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Evaluating spatial and temporal patterns of MODIS GPP over the conterminous U.S. against flux measurements and a process model

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ABSTRACT

Gross primary productivity (GPP) quantifies the photosynthetic uptake of carbon by ecosystems and is an important component of the terrestrial carbon cycle. Empirical light use efficiency (LUE) models and process-based Farquhar, von Caemmerer, and Berry (FvCB) photosynthetic models are widely used for GPP estimation. In this paper, the MODIS GPP algorithm using the LUE approach and the Boreal Ecosystem Productivity Simulator (BEPS) based on the FvCB model in which a sunlit and shaded leaf separation scheme is evaluated against GPP values derived from eddy-covariance (EC) measurements in a variety of ecosystems. Although the total GPP values simulated using these two models agree within 89% when they are averaged for the conterminous U.S., there are systematic differences between them in terms of their spatial and temporal distribution patterns. The spatial distribution of MODIS GPP therefore differs substantially from that produced by BEPS. These differences may be due to an inherent problem of the LUE modeling approach. When a constant maximum LUE value is used for a biome type, this simplification cannot properly handle the contribution of shaded leaves to the total canopy-level GPP. When GPP is modeled by BEPS as the sum of sunlit and shaded leaf GPP, the problem is minimized, i.e., at the low end, the relative contribution of shaded leaves to GPP is small and at the high end, the relative contribution of shaded leaves is large. Compared with monthly and annual GPP derived from eddy covariance data at 40 tower sites in North America, BEPS performed better than the MODIS GPP algorithm. The difference between MODIS and BEPS GPP widens as with the fraction of shaded leaves increases. The simpler LUE modeling approach should therefore be further improved to reduce this bias issue for effective estimation of regional and temporal GPP distributions.
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1. Introduction

The terrestrial gross primary productivity (GPP), defined as the total photosynthetic uptake of carbon per unit of time and space, is a critical variable in terrestrial biosphere models (TBM), as it often represents the control factor for many other processes in the model (Jung et al., 2007). However, estimates of GPP can vary greatly among TBM, even under similar environmental conditions, because of different algorithms used to describe the basic photosynthetic processes in response to environmental conditions (Coops et al., 2009). Validation of these algorithms against GPP observations is therefore critical to improve the performances of TBM and our understanding of the interactions between terrestrial ecosystems and the atmosphere.

Different underlying assumptions on the mechanisms and controls of the photosynthetic process, and the spatio-temporal resolution of the associated biotic and abiotic drivers originated a wide variety of TBM. For example, some prognostic TBM estimate GPP based on surface observations, like soil and meteorological conditions (Foley et al., 1996; Haxeltine & Prentice, 1996; Polcher et al., 1998). However, remote sensing observations are particularly useful for assessing the regional distribution of GPP using diagnostic TBM (Ruimy et al., 1999). Despite the large number of TBM available, it is possible to identify two main strategies used to estimate GPP. In the first group of models an empirical relationship is used to quantify GPP as a function of light use efficiency (LUE) and environmental conditions (Houborg et al., 2009). In these models (henceforth, LUE models), such as CASA (Potter et al., 1993), GLO-PEM (Prince & Goward, 1995), and the MODIS algorithm (Zhao & Running, 2010), GPP is proportional to the photosynthetically active radiation (PAR) absorbed by the canopy (APAR), and LUE is derived from empirical observations of GPP and APAR (Montieth, 1972). One advantage of LUE

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models is the very limited number of parameters required to characterize LUE under non-water limited conditions and for specific vegetation types. However, the reliability of this approach in assessing GPP, in particular for spatial and temporal scales beyond those used to derive the empirical relationships, has been questioned, and modifications of the original approach have been proposed (Sims et al., 2008).

The second group of TBM is based on the mechanistic description of the photosynthetic biochemical processes occurring at leaf level (Farquhar et al., 1980). In these models (henceforth, process-based models), such as SIB2 (Sellers et al., 1996), BIOME3, CLASS (Wang et al., 2001), Boreal Ecosystem Productivity Simulator (BEPS) (Chen et al., 1999), and InTEC (Chen et al., 2000), GPP is first computed at the leaf level and then scaled-up to the whole canopy Big-leaf models, which reduce the complexity of the canopy to a single leaf (Sellers et al., 1996) have been extensively used mainly for their simplicity, but have been shown to introduce significant errors into the calculations of canopy photosynthesis (Dai et al., 2004; De Pury & Farquhar, 1997; Norman, 1980; Wang & Leuning, 1998). Another scaled-up approach is to separate a canopy into multiple layers and to integrate them for the whole canopy to obtain the canopy-level flux (Leuning et al., 1995). The multiple-layer approach overcomes the limitation of the big-leaf approach, but is itself limited by the ability to reliably describe the structural and functional complexity of the canopy. The two-leaf approach differentiates between sunlit and shaded leaves and largely overcomes the deficiencies of the big-leaf approach, as it includes the highly non-linear response of leaf photosynthesis under sunlit and shaded conditions (Norman, 1982). In addition, this approach does not require the same level of complexity in describing the canopy structure and it is computationally more efficient than the multi-layer scheme (Dai et al., 2004; Wang & Leuning, 1998).

LUE- and process-based models differ in their ways of simulating photosynthesis processes and overall complexities. We therefore expect differences in the simulated GPP between these two approaches. The objectives of this study are to (1) quantify the biases existing with LUE models in generating the spatial and temporal distribution patterns of GPP and (2) investigate the underlying reasons for these biases using a process-based model. The BEPS model, which is a process-based two-leaf model (Chen et al., 1999; Ju et al., 2006; Liu et al., 1997), is used for this purpose. Monthly and annual GPP values, simulated by the MODIS algorithm and BEPS, are evaluated against GPP derived from eddy-covariance (EC) measurements from a variety of ecosystems across the continental U.S. from 2000 to 2005.

2. The models

2.1. BEPS model

The BEPS model used in this study is an hourly process-based diagnostic model (Chen et al., 1999; Ju et al., 2006) that computes the canopy-level GPP as the sum of sunlit and shaded leaf groups using the FvCB photosynthesis model (Farquhar et al., 1980). BEPS was initially developed for boreal ecosystems as a daily model (Liu et al., 1997), but it has been expanded for temperate and tropical ecosystems (Feng et al., 2007; Matsushita & Tamura, 2002; Zhang et al., 2010) and modified to run on hourly time-scale (Ju et al., 2006). BEPS is driven by remote sensing, meteorological, and soil data with a set of biome-dependent biophysical parameters. In the hourly version of BEPS, stomatal conductance for sunlit and shaded leaves is iteratively calculated using the Ball–Berry equation (Ball, 1988) and scaled using a soil water stress index (Ju et al., 2006). Despite its intense computational requirements, the hourly version of BEPS, was preferred and used in this work because the stomatal conductance calculation is stable and reliable. On the other side, the parameterization scheme based on Jarvis (1976) lacks sufficient empirical data for simulations at the continental scale (Van Wijk et al., 2000). The major characteristics of BEPS are summarized in Table 1 and the major functions used in BEPS that are directly relevant to this study are given in Appendix A.

Table 1
Description of the processed BEPS GPP submodel and MODIS GPP algorithm used in this study.

	Model descriptions	BEPS	MODIS GPP algorithm
Time step		Hourly	8-day
Inputs	Satellite data	LAI	
		Clumping index	MODIS fPAR
		Land cover	Land cover
	Climate data	Temperature	Temperature
		Radiation	Radiation
		Relative humidity	VPD
		Precipitation	
		Wind	
	Atmospheric data	CO_2	\
	Soil data	Soil texture	\
GPP calculation			f(fPAR, LUE,T_{min},PAR,VPD)
Processes	Canopy structure	Two leaves	\
	Distinguish sunlit/ shaded leaves?	Yes	No
	Scaling	Yes	No
	Photosynthesis approach	FvCB	\
	Stomatal conductance	Ball–Berry	\
	Evaportansipiration	Penman–Monteith	Penman–Monteith
	Explicit interception losses of precipitation	Yes	No
	Soil water factor	Yes	\
	Coupled photosynthesis and transpiration	Yes	\
	Rate dynamics	First order	\
	Moisture parameter	SWC	\
	Soil layer	5	\

"FvCB" indicates that photosynthesis calculations are based on enzyme kinetics and light absorption following Farquhar et al. (1980). Here, the FvCB model is applied to sunlit and shaded leaves separately (Norman, 1982). "Ball–Berry" indicates a coupled stomatal conductance-photosynthesis model following Ball (1988) using the relative humidity as a scalar. We use an analytical solution of the Ball–Berry equation to determine stomatal conductance (Baldocchi, 1994) in order to improve the computation efficiency for regional and global simulations.

2.2. MODIS GPP algorithm

The MODIS GPP algorithm is designed to provide a regular eight-day measure of the growth of the terrestrial vegetation (Zhao et al., 2005). It is calculated daily at 1 km resolution using an empirical LUE model with the following equations:

$$\mathrm{GPP} = \mathrm{LUE} \times \mathrm{fPAR} \times \mathrm{PAR}, \tag{1}$$

$$\mathrm{LUE} = \mathrm{LUE}_{\max} \times f(VPD) \times g(T_{\min}), \tag{2}$$

$$\mathrm{fPAR} = 1 - e^{-k \times LAI}, \tag{3}$$

where LUE_{max} is the maximum light use efficiency, $f(VPD)$ is the scalar of daily vapor pressure deficit (VPD), $g(T_{min})$ is the scalar of daily minimum air temperature (T_{min}) and fPAR is the fraction of the photosynthetically active radiation absorbed by the canopy. Biome physiological parameters are specified based on the MODIS land cover classification system using a biome property look-up table (BPLUT) (Zhao & Running, 2010; Table 1).

3. Data and methods

All inputs and auxiliary data used in this study, including reanalysis meteorological data from the National Center for Environmental Prediction (NCEP), leaf area index (LAI), foliage clumping index, land cover map, soil texture data, and other vegetation parameters, are described in Section 3.4.

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