Quantitative Assessment of the Relative Contributions of Climate and Human Factors to Net Primary Productivity in the Ili River Basin of China and Kazakhstan

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Abstract: It is necessary to quantitatively study the relationship between climate and human factors on net primary productivity (NPP) inorder to understand the driving mechanism of NPP and prevent desertification. This study investigated the spatial and temporal differentiation features of actual net primary productivity (ANPP) in the Ili River Basin, a transboundary river between China and Kazakhstan, as well as the proportional contributions of climate and human causes to ANPP variation. Additionally, we analyzed the pixel-scale relationship between ANPP and significant climatic parameters. ANPP in the Ili River Basin increased from 2001 to 2020 and was lower in the northeast and higher in the southwest; furthermore, it was distributed in a ring around the Tianshan Mountains. In the vegetation improvement zone, human activities were the dominant driving force, whereas in the degraded zone, climate change was the primary major driving force. The correlation coefficients of ANPP with precipitation and temperature were 0.322 and 0.098, respectively. In most areas, there was a positive relationship between vegetation change, temperature and precipitation. During 2001 to 2020, the basin's climatic change trend was warm and humid, which promoted vegetation growth. One of the driving factors in the vegetation improvement area was moderate grazing by livestock.

Keywords: net primary productivity (NPP); actual net primary productivity (ANPP); climate change; human activities; Ili River Basin

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1 Introduction

Vegetation is an essential component of the global ecosystem because it serves to control the global carbon balance and preserve climatic stability [\(Abdi et al](#page-11-0)., [2013](#page-11-0); [Erb et al., 2018](#page-12-0)). According to previous research, temperature and precipitation have an impact on vegetation development, and the relationship between them and vegetation has regional variability ([Park et al., 2015](#page-12-1); [Fang et al., 2018](#page-12-2)). The breadth and depth of human actions on the ecological environment continue to strengthen, and they are gradually becoming an influencing element of vegetation change on a global and regional scale due to the rapid expansion of the social economy and increase in population [\(Wang et al., 201](#page-13-0)6). Thus, quantifying the proportional influences of climate and human factors on vegetation is essential for national and regional strategic planning to address the challenges

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posed to ecosystems by these factors [\(Li et al., 2012\)](#page-12-3).

The primary methodologies for accurate and quantitative examination of the relative roles of climatic and human influences in vegetation dynamics include model variable analyses, coefficient of variation analyses, and residual trend studies [\(Rojstaczer et al., 2001](#page-12-4)). The potential net primary productivity (PNPP) and actual net primary productivity (ANPP) difference methods are based on residual trend analysis. Each driving factor of NPP is utilized to represent the effect of alterations in the vegetation transition process. NPP can intuitively and truly reflect the change in vegetation in the ecosystem ([Andersen et al., 2015](#page-11-1); [Plutzar et al., 2016](#page-12-5)). [Zhang](#page-13-1) [et al. \(2011\)](#page-13-1) and [Zhou et al. \(2015\)](#page-13-2) applied this method to explore the relative effects of climate and human factors on NPP of vegetation in Shiyang River Basin and northwest China, respectively. Chen et al.([2019\)](#page-11-2) studied the spatiotemporal pattern of the Central Asian grassland ecosystem, and the findings revealed that overgrazing was a key contributor to grassland deterioration. Zhou et al. [\(2017](#page-13-3)) investigated the factors that contribute to grassland degradation in China and concluded that human activities had a substantial impact on grassland restoration. Guan et al. [\(2021](#page-12-6)) assessed the influence of human activities on vegetation in Xinjiang, China, and the findings demonstrated that the anthropogenic effect of vegetation transformation was mostly positive. The research described above are all quantitative evaluations of the effects of climate and human variables on vegetation at a wide regional scale, but few studies have quantified vegetation change at a spatial scale in transboundary river basins.

The Ili River Basin is located in Central Asia's semiarid region. Due to the influence of various factors, such as natural forces and human activities, the lower reaches of the Ili River delta suffer from ecological problems, such as salinization of the land, a decrease in biodiversity, and a reduction in the Ili River's inflow of lake water [\(Pueppke et al., 2018a](#page-12-7)). As the international river basin between China and Kazakhstan, the Ili River Basin has become a shared priority of both nations for effective conservation of the vulnerable environment. Scholars are now conducting research on NPP in the Ili River Basin. Jiao et al. [\(2018](#page-12-8)) studied the spatiotemporal pattern of NPP in the Ili Valley and its association with important climatic parameters. Qi et al. ([2020\)](#page-12-9) analyzed the changes in NPP in the Balkhash Basin and concluded that vegetation changes in the Balkhash Lake area were characterized by unstable to somewhat stable circumstances. The studies of the above two scholars are limited to national-scale vegetation change and its correlation with climate factors. To summarize, most studies on the geographical scale have focused on the changes in NPP in China or the Balkhash Lake area, with a lack of studies on the changing features of NPP in the whole basin and its link with meteorological elements. In terms of research content, the bulk of research has focused on NPP's spatial and temporal variation characteristics; quantitative evaluations of the effect of climate and human influences on NPP are lacking. Ignoring the spatial integrity and temporal continuity of watershed ecology and hydrology inhibits China and Kazakhstan efforts for cross-border river protection in the Ili River Basin.

In this study, NPP was used as the evaluation index of vegetation status, and the relative role of climate and human factors was quantitatively assessed from a basinwide perspective. 1) Spatiotemporal variation in ANPP in the Ili River Basin was obtained from 2001 to 2020. 2) To estimate ANPP and PNPP and quantify the relative influences of climate and human factors on ANPP based on scenarios, the CASA (Carnegie-Ames-Stanford Approach) and Thornthwaite Memorial models were utilized. 3) The link between ANPP and the primary meteorological parameters was investigated using partial correlation and multiple correlation approaches. This study is not only a supplement to the quantitative study of climate and human factors on terrestrial ecological environment, but also has practical implications for transboundary river ecosystem management and nations along the Belt and Road Initiative.

2 Materials and Methods

2.1 Study area

The Ili River Basin is located at 42°16′N−49°22′N and 73°18′E−85°00′E([Pueppke et al., 2018](#page-12-10)b, [Fig. 1](#page-2-0)). The upper reaches contain diverse topography and considerable precipitation, which can provide favorable conditions for vegetation growth. The vegetation types are complex and mainly include desert vegetation, grassland, meadows, and forest. The middle reaches contain various deserts, the Gobi, and a small amount of arable land, while the vegetation in the lower reaches is mostly *Populus euphratica* and *Phragmites australis*. From high to low elevations, vertical vegetation zones in-

Fig. 1 Elevation of the Ili River Basin

clude tundra, alpine meadows, coniferous forests, deciduous trees and shrubs mixed with grassland, grassland and desert ([Yang et al., 2010](#page-13-4); [Thevs et al., 2017](#page-13-5)). The Ili is a border-crossing river that connects China and Kazakhstan. It is one of the world's best-preserved semiarid regional natural environments.

2.2 Data and methods

2.2.1 Data sources and preprocessing

Remote sensing data: normalized difference vegetation index (NDVI) data are from NASA's (USA National Aeronautics and Space Administration) MOD13Q1 dataset [\(https://ladsweb.modaps.eosdis.nasa.gov/](https://ladsweb.modaps.eosdis.nasa.gov/)). The temporal resolution is 16 d, and the spatial resolution is 250 m. Tiles H22V04, H23V04, and H24V04, where the Ili River Basin is located, are selected. The maximum value composite (MVC) technique is used to reduce the participation of meteorological components. To verify the NPP's validity, NPP yearly scale data product with a spatial resolution of 500 m from NASA's MOD17A3 dataset was acquired, which was calculated using the Biome-BGC model that has been verified and widely utilized in vegetation change research at global and regional scales ([De Leeuw et al., 2019\)](#page-12-11).

Meteorological data: the Famine Land Data Assimilation System (FLDAS) dataset is used for temperature, precipitation, and solar radiation, with a spatial resolution of 0.1° and a temporal resolution of a month [\(https://ldas.gsfc.nasa.gov/index.php/fl-das/\)](https://ldas.gsfc.nasa.gov/index.php/fl-das/). The dataset assists developing countries with scarce data in food security assessments and includes information on many climate-related variables [\(McNally et al., 201](#page-12-12)7). The MOD17A3 NPP data product was calculated using the Biome-BGC model, which has been verified and widely utilized in ve[getation change researc](#page-12-11)h at global and regional scales ([De Leeuw et al., 2019\)](#page-12-11).

Vegetation type: global land cover products developed by the European Aviation Agency provide data on vegetation types([https://cds.climate.copernicus.eu/\)](https://cds.climate.copernicus.eu/) with a spatial resolution of 300 m. We reclassified the ground feature types and eliminated urban land, water bodies, and permanent ice and snow vegetation coverage areas. Finally, we obtained four types of vegetation types, namely, grassland, forestland, cultivated land, and bare land.

2.3 Methods

The term 'PNPP' refers to the NPP in its natural condition, which is not disrupted by human activity, and its value is impacted by only meteorological factors. The term 'ANPP' refers to an NPP that has been impacted by climate and human factors. As a result, the difference in PNPP and ANPP values may be used to illustrate how human activities affect ANPP or human net primary productivity (HNPP) ([Qin et al., 2021\)](#page-12-13).

$$
PNPP - ANDP = HNPP
$$
 (1)

2.3.1 Calculation of ANPP

The CASA model is a light energy use model that takes into account NDVI, temperature, precipitation, solar radiation, and vegetation types([Potter et al., 1993](#page-12-14)). The model relies on remote sensing to collect full coverage data, allowing for estimates of NPP on regional and global scales.

$$
ANPP(x,t) = APAR(x,t) \times \varepsilon(x,t)
$$
\n(2)

where $ANPP(x, t)$ is the net primary productivity of pixel *x* in month *t*; *APAR* (x, t) and ε (x, t) are the absorbed photosynthetic effective radiation (MJ $/m²$) and actual light energy utilization (C, g/MJ), respectively. *APAR* (x, t) and ε (x, t) are calculated as follows:

$$
APAR(x,t) = SOL(x,t) \times FPAR(x,t) \times 0.5
$$
 (3)

$$
\varepsilon(x,t) = T_{g1}(x,t) \times T_{g2}(x,t) \times W_z(x,t) \times \varepsilon_{\text{max}} \tag{4}
$$

where $SOL(x, t)$ and $FPAR(x, t)$ are the ratio of total solar radiation $(MJ/m²)$ and incident photosynthetic effective radiation absorbed by vegetation, respectively, *FPAR* can be calculated from NDVI and 0.5 is the proportion of the ratio of total solar radiation intercepted by the vegetation. $T_{g1}(x, t)$ and $T_{g2}(x, t)$ are the temperature stress coefficients for light-use efficiency; $W_Z(x, t)$ represents the water stress coefficient; $ε_{max}$ is the maximum light-use efficiency under ideal conditions. The parameter settings of different vegetation types refer to the research of Zhu et al. ([2006\)](#page-13-6).

2.3.2 Calculation of PNPP

The Thornthwaite Memorial model, which was created

by least-square regression between NPP measurement data and temperature and precipitation data, was used for the PNPP estimate [\(Raich et al., 1991\)](#page-12-15).

$$
PNPP = 3000[1 - e^{-0.0009695(\nu - 20)}]
$$
\n(5)

where *PNPP* stands for the potential net primary productivity $(C, g/(m^2 \cdot yr))$, *v* represents the actual evaporation of vegetation (mm), and its calculation formula is as follows:

$$
v = \frac{1.05r}{\sqrt{1 + (1.05r/L)^2}}
$$
(6)

$$
L = 3000 + 25q + 0.05q^3 \tag{7}
$$

where *L* is the potential evaporation, the amount of evaporation under the condition of sufficient water supply (mm), *r* is the total precipitation (mm), and *q* is the average temperature (°C).

2.3.3 Trend analysis

To determine the temporal variation trend of NPP, the least-square approach was used. This method can more accurately and properly describe the variable trend.

$$
slope = \frac{n \times \sum_{i=1}^{n} i \times NPP_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} NPP_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2}
$$
(8)

where *n* is the length of the research time series, *i* represents year *i*, NPP_i represents the NPP value of vegetation in year *i*, and the *slope* denotes the trend line's slope.

2.3.4 Scenario design

Six scenarios were developed after reading relevant lit[eratures](#page-3-0) to [objectively analyz](#page-13-7)[e the relative co](#page-13-8)ntributions [\(Table 1](#page-3-0)) ([Zhang et al., 2018;](#page-13-7) [Yin et al., 2020](#page-13-8)).

2.3.5 Correlation analysis and significance test

The partial correlation was utilized in this work to investigate the link between ANPP and temperature, as well as that between ANPP and precipitation.

$$
r_{xy,z} = \frac{r_{xy} - r_{xz} - r_{yz}}{\sqrt{(1 - r^2_{xz})(1 - r^2_{yz})}}
$$
(9)

where r_{xy} , r_{xz} and r_{yz} are the correlation coefficients among the three variables, and r_{xyz} is the partial correlation coefficient between *x* and the *y* variable after *z* is fixed. In this study, where *x* denotes the ANPP, *y* and *z* denote the temperature and precipitation, respectively.

The link between ANPP and temperature and precipitation was calculated using multiple correlation coefficients in this study.

$$
r_{x,yz} = \sqrt{1 - \left(1 - r^2_{xy}\right)\left(1 - r^2_{xz,y}\right)}\tag{10}
$$

where $r_{x,yz}$ denotes the multiple correlation coefficient and r_{xy} and $r_{xz,y}$ denote the correlation coefficient and partial correlation coefficient of the relevant variables, respectively.

3 Results and Analyses

3.1 Validation of model accuracy

A correlation study was undertaken between the simulated ANPP and the measured NPP based on the aboveground biomass data of Ili Kazakh Autonomous Prefecture in June 2018, and the findings revealed that the simulated ANPP was strongly associated with the observed data $(R^2 = 0.73, P < 0.01)$ ([Fig. 2a](#page-4-0)).

The validation accuracy of biomass data obtained from field surveys is high, but it is difficult to carry out large-scale and relatively uniform field survey sampling

Table 1 Assessment methods of vegetation dynamics under the six possible scenarios

Region	Scenario	SANPP	SPNPP	SHNPP	Contribution of climate change $/$ %	Contribution of human activities / %	Description
The areas with improved vegetation	Scenario 1	> 0	> 0	> 0	100	θ	Climate change
	Scenario 2	> 0	< 0	< 0	Ω	100	Human activity
	Scenario 3	> 0	> 0	< 0	$100 \times S_{\text{PNPP}} $	$100 \times S_{HPPP} $	Both
					$ S_{PNNP} + S_{HNPP} $	$ S_{PNNP} + S_{HNPP} $	
The areas with degenerated vegetation	Scenario 1	< 0	< 0	< 0	100	$\mathbf{0}$	Climate change
	Scenario 2	< 0	> 0	> 0	θ	100	Human activity
	Scenario 3	< 0	< 0	> 0	$100 \times S_{\text{PNPP}} $ $ S_{PNNP} + S_{HNPP} $	$100 \times S_{HPPP} $ $ S_{PNNP} + S_{HNPP} $	Both

Notes: S_{ANPP} , slope of actual net primary productivity; S_{PNPP} , slope of potential net primary productivity; S_{HNPP} , slope of actual net primary productivity under the influence of human activities

Fig. 2 Validation of net primary productivity (NPP) model accuracy in Ili River Basin. a. Validation of NPP and measured NPP; b. validation of NPP and MOD17A3 NPP. CASA, Carnegie-Ames-Stanford Approach

in the whole basin. For this purpose, the CASA model estimation results were compared with MOD17A3 data products from 2001 to 2020. One thousand random points were produced at random, and the mean values of ANPP and MOD17A3 were calculated based on the points. Correlation analysis was performed on the data, and the correlation analysis results revealed that the coefficient of determination of the two was $R^2 = 0.89$, *P <* 0.01 ([Fig. 2b](#page-4-0))*.* According to the above two verification results, the ANPP calculated by the CASA model in this paper was suitable for estimating the NPP.

3.2 Temporal and spatial variations in ANPP *3.2.1 Interannual variation in ANPP*

The interannual variation in ANPP in the Ili River Basin from 2001 to 2020 showed a fluctuating increase [\(Fig. 3](#page-4-1)), with fluctuation values ranging from 265.41 to 363.92 g/(m²· yr). The mean ANPP was 309.36 g/(m²· yr), and it reached its peak value in 2016, which was 16.67% higher than the multiyear average. The lowest ANPP of vegetation was in 2008, which was 14.21% lower than the multiyear average. The period from 2014

Fig. 3 Interannual variation of actual net primary productivity (ANPP) in Ili River Basin from 2001 to 2020

to 2015 was a continuous growth stage, and the growth rate was relatively obvious, with an increase of 92.13 $g/(m^2$ yr). ANPP decreased significantly in 2007–2008 and 2013–2014, with decreases of 56.96 $g/(m^2 \cdot yr)$ and 53.43 $g/(m^2 \cdot yr)$, respectively.

3.2.2 Spatial variation in ANPP

The mean value of ANPP in the Ili River Basin from 2001 to 2020 was 0.03 to 1103.17 $g/(m^2 \cdot yr)$, with obvious spatial differentiation ([Fig. 4a](#page-4-2)). The ANPP was low

Fig. 4 Changes of actual net primary productivity (ANPP) in Ili River Basin from 2001 to 2020. a. Spatial distribution of ANPP; b. trends of ANPP; c. significance test of ANPP

in the northeast and high in the southwest, and it was distributed in a ring along the Tianshan Mountains range of China, with high values in the foothills of Tianshan Mountains and low values in the Ili River Valley of Kazakhstan. Additionally, China has a much larger ANPP than Kazakhstan at the watershed scale.

The spatial distribution of the interannual variation slope of ANPP was obtained from 2001 to 2020 ([Fig. 4b\)](#page-4-2). The interannual variation in NPP varied from −57.32 to 46.09 $g/(m^2 \cdot yr)$, and regions with an increasing trend $(slope > 0)$ made up 57.33% of the overall area, largely in the middle and lower reaches. NPP (slope \leq 0) accounted for 42.67% of the whole region, with the majority concentrated in the upper reaches. The significance test of ANPP found that only 12.87% of the regions passed the significance test, and the significant increase areas were mainly located in the Ili Valley and around Balkhash Lake of Kazakhstan, while the significant degradation areas were scattered only in the Tianshan Mountains of China [\(Fig. 4c](#page-4-2)).

3.3 Impacts of climate and human factors on ANPP *3.3.1 Trends of PNPP and HNPP*

This study investigated the changing trends of PNPP

and HNPP from 2001 to 2020. The changing trend of PNPP showed that climate change had a negative growth trend for the whole basin ([Fig. 5a](#page-5-0)). The proportion of *SPNPP* < 0 accounted for approximately 72.30% of the entire area and was mainly found in the middle reaches, indicating that climate change and lack of precipitation accelerated vegetation deterioration. The proportion of *SPNPP* > 0 accounted for approximately 27.70% of the total area. A total of 14.79% of the regions passed the significance test, and the changing trend was mainly significant reduction, which was mainly located in Kapchagay Reservoir, Taldyqorghan City of Kazakhstan and the western region of the basin ([Fig. 5b](#page-5-0)).

The variation trend of HNPP showed that human activities were positive for vegetation growth in 78.68% of the total area. Human-caused vegetation degradation was mostly seen in Yining City of China and around Balkhash Lake of Kazakhstan, which accounted for 21.32% of the entire area ([Fig. 5c\)](#page-5-0). HNPP increased significantly in 18.86% of the total area, mainly around Kapchagay Reservoir of Kazakhstan. Due to Kazakhstan's policies, farmland near Kapchagay Reservoir of Kazakhstan had been mostly transformed into natural

Fig. 5 Changes of potential net primary productivity (PNPP) and human net primary production (HNPP) in Ili River Basin from 2001 to 2020. a and b show the PNPP trend and significance test, respectively; c and d show the HNPP trend and significance tests, respectively

grassland ([Fig. 5d](#page-5-0)).

3.3.2 The relative role of climate and human factors Using the criteria in [Table 1](#page-3-0), the proportionate influence of climate and human factors on ANPP was examined. Climate change-affected regions made up 43.31% of the basin's total area and were mostly concentrated near Kapchagay Reservoir of Kazakhstan and the western region downstream [\(Fig. 6](#page-6-0)). Only human activities impacted the region in the middle reaches, which accounted for 39.89% of the entire area. The area affected by both causes was 16.8% of the entire area; the areas around Yining City of China and Balkhash City of Kazakhstan were the most significant, indicating that the vegetation was influenced by both climate and human factors, with the impact of climate being slightly higher than that of human activities.

Only 32.73% of the vegetation improvement region was affected by climate change; this area encompassed mainly a small part of Yinin[g City](#page-6-1) of China and Balkhash City of Kazakhstan [\(Fig. 7a](#page-6-1)). A total of 67.27% of the improved area was in places where human activities had a significant impact on vegetation improvement; this area was mostly distributed in the

Fig. 6 Spatial distribution of relative role of climate change and human activities in Ili River Basin from 2001 to 2020

middle reaches and Ayakoz City of Kazakhstan ([Fig. 7b\)](#page-6-1). When compared to climate change, this finding suggests that human activities have had a significant influence on vegetation restoration.

Climate change affected a substantial percentage of the vegetation degradation area and accounted for 79.97% of the degraded area, which was mostly dispersed in the Tianshan Mountains of China [\(Fig. 7c](#page-6-1)). Human-caused vegetation degradation accounted for 20.03% of the degraded area, mostly in the Ili River Valley and surrounding Balkhash Lake of Kazakhstan ([Fig. 7d](#page-6-1)). The major cause of vegetation degradation

Fig. 7 The relative role of climate change and human activities in the mitigation area and the exacerbation area in Ili River Basin from 2001 to 2020. a and b show the relative role of climate change and human activities in the mitigation area, respectively; c and d show the relative role of climate change and human activities in the exacerbation area, respectively

was climate change.

3.4 Relationship between ANPP and climatic factors

3.4.1 Multiple correlation

The majority of earlier research focused on the link between vegetation NPP and single climatic variables [\(Jiao et al., 2018](#page-12-8)). This study investigated the response of ANPP and climate factors through multiple correlations. The ANPP multiple correlation coefficients with temperature and precipitation ranged from 0 to 0.935, with a mean of 0.434. Almaty City, the Kapchagay Reservoir area, and Ayakoz City of Kazakhstan had the highest association between ANPP and climatic parameters([Fig. 8a](#page-7-0)). The spatial distribution of areas that passed the significance test $(F > F_{0.01})$ was essentially consistent with that of [the reg](#page-7-0)ion with a high multiple correlation coefficient ([Fig. 8b\)](#page-7-0).

3.4.2 Partial correlation

The connection between ANPP and temperature and precipitation was characterized into four grades according to the *t* test result: SPC (significant positive correlation) ($P < 0.05$, $R > 0$), NSPC (no significant positive correlation) ($P > 0.05$, $R > 0$), SNC (significantly negative correlation) ($P < 0.05$, $R < 0$), and NSNC (no significant negative correlation) $(P > 0.05, R < 0)$.

There was a clear regional difference between the positive and negative correlations between ANPP and precipitation([Fig. 9a](#page-7-1)). The correlation value ranges from −0.881 to 0.934, with an average of 0.322. The Ili River Valley of Kazakhstan and the downstream region had the most positive connection. Negative correlations were mostly found in Tianshan Mountain and Balkhash Lake.

The association between ANPP and precipitation at pixel size in the research region was classified using classification statistics [\(Fig. 9b](#page-7-1)). The proportions of each correlation grade are described as follows: no significant positive correlation (50.30%) > significant positive correlation (36.54%) > no significant negative correlation (11.79%) > significant negative correlation (1.37%); these results indicate that in most sections of the basin, there was no significant positive connection between ANPP and precipitation.

Fig. 8 Multiple correlation coefficients (a) and significance test result (b) between meteorological elements and actual net primary production (ANPP) in Ili River Basin from 2001 to 2020

Fig. 9 Correlation coefficients (a) and significance test result (b) between precipitation and actual net primary production (ANPP) in Ili River Basin from 2001 to 2020.SPC: significant positive correlation; NSPC: no significant positive correlation; SNC: significantly negative correlation; NSNC: no significant negative correlation

ANPP and temperature had a correlation coefficient ranging from −0.853 to 0.895([Fig. 10a](#page-8-0)). The correlation coefficient between ANPP and temperature averaged 0.098. The positive correlation occurred mostly in the piedmont of Tianshan Mountain and the Kapchagay Reservoir, while the negative correlation was mainly distributed in the Ili Valley and the area around Balkhash Lake. The proportions of each correlation grade are described as follows [\(Fig. 10b](#page-8-0)): no significant positive correlation (62.15%) > no significant negative correlation (32.06%) > significant positive correlation (4.98%) > significant negative correlation (0.81%) ; these results reveal that in most sections of the basin, there was no significant positive association between ANPP and temperature.

3.4.3 Driving forces of ANPP change

To determine the main climate factors affecting the ANPP change area, [we investigated](#page-13-8) the factors that influence NPP change ([Yin e](#page-13-8)[t al., 2](#page-8-1)[020](#page-13-8)), and the classification criteria are shown in [Table 2.](#page-8-1)

The results revealed that precipitation was the dominant driver of the ANPP change from 2001 to 2020, according to the zoning of the NPP change-driving force ([Fig. 11](#page-9-0)), with obvious spatial heterogeneity. Precipitation-driven area accounting for 76.62% of the climatedriven area and mainly distributed in the Ili River Valley and Almaty City of Kazakhstan. The area with strong temperature and precipitation driving forces accounted for 13.00% of the climatic driving force area, which was mainly concentrated in the Kapchagay Reservoir of Kazakhstan. The areas weakly driven by temperature and precipitation and the temperature-driven area accounted for 4.82% and 5.56% of the climatedriven areas, respectively, which were more obvious in Yining City of China and around Balkhash Lake of Kazakhstan.

4 Discussion

4.1 Impact of climate factors on ANPP

The primary climatic elements impacting the distribution and fluct[uation trend of](#page-12-16) NPP are temperature and precipitation [\(Liu et al., 2015](#page-12-16)). In this study, the single and double factors of ANPP and meteorological elements were analyzed. The findings revealed regional variations in the relationship between ANPP and cli-

Fig. 10 Correlation coefficients (a) and significance test result (b) between temperature and actual net primary productivity (ANPP) in Ili River Basin from 2001 to 2020. SPC, significant positive correlation; NSPC, no significant positive correlation; SNC, significantly negative correlation; NSNC, no significant negative correlation

Table 2 The regional rules of the driving factors for actual net primary productivity changes in Ili River Basin

Driving factor	Driving type		Classification criteria	
Strongly driven by temperature and precipitation	$[T+P]+$	$F_C < F_{0.01}$	$t_T < t_{0.05}$	$t_P < t_{0.05}$
Precipitation driven	[P]	$F_C < F_{0.01}$	$t_T \geq t_{0.05}$	$t_P \geq t_{0.05}$
Temperature driven		$F_C < F_{0.01}$	$t_T < t_{0.05}$	$t_P \geq t_{0.05}$
Weakly driven by temperature and precipitation	$[T+P]-$	$F_C < F_{0.01}$	$t_T \geq t_{0.05}$	$t_P < t_{0.05}$

Notes: $F_{\rm C}$, significance test of multiple correlation between actual net primary production and temperature and precipitation; t_T , significance test of correlation between actual net primary production and temperature; *t_P*, significance test of multiple correlation between actual net primary production and precipitation; $t_{0.05}$, *t* test at significance level of 0.05; $F_{0.05}$, *F* test at significance level of 0.05; T, change driven by temperature mainly; P: change driven by precipitation mainly

Fig. 11 Spatial distribution of actual net primary productivity (ANPP) climate driving force in Ili River Basin. Meaning of driving factors were in Table 2

mate parameters, which were most likely connected to the basin's altitude, climate change, and vegetation cover type ([Zhou et al., 2019](#page-13-9)). The Ili River Basin of Kazakhstan is located in a semiarid region that is susceptible to changes in climatic conditions [\(Zhou et al., 201](#page-13-10)6). This study examined the temperature and precipitation change trends from 2001 to 2020. Most areas showed a warm and humid trend [\(Fig. 12](#page-9-1)). Since the end of the 1980s, the climate in Northwest China has evolved from warm and dry to warm and humid, according to recent studies [\(Shi et al., 200](#page-13-11)7). The results showed that although the Ili River was a transboundary river, its temperature and precipitation trends were consistent with those in Northwest China.

Precipitation has been shown in previous research to be a primary factor affecting NPP and its variations in arid and semiarid environments [\(Liang et al., 2015\)](#page-12-17). The change trend of ANPP in the Ili River Basin from 2001 to 2020 was in an increasing trend. The increase in ANPP is the response to warm and humid conditions because the increase in temperature increases the photosynthetic rate of vegetation, prolongs the length of the vegetation growth season, and promotes the effective utilization of soil water by melting ice and snow. The temperature increase provides more effective water for plant growth over a relatively long time [\(Xiong et al.](#page-13-12), [2019](#page-13-12)). In addition, a moist environment increases soil moisture, facilitating the absorption of water by vegetation and providing better wetness for its own development [\(Xiong et al., 2016](#page-13-13)). Conversely, in the high-altitude area of the Tianshan Mountains, when precipitation exceeds the range necessary for vegetation development, it reduces solar radiation and increases relative humidity, reducing the photosynthetic rate of vegetation([Ukkola et al., 2016](#page-13-14)). Excessive precipitation also aggravates soil erosion and flood disasters([Qu et al](#page-12-18)., [2018](#page-12-18)). As a result, vegetation degradation induced by climate change is concentrated mostly in the Tianshan Mountains.

Only some areas in the basin changed to a warm and dry trend; these areas were mainly concentrated in Balkhash City and Ayakoz City around Balkhash Lake of Kazakhstan because precipitation near Balkhash Lake is relatively rare, and the annual precipitation is less than 100 mm. Furthermore, several studies have demonstrated that increasing temperatures speed up photosynthesis and carbon absorption in vegetation, but when temperatures surpass the threshold of the vegetation ecosystem, the NPP decreases [\(Mowll et al., 2015](#page-12-19)). Climate warming and precipitation reduction in this area will lead to an increase in drought frequency [\(Zeng and](#page-13-15) [Yang, 2008](#page-13-15)). The vegetation growth and development conditions in this area were poor, so the annual mean value of ANPP was small.

4.2 The impact of human activities on ANPP

Climate change does not totally modify the dynamic characteristics of vegetation; human influences also in-fluence NPP change ([Chen et al., 2017](#page-11-3); [Li et al., 2021](#page-12-20)). Overgrazing, conversion of grassland to farmland, over-

Fig. 12 The slop of temperature (a) and precipitation (b) in Ili River Basin from 2001 to 2020

harvesting, and overexploitation of water resources are all examples of human-caused vegetation deterioration in recent decades ([Qin et al., 2021](#page-12-13)). However, this study shows that human activities have a significant impact on vegetation restoration. In 1999, for example, the Chinese government began implementing a scheme to convert cropland to forest. The policy's effective execution changed wasteland and farmed land in China's most vulnerable districts into grassland and woodland [\(Wang](#page-13-0) [et al., 2016](#page-13-0)), and vegetation degradation areas were restored. Human activities were the major element determining the increase in vegetation, according to Chen et al. [\(Chen et al., 2014](#page-11-4)) in their study on the Qinghai-Tibet Plateau, and the implementation of national conservation measures had a vital influence on vegetation restoration.

Grazing was formerly thought to be one of the most important anthropogenic variables impacting NPP in Central Asia [\(Chen et al., 2019](#page-11-2)). According to the findings of this study, human activities have benefited vegetation, particularly in Kazakhstan. The Food and Agriculture Organization (FAO) of the United Nations gathered livestock data for Kazakhstan from 1992 to 2019 to analyze the influence of grazing on NPP [\(http://www.fao.org/faostat/\)](http://www.fao.org/faostat/). The relationship between grazing and NPP was investigated using the variation trend in this study. [Fig. 13](#page-10-0) shows that 2000 was the turning point; since then, the number of herding animals in Kazakhstan has changed greatly. Under the Soviet Union, Kazakhstan had a high standard for livestock operations. Following the disintegration of the Soviet Union, the number of livestock operations plummeted. After 2000, the change trend was small, and the number of these operations increased steadily. The

Fig. 13 Interannual variation in livestock numbers in Kazakhstan from 1992 to 2019

amount and intensity of grazing are favorable for this vegetation to return to a high vegetation cover area, and the pressure on grazing is also relieved([Hauck et al.](#page-12-21), [2016](#page-12-21)).

The mechanism of NPP and grazing under various grazing settings is unknown, and the impact of grazing on vegetation change may differ geographically. These spatial differences are largely determined by vegetation type and community composition, grazing pattern and livestock density, and local environment [\(Cugny et al.](#page-12-22), [2010](#page-12-22); [Sanaei et al., 2019](#page-13-16)). Improper grazing will lead to vegetation degradation and even land desertification ([Abdi et al., 201](#page-11-0)3). However, previous research has demonstrated that the response of NPP to grazing intensity is strongly reliant on the climatic conditions of Central Asian grassland ecosystems. Grazing can promote grassland growth at a certain grazing intensity because it can reduce vegetation evapotranspiration and thus increase soil moisture [\(Luo et al., 2012](#page-12-23)). Overgrazing also aroused the concern of the Central Asian governments; governments have corresponding policies to strengthen the cooperation and communication between countries and have put more money into a variety of activities, such as improving relevant laws and regulations; these include laws governing the degradation of grassland grazing behavior, reseeding improvements, fence closures, and grass for livestock; law instituting strict controls for grassland grazing capacity; and laws designed to achieve a balance between grass and livestock [\(Yin et al., 2019](#page-13-17)). With the recovery of the local Kazakh economy, abandoned state-owned pastures have been reused, and the government has taken effective ecological restoration measures to improve degraded land([Zhang et al., 202](#page-13-18)1). These measures have been crucial for the restoration of vegetation.

4.3 Uncertainty

The variables ANPP, PNPP, and HNPP were used to explore the impacts of climate and human influences on NPP. However, this study also has some limitations and can be further improved. First, the Thornthwaite memorial model was selected to calculate PNPP. This model's input parameters included temperature and precipitation data, and solar radiation data, one of the climatic elements impacting NPP, was not taken into account([Piao et al., 200](#page-12-24)6). Additionally, the calculated PNPP value was not verified by measured data, so the calculated PNPP value had uncertainty.

In the next step, biomass in areas not affected by human activities should be collected to conduct correlation analysis with the model, and the optimal model should be selected to simulate the value of PNPP. The Ili River Basin is a cross-border river, and the distribution of stations and data continuity are poor. Few studies can choose only high spatial resolution meteorological data products as input data ([Hu et al., 2014](#page-12-25)). It is critical to ensure consistency in the spatial resolution of all data sources while utilizing the CASA model to invert NPP. Therefore, resampling of meteorological data was carried out, which lost the detailed pixel information to a certain extent. More accurately measured data, such as meteorological and biomass data, are needed in future research.

5 Conclusion

In the Ili River Basin from 2001 to 2020, the relative contributions of climate and human factors to ANPP change were quantified, and the regional features of ANPP and its response to climatic factors were examined. The findings of the study can have a significant impact on the Ili River Basin's ecological development and long-term growth. The following points represent our primary conclusions:

(1) In terms of temporal characteristics, the annual variation in ANPP showed a fluctuating increase, with fluctuation values ranging from 265.41 to 363.92 g / $(m²$ yr). The mean ANPP in the last 20 years was 309.36 $g/(m^2 \cdot yr)$. In terms of spatial characteristics, the ANPP was low in the northeast and high in the southwest and distributed in a circular pattern around the Tianshan Mountains of China. The high-value region was located in the Tianshan Mountains of China, and the low-value region was located in the Ili River Valley of Kazakhstan. The middle and lower reaches of the ANPP had a rising tendency, while ANPP with a decreasing trend was mainly distributed in the Ili River Valley of Kazakhstan and the Tianshan Mountains of China on both sides. Additionally, the overall change trend of ANPP was an increasing trend.

(2) Human activities played a critical part in vegetation improvement in 67.27% of cases, whereas climate change played a large role in only 32.73% of cases, indicating that human activities aided in the restoration of

vegetation. Climate was responsible for 79.97% of the vegetation degradation area, whereas human activities were responsible for 20.03%, demonstrating that climate change was the primary driver of vegetation degradation.

(3) Between ANPP and precipitation, the partial correlation value varied from −0.881 to 0.934; the proportions of the correlation grades between ANPP and precipitation in the area of the basin are described as follows: no significant positive correlation $(50.30\%) > sig$ nificant positive correlation (36.54%) > no significant negative correlation (11.79%) > significant negative correlation (1.37%). Between ANPP and temperature, the partial correlation value varied from −0.853 to 0.895; the proportions of the correlation grades between ANPP and temperature in the area of the basin are described as follows: no significant positive correlation (62.15%) > no significant negative correlation (32.06%) > significant positive correlation (4.98%) > significant negative correlation (0.81%).

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References

- Abdi O A, Glover E K, Luukkanen O, 2013. Causes and impacts of land degradation and desertification: case study of the Sudan. *[International Journal of Agriculture and Forestr](https://doi.org/10.5923/j.ijaf.20130302.03)y*, 3(2): 40–51. doi: [10.5923/j.ijaf.20130302.03](https://doi.org/10.5923/j.ijaf.20130302.03)
- Andersen C B, Donovan R K, Quinn J E, 2015. Human appropriation of net primary production (HANPP[\) in an](https://doi.org/10.3390/land4020513) agriculturallydo[minated watershed, sout](https://doi.org/10.3390/land4020513)heastern USA. *[Land](https://doi.org/10.3390/land4020513)*, 4(2): 513–540. doi: [10.3390/land4020513](https://doi.org/10.3390/land4020513)
- Chen B X, Zhang X Z, Tao J et al., 2014. The impact of climate change and anthropogenic activities on alpine grassland over the Qinghai-Tibet Plateau. *Agricultural and Forest Meteorology*, 189–190: 11–18. doi: 10.1016/j.agrformet.2014.01.002
- Chen T, Bao A M, Jiapaer G et al., 2019. Disentangling the relative impacts of climate change and human activities on arid [and](https://doi.org/10.1016/j.scitotenv.2018.11.058) [semiarid grasslands in Centra](https://doi.org/10.1016/j.scitotenv.2018.11.058)l Asia during 1982–[2015.](https://doi.org/10.1016/j.scitotenv.2018.11.058) *[Sci](https://doi.org/10.1016/j.scitotenv.2018.11.058)[ence of the Total Environment](https://doi.org/10.1016/j.scitotenv.2018.11.058)*, 653: 1311–1325. doi: [10.1016/j.](https://doi.org/10.1016/j.scitotenv.2018.11.058) [scitotenv.2018.11.058](https://doi.org/10.1016/j.scitotenv.2018.11.058)
- Chen Y Z, Ju W M, Groisman P et al., 2017. Quantitative assessment of carbon sequestration reducti[on induced by disturb](https://doi.org/10.1088/17489326/aa849b)ances in temperate Eurasian steppe. *[Environmental Research](https://doi.org/10.1088/17489326/aa849b)*

[Letters](https://doi.org/10.1088/17489326/aa849b), 12(11): 115005. doi: [10.1088/17489326/aa849b](https://doi.org/10.1088/17489326/aa849b)

- Cugny C, Mazier F, Galop D, 2010. Modern and fossil non-pollen palynomorphs from the Basque mountains (western Pyrenees, France): the use of coprophilous fungi to reconstruct pastoral activity. *[Vegetation History and Archaeobotan](https://doi.org/10.1007/s00334-010-0242-6)y*, 19(5): 391–408. doi: [10.1007/s00334-010-0242-6](https://doi.org/10.1007/s00334-010-0242-6)
- De Leeuw J, Rizayeva A, Namazov E et al., 2019. Application of the MODIS MOD 17 Net primary production product in grassland carrying capacity assessment. *[International Journal of Ap](https://doi.org/10.1016/j.jag.2018.09.014)[plied Earth Observation and Geoinformation](https://doi.org/10.1016/j.jag.2018.09.014)*, 78: 66–76. doi: [10.1016/j.jag.2018.09.014](https://doi.org/10.1016/j.jag.2018.09.014)
- Erb K H, Kastner T, Plutzar C et al., 2018. Unexpectedly large impact of forest management and grazing on global vegetation biomass. *[Nature](https://doi.org/10.1038/nature25138)*, 553(7686): 73–76. doi: [10.1038/nature25138](https://doi.org/10.1038/nature25138)
- Fang J Y, Yu G R, Liu L L et al., 2018. Climate change, human impacts, and carbon sequestration in China. *[Proceedings of the](https://doi.org/10.1073/pnas.1700304115) [National Academy of Sciences of the United States of America](https://doi.org/10.1073/pnas.1700304115)*, 115(16): 4015–4020. doi: [10.1073/pnas.1700304115](https://doi.org/10.1073/pnas.1700304115)
- Guan J Y, Yao J Q, Li M Y et al., 2021. Assessing the spatiotemporal evolution of anthropogenic impacts on remotely sensed vegetation dynamics in Xinjiang, China. *[Remote Sensing](https://doi.org/10.3390/rs13224651)*, 13(22): 4651. doi: [10.3390/rs13224651](https://doi.org/10.3390/rs13224651)
- Hauck M, Artykbaeva G T, Zozulya T N et al., 2016. Pastoral livestock husbandry and rural livelihoods in the forest-steppe of east Kazakhstan. *[Journal of Arid Environme](https://doi.org/10.1016/j.jaridenv.2016.05.009)nts*, 133: 102–111. doi: [10.1016/j.jaridenv.2016.05.009](https://doi.org/10.1016/j.jaridenv.2016.05.009)
- Hu Z Y, Zhang C, Hu Q et al., 2014. Temperature changes in Central Asia from 1979 to 2011 based on multiple datasets. *[Journal of Climate](https://doi.org/10.1175/JCLI-D-13-00064.1)*, 27(3): 1143–1167. doi: [10.1175/JCLI-D-13-](https://doi.org/10.1175/JCLI-D-13-00064.1) [00064.1](https://doi.org/10.1175/JCLI-D-13-00064.1)
- Jiao W, Chen Y N, Li W H et al., 2018. Estimation of net primary productivity and its driving factors in the Ili River Valley, China. *[Journal of Arid Lan](https://doi.org/10.1007/s40333-018-0022-1)d*, 10(5): 781–793. doi: [10.1007/](https://doi.org/10.1007/s40333-018-0022-1) [s40333-018-0022-1](https://doi.org/10.1007/s40333-018-0022-1)
- Li A, Wu J G, Huang J H, 2012. Distinguishing between humaninduced and climate-driven vegetation changes: a critical application of RESTREND in Inner Mongolia. *[Landscape Eco](https://doi.org/10.1007/s10980-012-9751-2)[logy](https://doi.org/10.1007/s10980-012-9751-2)*, 27(7): 969–982. doi: [10.1007/s10980-012-9751-2](https://doi.org/10.1007/s10980-012-9751-2)
- Li H, Zhang H Y, Li Q X et al., 2021. Vegetation productivity dynamics in response to climate change and human activities under different topography and land cover in Northeast China. *[Remote Sensing](https://doi.org/10.3390/rs13050975)*, 13(5): 975. doi: [10.3390/rs13050975](https://doi.org/10.3390/rs13050975)
- Liang W, Yang Y T, Fan D M et al., 2015. Analysis of spatial and temporal patterns of net primary production and their climate controls in China from 1982 to 2010. *[Agricultural and Forest](https://doi.org/10.1016/j.agrformet.2015.01.015) [Meteorology](https://doi.org/10.1016/j.agrformet.2015.01.015)*, 204: 22–36. doi: [10.1016/j.agrformet.2015.01.](https://doi.org/10.1016/j.agrformet.2015.01.015) [015](https://doi.org/10.1016/j.agrformet.2015.01.015)
- Liu C Y, Dong X F, Liu Y Y, 2015. Changes of NPP and their relationship to climate factors based on the transformation of different scales in Gansu, China. *[Catena](https://doi.org/10.1016/j.catena.2014.10.027)*, 125: 190–199. doi: [10.](https://doi.org/10.1016/j.catena.2014.10.027) [1016/j.catena.2014.10.027](https://doi.org/10.1016/j.catena.2014.10.027)
- Luo G P, Han Q F, Zhou D C et al., 2012. Moderate grazing can promote aboveground primary production of grassland under water stress. *[Ecological Complexity](https://doi.org/10.1016/j.ecocom.2012.04.004)*, 11: 126–136. doi: [10.1016/](https://doi.org/10.1016/j.ecocom.2012.04.004)

[j.ecocom.2012.04.004](https://doi.org/10.1016/j.ecocom.2012.04.004)

- McNally A, Arsenault K, Kumar S et al., 2017. A land data assimilation system for sub-Saharan Africa food and water security applications. *[Scientific Data](https://doi.org/10.1038/sdata.2017.12)*, 4(1): 170012. doi: [10.1038/](https://doi.org/10.1038/sdata.2017.12) [sdata.2017.12](https://doi.org/10.1038/sdata.2017.12)
- Mowll W, Blumenthal D M, Cherwin K et al., 2015. Climatic controls of aboveground net primary production in semi-arid grasslands along a latitudinal gradient portend low sensitivity to warming. *[Oecologia](https://doi.org/10.1007/s00442-015-3232-7)*, 177(4): 959–969. doi: [10.1007/s00442-](https://doi.org/10.1007/s00442-015-3232-7) [015-3232-7](https://doi.org/10.1007/s00442-015-3232-7)
- Park H, Jeong S J, Ho C H et al., 2015. Nonlinear response of vegetation green-up to local temperature variations in temperate and boreal forests in the Northern Hemisphere. *[Remote Sens](https://doi.org/10.1016/j.rse.2015.04.030)[ing of Environment](https://doi.org/10.1016/j.rse.2015.04.030)*, 165: 100–108. doi: [10.1016/j.rse.2015.04.](https://doi.org/10.1016/j.rse.2015.04.030) [030](https://doi.org/10.1016/j.rse.2015.04.030)
- Piao S, Fang J Y, He J S, 2006. Variations in vegetation net primary production in the Qinghai-Xizang Plateau, China, from 1982 to 1999. *Climatic Change*, 74(1 –3): 253 –267. doi: 10.1007/s10584-005-6339-8
- Plutzar C, Kroisleitner C, Haberl H et al., 2016. Changes in the spatial patterns of human appropriation of net primary production (HANPP) in Europe 1990–2006. *[Regional Environmental](https://doi.org/10.1007/s10113-015-0820-3) [Change](https://doi.org/10.1007/s10113-015-0820-3)*, 16(5): 1225–1238. doi: [10.1007/s10113-015-0820-3](https://doi.org/10.1007/s10113-015-0820-3)
- Potter C S, Randerson J T, Field C B et al., 1993. Terrestrial ecosystem production: a process model based on global satellite and surface data. *[Global Biogeochemical Cyc](https://doi.org/10.1029/93GB02725)les*, 7(4): 811–841. doi: [10.1029/93GB02725](https://doi.org/10.1029/93GB02725)
- Pueppke S G, Nurtazin S T, Graham N A et al., 2018a. Central Asia 's Ili River ecosystem as a wicked problem: unraveling complex interrelationships at the interface of water, energy, and food. *[Water](https://doi.org/10.3390/w10050541)*, 10(5): 541. doi: [10.3390/w10050541](https://doi.org/10.3390/w10050541)
- Pueppke S G, Zhang Q L, Nurtazin S T, 2018b. Irrigation in the Ili River basin of Central Asia: from ditches to dams and diversion. *[Water](https://doi.org/10.3390/w10111650)*, 10(11): 1650. doi: [10.3390/w10111650](https://doi.org/10.3390/w10111650)
- Qi J G, Tao S Q, Pueppke S G et al., 2020. Changes in land use/land cover and net primary productivity in the transboundary Ili-Balkhash basin of Central Asia, 1995 –2015. *[Environ](https://doi.org/10.1088/2515-7620/ab5e1f)[mental Research Communications](https://doi.org/10.1088/2515-7620/ab5e1f)*, 2(1): 011006. doi: [10.1088/](https://doi.org/10.1088/2515-7620/ab5e1f) [2515-7620/ab5e1f](https://doi.org/10.1088/2515-7620/ab5e1f)
- Qin X, Liu W B, Mao R C et al., 2021. Quantitative assessment of driving factors affecting human appropriation of net primary production (HANPP) in the Qilian Mountains, China. *[Ecolo](https://doi.org/10.1016/j.ecolind.2020.106997)[gical Indicator](https://doi.org/10.1016/j.ecolind.2020.106997)s*, 121: 106997. doi: [10.1016/j.ecolind.2020.](https://doi.org/10.1016/j.ecolind.2020.106997) [106997](https://doi.org/10.1016/j.ecolind.2020.106997)
- Qu S, Wang L C, Lin A W et al., 2018. What drives the vegetation restoration in Yangtze River basin, China: climate change or anthropogenic factors? *[Ecological Indicators](https://doi.org/10.1016/j.ecolind.2018.03.029)*, 90: 438–450. doi: [10.1016/j.ecolind.2018.03.029](https://doi.org/10.1016/j.ecolind.2018.03.029)
- Raich J W, Rastetter E B, Melillo J M et al., 1991. Potential net primary productivity in South America: application of a global model. *[Ecological Applications](https://doi.org/10.2307/1941899)*, 1(4): 399–429. doi: [10.2307/](https://doi.org/10.2307/1941899) [1941899](https://doi.org/10.2307/1941899)
- Rojstaczer S, Sterling S M, Moore N J, 2001. Human appropriation of photosynthesis products. *[Science](https://doi.org/10.1126/science.1064375)*, 294(5551):

2549–2552. doi: [10.1126/science.1064375](https://doi.org/10.1126/science.1064375)

- Sanaei A, Li M S, Ali A, 2019. Topography, grazing, and soil textures control over rangelands' vegetation quantity and quality. *[Science of the Total Environmen](https://doi.org/10.1016/j.scitotenv.2019.134153)t*, 697: 134153. doi: [10.](https://doi.org/10.1016/j.scitotenv.2019.134153) [1016/j.scitotenv.2019.134153](https://doi.org/10.1016/j.scitotenv.2019.134153)
- Shi Y F, Shen Y P, Kang E S et al. , 2007. Recent and future climate change in northwest China. *Climatic Change*, 80(3 –4): 379–393. doi: 10.1007/s10584-006-9121-7
- Thevs N, Beckmann V, Akimalieva A et al., 2017. Assessment of ecosystem services of the wetlands in the Ili River Delta, Kazakhstan. *[Environmental Earth Sciences](https://doi.org/10.1007/s12665-016-6346-2)*, 76(1): 30. doi: [10.1007/](https://doi.org/10.1007/s12665-016-6346-2) [s12665-016-6346-2](https://doi.org/10.1007/s12665-016-6346-2)
- Ukkola A M, Prentice I C, Keenan T F et al., 2016. Reduced streamflow in water-stressed climates consistent with $CO₂$ effects on vegetation. *[Nature Climate Change](https://doi.org/10.1038/nclimate2831)*, 6(1): 75–78. doi: [10.1038/nclimate2831](https://doi.org/10.1038/nclimate2831)
- Wang C, Gao Q, Wang X et al., 2016. Spatially differentiated trends in urbanization, agricultural land abandonment and reclamation, and woodland recovery in Northern China. *[Scientif](https://doi.org/10.1038/srep37658)[ic Reports](https://doi.org/10.1038/srep37658)*, 6(1): 37658. doi: [10.1038/srep37658](https://doi.org/10.1038/srep37658)
- Xiong Q L, Pan K W, Zhang L et al., 2016. Warming and nitrogen deposition are interactive in shaping surface soil microbial communities near the alpine timberline zone on the eastern Qinghai–Tibet Plateau, southwestern China. *[Applied Soil Eco](https://doi.org/10.1016/j.apsoil.2016.01.011)[logy](https://doi.org/10.1016/j.apsoil.2016.01.011)*, 101: 72–83. doi: [10.1016/j.apsoil.2016.01.011](https://doi.org/10.1016/j.apsoil.2016.01.011)
- Xiong Q L, Xiao Y, Halmy M W A et al., 2019. Monitoring the impact of climate change and human activities on grassland vegetation dynamics in the northeastern Qinghai-Tibet Plateau of China during 2000 –2015. *[Journal of Arid La](https://doi.org/10.1007/s40333-019-0061-2)nd*, 11(5): 637–651. doi: [10.1007/s40333-019-0061-2](https://doi.org/10.1007/s40333-019-0061-2)
- Yang Y H, Chen Y N, Li W H et al., 2010. Distribution of soil organic carbon under different vegetation zones in the Ili River Valley, Xinjiang. *[Journal of Geographical Scienc](https://doi.org/10.1007/s11442-010-0807-4)es*, 20(5): 729–740. doi: [10.1007/s11442-010-0807-4](https://doi.org/10.1007/s11442-010-0807-4)
- Yin L, Dai E F, Zheng D et al., 2020. What drives the vegetation dynamics in the Hengduan Mountain region, southwest China: climate change or human activity? *[Ecological Indicators](https://doi.org/10.1016/j.ecolind.2019.106013)*, 112: 106013. doi: [10.1016/j.ecolind.2019.106013](https://doi.org/10.1016/j.ecolind.2019.106013)
- Yin Y T, Hou Y L, Langford C et al., 2019. Herder stocking rate and household income under the Grassland Ecological Protec-

[tion Award Policy i](https://doi.org/10.1038/s41598-018-21089-3)n northern China. *[Land Use Policy](https://doi.org/10.1016/j.landusepol.2018.11.037)*, 82: 120–129. doi: [10.1016/j.landusepol.2018.11.037](https://doi.org/10.1016/j.landusepol.2018.11.037)

- Zeng B, Yang T [B, 2008. Impacts of climate warm](https://doi.org/10.1016/j.landusepol.2018.11.037)ing on vegeta[tion in Qaidam](https://doi.org/10.3390/su13115887) Area from 1990 to 2003. *[Environment](https://doi.org/10.3390/su13115887)[al Monit](https://doi.org/10.1007/s10661-007-0003-x)[oring and Assessment](https://doi.org/10.1007/s10661-007-0003-x)*, 144(1): 403–417. doi: [10.1007/s10661-](https://doi.org/10.1007/s10661-007-0003-x) [007-0003-x](https://doi.org/10.1007/s10661-007-0003-x)
- Z[hang C, Wan](https://doi.org/10.1007/s10661-007-0003-x)g X, Li J, 2011. Roles of climate changes [and hu](https://doi.org/10.1007/s10584-019-02524-4)[man interv](https://doi.org/10.1007/s10584-019-02524-4)entions in land de[gradation: a case study by n](https://doi.org/10.1007/s10584-019-02524-4)et primary productivity analysis in China's Shiyanghe Basin. *[En](https://doi.org/10.1007/s12665-011-1046-4)[vironmental Earth Sciences](https://doi.org/10.1007/s12665-011-1046-4)*, 64(8): 2183–2193. doi: [10.1007/](https://doi.org/10.1007/s12665-011-1046-4) [s12665-011-1046-4](https://doi.org/10.1007/s12665-011-1046-4)
- Z[hang R P, Liang T G](https://doi.org/10.1007/s12665-011-1046-4)[, Guo J et al., 2018. Grassland d](https://doi.org/10.1016/j.scitotenv.2016.07.206)ynamics in response to climate change and human activities in Xinjiang from 2000 to 2014. *[Scientific Reports](https://doi.org/10.1038/s41598-018-21089-3)*, 8(1): 2888. doi: [10.1038/](https://doi.org/10.1038/s41598-018-21089-3) [s41598-018-21089-3](https://doi.org/10.1038/s41598-018-21089-3)
- Z[hang Y Z, Wang Q,](https://doi.org/10.1038/s41598-018-21089-3) Wa[ng Z Q et al., 2021.](https://doi.org/10.1016/j.ecolind.2014.08.043) Dynamics and driv[ers of grasslands in the Eurasia](https://doi.org/10.1016/j.ecolind.2014.08.043)n steppe during 2000–2014. *[Sustainability](https://doi.org/10.3390/su13115887)*, 13(11): 5887. doi: [10.3390/su13115887](https://doi.org/10.3390/su13115887)
- Z[hou D C, Hao](https://doi.org/10.3390/su13115887) L, Kim J B et al., [2019. Potential impac](https://doi.org/10.3390/su13115887)ts of climate change on vegetation dynamicsa[nd ecosystem function](https://doi.org/10.1016/j.ecolind.2017.08.019) [in a mount](https://doi.org/10.1007/s10584-019-02524-4)ain wat[ershed on the Qinghai-Tibet Pl](https://doi.org/10.1016/j.ecolind.2017.08.019)ateau. *[Climat](https://doi.org/10.1007/s10584-019-02524-4)[ic Change](https://doi.org/10.1007/s10584-019-02524-4)*, 156(1): 31–50. doi: [10.1007/s10584-019-02524-4](https://doi.org/10.1007/s10584-019-02524-4)
- Z[hou J H, Cai W T, Qin Y](https://doi.org/10.1007/s11434-006-0457-1) et al., 2016. Alpine v[egetation pheno](https://doi.org/10.1007/s11434-006-0457-1)[logy dynam](https://doi.org/10.1007/s11434-006-0457-1)ic over 16 years [and its covariation with climate in](https://doi.org/10.1016/j.scitotenv.2016.07.206) a semi-arid region of China. *[Science of the Total Environment](https://doi.org/10.1016/j.scitotenv.2016.07.206)*, 572: 119–128. doi: [10.1016/j.scitotenv.2016.07.206](https://doi.org/10.1016/j.scitotenv.2016.07.206)
- Zhou W, Gang C, Zhou F et al., 2015. Quantitative assessment of the individual contribution of climate and human factors to desertification in Northw[est China using net](https://doi.org/10.1016/j.ecolind.2014.08.043) primary product[ivity as an indicator.](https://doi.org/10.1016/j.ecolind.2014.08.043) *[Ecological Indicators](https://doi.org/10.1016/j.ecolind.2014.08.043)*, 48: 560–569. doi: [10.1016/j.ecolind.2014.08.043](https://doi.org/10.1016/j.ecolind.2014.08.043)
- Zhou W, Yang H, Huang L et al., 2017. Grassland degradation remote sensing monitoring and driving [factors quantitative as](https://doi.org/10.1016/j.ecolind.2017.08.019)sessment in Chin[a from 1982 to 2010.](https://doi.org/10.1016/j.ecolind.2017.08.019) *[Ecological Indicators](https://doi.org/10.1016/j.ecolind.2017.08.019)*, 83: 303–313. doi: [10.1016/j.ecolind.2017.08.019](https://doi.org/10.1016/j.ecolind.2017.08.019)
- Zhu W Q, Pan Y Z, He H et al., 2006. Simulation of maximum [light use efficiency for s](https://doi.org/10.1007/s11434-006-0457-1)ome typical vegetatio[n types in China.](https://doi.org/10.1007/s11434-006-0457-1) *[Chinese Science Bulletin](https://doi.org/10.1007/s11434-006-0457-1)*, 51(4): 457–463. doi: [10.1007/s11434-](https://doi.org/10.1007/s11434-006-0457-1) [006-0457-1](https://doi.org/10.1007/s11434-006-0457-1)