Spatiotemporal Evolution of Vegetation Carbon Use Efficiency and Its Driving Factors in Xinjiang: Postprint

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Abstract

Investigating vegetation carbon use efficiency (CUE) contributes to a deeper understanding of regional carbon cycle mechanisms and provides a scientific basis for achieving carbon neutrality goals. Based on MODIS imagery and meteorological data, this study employs the Hurst index, partial correlation analysis, and residual analysis to examine the spatiotemporal variations and driving factors of vegetation CUE in Xinjiang from 2001 to 2023. The results show that: (1) From 2001 to 2023, vegetation CUE in Xinjiang exhibited a gently fluctuating downward trend, with high values mainly distributed in regions such as the Tianshan Mountains and the Kunlun Mountains. (2) In 55.97% of the area, vegetation CUE showed a decreasing trend during the study period, but is projected to shift to an increasing trend in the future; these areas are primarily located in the Ili River Valley, around the Junggar Basin, and in oasis regions along the margins of the Tarim Basin. (3) Over most of Xinjiang, vegetation CUE is negatively correlated with potential evapotranspiration, while its correlations with temperature and precipitation display a spatial pattern of north–south differentiation: in northern Xinjiang, CUE is mainly negatively correlated with temperature and positively correlated with precipitation, whereas the opposite is observed in southern Xinjiang. Moreover, CUE shows a stronger response to potential evapotranspiration. (4) Approximately 58% of the regional variation in vegetation CUE is jointly driven by climate change and human activities. Areas where human activities exert a promoting effect on vegetation CUE are mainly distributed in low-altitude regions and in the surroundings of urban agglomerations where human activities are more frequent.

Full Text

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Spatiotemporal Evolution and Driving Factors of Vegetation Carbon Use Efficiency in Xinjiang

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Abstract

Research on vegetation carbon use efficiency (CUE) helps deepen our understanding of regional carbon cycle mechanisms and provides a basis for achieving carbon neutrality goals. Based on MODIS imagery and meteorological data, this study investigated the spatiotemporal variations and driving factors of vegetation CUE in Xinjiang from 2001 to 2023 using methods including the Hurst exponent, partial correlation analysis, and residual analysis. The results show that: (1) The CUE of vegetation in most areas of Xinjiang exhibited a fluctuating and gently decreasing trend during the study period, with high values mainly distributed in the Tianshan and Kunlun Mountains. (2) Approximately 55.97% of the areas where the current vegetation CUE is decreasing, mainly located in regions such as the Ili River Valley, the periphery of the Junggar Basin, and the oasis areas along the edge of the Tarim Basin, are likely to experience an increase in the future. (3) In most areas of Xinjiang, the vegetation CUE was negatively correlated with potential evapotranspiration. The correlations of CUE with temperature and precipitation displayed spatial differences between northern and southern Xinjiang. In northern Xinjiang, CUE was negatively correlated with temperature and positively correlated with precipitation, whereas the opposite was found in southern Xinjiang. Moreover, CUE had a stronger response to potential evapotranspiration than to temperature and precipitation. (4) Approximately 58% of the vegetation CUE changes across the regions were jointly driven by climate change and human activities. The regions where human activities played a promoting role in vegetation CUE were mainly distributed in low-altitude areas and regions with relatively frequent human activities around urban agglomerations.

Keywords: vegetation CUE; spatiotemporal dynamics; climate change; human activities; Xinjiang

1.1 Study Area Overview

Xinjiang is located in the hinterland of the Eurasian continent, in the northwestern border region of China. The region is vast in territory, with a terrain characterized by the "three mountains sandwiching two basins" (Fig. [Figure 1:

see original paper]), encompassing various complex landform types. It belongs to a typical temperate continental arid climate, with scarce annual precipitation and extremely uneven spatiotemporal distribution of rainfall, coupled with high evaporation rates. These conditions lead to water resource scarcity and sparse vegetation, frequent wind-sand activities, severe land desertification, and extremely harsh natural conditions for vegetation growth, making the region highly sensitive to climate change and human activities.

1.2 Data Sources and Processing

This study utilized MODIS data products, including the MOD17A3HGF dataset with an annual temporal resolution and 500 m spatial resolution, and the MOD17A2H dataset with an 8-day temporal resolution and 500 m spatial resolution. The data covered the period from 2001 to 2023. Annual GPP values were obtained by accumulating MOD17A2H data for each year, and CUE was calculated as GPP/PAR. The MOD17A3HGF dataset has been validated across different regions, confirming its reliability.

The monthly temperature, precipitation, and potential evapotranspiration dataset for China developed by Peng Shouzhang’ s team was employed, with a spatial resolution of 0.5°. This dataset integrates global climate data and the WorldClim dataset, refined for the Chinese region using Delta scaling techniques and validated through 728 independent meteorological observation stations, ensuring data accuracy and reliability. This study selected temperature, precipitation, and potential evapotranspiration data from 2001 to 2023, processing them to obtain annual mean temperature, annual total precipitation, and annual mean potential evapotranspiration. Resampling was performed to reduce inconsistencies and uncertainties arising from spatial resolution differences between various data sources.

1.3.1 Trend Analysis

The Theil-Sen median trend analysis method and Mann-Kendall test were combined to analyze CUE trend and test significance, effectively reducing interference from data outliers. This method has been widely used for analyzing trends in long time series data.

The Theil-Sen median trend analysis formula is:

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

where β is the trend magnitude, $\beta > 0$ indicates an increasing trend, $\beta < 0$ indicates a decreasing trend; j and i are years; x_j is the pixel value in year j; x_i is the pixel value in year i; and n is the number of study years.

The Mann-Kendall test formula is:

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

$$\operatorname{sgn}(x_j - x_i) = \begin{cases} 1 & x_j - x_i > 0 \\ 0 & x_j - x_i = 0 \\ -1 & x_j - x_i < 0 \end{cases}$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{\operatorname{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\operatorname{Var}(S)}} & S < 0 \end{cases}$$

where m is the number of study years; x_j is the pixel value in year j; x_i is the pixel value in year i; and Z is the standard normal distribution statistic.

Combining the β trend magnitude from Theil-Sen median trend analysis and the Z value from Mann-Kendall test, CUE change trends were classified into six categories: extremely significant increase ($\beta > 0, |Z| \geq 2.58$), significant increase ($\beta > 0, 1.96 \leq |Z| < 2.58$), non-significant increase ($\beta > 0, |Z| < 1.96$), non-significant decrease ($\beta < 0, |Z| < 1.96$), significant decrease ($\beta < 0, 1.96 \leq |Z| < 2.58$), and extremely significant decrease ($\beta < 0, |Z| \geq 2.58$).

1.3.2 Trend Prediction

The Hurst exponent enables precise quantitative assessment of time series trends, providing reliable support for correlation analysis. This study employed R/S analysis (rescaled range analysis) to calculate the Hurst exponent. The calculation procedure is as follows: a time series of length N is divided into A continuous sub-intervals of length n. Each sub-interval is mean-normalized and its cumulative deviation is calculated. The range R_a of each sub-interval is obtained by subtracting the minimum from the maximum cumulative deviation. The standard deviation S_a of squared deviations for each sub-sequence is calculated. The ratio of R_a to S_a yields the rescaled range $(R/S)_n$ for each sub-interval. Finally, with $\log(n)$ as the x-axis and $\log(R/S)_n$ as the y-axis, the regression coefficient obtained through linear fitting is designated as the Hurst exponent.

1.3.3 Stability Analysis

The coefficient of variation was used to analyze the relative fluctuation degree of vegetation CUE. The calculation formula is:

$$C_v = \frac{\sigma_x}{\bar{x}}$$

where C_v is the coefficient of variation, σ_x is the standard deviation of the data, and $\bar{x}$ is the mean of the series. The results were classified into low fluctuation ($C_v \leq 0.1$), relatively low fluctuation ($0.1 < C_v \leq 0.15$), relatively high fluctuation ($0.15 < C_v \leq 0.2$), and high fluctuation ($C_v > 0.2$).

1.3.4 Partial Correlation Analysis

Partial correlation calculates the correlation coefficient between two variables while controlling for other variables, truly reflecting the statistical relationship between the two variables. The calculation formula is:

$$r_{ij\cdot h} = \frac{r_{ij} - r_{ih}r_{jh}}{\sqrt{(1-r_{ih}^2)(1-r_{jh}^2)}}$$

where $r_{ij\cdot h}$ is the partial correlation coefficient between variables i and j while controlling for variable h, with a value range of $[-1, 1]$; $r_{ij\cdot h} > 0$ indicates positive correlation; $r_{ij\cdot h} < 0$ indicates negative correlation; $r_{ij\cdot h} = 0$ indicates no linear correlation; r_{ij}, r_{ih}, and r_{jh} are the simple correlation coefficients between variables i and j, i and h, and j and h, respectively.

The significance of partial correlation coefficients was tested using the t-test method:

$$t = \frac{r_{ij\cdot h}\sqrt{n-k-2}}{\sqrt{1-r_{ij\cdot h}^2}}$$

where n is the sample size and k is the number of controlled variables.

1.3.5 Residual Analysis

Residual analysis can decouple the effects of climate factors and human activities on vegetation CUE. With CUE as the dependent variable and temperature and precipitation data as independent variables, a multiple linear regression equation was established to obtain predicted CUE values and calculate residuals.

$$\mathrm{CUE}_P = a \times \mathrm{tem} + b \times \mathrm{pre} + c$$

$$\mathrm{CUE}_H = \mathrm{CUE}_A - \mathrm{CUE}_P$$

where CUE_P is the predicted CUE; pre is precipitation data; tem is temperature data; CUE_A is the actual CUE; CUE_H is the residual and represents CUE loss or gain under human activity influence.

By conducting trend analysis and classification of the slopes of CUE_A, CUE_P, and CUE_H, and combining with Table 1 to determine the driving factors of vegetation CUE, their spatial distribution was obtained.

Table 1
Evaluation of the drivers of climate change and human activities in CUE changes

Driving Factor Category	Description
Climate change and human activities causing greening	
Climate change causing greening	
Human activities causing greening	
Climate change and human activities causing browning	
Climate change causing browning	
Human activities causing browning	

2. Results and Analysis

2.1 Interannual Variation Characteristics of Vegetation CUE

As shown in the trend diagram (Fig. [Figure 2: see original paper]), the maximum CUE value for Xinjiang vegetation from 2001 to 2023 was 0.58, and the minimum was 0.36, indicating relatively small overall variation. The largest increase occurred from 2002 to 2003 with an increment of 0.05, while the largest decrease occurred from 2022 to 2023 with a decrement of 0.04. The indicator showed a fluctuating decreasing trend. Overall, during 2001-2010, despite a brief rebound in 2008, the general trend was downward. From 2011 to 2016, after reaching the maximum value, it remained at a relatively high level with fluctuations. From 2017 to 2023, it showed a continuous decreasing trend. Linear fitting based on 2001-2023 data yielded a slope of -0.001, indicating a relatively gentle change.

2.2 Stability and Sustainability of Vegetation CUE

Vegetation CUE in most areas of Xinjiang exhibited low fluctuation, accounting for 84.5% of the region, indicating relatively stable changes during the study period (Fig. [Figure 4: see original paper]). High-fluctuation areas accounted for 0.54%, mainly distributed in oasis areas along the edge of the Tarim Basin and parts of the northern Tianshan slope (Fig. [Figure 4: see original paper]), demonstrating strong sensitivity of vegetation CUE in these regions to climate and human activity factors.

Spatially, high CUE values (>0.5) in Xinjiang were mainly distributed in the Tianshan Mountains, Kunlun Mountains, and Altai Mountains and their surrounding areas, particularly with continuous distribution in the central and western sections of the Tianshan Mountains, reflecting high carbon absorption and utilization efficiency in these regions. Medium-value areas (0.4-0.5) were widely distributed, mainly in the Ili River Valley and some low-altitude mountainous areas in northern Xinjiang. Low-value areas (0-0.4) were mainly distributed in oasis areas along the edge of the Tarim Basin and parts of the northern Tianshan slope (Fig. [Figure 3: see original paper]).

The mean Hurst exponent was 0.48. A Hurst exponent <0.5 indicates strong anti-persistence between future and past trends. Areas with Hurst exponent

<0.5 accounted for approximately 55.97%, mainly distributed in the Tianshan and Altai Mountains, suggesting that future CUE trends in these regions will be opposite to past trends. Areas with Hurst exponent >0.5 accounted for approximately 44.03%, with scattered distribution.

As shown in the future trend change distribution map (Fig. [Figure 5: see original paper]), results indicate that areas showing future increase accounted for 58.13%, among which areas shifting from decrease to increase accounted for 55.97%, mainly located in the Ili River Valley, the periphery of the Junggar Basin, and oasis areas along the edge of the Tarim Basin; areas with continuous increase accounted for 2.16%. Areas showing future decrease accounted for 41.87%, among which areas with continuous decrease accounted for 28.33%, mainly distributed in the Tianshan and Altai Mountains; areas shifting from increase to decrease accounted for 13.54%, located in areas surrounding the northern Tianshan slope and southern Altai (Fig. [Figure 5: see original paper]).

Table 2
The proportion of the area with changing future trends of CUE

Future Trend Change	Area Proportion
Increase to decrease	
Decrease to increase	

Note: "Increase to decrease" represents areas where the CUE trend is increasing and will shift to decreasing in the future.

2.3 Relationship Between Vegetation CUE and Climate Factors

In terms of the correlation between Xinjiang vegetation CUE and temperature, negative correlation accounted for 52.88% of vegetated areas, mainly concentrated in the northern Tianshan northern slope, northwestern Tacheng area, and northern Altai area in northern Xinjiang. Positive correlation areas were mainly distributed in southern Altai area, western Ili River Valley, southern Tianshan section, and oasis areas along the southern and southwestern edges of the Tarim Basin (Fig. [Figure 6: see original paper]a). Overall, the correlation between temperature and CUE

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

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