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# Estimating time series of land surface energy fluxes using optimized two source energy balance schemes: Model formulation, calibration, and validation

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ABSTRACT

Due to the limited availability of land surface temperature (LST) images, thermal-based evapotranspiration (ET) models can only provide instantaneous ET snapshots. In contrast, models that are based on near surface soil moisture (SM) and leaf area index (LAI) can operate at daily scales. However, their transpiration schemes need to be more physically realistic and their model parameters usually need to be calibrated by flux measurements. In this study, we incorporated a biophysical canopy conductance (Gc) model into a two source energy balance (TSEB) scheme to replace the original Priestly–Taylor (PT) approximation and then optimized both models (Gc-TSEB and PT-TSEB) at pixel scales using qualified MODIS LST data. The results show that using LST is almost as effective in the calibration as using flux measurements. This is promising because unlike flux measurements, LST can be acquired at various spatial resolutions by remote sensing, which makes model calibration feasible for any land pixel. In addition, ET and its partitioning between the canopy and soil layers were found to be reasonable at both validation sites. The day to day and diurnal variations of the predicted ET generally matched the trends and peaks of the flux measurements, although systematic biases were also found due to the decoupling effect of soil moisture at different depths. Furthermore, both models are robust with ±50% changes of SM or LAI because the parameters were automatically adjusted by the LST-calibration. The models are sensitive to LST. However, if the added noise of the LST is less significant than $N(\pm 1, 2.5^2)$, the medians of the RMSEs in the LE predictions from the LST-calibrated models were quite similar to those from the flux-calibrated models. Both models were found to be accurate, but Gc-TSEB provides slightly more precise and robust predictions than PT-TSEB.



## 1. Introduction

Evapotranspiration (ET), which includes evaporation and plant transpiration, is a crucial hydro-meteorological component that influences water availability and energy partitioning at the land surface. More than 60% of the land surface precipitation and over half of the solar radiation that are absorbed by the land surface are consumed by ET on annual time scales (Oki and Kanae, 2006; Trenberth et al., 2009, 2007). Quantifying the spatial variability of ET is important for increasing our understanding of the hydrological cycle, ecology system, and water resource management (McCabe and Wood, 2006).

Remote sensing has long been recognized as the most feasible way to estimate land surface ET (usually expressed as its accompanying energy flux, the latent heat flux, which is denoted as LE) over regional and global scales (Kustas and Norman, 1999; Mu et al., 2011). Diagnostic ET models mainly use remotely sensed land surface temperature (LST), near surface soil moisture or leaf area index (LAI) as key boundary conditions to determine LE through surface energy balance equations.

One such diagnostic model that uses LST, the two source energy balance model ($TSEB_{TR}$) that was developed by Norman et al. (1995), has been widely applied to various landscapes (Colaizzi et al., 2012; French et al., 2005) and has been shown to be superior to other thermal-based models (Gao and Long, 2008; Timmermans et al., 2007). Transpiration is estimated in $TSEB_{TR}$ through the

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Priestly–Taylor (PT) approach (Priestley and Taylor, 1972) with the coefficient ($\alpha_{PT}$), which is initially set to 1.26 and can be adjusted if the calculated soil evaporation is unrealistic. In addition, studies that incorporate canopy conductance ($G_c$) models into TSEB schemes have found that $G_c$ models are useful in modeling instantaneous transpiration under various atmospheric and soil moisture conditions if LST is used as a key constraint (Anderson et al., 2008, 2000; Zhan and Kustas, 2001).

$TSEB_{TR}$ does not require calibration, but the extrapolation of instantaneous LE from $TSEB_{TR}$ to continuous daily series is still not well understood, especially under cloudy conditions. To address this problem, Kustas et al. (2001, 1998, 1999) replaced LST with microwave-derived near surface (0 ∼ 5 cm) soil moisture as a key boundary condition within the TSEB framework (denoted as $TSEB_{SM}$) to estimate daily ET. Soil evaporation is constrained by the near surface soil moisture through two soil texture-dependent coefficients (Sellers et al., 1992). Although the model performance was found to be sensitive to these two coefficients (Li et al., 2006), no study has provided corresponding values of these coefficients for each type of soil texture. In addition, $TSEB_{SM}$ cannot easily adjust $\alpha_{PT}$ (Kustas et al., 2003) to accommodate a range of environmental conditions because LST is not included in the model. Modeling transpiration in a more physically realistic way and calibrating the model parameters are necessary before $TSEB_{SM}$ can be widely applied.

In addition to utilizing LST and soil moisture, many studies have also integrated the remotely sensed LAI into the $G_c$-based Penman–Monteith (PM) approach (Monteith, 1965; Penman, 1948) to estimate daily ET (Cleugh et al., 2007; Mu et al., 2007). Gc-PM models are usually calibrated at pixel scales by eddy covariance (EC) flux measurements (Leuning et al., 2008) or at catchment scales by runoff measurements (Zhang et al., 2008, 2010). In addition, Yan et al. (2012) used a soil water balance sub-model to scale potential ET from a Gc-PM model to actual ET and thus avoided the need for site-specific parameter calibration.

Calibrating ET models that are based on soil moisture or LAI at pixel scales without in-situ measurements is of great practical significance. Several studies have successfully used ET estimated by thermal-based models to calibrate daily-scale models (Liu, 2012; Long and Singh, 2010). However, it is more intriguing to calibrate model parameters at pixel scales using remotely sensed LST without introducing additional errors other than the uncertainty of the LST itself.

In this study, we incorporated the $G_c$ model that was developed by Leuning et al. (2008) into $TSEB_{SM}$ to replace the original PT formulation and evaluated the strength of using the quality-controlled MODIS LST in optimizing resistance networks of the TSEB model (including the Gc version, Gc-TSEB, and the PT version, PT-TSEB). Because LST is an important indicator of the energy balance and thermal state of the land surface, the models are expected to give reasonable energy fluxes when they predict the best LST with the optimized parameters. The calibrated models were used to calculate energy fluxes at a half hourly resolution without remotely sensed LST data. EC flux measurements and predictions from models that were calibrated by flux data were used as references to evaluate the LST-calibrated models at half hour and daytime scales. We also performed sensitivity analyses to test the robustness of both models with ±50% changes of LAI or near surface soil moisture as well as a series of assumed uncertainties of the LST itself.

## 2. Resistance networks of the models

A resistance network links the instantaneous surface state (LST and soil moisture) to the energy fluxes. In this section, we provide a detailed description of the models' resistance networks (Fig. 1),

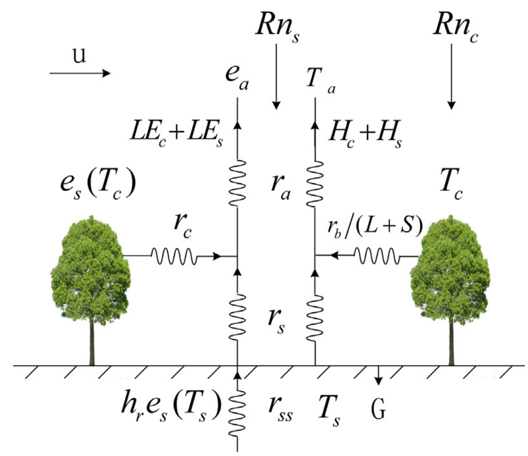


**Fig. 1.** Resistance network of the model.

in which most of the components are adopted from the original TSEB model (Kustas et al., 1998; Norman et al., 1995), and some are updated by recent studies from the literature.

The term $r_a$ ($z_h$) represents the aerodynamic resistance, which is estimated from the wind speed and surface roughness (Li et al., 2005). The canopy conductance ($G_c$) is modeled as a function of the LAI, water vapor deficit ($D_a$), and visible radiation ($Q_h$) (Leuning et al., 2008).

$$G_c = \frac{g_{sx}}{k_Q} \ln\left[\frac{Q_h + Q_{50}}{Q_h \exp(-k_Q LAI) + Q_{50}}\right]\left[\frac{1}{1 + D_a/D_{50}}\right] \quad (1)$$

where $g_{sx}$ is the maximum stomatal conductance, $k_Q$ is the extinction coefficient for shortwave radiation, $Q_{50}$ and $D_{50}$ are the visible radiation and the humidity deficit, respectively, when the stomatal conductance is half of its maximum. $g_{sx}$, $k_Q$, $Q_{50}$, and $D_{50}$ are the parameters to be calibrated. The canopy resistance ($r_c$) is the reciprocal of the canopy conductance.

$$r_c = \frac{1}{G_c} \quad (2)$$

The leaf boundary layer resistance ($r_b$) represents the resistance exerted by leaves on the canopy heat fluxes and is formulated as in the Community Land Model (Oleson et al., 2010).

$$r_b = \frac{20}{\sqrt{u_*}} \quad (3)$$

where $u^*$ is the friction velocity, which represents the surface shear stress. $L$ and $S$ (Fig. 1) are the LAI and stem area index, respectively.

The resistance to sensible and latent heat fluxes between the soil surface and the canopy displacement height (under-canopy resistance, $r_s$) is formulated as in the Community Land Model (Zeng et al., 2005) instead of the original formulation in TSEB.

$$r_s = \frac{1}{(c_s u_*)} \quad (4)$$

where $c_s$ is the turbulent transfer coefficient, which is obtained by the interpolation between the values for the bare soil and dense canopy (Zeng et al., 2005).

$$c_s = c_{s,bare} w_s + c_{s,\,dense}(1 - w_s) \quad (5)$$

$$c_{s,bare} = \frac{k}{a}\left(\frac{z_{0m,g}\ u_*}{\nu}\right)^{-0.45} \quad (6)$$

where $z_{0m,g}$ is the ground momentum roughness length, which is taken as 0.01 m; $\nu = 1.5 \times 10^{-5}\ m^2\ s^{-1}$ is the kinematic viscosity of air, $a = 0.13$, and $c_{s,\,dense}$ is taken as 0.004 (Zeng et al., 2005).