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Improved global simulations of gross primary product based on a new definition of water stress factor and a separate treatment of C3 and C4 plants

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ABSTRACT

Accurate simulation of terrestrial gross primary production (GPP), the largest global carbon flux, benefits our understanding of carbon cycle and its source of variation. This paper presents a novel light use efficiency-based GPP model called the terrestrial ecosystem carbon flux model (TEC) driven by MODIS FPAR and climate data coupled with a precipitation-driven evapotranspiration (E) model (Yan et al., 2012). TEC incorporated a new water stress factor, defined as the ratio of actual E to Priestley and Taylor (1972) potential evaporation (E_{PT}). A maximum light use efficiency (ε^*) of 1.8 gC MJ^{-1} and 2.76 gC MJ^{-1} was applied to C3 and C4 ecosystems, respectively. An evaluation at 18 eddy covariance flux towers representing various ecosystem types under various climates indicates that the TEC model predicted monthly average GPP for all sites with overall statistics of $r = 0.85$, RMSE = 2.20 gC m^{-2} day^{-1}, and bias = −0.05 gC m^{-2} day^{-1}. For comparison the MODIS GPP products (MOD17A2) had overall statistics of $r = 0.73$, RMSE = 2.82 gC m^{-2} day^{-1}, and bias = −0.31 gC m^{-2} day^{-1} for this same set of data. In this case, the TEC model performed better than MOD17A2 products, especially for C4 plants. We obtained an estimate of global mean annual GPP flux at 128.2 ± 1.5 Pg C yr^{-1} from monthly MODIS FPAR and European Centre for Medium-Range Weather Forecasts (ECMWF) ERA reanalysis data at a 1.0° spatial resolution over 11 year period from 2000 to 2010. This falls in the range of published land GPP estimates that consider the effect of C4 and C3 species. The TEC model with its new definition of water stress factor and its parameterization of C4 and C3 plants should help better understand the coupled climate-carbon cycle processes.

1. Introduction

In the past decades (1980s and 1990s), the Earth experienced dramatic environment changes. It had the warmest decades in the instrumental record and a significant increase in atmospheric CO_2 levels (Houghton et al., 2001; Hansen et al., 2007). Terrestrial ecosystems, including both vegetation and soil carbon pools, play an important role in the carbon cycle between land and

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atmosphere through photosynthesis and respiration. Gross primary production (GPP) is a measure of gross primary photosynthesis. Autotrophic respiration consumes about half of GPP (Chapin et al., 2002); the remainder is the net primary production (NPP). Accurate estimation of terrestrial ecosystem production at various temporal scales will improve our understanding of global carbon cycle and its relationship with climate change and atmospheric CO_2 change. For example, analysis of satellite-based NPP reveals that recent climatic changes have enhanced plant growth in northern mid-latitudes and high latitudes from 1982 to 1999 (Nemani et al., 2003). Improving operational light use efficiency (LUE) algorithms for monitoring global GPP and NPP benefits the study of trends in the global carbon budget (Huntzinger et al., 2012; Turner et al., 2003).

For this reason, efforts have been made to improve estimated GPP and NPP by using both statistical models and process models. Several statistical models such as the simple temperature and greenness model (TG model; Sims et al., 2008), the regression tree approach (Xiao et al., 2010), the support vector machine model (SVM; Yang et al., 2007), model tree ensembles (MTE; Jung et al., 2011), remote sensing based greenness and radiation model (GR; Wu et al., 2011), the total canopy chlorophyll content and potential incident photosynthetically active radiation model (Gitelson et al., 2012), the temperature and greenness rectangle model (TGR; Yang et al., 2013), and the photosynthetic capacity model (PCM; Gao et al., 2014) have been developed to estimate GPP. Calibrations are required to build statistical GPP models. Conversely, training data determine the accuracy of GPP models. Another feature of statistical GPP models is that while they match the particular climate or vegetation types characterizing the training data, they may need re-calibration when extended to other climates or vegetation types. Recently, Yang et al. (2014) presented a simple model to estimate GPP in nonforest ecosystems by inverting the MODIS evapotranspiration (E) product (MOD16) using ecosystem water use efficiency (WUE = GPP/E).

Process models require detailed parameterization of vegetation, as well as soil and atmosphere, to simulate the vegetation's physiology (*e.g.*, photosynthesis, autotrophic respiration, and transpiration). Since satellites can supply large-scale observation of terrestrial vegetation, a diverse set of satellite-based process models have developed quickly during recent years. These have the potential to accurately predict GPP and NPP from regional to continental scales (Potter et al., 1993; Ruimy et al., 1994; Field et al., 1995; Running et al., 2000; Xiao et al., 2005a; Yuan et al., 2007; Yang et al., 2007). Remote sensing-based process models are principally based on the light-use-efficiency theory – photosynthesis production correlates with the absorbed photosynthetically active radiation (APAR) (Monteith, 1972; Asrar et al., 1984) and FPAR is derived from remote sensing data,

$$\mathrm{GPP} = \varepsilon \times \mathrm{APAR} = \varepsilon * \times S_{\mathrm{stress}} \times \mathrm{FPAR} \times \mathrm{PAR} \quad (1)$$

where GPP is the gross primary production (gC m^{-2} month^{-1}), ε is the actual LUE (gC MJ^{-1}) including environmental stresses and is often defined as $\varepsilon^* \times S_{\mathrm{stress}}$, ε^* is the maximum LUE and S_{stress} refers to environmental stresses, FPAR is the fraction of PAR absorbed by the canopy, and PAR is the incident photosynthetically active radiation (MJ m^{-2} month^{-1}). The fraction of PAR in the incident global radiation Q (MJ m^{-2} month^{-1}) is assumed to be 0.48 (McCree, 1972). Because of remote sensing data adopted as model inputs, they are sometimes called 'diagnostic models' (Ruimy et al., 1996; King et al., 2011).

Most LUE models attempt to couple the effects of temperature and water (*e.g.*, soil moisture (SM), vapor pressure deficit (D), canopy water content) on the maximum light-use-efficiency which is either a universal constant for different ecosystems (Potter et al., 1993; Yuan et al., 2007), or changes in different ecosystem (Running et al., 2000).

As a key variable in LUE models, estimation of ε has attracted multiple studies resulting in different parameterizations (Table 1). TURC GPP model simply defines ε as a constant of 1.21 g C MJ^{-1} (Ruimy et al., 1996). C-Fix GPP model sets ε–ε^* multiplied by a simple function of temperature (T_ε) and, as a partial water-limited-model, assumes NDVI-derived FPAR depending on plant water availability at month scale (Veroustraete et al., 2002; Verstraeten et al., 2006).

As SM and D directly affect photosynthesis, recent GPP models explicitly consider the effect of moisture in addition to temperature. However, the effect of water stress on ecosystem photosynthesis is probably the most uncertain factor in current LUE GPP models (Grant et al., 2006) and numerous definitions of water-stress factor (*i.e.*, SM, D, evaporative fraction (EF), and satellite-derived land surface water index) have been applied (Table 1).

Table 1
The definition of light use efficiency ε, water stress factor W_ε, and maximum light use efficiency ε^* in twelve remote sensing-based GPP or NPP models.

Model	ε (g C MJ^{-1})[a]	W_ε	ε^* (g C MJ^{-1})	Citation
TURC	$\varepsilon_g = \varepsilon^*$	No	1.21	Ruimy et al. (1996)
C-Fix	$\varepsilon_g = \varepsilon^* \times T_\varepsilon$	No	1.1 for forest	Veroustraete et al. (2002)
MOD17	$\varepsilon_g = \varepsilon^* \times T_\varepsilon \times W_\varepsilon$	$W_\varepsilon = \frac{D_{\max} - D}{D_{\max} - D_{\min}}$	0.604–1.259	Running et al. (2000)
VPM	$\varepsilon_g = \varepsilon^* \times T_\varepsilon \times W_\varepsilon$	$W_\varepsilon = \frac{(1 + \mathrm{LSWI})}{(1 + \mathrm{LSWI}_{\max})}$	2.208, 2.484 for forest	Xiao et al. (2005a,b)
BEAMS	$\varepsilon_g = \varepsilon^* \times P_{\mathrm{actual}} \times P_{\max}$	$W_\varepsilon = P_{\mathrm{actual}}/P_{\max}$	$0 \sim 1$	Sasai et al. (2007)
GLO-PEM	$\varepsilon_g = \varepsilon^* \times T_\varepsilon \times W_\varepsilon$	$W_\varepsilon = \min(f(\mathrm{SM}), f(D))$	55.2α for C3; 2.76 for C4	Prince and Goward (1995)
TOPS	$\varepsilon_g = \varepsilon^* \times \min(T_\varepsilon, W_\varepsilon)$		Variable	Nemani et al. (2009)
3-PG	$\varepsilon_g = \varepsilon^* \times T_\varepsilon \times W_\varepsilon \times S_a$	$W_\varepsilon = \min(f(\mathrm{SM}), f(D))$	1.8	Landsberg and Waring (1997)
CFLUX	$\varepsilon_g = \varepsilon^* \times T_\varepsilon \times W_\varepsilon \times S_a$	$W_\varepsilon = \min(f(\mathrm{SM}), f(D))$	$0.9 \sim 4.0$	King et al. (2011)
CASA	$\varepsilon_n = \varepsilon^* \times T_{\varepsilon 1} \times T_{\varepsilon 2} \times W_\varepsilon$	$W_\varepsilon = 0.5 + 0.5E/E_{\mathrm{Th}}$	0.39	Potter et al. (1993)
EC-LUE	$\varepsilon_g = \varepsilon^* \times \min(T_\varepsilon, W_\varepsilon)$	$W_\varepsilon = E/R_n$	2.14	Yuan et al. (2007)
TEC	$\varepsilon_g = \varepsilon^* \times T_\varepsilon \times W_\varepsilon$	$W_\varepsilon = E/E_{\mathrm{PT}}$	1.8 for C3; 2.76 for C4	This study

[a] ε_g and ε_n is light use efficiency (LUE) for calculating GPP and NPP, respectively. Stress variables include temperature (T_ε), water vapor pressure deficit (D), remote sensing-derived Land Surface Water Index (LSWI), standing age (S_a), photosynthesis rate (P), soil moisture (SM), actual evapotranspiration (E), Thornthwaite (1948) potential evaporation (E_{Th}), net radiation (R_n), Priestley and Taylor (1972) potential evaporation (E_{PT}).