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Modeling evapotranspiration by combing a two-source model, a leaf stomatal model, and a light-use efficiency model

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SUMMARY

Modeling and partitioning ecosystem evapotranspiration (ET) are important in predicting the responses of ecosystem water cycles to global climate change and land use. By incorporating the Ball–Berry stomatal conductance model and a light use efficiency-based gross primary productivity (GPP) model into the Shuttleworth–Wallace model, we developed a new model, SWH, for estimating ET with meteorological data and remote sensing products. Since the new model solved the problem of estimating canopy stomatal conductance, it can be used at sites equipped with meteorological observation systems around the world. Compared with eddy covariance measurements, the SWH model demonstrated satisfactory estimates of ET at a temperate forest and an alpine grassland. Eight meteorological variables and two remote sensing products (i.e., leaf area index, LAI, and enhanced vegetation index, EVI or normalized difference vegetation index, NDVI, or fraction of photosynthetically active radiation, FPAR) are required in our model. This will facilitate estimates of ET and its components, and further elucidate the mechanisms underlying their variations at regional scale. In addition, our model estimates ET and GPP simultaneously, making it convenient to address the coupling of these two key fluxes in terrestrial ecosystems.

1. Introduction

Evapotranspiration (ET) is an important process for ecosystem water cycles and energy balance, and is closely linked to ecosystem productivity (Jung et al., 2010; Oki and Kanae, 2006). It is therefore important to provide spatiotemporal information of ET across diverse ecosystems in order to predict the responses of ecosystem carbon and water cycles to changes in global climate and land use (Jung et al., 2010). Modeling of ET has a history of several decades (Li et al., 2009; Monteith, 1965; Shuttleworth and Wallace, 1985). Some process-based models have been developed or improved to estimate ET at diverse spatiotemporal scales (Bastiaanssen et al., 2005; Hu et al., 2009; Kustas and Anderson, 2009; Monteith, 1965; Overgaard et al., 2006; Shuttleworth and Wallace, 1985; Vinukollu et al., 2011). Among these models, the Penman–Monteith model (P–M model, Monteith, 1965;) and the Shuttleworth–Wallace model (S–W model, Shuttleworth and Wallace, 1985) are mostly used (Anadranistakis et al., 2000; Hu et al., 2009; Iritz et al., 1999; Kato et al., 2004; Stannard, 1993; Tourula and Heikinheimo, 1998).

The S–W model is a two-source model developed from P–M to estimate plant transpiration and soil water evaporation separately. Studies indicate that the performance of S–W model is better than other ET models (including P–M model) at diverse ecosystems (Stannard, 1993; Zhang et al., 2008). However, one factor hindering the application of the S–W model is the estimation of canopy stomatal resistance. Canopy stomatal resistance is critical in modeling ET but usually regarded as a constant due to the difficulty in measurements or calculation. In our previous work, we used the Ball–Berry model (Ball et al., 1987) to estimate canopy stomatal resistance in S–W, which yielded good agreement between the ET prediction and observations at four grassland ecosystems (Hu et al., 2009). The Ball–Berry model incorporates the correlation between photosynthesis and stomatal conductance, air humidity, and ambient CO_2 concentrations based on observations and Cowan's theory of "maximum carbon gain and minimizing water loss" (Cowan and Farquhar, 1977). This model captures the essence of the coupling between photosynthesis and transpiration, and it implicitly covers the effects of diverse environmental factors on stomatal conductance (Leuning, 1995). Therefore it illustrates a strong predictive power and has been widely used to estimate stomatal conductance in physiological models (Leuning, 1995; Tuzet et al., 2003). In the Ball–Berry model, however, an important

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variable, photosynthetic rate (P_n), needs to be provided to estimate stomatal conductance. The gross primary productivity (GPP) calculated from eddy covariance measurement was used to replace P_n and illustrated satisfactory performance in our previous work. Therefore, as a substitute of P_n, GPP is needed in the combined S–W model and Ball–Berry model.

Eddy covariance measurements of GPP are only available at a limited number of sites. Fortunately, light use efficiency (LUE)-based GPP models have been developed and have yielded good predictions at individual sites to global scales. Example LUE-based models include CASA (Potter et al., 1993), GLO-PEM (Prince and Goward, 1995), VPM (Xiao et al., 2004), and EC-LUE (Yuan et al., 2007). NASA has also released a global GPP product, i.e., the MODIS (Moderate resolution Imaging Spectroradiometer) GPP product, which was calculated with a similar approach (Zhao et al., 2005). In terms of application, the LUE-based GPP model needs a few climate variables and remote sensing products, which are readily available globally.

In this study, our objective is to develop a new ET model through combining the S–W model, Ball–Berry model, and a LUE-based GPP model to estimate and partition ET with meteorological variables and remote sensing products. We will test the performance of the new model with *in site* measurements at a forest site and a grassland site. The main orientation of this work is that there are a large number of meteorological stations across the world, at which the meteorological variables are continuously measured. By using this rich dataset with the approach of this study, it would be possible to address the spatiotemporal variations in ET at diverse ecosystems in the world. Our work in this study might be a helpful beginning for this endeavor.

2. Materials and methods

2.1. Modeling

The S–W model describes the water vapor flows from soil to the atmosphere as being analogous to the flows of electric currents. It estimates the latent heat flux from the soil surface (i.e., soil water evaporation) and from the plant (i.e., plant transpiration) as two separate sources. Details of the model are available in Shuttleworth and Wallace (1985) and Hu et al. (2009).

Soil surface resistance r_{ss} and canopy stomatal resistance, r_{ac}, (i.e., the reverse of canopy stomatal conductance) are two critical input variables in the S–W model. In this study, r_{ss} was estimated as the function of soil water content (Lin and Sun, 1983):

$$r_{ss} = b_1\left(\frac{SW_s}{SW}\right)^{b_2} + b_3 \tag{1}$$

where SW and SW_s are the soil water content and saturated water content in the surface soil ($m^3\ m^{-3}$), and b_1 ($s\ m^{-1}$), b_2, b_3 ($s\ m^{-1}$) are empirical constants with b_1 fixed as $3.5\ s\ m^{-1}$ (Lin and Sun, 1983).

We estimated r_{ac} by introducing the Ball–Berry model in our study (Ball et al., 1987):

$$r_{sc} = \frac{1}{g_0 + a_1 P_n h_s / C_S} \tag{2}$$

where g_0, a_1 are empirical parameters, P_n ($\mu mol\ m^2\ s^{-1}$) is photosynthetic rate, h_s is leaf surface relative humidity, and C_S is leaf surface CO_2 content (fixed as 390 ppm).

P_n is a key driving variable to estimate r_{sc}. We used the gross primary productivity (GPP) estimated from the measurements of eddy covariance systems in our previous work (Hu et al., 2009). For the purpose of applications at the sites without GPP measurements, we estimated GPP with a satellite-based light use efficiency model, whose scheme was similar to the GLO-PEM model (Prentice and Goward, 1995):

$$\mathrm{GPP} = \varepsilon \times \mathrm{PAR} \times \mathrm{FPAR} \tag{3}$$

where PAR is the incident photosynthetically active radiation ($\mu mol\ m^{-2}\ s^{-1}$), FPAR is the fraction of PAR being absorbed by the canopy. There are four methods being widely used to estimate FPAR: (1) estimated as the function of LAI and light extinction coefficient with Beer's law; (2) estimated as the function of NDVI (FPAR = 1.24NDVI − 0.168, Sims et al., 2006), or (3) Enhance Vegetation Index, EVI (FPAR = 1.2EVI, Fisher et al., 2008); and (4) the Moderate resolution Imaging Spectroradiometer (MODIS) FPAR product. In this study, we compared the performance of the four methods on estimating GPP and ET. ε is the light use efficiency ($\mu mol\ CO_2\ \mu mol^{-1}$ PPFD), and is down-regulated by air temperature, soil water moisture, and vapor pressure deficit (VPD):

$$\varepsilon = \varepsilon_0 \times f(T) \times f(\mathrm{SW}) \times (\mathrm{VPD}) \tag{4}$$

$$f(T) = \frac{(T - T_{\min})(T - T_{\max})}{(T - T_{\min})(T - T_{\max}) - (T - T_{opt})^2} \tag{5}$$

$$f(\mathrm{SW}) = \frac{\mathrm{SW} - Q_w}{Q_f - Q_w} \tag{6}$$

$$f(\mathrm{VPD}) = \frac{\mathrm{VPD}_{\max} - \mathrm{VPD}}{\mathrm{VPD}_{\max}} \tag{7}$$

where ε_0 is the apparent quantum yield or maximum light use efficiency, and $f(T)$, $f(W)$ and $f(\mathrm{VPD})$ are the downward-regulation scalars for the effects of temperature, soil moisture and VPD on light use efficiency of vegetation, respectively. $T_{\min}$, $T_{\max}$ and T_{opt} are minimum, maximum and optimum air temperature (°C) for photosynthetic activity, respectively. If air temperature falls below $T_{\min}$ or increases beyond $T_{\max}$, $f(T)$ is set to zero. In this study, $T_{\min}$, T_{opt} and $T_{\max}$ are set to 0, 20 and 40 °C, respectively (Xiao et al., 2004). Q_w and Q_f are the soil water content at wilting point and field capacity, which were set to the observed maximum and minimum volumetric water content during the study period. If soil moisture increases beyond $0.35\ m^3\ m^{-3}$, $f(W)$ was set to one, and if VPD falls below 0.5 kPa, $f(\mathrm{VPD})$ was also set to one (Zhao et al., 2005).

For the new S–W model, which was incorporated with the Ball–Berry stomatal conductance model and the LUE-based GPP model, referred to as the SWH model hereafter, the input driving variables are *T*a, RH, *D*, SW, R_n, *G*, PAR, WS, LAI, NDVI (or EVI, or FPAR), respectively. The parameters need to be optimized or estimated are b_2, b_3, *a*, g_0, *k*, and ε_0, respectively. The model time step was set as 16-day as the satellite products were calculated as 16-day composites. MODIS products, i.e., LAI/FPAR (MOD15A2) and NDVI/EVI (MOD13Q1) are the satellite products acquired from the website of Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC, 1 km, http://daac.ornl.gov). These MODIS products contain some cloud-contaminated or missing data (Hill et al., 2006). Therefore, before being input to the model, these products were processed with a software package TIMESAT3.0 (asymmetric Gaussian method was used) to exclude the noises and fill the gaps (Jönsson and Eklundh, 2004).

2.2. Parameterization and measurements of meteorological variables

The six parametersb_2, b_3, *a*, g_0, *k*, and ε_0 were estimated through Monte Carlo simulations (details are described in Hu et al., 2009). Briefly, we performed 10,000 Monte Carlo simulations to select ten top-performance parameter sets, and the mean of the ten top-performance parameter sets was regarded as the best-fit parameter set. Using the data for calibration, we calculated the ratio of the