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Spatio-temporal variations and impacting factors of vegetation NPP in the Junggar Basin, China

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Abstract

The Junggar Basin investigated in this study has seen significant land cover and climate change. However, the spatiotemporal relationship between net primary productivity (NPP) and environmental factors remain unclear. Thus, we applied trend analysis and correlation methods to investigate the spatiotemporal characteristics of NPP and its relationship with driving factors using remotely sensed data and measured climate data from 2000 to 2015. During the study period, high values of NPP mainly occurred in the forests of the mid-elevation mountain areas. The NPP values showed an increasing trend in the different vegetation types, most likely due to climate change in combination with other factors. The annual trend of NPP in the study area varied in the range from –12.4 to 11.3 g C m^{-2} a^{-2}. The desert area exhibited no significant trends, but most of the mountain areas showed a significantly increasing trend. NPP was significantly correlated with temperature and precipitation. The dominant factor affecting NPP was temperature, mainly in the Ili river watershed and the Tien Shan mountain range. However, human activity and land cover changes were also important factors affecting the fluctuations in NPP. The results of this study highlight the need for appropriate land-use strategies for managing vegetation resources in arid land ecosystems.

Zusammenfassung

Im Junggar-Becken (China), das im vorliegenden Beitrag behandelt wird, ist eine signifikante Veränderung in Bezug auf Landbedeckung und Klima festzustellen. Allerdings ist die raumzeitliche Beziehung zwischen Nettoprimärproduktion (NPP) und Umweltfaktoren bislang ungeklärt. In dieser Studie wurden Trendanalysen und Korrelationsmethoden angewendet, um die raumzeitlichen Charakteristika der NPP sowie das Verhältnis zwischen NPP und den sie beeinflussenden Umweltfaktoren zu analysieren, indem Fernerkundungsdaten sowie Klimamessdaten von 2000 bis 2015 herangezogen wurden. Im untersuchten Zeitraum wurden hohe NPP-Werte hauptsächlich in den Wäldern mittlerer Höhenlagen beobachtet. Steigende NPP-Werte zeigten sich bei verschiedenen Vegetationstypen aufgrund von Klimaveränderungen und anderer Faktoren. Die Variation der NPP im Untersuchungsgebiet lag zwischen –12,4 und 11,3 g C m^{-2} a^{-2}, wobei sich im Wüstengebiet keine signifikante Veränderung, aber in den meisten der Gebirgsregionen ein signifikanter Anstieg zeigte. Die NPP korrelierte deutlich mit Temperatur und Niederschlag. Der dominante Faktor, der die NPP beeinflusste, war dabei Temperatur, hauptsächlich entlang des Ili-Flusslaufs und im Tienshan-Gebirge. Allerdings waren auch anthropogene

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Einflüsse und Veränderungen der Landbedeckung wichtige Faktoren mit Einfluss auf die Fluktuation der NPP. Die Ergebnisse der vorliegenden Studie betonen die Notwendigkeit angepasster Landnutzungsstrategien für das Vegetationsmanagement in ariden Ökosystemen.

Keywords partial correlation, climate factors, vegetation type, driving rule, land-use change

1. Introduction

Terrestrial plants convert atmospheric carbon dioxide (CO_2), water, and nutrients into organic carbon compounds through photosynthesis, a process known as gross primary production (GPP). A significant fraction of GPP is used for plant growth and maintenance while the remainder is net primary production (NPP), calculated as the difference between GPP and autotrophic respiration. As an important component of terrestrial ecosystems, vegetation provides materials for the survival of other organisms, performing a vital role in ecosystems (*Chen* and *Zeng* 2016; *Behera* et al. 2015; *Li* et al. 2019; *Yu* and *Liu* 2019). The NPP is an indication of the efficiency of plants in fixing and converting CO_2 to biomass during photosynthesis, a general indication of ecosystem health status and terrestrial ecosystem carbon budgets (*Li* et al. 2017; *Zhao* et al. 2011). Therefore, knowledge on the spatiotemporal dynamics of terrestrial NPP and its interaction with climate factors is essential for assessing terrestrial carbon budgets and developing principles and approaches to vegetation management and restoration (*Wang* et al. 2017; *Wang* et al. 2009). Furthermore, NPP can be used to estimate the carrying capacity of the Earth and to evaluate the sustainable development of terrestrial ecosystems. Thus, understanding the spatiotemporal dynamics of terrestrial NPP and its interactions with driving forces is critical for the assessment of ecosystem health and sustainability (*Zhang* et al. 2014; *Gulbeyaz* et al. 2018; *Zhao* et al. 2004).

Previous studies on vegetation dynamics have shown that the increasingly prominent roles of human activities and climate change are affecting ecosystem productivity. Thus, NPP is influenced by a complex interaction of soil, environmental conditions, plant community composition, and herbivorous animals, particularly human-managed livestock (*Tang* et al. 2016). Accurate measurements of ecosystem NPP and its spatiotemporal variation are important for the balanced utilization and protection of ecosystem (*Peng* et al. 2012; *Qi* et al. 2016; *Zhang* et al. 2016). Remote sensing data are characterized by their periodicity and the extent of the land coverage. As a result, remote sensing data and models have been relatively frequently used to estimate NPP in recent years (*Running* et al. 2011; *Nayak* et al. 2015; *Li* et al. 2019).

The Junggar Basin is one of the continental cold arid climate areas in northwestern China. The ecosystem in this area is very fragile and significantly sensitive to climate change. Therefore, investigating spatial and temporal variation in NPP will enhance our understanding of how climate change interacts with ecosystem processes that affect ecosystem dynamics and consequently impact their sustainability in the Junggar Basin. To date, a few studies have been conducted to reveal the dynamics of some arid areas using NPP at a regional scale and its response to climate factors (*Zhang* et al. 2017*; Liu* et al. 2018). However, spatiotemporal dynamics of ecosystem NPP in the Junggar Basin and its controlling factors still remain to be elucidated. Thus, the present study was conducted to assess the dynamics of spatiotemporal variations of NPP in the Junggar Basin from 2000 to 2015.

There are two objectives of this study: (1) to explore the temporal and spatial variation of ecosystem NPP; and (2) to analyze the effects of climate factors on NPP during the study period. The results of this study can provide a scientific indication for sustainable use of the ecosystems, environmental management and related policy-oriented activities.

2. Study area

The Junggar Basin is located between the Tien Shan and the Altay mountains in Xinjiang (80°58′–95°53′ E, 41°51′–48°46′ N). The total area covers 380,312 km^2, the elevation ranges from 189 m to 5958 m (*Fig. 1*), and features a continental cold arid climate. The average annual temperature is in the range 5.0~7.5 °C, the average annual precipitation is around 155 mm, and most of the precipitation occurs from January to September, which is the period of low precipitation in many other regions in China. Due to the special geographical location, landform, and arid climate, the Junggar Basin has an extremely fragile ecosystem with sparse vegetation cover and a simple vegetation class. The main vegetation types in the Junggar Basin are grassland, steppe, shrub land and forest. Kurbantuggut is the second largest desert in China.

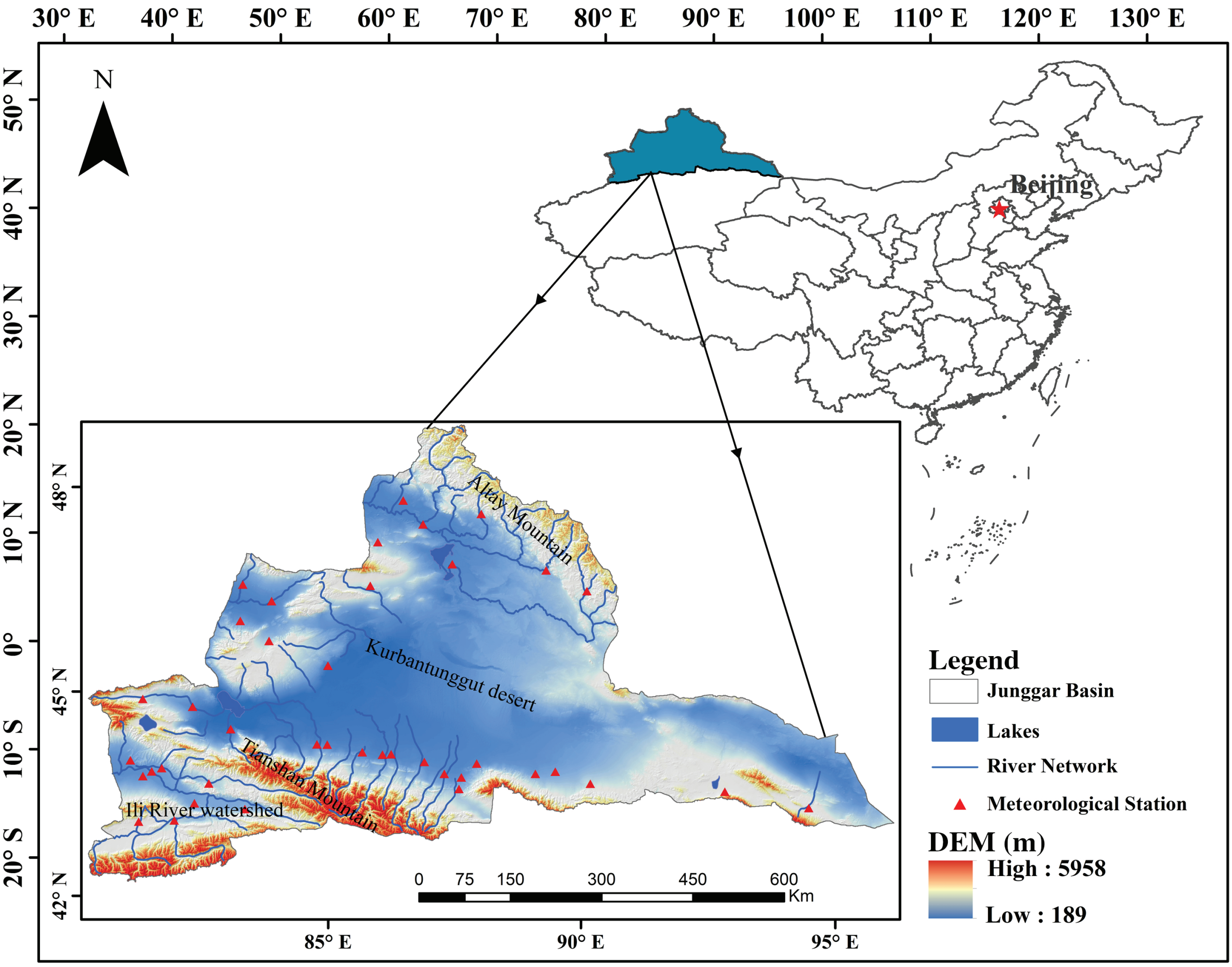

Fig. 1 Map of the study area. Source: own elaboration

3. Data sources and methods

3.1 Data sources

The NPP dataset at spatial resolution of 1 km was obtained from the annual MOD17A3 products (version 55) of the NASA Earth Observation System (EOS) program, which are produced by the Numerical Terra dynamic Simulation Group (NTSG) of the University of Montana (*Running* et al. 2016). The MOD17A3 products were generated using the MOD17 algorithm from the original NASA/USGS LPDAAC (Land Processes Distributed Active Archive Center) 8-day and annual v5 products, with data gaps in the 8-day temporal MODISFPAR/LAI caused by cloudiness filled with information from accompanying quality assessment flags (*Zhao* et al. 2011). Additionally, the MOD12Q1 product of LUCC (land use and land cover changes) data at 500 m resolution was used. Soil type data were downloaded from the Resources and Environment data cloud platform of China (http://www.resdc.cn).

The meteorological data mainly included precipitation and temperature for the period 2000–2015 used in this study, which are derived from the gridded daily dataset (CN05.1) with a spatial resolution of 1 km. The multiple correlation coefficient (R^2) of the linear regression was 0.67 for precipitation ($p < 0.01$) and the root-mean square error (RMSE) was 18.50 mm. The performance of the interpolated temperature data was satisfactory with an R^2 of 0.94 ($p < 0.01$), suggesting that the interpolated results could explain the spatial and temporal variability of 94% of the observed temperature data from the towers included in the interpolation out of 2400 observing stations in China (*Wang* et al. 2015).

The digital elevation model (DEM) used in this study is the Shuttle Radar Topography Mission product (V4.1) with a spatial resolution of 90 m. The DEM was obtained from the international scientific data mirroring website (http://www.gscloud.cn) of the Computer Network Information Center at the Chinese Academy of Sciences. The data on the prefecture/provincial-level administrative divisions were obtained from the geographic information dataset (scale 1:250,000) released by the China Meteorological Administration. A topological check was conducted for all data.

3.2 Study methods

3.2.1 Trend analysis

We determined the linear trend of the annual NPP on a per-pixel basis to establish a linear regression relationship between NPP and time (*Liu* et al. 2018),

$$T_{slope} = \frac{n \times \sum_{i=1}^{n}(i \times NPP_i) - \sum_{i=1}^{n} i \sum_{i=1}^{n} NPP_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}, \quad (1)$$

where n denotes the number of the year (time series 2000–2015; n=16), NPP_i represents the NPP value of the ith year in the study area, T_{slope} is the linear regression equation for the inter-annual variation of each NPP pixel in the study area. T_{slope} indicates the overall trend of the NPP in the time series; NPP has an increasing trend for $T_{slope} > 0$ and a decreasing trend for $T_{slope} < 0$. By coupling the test results and the slopes, the trends of the changes are classified into five levels: extremely significantly increasing trends ($T_{slope} > 0$, $p < 0.01$), significantly increasing trends ($T_{slope} > 0$, $0.01 < p < 0$), insignificant trends ($p > 0.05$), significantly decreasing trends ($T_{slope} < 0$, $0.01 < p < 0.05$), and extremely significantly decreasing trends ($T_{slope} < 0$, $p < 0.01$).

3.2.2 Correlation analysis

The correlation between NPP and the influencing factors was determined on a per-pixel basis as

$$R_{xy} = \frac{\sum_{n}^{i=1}\left((X_i - \overline{X})(Y_i - \overline{Y})\right)}{\sqrt{\sum_{n}^{i=1}\left((X_i - \overline{X})(Y_i - \overline{Y})\right)}}, \quad (2)$$

where R_{xy} is the correlation between the x and y factors; X_i and Y are the values of the variables in the i^{th} year; $\overline{X}$ and $\overline{V}$ are the annual mean values (*Pan* et al. 2015).

Partial correlation is based on linear correlation analysis; it is used to determine the correlation between two factors (i.e., NPP and temperature and precipitation, etc.) while disregarding the influence of the other driving factors. The partial correlation is calculated as

$$R_{xy,z} = \frac{R_{xy} - R_{xz} + R_{yz}}{\sqrt{(1 - R_{xz}^2)}\sqrt{(1 - R_{yz}^2)}}, \quad (3)$$

where x denotes NPP, y denotes temperature, z denotes precipitation, and $R_{x,yz}$ is the partial correlation coefficient of NPP and temperature (*Zhou* et al. 2018). Student's t-value to test for statistical significance of the partial correlation coefficient was computed as

$$t = \frac{R_{xyz}}{\sqrt{1 - R_{x,yz}^2}} \times \sqrt{n - m - 1}, \quad (4)$$

where n is the number of years (time series 2000–2015; n=16), and m is the count of variables.

Multiple correlation analysis is based on a combination of multiple driving factors and incorporates two or more impact factors and calculates the correlation between multiple factors,

$$R_{x,yz} = \sqrt{1 - (1 - R_{xy}^2)(1 - R_{xz,y}^2)}, \quad (5)$$

where $R_{x,yz}$ is the multiple correlation coefficient between NPP and the driving factors; R_{xy} is the linear correlation coefficient between two factors, $R_{xz,y}$ is the partial correlation coefficient between NPP and the independent variable.

$$F = \frac{R_{x,yz}^2}{1 - R_{x,yz}^2} \times \frac{n - k - 1}{k}, \quad (6)$$

where n denotes the number of the year (time series 2000–2015; n=16), and m is the variable count.

The t-test and F-test are used to conduct significance tests of the partial correlations and multiple correlations (*Tan* et al. 2018).

Driving factor analysis was applied in this study on the basis of partial and multiple correlations (T+P)+, if the condition satisfied the following requirements at the same time: $|t_1| > t_{0.01}$, $|t_2| > t_{0.01}$, and $F > F_{0.05}$. (T+P)– resulted, if the condition satisfied the following requirements at the same time: $|t_1| > t_{0.05}$, $|t_2| > t_{0.05}$, and $F > F_{0.05}$). If the condition satisfied the requirement ($|t_1| > t_{0.01}$ and $F > F_{0.05}$) or ($|t_2| > t_{0.01}$ and $F > F_{0.05}$), then this was treated zone of influence of temperature or precipitation, respectively.

4. Results

4.1 Spatiotemporal trend of NPP

To obtain the average values of annual NPP in the whole study area, we first extracted the annual values of NPP in each pixel, then the mean values were calculated as the mean of all pixels in a given year. The spatial map of NPP values were produced with ArcGIS10.2 using the average values for the 2000–2015 period for each individual grid cell. A simple linear regression method was applied to analyze the inter-annual variability and the trend of each pixel during 2000–2015. The slopes of linear regression represent the temporal and spatial trends: a positive value indicates an upward trend, and a negative value indicates a downward trend. A greater absolute value of the slope corresponds to a more drastic variation. Spatial trend analysis was performed using Python 3.7.4.

Over the period 2000–2015, the ecosystem annual NPP varied markedly inter-annually, ranging between 1401 and 175 g C m^{-2} a^{-1}, with an average value of 161 g C m^{-2} a^{-1} (*Fig. 2*). An insignificant increasing trend was observed with a rate of 0.14 g C m^{-2} a^{-1}. The degree of deviation of NPP from the multi-year average for 2000–2015 was analyzed by using the percentage deviation. NPP exhibited an increasing – decreasing – increasing tendency: in 2008, 2013 and 2014 the percentages of deviations were significantly different from zero, indicating that the deviations from the average level were substantial. In 2008 NPP was lowest (141 g C m^{-2} a^{-1}), which was lower than the average level by 14.0%. Beginning in 2011, the NPP values were higher than the average value. In 2013, the NPP value was highest (175 g C m^{-2} a^{-1}) which was 8.1% higher than the average level. In the other years, the NPP values fluctuated within approximately 5% of the average level.

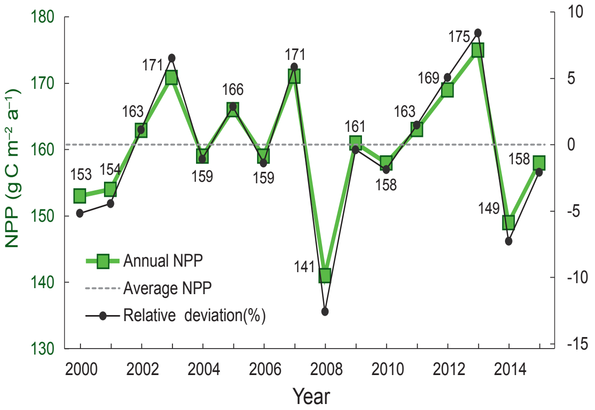

Fig. 2 *Inter-annual variation in vegetation-averaged NPP during 2000–2015 in the Junggar Basin. The horizontal broken line shows the average NPP over all years. Source: own elaboration*

As shown in *Fig. 3*, the annual average NPP in the Junggar Basin exhibits significant spatial differences. Regions of high annual average NPP were mainly found in the western part of the study area where abundant soil moisture and high vegetation cover dominate, which results in high NPP values. Regions with low NPP are mainly distributed in the eastern part of the study area, the desert plains. This area is characterized by desert with sparse vegetation cover and low moisture conditions. In these regions NPP was lower than 100 g C m^{-2}. These regions are mainly distributed in the middle of the Junggar Basin which accounted for 40.3% of the NPP of the whole study area.

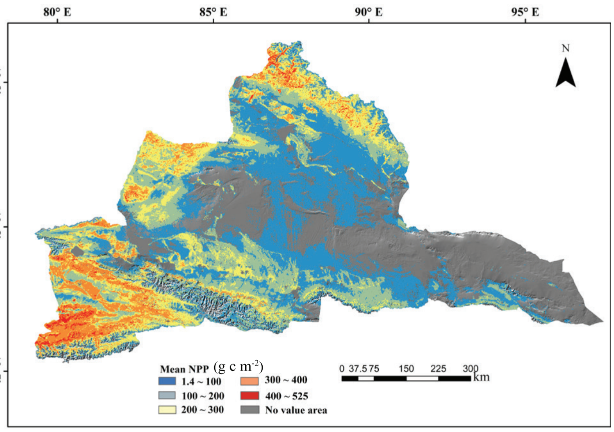

Fig. 3 *Spatial distribution of annual average NPP. Source: own elaboration*

The NPP variation trend in the Junggar Basin was in the range of –12.4 to 11.3 g C m^{-2} a^{-1} from 2000 to 2015. The NPP values exhibited spatial variations, and most of the area showed insignificant change during the study period (*Fig. 4a*), 6.2% of the area showed significantly increasing trends, and 6.7% of the area showed extremely significantly increasing trends, mainly in the southwestern part of the study area. During the study period 74.3% of the area remained under stable conditions (i.e., deviations from the mean < ±5%). Roughly 10.4% of the area showed a decreasing trend in which 2.8% of the area even showed an extremely significantly decreasing trend in the study area (*Fig. 4b*).

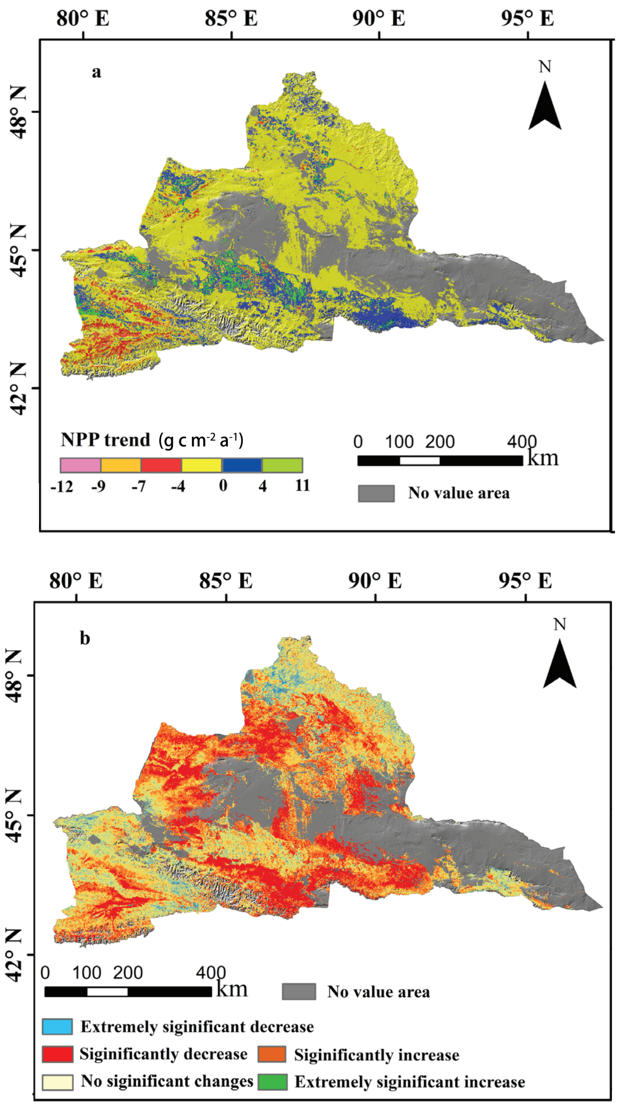

Fig. 4 *NPP spatial variations of temporal trend (a) and test for significance of trend (b) in the Junggar Basin from 2000 to 2015. Source: own elaboration*

4.1.1 The annual average NPP in different LUCC classes

As shown in *Fig. 5*, the annual average NPP changed in different land cover during the study period, but differences were observed in different LUCC types. The results indicate that interannual variations of NPP in different LUCC types were generally following the average NPP variations over the study period. Evergreen broad leaf forest NPP was largest with 488 g C m^{-2} a^{-1} > evergreen needle leaf forest 324 g C m^{-2} a^{-1} > cropland 311 g C m^{-2} a^{-1} > mixed forest 247 g C m^{-2} a^{-1} > deciduous needle leaf forest 162 g C m^{-2} a^{-1} > shrub 142 g C m^{-2} a^{-1} > deciduous broad leaf forest 141 g C m^{-2} a^{-1} > grassland 131 g C m^{-2} a^{-1}. The results indicate that evergreen broad leaf forest has a stronger carbon uptake capability than other vegetation types, and grassland has a rather weak carbon uptake capability in the area. In the years 2003, 2008, 2010 and 2012 a significant annual fluctuation can be seen, and evergreen needle leaf forest and mixed forest showed the largest overall fluctuations over the study period.

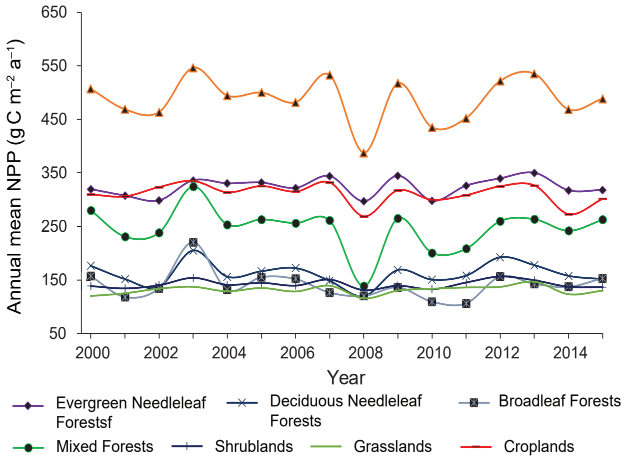

Fig. 5 *Annual variations of NPP in different vegetation types in the Junggar Basin from 2000 to 2015. Source: own elaboration*

4.1.2 The annual average NPP in different soil types

As shown in *Table 1*, the various soil types representing differences in mineral substance, organic material, water content and microbial biomass, directly impact the growth of vegetation, which results in the soil type specific differences in NPP. Distribution and variation of NPP were calculated according to the statistical analysis of soil types, 27 soil types of variable abundance were distributed in the Junggar Basin, with Chestnut soils (17.5%) and Brown calcic soil (18.8%)

being the dominant soil types in the area. The Brown coniferous forest soil showed highest NPP with values around 339 g C m^{-2} a^{-1}, and Adobe soil showed lowest NPP with 74 g C m^{-2} a^{-1} over the study period. The NPP of vegetation growing on other soil types showed a decreasing trend, except for Chernozem, Chestnut soil, and Sierozem.

Table 1 Comparison of NPP of vegetation growing on different soil types. Source: own elaboration

Soil type	Average NPP (g C m^{-2} a^{-1})	Trend (g C m^{-2} a^{-1})
Chernozem (8.2)	246	2.03
Felty soil (5.75)	149	-0.45
Brown coniferous forest soil (0.3)	338	-0.78
Frigid frozen soil (1.09)	84	-0.58
Black soil (8.27)	270	-0.01
Gray forest soil (1.32)	292	-0.34
Chestnut soil (17.47)	162	0.89
Aeolian sandy soil (7.44)	81	-3.46
Meadow soil (4.27)	194	-3.90
Bog soil (1.04)	243	-0.74
Brown calcic soil (18.76)	103	-5.72
Saline (2.49)	143	-1.48
Fluvo-aquic soil (1.85)	220	-0.87
Shrubby meadow soils (0.59)	190	-2.37
Adobe soil (0.18)	73	-3.47
Cold calcic soil (1.13)	163	-0.49
Solonetz (0.01)	115	-2.67
Saline soil (0.64)	105	-1.17
Gray desert soil (5.02)	142	-2.36
Grey-brown desert soil (7.3)	76	-1.52
Grey-cinnamon soil (1.31)	234	-0.81
Irrigated desert soil (0.47)	219	-0.99
Brown-desert soil (0.16)	127	-0.94
Litho soil (0.23)	80	-0.26
Sierozem (2.15)	217	0.69
Anthropogenic-alluvial soil (0.03)	223	-0.32
Paddy soil (0.07)	157	-0.68

The numbers in parentheses are the percentage area of the respective soil types (%).

4.1.3 The annual average NPP at different elevations

The terrain of the Junggar Basin is complex mountainous terrain, and thus NPP showed significant variations along the elevation gradient. The highest NPP values were mainly found in high mountain areas with an average of 230 g C m^{-2} a^{-1}. Conversely, the lowest NPP values mainly appeared in the lower-elevation plain area with an average of 101 g C m^{-2} a^{-1}. In general, NPP increased with increasing elevation during the study period (*Fig. 6*).

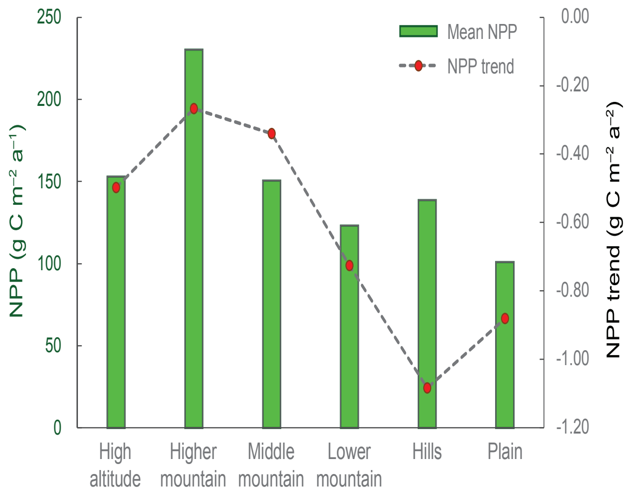

Fig. 6 Comparison of NPP in different elevations (green bars) and the trend of NPP over time during the study period (red symbols, right axis). Source: own elaboration

4.2 Spatial variations of temperature and precipitation

During the study period, precipitation showed an upward trend in the eastern part and some western plains which accounted for 11.5% of precipitation in the area. Contrastingly, the greatest precipitation decreases have occurred in the mountain areas and most parts of the central and western study area, showing a decreasing trend over the study period of 88.5% of the precipitation in the area (*Fig. 7a*). Temperature increases and decreases have not been consistent across the Junggar Basin over the past 16 years. The greatest increases (0.18 °C a^{-1}) have occurred in the mountain area which accounted for 14.9% of temperature in the study area (*Fig. 7b*). In most of the remaining study area a decreasing trend could be observed (88.5% of the temperature in the study area). Most parts of the Junggar Basin except the mountain areas have become drier over the past 16 years (*Fig. 7a*).

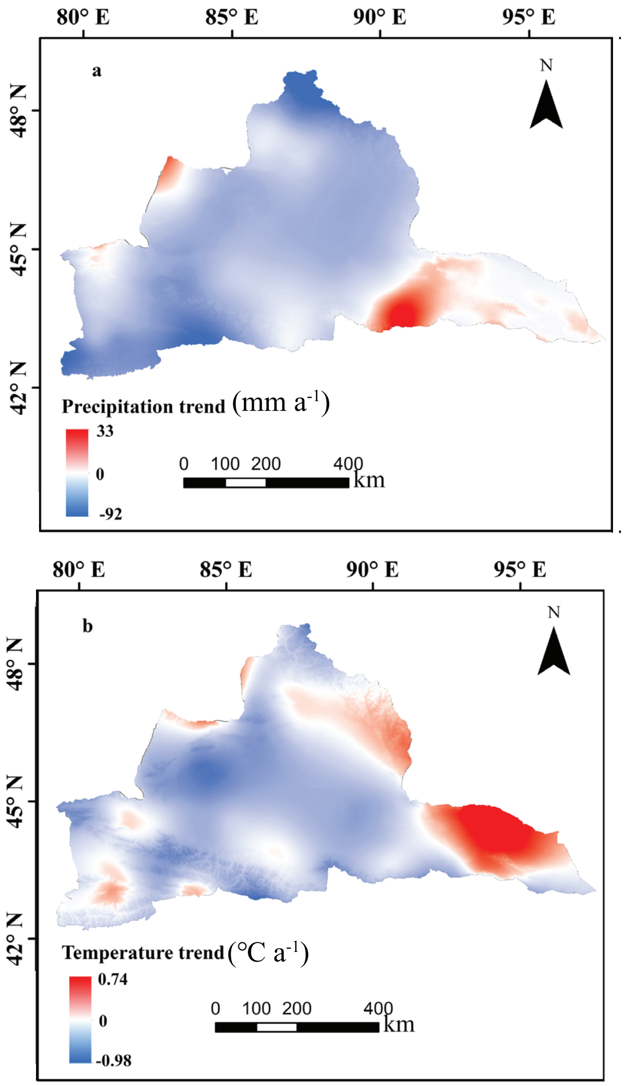

Fig. 7 *Spatial distribution of trend of precipitation (a) and temperature (b) over the study period 2000–2015. Source: own elaboration*

4.3 Analysis of the factors influencing NPP

The range of partial correlation coefficients for the relationship between NPP and precipitation was from −0.86 to 0.83, and most of the region exhibited positive correlations with precipitation (52.3% of the area). When the temperature and other factors remained constant, an increase in precipitation resulted in an increase in NPP over the study area. Some parts of the study area had negative correlations between precipitation and NPP (47.7% of the study area); these parts were mainly distributed at high elevations (3000–4000 m) and low vegetation cover areas (*Fig. 8a*). The range of partial correlation coefficients for the relationship between NPP and temperature was between −0.81 and 0.93 (*Fig. 8b*). Most of the area exhibited positive correlations with temperature (75.5% of the total study area). These areas were mainly distributed in the southern and northwestern parts of the study area. The western edge of the study area exhibited a negative correlation with temperature (24.5% of the area).

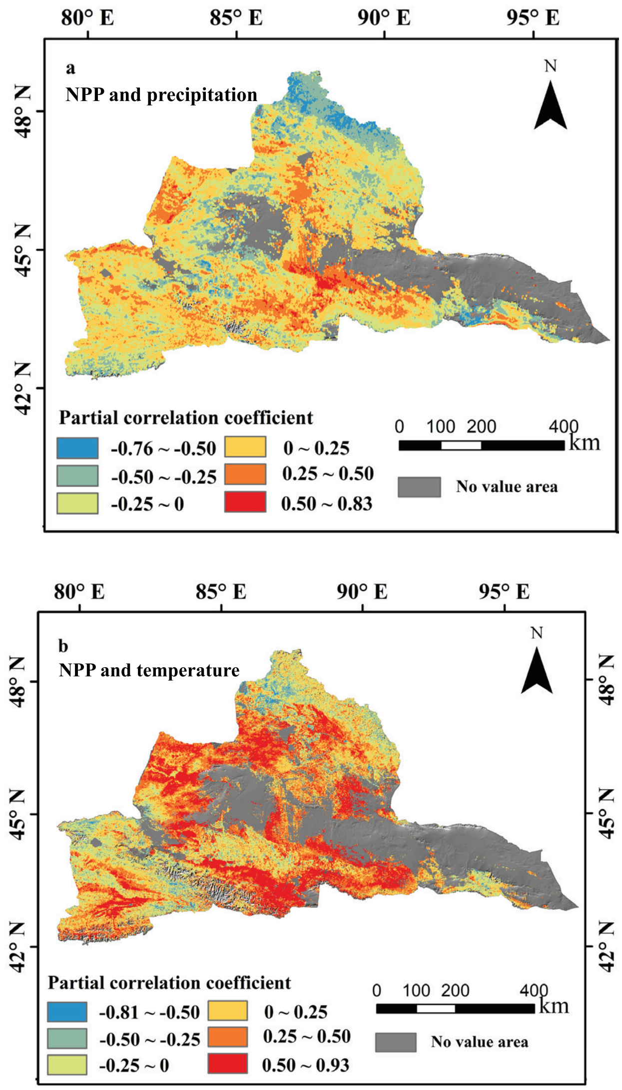

Fig. 8 *Partial correlations between NPP and precipitation (a) and NPP and temperature (b). Source: own elaboration*

The multiple correlation coefficients for the relationship between NPP and temperature or precipitation were in the range of 0.00 to 0.78, and the average multiple correlation coefficient was 0.21 (*Fig. 9a*). Most of the mountain areas exhibited more significant correlations between NPP and the other factors than low elevation areas. The *F*-test results showed that 34.4% of the area passed a significance level of $p < 0.05$, and

23.2% of the area passed a significance level of $p < 0.01$. Low-elevation and high-vegetation cover areas showed significant correlations because these areas receive high solar radiation inputs, have sufficient soil moisture, leading to an increase in NPP. However, NPP variability in the Junggar Basin could not fully be explained by climate factors like precipitation and temperature. Rather, other factors, such as NDVI relative humidity and human activity, should be considered when determining climate change impacts on NPP.

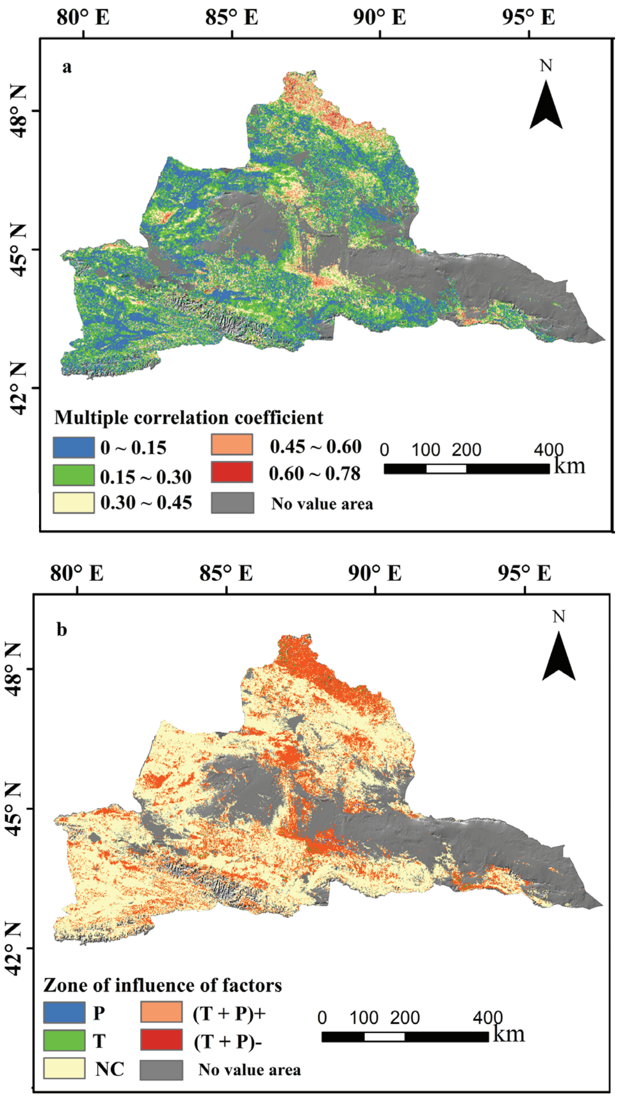

Fig. 9 *Multiple correlations between NPP and precipitation or temperature (a), and zone of influence of climate factors on NPP (b). (T+P)+: Zone of strong influence of temperature and precipitation; T: Zone of influence of temperature; P: Zone of influence of precipitation; (T+P)–: Zone of weak influence of temperature and precipitation; NC: not driven by climate factors. Source: own elaboration*

Climate and human activity were the dominant factors resulting in variations of vegetation NPP, especially growth of vegetation which was directly impacted by fluctuations in temperature and precipitation. In this study based on the driving factor rules of frontier researchers (*Aierken* et al. 2020), we conducted a NPP driving factor analysis for the Junggar Basin which obtained the driving result shown in *Table 2.*

Table 2 *Driving factors for the dynamic change of NPP in the Junggar Basin 2000–2015. Source: own elaboration*

Driving factors of NPP changes			**Driving rules**		
			R1	**R2**	**R3**
Climate factors	Zone of strong influence of two factors	(T+P)+	$\lvert t_1 \rvert > t_{0.01}$	$\lvert t_2 \rvert > t_{0.01}$	$F > F_{0.05}$
	Zone of influence of precipitation	P	$\lvert t_1 \rvert > t_{0.01}$		$F > F_{0.05}$
	Zone of influence of temperature	T		$\lvert t_2 \rvert > t_{0.01}$	$F > F_{0.05}$
	Zone of influence of two factors	(T+P)–	$\lvert t_1 \rvert > t_{0.05}$	$\lvert t_2 \rvert > t_{0.05}$	$F > F_{0.05}$
NC	Non-climate factors	NC			$F \leq F_{0.05}$

R1: t-test of significance of the partial correlations between NPP and temperature
R2: t-test for significance of the partial correlations between NPP and precipitation
R3: F-test for significance of the multiple correlations between NPP and temperature-precipitation(T+P)+: Zone of strong influence of temperature and precipitation
T: Zone of influence of temperature
P: Zone of influence of precipitation(T+P)–: Zone of weak influence of temperature and precipitation
NC: Change not driven by climate factors

The result of the NPP driving factors in Junggar Basin (*Fig. 9b*) showed that most of the study area was influenced by the non-climate factors. The area of influence of temperature was mainly distributed in the Ili river watershed and Tien Shan (or Tian Shan) mountain range. The zone of influence of precipitation was accounting for only 0.21% of the study area, and the zone of influence of the temperature was restricted to 0.57% of the study area. The zone of strong influence of temperature and precipitation accounted for 0.05% and the zone of weak influence (T+P)– of the temperature and precipitation accounted for 27.2% of the study area. In consequence, the result of all NPP driving factors shows that more than 70% of the area's NPP is most likely driven by non-climatic factors.

5. Discussion

In this study, we used existing MOD17A3-NPP data from 2000 to 2015 in combination with MOD12Q and climatic data to investigate the spatiotemporal variations and driving factors of net primary productivity in the Junggar Basin of Northeast China. Although some caution should be taken when using the MODIS data which are not locally validated, many regional and global studies so far have demonstrated good reliability of the MODIS NPP data product, including the studies of regional NPP in Chinese ecosystems (*Zhang* et al. 2016*; Basuki* et al. 2019). We found that NPP in our study area showed an obvious decrease during the 2007–2009 period, almost coinciding with a temperature decreasing during 2008–2010, so that NPP decrease potentially resulted from temperature decrease (*Tang* et al. 2016*; Qi* et al. 2016).

Climatic factors are critical determinants of vegetation and play a crucial role in shaping spatial patterns and temporal dynamics of ecosystem NPP, which have been investigated in many studies. *Nayak* et al. (2015) reported that temperature and precipitation are the dominant factors controlling the spatial distribution of NPP in India and the NPP of Chinese forests is positively correlated with annual mean temperature and precipitation. *Zhao* et al. (2004) found that NPP was positively correlated with precipitation, but negatively with temperature. Our study results have a significant similarity with the findings that were presented by *Nayak* et al. (2015). The driving strength of precipitation and temperature varied over the Junggar Basin due to the terrain characteristics and elevation of our study area. Still, the effect of temperature was significant, most likely due to the relatively broad geographical range of the study area, which resulted in significant variations of mean annual temperature during the study period. The grassland ecosystems predominate in the Junggar Basin, while the proportion of forestlands is relatively low. In the middle part of the study area desert dominates with low vegetation cover. Annual variations in NPP in different land use and land cover types were mainly coinciding with the domain-averaged NPP variation over the study period. While NPP differed among vegetation types, evergreen broadleaf forests showed highest NPP, although with a slightly decreasing trend in the forestlands. Within the croplands, two thirds of the area showed an increase in NPP and one third showed a decrease in NPP.

Due to the large geographical extent of the study area with complex terrain characteristics, meteorological factors showed a significant spatial variability over the study area. But over the study period, NPP variation of most regions were mainly impacted by non-climate factors, it would be impacted by human activity.

6. Conclusions

In this study, across a temperate desert landscape in Northeast China, we investigated the patterns of spatial and temporal variations in ecosystem productivity (i.e., net primary production, NPP) and its controlling factors. Climate factors, environmental conditions, vegetation and soil type all played important roles determining NPP and its relationship with driving factors. The pixel-based time-series regression analysis showed that the areas with a highly significant increase ($p < 0.01$), a significant increase ($p < 0.05$), no significant changes, a significant decrease ($p < 0.05$) and a highly significant decrease ($p < 0.01$) in NPP from 2000 to 2015 accounted for 6.7%, 6.2%, 74.3%, 10.4% and 2.8% of the entire study area, respectively. Generally, the NPP of vegetation in the study area showed a weakly increasing trend from 2000 to 2015. This increasing trend is most likely primarily due to the enhancement of productivity of the agricultural lands, the mixed shrublands, and the grasslands in the study area. The driving factor analysis showed that non-climate factors are the dominant factors affecting NPP in the study area. The zone of weak influence of the temperature and precipitation was accounting for 27.2% of the study area.

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Conflict of Interest

The authors declare no conflict of interest.

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