied for ecosystem productivity and soil carbon simulation. ANPP is determined by absorbed photosynthetically active radiation (APAR) and light use efficiency ( ):

$$ANPP(x,t) = APAR(x,t) \times \varepsilon(x,t)$$

where $APAR(x,t)$ is the absorbed photosynthetically active radiation (g C $\cdot$ m^{-2} $\cdot$ month^{-1}) and $\varepsilon(x,t)$ is the actual light use efficiency (g C $\cdot$ MJ^{-1}) for pixel x in month t.

APAR is calculated as:

$$APAR(x,t) = SOL(x,t) \times FPAR(x,t) \times 0.5$$

where $SOL(x,t)$ is the total solar radiation (MJ $\cdot$ m^{-2} $\cdot$ month^{-1}), $FPAR(x,t)$ is the fraction of photosynthetically active radiation absorbed by vegetation, and 0.5 represents the proportion of effective solar radiation in the 0.38–0.71 m wavelength range.

Total solar radiation was calculated using the formula for western China:

$$SOL(x,t) = SOL_0(x,t) \times (0.185 + 0.595 \times S(x,t))$$

where $SOL_0(x,t)$ is the astronomical radiation (MJ $\cdot$ m^{-2} $\cdot$ month^{-1}) and $S(x,t)$ is the sunshine percentage.

FPAR has a linear relationship with NDVI:

$$FPAR(x,t) = \frac{NDVI(x,t) - NDVI_{i,min}}{NDVI_{i,max} - NDVI_{i,min}} \times (FPAR_{max} - FPAR_{min}) + FPAR_{min}$$

where $NDVI(x,t)$ is the monthly NDVI value, $NDVI_{i,max}$ and $NDVI_{i,min}$ are the maximum and minimum NDVI values for vegetation type i, and $FPAR_{max}$ and $FPAR_{min}$ are constants (0.95 and 0.001, respectively).

Actual light use efficiency is calculated as:

$$\varepsilon(x,t) = T_{\varepsilon 1}(x,t) \times T_{\varepsilon 2}(x,t) \times W_{\varepsilon}(x,t) \times \varepsilon_{max}$$

where $T_{\varepsilon 1}$ and $T_{\varepsilon 2}$ are temperature stress coefficients, W_{ε} is the water stress coefficient, and ε_{max} is the maximum light use efficiency under ideal conditions. ε_{max} values for different vegetation types follow those proposed by Zhu et al.

2.2.2 Potential Net Primary Productivity (PNPP) We estimated PNPP using the Thornthwaite Memorial model, a widely accepted empirical model based on least-squares regression between measured NPP data and temperature and precipitation:

$$PNPP = 3000 \times \left[1 - e^{-0.0009695 \times (v-20)}\right] \times \left[1 + 1.05 \times \frac{r}{L}\right]$$

where $v = 3000 + 25t + 0.05t^3$ is the annual mean evapotranspiration (mm), r is annual total precipitation (mm), t is annual mean temperature (°C), and L is annual mean actual evapotranspiration (mm).

2.2.3 Difference Comparison Method The difference comparison method directly reflects vegetation changes in ecological environments and determines the relative roles of different factors. The difference between PNPP and ANPP represents the change in NPP due to human activities (HNPP):

$$HNPP = PNPP - ANPP$$

where PNPP is potential NPP, ANPP is actual NPP, and HNPP is the change under human influence. The sign of HNPP indicates the direction of human impact: positive values indicate human-induced NPP reduction, while negative values indicate human-induced NPP increase. To analyze the trend and direction of human impacts, we superimposed the sign and trend of HNPP following the method of Zhou Yanyan et al.

2.2.4 NPP Interannual Change Rate NPP dynamics directly reflect vegetation improvement or degradation. We calculated interannual trends using least-squares linear regression:

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

where n is the number of years and NPP_i is the NPP value in year i. A positive Slope indicates an increasing trend. We used F-test to verify significance:

$$F = \frac{\sum_{i=1}^{n}(\hat{x}_i - \bar{x})^2}{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2/(n-2)}$$

where x_i is the NPP value in year i, $\hat{x}_i$ is the regression value, and $\bar{x}$ is the mean NPP. Based on the F-test, trends were classified as: extremely significant improvement (Slope > 0, $P \leq 0.01$), significant improvement (Slope > 0, $0.01 < P \leq 0.05$), no significant change, significant degradation (Slope < 0, $0.01 < P \leq 0.05$), and extremely significant degradation (Slope < 0, $P \leq 0.01$). The total change in NPP over the study period was calculated as $\Delta NPP = (n-1) \times Slope$.

2.2.5 Quantitative Attribution Assessment Method To differentiate the relative contributions of climate change and human activities to vegetation improvement or degradation, we calculated the change trends of PNPP and HNPP. Following Liu Bin et al.' s scenario framework, we defined four scenarios (Table 1) to calculate the relative contribution rates of climate change and human activities to vegetation changes.

Table 1 Methods for assessing the relative contributions of climate change and human activities to vegetation change under different scenarios

Vegetation Change Status	Climate Change Contribution	Human Activity Contribution
ANPP > 0 (Improvement)	$\frac{\|\Delta PNPP\|}{\|\Delta PNPP\|+\|\Delta HNPP\|} \times 100\%$	$\frac{\|\Delta HNPP\|}{\|\Delta PNPP\|+\|\Delta HNPP\|} \times 100\%$
ANPP < 0 (Degradation)	$\frac{\|\Delta PNPP\|}{\|\Delta PNPP\|+\|\Delta HNPP\|} \times 100\%$	$\frac{\|\Delta HNPP\|}{\|\Delta PNPP\|+\|\Delta HNPP\|} \times 100\%$

Where $\Delta PNPP$ and $\Delta HNPP$ are the change amounts of PNPP and HNPP, respectively. Based on these scenarios, we calculated the relative contribution rates of climate change and human activities to vegetation changes.

3.1 ANPP Simulation and Validation

We conducted pixel-scale validation by comparing simulated ANPP values with corresponding MODIS NPP products (Figure 2). The simulation showed high accuracy with a coefficient of determination (R^2) of 0.54 ($P < 0.01$), indicating that the estimated values closely matched the MODIS NPP data.

Figure 2 Comparison of MODIS NPP and ANPP simulation values

3.2 Spatiotemporal Trends of ANPP

From 2000 to 2020, the mean annual ANPP in Yanchi County showed a fluctuating but overall increasing trend, with a growth rate of 5.59 g $C \cdot m^{-2} \cdot yr^{-1}$ ($R^2 = 0.54$, $P < 0.01$). The multi-year average ANPP ranged from 14.75 to 514.07 g $C \cdot m^{-2} \cdot yr^{-1}$, with a mean of 202.00 g $C \cdot m^{-2} \cdot yr^{-1}$. Spatially, ANPP exhibited a decreasing gradient from southeast to northwest, with several distinct high- and low-value zones (Figure 4). High-value areas (250–500 g $C \cdot m^{-2} \cdot yr^{-1}$) were concentrated in cultivated land and irrigation districts, expanding over time with the implementation of ecological projects. Low-value areas (30–120 g $C \cdot m^{-2} \cdot yr^{-1}$) were distributed in sandy regions of Gaoshawo, Dashuikeng, and Mahuangshan towns.

Figure 3 Interannual ANPP change in Yanchi County during 2000–2020

Figure 4 Spatial distributions of ANPP in 2000, 2010, 2020 and multi-year average in Yanchi County

Trend significance analysis revealed that 99.39% of the county showed improvement trends, while only 0.61% showed degradation. Extremely significant improvement covered 68.91% of the study area, significant improvement covered 17.23%, and degraded areas were scattered at the margins of desert and desert steppe zones as well as in densely populated regions (Figure 5).

Figure 5 Interannual variation trend and significance test of ANPP in Yanchi County during 2000–2020

3.3.1 Relative Contributions in Vegetation-Improved Areas

In vegetation-improved areas, climate change contributed 59.77% while human activities contributed 40.23%. Spatially, climate-dominated improvement was mainly distributed in sparsely populated areas of western Yanchi (Gaoshawo and Wanglejing towns), whereas human activity-dominated improvement was concentrated in eastern areas with denser populations. The relative contributions varied significantly across improvement levels: in extremely significant improvement zones, human activities contributed 76.01% and climate contributed

23.99%; in significant improvement zones, climate contributed 82.13% and human activities contributed 17.87% (Figure 7).

Figure 6 Spatial distributions of climate change, human activities and their combined effects on vegetation improvement and degradation

Figure 7 Contribution rates of climate change and human activities to vegetation improvement in Yanchi County during 2000–2020

Across vegetation types, human activities were the primary driver of improvement in desert and desert steppe areas, while climate change dominated improvement in typical steppe, grain and economic crop areas, meadows, and deciduous shrublands (Table 3).

3.3.2 Relative Contributions in Vegetation-Degraded Areas

In vegetation-degraded areas, human activities accounted for 91.77% of the relative contribution, far exceeding climate change' s 8.23%. Climate-dominated degradation occurred in only 0.47% of the degraded area. Spatially, all degraded areas in Fengjigou Township were caused by human activities (Figure 8).

Figure 8 Contribution rates of climate change and human activities to vegetation degradation in Yanchi County during 2000–2020

3.3.3 Spatial Heterogeneity of Impacts and Relative Contributions

The relative contributions of climate change and human activities showed significant spatial heterogeneity. In all degradation levels, human activities contributed over 91% to vegetation degradation. Degraded vegetation included desert, desert steppe, typical steppe, and grain and economic crop types, with human activities as the dominant degradation driver in all types, particularly in typical steppe areas (91.67%) (Tables 2 and 3).

Table 2 Relative contribution of climate change and human activities to different degrees of vegetation change

Vegetation Change Level	Pixel Percentage	Climate Contribution	Human Activity Contribution
Extremely significant improvement	68.91%	23.99%	76.01%
Significant improvement	17.23%	82.13%	17.87%
No significant improvement	8.23%	59.77%	40.23%

Vegetation Change Level	Pixel Percentage	Climate Contribution	Human Activity Contribution
Extremely significant degradation	0.47%	8.23%	91.77%
Significant degradation	0.11%	8.23%	91.77%
No significant degradation	0.03%	8.23%	91.77%

Table 3 Relative contribution of climate change and human activities to the improvement and degradation of different vegetation types

Vegetation Type	Improvement Area		Degradation Area	
	Climate Contribution	Human Activity Contribution	Climate Contribution	Human Activity Contribution
Desert	22.65%	77.35%	8.23%	91.77%
Desert steppe	27.05%	72.95%	8.23%	91.77%
Typical steppe	74.14%	25.86%	8.23%	91.67%
Grain and economic crops	59.77%	40.23%	8.23%	91.77%
Deciduous shrubland	59.77%	40.23%	-	-
Meadow	59.77%	40.23%	-	-

3.4.1 Correlation Between Vegetation NPP and Climate Factors

Climate change is an important driver of vegetation NPP variation, with precipitation and temperature being the most direct and sensitive factors. We analyzed correlations between annual NPP and mean annual precipitation/temperature at the pixel scale. Results showed that NPP was positively correlated with precipitation across the study area, with significant and extremely significant positive correlations covering 63.37% of the region. In contrast, significant positive correlations with temperature covered only 7.85% of the area (Figure 9). This indicates that vegetation in Yanchi County is highly sensitive to precipitation, which is the primary meteorological factor affecting vegetation improvement.

Figure 9 Spatial distributions of correlation coefficients between vegetation NPP and climate factors in Yanchi County during 2000–2020

3.4.2 Impacts of Human Activities on Vegetation NPP

Human activities dominated 40.23% of vegetation-improved areas and 91.77% of vegetation-degraded areas, demonstrating both positive (ecological restoration) and negative (urban expansion, mining) effects. The spatial distribution of mean annual HNPP revealed that areas with HNPP < 0 (positive human impact) accounted for 70.74% of the study area, primarily distributed in desert and desert steppe regions, Mahuangshan area, and irrigation districts of various townships, indicating that human activities promoted vegetation improvement in these regions. Areas with HNPP > 0 (negative human impact) covered 29.26% of the area, showing that negative human impacts have weakened overall (Figure 10).

Figure 10 Spatial distributions of annual average HNPP in Yanchi County during 2000–2020, and the direction and trend of influence of human activities on NPP

By superimposing HNPP sign and trend, we identified four patterns: (1) Positive-positive (human degradation weakening) covered 9.31% of the area; (2) Positive-negative (human degradation intensifying) covered 2.08%; (3) Negative-positive (human improvement weakening) covered 14.55%; and (4) Negative-negative (human improvement strengthening) covered 61.49%, showing the most extensive distribution.

4.1 Vegetation Spatiotemporal Change Trends

Since 2000, the implementation of the Grain-for-Green Program, grazing bans, and enclosure policies has led to overall vegetation improvement in the study area, with minor negative fluctuations due to climate variability. Our simulated multi-year average ANPP range (14.75–514.07 g $C \cdot m^{-2} \cdot yr^{-1}$, mean 202.00 g $C \cdot m^{-2} \cdot yr^{-1}$) is consistent with results from nearby regions using similar methods, confirming good reliability. Ecological restoration has reduced human disturbance, converted extensive slope farmland to grassland and forest, and increased vegetation cover, particularly in desert steppe, desert, and former cultivated land areas.

4.2 Driving Mechanism Analysis of Vegetation Dynamics

Precipitation is the primary climatic factor driving vegetation improvement in the study area. The area showing significant correlation between NPP and precipitation far exceeds that for temperature, consistent with findings that precipitation is most significant for temperate desert steppe NPP. Although vegetation restoration has positively affected local precipitation increases in the Loess Plateau, large-scale ecological construction has increased plant water demand. Under precipitation fluctuations, this can cause NPP declines, confirming our finding that precipitation drives vegetation stability and growth.

While temperature showed overall positive correlation with NPP, the relationship was not significant. Temperature increases may prolong growing seasons but also enhance evapotranspiration, reduce water use efficiency, and create soil dry layers that limit grass growth, potentially slowing vegetation improvement.

Human activities remain the main driver of vegetation degradation through urban expansion, mining, and illegal grazing, though their scope is limited. Conversely, enclosure grazing, grazing bans, Grain-for-Green programs, and ecological restoration projects have had significant positive effects on large-scale vegetation improvement. The difference comparison method effectively separates climatic and human impacts, enabling quantitative assessment of anthropogenic effects and ecological project effectiveness while clarifying the contribution rates of each factor.

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5 Conclusions

This study used MODIS NDVI time series, meteorological data, and land cover data to simulate the spatiotemporal changes of NPP in Yanchi County using the CASA and Thornthwaite Memorial models. Through difference comparison, we quantitatively assessed the relative contributions of climate change and human activities to vegetation restoration and degradation. The main conclusions are:

1. From 2000 to 2020, vegetation NPP in Yanchi County showed a fluctuating but overall increasing trend. Climate change and human activities jointly drove the overall NPP increase.
2. The relative contributions of climate change and human activities to vegetation improvement and degradation showed significant spatial heterogeneity. In vegetation-improved areas, climate change contributed 59.77% while human activities contributed 40.23%. In vegetation-degraded areas, human activities contributed 91.77%, far exceeding climate change's 8.23%. This indicates that while climate and human activities jointly promoted overall vegetation recovery, human activities caused degradation in small localized areas, though this degradation trend has significantly weakened.

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