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Approaches of climate factors affecting the spatial variation of annual gross primary productivity among terrestrial ecosystems in China

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ABSTRACT

Analyzing the approaches that climatic factors affect the spatial variation of annual gross primary productivity (GPP_{yr}) would improve our understanding on its spatial pattern. Based on network eddy covariance measurements and published data in literature, we separated GPP_{yr} into radiation use efficiency (RUE) and annual absorbed photosynthesis active radiation ($APAR_{yr}$), where $APAR_{yr}$ can be regarded as the product of the fraction of absorbed annual photosynthesis active radiation ($FPAR_{yr}$) and annual PAR (PAR_{yr}). Given that PAR_{yr} affects the spatial variation of GPP_{yr} directly through itself, we investigated factors affecting the spatial variations of RUE and $FPAR_{yr}$, to reveal how climatic factors affect the spatial variation of GPP_{yr}. Results suggest that the spatial variation of RUE was directly affected by annual mean air temperature (MAT) and annual mean CO_2 mass concentration (ρ_{cyr}). The increasing MAT and ρ_{cyr} directly enhanced RUE. The increasing annual precipitation (MAP) directly prompted $FPAR_{yr}$. Therefore, MAT and ρ_{cyr} affected the spatial variation of GPP_{yr} through altering RUE while the effect of MAP was achieved through altering $FPAR_{yr}$. Our study could also provide an alternative way for regional GPP_{yr} assessment.

1. Introduction

Gross primary productivity (GPP) is the amount of CO_2 that is taken up by plants from the atmosphere through photosynthesis (Chen et al., 2012), serving as the largest carbon flux between terrestrial ecosystems and the atmosphere (Beer et al., 2010). Along with ecosystem respiration, GPP controls the CO_2 exchange between terrestrial ecosystems and the atmosphere (Beer et al., 2010), which is of significant importance in regulating the terrestrial carbon budget (Chapin et al., 2006; Yuan et al., 2010) and then climate change (Ciais et al., 2013; Hilker et al., 2008; Li et al., 2013). Additionally, as the start of biogeochemical cycles, GPP drives several ecosystem functions (Beer et al., 2010) and contributes to ecosystem services such as food and wood production. Therefore, it is worthwhile to quantify the magnitude of GPP and its spatial variation at the regional scale.

Based on network eddy covariance measurements, many investigations have analyzed the spatial variation of annual GPP (GPP_{yr}) and its affecting factors (Baldocchi, 2008; Chen et al., 2013b; Kato and Tang, 2008; Law et al., 2002; Luyssaert et al., 2007; Wang et al., 2008b; Yu et al., 2013). Many factors, especially climatic variables such as annual mean air temperature (MAT) (Chen et al., 2013b; Kato and Tang, 2008; Luyssaert et al., 2007; Magnani et al., 2007; Reichstein et al., 2007; Yu et al., 2013) and annual precipitation (MAP) (Chen et al., 2013b; Kato and Tang, 2008; Luyssaert et al., 2007; Yu et al., 2013), were found to strongly affect the spatial

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variation of GPP_{yr}. However, how these climatic factors affect the spatial variation of GPP_{yr} was not well documented, which impeded our fully understanding on the spatial variation of GPP_{yr}.

Radiation use efficiency theory is widely used to describe the dynamics of GPP over the world (Running et al., 2004; Wang et al., 2010; Wu et al., 2010a; Zhao and Running, 2010), which provides a solid basis for revealing how climatic factors affect the spatial variation of GPP_{yr}. According to the radiation use efficiency theory (Monteith, 1972), GPP_{yr} can be considered as the product of radiation use efficiency (RUE) and absorbed annual photosynthesis active radiation ($APAR_{yr}$), where $APAR_{yr}$ was the fraction of $APAR_{yr}$ ($FPAR_{yr}$) multiplying annual photosynthesis active radiation (PAR_{yr}). Given that PAR_{yr} affects the spatial variation of GPP_{yr} by itself, analyzing factors affecting the spatial variations of RUE and $FPAR_{yr}$ would thus underpin our understanding on how factors affect that of GPP_{yr}. Factors affecting the spatial variation of RUE have been extensively investigated. For example, the spatial variation of RUE was found to be affected by that of MAT (Schwalm et al., 2006) or MAP (Garbulsky et al., 2010), while most of these studies were conducted among European (Garbulsky et al., 2010) or American ecosystems (Schwalm et al., 2006), which covered a limited range of altitude. Though climatic and global change were found to influence the interannual variation of $FPAR_{yr}$ (Ciais et al., 2005; Nemani et al., 2003), little attention was paid to factors affecting the spatial variation of $FPAR_{yr}$ as it can be directly calculated from satellite products. Therefore, our current understandings on how climatic factors affect the spatial variation of RUE and $FPAR_{yr}$ thus GPP_{yr} may be insufficient, which impeded our understanding on GPP_{yr} spatial variation.

Situated in the eastern of Asia, China experiences a unique climate and huge altitude gradient because of the uplift of Qinghai-Tibetan Plateau and Asian monsoon (Wu et al., 2007). Therefore, analyzing the spatial variations of RUE and $FPAR_{yr}$ in China would help to reveal how various factors affect the global variation of GPP_{yr}, which would also provide an alternative tool to assess the spatiotemporal variation of GPP_{yr}, the basis for carbon management policy aiming at mitigating climate change (Houghton, 2007; Piao et al., 2009). Chinese scientists have conducted eddy covariance measurements, which simultaneously measured CO_2 fluxes and meteorological variables, for many years (Yu et al., 2013), making it possible to conduct such an analysis.

Therefore, based on radiation use efficiency theory and eddy covariance measurements in China (Fig. 1), we first separated GPP_{yr} into RUE, $FPAR_{yr}$, and PAR_{yr}. Then factors affecting the spatial variations of RUE and $FPAR_{yr}$ were detailed investigated. The specific objectives of our study were to: 1) reveal factors affecting the spatial variations of RUE and $FPAR_{yr}$ in terrestrial ecosystems of China, and 2) further clarify how climatic factors affect the spatial variation of GPP_{yr}.

2. Material and methods

2.1. Site information

By integrating ChinaFLUX observations and other measurements in literature, we built a dataset containing 55-site GPP_{yr} data (Fig. 1). This dataset covered most ecosystem types (Fig. 1) and fully represented the spatial distribution of typical ecosystems in China. The detailed site information was provided in Table 1.

2.2. GPP_{yr} and climatic data processing

In this study, GPP_{yr} was estimated from eddy covariance measurements, which was collected from literature. When collecting GPP_{yr} data, we simultaneously gathered geographical information and main climatic variables, including latitude, longitude, altitude, MAT, MAP, and PAR_{yr}, most of which were thought to potentially affect the spatial variation of GPP_{yr}. If the site missed MAT and MAP, we used its multi-year average as the substitution. If there were no PAR_{yr} observations, we obtained its value from the interpolated PAR_{yr} (Zhu et al., 2010).

In addition, CO_2 was found to affect the seasonal and interannual variation of instaneous GPP (Norby et al., 2005). Therefore, we introduced annual mean CO_2 mass concentration (ρ_{cyr}) as another climatic variable. Given that no ρ_{cyr} was directly reported at most sites, we calculated ρ_{cyr} based on the CO_2 mole fraction (b_c) from Mauna Loa (Keeling et al., 1976; Thoning et al., 1989), CO_2 mole mass (M_c, 44 g mol^{-1}), and mole volume at the current state (V_1) as:

$$\rho_{cyr} = \frac{b_c \times M_c}{V_1} \tag{1}$$

Where V_1 can be calculated based on the ideal gas state equation as:

$$\begin{aligned} V_1 &= \frac{P_0 \times V_0}{(273.15 + T_{a0})} \times \frac{(273.15 + T_{a1})}{P_1} \\ &= \frac{101325 \times 22.4 \times 10^{-3}}{298.15} \times \frac{(273.15 + T_{a1})}{P_1} \end{aligned} \tag{2}$$

where P_1 and T_{a1} are the atmospheric pressure and MAT at the current state, respectively. While P_0, V_0, and T_{a0} are the atmosphere pressure, mole volume, and MAT at the normal state, respectively, which equal to 101325 Pa, 22.4×10^{-3} m^3 mol^{-1}, and 25 °C, respectively.

According to the pressure-height formula, we calculated P_1 from altitude (Alt, with the unit of m) and MAT (with the unit of °C) as:

$$P_1 = 1013.25/10^{\left(\frac{\text{Alt}}{18400\times(1+\frac{\text{MAT}}{273})}\right)} \tag{3}$$

In addition, if the site had multiyear observations, we calculated the mean GPP_{yr} and climatic variables among the measuring period, which may exclude the effect of inter-annual variation.

2.3. Leaf area index data processing

At each site, we extracted LAI data with 8-day temporal resolution from the global land surface satellite dataset (Liang et al., 2013) and calculated the annual mean LAI (LAI_{yr}) for the year that GPP_{yr} was observed as:

$$LAI_{yr} = \frac{1}{46}\sum_{i=1}^{46} LAI_i \tag{4}$$

where LAI_i is the 8-day LAI values.

If the site had multiyear observations, we also used the mean LAI_{yr} for the measuring period to represent its biotic factor.

2.4. RUE calculation

According to the radiation use efficiency theory, GPP_{yr} is the product of RUE, $FPAR_{yr}$, and PAR_{yr}. $FPAR_{yr}$ can be calculated from LAI_{yr} based on Beer-lambert law as:

$$FPAR_{yr} = 1 - \exp(-k \times LAI_{yr}) \tag{5}$$

where k is the extinction coefficient, which is set to 0.5 according to Yuan et al. (2010). Therefore, RUE (gC MJ^{-1}) was calculated as

$$RUE = \frac{GPP_{yr}}{FPAR_{yr} \times PAR_{yr}} \tag{6}$$