Ecological Indicators 72 (2017) 153–164

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Assessing the ability of MODIS EVI to estimate terrestrial ecosystem gross primary production of multiple land cover types

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A R T I C L E I N F O

Article history:
Received 11 August 2015
Received in revised form 11 June 2016
Accepted 11 August 2016

Keywords:
Remote sensing
MODIS
Enhanced vegetation index
Gross primary production
Land cover types
Leaf area index

A B S T R A C T

Terrestrial ecosystem gross primary production (GPP) is the largest component in the global carbon cycle. The enhanced vegetation index (EVI) has been proven to be strongly correlated with annual GPP within several biomes. However, the annual GPP-EVI relationship and associated environmental regulations have not yet been comprehensively investigated across biomes at the global scale. Here we explored relationships between annual integrated EVI (iEVI) and annual GPP observed at 155 flux sites, where GPP was predicted with a log-log model: $\ln(GPP) = a \times \ln(iEVI) + b$. iEVI was computed from MODIS monthly EVI products following removal of values affected by snow or cold temperature and without calculating growing season duration. Through categorisation of flux sites into 12 land cover types, the ability of iEVI to estimate GPP was considerably improved (R^2 from 0.62 to 0.74, RMSE from 454.7 to 368.2 $g\,C\,m^{-2}\,yr^{-1}$). The biome-specific GPP-iEVI formulae generally showed a consistent performance in comparison to a global benchmarking dataset ($R^2 = 0.79$, RMSE = 387.8 $g\,C\,m^{-2}\,yr^{-1}$). Specifically, iEVI performed better in cropland regions with high productivity but poorer in forests. The ability of iEVI in estimating GPP was better in deciduous biomes (except deciduous broadleaf forest) than in evergreen due to the large seasonal signal in iEVI in deciduous biomes. Likewise, GPP estimated from iEVI was in a closer agreement to global benchmarks at mid and high-latitudes, where deciduous biomes are more common and cloud cover has a smaller effect on remote sensing retrievals. Across biomes, a significant and negative correlation ($R^2 = 0.37$, $p < 0.05$) was observed between the strength (R^2) of GPP-iEVI relationships and mean annual maximum leaf area index (LAI_{max}), and the relationship between the strength and mean annual precipitation followed a similar trend. LAI_{max} also revealed a scaling effect on GPP-iEVI relationships. Our results suggest that iEVI provides a very simple but robust approach to estimate spatial patterns of global annual GPP whereas its effect is comparable to various light-use-efficiency and data-driven models. The impact of vegetation structure on accuracy and sensitivity of EVI in estimating spatial GPP provides valuable clues to improve EVI-based models.

1. Introduction

Terrestrial gross primary production (GPP) is the amount of carbon captured from the atmosphere through vegetation photosynthesis (Beer et al., 2010). Vegetation GPP is a key component of

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http://dx.doi.org/10.1016/j.ecolind.2016.08.022
1470-160X/

the terrestrial carbon balance and is of fundamental importance to human society because plants provide food, fiber and wood supply and also contribute to the production of environmental conditions suitable for human habitation (Melillo et al., 1993; Xiao et al., 2005; Zhao et al., 2005). Therefore, continuous monitoring and accurate estimation of GPP is required to ensure the long term security of terrestrial ecosystem services and to address issues pertaining to the global carbon cycle including determination of the size of the terrestrial carbon sink, prediction of vegetation dynamics, and management of forests and grasslands (Ciais et al., 2005; Ma et al., 2013; Sims et al., 2006b).

GPP can be calculated as the sum of vegetation assimilated carbon flux, partitioned from net carbon exchange measured at eddy covariance (EC) tower sites (Baldocchi et al., 2001; Reichstein et al., 2007), but such observations are limited, both temporally and spatially. Remote sensing technique provides a promising approach to overcome these limitations. Various diagnostic models taking advantage of spatially extensive remote sensing and meteorological data have been developed to estimate GPP across stand-to-global scales for a relatively long period (e.g., Jung et al., 2008; Running et al., 2004; Sims et al., 2008; Xiao et al., 2005). These models can be generally partitioned into three categories: light-use-efficiency (LUE) models, machine learning algorithms and simple empirical models (Verma et al., 2014). The LUE theory was first proposed by Monteith (1972), in which GPP is generally represented as the product of LUE, photosynthetically active radiation (PAR), the fraction of PAR absorbed by vegetation (fAPAR), and environmental scalars. fAPAR is a strong function of vegetation greenness, as measured by vegetation indices (VIs), such as the normalized difference vegetation index (NDVI; e.g., Goward and Huemmrich, 1992) and the enhanced vegetation index (EVI; e.g., Xiao et al., 2004a,b). However, it is difficult to estimate LUE, which varies among plant functional types, and can be down-regulated by temperature, soil water content, vapour pressure deficit (VPD), and leaf phenology (Xiao et al., 2005). Another deficiency of LUE models is the coarse resolution of climate inputs, which are often only available at a large scale. This may introduce significant errors to estimations of GPP (Heinsch et al., 2006; Zhao et al., 2005) and hinder the acquisition of fine-resolution GPP estimates at large scales. Machine learning algorithms, such as artificial neural networks (Papale and Valentini, 2003), support vector machines (Yang et al., 2007), and model tree ensembles (Jung et al., 2009), predict GPP based on the non-functional patterns extracted in training data set. Obviously, the accuracy of machine learning algorithms relies on the abundance and representativeness of input information including remote sensed vegetation properties, meteorological, and land cover data (Jung et al., 2011). Therefore, the use of machine learning algorithms is also limited by the coarse resolution of meteorological data. Moreover, in many cases machine learning algorithms show no better performance than LUE models in specific ecosystems (e.g., Yang et al., 2007). Consequently, simple empirical models utilizing remote sensing proxies of vegetation photosynthesis activity (with or without meteorological data) gain consistent interest in estimating both spatial and temporal variations of GPP (e.g., Jung et al., 2008; Rahman et al., 2005; Sims et al., 2006b).

The growing season NDVI and EVI show strong relationships with vegetation production over one or two week intervals (e.g., Mao et al., 2014; Rahman et al., 2005; Sims et al., 2006a,b; Wylie et al., 2003). Vegetation indices per se are transformations of two or more spectral bands to enhance the signal derived from vegetation properties (Huete et al., 2002). Both NDVI and EVI employ surface bidirectional reflectances of red and near-infrared spectral bands that are sensitive to leaf chlorophyll content (Huete et al., 2002), which converts light to energy consumed by photosynthesis. NDVI is limited due to its saturation over dense vegetation and large sensitivity to canopy background brightness (Huete et al., 2002), whereas EVI can improve performance in regions of high biomass through a decoupling of the canopy and background signals and a reduction in the influence of atmospheric conditions using a blue spectral reflectance (Huete et al., 2002). This makes EVI more responsive to canopy structural variations and thus EVI is better correlated with GPP than NDVI in evergreen (Xiao et al., 2004a) and deciduous (Xiao et al., 2004b) forests as well as in croplands (Xiao et al., 2005). Compared to LUE models, the growing season EVI or EVI-based models (e.g., Temperature-Greenness model; Sims et al., 2008) provide a comparable or better estimation of GPP at both the 16-day (Sims et al., 2008, 2006b) and annual (Verma et al., 2014) time-scales. As well as EVI, cumulative growing season fAPAR with separate functions for herbaceous plants, evergreen forests and all other vegetation types has been used to predict annual GPP in Europe (Jung et al., 2008). The disadvantage of selecting fAPAR against EVI is subtle: fAPAR consists of fractional absorbance of PAR absorbed by both chlorophyll and by non-photosynthetic pigments (Zhang et al., 2005), while EVI is much closer to the fraction of PAR absorbed by chlorophyll. Moreover, fAPAR shows no significant correlation with GPP in deciduous broadleaf forests (Jung et al., 2008). Therefore, the use of EVI should be favored over fAPAR in correlating to GPP. However, current studies on EVI-GPP relationships or EVI-based models have been focused within only a limited number of biomes and these EVI-based models generally need to compute the start and end or the length of the growing season period (Jung et al., 2008; Sims et al., 2008, 2006b; Verma et al., 2014), which constitutes an extra source of uncertainty. Simultaneously, environmental influences on the ability of EVI to estimate GPP across a wide spectrum of biomes have not yet been investigated (Sims et al., 2006b; Sjöström et al., 2011).

In this study, we used the annual integral of MODIS EVI (iEVI), which only needs removal of those values that have been affected by cold temperature or snow and subtracting the soil background signal, to regress with annual eddy covariance measured GPP across 12 land cover types. The developed set of formulae were then applied at the global scale and compared with a widely used GPP benchmark dataset to evaluate the effectiveness and robustness of iEVI, thereby determining whether iEVI can serve as a reference for other GPP models over a fine-to-coarse resolution. The impacts of environmental conditions on iEVI in estimating GPP were further investigated across biomes, to improve our understanding of the underlying mechanistic processes that differentiate responses of vegetation photosynthetic activity to remote sensing spectral measurements among biomes.

2. Data and methods

2.1. Eddy covariance and meteorological data

The eddy covariance method is a micrometeorological technique that directly measures net carbon, water and energy fluxes across a horizontal plane between vegetation canopies and the atmosphere (Aubinet et al., 2000; Baldocchi et al., 2001). In the present study a total of 155 sites (Supplementary Table S1) were selected, consisting of 624 site-years of data and representing a worldwide spectrum of biomes and climate regimes with excellent coverage in North America, Eurasia and Oceania (Table 1, Fig. 1; Baldocchi, 2008; Baldocchi et al., 2001; Wang and Dickinson, 2012).

The flux data were obtained from three sources: (1) a small fraction (mainly high-latitude and wetland sites) was collected directly from published studies, which only included annual values of flux and meteorological forcing; (2) a larger fraction was contributed directly from participating site researchers; and (3) the majority were from FLUXNET level 2 or level 4 products that were downloaded from the database. Of the latter two cat-