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Are vegetation-specific model parameters required for estimating gross primary production?

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Abstract

Models of gross primary production (GPP) are currently parameterized with vegetationspecific parameter sets and therefore require accurate information on the distribution of vegetation to drive them. Can this parameterization scheme be replaced with a vegetation-invariant set of parameter that can maintain or increase model applicability by reducing errors introduced from the uncertainty of land cover classification? Based on the measurements of ecosystem carbon fluxes from 150 globally distributed sites in a range of vegetation types, we examined the predictive capacity of seven light use efficiency (LUE) models. Two model experiments were conducted: (i) a constant set

of parameters for various vegetation types and (ii) vegetation-specific parameters. The results showed no significant differences in model performances to simulate GPP while using both sets of parameters. These results indicate that a universal set of parameters, which is independent of vegetation cover type and characteristics can be adopted in prevalent LUE models. Availability of this well tested and universal set of parameters
 ¹⁵ would help to improve the accuracy and applicability of LUE models in various biomes and geographic regions.

1 Introduction

In the past decades, a long series of terrestrial ecosystem models have been developed to simulate and predict the vegetation primary productivity, which play an important role in the global carbon cycle at various spatiotemporal scales (Cramer et al., 2001). However, modeling the carbon cycle using ecosystem models at continental to global scale is subject to large uncertainties, primarily due to uncertainties of model parameterizations (Knorr and Heimann, 2001). The conventional parameterization schemes assume a constant parameter sets for each vegetation types. Consequently, land cover products based on remote sensing technology are routinely used to characterize vegetation characteristics for model



applications. However, classifying remote sensing images to obtain reliable and accurate land cover type and associated vegetation characteristics over large areas remains a major challenge because of the complexity of landscapes, availability and suitability of remote sensing data, uncertainty of image processing and classification ⁵ methods, etc. (Hansen et al., 2003).

Satellite-based light use efficiency (LUE) models have been widely used because they rely on simple algorithms to estimate gross primary production (GPP). Most LUE models are based on look-up tables to set the parameter values for given vegetation types (Running et al., 2004). Yet a few LUE models (CASA and EC-LUE) use a set of constant parameters regardless of vegetation type by arguing that photosynthesis is independent of species and vegetation but driven by biophysical conditions such as mainly light, temperature and available water (Potter et al., 1993; Yuan et al., 2007, 2010). Moreover, Aber and Federer (1992) argued that the amount of carbon fixed through photosynthesis per light quantum intercepted is invariant of species. The

- ¹⁵ use of invariant parameter values across vegetation types would clearly simplify the parameterization of LUE models at broad spatial scales and the prediction of GPP over large areas. However, the advantages of this approach have not yet been verified against surface observations. In this study, we tested a series of popular LUE models by using both vegetation invariant and vegetation dependent parameters across a range
- ²⁰ of geographic regions and ecosystem types. Model predictions of GPP are finally validated using in situ observations from flux towers belonging to the global Fluxnet network (Baldocchi et al., 2001).

2 Data and methods

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The LUE models are in general built on two fundamental assumptions (Goetz and
 Prince, 1999; Running et al., 2004): (1) ecosystem GPP is linearly related to absorbed photosynthetically active radiation (APAR) through LUE, where LUE is defined as the amount of carbon fixed per unit of APAR, and (2) potential LUE may be reduced below



its theoretical potential value (i.e., realized LUE) by environmental stresses such as low temperature or water shortage (Landsberg and Sands, 2010). In this study, seven LUE models were selected to conduct a global comparison of model performance against GPP estimates from flux tower measurement: CASA (Potter et al., 1993), CFix (Versustrate et al., 2002). CFixer (Turner et al., 2006) King et al., 2011). FC

⁵ CFix (Veroustraete et al., 2002), CFlux (Turner et al., 2006; King et al., 2011), EC-LUE (Yuan et al., 2007, 2010), MODIS-GPP (Running et al., 2004), VPM (Xiao et al., 2004) and VPRM (Mahadevan et al., 2008). Detailed informations about these models are reported in the supplementary online material.

The LaThuile FLUXNET dataset was used in this study (http://www.fluxdata.org).

- A total of 150 eddy covariance (EC) towers from five major terrestrial biomes were analysed: deciduous broadleaf forest (DBF, 25 sites), evergreen broadleaf forest (EBF, 14 sites), evergreen needleleaf forest (ENF, 62 sites), grassland (GRA, 40 sites) and mixed forest (MF, 9 sites) (Table S1; Fig. S1). Detailed information on data processing and site information (i.e. vegetation, climate and soils) are available at the LaThuile
 FLUXNET web portal (http://www.fluxdata.org). The methodology applied to derive
- GPP from the net ecosystem exchange is reported in Reichstein et al. (2005).

Two model experiments were conducted to evaluate the vegetation-invariant parameters in LUE models. First, we calibrated the seven LUE models each with a set of invariant model parameters that did not change across all vegetation types. Half of

- the sites were randomly selected to calibrate model parameters, and the remaining half were used for model validation. The nonlinear regression procedure (Proc NLIN) in the Statistical Analysis System (SAS, SAS Institute Inc., Cary, NC, USA) was used to optimize the model parameters. Second, model parameters were calibrated for each model and vegetation type. Same site selection criterion and calibration process were
- ²⁵ applied within each vegetation type. Two metrics, the coefficient of determination (R^2) and the root mean square error (RMSE), were used to evaluate the performance of the LUE models.

The 8 day MODIS-NDVI/EVI data (MOD13) and MODIS-fPAR/LAI (MOD15) with 1 km spatial resolution were the basis for model verification at the EC sites. Quality



control (QC) flags, which signal cloud contamination in each pixel, were examined to screen and reject NDVI, EVI and fPAR data of insufficient quality. We temporally filled the missing or unreliable values at each 1 km MODIS pixel based on their corresponding quality assessment data fields as proposed by Zhao et al. (2005).

5 3 Results and discussion

Calibrated parameters of several models across most vegetation types did not show significant differences with those derived from individual vegetation types (Table 1). In the CASA model, potential LUE value (ε_0) calibrated at all sites was $0.91 \pm 0.14 \,\mathrm{gCm^{-2}\,MJ^{-1}}$, which only significantly differed from the calibrated values at grassland ($0.78 \pm 0.17 \,\mathrm{gCm^{-2}\,MJ^{-1}}$). Similar results were found at the EC-LUE and VPM models, the calibrated ε_0 value ($1.73 \pm 0.12 \,\mathrm{gCm^{-2}\,MJ^{-1}}$ and $2.08 \pm$ $0.17 \,\mathrm{gCm^{-2}\,MJ^{-1}}$) for all sites did not show the significant differences with those of other vegetation types (Table 1). There were more than one parameter at other models, and the results showed complex relationships among parameters (Table 1).

¹⁵ For example, in the VPRM model, the calibrated ε_0 and PAR₀ at all sites significantly differed from those of deciduous broadleaf forest, however, they showed larger and lower inversed parameter values over all sites, respectively (Table 1).

Among the seven LUE models there were no significant differences in model performance between the two different parameterization schemes according to mean (22)

GPP, RMSE and coefficient of determination (*R*²) (Fig. 1). Especially, the slopes of regression lines between mean GPP estimations did not show significant differences, indicating that these two different parameterizations rarely changed the magnitude of GPP predictions (Fig. 1). These results indicate that the parameterization scheme of the LUE models can potentially be simplified using a set of constant vegetation independent parameter values for each model, which will reduce the uncertainty generated from land cover misclassification, while simplifying their use.



Our conclusion is supported by plant physiological evidences. Although different photosynthesis pathway can occur in different species, some features are always the same. Theoretically, plants can assimilate 1 mol CO₂ using 8 mol absorbed radiation (Hall and Rao, 1999). Another reason for the good performance of the vegetation-⁵ invariant model parameters in the tested LUE models is the use of a satellitederived vegetation index, which holistically captures the overall state of structural and physiological vegetation characteristics (e.g. leaf area index, chlorophyll and nitrogen content).

Most LUE models assume the potential LUE to occur at optimal temperature and water condition. However, other environment variables, like leaf nitrogen content, have also been found to influence the photosynthetic potentials (Kergoat et al., 2008; Peltoniemi et al., 2012). Remotely sensed vegetation index, however, is highly related to leaf nitrogen content (Hansen and Schjoerring, 2003; Zhu et al., 2008; Yao et al., 2010; Li et al., 2010). A strong correlation exists between leaf chlorophyll and leaf nitrogen concentration (Ercoli et al., 1993), and the visible light reflectance is primarily determined by the chlorophyll of the leaf (Campbell, 2002; Alchanatis et al., 2005). Therefore, NDVI is an effective index for relative plant nitrogen status. Previous studies have shown that remotely sensed imagery can provide valuable information about in-

field nitrogen variability (Chang et al., 2003; Sripada et al., 2005).

²⁰ Most current LUE models use look-up tables to define vegetation specific model parameters for regional and global applications. Therefore the availability of satellite derived land cover products is a prerequisite for model parameterization. For example, the MODIS land cover product (MOD-12) is used to run the MODIS-GPP product (Running et al., 2004). However, a previous study showed the accuracy of the MODIS land cover product is only about 75 % (Friedl et al., 2010). If such products were used

for estimating GPP, additional errors would be introduced from the uncertainty in land cover classification to the regional estimates of GPP.

Results from this study clearly show similar performance of the LUE models in predicting GPP using either the vegetation-dependent or invariant model parameters.



This result implies that such approach may significantly reduce the uncertainty of GPP estimates at regional to global scales. This will also increase the feasibility of quantifying and mapping GPP changes over time and land use change. This is particularly the case since acquiring frequent high-quality land cover change information over large areas has been a major challenge (Hansen et al., 2003).

4 Summary and conclusions

Selecting adequate model parameter values is critical for estimating vegetation production within various process models. Considering the variability and uniqueness of various ecosystems in primary production, assigning a varying parameter set in accordance with vegetation types has been a common parameterization strategy. However, this approach requires high-quality vegetation cover information. Current vegetation cover datasets over large areas contain large uncertainties that propagate into GPP simulations at regional and global scales. In this study, two model experiments were conducted to examine the differences in GPP predictions by seven LUE models using alternatively vegetation variant and invariant parameters. No significant differences were found between the two parameterization schemes. These results indicate that the application of LUE models can potentially be simplified with a constant parameterization scheme that is independent of land cover types and associated vegetation characteristics.

²⁰ Supplementary material related to this article is available online at http://www.geosci-model-dev-discuss.net/6/5475/2013/ gmdd-6-5475-2013-supplement.pdf.



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Parameter		Vegetation Type					
		All ^a (150) ^b	DBF ^c (25)	EBF (14)	ENF (62)	GRA (40)	MF (9)
CASA	ε	0.91 ± 0.14^{G}	1.22 ± 0.43	0.87 ± 0.15	0.85 ± 0.18	0.78 ± 0.17	1.04 ± 0.36
CFix	ε _{max} ε _{min}	1.87 ± 0.18 $1.16 \pm 0.08^{D,E}$	1.92 ± 0.18 1.27 ± 0.07	1.85 ± 0.35 1.33 ± 0.15	1.94 ± 0.19 1.09 ± 0.06	1.86 ± 0.33 1.14 ± 0.09	1.79 ± 0.27 1.16 ± 0.13
CFlux	ε _{max} ε _{cs} Τ _{min} Τ _{max} VPD _{min} VPD _{max}	$\begin{array}{c} 2.56 \pm 0.16^{D,E,EN} \\ 1.04 \pm 0.06^{D,E} \\ -14.16 \pm 3.77^{D,G} \\ 10.83 \pm 1.71^{E,EN,G} \\ 0.11 \pm 0.02 \\ 2.89 \pm 0.15^{G} \end{array}$	3.07 ± 0.25 1.17 ± 0.07 -4.35 ± 2.13 13.08 ± 3.23 0.11 ± 0.01 2.99 ± 0.32	$\begin{array}{c} 3.02 \pm 0.18 \\ 1.12 \pm 0.10 \\ -14.46 \pm 4.35 \\ 20.00 \pm 0.00 \\ 0.12 \pm 0.07 \\ 2.56 \pm 0.32 \end{array}$	$\begin{array}{c} 2.29 \pm 0.12 \\ 0.95 \pm 0.05 \\ -14.20 \pm 2.40 \\ 8.25 \pm 1.82 \\ 0.11 \pm 0.00 \\ 2.79 \pm 0.13 \end{array}$	2.53 ± 0.15 1.08 ± 0.08 -20.12 ± 7.06 9.55 ± 5.87 0.12 ± 0.01 3.23 ± 0.47	2.53 ± 0.25 1.05 ± 0.13 -14.26 ± 4.17 13.79 ± 3.74 0.12 ± 0.02 2.44 ± 0.32
EC-LUE	ε_0	1.73 ± 0.12	1.71 ± 0.19	1.70 ± 0.11	1.85 ± 0.20	1.59 ± 0.41	1.72 ± 0.31
MODIS	ε ₀ T _{min} T _{max} VPD _{min} VPD _{max}	$\begin{array}{c} 1.52 \pm 0.09^{,D,EN} \\ -14.16 \pm 4.01^{D,G} \\ 10.83 \pm 2.08^{E,EN,G} \\ 0.11 \pm 0.01 \\ 2.89 \pm 0.36^{G} \end{array}$	$\begin{array}{c} 1.77 \pm 0.19 \\ -4.35 \pm 2.13 \\ 13.08 \pm 3.23 \\ 0.11 \pm 0.01 \\ 2.99 \pm 0.32 \end{array}$	$\begin{array}{c} 1.68 \pm 0.10 \\ -14.46 \pm 4.35 \\ 20.00 \pm 0.00 \\ 0.12 \pm 0.07 \\ 2.56 \pm 0.32 \end{array}$	$\begin{array}{c} 1.36 \pm 0.08 \\ -14.20 \pm 2.40 \\ 8.25 \pm 1.82 \\ 0.11 \pm 0.02 \\ 2.79 \pm 0.13 \end{array}$	$1.52 \pm 0.16 \\ -20.12 \pm 7.06 \\ 9.55 \pm 5.87 \\ 0.12 \pm 0.01 \\ 3.23 \pm 0.47 \\ \end{array}$	1.64 ± 0.22 -14.26 ± 4.17 13.79 ± 3.74 0.12 ± 0.02 2.44 ± 0.32
VPM	ε ₀	2.08 ± 0.17	2.11 ± 0.11	2.17 ± 0.16	2.17 ± 0.10	1.92 ± 0.12	2.03 ± 0.24
VPRM	ε_0 PAR ₀	$11.31 \pm 2.03^{D,EN,G}$ $2.38 \pm 0.41^{D,EN,G}$	8.63 ± 1.14 3.15 ± 0.44	10.88 ± 2.17 2.37 ± 0.75	14.89 ± 2.10 1.61 ± 0.24	7.87 ± 1.08 3.07 ± 0.52	10.16 ± 3.04 2.50 ± 0.81

 Table 1. Calibrated model parameter values for seven LUE models and two parameterization schemes.

^a All: parameter values calibrated through all sites, and detailed information about these parameters are reported in the supplementary online material.

^b The numbers indicate the site number of each vegetation type.

^c DBF, EBF, ENF, GRA, MF: calibrated parameter values within deciduous broadleaf forest, evergreen broadleaf forest, evergreen needleleaf forest, grassland, mixed forest respectively. The capital letters, showed at the column "All", indicate the significant differences with parameters calibrated within vegetation types (D, E, EN, G, M represent DBF, EBF, ENF, GRA, MF). The lowercase letters at the other columns indicate significant differences among several of vegetation types. Parameters information is provided in the Supplement. The unit of parameters: $g Cm^{-2} MJ^{-1} APAR$ for $\mathcal{E}_{0/max/min/cs/}$; KPa for VPD_{min/max}; ^o for $\mathcal{T}_{min/max}$; MJ m⁻² for PAR₀.



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