Remote Sensing of Environment 215 (2018) 411–437

Contents lists available at ScienceDirect

Remote Sensing of Environment

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

A remote sensing-based two-leaf canopy conductance model: Global optimization and applications in modeling gross primary productivity and evapotranspiration of crops

Yun Bai[a,b], Jiahua Zhang[a,b,*], Sha Zhang[a,b], Fengmei Yao[b,*], Vincenzo Magliulo[c]

[a] Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing, China
[b] University of Chinese Academy of Sciences, Beijing, China
[c] Institute for Agriculture and Forestry Systems in the Mediterranean, National Research Council, Napoli, Italy

ARTICLE INFO

Keywords:
Remote sensing
Two-leaf canopy conductance model
Jarvis-type model
C_3 and C_4 crops
Penman-Monteith equation
Inverted Ball-Berry-Leuning model
Soil water balance
Gross primary productivity
Evapotranspiration

ABSTRACT

The temporal dynamics of optimum stomatal conductance (g_{smax}), as well differences between C_3 and C_4 crops, have rarely been considered in previous remote sensing (RS)-based Jarvis-type canopy conductance (G_c) models. To address this issue, a RS-based two-leaf Jarvis-type G_c model, RST-G_c, was optimized and validated for C_3 and C_4 crops using 19 crop flux sites across Europe, North America, and China. RST-G_c included restrictive functions for air temperature, vapor pressure deficit, and soil water deficit, and it used satellite-retrieved NDVI to formulate the temporal variation of g_{smax} defined at a photosynthetic photon flux density (PPFD) of 2000 μmol m^{-2} s^{-1} ($g_{sm,\ 2000}$). Results showed that the parameters of RST-G_c differed between C_3 and C_4 crops. RST-G_c successfully simulated variations in Penman–Monteith (PM)-derived daytime G_c with $R^2 = 0.57$ for both C_3 and C_4 crops. RST-G_c was incorporated into a revised evapotranspiration (ET) model and a new gross primary productivity (GPP) model. The two models were validated at 19 crop flux sites. Daily mean inputs were generally incorporated into a PM approach to model daily transpiration. This is inappropriate because available energy and stomatal conductance vary significantly on a diurnal basis, with both non-linearly regulating transpiration rate. The PM approach with daily mean inputs produced unreasonable transpiration rate estimates. Efforts were made in the revised ET model (denoted as RS-WBPM2), which was modified from the water balance based RS-PM (RS-WBPM) model of Bai et al. (2017), to address this issue by calculating transpiration using daytime inputs. The photosynthesis-based stomatal conductance model, developed by Ball et al. (1987a) and improved by Leuning (1995) (BBL model), was inverted to calculate GPP using canopy conductance; the inverted model was denoted as IBBL. Cross validation showed good agreement between flux tower measurements and modeled ET ($R^2 = 0.79$, RMSE (root mean standard error) = 20.66 W m^{-2} for daily ET and $R^2 = 0.87$, RMSE = 15.32 W m^{-2} for 16-day ET) and GPP ($R^2 = 0.83$, RMSE = 2.49 gC m^{-2} d^{-1} for daily GPP and $R^2 = 0.86$, RMSE = 1.96 gC m^{-2} d^{-1} for 16-day GPP) for the two models. Within-site validations demonstrated the successful performance of the two models at 18 sites (albeit with one outlier). Inter-site variations in ET and GPP were also successfully reproduced by the models. NDVI-derived $g_{sm,\ 2000}$ outperformed the fixed $g_{sm,\ 2000}$ in both ET and GPP estimates. The results imply that the RS-WBPM2 and IBBL models are useful tools for modeling regional and global ET and GPP.

1. Introduction

Canopy conductance (G_c), as up-scaled from stomatal conductance (g_{st}), plays a significant role in regulating evapotranspiration (ET) and photosynthesis (Flexas et al., 2006). ET is even directly determined by G_c in arid/semi-arid regions (Zhang et al., 2007), and G_c is an essential input in multiple Earth system models (ESMs) for water (e.g., Mu et al. (2011), Yan et al. (2012), Yebra et al. (2013) and Bai et al. (2017)) and carbon (e.g., Running and Coughlan (1988), Chen et al. (1999), Ryu et al. (2011), De Kauwe et al. (2015), Yebra et al. (2015), Jiang and Ryu (2016) and Zhang et al. (2018)) flux simulations. To understand the water and carbon cycles of terrestrial ecosystems, the accurate estimation of G_c is highly important.

Remote sensing (RS) provides continuous spatial information for understanding the heterogeneity of land and is thus of great potential in modeling the spatial dynamics of G_c over broad regions. On a regional

* Corresponding authors.
E-mail addresses: zhangjh@radi.ac.cn (J. Zhang), yaofm@ucas.ac.cn (F. Yao).

https://doi.org/10.1016/j.rse.2018.06.005
Received 22 September 2017; Received in revised form 29 May 2018; Accepted 5 June 2018

or global scale, three types of widely used canopy conductance (G_c) model, i.e., the empirical model (Cleugh et al., 2007; Yebra et al., 2013), Ball-Berry–Luening (BBL)-type model (Collatz et al., 1992; Kowalczyk et al., 2006; Myneni et al., 1992; Wang and Leuning, 1998) and Jarvis-type model (Leuning et al., 2008; Mu et al., 2007; Mu et al., 2011; Yan et al., 2012; Zhang et al., 2009), have been implemented using RS data. The empirical model is characterized by its simple formulation; it uses RS data alone to calculate G_c. The BBL-type model includes more physiological mechanisms relating to stomata than do the other two models; it is generally coupled with a RS-based photosynthesis module. The Jarvis-type model adopts the framework of the model of Jarvis (1976) and uses multiple environmental restrictive factors to scale a RS-derived maximum canopy conductance to the actual value. The framework of the Jarvis-type model is simpler than that of the BBL-type. However, this framework has one shortcoming, i.e., potential interaction effects of environmental factors on stomata are excluded. For example, Bunce (1998) found that stomata were insensitive to changes in ambient CO_2 concentration under a low vapor pressure deficit (VPD). However, the Jarvis-type model has been found useful and is used widely in RS-based land process models (Chen et al., 1999; Damour et al., 2010; Leuning et al., 2008; Liu et al., 1999; Mu et al., 2011; Zhang et al., 2010). In addition, Raab et al. (2015) found that the Jarvis-type model performance was comparable that of with the BBL-type model; therefore, the Jarvis-type model with its simpler framework is favorable.

The Jarvis-type G_c model has been widely employed by RS-based land process models (Chen et al., 1999; Liu et al., 1999; Mu et al., 2011; Running and Coughlan, 1988); however, the G_c values of crop lands were only roughly parameterized in these models. A significant remaining problem is that differentiation between C_4 and C_3 crops has rarely been considered. For instance, both the MODIS gross primary productivity (GPP) algorithm (MOD17) and ET algorithm (MOD16) incorporated the Jarvis-type model using the same parameter set for C_4 and C_3 crops (Mu et al., 2011; Running et al., 1999; White et al., 2000). By contrast, the Breathing Earth System Simulator (BESS) developed by Ryu et al. (2011) did consider this issue. The recently released 1-km ET and GPP products produced using BESS significantly outperformed the MODIS ET and GPP products on crop lands (Jiang and Ryu, 2016). The performances of the new products indicate the advantages of differentiating between C_3 and C_4 crops when parameterizing RS-based land process models. Similarly, the evaluation of different light use efficiency (LUE) models by Yuan et al. (2015) also suggested that modeling the GPP of C_3 and C_4 crops using the same parameter set might induce large uncertainties. As photosynthesis is closely coupled with stomatal conductance (Ball et al., 1987b; Leuning, 1995; Wong et al., 1979), G_c estimates could also be biased if a single parameter set is applied for C_3 and C_4 crops,

Another problem with the RS-based Jarvis-type model is that maximum stomatal conductance (g_{smax}) is specified by plant functional type (PFT) and assumed to be temporally invariant. In fact, g_{smax} tends to vary throughout the growing season, even for a certain PFT. One obvious piece of evidence for this is the close relationship between g_{smax} and leaf nitrogen content (LNC) or the maximum photosynthetic capacity (Kelliher et al., 1995; Schulze et al., 1994; Wong et al., 1979). A fixed g_{smax} could cause uncertainties when estimating G_c. Zhang et al. (1997) found that the Jarvis-type model with a fixed g_{smax} value, which was calibrated from field samples, underestimated canopy conductance at a high value. However, it is not easy to directly retrieve the LNC or photosynthetic capacity of leaves from satellite data and then estimate the temporal dynamic of g_{smax}. Alternatively, we could refer to chlorophyll (Chl) content when estimating the temporal dynamic of g_{smax} since Chl content is strongly correlated with the leaf photosynthetic capacity parameter, maximum carboxylation rate (V_{cmax25}) (Croft et al., 2016), as well as some simple vegetation indices like NDVI (Hashemi and Chenani, 2011; Wu et al., 2009). Indeed, Matsumoto et al. (2005) suggested a positive effect of Chl content on stomatal conductance for *Quercus serrate* trees. Therefore, NDVI is potentially useful for estimating the temporal dynamic of g_{smax}. Satellite-retrieved NDVI is strongly correlated with leaf area index (LAI); in turn, the LAI of crops greatly depends on the phenological phase, which determines the leaf Chl content of the crop (Jeganathan et al., 2010). The phenology of land vegetation can be fairly well indicated by satellite-NDVI (Chang et al., 2016; Chu et al., 2014b; Lee et al., 2002). This highlights the potential to parameterize g_{smax} using the satellite-retrieved vegetation index, NDVI.

In this study, we aimed to calibrate a RS-based Jarvis-type G_c model and apply it to the modeling of daily GPP and ET at 19 cropped, eddy covariance flux sites across Europe, North America, and China. The main objectives were: (a) optimize the restrictive functions of four environmental factors, i.e., air temperature, VPD, soil water deficit, and solar radiation, using eddy covariance observations for C_3 and C_4 crops; (b) use satellite-retrieved NDVI to parameterize g_{smax}; (c) improve the water balance and Penman–Monteith equation (Monteith, 1965) (PM)-based ET model, RS-WBPM (Bai et al., 2017) and use it to model daily ET of crop lands; (d) use an inverted BBL-type model (IBBL) to estimate crop GPP along with the optimized G_c model; and (e) validate the improved RS-WBPM and IBBL models. Three models were used in this study, i.e., the canopy conductance model RST-G_c, the revised RS-WBPM model, and the IBBL model. Details of the three models are presented in Section 2 and overviews of the three models are given in Appendix A. Variables and symbols appearing in the three models are explained in Appendix F.

2. Methodology

2.1. Calculating G_c for model optimization and validation

Both the inverted PM equation and the BBL model (Leuning, 1995), along with eddy covariance flux data, are used to calculate G_c. G_c calculated using the inverted PM equation (PM-G_c) is used for validating modeled G_c, whereas that calculated using the BBL model is used for optimizing the Jarvis-type G_c model. The inverted PM equation uses latent heat flux and net radiation to calculate G_c, whereas the BBL model uses GPP. Therefore, PM-derived G_c will inevitably be affected by soil evaporation. Thus, if we remove just the data with low LAI levels, the sample size would be considerably reduced. By contrast, using the BBL model to calculate G_c can avoid the effect of soil evaporation and increase the available sample size by a significant margin.

2.1.1. PM-derived daytime G_c (PM-G_c) for model validation

The inverted PM equation used to calculate G_c is presented as follows (Yebra et al., 2013):

$$G_c = \frac{\gamma \cdot \lambda E \cdot G_a^c}{\Delta \cdot (Rn - G) - (\Delta + \gamma) \cdot \lambda E + \rho \cdot c_p \cdot VPD \cdot G_a^c}, \tag{1}$$

We only applied Eq. (1) on rain-free days, with the result referred as G_c (Yebra et al., 2013).

Aerodynamic conductance for canopy vapor tranfer, $G_a{}^c$, is calculated according to Thom (1975):

$$\frac{1}{G_a^j} = \frac{1}{\kappa^2 \cdot u} \cdot \ln\left(\frac{z_m - d}{z_{om}^j}\right) \cdot \ln\left(\frac{z_h - d}{z_{oh}^j}\right), \tag{2}$$

For calculating $G_a{}^c$, parameters d, z_{om} and z_{oh} were estimated as $0.66h$, $0.123h$ and $0.1z_{om}$, respectively (Yan et al., 2012), where h is the canopy height. For a soil surface substrate, d was set to 0, and z_{om} was set to 0.004 m, the median value of the z_{om} range of various soil surfaces (Monteith and Unsworth, 2013). For a paddy land substrate, z_{om} was set to 0.002 m, the minimum value for a water surface (Monteith and Unsworth, 2013), because the water surface roughness under a crop canopy is generally less disturbed by wind than that of an open water surface.