

# Spatiotemporal variation in vegetation net primary productivity and its relationship with meteorological factors in the Tarim River Basin of China from 2001 to 2020 based on the Google Earth Engine postprint

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## Abstract

Vegetation growth status is an important indicator of ecological security. The Tarim River Basin is located in the inland arid region of Northwest China and has a highly fragile ecological environment. Assessing vegetation net primary productivity (NPP) of the Tarim River Basin can provide insights into vegetation growth variations in the region. Therefore, based on the Google Earth Engine (GEE) cloud platform, we studied the spatiotemporal variation of vegetation NPP in the Tarim River Basin (except for the eastern Gobi and Kumutag deserts) from 2001 to 2020 and analyzed the correlations between vegetation NPP and meteorological factors (air temperature and precipitation) using the Sen slope estimation method, coefficient of variation, and rescaled range analysis method. In terms of temporal characteristics, vegetation NPP in the Tarim River Basin showed an overall fluctuating upward trend from 2001 to 2020, with the smallest value of  $118.99 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in 2001 and the largest value of  $155.07 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in 2017. Regarding spatial characteristics, vegetation NPP in the Tarim River Basin showed a downward trend from northwest to southeast along the outer edge of the study area. The annual average value of vegetation NPP was  $133.35 \text{ g C}/(\text{m}^2 \cdot \text{a})$ , and the area with annual average vegetation NPP values greater than  $100.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  was  $82,638.75 \text{ km}^2$ , accounting for 57.76% of the basin. The future trend of vegetation NPP was dominated by anti-continuity characteristic; the percentage of the area with anti-continuity characteristic was 63.57%. The area with a significant positive correlation between vegetation NPP and air temperature accounted for 53.74% of the regions that passed the significance test, while the area with a significant positive correlation between vegetation NPP and precipitation occupied 98.68% of the regions that passed

the significance test. Hence, the effect of precipitation on vegetation NPP was greater than that of air temperature. The results of this

## Full Text

### Spatiotemporal Variation in Vegetation Net Primary Productivity and Its Relationship with Meteorological Factors in the Tarim River Basin of China from 2001 to 2020 Based on Google Earth Engine

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## Abstract

Vegetation growth status is an important indicator of ecological security. The Tarim River Basin is located in the inland arid region of Northwest China and has a highly fragile ecological environment. Assessing vegetation net primary productivity (NPP) of the Tarim River Basin can provide insights into vegetation growth variations in the region. Therefore, based on the Google Earth Engine (GEE) cloud platform, we studied the spatiotemporal variation of vegetation NPP in the Tarim River Basin (except for the eastern Gobi and Kumutag deserts) from 2001 to 2020 and analyzed the correlations between vegetation NPP and meteorological factors (air temperature and precipitation) using the Sen slope estimation method, coefficient of variation, and rescaled range analysis method. In terms of temporal characteristics, vegetation NPP in the Tarim River Basin showed an overall fluctuating upward trend from 2001 to 2020, with the smallest value of 118.99 g C/(m<sup>2</sup> · a) in 2001 and the largest value of 155.07 g C/(m<sup>2</sup> · a) in 2017. Regarding spatial characteristics, vegetation NPP in the Tarim River Basin showed a downward trend from northwest to southeast along the outer edge of the study area. The annual average value of vegetation NPP was 133.35 g C/(m<sup>2</sup> · a), and the area with annual average vegetation NPP values greater than 100.00 g C/(m<sup>2</sup> · a) was 82,638.75 km<sup>2</sup>, accounting for 57.76% of the basin. The future trend of vegetation NPP was dominated by anti-continuity characteristic; the percentage of the area with anti-continuity characteristic was 63.57%. The area with a significant positive correlation between vegetation NPP and air temperature accounted for 53.74% of the regions that passed the significance test, while the area with a significant positive correlation between vegetation NPP and precipitation occupied 98.68% of the regions that passed

the significance test. Hence, the effect of precipitation on vegetation NPP was greater than that of air temperature. The results of this study improve understanding of the spatiotemporal variation of vegetation NPP in the Tarim River Basin and the impact of meteorological factors on vegetation NPP.

**Keywords:** vegetation net primary productivity (NPP); air temperature; precipitation; Hurst index; Google Earth Engine; Tarim River Basin

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## 1 Introduction

Net primary productivity (NPP) is the total amount of organic matter produced by green plants under photosynthesis minus the organic matter consumed by autotrophic respiration [?, ?, ?, ?, ?, ?]. Vegetation NPP is the result of the combined action of vegetation physiological characteristics and the external environment, which can reflect the quality of terrestrial ecosystems [?, ?] and the productivity of surface vegetation under natural environmental conditions, and is an important determining factor of regional ecological support capacity [?, ?]. NPP is also an important indicator of vegetation growth status and a critical indicator of ecological security. Thus, assessing vegetation NPP provides insights into ecosystem health and integrity. Therefore, studying global or regional spatiotemporal characteristics of vegetation NPP can be used to evaluate ecosystem health and stability and address ecological and environmental challenges [?, ?].

Relatively few studies have focused on the long-term spatiotemporal variation of vegetation NPP and its relationship with meteorological factors in the Tarim River Basin of Xinjiang Uygur Autonomous Region, China; however, previous studies have explored vegetation NPP in western arid regions of China [?]. For example, Zhang et al. [?] used the Thornthwaite Memorial Model to estimate vegetation NPP in the Shiyang River Basin of China and found that variations in vegetation NPP are primarily increasing and precipitation is the main influencing factor. Bai et al. [?] used measured herbaceous NPP and water burial depth data from the lower reaches of the Tarim River to establish a relationship model and determined that herbaceous NPP shows a decreasing trend correlated with increasing groundwater burial depth. Cui et al. [?] recently estimated vegetation NPP of the Tarim River Basin during the growing season from 2006 to 2016 using an improved Carnegie-Ames-Stanford Approach (CASA) model and showed that vegetation NPP has a fluctuating increasing trend, whereas the

spatial distribution exhibits a decreasing trend from northwest to southeast. Additionally, Zhao et al. [?] used MOD17A3 remote sensing data to analyze spatiotemporal variation of vegetation NPP in the Bortala-Jinghe River Basin in Xinjiang from 2000 to 2015 and found that vegetation NPP is high in the middle of the basin but low in surrounding areas, with precipitation being the most influential factor. In existing research on vegetation NPP in arid and semi-arid regions, NPP data have mainly been obtained from NPP estimation models, NPP measured data, and existing data products. Although these data acquisition methods are reliable, they are relatively common, and the process of data acquisition and preprocessing can be complex and time-consuming.

Google Earth Engine (GEE) is a remote sensing big data analysis platform launched in 2010 based on Google Cloud Service infrastructure and dedicated to geographical data processing and analysis [?, ?, ?]. This platform stores massive multisource data publicly available from many organizations [?, ?], with technical advantages such as excellent cloud computing, standardized user interfaces, good development ecology, and free service platform. Using literature reviews, Gorelick et al. [?], Kumar and Mutanga [?], Mutanga and Kumar [?], Amani et al. [?], and Tamiminia et al. [?] assessed GEE, focusing on its birth, applications, trends, and potential uses.

Currently, GEE is used in a wide range of research fields [?, ?, ?, ?], including forest ecosystem change, food security, disaster early warning systems, water resources management, climate change, environmental protection, and vegetation dynamics. Yin et al. [?] used GEE to analyze spatiotemporal patterns of global forest NPP from 2004 to 2013 and their relationships with various influencing factors, observing that climate has a large influence on forest NPP and patterns of climate oscillations are synchronized with forest growth conditions to some extent. Additionally, Li and He [?] used GEE to quantitatively explore vegetation NPP changes and their mechanisms under different drought stress conditions in Central Asia from 1990 to 2020 and found that the effect of land cover change on vegetation NPP is higher than that of climate change. Moreover, Zhang et al. [?] studied spatiotemporal characteristics of vegetation NPP on the Tibetan Plateau from 2001 to 2017 based on GEE and discussed the effects of climate change, altitude, and human activities on vegetation NPP.

Based on GEE, Gu et al. [?] analyzed spatiotemporal variation in vegetation NPP in the Greater Mekong Subregion from 2001 to 2019 and found that the overall vegetation NPP trend is insignificant and significantly negatively correlated with annual average air temperature, showing a spatial heterogeneity pattern. For the Tarim River Basin, there have been limited studies on vegetation NPP based on GEE, and data on vegetation NPP using this platform are also lacking.

Therefore, in this study, we used GEE to analyze the relationship between vegetation NPP and key factors to provide insights into vegetation NPP changes in the Tarim River Basin. Vegetation NPP data were preprocessed on GEE and can be used immediately after downloading, which shortens data process-

ing time, improves data processing efficiency, and is more convenient and faster than other NPP data acquisition methods. Prior research on vegetation NPP in the Tarim River Basin has mainly focused on grassland NPP rather than vegetation NPP in the whole basin [?]. The Tarim River Basin is located in an arid area dominated by desert and bare desert substrates, where vegetation plays an important role in water conservation. The ecological environment is highly fragile; hence, vegetation growth and changes have been closely monitored. Evaluating spatiotemporal variation in vegetation NPP and analyzing the influence of meteorological factors are important for understanding carbon cycle characteristics in the basin. The findings can also inform protection and sustainable utilization of vegetation resources, determine the effectiveness of construction projects such as reforestation and holistic watershed management, and provide a basis for formulation of ecological construction and sustainable development strategies.

## 2.1 Study Area

The Tarim River Basin is in the southern part of Xinjiang Uygur Autonomous Region in China, between 71°39′–93°45′E and 34°20′–43°39′N. The basin sits between the Tianshan Mountains and Kunlun Mountains, with a length of 1100 km from east to west, a width of 600 km from north to south, and a total area of  $1.028 \times 10^6$  km<sup>2</sup>. It is the largest inland river basin in the world [?], consisting of the Kashgar River Basin, Yarkant River Basin, Hotan River Basin, Kriya River Basin, Cherchen River Basin, Kaikong River Basin, Weigan River Basin, Aksu River Basin, Tarim River main stream Basin, and Taklimakan, eastern Gobi, and Kumutag deserts (Fig. 1 [Figure 1: see original paper]). As the eastern Gobi and Kumutag deserts are largely devoid of vegetation growth in all seasons, these two regions were removed from the study during computational analysis.

## 2.2 Data Sources

Remote sensing data were derived from MOD17A3HGF NPP and Landsat 8 NDVI data provided by GEE, with time series of year-by-year data from 2001 to 2020. The spatial resolution of NPP data is 500 m and the temporal resolution is 1 a. Air temperature and precipitation data were obtained from the National Earth System Science Data Center, National Science & Technology Infrastructure of China (<http://www.geodata.cn/>), with a time series of 2001–2020 and a spatial resolution of 1000 m. To maintain consistency with the spatial resolution of NPP data, we resampled the spatial resolution of meteorological data to 500 m and the temporal resolution to 1 month. Air temperature data were selected for the growing season (April–October) of each year.

### 2.3.1 Trend Analysis of Vegetation NPP Change

The Sen slope estimation method is often used to assess linear relationships [?] and has been applied in several previous studies [?, ?]. Compared with linear regression analysis, the Sen slope estimation method is not affected by total data error or outliers and can effectively reduce noise interference [?]. The calculation formula is as follows [?, ?]:

where  $\beta$  is the Sen slope;  $x_j$  and  $x_i$  are the time series data; and  $i$  and  $j$  are the time series attribute values ( $i \neq j$ ).  $\beta$  greater than zero indicates that the time series is in an upward trend, whereas  $\beta$  lower than zero indicates a downward trend. To verify calculation accuracy, we combined the Sen slope estimation method and Mann-Kendall test to complete the slope calculation results [?].

For a time series  $X_i$  ( $i=1, 2, \dots, i, \dots, j, \dots, n$ ), the standardized test statistic  $Z$  can be calculated using the following equations:

$$\text{median}_{j < i} (x_j - x_i) / \sqrt{\frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n (x_j - x_i)^2} \cdot \text{sign}(x_j - x_i)$$

where  $\text{Var}(S)$  is the variance of the accumulated number  $S$ ;  $\text{sign}$  is the sign function;  $n$  is the number of data;  $x_j - x_i$  is the difference of  $x_j$  and  $x_i$  ( $=x_j - x_i$ ); and  $E(S)$  is the mean of the accumulated number  $S$ . When  $n \geq 8$ , the standardized test statistic  $Z$  is approximately normally distributed.

The rate of change indicates the percentage change of vegetation NPP. The calculation formula is as follows:

where  $NPP_c$  is the rate of change in vegetation NPP ( $\text{g C}/(\text{m}^2 \cdot \text{a})$ ); and for  $n$  years ( $\text{g C}/(\text{m}^2 \cdot \text{a})$ ), where  $n$  is the number of data (years).

### 2.3.2 Stability Analysis of Vegetation NPP

Coefficient of variation (CV), also known as coefficient of stability, was used to characterize the volatility of vegetation NPP and stability of the time series. The CV for each raster vegetation NPP in the Tarim River Basin from 2001 to 2020 was calculated, and results were further analyzed. The larger the calculated result, the greater the fluctuation and instability of vegetation NPP with time. The calculation formula is as follows [?]:

is the average NPP where  $\sigma$  is the standard deviation; and  $\bar{x}$  is the arithmetic mean.

### 2.3.3 Analysis of Future Trend of Vegetation NPP Change

The Hurst index, calculated based on the rescaled range analysis method, was proposed to characterize persistence characteristics of vegetation NPP [?, ?, ?, ?]. The Hurst index can better distinguish autocorrelation of time series data; hence, it is often used in vegetation cover change studies. The Hurst index size can evaluate time series data persistence, where the Hurst index is between 0.0 and 1.0. If  $0.0 < \text{Hurst index} < 0.5$ , it indicates that the time series is anti-continuity; that is, the future trend of change is opposite to the past trend (the closer the Hurst index is to zero, the stronger the anti-continuity). Conversely, if  $\text{Hurst index} = 0.5$ , the time series is random, and there is no long-term correlation between future and past trends. Moreover, if  $0.5 < \text{Hurst index} < 1.0$ , the time series shows sustainability; that is, the future trend is consistent with the past trend and has long-term correlation characteristics (the closer the Hurst index is to 1.0, the stronger the sustainability) [?].

The time series is defined as  $(t)$  (where  $t=1, 2, \dots$ ), the sequence is defined as  $\tau$  (where  $\tau=1, 2, \dots$ ), and  $\tau$  represents the mean series, as follows [?]:

The cumulative deviation ( $X(t, \tau)$ ) at time  $t$  is defined as follows:

where  $u$  is the cumulative summation variable.

The polar difference  $R$  is defined as follows:

The standard deviation  $S$  is defined as follows:

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$NPP100\%NPPcn$

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$R, S,$  and  $\tau$  are related as follows:

where  $R(\tau)$  is the extreme deviation;  $S(\tau)$  is the standard deviation;  $c$  is a constant; and  $H$  is the Hurst index. The Hurst index ( $H$ ) is fitted using the least squares method and calculated by Equation 14:

where  $\log(R/S)\tau$  series is the independent variable; and  $\log(\tau)$  series is the dependent variable.

### 2.3.4 Correlation Analysis of Vegetation NPP and Meteorological Factors

Air temperature and precipitation are the main climatic factors affecting vegetation NPP, and correlations of vegetation NPP with these factors were analyzed. The partial correlation coefficients of vegetation NPP with air temperature and precipitation were calculated separately, and correlation coefficients were calculated before partial correlation coefficients. The calculation formula is as follows:

where  $R_{xy}$  is the correlation coefficient of the two variables  $x$  and  $y$ ;  $x_g$  and  $y_g$  are the values of  $x$  and  $y$  in the  $g$ th year, respectively;  $n$  is the number of years;  $\bar{y}$  is the mean of  $y$  values. The more the correlation coefficient tends to 1, the higher the correlation between variables, whereas the more the correlation coefficient is close to 0, the weaker the correlation. If the calculated result is higher than zero, the correlation is positive, while if lower than zero, the correlation is negative.  $\bar{x}$  is the mean of  $x$  values; and

The partial correlation coefficients of vegetation NPP with air temperature and precipitation are calculated as:

where  $R_{xy,z}$  is the partial correlation coefficient between dependent variable  $x$  and independent variable  $y$  after fixing independent variable  $z$ ;  $R_{xz}$  is the correlation coefficient of variables  $x$  and  $z$ ; and  $R_{yz}$  is the correlation coefficient of variables  $y$  and  $z$ . In this study, the dependent variable was vegetation NPP and the independent variables were mean air temperature and precipitation. The significance test of the partial correlation coefficient is generally performed using the  $t$ -test:

where  $m$  is the number of independent variables ( $m=2$ ).

As shown in Figure 2 [Figure 2: see original paper], we used vegetation NPP data of the Tarim River Basin in GEE, analyzed spatiotemporal changes using GEE, preprocessed meteorological data, and analyzed correlations between vegetation NPP and meteorological factors. The vegetation changes in the Tarim River Basin were obtained to provide deeper insights into vegetation NPP.

### 3.1 Temporal Distribution Characteristics of Annual Average Vegetation NPP

Statistical analyses of the trend graph of annual average vegetation NPP in the Tarim River Basin (Fig. 3 [Figure 3: see original paper]) showed an overall volatility uptrend from 2001 to 2020. Specifically, annual average vegetation NPP ranged from 118.99 to 155.07  $\text{g C}/(\text{m}^2 \cdot \text{a})$ , with the maximum value of 155.07  $\text{g C}/(\text{m}^2 \cdot \text{a})$  occurring in 2017, the minimum value of 118.99  $\text{g C}/(\text{m}^2 \cdot \text{a})$  in 2001, and an average annual vegetation NPP of 135.39  $\text{g C}/(\text{m}^2 \cdot \text{a})$  during 2001–2020. Annual average NPP for each year from 2001 to 2020 was divided into five classes (0.00–50.00, 50.00–100.00, 100.00–150.00, 150.00–350.00, and

$>350.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$ ), and the percentage of area occupied by each class was calculated. The percentage of area occupied by annual average vegetation NPP of  $0.00\text{--}50.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  and  $50.00\text{--}100.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  showed a fluctuating decreasing trend, the percentage of area occupied by  $100.00\text{--}150.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  fluctuated insignificantly, and the percentage of area occupied by  $150.00\text{--}350.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  and  $>350.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  showed a fluctuating increasing trend.

### 3.2.1 Spatial Distribution Characteristics of Annual Average Vegetation NPP

Annual average vegetation NPP of the Tarim River Basin from 2001 to 2020 showed a significant spatially divergent pattern (Fig. 4a [Figure 4: see original paper]). The total annual average vegetation NPP was  $76,308,679.00 \text{ g C}/\text{a}$ , with a mean value of  $133.35 \text{ g C}/(\text{m}^2 \cdot \text{a})$  and a maximum value of  $589.64 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in the Kashgar River Basin. The area with annual average vegetation NPP values greater than  $100.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  was  $82,638.75 \text{ km}^2$ , accounting for 57.76% of the basin, whereas the area with values less than  $100.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  was  $60,423.25 \text{ km}^2$ , accounting for the remaining 42.24%. In terms of spatial distribution, annual average vegetation NPP generally decreased from northwest to southeast along the outer edge of the study area. All river basins showed higher average annual vegetation NPP values in intermountain, pre-mountain alluvial, and oasis zones where rivers originated. Moreover, average annual vegetation NPP values were lower in the marginal zone of the Taklimakan Desert and the edge of the Tarim River Basin.

To further study spatial distribution in each river basin, we analyzed the percentage of area occupied by different classes of annual average vegetation NPP (Fig. 4b [Figure 4: see original paper]). The percentage of area with values less than  $100.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in the Kashgar River Basin, Cherchen River Basin, and Tarim River main stream Basin exceeded 50.00% of the basin area, whereas the percentage of area with values greater than  $100.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in the Yarkant River Basin, Hotan River Basin, Kriya River Basin, Kaikong River Basin, Weigan River Basin, and Aksu River Basin was extremely low. Additionally, the percentage of area with values greater than  $350.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in the Yarkant River Basin, Hotan River Basin, and Kriya River Basin was extremely low; likewise, the percentage of area with values greater than  $350.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  and within  $100.00\text{--}150.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in the Tarim River main stream Basin was extremely low. In the desert zone at the edge of the Taklimakan Desert in the Tarim River main stream Basin, annual average vegetation NPP values were all below  $150.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  due to poor growth conditions.

### 3.2.2 General Spatial Trends of Vegetation NPP

Temporal trends of vegetation NPP were calculated for each image element using Sen slope estimation analysis (Fig. 5a [Figure 5: see original paper]). Vegetation NPP showed an overall increasing trend. Specifically, vegetation

NPP with Sen slope values higher than zero occupied 122,299.75 km<sup>2</sup> or 87.46% of the total basin, while vegetation NPP with values lower than zero occupied 17,535.75 km<sup>2</sup> or 12.54%. Vegetation NPP in other river basins, except for the Tarim River main stream Basin, also showed an overall increasing trend, whereas the Kaikong River Basin, Weigan River Basin, Aksu River Basin, and Kashgar River Basin showed decreasing trends in intermountain areas of river origins. Sen slope estimation results were tested for significance using a combination of Sen slope estimation and Mann-Kendall tests (Fig. 5b [Figure 5: see original paper]). Overall, vegetation NPP change in 39.67% of the total basin passed significance testing, whereas 60.33% did not.

The area of vegetation NPP with an upward trend that passed significance testing was 54,709.00 km<sup>2</sup>, accounting for 98.63% of the total area that passed, whereas the area with a downward trend that passed was 759.25 km<sup>2</sup>, accounting for the remaining 1.37%. Vegetation NPP change in the Kaikong River Basin, Weigan River Basin, Aksu River Basin, Kashgar River Basin, and Yarkant River Basin, as well as central areas of the Hotan River Basin passed significance testing and showed an upward trend. Moreover, vegetation NPP change in the Kashgar River Basin and Yarkant River Basin, as well as central areas of the Hotan River Basin passed significance testing and exhibited a downward trend.

Based on Sen slope calculation of the percentage of area occupied by different vegetation NPP change rates (Fig. 5c [Figure 5: see original paper]), we found that the overall trend of vegetation NPP change rate was increasing. Specifically, the area with change rate greater than 0.00% was 122,299.75 km<sup>2</sup>, accounting for 87.47% of the total basin area, whereas the area with change rate lower than 0.00% occupied 17,535.75 km<sup>2</sup>, accounting for 12.53%. At the intersection of the Tarim River main stream Basin, vegetation NPP change rate was lower than 0.00% in the Weigan River Basin, the Tarim River main stream Basin, and the central part of the oasis in the Kashgar River Basin.

### 3.3 Stability Characteristics of Vegetation NPP Change

CV results of vegetation NPP change from 2001 to 2020 were analyzed (Fig. 6 [Figure 6: see original paper]). Figure 6a shows that CVs ranged from 0.0246–4.4721, with an average of 0.1575. From 2001 to 2020, vegetation NPP fluctuated little with time and showed stability, and spatial variability was not significant (Fig. 6b). CVs of vegetation NPP change can be divided into four classes: very stable, stable, unstable, and very unstable, with area percentages of 20.47%, 61.00%, 12.81%, and 5.71%, respectively. Vegetation NPP was more stable in intermountain areas where rivers originate and in central oasis areas, whereas CVs were larger and vegetation NPP less stable in marginal areas of the Taklimakan Desert and oasis-desert ecotone. Vegetation NPP was less stable in the Tarim River main stream Basin, downstream area of the Yarkant River Basin, and intermountain area of the Kashgar River Basin.

### 3.4 Persistence of Vegetation NPP Change

This study predominantly analyzed spatiotemporal variation and stability of vegetation NPP from 2001 to 2020 and predicted future variation trends by calculating the Hurst index. Anti-continuity of vegetation NPP was strong (Fig. 7a [Figure 7: see original paper]), with Hurst index values ranging from 0.1074–0.9477 (average of 0.4613). Vegetation NPP in intermountain zones of the Kaikong River Basin, Weigan River Basin, Aksu River Basin, Kashgar River Basin, and Yarkant River Basin showed more sustainability, whereas remaining areas showed anti-continuity.

Predicted future vegetation NPP trends were tested for significance by combining Sen slope estimation (Fig. 7b [Figure 7: see original paper]). The area of future vegetation NPP change with Hurst index that passed significance testing was 69,304.00 km<sup>2</sup>, or 50.26% of the total basin area, whereas the area that did not pass was 68,576.75 km<sup>2</sup>, accounting for 49.74%. Future vegetation NPP trends (indicated by significance testing of the Hurst index) were classified into five categories: increasing-increasing, increasing-decreasing, decreasing-decreasing, decreasing-increasing, and random (Table 1), with area percentages of 22.18%, 52.59%, 4.57%, 10.98%, and 9.68%, respectively. Thus, the area percentage with sustainability characteristic was 26.75%, whereas the area percentage with anti-continuity characteristic was 63.57%. The increasing-increasing trend with sustainability characteristic was mainly found in mountainous areas where rivers originated in the Kaikong River Basin, Weigan River Basin, and northern Aksu River Basin, showing that with effective ecological management, the vegetation ecosystem will continue to improve. The decreasing-decreasing trend with sustainability characteristic was primarily found in mountainous areas where flows originated in the Kaikong River Basin and Weigan River Basin, oasis margins, and northern Kashgar River Basin, indicating that ecological restoration is insufficient and the vegetation ecosystem will continue to deteriorate. Finally, increasing-decreasing and decreasing-increasing inverse sustainability characteristics were found in all river basins, also implying that ecological restoration is insufficient and the vegetation ecological environment will deteriorate. Vegetation ecological restoration should be enhanced to improve the vegetation ecological environment. The random trend was mainly found in the Kaikong River Basin, Weigan River Basin, Aksu River Basin, and Kashgar River Basin.

#### 3.5.1 Correlation Between Vegetation NPP and Air Temperature

Air temperature affects vegetation NPP, and correlation coefficients and partial correlation coefficients between vegetation NPP and air temperature were calculated (Fig. 8 [Figure 8: see original paper]). Figure 8a shows that correlation coefficients ranged from -0.9186 to 0.9180, with an average of 0.0126. The percentage of area with positive correlation was 53.42%, whereas that with negative

correlation was 46.58%. Partial correlation coefficients ranged from  $-0.9014$  to  $0.9260$ , with an average of  $0.1033$  (Fig. 8b). The percentage of area with positive partial correlation was 62.86% and that with negative partial correlation was 37.14%.

Table 2 lists significance of correlation analysis and significance testing. Specifically, 16.77% of correlation coefficients passed significance testing; among these, area with significant positive correlation occupied 53.74% of regions that passed, whereas 46.26% showed negative correlation (Fig. 8c; Table 2). Finally, 21.88% of partial correlation coefficients passed significance testing; among these, 77.02% of regions showed significantly positive partial correlation, whereas 22.98% exhibited negative partial correlation (Fig. 8d; Table 2).

### 3.5.2 Correlation Between Vegetation NPP and Precipitation

Precipitation also influences vegetation NPP, and correlation coefficients and partial correlation coefficients were calculated (Fig. 9 [Figure 9: see original paper]). Figure 9a shows that correlation coefficients ranged from  $-0.7734$  to  $-0.8703$ , with an average of  $0.2443$ . The percentage of area with positive correlation was 86.04% and that with negative correlation was 13.96%. Partial correlation coefficients ranged from  $-0.7876$  to  $0.9311$ , with an average of  $0.2835$  (Fig. 9b). The percentage of area with positive partial correlation was 88.57%, whereas that with negative partial correlation was 11.43%. About 21.61% of correlation coefficients passed significance testing; among these, 98.68% of regions showed significant positive correlation, whereas 1.32% exhibited significant negative correlation (Table 2; Fig. 9c). Moreover, 25.61% of partial correlation coefficients passed significance testing; among these, 98.91% of regions showed significant positive partial correlation, whereas 1.09% exhibited significant negative partial correlation (Table 2; Fig. 9d).

## 4 Discussion

We conducted this study based on MODIS NPP dataset from GEE. Results showed that the annual average vegetation NPP in the Tarim River Basin from 2001 to 2020 was  $133.35 \text{ g C}/(\text{m}^2 \cdot \text{a})$ . Given that previous research mainly focused on grassland NPP rather than whole-basin vegetation NPP, we compared our results with other studies. Tong et al. [?] reported  $100.00\text{--}150.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  whereas Zhu et al. [?] reported  $110.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  based on simulation of vegetation NPP in Northwest China. Jiang [?] estimated annual average vegetation NPP as  $120.00 \text{ g C}/(\text{m}^2 \cdot \text{a})$  in the Tarim River Basin, similar to our study.

We analyzed responses of vegetation NPP to air temperature and precipitation, calculated correlation and partial correlation coefficients, and performed significance tests. Percentages of area with positive correlation and partial correlation between vegetation NPP and both air temperature and precipitation were much

higher than those with negative correlations. Therefore, vegetation NPP was generally positively correlated with air temperature and precipitation, affected by their joint action. The area where vegetation NPP was significantly positively correlated with precipitation accounted for 98.68% of regions that passed significance testing, whereas the area with significant positive correlation between vegetation NPP and air temperature occupied 53.74%. Therefore, precipitation is the main climatic factor affecting vegetation NPP in the Tarim River Basin [?, ?, ?, ?, ?, ?]. Moreover, Jiao et al. [?] showed that correlation between vegetation NPP and air temperature is not significant, consistent with our findings. Mountains, oases, and deserts in arid areas constitute a complete complex system [?], and vegetation NPP is mainly concentrated in mountainous areas where rivers originate, pre-mountainous oasis regions, and margins of the Taklimakan Desert. In areas where vegetation NPP and air temperature are positively correlated, air temperature influence is much higher in intermountain areas than in oasis and plain areas. Because mountainous areas are relatively high above sea level, vegetation presents vertical zonal characteristics, and air temperature changes with altitude variation [?]. Additionally, our analysis shows vegetation NPP is influenced by combined effects of air temperature and precipitation, with precipitation having greater effect. Figure 8 indicates that air temperature has higher impact on vegetation NPP in mountainous areas where rivers originate than in oasis and plain areas. Moreover, Figure 9 shows that overall vegetation NPP is more influenced by precipitation.

Average annual vegetation NPP showed an upward fluctuating trend. Owing to the highly fragile ecological environment, the government has implemented policies such as forest closure and reforestation to protect relatively intact areas and restore damaged areas, improving ecological environment, vegetation cover, and growth conditions [?]. Therefore, vegetation NPP has shown a positive trend over time. Vegetation NPP is higher in intermountain and pre-mountain alluvial areas where rivers originate, and lower in marginal areas of the Taklimakan Desert and southern marginal areas, where grasslands, meadows, coniferous forests, and other vegetation types are predominantly distributed. These areas generally have higher vegetation cover and NPP. In pre-mountain alluvial areas (including oasis areas with fertile soils), vegetation cover is higher, and NPP increases during the growing season. The marginal zone of the Taklimakan Desert is characterized by poor water resources, vegetation growth environment, and low soil fertility. Only some plants can grow on sandy soils, resulting in low vegetation cover and NPP. The southern edge is dominated by high mountains covered with snow throughout the year, with no vegetation growing on summits, leading to low NPP. Sen trend results showed overall increasing vegetation NPP. Owing to implementation of fallowing and forestry ecological construction projects, by the end of 2019, 230.12 km<sup>2</sup> had been fallow and protected in the middle and upper reaches, 667.00 km<sup>2</sup> of poplar and shrub forests planted in the upper reaches, and 66.70 km<sup>2</sup> of desert forests restored in the lower reaches [?]. Implementation of various ecological construction projects has led to vegetation cover expansion and overall upward NPP trend. High vegetation NPP in the

marginal zone of the Taklimakan Desert and oasis-desert ecotone indicates high degradation degree, and vegetation protection should be strengthened.

Vegetation NPP change showed anti-continuity characteristics, mainly because the Tarim River Basin is an ecologically damaged area with human interference [?]. Under current climate warming, inflow from source areas has increased, although water supplied to the main channel has not substantially increased. Even during high-water periods, environmental deterioration in the main channel cannot be alleviated. Owing to lack of effective unified management, water resource use is relatively low. Although emergency water diversion projects have been implemented, such projects only alleviate temporary problems. Destruction of the ecological environment remains a serious challenge [?].

## 5 Conclusions

The ecological environment in the Tarim River Basin is fragile, and vegetation growth status is of great concern. Detailed analysis of vegetation NPP is important for promoting sustainable development. This study analyzed spatiotemporal variation from 2001 to 2020 based on GEE, using vegetation NPP data and available meteorological data, combining Sen slope estimation, stability coefficient, and rescaled range analysis methods. Correlation analyses determined relationships between vegetation NPP and meteorological factors. Overall, vegetation NPP showed a fluctuating upward trend, spatially characterized by decrease from northwest to southeast along the outer edge. Maximum vegetation NPP appeared in the Kashgar River Basin (589.64 g C/(m<sup>2</sup>·a)). Mean stability coefficient (CV) was 0.1575, mean Hurst index from future change simulation was 0.4613, area with anti-continuity characteristic accounted for 63.57%, and future change trend was dominated by anti-continuity. Among correlation coefficients, area with significant positive correlation between vegetation NPP and air temperature accounted for 53.74% of regions passing significance testing, while area with significant positive correlation between vegetation NPP and precipitation occupied 98.68%. Precipitation was significantly positively correlated with vegetation NPP, whereas correlation with air temperature was not significant. The resolution of vegetation NPP was low, with mixed pixel issues. Additionally, we only selected main meteorological factors, and selected influencing factors were relatively limited. Therefore, we recommend considering multiple influencing factors under different scenarios in future research.

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