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Improved modeling of gross primary production from a better representation of photosynthetic components in vegetation canopy

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ABSTRACT

Non-photosynthetic components within the canopy (e.g., dry leaves and stem) contribute little to photosynthesis and therefore, remote sensing of gross primary production (GPP) could be improved by the removal of these components. A scaled enhanced vegetation index (EVI), which is usually regarded as a linear function of EVI, was found to have the strongest relationship with chlorophyll level fraction of absorbed photosynthetically active radiation (FPARchl) and can help improve GPP estimation in croplands compared to canopy level FPAR (FPARcanopy). However, the application of the FPARchl theory to other plant functional types (PFTs) and the underlying reasons remain largely unknown. In this study, based on standard MODIS algorithm we comprehensively assessed the performances of FPARcanopy, scaled EVI (FPARchl1), normalized difference vegetation index (NDVI), scaled NDVI (FPARchl2) and EVI as proxies of FPAR for estimating GPP at four forest and six non-forest sites (e.g., grasslands, croplands and wetlands) from ChinaFLUX, representing a wide range of ecosystems with different canopy structures and eco-climatic zones. Our results showed that the scaled EVI (FPARchl1) as FPAR effectively improved the accuracy of estimated GPP for the entire PFTs. FPARchl1 substantially improved forest GPP estimations with higher coefficient of determination (R^2), lower root mean square error (RMSE) and lower bias. In comparison, for non-forest PFTs, the improvement in R^2 between estimated GPP based on FPARchl1 (GPPchl1) and flux tower GPP was less evident than those between flux GPP and GPP estimations from FPARcanopy (GPPcanopy), FPARchl2, NDVI and EVI. The temperature and water attenuation scalars played important roles in reducing the difference of various GPP and indirectly reducing the impact of different FPARs on GPP in non-forest PFTs. Even so, FPARchl1 is an ecologically more meaningful parameter since FPARchl1 and flux tower GPP dropped to zero more synchronously in both forest and non-forest sites. In particular, we found that the improvement of GPPchl1 relative to GPPcanopy was positively correlated with the maximum leaf area index (LAI), implying the importance of site characteristic in regulating the strength of the improvement. This is encouraging for remote sensing of GPP for which vegetation parameter retrieval has often been found to be less successful at high LAI due to saturations in reflective and scattering domains. Our results demonstrate the significance of accurate and ecologically meaningful FPAR parameterization for improving our current capability in GPP modeling.

1. Introduction

Accurately accounting of ecosystem level carbon cycle is a key issue in global climate change research (Keenan et al., 2012; Richardson et al., 2012). Gross Primary Production (GPP) is defined as the total amount of carbon dioxide fixed by plants through the process of vegetation photosynthesis which is an important component of the terrestrial carbon cycle (Gitelson et al., 2006; Liu et al., 2014b; Running and Nemani, 1988; Running et al., 2004; Wu et al., 2009). In recent decades, improving ecosystem model parameterizations to reduce uncertainty of GPP estimation has become a critical focus for understanding of vegetation response to global cli-

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mate change (Cheng et al., 2014; Liu et al., 2015; Yuan et al., 2015, 2007; Zhang et al., 2015). To this regard, the Eddy Covariance (EC) technique from global flux tower networks provides valuable data sources for validating and calibrating the parameters of ecosystem models to improve GPP estimation capability (Schimel et al., 2015; Wu et al., 2011).

Satellite remote sensing data provides input data to calculate GPP in time and space for continuous monitoring of dynamic vegetation cover. Running and Nemani (1988) and Running et al. (2004) employed the Normalized Difference Vegetation Index (NDVI) as a proxy of Fraction of absorbed Photosynthetically Active Radiation (FPAR) to compute GPP as NDVI was found to be comparable to FPAR. A scaled NDVI was employed as FPAR in a considering conductance-limited and radiation-limited GPP model (Yebra et al., 2015). Moderate resolution Imaging Spectroradiometer (MODIS) standard GPP algorithm (MOD17) was directly forced by MODIS FPAR (MOD15A2) product derived from a radiative transfer model and a back-up algorithm considering the relationship between NDVI and FPAR when radiative transfer model fails (Knyazikhin et al., 1998; Myneni et al., 2002; Zhao et al., 2005). Huete et al. (1997) first developed the Enhanced Vegetation Index (EVI) using three spectral bands, blue (459–479 nm), red (620–670 nm) and near-infrared (941–876 nm) and demonstrated that EVI was more sensitive to high vegetation compared to NDVI. Therefore, in several light use efficiency (LUE) models, EVI was also employed as a proxy of FPAR, such as Vegetation Photosynthesis Model (VPM) (Xiao et al., 2004a; Xiao et al., 2004b), Greenness and Radiation (GR) model (Gitelson et al., 2006; Peng et al., 2013), and Vegetation Index (VIM) model (Wu et al., 2010). Scaled vegetation index (SVI, e.g. scaled EVI or scaled NDVI) is usually regarded as a linear function of vegetation index (VI), where $SVI = a_0 \times VI + b_0$ (a_0 is the scaling factor, and b_0 is the y-intercept). Earlier study employed scaled EVI in Temperature and Greenness (TG) model based entirely on remote sensing data to calculate GPP estimates, and suggested that scaled EVI better captures GPP variations in their empirical model (Sims et al., 2008). A recent study indicated that the empirical linear regression between Absorbed Photosynthetically Active Radiation (APARcanopy) and GPP measured from flux towers did not pass through the zero intercept, which consequently limited the application of vegetation indices for GPP modeling (Zhang et al., 2015). These results consistently suggested that scaled vegetation indices effectively improved the performance of LUE models, and scaled EVI had the strongest capability for GPP estimation because it was more physiologically meaningful due to a better relationship with chlorophyll level FPAR (Zhang et al., 2015). However, such findings mainly focused on croplands that have less canopy heterogeneity and clumping, and therefore its capability is largely unknown for other plant functional types (PFTs, e.g. forests, grasslands and wetlands) with much complicated range of canopy structures and heterogeneity (Zhang et al., 2014a; Zhang et al., 2014b; Zhang et al., 2015).

In order to investigate the feasibility of scaled EVI as FPAR for improving GPP estimates in non-crop ecosystems, we employed MOD17 algorithm and different FPAR products to compare simulated GPP accordingly. The MOD17 algorithm follows the Monteith's equation, in that GPP can be calculated by computing the LUE and APAR, respectively (Monteith, 1972; Zhao et al., 2005). APAR is a product of Photosynthetically Active Radiation (PAR) and FPAR, the latter being approximated using vegetation indices. MOD17 product employs MOD15A2 FPAR which is regarded as a canopy level FPAR (FPARcanopy), comprised of both photosynthetic and non-photosynthetic components together (Cheng et al., 2014; Myneni et al., 2002; Zhang et al., 2014a). Previous study explored the relationship between FPARcanopy and FPAR at chlorophyll level in leaf (FPARchl, that is photosynthetic component of FPARcanopy): FPARcanopy = FPARleaf + FPARstem, and FPARleaf = FPARchl + FPARdry_matter + FPARbrown_pigment (FPARleaf, FPARstem, FPARdry_matter, FPARbrown_pigment are FPAR of leaf, stem, dry matter in leaf, and brown pigment in leaf, respectively) (Zhang et al., 2012b, 2009, 2005). As only FPARchl contributes to plant photosynthesis, it is more reasonable to use FPARchl for calculating GPP estimates in theory. Therefore, in this study, we separately used five FPARs (FPARcanopy, scaled EVI as FPARchl1, scaled NDVI as FPARchl2, NDVI and EVI) to calculate GPP at ten flux tower sites (four forest sites and six non-forest sites) in ChinaFLUX network. The objectives are (1) to analyze whether using FPARchl (e.g. scaled EVI) can improve GPP modeling in forests, grasslands and wetlands, (2) to investigate the influences of PFTs on these improvements, and (3) to determine the underlying reasons (e.g., site characteristics) for such improvements.

2. Materials and methods

2.1. Sites description

We investigated the predicted abilities of LUE-based GPP model with different derived FPARs inputs at 10 flux tower sites in ChinaFLUX network (Fu et al., 2006; Luo et al., 2011; Wang et al., 2006; Wen et al., 2006; Yan et al., 2008; Yu et al., 2006; Zhang et al., 2006). As shown in Fig. 1 and Table 1, four forest sites were comprised of a mixed forest (Changbaishan site (CBS)), an evergreen needleleaf forest (Qianyanzhou site (QYZ)) and two evergreen broadleaf forest sites (Xishangbanna site (XSBN) and Dinghushan site (DHS)); and six non-forest sites included, a wheat-maize rotation cropland (Yucheng site (YC)), four grassland sites (Xilinguolesite (XLGL), Haibei site (HB), Dangxiong site (DX) and Jilichangling site (JLCL)) and a wetland site (Chongmingdongtan1 site (CM1)). The selection of these sites was mainly based on the availability of carbon flux and micrometeorological observations.

2.2. Flux tower data processing

The ChinaFLUX website provides carbon-water-energy fluxes and meteorological data at half-hourly scale (http://www.cerndata.ac.cn/). The data including downward shortwave radiation, PAR, air temperature, humidity, ecosystem respiration (Re) and net ecosystem exchange (NEE), were gap-filled and quality-controlled based on guidelines and earlier studies (Yu et al., 2008, 2006, 2013). Daily data were integrated based on the gap-filled half-hourly values. Daily gross primary production (GPP) is derived by subtracting Re from NEE as: GPP = NEE − Re. Then, flux derived GPP, GPP = − GEE, and flux derived GPP (GPP_{EC}) are presented in the unit of $gC/m^2/day$ (Liu et al., 2015). Finally, 8-day integrated meteorological and carbon flux data from daily values were used for calculating GPP at the site scale.

2.3. MODIS data

The MODIS collection 5 products, including 8-day MOD09A1 reflectance and MOD15A2 LAI/FPAR (hereafter, MOD15A2 FPAR is regarded as FPARcanopy and MOD15A2 LAI is regarded as LAI), were obtained from Land Processes Distributed Active Archive Center (LPDAAC, https://lpdaac.usgs.gov/). The retrieval of FPARcanopy is mainly based on a three-dimensional formulation of the radiative transfer process in vegetation canopy, and meanwhile a look-up-table method is used for inversion of three-dimensional radiative transfer problem (Knyazikhin et al., 1998; Myneni et al., 2002).

The 8-day temporal resolution MOD09A1 gives seven reflectance spectral bands, red (620–670 nm), NIR1 (841–876 nm), blue (459–479 nm), green (545–565 nm), NIR2 (1230–1250 nm), SWIR1 (1628–1652 nm) and SWIR2 (2015–2155 nm). We com-