Ecological Indicators 142 (2022) 109100

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Divergent dynamics between grassland greenness and gross primary productivity across China

Yanni Zhao [a], Jian Peng [b,*], Zihan Ding [b], Sijing Qiu [b], Xuebang Liu [b], Jiansheng Wu [a,b], Jeroen Meersmans [c]

[a] Key Laboratory for Environmental and Urban Sciences, School of Urban Planning & Design, Shenzhen Graduate School, Peking University, Shenzhen 518055, China
[b] Laboratory for Earth Surface Processes, Ministry of Education, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China
[c] TERRA Teaching and Research Centre, Gembloux Agro-Bio Tech, University of Liège, Gembloux 5030, Belgium

ARTICLE INFO

Keywords:
Grassland dynamics
Gross primary productivity
Normalized difference vegetation index
Change consistency
China

ABSTRACT

Grassland, the most widespread vegetation type in China, has been greening recently.However, the extent to which the greenness has been translated into productivity and the underlying mechanism of the decoupled grassland greenness and productivity remains unclear. In this study, we detected the trend of normalized difference vegetation index (NDVI) and gross primary productivity (GPP) of grassland in China from 2000 to 2019 and analyzed the driving mechanism of the inconsistency between them. It was found that the relative increase rate of productivity (27.27%, $p < 0.05$) was much greater than that of greenness (14.54%, $p < 0.05$) across grasslands in China from 2000 to 2019, especially in temperate regions. The temperature and precipitation were the main factors influencing the grassland growth change, and the impact of temperature and shortwave radiation on productivity was greater than on greenness. However, the increase of grassland greenness was not fully translated into productivity in subtropical and tropical grass as well as shrub. This study revealed the dominance of climatic factors in the translation process from ecosystem structure to function, which highlighted the challenge in enhancing carbon uptake capacity of terrestrial ecosystem facing accelerated climate change.

1. Introduction

Grassland occupies about 40% of the global ice-free land area (Bardgett et al., 2021; Rogiers et al., 2008; White et al., 2000), accounting for about 20% of the total carbon storage of soil and vegetation (Zhang et al., 2017; Adams et al., 1990). Grassland plays an important role in global climate change and global carbon balance, providing key ecosystem services such as carbon fixation, water conservation, and soil retention (Liu et al., 2019; Zhang et al., 2018). However, the changing climate has greatly influenced grassland dynamics because of increased global temperature and altered precipitation (Chen et al., 2020; Gang et al., 2014). Therefore, the study on grassland dynamics and its response to climatic factors can improve the understanding of the carbon cycle of grassland and is conducive to adaptive management to cope with climate change (Sha et al., 2020).

Satellite-based evidences have confirmed that the northern hemisphere has experienced rapid greening in recent decades (Piao et al., 2020; Chen et al., 2019a; Chen et al., 2019b). However, the increase of vegetation greenness does not mean the improvement of ecosystem function to the same extent, such as gross primary productivity. For instance, the increase in vegetation greenness did not lead to the same proportion of GPP increase in the global (Zhang et al., 2019). Furthermore, the changes of different vegetation indices showed distinct spatial heterogeneity. It was reported that nearly half of global vegetated area experienced inconsistent vegetation growth in greenness, cover, and productivity (Ding et al., 2020), and there was a much weaker increase of productivity than greenness in South Asia during 2003–2017 (Sarmah et al., 2021). The potential reasons for this phenomenon, which were the effects of different climatic factors on the divergent trends of greenness and productivity, remained unclear. In addition, vegetation dynamics studies at global scale, were always followed by national and regional studies, with a special target of supplement and validation.

In general, the response of vegetation GPP to climate change is faster than that of NDVI (Yan et al., 2019), since the change of environmental factors will directly affect the light energy utilization efficiency of vegetation and then influence productivity (Walther et al., 2018).

* Corresponding author.
E-mail address: jianpeng@urban.pku.edu.cn (J. Peng).

https://doi.org/10.1016/j.ecolind.2022.109100
Received 14 April 2022; Received in revised form 17 June 2022; Accepted 22 June 2022

Climate warming may further alleviate the temperature stress in cold regions and thus increase GPP (Nemani et al., 2003), however, higher temperature and lower precipitation may also introduce an increase in vegetation growth stress in moderate to warm climates and reduce GPP (Anderegg et al., 2015). Therefore, the impact of environmenal conditions on productivity is complicated, with distinct spatial heterogeneity in different climate zones.

The total area of natural grassland in China is 3.95 million km^2, accounting for 41.7% of the total land area, ranking second in the world after Australia (Shen et al., 2016). China has a wide range of latitudes and altitudes, resulting in diverse types of grassland, and therefore, the trends of vegetation activity and its driving factors are quite different among these different types of grassland (Zhang et al., 2018; Liu et al., 2017). In previous studies, single vegetation index of greenness or productivity was often used to explore the spatiotemporal dynamics of grasslands and associated driving factors (Zhang et al., 2020; Pan et al., 2018; Zhang et al., 2018; Piao et al., 2006). In most grasslands of China, vegetation activity showed an overall increasing trend since 2000 (Liu et al., 2019; Zhou et al., 2014). Precipitation was identified as the main climatic factor driving productivity change (Liu et al., 2019; Shen et al., 2015), while the temperature had a negative effect on productivity in arid and tropical regions (Feng et al., 2021; Zhang et al., 2019; Shen et al., 2015; Corlett, 2011). However, there are few studies about the driving factors of the inconsistent change trend of grassland greenness and productivity, which has limited our understanding of grassland ecosystem carbon uptake and adaptation to future climate change.

In this study, we used NDVI, one of the most widely used vegetation indices obtained directly from satellites to represent greenness (Piao et al., 2020; Tucker, 1979).And GPP was introduced to quantify the organic carbon fixed by green plants through photosynthesis (Zhao et al., 2006; Fang et al., 2001; Running et al., 2000). The change trend of NDVI and GPP of grassland in China during 2000 to 2019 was analyzed, followed by the driving factors of the inconsistency between greenness and productivity. In details, the aims are: (1) to measure the change trend of grassland NDVI and GPP; (2) to compare the change consistency between grassland NDVI and GPP among different grassland types; and (3) to analyze the effects of climatic factors (i.e. temperature, precipitation, and shortwave radiation) on grassland NDVI and GPP.

2. Data and methods

2.1. Study area and data source

Grassland in China has a wide range of latitudes and altitudes, resulting in the variability in climate-soil type combinations and numerous grassland types (Fig. 1). We used the vegetation type map with the scale of 1:1000000 (https://www.resdc.cn/), to obtain the nine grassland types across China. Besides, the unchanged grassland area was extracted using MCD12Q2 land use/cover data during 2001 and 2019. The study area was set as the intersection of nine grassland types and areas whose land use was permanently grassland in the study period, in order to reduce data errors.

NDVI and GPP during 2000–2019 were obtained from Moderate-resolution Imaging Spectroradiometer (MODIS) Terra Collection 6 (C6) data products (https://modis.gsfc.nasa.gov/). MODIS C6 data were calibrated to distinguish vegetation from the background more accurately (Piao et al., 2020). In order to avoid the biased NDVI and GPP values caused by winter snow, the growing season, defined from April to October in the study area, was selected (Piao et al., 2006). NDVI data from 16 days of MOD13A2 synthetic product was used, of which the maximum value composite (MVC) was used to extract monthly NDVI values. GPP data from 8 days of MOD17A2H synthetic product was used, of which the sum value was used to extract monthly GPP values.

Temperature, precipitation, and shortwave radiation were selected to compare the effects of climatic factors on the change of grassland greenness and productivity. We used monthly temperature and precipitation data at 1 km resolution during 2000-2019 from National Earth System Science Data Center (https://www.geodata.cn). The data were generated in China using the method of downscaling based on global climatic data released by CRU and global high-resolution climatic data released by WorldClim. 496 independent meteorological observation points were used to verify the reliability of the results (Peng et al., 2019). Besides, we used 0.1°monthly downward shortwave radiation acquired from National Tibetan Plateau Data Center. This dataset was made based on the existing international Princeton reanalysis data, GLDAS data, GEWEX-SRB radiation data, and TRMM precipitation data, together integrating the meteorological observation data of China Meteorological Administration (He et al., 2020). All data were resampled to the spatial resolution of 1 km.

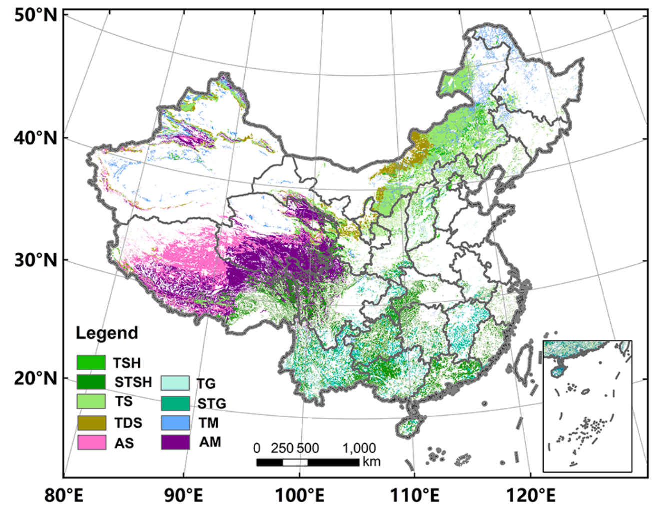

Fig. 1. Spatial distribution of grassland in China. TSH, Temperate shrub; STSH, Subtropical and tropical shrub; TS, Temperate steppe; TDS, Temperate desert steppe; AS, Alpine steppe; TG, Temperate grass; STG, Subtropical and tropical grass; TM, Temperate meadow; and AM, Alpine meadow.

2.2. Measuring grassland change trend

Mann-Kendall is a nonparametric statistical test method (Mann, 1945; Salmi, 2002), which has been used to estimate the change significance of NDVI and GPP from 2000 to 2019 at a pixel scale. The advantage of this method is that it does not require samples to obey a certain distribution and is less sensitive to outliers. Firstly, the statistical value of S was calculated from NDVI or GPP time series data according to the following formulas:

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

$$sgn(x_j - x_i) = \left\{ \begin{array}{c} +1, x_j - x_i > 0 \\ 0, x_j - x_i = 0 \\ -1, x_j - x_i < 0 \end{array} \right\} \tag{2}$$

Where $x_1, x_2, \ldots, x_n$ represent NDVI or GPP sequence, n is the number of years, and the pixel values of the year i and j are expressed as x_i and x_j ($j > i$).

Then the Z-test value was used to examine the significance of the change trend, which was calculated as following:

$$VAR(S) = \frac{n(n-1)(2n+5)}{18} \tag{3}$$

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{VAR(S)}}, S < 0 \end{cases} \tag{4}$$

In the change trend identification of grassland greenness and productivity, the significant level of 0.05 was used, and as such (i) when Z was greater than 1.96, the sequence showed a significant increasing trend, (ii) when |Z| was less than 1.96, the sequence showed a non-significant trend, and (iii) when Z was less than −1.96, the sequence showed a significant decreasing trend.

The Sen slope, together with Mann-Kendall test, usually indicates the extent of change (Sen, 1968; Thiel, 1950), which can reduce the impact of outliers. Therefore, the Sen slope of NDVI and GPP from 2000 to 2019 was calculated using Equation 5. In order to make the change trend of the two vegetation indices comparable, the change rate of the Sen slope relative to that in the initial year was further calculated using Equation 6:

$$\beta = Median\left(\frac{x_k - x_j}{k - j}\right), \forall j > k \tag{5}$$

$$\beta' = \frac{\beta}{x_0} \tag{6}$$

where β is the Sen slope, x_0 is the NDVI or GPP in the initial year, and β' is the ratio of change relative to that in the initial year.

2.3. Consistency analysis of grassland change trends

In different grassland types, linear regression was used to analyze the consistency between the Sen slope of greenness and productivity from 2000 to 2019. The slope of the linear regression coefficient represents the increase or decrease of GPP relative to NDVI. The grassland type in which the slope is closer to 1 shows higher consistency between the Sen slope of GPP and NDVI. If the slope is bigger than 1, it shows the increase of GPP is greater than that of NDVI.

There are complex interaction effects of temperature, precipitation and shortwave radiation on vegetation growth (Zhang et al., 2020; Chen et al., 2020; Liu et al., 2016; Nemani et al., 2003). The second-order partial correlation analysis was applied to explore the relationship between climatic drivers and the grassland dynamics to distinguish the role of each climatic factor. When the partial correlation coefficient of the single climatic factor was calculated, the other two climatic factors acted as control variables. The calculations were accomplished using MATLAB R2020b.

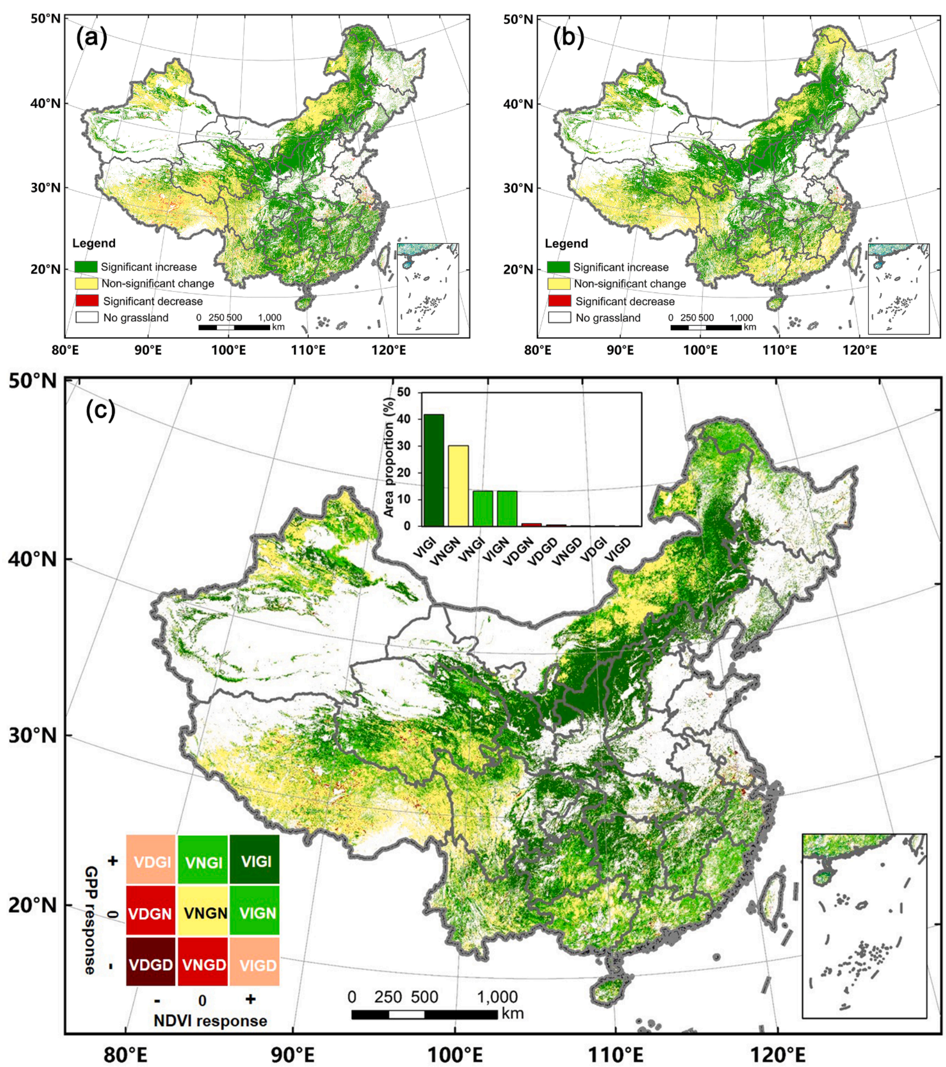

Fig. 2. Change trends of annual grassland NDVI (a) and GPP (b) from 2000 to 2019, and their combinations (c). VIGI represents a significant increase in NDVI and significant increase in GPP; VIGN represents a significant increase in NDVI and non-significant change in GPP; VNGI represents a non-significant change in NDVI and significant increase in GPP; VNGN represents a non-significant change in NDVI and non-significant change in GPP; VIGD represents a significant increase in NDVI and significant decrease in GPP; VDGI represents a significant decrease in NDVI and significant increase in GPP; VNGD represents a non-significant change in NDVI and significant decrease in GPP; VDGN represents a significant decrease in NDVI and non-significant change in GPP; and VDGD represents a significant decrease in NDVI and significant decrease in GPP.

3. Results

3.1. NDVI and GPP dynamics of grassland

The overall inter-annual changes of NDVI and GPP showed an increasing trend from 2000 to 2019, but GPP had manifested a higher increasing rate compared with NDVI. From 2000 to 2019, the average annual increase of GPP was 5.98 $gCm^{-2}y^{-1}$, which corresponded to a relative increase of 27.27% ($R^2 = 0.81$, $P < 0.05$), whereas the average annual increase of NDVI was 0.0031, corresponding to a relative increase of 14.54% ($R^2 = 0.95$, $P < 0.05$).

From 2000 to 2019, the area proportion of grassland characterized by an increased GPP was slightly higher than that of NDVI (Fig. 2). NDVI significantly increased in 54.97% of grassland areas across China, which was mainly distributed in the northern Loess Plateau, the eastern Inner Mongolia Plateau as well as large areas of southern China (Fig. 2a). NDVI did not change significantly in 43.52% of grassland areas, mainly located in the north of Inner Mongolia, most of the Tibet Plateau and the southern and northern parts of the Tianshan Mountains. The area with a significant increase in GPP accounted for 55.09%, mainly distributed in the Loess Plateau, eastern Inner Mongolia, the central and northeastern part of Tibet Plateau as well as the middle and lower reaches of the Yangtze River (Fig. 2b). Whereas 44.23% of the grassland areas did not show any significant changes in GPP, mainly distributed in southeast coastal areas of China, southern Tibet Plateau, and northern Greater Khingan Mountains. Only a very small proportion of the grassland areas across china (i.e. 0.68%) was characterized by a significant decrease of GPP which were in the highly urbanized areas of eastern China. Overall, although greenness and productivity of most areas showed consistently increasing trend, there were still some notable regions that showed inconsistent change.

Considering the spatial distribution of both indices, 72% of the grassland area showed the same change trend in NDVI and GPP (Fig. 2c). More precisely, a consistent significant increase was detected in 41.86%

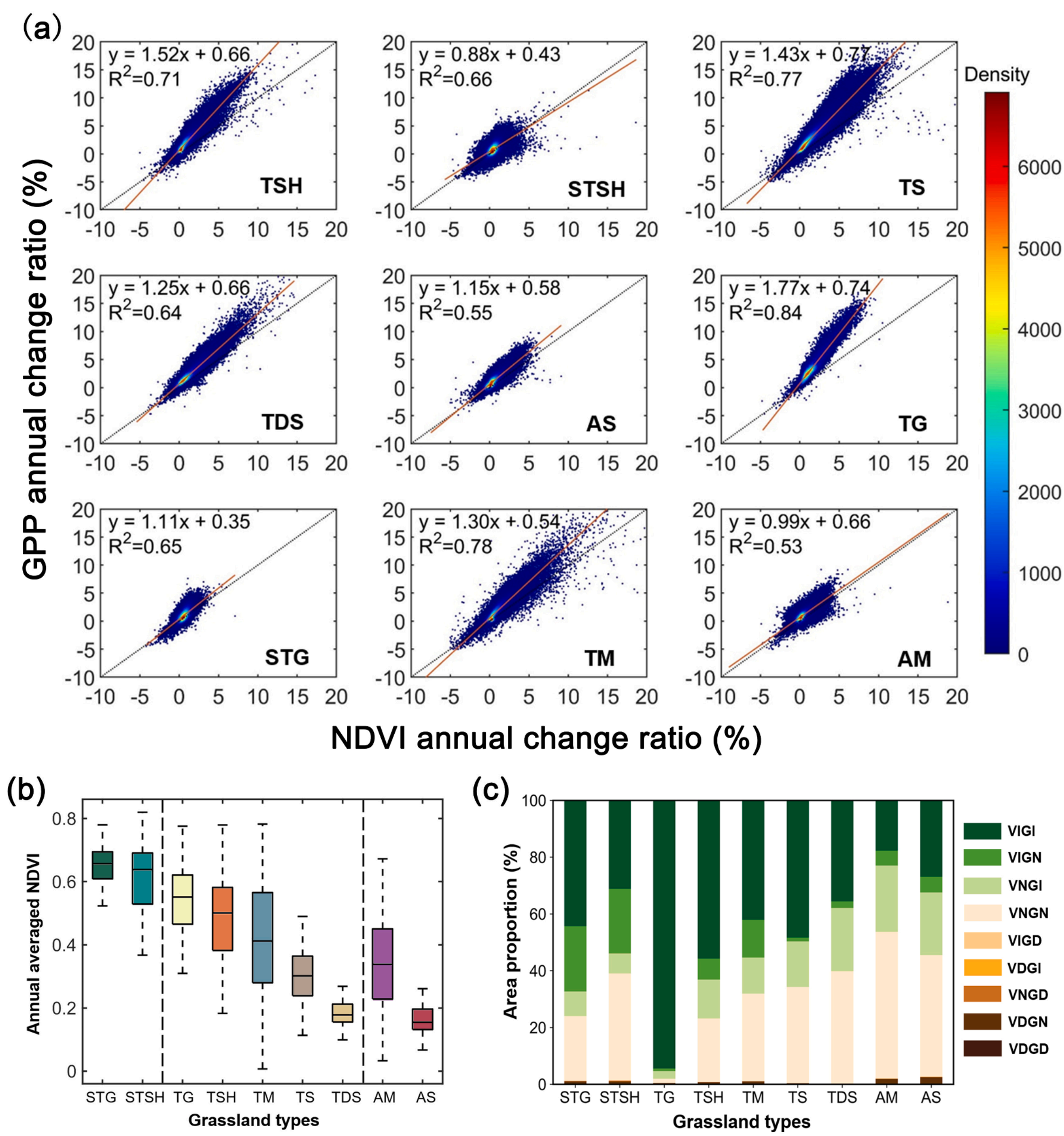

Fig. 3. Consistency of change trends between NDVI and GPP across different grassland types. Comparison of the annual change ratio between greenness and productivity (a), boxplot of annual averaged NDVI across grassland types (b), and area proportion of different change trend types (c). The central line is the median, the upper and bottom edge of the box correspond to the 25th and 75th percentiles respectively, and the whiskers show the range of the data.

of the grassland area, which was distributed in the Loess Plateau, the Middle-Lower Yangtze plains, the northeast of Inner Mongolia as well as the central and eastern part of the Tibet Plateau, whereas a consistently non-significant change was in 30.14% of the grassland area, which was mainly located in the southernTibet Plateau and northwestern Inner Mongolia. Areas of consistent grassland degradation were sparse and scattered mainly across the Tibet Plateau and Yangtze River Delta.

It should be noted that the proportion of the total area in which NDVI and GPP did not increase synchronously accounted for 26.3%. In particular, there was 13.2% of the grassland areas characterized by a significant increase in NDVI but non-significant change in GPP which could be found mainly along the southeast coast of China and the northern Greater Khingan Mountains (Fig. 2c). Hence, the greenness of these grasslands increased significantly, but their improvement in productivity were not significant. Besides, a similar area (i.e. 13.1%) had been characterized by a significant increase in GPP but non-significant change in NDVI, mainly distributed in the central part of the Tibet Plateau, and Northern Xinjiang. These were the areas in which the productivity increased significantly, but the greenness did not increase significantly (Fig. 2c).

3.2. Contrast of the change trends between GPP and NDVI

The slope for the change ratio relative to the initial year was shown to represent the extent of consistency in diverse grassland types (Fig. 3a). Except for subtropical and tropical shrub and alpine meadow, the slope of most grassland types were greater than 1, which indicated that the change ratio of GPP was higher than that of NDVI. For example, in temperate grass, temperate steppe, temperate shrub, and temperate meadow, the slopes were all no less than 1.3, which meant that the improvement of GPP were distincly more than that of NDVI in temperate regions. In addition, the proportion of VIGI was also high across these

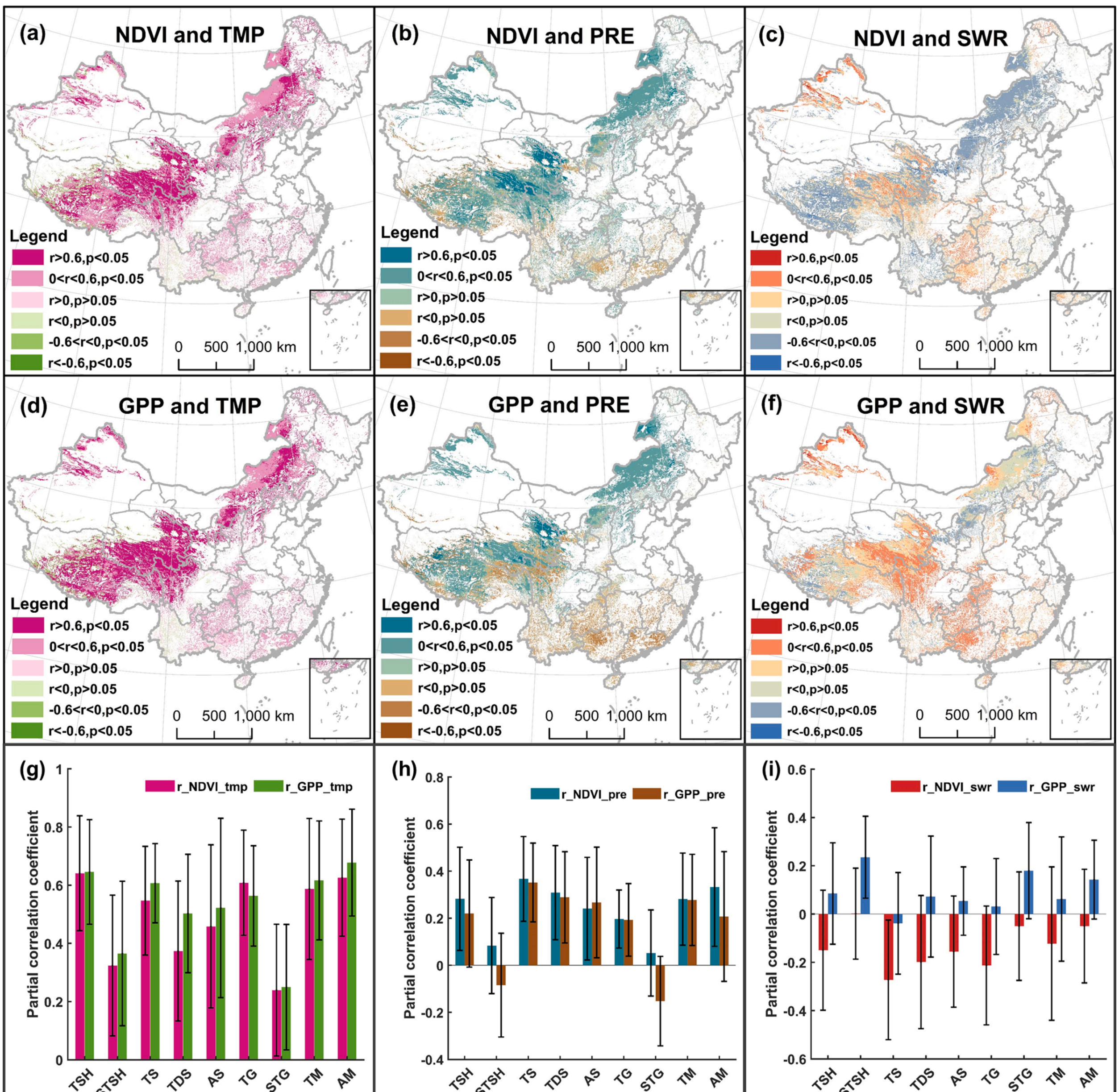

Fig. 4. Partial correlation coefficient between temperature, precipitation, as well as shortwave radiation and NDVI as well as GPP of grassland (a-f), and the mean of the coefficient across all grassland types (g-i). The upper and bottom edge of the solid line correspond to one standard deviation of the average coefficient, respectively.

grassland types (Fig. 3c), showing a consistent increase of greenness and productivity.

The relative increase of GPP was low in the alpine steppe, but it was slightly higher than that in subtropical and tropical shrubs and subtropical grass (Fig. 3a). That was also demonstrated by a higher proportion of only greenness increased area in subtropical and tropical shrubs and subtropical grass (i.e. 22.67% and 22.98%) than other grassland types (Fig. 3c), showing a high NDVI increase trend. In conclusion, the change ratio and consistency between GPP and NDVI showed obvious latitudinal and vertical heterogeneity. The extent of GPP increased relative to NDVI was the highest in the temperate region, followed by the alpine region, and the lowest subtropical and tropical region .

3.3. Sensitivity of grassland change to climatic factors

The impacts of climatic factors on grassland NDVI and GPP dynamics were different (Fig. 4). It was found the primary climatic factor driving grassland changes was temperature, and the positive correlation between temperature and GPP was higher than that of NDVI. The partial correlation coefficient between temperature and GPP was 0.54, with 0.49 for NDVI. Except for temperate grass, the correlation between temperature and GPP was higher than that of NDVI in other grassland types (Fig. 4g). Moreover, the impacts of temperature showed a great spatial heterogeneity among different regions and vegetation types (Fig. 4a and 4d). There was a positive correlation between temperature and grassland NDVI and GPP in Qinghai-Tibet Plateau, Gansu Province, Inner Mongolia, and Xinjiang Autonomous Region, with a small correlation in southeastern China. Temperature was the main factor affecting grassland growth, especially in temperate shrub, alpine meadow, temperate meadow, temperate grass, and temperate steppe, and the partial correlation coefficient in subtropical and tropical shrub was relatively low.

Compared with the temperature, the influence of precipitation on the dynamics of grassland was low. Except for alpine steppe, the partial correlation coefficient between precipitation and NDVI in different grassland types was higher than that of GPP (Fig. 4h). The partial correlation coefficient between precipitation and NDVI was 0.25, with 0.18 for GPP. The effect of precipitation on grassland change was spatially heterogeneous. For example, the grassland growth in Gansu Province, Inner Mongolia Autonomous Region, and parts of the Tibetan Plateau showed a positive correlation with precipitation. However, there was a negative correlation between GPP and precipitation in Yunnan, Guizhou, Guangxi, and Guangdong provinces, where subtropical and tropical shrubs as well as grass dominated (Fig. 4b and 4e).

The correlation between shortwave radiation and grassland dynamics was much weak, and the influences of shortwave radiation on grassland greenness and productivity were opposite in most grassland types (Fig. 4i). The increase of shortwave radiation caused a slight decrease in NDVI but an increase in GPP. The partial correlation coefficient between shortwave radiation and NDVI was −0.12, with 0.1 for GPP. Particularly, there was a positive correlation between shortwave radiation and GPP in subtropical and tropical shrub as well as grass, and a high negative correlation between shortwave radiation and NDVI in the temperate steppe, temperate desert steppe, and temperate grass.

4. Discussion

4.1. Effects of climatic factors across different grassland types

In this study, it was shown that temperature was the most sensitive driver for grassland growth change, which was demonstrated by the high partial correlation coefficients across different grassland types, and that was consistent with previous studies (Shen et al., 2016; Zhou et al., 2014). There was a strong positive correlation between grassland growth and temperature in temperate and alpine regions. However, in contrast, the correlation was weak in the subtropical and tropical region. It was probably because most alpine meadows and temperate meadows had sufficient water availability, but were constrained by temperature, resulting in vegetation growth more sensitive to temperature (Zhu et al., 2016; Piao et al., 2006).

However, this positive effect of temperature was diminishing in arid and subtropical regions, which might face the heat and drought risks from the climate change due to water deficit and exceeding the optimum temperature for photosynthesis (Zhang et al., 2019; Huang et al., 2019). The effect of high temperatures on plant productivity have been explained in previous studies. For example, it has been reported that the rising temperature is usually accompanied by the higher vapor pressure deficit, which can control stomatal closure, accelerate leaf senescence, and thus limit the canopy photosynthesis (Huang et al., 2019; Williams et al., 2013; Niinemets, 2001).

It was also shown that precipitation was positively correlated with the two indices in most grassland types, especially in temperate steppe, and temperate desert steppe. Consistent with the results of previous studies, the sensitivity of productivity to precipitation change was higher in the arid grassland and decreased with increasing mean annual precipitation and temperature (Wang et al., 2022; Fang et al., 2018). However, when precipitation was sufficient, the growth rate of GPP was negatively correlated with precipitation (Knapp et al., 2016; Ponce-Campos et al., 2013; Huxman et al., 2004), for instance, in the subtropical and tropical shrub as well as grass (Fig. 4h). That might be the consequence of an increase in cloud cover which resulted in the decrease in grassland incident radiation and thus the restriction of grassland productivity.

4.2. Decoupled change of grassland greenness and productivity

The different impacts of climatic factors on NDVI and GPP may lead to inconsistency. The asynchronous trend of grassland change in southeast China was demonstrated by the increase of NDVI rather than GPP, which was consistent with a previous finding of increasing vegetation greenness but slightly decreasing productivity (Ding et al., 2020). In subtropical and tropical grass as well as shrub, precipitation and shortwave radiation jointly led to the change inconsistency of NDVI and GPP. A previous study showed that there was still a slight increase in greenness under extreme drought conditions in the Amazon, but there showed a decrease in productivity (Yang et al., 2018), indicating the increased greenness might not be proportionally translated into productivity. Similarly, subtropical and tropical areas tended to have limited GPP due to the risk of heat stress and the radiation deficit caused by increased precipitation. Thus, environmental conditions could play a more important role in photosynthesis than canopy structure in this area (Lee et al., 2013).

While in temperate and alpine regions, the grassland tended to show an increased GPP but a non-significantly changed NDVI. This might be caused by the combined effects of temperature and shortwave radiation, and the increase of GPP was greater than that of NDVI due to the warming climate. However, these areas were faced with a certain extent of water deficit, and the increase of radiation would be accompanied by the decreased precipitation, leading to the aggravation of ecosystem drought and thus restraining grassland greening.

There are also other potential reasons for the decoupled vegetation greenness and productivity. Although climatic factors are known as important drivers affecting vegetation growth (Solangi et al., 2019; Gao et al., 2016), human activities are also important pathways to increasing terrestrial carbon sink (Sha et al., 2020). Despite ecological engineering bringing vegetation greenness to recover rapidly, the restoration of ecological functions such as productivity may take a much longer time (Ding et al., 2020), which resulted in the asynchronous change of vegetation greenness and productivity. Besides, sensor errors may also bring some uncertainty to the data, and the saturation effect occurs when NDVI is greater than 0.8 due to the dense plants coverage, reducing the sensitivity of NDVI to vegetation growth (Wang et al., 2020; Piao et al., 2020; Yang et al., 2008). All may underestimate the greenness of the grassland in summer and lead to the inconsistency in the tropical and subtropical regions.

4.3. Limitations and future research directions

In this study, the inconsistent change trend and different drivers of grassland greenness and productivity in China was revealed using the indices of NDVI and GPP. However, there are still some limitations. Firstly, we extracted the unchanged grassland land in the study period as the study area and eliminated the impact of human activities through the land use change to the most extent. However, there are still human activities in the grassland management, which may also lead to inconsistency. Secondly, this study was only focused on the vegetation type of grassland, and more studies across different vegetation types are needed to clarify the translating mechanism from the greenness to productivity. Lastly, in the case of large inconsistencies between different vegetation products (Ding et al., 2020; Jiang et al., 2017), we used greenness and productivity data from the same sensor, which to some extent could reduce the data uncertainty caused by different sensor errors. However, there may still be data uncertainties, and the results need to be validated with more case studies in the future.

5. Conclusions

In this study, NDVI and GPP were used for comprehensive monitoring of grassland dynamics across China to explore the trend inconsistency and its driving factors. It was found that the relative increase rate of productivity (27.27%, $p < 0.05$) was much greater than that of greenness (14.54%, $p < 0.05$) across grasslands in China from 2000 to 2019, especially in temperate regions including temperate grass, temperate shrub, temperate steppe, and temperate meadow. Moreover, the inconsistent change trend in subtropical and tropical regions tended to be characterized by an increase in greenness but a non-significant increase in productivity. Temperature and precipitation were the main factors influencing the grassland growth. Moreover, the influences of temperature and shortwave radiation on productivity were greater than on greenness, but the impact of precipitation on productivity was less than on greenness, especially in subtropical and tropical regions. This study revealed the effect of climatic factors on the change consistency between greenness and productivity in different grassland types, highlighting the challenge in enhancing carbon uptake capacity of terrestrial ecosystem in the context of climate change.

CRediT authorship contribution statement

Yanni Zhao: Conceptualization, Software, Writing – original draft. **Jian Peng:** Conceptualization, Methodology, Writing – review & editing. **Zihan Ding:** Conceptualization, Methodology, Software. **Sijing Qiu:** Methodology, Software, Writing – review & editing. **Xuebang Liu:** Methodology, Software, Writing – review & editing. **Jiansheng Wu:** Conceptualization, Supervision. **Jeroen Meersmans:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgment

This study was financially supported by the National Key Research and Development Program of China (No.2017YFA0604704).

References

Adams, J.M., Faure, H., Faure-Denard, L., et al., 1990. Increases in terrestrial carbon storage from the Last Glacial Maximum to the present. Nature 348, 711–714. https://doi.org/10.1038/348711a0.

Anderegg, W.R.L., Schwalm, C., Biondi, F., et al., 2015. Pervasive drought legacies in forest ecosystems and their implications for carbon cycle models. Science 349, 528–532. https://www.science.org/doi/10.1126/science.aab1833.

Bardgett, R.D., Bullock, J.M., Lavorel, S., et al., 2021. Combatting global grassland degradation. Nat. Rev. Earth Environ. 2, 720–735. https://doi.org/10.1038/s43017-021-00207-2.

Chen, C., Park, T., Wang, X., et al., 2019a. China and India lead in greening of the world through land-use management. Nat. Sustainability 2, 122–129. https://doi.org/10.1038/s41893-019-0220-7.

Chen, J.M., Ju, W., Ciais, P., et al., 2019b. Vegetation structural change since 1981 significantly enhanced the terrestrial carbon sink. Nat. Commun. 10, 4259. https://doi.org/10.1038/s41467-019-12257-8.

Chen, Z., Wang, W., Fu, J., 2020. Vegetation response to precipitation anomalies under different climatic and biogeographical conditions in China. Sci. Rep. 10, 830. https://doi.org/10.1038/s41598-020-57910-1.

Corlett, R.T., 2011. Impacts of warming on tropical lowland rainforests. Trends Ecol. Evol. 26, 606–613. https://doi.org/10.1016/j.tree.2011.06.015.

Ding, Z., Peng, J., Qiu, S., et al. Nearly half of global vegetated area experienced inconsistent vegetation growth in terms of greenness, cover, and productivity. Earth's Future 8, e2020EF001618. Doi: 10.1029/2020EF001618.

Fang, J., Ke, J., Tang, Z., et al., 2001. Implications and Estimations of four Terrestrial Productivity Parameters(in Chinese). Chin. J. Plant Ecol. 25, 414–419. https://www.plant-ecology.com/EN/Y2001/V25/I4/414.

Fang, Q., Wang, G., Xue, B., et al., 2018. How and to what extent does precipitation on multi-temporal scales and soil moisture at different depths determine carbon flux responses in a water-limited grassland ecosystem? Sci. Total Environ. 635, 1255–1266. https://doi.org/10.1016/j.scitotenv.2018.04.225.

Feng, X., Fu, B., Zhang, Y., et al., 2021. Recent leveling off of vegetation greenness and primary production reveals the increasing soil water limitations on the greening Earth. Sci. Bull. 66 (17), 1462–1471. https://doi.org/10.1016/j.scib.2021.02.023.

Gang, C., Zhou, W., Chen, Y., et al., 2014. Quantitative assessment of the contributions of climate change and human activities on global grassland degradation. Environ. Earth Sci. 72, 4273–4282. https://doi.org/10.1007/s12665-014-3322-6.

Gao, Q., Zhu, W., Schwartz, M.W., et al., 2016. Climatic change controls productivity variation in global grasslands. Sci. Rep. 6, 26958. https://doi.org/10.1038/srep26958.

He, J., Yang, K., Tang, W., 2020. The first high-resolution meteorological forcing dataset for land process studies over China. Sci. Data 7, 25. https://doi.org/10.1038/s41597-020-0369-y.

Huang, M., Piao, S., Ciais, P., et al., 2019. Air temperature optima of vegetation productivity across global biomes. Nat. Ecol. Evol. 3, 772–779. https://doi.org/10.1038/s41559-019-0838-x.

Huxman, T.E., Smith, M.D., Fay, P.A., et al., 2004. Convergence across biomes to a common rain-use efficiency. Nature 429, 651–654. https://doi.org/10.1038/nature02561.

Jiang, C., Ryu, Y., Fang, H., et al., 2017. Inconsistencies of interannual variability and trends in long-term satellite leaf area index products. Glob. Change Biol. 23, 4133–4146. https://doi.org/10.1111/gcb.13787.

Knapp, A.K., Ciais, P., Smith, M.D., 2016. Reconciling inconsistencies in precipitation–productivity relationships: implications for climate change. New Phytol. 214, 41–47. https://doi.org/10.1111/nph.14381.

Lee, J.E., Frankenberg, C., van der Tol, C., et al., 2013. Forest productivity and water stress in Amazonia: observations from GOSAT chlorophyll fluorescence. Proc. R. Soc. B 280, 20130171. https://doi.org/10.1098/rspb.2013.0171.

Liu, Q., Fu, Y.H., Zeng, Z., et al., 2016. Temperature, precipitation, and insolation effects on autumn vegetation phenology in temperate China. Glob. Change Biol. 22, 644–655. https://doi.org/10.1111/gcb.13081.

Liu, S., Cheng, F., Dong, S., et al., 2017. Spatiotemporal dynamics of grassland aboveground biomass on the Qinghai-Tibet Plateau based on validated MODIS NDVI. Sci. Rep. 7, 4182. https://doi.org/10.1038/s41598-017-04038-4.

Liu, Y., Wang, Q., Zhang, Z., et al., 2019. Grassland dynamics in responses to climate variation and human activities in China from 2000 to 2013. Sci. Total Environ. 690, 27–39. https://doi.org/10.1016/j.scitotenv.2019.06.503.

Mann, H.B., 1945. Nonparametric tests against trend. Econometrica 13, 245–259. https://doi.org/10.2307/1907187.

Nemani, R.R., Keeling, C.D., Hashimoto, H., et al., 2003. Climate-Driven Increases in Global Terrestrial Net Primary Production from 1982 to 1999. Science 300, 1560–1563. https://www.science.org/doi/10.1126/science.1082750.

Niinemets, Ü., 2001. Global-scale climatic controls of leaf dry mass per area, density, and thickness in trees and shrubs. Ecology 82, 453–469. https://doi.org/10.2307/2679872.

Pan, N., Feng, X., Fu, B., et al., 2018. Increasing global vegetation browning hidden in overall vegetation greening: Insights from time-varying trends. Remote Sens. Environ. 214, 59–72. https://doi.org/10.1016/j.rse.2018.05.018.

Peng, S., Ding, Y., Liu, W., et al., 2019. 1 km monthly temperature and precipitation dataset for China from 1901 to 2017. Earth Syst. Sci. Data 11, 1931–1946. https://doi.org/10.5194/essd-11-1931-2019.

Piao, S., Mohammat, A., Fang, J., et al., 2006. NDVI-based increase in growth of temperate grasslands and its responses to climate changes in China. Global Environ. Change 16, 340–348. https://doi.org/10.1016/j.gloenvcha.2006.02.002.

Piao, S., Wang, X., Park, T., et al., 2020. Characteristics, drivers and feedbacks of global greening. Nat. Rev. Earth Environ. 1, 14–27. https://doi.org/10.1038/s43017-019-0001-x.

Ponce-Campos, G.E., Moran, M.S., Huete, A., et al., 2013. Ecosystem resilience despite large-scale altered hydroclimatic conditions. Nature 294, 349–352. https://doi.org/10.1038/nature11836.

Rogiers, N., Conen, F., Furger, M., et al., 2008. Impact of past and present land-management on the C-balance of a grassland in the Swiss Alps. Glob. Change Biol. 14, 2613–2625. https://doi.org/10.1111/j.1365-2486.2008.01680.x.

Running, S.W., Thornton, P.E., Nemani, R.R., et al., 2000. In: Global terrestrial gross and net primary productivity from the Earth Observing System, in Methods in Ecosystem Science. Springer, New York, pp. 44–57. https://doi.org/10.1007/978-1-4612-1224-9_4.

Salmi, T., 2002. Detecting trends of annual values of atmospheric pollutants by the Mann-Kendall test and Sen's slope estimates-the Excel template application MAKESENS. Helsinki, Finnish Meteorological Institute 31.

Sarmah, S., Singha, M., Wang, J., et al., 2021. Mismatches between vegetation greening and primary productivity trends in South Asia - A satellite evidence. Int. J. Appl. Earth Observat. Geoinformat. 104, 102561 https://doi.org/10.1016/j.jag.2021.102561.

Sen, P.K., 1968. Robustness of some nonparametric procedures in linear models. Ann. Math. Stat. 39, 1913–1922. http://www.jstor.org/stable/2239290.

Sha, Z., Bai, Y., Lan, H., et al., 2020. Can more carbon be captured by grasslands? A case study of Inner Mongolia. China. Sci. Total Environ. 723, 138085 https://doi.org/10.1016/j.scitotenv.2020.138085.

Shen, H.H., Zhu, Y.K., Zhao, X., et al., 2016. Analysis of current grassland resources in China (in Chinese). Chin. Sci. Bull. 61, 139–154.

Shen, X., Liu, B., Li, G., et al., 2015. Impact of climate change on temperate and alpine grasslands in China during 1982–2006. Adv. Meteorol. 2015, 180614 https://doi.org/10.1155/2015/180614.

Solangi, G.S., Siyal, A.A., Siyal, P., 2019. Spatiotemporal dynamics of land surface temperature and its impact on the vegetation. Civil Eng. J. 5, 1753–1763. https://doi.org/10.28991/cej-2019-03091368.

Thiel, H., 1950. A rank-invariant method of linear and polynomial regression analysis. Proceed. Roy. Netherl. Acad. Sci. 53, 386–392. https://doi.org/10.1007/978-94-011-2546-8_20.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ. 8, 127–150. https://doi.org/10.1016/0034-4257(79)90013-0.

Walther, S., Guanter, L., Heim, B., et al., 2018. Assessing the dynamics of vegetation productivity in circumpolar regions with different satellite indicators of greenness and photosynthesis. Biogeosciences 15, 6221–6256. https://doi.org/10.1073/pnas.1700294115.

Wang, F., Chen, B., Lin, X., et al., 2020. Solar-induced chlorophyll fluorescence as an indicator for determining the end date of the vegetation growing season. Ecol. Ind. 109, 105755 https://doi.org/10.1016/j.ecolind.2019.105755.

Wang, C., Vera-Vélez, R., Lamb, E.G., et al., 2022. Global pattern and associated drivers of grassland productivity sensitivity to precipitation change. Sci. Total Environ. 806 https://doi.org/10.1016/j.scitotenv.2021.151224.

White, R.P., Murray, S., Rohweder, M., et al., 2000. Grassland ecosystem. DC, World Resources Institute, Washington.

Williams, A.P., Allen, C.D., Macalady, A.K., et al., 2013. Temperature as a potent driver of regional forest drought stress and tree mortality. Nat. Clim. Change 3, 292–297. https://doi.org/10.1038/nclimate1693.

Yan, D., Scott, R.L., Moore, D.J.P., et al., 2019. Understanding the relationship between vegetation greenness and productivity across dryland ecosystems through the integration of PhenoCam, satellite, and eddy covariance data. Remote Sens. Environ. 223, 50–62. https://doi.org/10.1016/j.rse.2018.12.029.

Yang, J., Guo, N., Huang, L., et al., 2008. Ananlyses on MODIS-NDVI Index Saturation in Northwest China. Plateau Meteorology 27, 896–903. http://www.gyqx.ac.cn/CN/Y2008/V27/I4/896.

J. Yang H. Tian S. Pan et al. Amazon drought and forest response: Largely reduced forest photosynthesis but slightly increased canopy greenness during the extreme drought of 2015/2016 Global Change Biol. 24 2018 10.1111/gcb.14056 https://doi.org/1919-1934.

Zhang, L., Zhou, G.S., Ji, Y.H., et al., 2017. Grassland carbon budget and its driving factors of the subtropical and tropical monsoon region in China during 1961 to 2013. Sci. Rep. 7, 14717. https://doi.org/10.1038/s41598-017-15296-7.

Zhang, R., Liang, T., Guo, J., et al., 2018. Grassland dynamics in response to climate change and human activities in Xinjiang from 2000 to 2014. Sci. Rep. 8, 2888. https://doi.org/10.1038/s41598-018-21089-3.

Zhang, Y., Song, C., Band, L.E., et al., 2019. No Proportional Increase of Terrestrial Gross Carbon Sequestration From the Greening Earth. J. Geophys. Res. Biogeosci. 124, 2540–2553. https://doi.org/10.1029/2018JG004917.

Zhang, Y., Wang, Q., Wang, Z., et al., 2020. Impact of human activities and climate change on the grassland dynamics under different regime policies in the Mongolian Plateau. Sci. Total Environ. 698, 134304 https://doi.org/10.1016/j.scitotenv.2019.134304.

Zhao, M., Running, S.W., Nemani, R.R., 2006. Sensitivity of moderate resolution imaging spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses. J. Geophys. Res. Biogeosci. 111, G01002. https://doi.org/10.1029/2004JG000004.

Zhou, W., Gang, C.C., Li, J.L., et al., 2014. Spatial-temporal dynamics of grassland coverage and its response to climate change in China during 1982–2010 (in Chinese). Acta Geograph. Sin. 69, 15–30. https://doi.org/10.11821/dlxb201401002.

Zhu, Z., Piao, S., Myneni, R.B., et al., 2016. Greening of the Earth and its drivers. Nat. Clim. Change 6, 791–795. https://doi.org/10.1038/nclimate3004.