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Estimation of gross primary production in China (1982–2010) with multiple ecosystem models

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ABSTRACT

Terrestrial gross primary production (GPP) is a major flux affecting land–atmosphere CO_2 exchange and is important for regulating atmospheric CO_2 concentrations, thereby affecting climate change. Dynamic global vegetation models (DGVMs) are important tools for simulation of vegetation productivity and can be coupled with other components of Earth system models. This study simulated GPP of terrestrial ecosystems in China from 1982 to 2010 utilizing five state-of-the-art DGVMs, which considered increasing atmospheric CO_2 concentrations and climate change. Our models consistently showed an ascending GPP gradient from northwest to southeast China. The annual total GPP in China estimated by the DGVMs (mean = 7.97 PgC yr^{-1}; range = 6.14–9.76 PgC yr^{-1}) were generally higher than estimations from previous studies. The greatest overestimation of GPP occurred in south China in warm, wet climates. All DGVMs and JU11 indicated that annual GPP in China increased from 1982 to 2010. There was a statistically significant correlation between simulated GPP and temperature in the Tibetan Plateau, which was supported by flux tower measurements. Additionally, there was a significant correlation between simulated GPP and precipitation in east China, though this should be interpreted cautiously. Further research is needed to improve simulations to better account for spatial and temporal variations in GPP at regional scales by improving representations of existing processes and incorporating currently unconsidered processes.

1. Introduction

Gross primary production (GPP), defined as the amount of carbon uptake by vegetation through photosynthesis, is the largest global carbon flux (Prentice et al., 2000). It is the basis for retaining development of human society by providing food, fiber and wood production (Beer et al., 2010). Furthermore, GPP is the starting point of the terrestrial carbon biogeochemical cycle and one of the major fluxes controlling land–atmosphere exchanges of carbon (Raupach et al., 2008). Fluctuations in terrestrial GPP are reflected in significant variations in atmospheric CO_2 concentration and further influence global climate change (Anav et al., 2013; Prentice et al., 2000). Therefore, understanding the mechanisms that control terrestrial GPP and its accurate estimation are of great importance (Le Quéré et al., 2013; Poulter et al., 2014).

Numerous approaches have been developed to quantify spatial and temporal variations in terrestrial GPP, such as Light Use Efficiency (LUE) models (He et al., 2013; Running et al., 2004; Yuan et al., 2010), process based ecosystem models (Krinner et al., 2005; Sitch et al., 2003; Wang et al., 2011), and machine learning upscaling models (Beer et al., 2010; Jung et al., 2011). However, even the same model may have quite inconsistent estimations of GPP in terms of magnitude, spatial distribution and trends, especially at regional scales. For example, numerous studies have aimed to quantify terrestrial GPP in China using LUE-based models, but these estimations vary greatly, ranging from 2.88 PgC yr^{-1} (Fang et al., 2003) to 12.26 PgC yr^{-1} (Chen et al., 2002) due to use of different driving datasets and parameterizations. This highlights the necessity of further refinements of GPP estimation models. Specifically, we should pay more attention to evaluating and completing process based ecosystem models, as they can be directly linked to other components of Earth system models to systematically simulate historical and project future global climate change (Prentice et al., 2000).

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Dynamic global vegetation models (DGVMs) were developed in the late 1980s to better quantify and understand terrestrial ecosystems (Prentice et al., 2000), and have been widely used to study interactions between the biosphere and abiotic aspects of Earth systems (Schimel et al., 2015; Sitch et al., 2003). However, DGVMs have limitations in their parameter values, driving data sets and model structures, all of which result in systematic uncertainties (Hashimoto et al., 2013; Le Quéré et al., 2013; Piao et al., 2013). Nonetheless, applying multiple models can quantify the uncertainties of DGVM simulations (Ciais et al., 2013; Martre et al., 2014). In this paper, we present a systematic study that shows the performance of five state-of-the-art DGVMs. These models are driven by identical atmospheric CO_2 concentration data and climate data to simulate the magnitude, spatial and temporal variations in terrestrial GPP in China from 1982 to 2010. In addition, we investigated the relationships between climate variables and model simulated terrestrial GPP in China. Two GPP estimates produced by an LUE model (Running et al., 2004) and a machine learning upscaling model (Jung et al., 2011) were used as references.

2. Materials and methods

2.1. Dynamic global vegetation models

This study used global monthly GPP simulated by five DGVMs: CABLE (Wang et al., 2010b), CLM4 (Lawrence et al., 2011), LPJ (Sitch et al., 2003), ORCHIDEE (Krinner et al., 2005) and VEGAS (Zeng et al., 2000). Models were uniformly run at a spatial resolution of 0.5°, from 1982 to 2010. The monthly outputs of GPP were composited to annual GPP for the study years across vegetated areas in China. All of these models were driven by global atmospheric CO_2 concentrations (Keeling and Whorf, 2005) and historical climate fields from the CRU-NCEP dataset (ftp://nacp.ornl.gov/synthesis/2009/frescati/model_driver/cru_ncep). These models have been widely used to investigate the global carbon cycle and climate change (Le Quéré et al., 2013; Piao et al., 2006, 2014a,b; Poulter et al., 2014; Schimel et al., 2015; Sitch et al., 2013). Additionally, numerous studies have assessed the performance of these models by comparing their simulations to satellite observations (Anav et al., 2013; Zhu et al., 2013), flux tower measurements (Jung et al., 2011; Piao et al., 2013), inventory data (Pan et al., 2011), statistical data (Le Quéré et al., 2013) and field experiments (Norby et al., 2010; Sun et al., 2014) over many regions and ecosystems (Mao et al., 2012; Peng et al., 2013; Tan et al., 2010).

2.2. FLUXNET observation based upscaling GPP

Jung et al. (2011) upscaled FLUXNET observations of CO_2, water and energy fluxes to global levels using the model tree ensemble (MTE) technique. The MTE was first trained at the site level and then were used to generate global GPP values at a 0.5° × 0.5° spatial resolution and a monthly temporal resolution from 1982 to 2010. Cross validation indicated that this empirically derived GPP product (JU11 GPP) was acceptable to be used for calibration and evaluation of land surface process models. The monthly JU11 GPP values were totaled to determine the annual GPP for the study years over the vegetated area of China.

2.3. MODIS GPP

We used the MODerate-resolution Imaging Spectroradiometer (MODIS) GPP product (MOD17, version 055), which provides monthly GPP values with a 0.05° spatial resolution for the period 2000–2010 (Zhao et al., 2005). This product was generated through the LUE model using MODIS vegetation indices as input surface vegetation information (Running et al., 2004). This product's accuracy has been independently assessed and deemed appropriate for scientific applications. We aggregated the MOD17 GPP values into a 0.5° × 0.5° spatial distribution to match outputs from DGVMs and JU11 GPP. The MOD17 GPP product was used only as reference for estimating annual total GPP and spatial distribution of annual GPP because its temporal coverage does not match DGVMs outputs or JU11 GPP.

2.4. Mapping mean annual GPP in the climate domain

Temperature and precipitation data from Climate Research Unit time-series version 3.22 (CRU TS 3.22) were used for this analysis (Harris et al., 2014). We defined a climate domain with mean annual temperatures between −10 and 30 °C and total annual precipitation between 0 and 2000 mm; this included most climate conditions of China's vegetated lands. We evenly divided this climate domain into a 100 × 100 matrix of subdomains, with each subdomain representing an increment of 0.4 °C × 20 mm. We then categorized all vegetated grid cells in China (~84,000 grid cells) into these climate subdomains based on temperature and precipitation. Under consideration of eliminating geographic errors, we calculated area-weighted average annual GPP within each climatic domain.

2.5. Statistical analyses

2.5.1. Trend analysis

We analyzed GPP trends in China at both the national and grid scale. For the grid scale trend analysis, we calculated annual total GPP of each grid cell for each year as estimated by the five DGVMs and JU11 and then used the linear least square regression method to estimate temporal trends. The same method was used for the national scale trend analysis.

2.5.2. Partial correlation analysis between GPP and climatic factors

We first detrended annual GPP, annual mean temperature, annual total precipitation and annual total shortwave radiation time series in each grid cell. We then calculated the partial correlation coefficients between GPP and climate factors for each vegetated grid cell in China for the period 1982–2010. Temperature and precipitation data are the same as used in Section 2.4 (CRU TS 3.22). The CRU-NCEP incoming shortwave radiation data, which provides 6-h shortwave radiation records with a spatial resolution 0.5° from 1982 to 2010, was totaled to determine the annual radiation flux (http://dods.ipsl.jussieu.fr/igcmg/IGCM/BC/OOL/OL/CRU-NCEP/v5.2/).

3. Results

3.1. Magnitude and trends in annual total GPP

To estimate the mean annual GPP in China, we separately calculated the arithmetic mean of annual GPP of 5 DGVMs, and of JU11 GPP. The 5 DGVMs estimated that the mean annual GPP in China was about 7.97 PgC yr^{-1}, with their estimates ranging from 6.14 PgC yr^{-1} (VEGAS) to 9.76 PgC yr^{-1} (CABLE). DGVMs (except VEGAS) estimated relatively higher annual GPP than JU11 (Fig. 1). In addition, we estimated mean annual GPP in China with MODIS GPP product (MOD17), which gave a relatively low estimate (5.09 PgC yr^{-1}). Four DGVMs (with the exception of CLM4) and JU11 indicated that annual GPP in China increased significantly from 1982 to 2010. The average value of the four statistically significant DGVM annual trends in GPP in China was 0.022 PgC yr^{-2} and ranged between 0.014 PgC yr^{-2} (ORCHIDEE, $p < 0.01$) and 0.032 PgC yr^{-2} (CABLE, $p < 0.01$). The annual trend in GPP estimated by JU11 was