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Deriving maximal light use efficiency from coordinated flux measurements and satellite data for regional gross primary production modeling

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ABSTRACT

Remote sensing models based on light use efficiency (LUE) provide promising tools for monitoring spatial and temporal variation of gross primary production (GPP) at regional scale. In most of current LUE-based models, maximal LUE (ε_{max}) heavily relies on land cover types and is considered as a constant, rather than a variable for a certain vegetation type or even entire eco-region. However, species composition and plant functional types are often highly heterogeneous in a given land cover class; therefore, spatial heterogeneity of ε_{max} must be fully considered in GPP modeling, so that a single cover type does not equate to a single ε_{max} value. A spatial dataset of ε_{max} accurately represents the spatial heterogeneity of maximal light use would be of significant beneficial to regional GPP models. Here, we developed a spatial dataset of ε_{max} by integrating eddy covariance flux measurements from 14 field sites in a network of coordinated observation across northern China and satellite derived indices such as enhanced vegetation index (EVI) and visible albedo to simulate regional distribution of GPP. This dynamic modeling method recognizes the spatial heterogeneity of ε_{max} and reduces the uncertainties in mixed pixels. Further, we simulated GPP with the spatial dataset of ε_{max} generated above. Both ε_{max} and growing season GPP show complex patterns over northern China that reflect influences of humidity, green vegetation fractions, and land use intensity. "Green spots" such as oasis meadow and alpine forests in dryland and "brown spots" such as build-up and heavily degraded vegetation in the east are clearly captured by the simulation. The correlation between simulated GPP and EC measured GPP indicate that the simulated GPP from this new approach is well matched with flux-measured GPP. Those results have demonstrated the importance of considering ε_{max} as both a spatially and temporally variable values in GPP modeling.

1. Introduction

Gross primary production (GPP), the flux of carbon into ecosystems via photosynthetic assimilation, is an important variable in global carbon cycle and a key process in land surface–atmosphere interactions (Coops et al., 2009; Jung et al., 2008). Continuous monitoring of spatial and temporal variations of GPP at regional scale with high accuracy can provide reliable data for carbon-related climate change studies and useful information for ecosystem management. Eddy covariance (EC) flux measurement is one of the best micrometeorological methods for estimating CO_2, water, and energy exchange between the atmosphere and terrestrial ecosystems (Li et al., 2007). It can provide valuable information on daytime GPP by measuring net ecosystem exchange (NEE) and estimating daytime ecosystem respiration at site level (Falge et al., 2002; Falge et al., 2002). Unfortunately, regional extrapolation of field based GPP measurements is still a challenging task due to the high spatial and temporal variability of terrestrial ecosystems across complex landscapes and regions (Maselli et al., 2009).

The application of satellite remote sensing has greatly enhanced global scale observations of vegetation dynamics, and has played an increasingly important role in estimation of GPP and net primary production (NPP) over heterogeneous landscapes. Remote sensing models based on light use efficiency (LUE) integrate satellite observations and ground measurements provide promising tools for regional GPP monitoring (Chasmer et al., 2009; Garbulsky et al., 2008; Landsberg & Waring, 1997; Potter et al., 1993; Prince & Goward, 1995; Running et al., 2004; Veroustraete et al., 2002; Xiao et al., 2004; Xiao et al., 2004). However, in many current LUE-based models, maximal LUE (ε_{max}) heavily relies on vegetation types and is considered as a constant, rather than a variable for a certain vegetation type or even entire eco-region. One obstacle of simulating regional GPP with LUE-based models is the uncertainties in distinguishing real world vegetation types. For most moderate to coarse resolution satellite data (such as MODerate resolution Imaging Spectroradiometer (MODIS)), there exist many mixed pixels with spatial resolutions

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ranging from 250 m to 1000 m. This may contain errors in the assignment of land cover type to a mixed pixel. Moreover, ε_{max} is a changing variable, and its spatial variation and temporal changes are largely influenced by land use change, disturbance history, and different successional stages of vegetation (Yan et al., 2009). So, it is illogical either to employ a fixed ε_{max} to represent certain biome or to reconcile one pixel as one fixed biome pattern. Detailed analyses of the spatial heterogeneity of ε_{max} at regional scale are badly needed for GPP modeling.

Deriving ε_{max} from remotely sensed data could greatly improve the ability of LUE-based model in estimating GPP in regions with heterogonous land cover. A large number of studies have demonstrated positive relationships between vegetation indices (VIs) and LUE (Cheng et al., 2009; Drolet et al., 2005, 2008; Jenkins et al., 2007; Nakaji et al., 2007). In this study, EVI (enhanced vegetation index) was chosen from VIs to simulate LUE considering its great sensitivity to both low and high biomass regions while minimizing soil and atmosphere influences on vegetation monitoring (Huete et al., 2002). Meanwhile, albedo is considered as the primary factor determining the fraction of photosynthetically active radiation (PAR) absorbed (Tian et al., 2004). Albedo modifies the amount of PAR and thus strongly affects vegetation productivity in a given region (Sellers et al., 1997). Here, we chose visible albedo (and combined with EVI) to calculate LUE considering its relevance to photosynthetic active radiation ranging from 400 nm to 800 nm. Consequently, we integrated remote sensing products including maximal EVI and minimal visible albedo of growing season with EC flux measurements to simulate maximal LUE (ε_{max}) for GPP modeling.

In this paper, we simulated GPP in northern China with a gridded parameter of ε_{max} retrieved from remote sensing data with full consideration of its heterogeneous nature. We firstly used a dynamic modeling method that combines maximal EVI and minimal visible albedo of growing season to retrieve ε_{max} for each pixel in the region. Compared to the treatment of ε_{max} in most current LUE-based models, this method considers ε_{max} as a variable at pixel scale and doesn't solely rely on land cover types. The ε_{max} we retrieved was also compared with those used for MODIS GPP algorithm (MOD17). Then, we simulated GPP in growing season of 2008 and validated the results with GPP retrieved from flux measurements. Finally, we analyzed the spatial patterns of ε_{max} and sum of GPP in growing season over the study area. The results of this study will likely improve carbon cycle modeling by capturing finer patterns with an integrated method of remote sensing and eddy flux measurements.

2. The study site and data

2.1. Site description

Field measured GPP, air temperature, solar radiation, and PAR were collected from the 14 field EC flux sites under a coordinated enhanced observation project in arid and semi-arid regions in northern China (Table 1). These 14 flux sites represent the dominant vegetation/land cover types in the region: temperate grassland, cropland, deciduous broadleaf forests, and evergreen needleleaf forests. For croplands, all the 5 sites (including Jinzhou (JZ), Linze (LZ), Tongyu-Crop (TYC), Dingxi (DX) and Yingke (YK)) are irrigated with intensive management. JZ, LZ and YK are planted with maize (*Zea mays*), TYC is planted with sunflower (*Helianthus annuus*) and DX is planted with wheat (*Triticum aestivum*). For forests, Dayekou (DYK) is a sub-alpine evergreen needleleaf forest site, while Changwu (CW) and Miyun (MY) are deciduous broadleaf forest sites. For grasslands, Arou (AR) is a sub-alpine meadow site, Zhangye (ZY) represents steppe desert, Tongyu-Grass (TYG) represents degraded meadow steppe, Yuzhong (YZ) represents typical steppe, Dongsu (DS) represent desert steppe, while Naiman (NM) is a sandy grassland site.

Table 1
Main characteristics of the 14 flux sites in the study region.

Site	Vegetation type	Location	EC above canopy (m)	Elevation (m)	Precipitation (mm)
JZ	Cropland (maize)	41°09 N, 121°12E	1	17	463
YK	Cropland (maize)	38°51 N, 100°15E	1	2859	382
LZ	Cropland (maize)	39°20 N, 100°25E	1	1382	376
TYC	Cropland (sunflower)	44°35 N, 122°52E	2	151	404
DX	Cropland (wheat)	35°33 N, 104°36E	2	1912	505
ZY	Steppe desert	39°05 N, 100°16E	2	1483	353
DS	Desert steppe	44°05 N, 113°34E	2	990	287
TYG	Degraded meadow steppe	44°34 N, 122°55E	2	151	404
AR	Sub-alpine meadow steppe	38°03 N, 100°28E	2	3033	396
YZ	Typical steppe	35°57 N, 104°08E	2	1968	382
NM	Desert steppe	42°56 N, 120°42E	2	371	405
DYK	Evergreen needleleaf forest	38°32 N, 100°15E	10	2823	360
CW	Deciduous broadleaf forest	35°15 N, 107°41E	20	1220	540
MY	Deciduous broadleaf forest	40°38 N, 117°19E	25	350	584

2.2. Field measurements and data quality control

The EC systems, which were mounted above canopy from 1 to 25 m (Table 1), consist of a three-dimensional sonic anemometer (Model CSAT3, Campbell Scientific Inc., Logan, Utah, USA except for LZ and CW which adopt WindMaster from Gill Instruments Ltd. Lymington, Hampshire, UK) and an open-path fast response infrared gas analyzer (IRGA, Model LI7500, LI-Cor Inc., Lincoln, Nebraska, USA). The raw data were recorded at a rate of 10 Hz, and the computations were done for each 30 min period by a Data-Logger (Model CR5000, Campbell Scientific Inc., Logan, Utah, USA). Intensive calibration was done weeks before the coordinated enhanced observation period (July to September, 2008) to ensure proper performance of the instruments and to make those site scale data comparable.

Webb, Pearman and Leuning (WPL) term (Webb et al., 1980) that accounts for errors introduced by fluctuations in water vapor density and temperature was applied to correct net ecosystem exchange (NEE) time series directly measured by EC. The periods of half-hour bad data caused by water vapor condensation and raindrops on the windows of the open-path infrared gas analyzer were removed. To fill small blocks (less than a few hours) of missing and bad data, a linear interpolation method was applied to each time series. Larger gaps were filled with values derived from the Michaelis–Menten equation of PAR (Falge et al., 2001). More details on data quality control have been described by Liu et al. (2008). NEE measured by EC in nighttime is treated as ecosystem respiration since photosynthesis is almost zero. The daytime respiration is calculated with the Q_{10} of respiration in nighttime when EC measures gross respiration without considering photosynthesis (Falge, Baldocchi, et al., 2002; Falge, Tenhunen, et al., 2002). GPP was finally estimated as NEE minus estimated daytime ecosystem respiration ($R_{Day\text{-}eco}$):

$$GPP = -\left(NEE - R_{Day-eco}\right). \quad (1)$$

Then, daily GPP were accumulated to 8-day integrated GPP to be consistent with MODIS 8-day products.