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Comparison of four light use efficiency models for estimating terrestrial gross primary production

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ABSTRACT

Light use efficiency (LUE) models that with different structures (i.e., methods to address environmental stresses on LUE) have been widely used to estimate terrestrial gross primary production (GPP) because of their theoretical soundness and practical conveniences. However, a systematic validation of those models with field observations across diverse ecosystems is still lacking and whether the model can be further improved by structural optimization remains unclear. Using GPP estimates at global 51 eddy covariance flux towers that cover a wide climate range and diverse vegetation types, we evaluated the performances of the four major LUE models (i.e., Carnegie-Ames-Stanford approach (CASA), Global Production Efficiency Model (GLO-PEM), Vegetation Photosynthesis Model (VPM), and Eddy Covariance-Light Use Efficiency (EC-LUE)) and examined the possible further improvement of the better-performed model(s) via model structural optimization. Our results showed that the GLO-PEM, VPM, and EC-LUE exhibited the similar capabilities in simulating GPP (explained around 68% of the total variations) and overall performed better than CASA (58%). Nevertheless, the EC-LUE and VPM were the optimal ones because they required less model inputs than the GLO-PEM. For the two optimal models, we found that the minimum method is better than the multiplication approach to integrate multiple environmental stresses on LUE. Moreover, we found that the VPM can be further improved by incorporating the constraint of water vapor deficit (VPD_s). We suggested that a modified VPM by using minimum method and adding VPD_s may be the best model in estimating large-scale GPP if high-quality remote sensing data available, otherwise, the modified models with the water stress reflected by VPD_s only is optimal.

1. Introduction

Gross Primary Production (GPP), the sum of photosynthetic carbon uptake by vegetation, is a critical indicator of ecosystem carbon cycle (Field et al., 1995; Goetz et al., 1999; Chapin and Matson, 2002). Because GPP cannot be directly observed at the regional or global scale, models have emerged as the major approaches for predicting terrestrial ecosystem GPP over large areas recently (Canadell et al., 2000). Among these, the light use efficiency (LUE) models have been widely used because of its theoretical soundness and practical convenience (Running et al., 2000).

The LUE models were usually developed based on two basic assumptions (Running et al., 2004): (a) the ecosystem GPP related directly to absorbed photosynthetically active radiation (APAR) through LUE, and (b) the actual LUE is lower than the potential value because of environmental stresses (e.g., low and high temperature and drought) (Landsberg, 1986). The GPP function of them takes the form of $GPP = PAR \times fPAR \times \varepsilon_{max} \times f$. Therein, PAR is the incident photosynthetically active radiation ($MJ\,m^{-2}$) per day or month, $fPAR$ is the fraction of PAR absorbed by the vegetation canopy, ε_{max} is the potential LUE ($g\,C\,m^{-2}\,MJ^{-1}$ APAR) without environment stress, and f is a scalar varying from 0 to 1 that represents the reduction of LUE relative to ε_{max} due to environmental stresses (e.g., air temperature stress and water availability). The $\varepsilon_{max} \times f$ indicates the actual LUE. Note that the actual LUE can be also defined as the function of Photochemical Reflectance Index (PRI) (Drolet et al., 2005, 2008), which is out the scope of this study.

In practice, several LUE models, such as Carnegie-Ames-Stanford approach (CASA, Potter et al., 1993), Global Production Efficiency Model (GLO-PEM, Prince and Goward, 1995; Goetz et al., 1999), Moderate Resolution Imaging Spectroradiometer (MODIS) GPP algorithm (Running et al., 1999, 2000), Vegetation Photosynthesis Model (VPM, Xiao et al., 2004a,b), and Eddy Covariance-Light Use Efficiency (EC-LUE, Yuan et al., 2007), had been developed using

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different *f* scalars. Specifically, there were two major differences in the structure of *f* across LUE models. First, the strategies to integrate multiple environmental stresses into *f* were different. Models such as GLO-PEM, CASA, and VPM (Potter et al., 1993; Prince and Goward, 1995; Xiao et al., 2004a) used the multiplicative method, while the EC-LUE (Yuan et al., 2010) utilized the minimum method based on the theory of Liebig's law. Second, the water stress scalar (*fw*), a key environmental constraint on the LUE, was quantified in different ways. It had been estimated by the water stress in the soil and (or) in the air (e.g., atmosphere water vapor deficit) in some models (e.g., GLO-PEM and CASA), and via land water index that can reflect the vegetation water stress in the other models (e.g., VPM and EC-LUE). For instance, *fw* was calculated by the evaporative fraction in the EC-LUE model (Yuan et al., 2007), which was considered to be a good indicator of moisture conditions (Kurc and Small, 2004). However, the performances of those models are rarely validated with field observations across large areas (e.g., Yuan et al., 2010), and little is known about whether the better-performed LUE models can be further improved by model structural optimization (Medlyn, 2011; Hashimoto et al., 2013; Yang et al., 2013). Specifically, most previous efforts focused on only one of the LUE models and compared the model with other kinds of models at quite a few flux sites (Zhang et al., 2007; Coops et al., 2009; Wu et al., 2010). Yuan et al. (2014) might be the first to compare multiple LUE models via field observations over large areas, but they did not investigate the strength and weakness of the various model structures, as a result, the potential of model improvement by structural optimization.

In this study, we evaluated the performances of the four widely used LUE models (i.e., CASA, GLO-PEM, VPM, and EC-LUE) by in situ GPP estimates at 51 global eddy covariance (EC) flux towers via using model-independent parameter values. Our objectives were to (1) identify the better-performed model(s) in estimating GPP over large areas and (2) investigate the optimal model structure, including the strategy to integrate multiple environmental stresses (i.e., multiplication or minimum) and the method to address water stress, for the further improvement of the LUE models. The performance of the well-known LUE-based MODIS-GPP algorithm was not assessed because the daily minimum temperature, an important parameter for the model, was not available in this study. However, the water stress expression used by it was evaluated when we discussed the optimal model structure.

2. Materials and methods

2.1. Model overview

2.1.1. The CASA model

Carnegie-Ames-Stanford approach (CASA) developed by Potter et al. (1993) can estimate monthly GPP and NPP with satellite data, monthly temperature and precipitation, and soil properties. The actual LUE (ε_g, g C m^{-2} MJ^{-1} APAR) in the model is defined as follows:

$$\varepsilon_g = \varepsilon_{\max} \times ft1 \times ft2 \times fw \tag{1a}$$

$$ft1 = \frac{1.1814(1 + e^{0.3(-T_{opt}-10+T)})}{1 + e^{0.2(T_{opt}-10-T)}} \tag{1b}$$

$$ft2 = 0.8 + 0.02T_{opt} - 0.0005T_{opt}^2 \tag{1c}$$

$$fw = W_s = \frac{0.5 + EET}{PET} \tag{1d}$$

where ε_{max} is the potential LUE (g C m^{-2} MJ^{-1} APAR), *ft1* represents the effects of very high and very low temperatures on ε_{max}, *ft2* indicates the effects of the temperature above or below the optimum temperature (T_{opt}) on ε_{max}, and *fw* represented by soil moisture condition (W_s) illustrates the water stress on ε_{max}. *EET* and *PET* are the estimated and potential evapotranspiration, respectively.

EET is calculated using the method proposed by Priestley and Taylor (1972) as follows:

$$EET = \min(PPT + (PET - PPT)RDR, (PPT + (SM - WPT))), \quad \text{when } PPT < PET \tag{1e}$$

$$EET = PET, \quad \text{when} \quad PPT = PET \tag{1f}$$

$$RDR = (1 + a)(1 + aSM^b) \tag{1g}$$

where *RDR* is the relatively drying rate scalar for potential water extraction, *SM* is the soil moisture (volumetric moisture content, m/m), *WPT*, *a*, and *b* are the texture-dependent empirical coefficients from Saxton et al. (1986).

Soil moisture is estimated using a one-layer bucket model (Malmström et al., 1997):

$$SM_t = SM_{t-1} - (PET_t - PPT_t)RDR_{t-1}, \quad \text{for} \quad PPT < PET \tag{1h}$$

$$SM_t = SM_{t-1} - (PPT_t - PET_t), \quad \text{for} \quad PPT = PET \tag{1i}$$

where SM_t and SM_{t-1} are the soil moisture at the 8*t* and 8(*t* − 1) days, respectively, in order to keep accordance with the temporal resolution of MODIS products that being used by us.

2.1.2. The GLO-PEM model

Global Production Efficiency Model (GLO-PEM) developed by Prince and Goward (1995) is driven by the variables derived almost entirely from satellite products. GLO-PEM has been successfully utilized to estimate global terrestrial GPP and NPP (Prince and Goward, 1995; Cao et al., 2004). The ε_g in the model is calculated as follows:

$$\varepsilon_g = \varepsilon_{\max} \times ft \times fw \tag{2a}$$

$$fw = W_s \times VPD_s \tag{2b}$$

where *ft* represents the effects of temperature on ε_{max}, and *fw* is reflected by soil moisture condition (W_s) and atmosphere moisture condition (VPD_s).

$$ft = \frac{(T - T_{\min})(T - T_{\max})}{[(T - T_{\min})(T - T_{\max})] - (T - T_{opt})^2} \tag{2c}$$

$$VPD_s = 1 - 0.05\delta_q \quad (\text{when} \quad 0 < dq = 15), \quad \text{or} \quad 0.25\,(\text{when} \quad dq > 15) \tag{2d}$$

$$\delta_q = Qw(T) - q \tag{2e}$$

where T_{min} and T_{max} are the minimum and maximum temperature for photosynthetic activities, respectively, δ_q is the specific humidity deficit (g kg^{-1}), $Qw(T)$ is the saturated specific humidity at the air temperature, and *q* is the specific air humidity. *ft* was set to be zero if the air temperature was lower than T_{min}. Since the calculation of W_s in the original GLO-PEM needs the variable of equilibrium evapotranspiration, and the accuracy of which is poor at local scale (Jarvis and McNaughton, 1986; Prentice et al., 1992, 1993; Cao et al., 2004), we thus adopted the W_s function in CASA (Eq. (1d)) for GLO-PEM in this study.

2.1.3. The VPM model

The Vegetation Photosynthesis Model (VPM) (Xiao et al., 2004a,b) assumes that the leaf and forest canopies consist of photosynthetically active vegetation (mostly chloroplast) and non-photosynthetic vegetation (mostly senescent foliage, branches, and stems). The VPM has been successfully used to simulate