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Trends and controls of terrestrial gross primary productivity of China during 2000–2016

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Abstract

Terrestrial gross primary productivity (GPP) is an important flux that drives the global carbon cycle. However, quantifying the trend and the control factor of GPP from the pixel level to the regional level is still a challenge. We generated monthly GPP dataset using the vegetation photosynthesis model and calculated the interannual linear trend for China during 2000–2016. The Breaks For Additive Seasonal and Trend method was applied to detect the timing of breakpoint and trends shift of monthly GPP, while boosted regression tree analysis was used to identify the most important factor and its relative influence on GPP based on gridded leaf area index (LAI), aerosol optical thickness, and NCEP-DOE Reanalysis II meteorological data. The results show that annual mean GPP was significantly $(P < 0.001, R^2 = 0.78)$ increased, especially in the Loess Plateau and South China, from 2000 to 2016. The change rate of annual mean GPP declined from 18.82 g C m $^{-2}$ yr $^{-1}$ in 2000–2008 to 3.48 g C m $^{-2}$ yr^{-1} in 2008–2016. About 55.4% of the breakpoints occur between 2009 and 2011 and was mainly distributed in Qinghai-Tibet Plateau, Central China, Southwestern China, and South China, and negative oriented GPP trends variation type still accounts for about 28.76%. LAI and temperature related factors generally had the highest relative influence on GPP in the north part and south part of China, respectively. Our study indicates that the ecological restoration projects and rapid urbanization have respectively induced the most obvious increase and decrease trends of GPP in China. Land cover change and climate change are the main reasons for GPP dynamics in the north and south part of China, respectively.

1. Introduction

Carbon (C) sequestrated by plants at a given unit space and time through photosynthesis, which is known as gross primary productivity (GPP), constitutes the basis of global C cycle (Monteith 1972). As the amount of total carbohydrate assimilated by terrestrial vegetation, terrestrial GPP has a potential in offsetting a considerable amount of anthropogenic C emission (Running 2008, Pan *et al* 2011), and it also plays a vital role in regulating ecosystem processes, determining land C sink (Zhao and Running 2010), and supporting lives on earth (Demmig-Adams and Adams 2000). However, the distribution and dynamics of terrestrial GPP have been notably impacted by global environment changes (Turner *et al* 2007, Mishra and Chaudhuri 2015). Even a small variation of GPP may have a significant impact on C balance at regional and global **IOP** Publishing

Letters

scales (Yao *et al* 2018). Detecting the variation of terrestrial GPP at multiple spatial scales is important for people to understand the dynamics of C sequestration of terrestrial ecosystems and is helpful for the government to make appropriate ecological and environmental management decisions (Andersson *et al* 2009).

Temporal trend of GPP over a period usually contains two types of dynamics: interannual dynamic and seasonal dynamic. Interannual dynamic describes the changes of GPP over years and is usually defined by a linear trend, which can provide the basic information about the annual increment of GPP especially over a long period (Zhang et al 2014b, Campbell et al 2017, Ma et al 2018, Yao et al 2018). Seasonal dynamic describes the changes of GPP within a year, which is highly related to land surface phenology (Verbesselt et al 2010b, Xia et al 2015). Although both aspects of the temporal variations can reflect the dynamics of GPP, they may not catch some abrupt changes due to external disturbances (Verbesselt et al 2010b, Fang et al 2018). However, detecting how and when GPP change with the abrupt disturbances can provide more insights into the GPP trends than either interannual or seasonal dynamic. Therefore, detecting the breakpoints of GPP over a period and comparing the difference of the trends before and after the breakpoints is imperative to understand long-term GPP variation.

Terrestrial productivity is influenced by a number of factors concerning climates and anthropogenic activities (Nemani et al 2003, Field et al 2007), among which climate change and land use/land cover change (LULCC) are regarded as the two most important driven factors. For examples, some studies have definitely reported that earth has experienced dramatic environmental changes (Nemani et al 2003) and vegetation photosynthesis, especially in the middle and high latitude areas of northern hemisphere, has increased accordingly since the 1980s (Piao et al 2006, Zhao and Running 2010, Yao et al 2018). Similarly, LULCC has also been proved to have a significant impact on vegetation phenology and carbon flux (Quaife et al 2008, Clapcott et al 2010, Wu et al 2016), which have a further impact on vegetation GPP (Berry and Roderick 2004). However, the responses of vegetation growth to climate change and LULCC are more prominent at large scales (global or continental level) (Gottfried et al 2012). Considering the complex variations of local ecosystem and interactions among different climate change and LULCC factors, it is still a challenge to specify the control factors of GPP at local or regional scales (Schimel et al 2001, Bai and Dent 2009, Migliavacca et al 2012).

China has experienced significant climate change in the past several decades, which has been reported to have conspicuous influences on vegetation growth and carbon sequestration (Piao *et al* 2012, Yuan *et al* 2016). Also, induced by large ecological restoration projects, rapid urbanization, and development of agriculture, tremendous LULCC has occurred over China in the same period. The LULCC in China occurred at a high speed after 2000 and had directly changed the dynamics of vegetation coverage and productivity (Yu et al 2009, Tao and Zhang 2013, Lu et al 2018). At the same period, some extreme climate events, such as drought, heat, and snowstorm, also occurred. Due to large spatial and temporal heterogeneities of climate change and LULCC over entire China and possible interactive effects between them on vegetation productivity (Piao et al 2010, Lu et al 2018), the responses of vegetation growth to climate change and LULCC exhibit remarkable regional contrasts. In the explorations of the dynamic of vegetation GPP of China, one important question is how climate change and LULCC affects GPP. It is still a challenge to identify when GPP disturbed by climate change and LULCC, how GPP trend changes under climate change and LULCC, and what is the most important factor influencing GPP dynamic for each site over entire China.

In this study, we applied the vegetation photosynthesis model (VPM) to develop spatial-based annual and seasonal (monthly) vegetation GPP dataset over China during 2000-2016 with 500 m spatial resolution based on Moderate-Resolution Imaging Spectroradiometer (MODIS) and National Center for Environmental Prediction-Department of Energy (NCEP-DOE) climate data. Dynamics of environmental factors including meteorological data, soil property, aerosol optical thickness (AOT) data, and land cover are all related to GPP. AOT affects the GPP by reducing solar radiation, while the influence of land cover on GPP is mainly related to the changes of vegetation photosynthesis due to disturbances (such as afforestation and forest harvesting), which can be reflected by leaf area index (LAI) in large part (Li et al 2018b). Therefore, factors concerning climate, soil property, and LAI were used to test the environment influence on GPP. The objectives of this study were to (1) estimate the spatiotemporal pattern of the GPP trend of China at both annual and seasonal scales during 2000-2016; (2) detect the breakpoints and the trends shift of GPP over China; and (3) identify the control environmental factors of GPP dynamic for each pixel during 2000-2016 over entire China.

2. Materials and methods

2.1. GPP dataset

The VPM, a satellite-based light use efficiency model, was applied to produce GPP dataset during 2000–2016 in this study. Simulation of GPP in the VPM was driven by MODIS products (MOD09A1 version 6 surface reflectance dataset, MYD11A2 version 6 land surface temperature dataset, and MCD12Q1 version 5 land cover dataset) and NCEP reanalysis II climate dataset (Zhang *et al* 2017). The detailed simulation processes of VPM are reported in the supplementary materials, available online at stacks.iop.org/ERL/14/ 084032/mmedia (Zhang et al 2017, Ma et al 2018). The VPM-simulated GPP data had a temporal resolution of 8 d and a spatial resolution of 500 m. The 8 d 500 m resolution GPP dataset was used in the analysis of interannual GPP trend and the detection of breakpoints and GPP trends shift, while the GPP dataset was aggregated into monthly 0.5° spatiotemporal resolution in the analysis of the relative influence of environmental factor on GPP. Moreover, the interannual variation of annual total GPP of China (measured as the total quantity of C in a year) was also calculated for the period of 2000-2016. The boundary map of China was used to subset the mosaicked GPP dataset to get GPP dataset of China.

2.2. LAI, AOT, climate, and land cover datasets

The satellite-based LAI dataset, used in this study, was derived from the newest Global Inventory Modeling and Mapping Studies third-generation LAI (GIMMS3g LAI) product (Zhu *et al* 2013). The GIMMS3g LAI product spans the period from 1981–2016 and has an interval of 15 d and a spatial resolution of $1/12^{\circ}$ (about 8 km at the Equator). The LAI data from 2000 to 2016 were aggregated into monthly 0.5° spatiotemporal resolution in the detection of environmental control factor of GPP.

MODIS gridded monthly AOT product (Levy *et al* 2015), with the spatial resolution of 0.5°, for the period of 2000–2016 was used in this study. The AOT data was regarded as an environmental factor that influences GPP dynamic and involved in the detection of the control factor of GPP.

Twelve monthly Gaussian gridded NCEP reanalysis II climate variables (Kanamitsu et al 2002), including mean air temperature (Temp), maximum air temperature (MaxTemp), minimum air temperature (MinTemp), mean precipitation rate (PreciRat), mean potential evaporation rate (PotEvapRat), downward solar radiation flux (DownSoRat), mean soil moisture of 0-10 cm (SoMois0 10), mean soil moisture of 10-200 cm (SoMois10_20), mean soil temperature of 0-10 cm (SoTemp0_10), and mean soil temperature of 10-200 cm (SoTemp10_200), for the period of 2000–2016 were used in this study (table 1, figure S1). All meteorological data were resampled to a uniform $0.5^{\circ} \times 0.5^{\circ}$ grid to match the GPP and AOT data in the detection of the control factor of GPP in China

The MODIS MCD12Q1 version 5 land cover product with 500 m resolution from 2000 to 2013 (Friedl and Sulla-Menashe 2015) was used to analyze the distribution of GPP in different biomes of China during 2000–2016. Sixteen land cover types including evergreen needleleaf forest, evergreen broadleaf forest, deciduous needleleaf forest, deciduous broadleaf forest, mixed forest (MF), closed shrublands, open



shrublands, woody savannas, savannas (SAV), grasslands (GRA), permanent wetlands (PW), croplands (CRO), urban and built-up (UBU), cropland/natural vegetation mosaic (CNV), snow and ice (SI), and barren or sparsely vegetated were adopted in this study. Considering the mismatch of the time span of between the MODIS MCD12Q1 land cover data and our study period, MCD12Q1 data in 2001 was used to represent the year 2000 and MCD12Q1 data in 2013 was used to represent the years 2014, 2015, and 2016. The land cover data from 2000 to 2016 were used to estimate the interannual variation of the distribution of annual total GPP in different biomes in China.

2.3. Annual GPP trend analysis

Annual GPP trend of China was analyzed at two spatial scales. At the national level, linear least square regression between annual mean GPP and time was conducted for entire China. The slope value of the linear regression is regarded as the direct measurement of the GPP trend, while the *p*-value of the linear regression represents the significance of GPP trend (with the threshold of 0.05). In order to detect whether there were significant breaks of annual GPP during 2000-2016, the 'changepoint' package in R software was used to detect the change point of annual GPP (Killick and Eckley 2014). The initial results showed that the year 2008 was a turning point of annual GPP for entire China during 2000-2016, and the GPP trends before and after 2008 may have a large difference. Therefore, annual linear GPP trends for the periods of 2000-2016, 2000-2008, and 2008-2016 were calculated, respectively. At the pixel level, the slope value and *p*-value of the linear regression between annual mean GPP and time during 2000-2016 for each cell were calculated and presented.

2.4. Detection of breakpoint and trends shift with time series GPP data

In order to detect the most important and obvious abrupt change of GPP, the 'bfast01' function in the Breaks For Additive Seasonal and Trend (BFAST) method (Verbesselt et al 2010a, 2010b) was applied in this study to detect the only one major breakpoint and trends shift based on the monthly GPP for each pixel of China during 2000-2016. BFAST is constructed based on an iterative algorithm that includes two main aspects: decomposing time series into seasonal, trend, and remainder components and detecting structural changes in both the trend and seasonal components (Verbesselt et al 2010a, Watts and Laffan 2014). The basic assumption of the BFAST method is that nonlinearity can be approximated by a piecewise linear model (de Jong et al 2012), which is iteratively fitted by an additive decomposition approach (Verbesselt et al 2012). The 'harmonic' seasonal model, considered as the best fit model of natural vegetation phenological change (Verbesselt et al 2010a), was selected in this

Table 1. Ranges and source of independent variables in the BRT analysis of China and the relevant influenced components in the vegetation photosynthesis model (VPM). The monthly mean values of the independent variables are regarded as the samples in BRT analysis.

Independent variables	Unit	Range	Source	Influenced component of in the VPM
Leaf area index (LAI)	_	0.02-6.05	GOMMS 3 g	fPARchl
Aerosol optical thickness (AOT)	_	0-1	MODIS product	PAR
Monthly mean air temperature (Temp)	°C	-30.6 to 29.7	NCEP-DOE Reanalysis-II	Tscalar
Monthly maximum air temperature (MaxTemp)	°C	-23.8 to 35.9	NCEP-DOE Reanalysis-II	Tscalar
Monthly minimum air temperature (MinTemp)	°C	-39.2 to 29.2	NCEP-DOE Reanalysis-II	Tscalar
Monthly mean precipitation rate (PreciRat)	$kg m^{-2} s^{-1}$	0-0.0002	NCEP-DOE Reanalysis-II	Wscalar
Monthly mean potential evaporation rate (PotEvapRat)	$W m^{-2}$	-7.2 to 755.7	NCEP-DOE Reanalysis-II	Wscalar
Monthly downward solar radiation flux (DownSoRat)	$\mathrm{W}\mathrm{m}^{-2}$	44.5-370.4	NCEP-DOE Reanalysis-II	PAR
Monthly mean soil moisture of 0–10 cm (SoMois0_10)	_	0.03-0.41	NCEP-DOE Reanalysis-II	Tscalar
Monthly mean soil moisture of 10–200 cm (SoMois10_200)	_	0.07-0.42	NCEP-DOE Reanalysis-II	Tscalar
Monthly mean soil temperature of 0–10 cm (SoTemp0_10)	°C	-30.58 to 29.45	NCEP-DOE Reanalysis-II	Wscalar
Monthly mean soil temperature of 10–200 cm (SoTemp10_200)	°C	-30.24 to 26.49	NCEP-DOE Reanalysis-II	Wscalar

4



Table 2. Location, biome type and annual GPP of 2010 for different selected sites of the four GPP trends variation types. PP: a positive trend changed into a positive trend, NP: a negative trend, NP: a negative trend changed into a positive trend, and NN: a negative trend changed into a negative trend.

Selected sites	Coordinates	Biome of 2010	GPP in 2010 (g C m^{-2})	
РР	110.038°E, 36.917°N	Grassland	803.1	
PN	98.242°E, 36.275°N	Grassland	468.8	
NP	115.690°E, 32.696°N	Cropland	1401.4	
NN	91.665°E, 31.731°N	Grassland	210.2	

study. The bandwidth parameter was set as 0.15 based on the assumption that a 30 month period was regarded as the moving data window, and a significance level of 0.05 was set in BFAST analysis.

The timing of the breakpoint indicates a change in the amplitude or direction of GPP trends that aroused by external disturbances. The breakpoint for each pixel of China was output in this study. The original monthly scale breakpoint was aggregated into annual scale. Moreover, the GPP trends of the pre-breakpoint period (PRB) and post-breakpoint period (POB) for each pixel of China were calculated and output. Positive and negative values of the GPP trend mean positive and negative GPP trends, respectively. Four types of GPP trends variation around the breakpoint were calculated based on the GPP trends' values from BFAST analysis: PP (a positive trend changed into a positive trend), PN (a positive trend changed into a negative trend), NP (a negative trend changed into a positive trend), and NN (a negative trend changed into a negative trend). For each GPP trends variation type, we selected a pixel as the hotspot to conduct further analysis of trends change and control factors of GPP. The hotspots were selected using the following regulation: the GPP trends variation type of each hotspot pixel must be of the same type as its eight surrounding adjacent pixels. Moreover, the most concerned areas (such as the Loess Plateau and the Qinghai-Tibet Plateau) of China where the vegetation changes greatly or significantly impacted by land use and climate change should be included. Based on these fundamental standards, a random point for each GPP trends variation type was generated and regarded as the relevant hotspot site.

The frequency distribution of the breakpoint, marked by different GPP trends variation type, with the year was calculated and showed in this study. Furthermore, the difference between GPP trends of PRB and POB for each pixel of China was also calculated and showed. R software with the packages of 'bfast' and 'raster' (R Development Core Team 2013) and ArcGIS were used to conduct BFAST analysis and raster-based data processing.

2.5. Identification of control factors and their relative influence on GPP dynamics

Boosted regression tree (BRT) analysis, a nonlinear regression model, was used to evaluate the relative

importance and marginal effects of individual environmental factors on GPP for China during 2000–2016. BRT analysis has strength in evaluating complex nonlinear relationship (Elith *et al* 2008, Ma *et al* 2015, 2017), which is reflected by the marginal effect and the relative influence of each independent variable on response variables. The marginal effect of an individual predictor variable is calculated based on the assumption that other independent variables are constant, and this effect will be regarded as the relative influence on the response variable. With the ability to accommodate any data distribution, there is no need to conduct transformation of the data in BRT analysis.

In this study, BRT analysis was conducted for each pixel of China. Before the conduction of BRT analysis, Pearson's linear correlation analysis was conducted to check the basic relationship between GPP and each environmental factors for entire China in this study (figure S2). Monthly GPP data from 2000 to 2016 was set as the response variable, and the monthly environmental factors for the same period were set as the independent variables which include meteorological data, soil property data, AOT data, and LAI data (table 1). Although some independent variables have connections with the inputs of the VPM, the direct parameters of the VPM were not included in the independent variables in BRT analysis. The sample size of the data in BRT analysis for each pixel was 204 (17 years multiplied by 12 months of each year). Parameters including 'Gaussian' error distribution, a learning rate of 0.005, a bag fraction of 0.5, and tenfold cross-validation were set in BRT analysis. R software with the package of 'gbm' was used to conduct BRT analysis (R Development Core Team 2013).

In the results, the first important environmental factor was regarded as the control factor of GPP. The distribution of the control factor and its relative contribution for each pixel of China was displayed, and the overall relative influence of the top three and five most important factors was also generated (figure S3). The relative influences of the first three important environmental factors and their marginal effects on GPP were showed for each GPP trends variation type hotspot site (PP, PN, NP, and NN). The details about the four hotspots were listed in table 2. Moreover, in order to test the consistency between the GPP and its control factor in both PRB and POB, the





annual dynamic of them for each hotspot site were also showed (figure S4).

3. Results

3.1. Interannual trend of annual mean GPP and annual total GPP

At the national scale, annual mean GPP of China significantly (P < 0.001, $R^2 = 0.78$) increased, with an average change rate of 9.68 g C m⁻² yr⁻¹, from 2000 to 2016 (figure 1(a)). Significant trends of annual mean GPP were also identified for both periods of 2000–2008 (P < 0.001, $R^2 = 0.87$) and 2008–2016 (P < 0.05, $R^2 = 0.35$). However, the change rate of annual mean GPP during 2000–2008 (18.82 g C m⁻² yr⁻¹) was higher than that of 2008–2016 (3.48 g C m⁻² yr⁻¹). The annual total GPP of China ranged from 5.54 Pg C in 2001 to 7.34 Pg C in 2013 (figure 1(b)).

At the biome scale, the biome-based composition of the annual total GPP for each year during 2000–2016 was generally constant. MF, CRO, and GRA were the top three contributions to the annual total GPP in China, and their mean proportions were 32.63%, 29.38%, and 17.53%, respectively.

At the pixel scale, about 85.3% pixels of entire China had positive linear trends of annual mean GPP was during 2000–2016 (figure 2). The most obvious positive annual GPP trend for China was mainly distributed in the Loss Plateau, Southern coastal area, and some parts of Southwestern China. The change rate of annual mean GPP of these areas was generally higher than 50 g C m⁻² yr⁻¹. The most obvious negative annual GPP trend for China was mainly distributed in the Yangtze River Delta urban agglomeration, riverfront regions of the Yangtze River, and some parts of Eastern Qinghai-Tibet Plateau and Inner Mongolia. The change rate of annual mean GPP of these areas was ranged from -40 to -10 g C m⁻² yr⁻¹. Significant linear GPP trend during 2000–2016, accounted for about 42.5% of vegetated China, was mainly distributed in most parts of Northeastern China, Loss Plateau, some parts of Central China, and South China (figure 2).

3.2. Timing and shift in trends of monthly time series GPP

Breakpoint years of GPP were identified for almost the entire vegetated China and ranged from 2003 to 2012 (figure 3(a)). The breakpoints, occurred between 2009 and 2011, accounted for about 55.4% of the total pixels and mainly distributed in Qinghai-Tibet Plateau, Central China, Southwestern China, and South China (figure 3(c)). Moreover, breakpoints that occurred in 2003 also accounted for a large percentage (about 12.8%) and mainly distributed in some parts of North China, Northeastern China, and Southeastern China.





Figure 2. Spatial distribution of the slope value and the *p*-value in the linear regression between annual mean GPP and time during 2000–2016 over entire China. (a) Slope value, (b) *p*-value.





PP was the most obvious GPP trends change type, with an area percentage of 69.91%, and mainly distributed in Eastern China (figure 3(b)). However, PN, NP, and NN were mainly distributed in East Qinghai-Tibet Plateau, some area of Central China, and Northeastern China and Qinghai-Tibet Plateau. Their area percentages were 11.78%, 1.33%, and 16.98%, respectively.

Positive GPP trends emerged in most pixels of China at both PRB and POB, while negative GPP trends extended from some parts of Northeastern China and Central China in PRB to some parts of Northwestern and Northeastern China in POB (figures 4(a) and (b)). The high value of the difference of GPP trends between PRB and POB (>1.5 g C m⁻² month⁻¹) was mainly distributed in the Great Xing'an Mountains area, North China Plain, and Southwestern China, while the low value of the difference of GPP trends between PRB and POB (<-1.5 g C m⁻² month⁻¹) was mainly distributed in the South part of Northeastern China, North China, Northwestern China, and coastal areas of Southeastern China (figure 4(c)).

3.3. Influence of environmental factors on GPP dynamic

At the national scale, large spatial heterogeneity existed in the distribution of the control factor of GPP for China during 2000–2016 (figure 5(a)). LAI was generally the control factor of GPP in the regions of central Northeastern China, the North China Plain, the Loess Plateau, and some parts of Northwestern China, while Temp, MaxTemp, and MinTemp mainly controlled the GPP in the south part of Northeastern China, the Yangtze River Basin area, and South China and Qinghai-Tibet Plateau area, respectively. Environmental factors related to water (PreciRat and PotEvapRat), radiation (SolRad), and soil (SoMois0_10, SoMois10_200, SoTemp0_10, and SoTemp10_200) only controlled the GPP of some pixels in Northeastern





Figure 4. Spatial distribution of (a) GPP trend before breakpoint year, (b) GPP trend after breakpoint year, and (c) difference of GPP trends before and after breakpoint year. The GPP trend is calculated in BFAST analysis.



Figure 5. Spatial distribution of the most important factor influencing GPP and its relative influence estimated by BRT analysis in China during 2000–2016. (a) The most important, (b) the relative influence of the most important.

China, Southwestern China, and north part of Qinghai-Tibet Plateau.

The high values of the relative influence of the control factor of GPP (>55%) were mainly distributed in central Northeastern China, the North China Plain, the Loess Plateau, south part of Qinghai-Tibet Plateau, and some parts of Northwestern China (figure 5(b)). The low values of the relative influence of the control factor of GPP (<25%) was mainly distributed in central Qinghai-Tibet Plateau, Southwestern China, and coastal areas of South and Southeastern China (figure 5(b)).

At hotspot scale, LAI, MaxTemp, LAI, and Min-Temp were the most important factors influencing GPP of the PP site, PN site, NP site, and NN site, which had relative importance of 37.52%, 28.55%, 41.24%, and 20.19%, respectively (figure 6). SoMois10_200, PreciRat, SoTemp10_200, and AOT, with their relative influence of 37.13%, 21.13%, 32.60%, and 19.54%, were consisted the second important factors influencing GPP of the PP site, PN site, NP site, and NN site. SoTemp10_200, SoMois10_200, AOT, and LAI were the third important factors influencing GPP of the PP site, PN site, NP site, and NN site, and their relative influences were all lower than 15%. Moreover, all the top three environmental factors were generally positively related to GPP of the four hotspot sites (figure 6).

4. Discussion

4.1. Spatial and temporal patterns of interannual variation of GPP

Our results show that annual mean GPP of China generally had an increasing trend from 2000 to 2016. This is in line with some previous studies (Piao *et al* 2009, Zhang *et al* 2014b, Ma *et al* 2018, Yao *et al* 2018) which have pointed that significant increase of vegetation growth occurred in China in the past several





Figure 6. The relative influence of the top three most important variables on monthly GPP of different GPP trends change type. Each dependency plot represents the marginal effect of a predictor variable on Monthly GPP. Marginal effects were constrained in the model to be monotonic. PP: a positive trend changed into a positive trend; PN: a positive trend changed into a negative trend; NP: a negative trend changed into a negative trend.

decades. Also, the rapid increase of GPP for China was consistent with the generally positive trend of global vegetation growth (Heimann and Reichstein 2008, Le Quere et al 2016). Our results indicate that vegetation in China exhibits a huge potential for C sequestration, which plays an important role in the global C cycle. However, the increasing trend was weakened after the year 2008, the increasing rate of annual mean GPP decreased from 18.82 to 3.48 g C m⁻² yr⁻¹ (figure 1). The dramatic change of GPP increasing rate may be attributed to three possible reasons. Firstly, a large number of ecological restoration projects had been conducted nationwide since the end of the 1990s (Lu et al 2018). However, the rapid restoration of the vegetation may approach a saturation status as time passed and cause the slowdown of the growth rate of vegetation (Sun et al 2015, Yin et al 2018). Secondly, a slowdown of climate warming (called as 'warming hiatus') mainly occurred at the low and middle latitudes of the Earth, especially in the boreal cold season (Sun *et al* 2017), which may have a negative effect on vegetation growth. Finally, some extreme climate events, including snow and ice storm 2008 in South China and long term drought during 2008–2010 in Southwestern China, have directly caused the decline of vegetation productivity.

There is a great heterogeneity of the distribution of interannual trend of GPP among different regions during 2000–2016, although it generally shows an increasing trend at the national scale (figure 2). The areas with the highest GPP increase rate are mainly located in the Loess Plateau, Southern coastal area, and some parts of Southwestern China. The most possible reason for the rapid rise of GPP is the positive effects of ecological restoration projects in these regions (Liu *et al* 2008, Feng *et al* 2013, Tong *et al* 2018). For example, China's Grain for Green project in the Loess Plateau had promoted the vegetation coverage by 12.5%

from 1998 to 2005 which had boosted the vegetation productivity significantly (Cao *et al* 2009). The most obvious decrease trend of GPP during 2000–2016 appears in the Yangtze River Delta urban agglomeration and cities of riverfront regions of the Yangtze River. This is most likely to be attributed to intense land cover changes under urbanization (Dobbs *et al* 2011, Seto *et al* 2012), which cause the decline of vegetation growth. A large amount of cropland has been encroached by build-up land in urban agglomerations alongside the Yangtze River over the past 15 years, which had induced dramatically decline of vegetation productivity (Xu *et al* 2012, Chen *et al* 2015, Cheng *et al* 2017).

In this study, the annual total GPP of China during 2000–2016 is 6.74 Pg C yr⁻¹ which is quite similar as the estimates from some other terrestrial models (Zhao et al 2005, Yuan et al 2010, Jung et al 2011, Li et al 2013, Cai et al 2014, Zhu et al 2014, Ichii et al 2017, Yao et al 2018) (table S1). This, to some extent, demonstrates that the simulation of GPP using the VPM in this study is accurate, which makes it feasible and reliable in the GPP trend analysis. The continuous increase of the annual total GPP in China was dominantly contributed by the biomes of MF and CRO. This is mainly attributed to their large areas and high ability of C sequestration as well as land cover and climate changes (Liu et al 2010, Guanter et al 2014, Bowling et al 2018). MF is widely distributed over entire China and has been protected by Natural Forest Protection Project which conducted since 1998, which had finally enhanced the C sequestration (Weyerhaeuser et al 2005, Yu et al 2011). Moreover, Paddy rice was expanded largely in Northeastern China and replaced natural wetland, which has increased the GPP (Dong et al 2016).

4.2. Patterns of GPP breakpoints and shift of GPP trends

The breakpoints for entire vegetated China range from 2003 to 2012 and different timing of breakpoints generally shows aggregation spatial distribution patterns. This demonstrates that there is great spatiotemporal heterogeneity in the factors that causing a dramatic change of GPP in China. None single factor can be used to interpret GPP dynamics at regional or continental scales. However, some major disturbances or promotion events during 2008-2011 were proved to have profound impacts on vegetation productivity (Cao 2011, Guo et al 2015, Luo et al 2015, Xie et al 2016, Song et al 2017) and could well explain the centrally distributed breakpoints of GPP for China during 2009-2011. Impacts of snow and ice storm in 2008 in south China, severe drought during 2009-2011 in southwest China, and vegetation restoration projects in the Loess Plateau on GPP are all identified by breakpoint detection analysis in this study. This still suggests that the reasons for GPP dynamics at large-scale are complex, and it is more appropriate to find drive force of GPP variation on a relatively small scale.



The GPP trends maintain to be positive after the breakpoints for most pixels of China, however, the GPP trends for about 11.78% of vegetated China turned from positive to negative. Also, 16.98% of the total vegetated pixels had continuous negative GPP trend during 2000–2016. The approximately 28.8% negative oriented alteration (PN and NN) of GPP disobeys the general increasing trend of terrestrial photosynthetic activity in North Hemisphere (Nemani et al 2003) and demonstrates that stresses from climate and human activities certainly affect the vegetation productivity in China. Moreover, in the comparison of GPP trends around the breakpoints, the most obvious positive $(>1.5 \,\mathrm{g\,C\,m^{-2}\,month^{-1}})$ and negative $(<-1.5 \,\mathrm{g\,C\,m^{-2}})$ month⁻¹) values of the difference of GPP trends between POB and PRB respectively reflect the promotion and suppression effect on driving factors that causing the emergence of breakpoints. Although GPP trend increased in the Great Xing'an Mountains area, North China Plain, and Southwestern China, the large proportion the decline of GPP trend after breakpoint reflects that vegetation growth was inhibited by environmental stresses especially in South part of Northeastern China (Zhao et al 2016), North China (Brogaard et al 2005), Northwestern China (Xu et al 2013), and coastal areas of Southeastern China (Zhang et al 2010). This calls for a large demand for further protection of the current vegetation and continuous conduction of more ecological restoration projects in the regions with PN and NN GPP trends shift types.

4.3. Environmental control factors of GPP

The results of cell-based BRT analysis show that LAI is the most widely distributed GPP control factor in the north part of China during 2000-2016, especially in the regions of central part Northeastern China, the North China Plain, the Loess Plateau, and some parts of Northwestern China (figure 5(a), table S2). This indicates that the variation of GPP in those areas are mainly caused by land cover change. Ecological restoration activities, such as Grain to Green Project, Natural Forest Protection Project, and Three-North Shelter Forest Program, were mainly conducted in those areas of China and had greatly enhanced the vegetation coverage and productivity (Gao and Yang 2015, Liu et al 2017). In addition, the relative influence of LAI is obviously higher in where it plays a role as the control environmental factor of GPP. This further confirms that land cover change is the most important and direct reason for the changes of GPP in those areas. Moreover, climate factors (Temp, Max-Temp, PotEvapRat, and SolRad) and soil factors (SoMois0_10, SoMois10_200, SoTemp0_10, and SoTemp10_200) also control the GPP dynamics, with high relative influence, especially in the Great Xing'an Mountains area. This is likely to be attributed to the facilitating effect of climate warming, which boosts the intensity photosynthesis (Liu et al 2016), extends the

length of growth season (Peng *et al* 2010, Chen *et al* 2011), and finally accelerates the carbon sequestration of vegetation there (Ma *et al* 2014, Hu *et al* 2016, Li *et al* 2018a). Also, our result concerning the control role of climate on GPP in the Great Xing'an Mountains area is in line with some previous findings (Peng *et al* 2009, Zhang and Zhou 2011, Ma *et al* 2016), which reported that climate change has significantly occurred in high latitude areas of northern hemisphere and has a significant impact on vegetation carbon sequestration.

Besides to LAI, climate factors, including Temp, MaxTemp, and MinTemp, are shown to be more important in regulating GPP in south part of China, however, the relative influence of those climatic control factors are relatively low (figure 5). This finding indicates that the drives for GPP dynamics in the south part of China are complex, which had reported by some studies that the GPP in those areas is mixed impacted by indicators related to climate change (Chen et al 2010, Wang et al 2014, 2015) and land cover change (Peng and Wang 2012, Jiang et al 2014). Moreover, although climate factors play a more important role in the south part of China than the north part of China, for some pixels in the south part of Qinghai-Tibet Plateau, LAI and MinTemp still control the GPP, and their relative influences are obviously higher than surrounding areas. There are two possible reasons for this phenomenon. Firstly, the main vegetation in Qinghai-Tibet Plateau is grassland, and the vegetation coverage, as well as productivity, is declined due to severe grazing (Zhou et al 2006, Huang et al 2016); secondly, the climate of Qinghai-Tibet Plateau is cold, and the extreme cold condition, can be reflected by MinTemp, is the limiting factor of vegetation growth (Wang et al 2012, Wang and Wu 2013).

In BRT analysis for the typical sites of different GPP trends variation types, LAI is the control factor for both PP site and NP site. This indicates that positively oriented variation (PP and NP) of GPP in China during 2000-2016 is mainly controlled by land cover change factors. PP site is located in the Loess Plateau, and the vegetation there had been significantly restored under the conduction of ecological restoration projects (Lu et al 2018). NP site is located in agricultural regions in Central China. The cropland there had experienced a first decline then increase trend during 2000–2010 (Fan et al 2007), and it may cause the NP GPP trends change type. However, for the PN site and NN site, climate-related factors (MaxTemp and MinTemp) are the control factors. These two sites are distributed in the Qinghai-Tibet Plateau, and climate conditions were considered as the most important factor influence vegetation growth (Zhang et al 2013). Our previous study had demonstrated that PN GPP trends change type is most likely to be attributed to vegetation phenology delay around 2006 (Ma et al 2018), and the variation of the phenology is most likely to be regulated by MaxTemp. NN site is located in the central part of Qinghai-Tibet Plateau, and



unreasonable grazing and climate change had jointly caused the continuous decline of vegetation growth (Zhou *et al* 2006, Huang *et al* 2016).

For all the four hotspot sites, the GPP control factors' trends are generally similar to GPP trends in both PRB and POB (figure S4). It indicates that the control factor, detected by BRT analysis, for each hotspot serves as the trigger of the variation of the GPP. Moreover, for the sites where GPP controlled by LAI, the variation of GPP can be explained by the dynamic of LAI for a large proportion. This further demonstrates that the impact of land cover change on vegetation productivity is quite significant in China during 2000–2016.

4.4. Insights and uncertainties of detecting trends and controls of GPP

Both interannual and seasonal trends, which reflects the dynamic of C sequestration ability of vegetation, represent the variation of GPP. However, neither can directly show the abrupt changes of GPP and can be used as the trace of GPP drive force detecting. We coupled the linear trend analysis of annual GPP and breakpoint detection using time series monthly GPP for China during 2000-2016. This ensures us to have a better understanding of the general variation of GPP as well as the main alteration of GPP trend, which is very important in estimating vegetation C sequestration and regional or global C balance. In this study, the most important factor that influences GPP for each pixel of China was also identified by a machine learning-based method. Compared to many previous studies that only consider a region as an integral section in analyzing the drive force of vegetation productivity (Gao et al 2013, Mao et al 2014, Zhang et al 2014a, 2014b), our approach is a new attempt to detect the specific control of GPP for each pixel of a large region, in which the spatial heterogeneity cannot be overlooked. The detected control factor of GPP in each pixel of China may provide useful information for policy-makers to better understand the variation of GPP and to make appropriate activities to enhance vegetation C sequestration. Moreover, the results also show that the overall relative influence of the top three (and five) most important factor is generally higher than 60% (figure S3) for most areas of China. This indicates that the main factors influencing GPP have been taken into account in the detection of the control factor, which enhances the credibility of the results.

Although our study had shown great potential in demonstrating further understanding of the change of vegetation productivity. Uncertainties exist in some aspects. Firstly, the accuracy of raster-based GPP, LAI, AOT, and meteorological data may have direct impacts on the GPP trends and controls analysis. Secondly, in the detection of control factor of GPP for each pixel of China, there are some factors of extreme climatic events that not included in the independent variables may influence the GPP, and they might be



identified as the controls. Finally, the spatial resolution of the climate data is too coarse ($\sim 1.875^{\circ} \times 2^{\circ}$) and cannot contain the information of the spatial heterogeneity of GPP and its influence factor. Nonetheless, this study has still demonstrated a feasible exploration of the trends and controls of GPP for China at such large spatial and temporal scales.

5. Conclusion

Based on the results of GPP trends and control factors detection, several conclusions were drawn as follows. The GPP was generally increased from 2000 to 2016, and the increasing rate of GPP slowed down after the year 2008. National wide drought and other extreme climate events in China may cause the concentrated distribution of GPP breakpoints between 2008 and 2011, and significant vegetation recovery projects and rapid urbanization are the most important reason for the increase GPP trend in the Loess Plateau and South China and for the decreasing trend in the Yangtze River Delta urban agglomeration, respectively. Moreover, although continuous positive trends emerged for most areas of China, the negatively oriented shift of GPP trends still accounted for a large proportion. GPP in the north part of China was more likely to be controlled by land cover change, while the climate dominates the GPP in the south part of China.

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