Impacts of Climate Factors and Human Activities on Vegetation Net Primary Productivity in the Pisha Sandstone Area Postprint

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Abstract

The Pisha sandstone area is one of the most severely soil-eroded regions on the Loess Plateau, and its vegetation growth status plays a crucial role in controlling soil erosion and maintaining ecological balance in this region. Based on the CASA model and Rclimdex 1.0, this study calculated vegetation net primary productivity (NPP) and 18 extreme climate indices in the Pisha sandstone area from 2001 to 2021. Using trend analysis, correlation analysis, random forest importance ranking, and residual analysis, we investigated the spatiotemporal variation of NPP and its response characteristics to climatic factors, and quantified the relative contributions of climatic factors and human activities to NPP in the Pisha sandstone area. The results indicate that: (1) From 2001 to 2021, NPP in the Pisha sandstone area exhibited a significant increasing trend; however, in the future, NPP in 82.5% of the region will shift from an increasing to a decreasing trend. (2) At the interannual scale, NPP in the Pisha sandstone area was predominantly positively correlated with annual mean temperature, annual total precipitation, and extreme heavy precipitation indices, while negatively correlated with cold nights (TN10P) and diurnal temperature range (DTR). At the seasonal scale, increases in spring mean temperature and warm nights were conducive to NPP increase, with a lag effect present. Increases in summer warm days were detrimental to vegetation growth, and NPP exhibited a 3-month lagged response to summer warm days. Summer extreme heavy precipitation was beneficial to NPP increase, whereas summer drought was detrimental to vegetation growth, and NPP showed a 3-month lagged response to consecutive dry days (CDD). (3) Climatic factors and human activities jointly promoted NPP increase in the Pisha sandstone area; climatic contributions were dominant in bare areas and sand-covered areas, with relative contributions of climatic factors of 62.13% and 60.06%, respectively; in soil-covered areas, human activity contributions were dominant, with a human activity contribution rate of 60.40%.

Full Text

Impact of Climatic Factors and Human Activities on Vegetation Net Primary Productivity in the Pisha Sandstone Area

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Abstract

The Pisha sandstone area represents one of the most severely eroded regions on the Loess Plateau, where vegetation growth plays a critical role in controlling soil erosion and maintaining ecological balance. This study estimated vegetation net primary productivity (NPP) and 18 extreme climate indices in the Pisha sandstone area from 2001 to 2021 using the CASA model and Rclimdex 1.0, respectively. We employed trend analysis, correlation analysis, random forest importance ranking, and residual analysis to investigate the spatiotemporal variation of NPP and its response characteristics to climatic factors, while quantifying the relative contributions of climate factors and human activities to NPP changes. The results indicate: (1) At the interannual scale, NPP in all subregions of the Pisha sandstone area showed a significant increasing trend from 2001 to 2021, but 82.5% of the area will shift to a decreasing trend in the future. (2) NPP was positively correlated with mean annual temperature, total annual precipitation, and extreme heavy precipitation indices, but negatively correlated with cold night days (TN10P) and diurnal temperature range (DTR). At the seasonal scale, increased mean temperature and warm night days in spring promoted NPP growth, with evident lag effects. Increased warm day days in summer negatively affected vegetation growth, while NPP exhibited a three-month lagged response to summer warm day days. Summer extreme heavy precipitation benefited NPP increase, whereas summer drought adversely affected vegetation growth, with NPP showing a three-month lagged response to consecutive dry days. (3) Climate factors dominated the relative contribution in bare and sand-covered areas (62.13% and 60.06%, respectively), while human activities dominated in soil-covered areas (60.40% contribution rate).

Keywords: Pisha sandstone area; vegetation net primary productivity (NPP); extreme climate; human activities; residual analysis

1 Data and Methods

1.1 Study Area Overview

The Pisha sandstone area is located between 108°52 -111°35 E and 38°42 -40°12 N, situated in the northern Loess Plateau at the junction of Shaanxi, Shanxi, and Inner Mongolia provinces within the Ordos Plateau [Figure 1: see original paper]. The region covers approximately 1.67×10^4 km^2, characterized by higher terrain in the northwest and lower in the southeast, with severely dissected gullies, serious soil erosion, and fragile ecological conditions, representing one of the most severely eroded areas on the Loess Plateau. Based on soil coverage degree, the Pisha sandstone area can be classified into bare areas, soil-covered areas, and sand-covered areas; according to erosion intensity, it can be further divided into intensely eroded bare areas and severely eroded bare areas. The region experiences a temperate arid/semi-arid continental monsoon climate with mean annual temperature of 6-9°C and annual precipitation of 315-442 mm, concentrated mainly in summer. In 2020, grassland accounted for 61.7% of the total area, forest for 14.9%, other land for 4.81%, and unused land for 18.59%, indicating that grassland is the dominant vegetation type.

1.2 Data Sources and Processing

NPP Data: The MOD13Q1 dataset was obtained from Google Earth Engine (https://code.earthengine.google.com/) with a spatial resolution of 250 m and temporal resolution of 16 days from 2001 to 2021. Land cover type data were acquired from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/).

Meteorological Data: Meteorological station data were obtained from the China Meteorological Data Network (https://data.cma.cn/). To ensure accurate spatial interpolation, we selected 25 meteorological stations within and around the Pisha sandstone area to acquire temperature, precipitation, and sunshine duration data from 2001 to 2021. Due to limited solar radiation stations, solar radiation was calculated using empirical formulas based on sunshine duration and latitude [cite]. Extreme climate indices were selected from the ETCCDI (Expert Team for Climate Change Detection and Indices) indicator system, including 11 extreme temperature indices and 7 extreme precipitation indices , calculated using Rclimdex 1.0. All meteorological data were spatially interpolated using ANUSPLIN software to generate meteorological raster datasets.

Topographic Data: The ASTER GDEM dataset was downloaded from the Geospatial Data Cloud platform of the Chinese Academy of Sciences (https://www.gscloud.cn/) with a spatial resolution of 30 m.

1.3 Research Methods

1.3.1 Trend Analysis This study employed the Sen+M-K non-parametric trend calculation method to compute the interannual variation trend of NPP in the Pisha sandstone area from 2001 to 2021 on a pixel-by-pixel basis. This method has been widely used for analyzing trends in long time series data [cite]. The calculation formula is:

$$\beta = \text{median}\left(\frac{NPP_j - NPP_i}{t_j - t_i}\right), \quad 2001 \leq i < j \leq 2021$$

where median represents the median function; β indicates the trend slope; NPPi and NPPj represent NPP values in different years; and ti and tj represent the time series. When $\beta > 0$, it indicates an upward trend; when $\beta < 0$, it indicates a downward trend. The Mann-Kendall test was used to assess the significance of trend analysis results.

1.3.2 Hurst Index The Hurst index was used to predict future trends in time series data. H $>$ 0.5 indicates that future trends will be consistent with past trends; H $<$ 0.5 indicates that future trends will be opposite to past trends; and H $=$ 0.5 indicates a random sequence with uncertain future trends. By superimposing the Hurst index with the trend analysis results, we determined the future trend of NPP in the Pisha sandstone area.

1.3.3 NPP Estimation This study adopted the CASA model proposed by Zhu et al. [cite] to estimate NPP in the Pisha sandstone area. The CASA model calculates NPP through absorbed photosynthetically active radiation (APAR) and light use efficiency. This model requires few parameters and has been widely applied [cite]. Detailed calculation methods can be found in the literature [cite].

1.3.4 Correlation Analysis Pearson correlation analysis was used to examine the relationship between NPP and climate factors. The calculation formula is:

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where R is the correlation coefficient between variables x and y; xi is the NPP value in year i; yi is the climate index value in year i; $\bar{x}$ and $\bar{y}$ represent multi-year average values; and n is the sample size (years).

1.3.5 Random Forest Importance Ranking Random forest is a machine learning algorithm based on classification and regression that can analyze complex nonlinear relationships between independent and dependent variables [cite]. This study used random forest to identify the importance of various extreme climate indices on NPP in the Pisha sandstone area. Using R 4.2.1, we obtained the %IncMSE (Increased Mean Squared Error) values, which reflect the impact of removing each variable on prediction accuracy. Higher %IncMSE values indicate greater importance, intuitively showing the importance of each extreme climate index to the target variable (NPP).

1.3.6 Multiple Linear Regression Residual and Relative Contribution Analysis Multiple linear regression residual analysis can distinguish the impacts of climate factors and human activities on NPP changes and has been widely used [cite]. Generally, multiple regression residual analysis selects average climate variables such as total precipitation and mean temperature as climate factors [cite], ignoring the impact of extreme climate on vegetation, which may lead to inaccurate estimation of climate contributions [cite]. Therefore, this study incorporated extreme climate indices and conducted multiple regression residual analysis with mean annual temperature, total annual precipitation, and extreme climate indicators as independent variables and NPP as the dependent variable. The steps are as follows:

1. Using NPP as the dependent variable and mean temperature (TEM), annual precipitation (PRE), and extreme climate index (incidex) as independent variables, we established a multiple linear regression model: NPPcc = a × PRE + b × TEM + c × incidex + , where NPPcc represents the NPP predicted value indicating the impact of climate factors on vegetation NPP, and a, b, c, are model parameters.
2. The difference between the observed NPP (NPPobs) and the climate-predicted NPP (NPPcc) was calculated as NPPHA = NPPobs - NPPcc, representing the impact of human activities on vegetation NPP.
3. Based on the method for calculating relative contributions [cite], we computed the relative contributions of climate factors and human activities to NPP changes by analyzing the linear trends of NPPcc (Slope(NPPcc)) and NPPHA (Slope(NPPHA)) relative to the observed NPP trend (Slope(NPPobs)) .

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2 Results

2.1 Evaluation of NPP Simulation and Meteorological Interpolation Results

We randomly extracted 10,000 pixels from the MODIS NPP dataset, obtaining 210,000 samples that showed good fitting results ($R^2 = 0.69$, $P < 0.01$) [Figure 2: see original paper]. The simulated NPP was significantly correlated with the MOD17A3 NPP dataset, demonstrating statistical significance and consistency with Liu et al.' s [cite] estimation range for the Loess Plateau at a larger scale ($197.68\ g\ C \cdot m^{-2} \cdot a^{-1}$). Overall, the improved CASA model provided reliable NPP estimation accuracy for the Pisha sandstone area.

Cross-validation was performed to assess meteorological data interpolation accuracy. We selected four meteorological stations (Dongsheng, Baode, Qingshuihe, Hequ) as test samples, with the remaining stations used for training. The results showed good agreement between interpolated and observed values for mean annual temperature ($R^2 = 0.77$) and annual precipitation ($R^2 = 0.69$) [Figure 2: see original paper], indicating high interpolation accuracy.

2.2 Spatiotemporal Variation of NPP in the Pisha Sandstone Area

The temporal variation trend showed that annual mean NPP in the Pisha sandstone area from 2001 to 2021 exhibited a fluctuating upward trend at a rate of $5.78\ \mathrm{g\ C \cdot m^{-2} \cdot a^{-1}}$ ($P < 0.01$). All subregions showed significant increasing trends, with the soil-covered area increasing fastest ($7.02\ \mathrm{g\ C \cdot m^{-2} \cdot a^{-1}}$), followed by the sand-covered area ($6.31\ \mathrm{g\ C \cdot m^{-2} \cdot a^{-1}}$), and the bare area slowest ($3.72\ \mathrm{g\ C \cdot m^{-2} \cdot a^{-1}}$). Spatially, average NPP values were closely related to soil coverage degree, decreasing in the order: soil-covered area ($217.38\ \mathrm{g\ C \cdot m^{-2} \cdot a^{-1}}$) > sand-covered area ($176.45\ \mathrm{g\ C \cdot m^{-2} \cdot a^{-1}}$) > bare area ($157.45\ \mathrm{g\ C \cdot m^{-2} \cdot a^{-1}}$).

Spatially, 96.94% of the region showed an increasing trend, with 84.60% exhibiting a significant increase. Areas with non-significant increases accounted for 12.34%. The Hurst index analysis revealed an average value of 0.23, indicating anti-persistence in future trends. Specifically, 82.50% of the region will shift from increasing to decreasing trends, 14.44% will continue to increase, and 1.96% will transition from decreasing to increasing [Figure 4: see original paper]. These results suggest that vegetation growth faces degradation risks due to climate change and human activities, necessitating continued protection and sustainable restoration efforts.

2.3 Correlation Between NPP and Climate Factors

2.3.1 Correlation with Temperature The spatial average correlation coefficient between NPP and temperature factors was generally weak (absolute value < 0.3). Specifically, NPP showed positive correlations with mean annual temperature (TEM) and growing season length (GSL), indicating that temperature increase and extended growing seasons benefit vegetation growth. However, NPP was negatively correlated with cold night days (TN10P) and diurnal temperature range (DTR). The significantly negative correlation with TN10P was mainly observed in bare, sand-covered, and southern soil-covered areas, suggesting that extreme temperatures may have more negative impacts on bare and sand-covered areas than on soil-covered areas. TN10P showed predominantly negative correlations, indicating that increased cold nights may lead to insufficient accumulated temperature, affecting vegetation growth. DTR showed significant negative correlations, with higher correlation coefficients and larger areas passing significance tests. Overall, both extreme warmth and extreme cold were detrimental to vegetation growth in the Pisha sandstone area.

2.3.2 Correlation with Precipitation In contrast to temperature indices, extreme precipitation indices showed widespread positive correlations with NPP [Figure 6: see original paper]. Annual total precipitation (PRCPTOT) and annual precipitation intensity (SDII) showed significant positive correlations across most of the Pisha sandstone area. Different intensities of extreme precipitation (RX1day, RX5day, R95p) also showed predominantly significant positive correlations, mainly distributed in bare areas, sand-covered areas, and southern soil-covered areas. Consecutive wet days (CWD) showed significant positive correlations mainly in soil-covered and southern sand-covered areas, indicating that short-term heavy precipitation helps increase NPP in bare areas, while prolonged precipitation may negatively affect bare area vegetation. Summer RX1day and RX5day showed significant positive correlations with lag effects of 1-3 months, demonstrating that increased summer precipitation has positive impacts lasting 1-3 months on vegetation growth. Conversely, summer consecutive dry days (CDD) showed significant negative correlations with a three-month lag effect, indicating that summer drought adversely affects vegetation growth with a three-month delayed impact.

2.4 Lagged Response of NPP to Climate Factors

NPP showed significant responses to temperature and precipitation indicators mainly in spring and summer, with certain lag effects. In spring, cold night days (TN10P) showed significant negative correlations with concurrent spring NPP with a 1-2 month lag. Warm night days (TN90P) showed extremely significant positive correlations with a 1-2 month lag. Spring mean temperature showed extremely significant positive correlations with a 1-2 month lag. Overall, increased spring temperature and warm night days benefited NPP increase. In summer, warm day days (TX90P) showed significant negative correlations with a 1-3 month lag effect, indicating that increased summer warm days negatively affected vegetation growth, but decreased summer diurnal temperature range was beneficial. Summer extreme heavy precipitation showed significant positive correlations with different degrees of lag effects, while summer drought showed significant negative correlations with a three-month lag effect [Figure 7: see original paper].

2.5 Importance of Extreme Climate Indices on Annual NPP Variation

Based on random forest importance ranking, DTR, GSL, and PRCPTOT ranked among the top three in importance among climate indicators, with importance values far exceeding other indices [Figure 8: see original paper]. In bare areas, NPP was mainly affected by DTR and TN10P. In sand-covered areas, NPP was mainly influenced by PRCPTOT and TN10P. In soil-covered areas, NPP was primarily affected by TX90P and DTR. These results indicate that different extreme climate indices have varying degrees of impact on NPP across different subregions.

2.6 Relative Contributions of Climate and Human Activities to NPP Variation

Considering the importance ranking results, we used multiple linear regression to construct the relationship between NPP and mean annual temperature, annual precipitation, and DTR. The residual and relative contribution analysis revealed the driving factors of NPP variation in the Pisha sandstone area [Figure 9: see original paper]. Climate factors and human activities jointly promoted NPP increase in 93.25% of the area. The average climate contribution across the entire region was 50.23%, while human activity contribution was 49.77%, indicating nearly equal contributions. However, dominant factors varied by subregion: climate factors dominated in bare areas (62.13% climate contribution, 37.87% human activity contribution) and sand-covered areas (60.06% climate contribution, 39.94% human activity contribution), whereas human activities dominated in soil-covered areas (60.40% human activity contribution, 39.60% climate contribution) [Figure 10: see original paper].

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3 Discussion

3.1 Spatiotemporal Variation of Vegetation NPP in the Pisha Sandstone Area

From 2001 to 2021, NPP in the Pisha sandstone area showed an overall fluctuating upward trend, with the soil-covered area exhibiting the fastest growth rate, followed by the sand-covered area, and the bare area the slowest. This pattern is closely related to soil coverage degree, as soil-covered areas have higher soil nutrient content [cite] and better site conditions, making ecological restoration more effective. In contrast, bare and sand-covered areas have lower vegetation survival rates [cite], limiting restoration effectiveness. Although NPP showed significant increases across all subregions, the Hurst index indicated weak persistence, with 82.5% of the area projected to shift from increasing to decreasing trends. This aligns with research on the Loess Plateau showing that although vegetation increased in recent decades, future sustainability is uncertain [cite]. Therefore, continued ecological protection projects and adaptive restoration strategies are needed to consolidate restoration benefits and promote sustainable vegetation recovery.

3.2 Impact of Climate Factors on NPP in the Pisha Sandstone Area

At the interannual scale, extreme cold, extreme warmth, and diurnal temperature range were negatively correlated with NPP, consistent with findings from the Loess Plateau [cite]. Mean annual temperature and growing season length showed positive correlations, suggesting that temperature increase may promote vegetation growth by extending the growing season [cite], though temperature thresholds exist [cite]. Excessive temperature increases enhance respiration and cause stomatal closure, affecting photosynthesis [cite], while low temperatures result in insufficient accumulated temperature, slowing vegetation development [cite]. DTR showed significant negative correlations with NPP, consistent with studies in northern China [cite]. DTR is influenced by extreme temperatures, and its decrease (higher minimum temperatures or lower maximum temperatures) may benefit vegetation growth in the Pisha sandstone area.

In contrast, extreme precipitation indices showed widespread positive correlations with NPP, consistent with research in Inner Mongolia [cite]. As a semi-arid region, vegetation growth in the Pisha sandstone area is water-limited, and increased precipitation promotes vegetation growth. At the seasonal scale, spring warming and increased warm night days benefited NPP, while summer high temperatures and drought negatively affected vegetation growth. The three-month lagged response of NPP to summer climate extremes indicates that vegetation growth is influenced by both current and previous climate conditions.

3.3 Impact of Human Activities on NPP in the Pisha Sandstone Area

Human activities influence NPP by altering land use types and improving soil conditions. From 2001 to 2021, forest and construction land areas increased, while grassland, cropland, and unused land decreased . Land use conversion areas accounted for 24.58% of the total area, with most conversion from grassland to forest and construction land. However, NPP increase in land use change areas only accounted for 25.12% of the total NPP increase, indicating that NPP improvement was primarily associated with vegetation condition improvement in areas without land use change. This reflects the success of ecological restoration policies such as the Grain for Green Program and Grassland Restoration Project [cite].

Artificially planted sea buckthorn and pine trees have effectively improved soil carbon and nitrogen content in the Pisha sandstone area [cite], promoting forest NPP increase. Human activities have predominantly promoted NPP growth, particularly in soil-covered areas where restoration efforts have been most effective (60.4% contribution). This is closely related to the implementation of ecological restoration projects, including the Sea Buckthorn Ecological Project initiated in 2006 and subsequent projects in the Kuye River basin [cite]. These measures have significantly improved vegetation coverage and growth conditions across the region.

4 Conclusion

Using the improved CASA model to estimate vegetation NPP in the Pisha sandstone area, this study analyzed its spatiotemporal variation characteristics and responses to mean and extreme climate factors, further quantifying the relative contributions of climate and human activities. The main conclusions are:

1) Spatially, NPP distribution aligned with soil coverage degree, decreasing in the order: soil-covered area > sand-covered area > bare area. Temporally, NPP showed significant increasing trends across all subregions from 2001 to 2021, but these trends lack strong persistence. Future projections indicate that 82.5% of the area will shift from increasing to decreasing trends, posing continued degradation risks.

2) NPP responded differently to various climate indicators. At the interannual scale, strong correlations with temperature were observed for DTR, GSL, and mean annual temperature (positive), and TN10P (negative). Extreme precipitation indices (PRCPTOT, RX1day, RX5day) showed widespread positive correlations. At the seasonal scale, NPP responses to mean and extreme climate in spring and summer showed significant lag effects. Spring warming promoted NPP increase, while summer precipitation increase significantly enhanced vegetation growth, but increased summer warm days negatively affected vegetation.

3) Recent ecological restoration projects have significantly promoted vegetation growth. Climate change and human activities contributed nearly equally to regional NPP increase (50.23% and 49.77%, respectively), though with regional variations. Climate factors dominated in bare and sand-covered areas (62.13% and 60.06%), while human activities dominated in soil-covered areas (60.40%).

4) Vegetation growth in the Pisha sandstone area is jointly affected by climate factors and human activities. To promote stable and healthy vegetation growth, continued protection and construction of forest and grassland vegetation should be strengthened, soil erosion control measures implemented, vegetation patterns in soil-covered areas optimized, and protection efforts in bare and sand-covered areas enhanced to mitigate the negative impacts of summer drought and high temperatures on vegetation growth.

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