A satellite-based hybrid algorithm to determine the Priestley-Taylor parameter for global terrestrial latent heat flux estimation across multiple biomes

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Abstract

Accurate estimation of the terrestrial latent heat flux (LE) for each plant functional type (PFT) at high spatial and temporal scales remains a major challenge. We developed a satellite-based hybrid algorithm to determine the Priestley-Taylor (PT) parameter for estimating global terrestrial LE across multiple biomes. The hybrid algorithm combines a simple empirical equation with physically based ecophysiological constraints to obtain the sum of the weighted ecophysiological constraints ($f(e)$) from satellite-based Normalized Difference Vegetation Index ($NDVI$) and ground-measured air temperature (T_a), relative humidity (RH), vapor pressure deficit (VPD) and LE for 2000 to 2009 provided by 240 globally distributed *FLUXNET* eddy covariance (*ECOR*) tower sites. Cross-validation analysis indicated that the optimization at a PFT level performed well with a $RMSE$ of less than 0.15 and a R^2 between 0.61 and 0.88 for estimated monthly $f(e)$. Cross-validation analysis also revealed good performance of the hybrid-based PT method in estimating seasonal variability with a $RMSE$ of the monthly LE varying from 4.3W/m^2 (for 6 deciduous needleleaf forest sites) to 18.1W/m^2 (for 34 crop sites) and with a R^2 of more than 0.67. The algorithm's performance was also good for predicting among-site and inter-annual variability with a R^2 of more than 0.78 and 0.70, respectively. We implemented the global terrestrial LE estimation from 2003 to 2005 for a spatial resolution of 0.05° by recalibrating the coefficients of the hybrid algorithm using Modern Era Retrospective Analysis for Research and Applications (*MERRA*) meteorological data, Moderate Resolution Imaging Spectroradiometer (*MODIS*) $NDVI$ product and ground-measured LE . This simple but accurate hybrid algorithm provides an alternative method for mapping global terrestrial LE , with a performance generally improved as compared to other satellite algorithms that are not calibrated with tower. The calibrated $f(e)$ differs for different PFT s, and all driving forces of the algorithm can be acquired from satellite and meteorological observations.

Keywords: Global latent heat flux; Hybrid algorithm; Plant functional type; Priestley-Taylor parameter; Ecophysiological constraints

1. Introduction

Terrestrial latent heat flux (LE), the flux of heat from the Earth's surface to the atmosphere for the processes of water evaporation and vegetation transpiration, is an important component of the Earth's surface energy budget and a key process in land surface-atmosphere interactions (Jung et al., 2010; Liang et al., 2010; Mu et al., 2011; Vinukollu et al., 2011a, 2011b; Wang et al., 2010a, 2010b; Wang & Dickinson, 2012). Accurate detection of spatio-temporal variations of LE with high accuracies at regional or global scales is essential for understanding the global water cycle and carbon uptake through photosynthesis. Since the 1990's, the eddy covariance ($ECOR$) flux measurements provided by *FLUXNET* projects have been considered to be a good micrometeorological method to measure LE exchanges between the atmosphere and terrestrial ecosystems (Baldocchi et al., 2001; Fisher et al., 2008; Liu et al., 2011, 2013; Twine et al., 2000; Yuan et al., 2010). However, it is still difficult to estimate LE at a regional scale because the spatial representation of sparse point LE estimates is questionable due to the complex heterogeneity of terrestrial ecosystems.

Satellite remote sensing has greatly improved global scale estimates of land surface variables (Liang et al., 2012) (*e.g.*, surface solar radiation (R_s), net radiation (R_n), land surface temperature (T_s), leaf area index (LAI), vegetation index (VI), albedo and biome type) that are linked to LE (Los et al., 2000; Mu et al., 2007; Wang et al., 2007). In general, satellite-based LE algorithms integrate satellite and meteorological observations to estimate regional LE for providing spatially distributed LE datasets. During the past few decades, many satellite-based LE algorithms have

been characterized by the parallel development of empirical/statistical algorithms that lack dynamics of evapotranspiration (*ET*) process (Jackson et al., 1977; Jin et al., 2011; Jung et al., 2011; Wang & Liang, 2008; Yang et al., 2006; Yao et al., 2011) and complicated physical models that contain realistic mechanisms (Allen et al., 2007; Anderson et al., 1997; Bastiaanssen et al., 1998; Fisher et al., 2008; Kustas & Norman, 1996; Miralles et al., 2011; Monteith, 1965; Mu et al., 2011; Norman et al., 1995; Priestley & Taylor, 1972; Yao et al., 2013). Therefore, the developmental trend of *LE* algorithms has tended to increased applicability, as opposed to complexity (Federer et al., 1996; Fisher et al., 2008).

Satellite-based empirical/statistical *LE* algorithms have been scaled up from site to regional scales by relating observed *LE* to satellite-based vegetation parameters and other key meteorological variables (Wang et al., 2007). Long-term ground measurements from the Atmospheric Radiation Measurement (*ARM*) and *FLUXNET* projects have provided an opportunity to develop a series of empirical/statistical *LE* algorithms (Wang & Liang, 2008; Wang et al., 2007, 2010a, 2010b). Other data-driven methods, such as model tree ensembles (*MTE*) (Jung et al., 2010), support vector machine (*SVM*) (Yang et al., 2006) and artificial neural network (*ANN*) (Lu & Zhuang, 2010), are also used to build relationships between system inputs (R_n , LAI , VI and T_a) and outputs (*LE*) using training data sets that are representative of all the behaviors found in the systems (Chen et al., 2014). Although these empirical algorithms have a comparable accuracy with other more complicated physical methods (Jiménez et al., 2011; Mueller et al., 2011), they require further recalibration

for different biomes due to their limited training data at certain sites. Much effort has been dedicated to proposing universal empirical LE algorithms that are suitable for multiple biomes, as reviewed in the literature (Kalma et al., 2008; Wang et al., 2007, 2010a, 2010b; Yuan et al., 2010; Zeng et al., 2014). However, the evaporation fraction (EF), the ratio of LE/R_n , differs greatly in different biomes due to physiological differences under similar environmental conditions (Bettes et al., 2007; Margolis & Ryan, 1997). Therefore, there are large errors in the estimated LE from the universal empirical LE algorithms when land cover types are ignored.

Satellite-based physical LE algorithms have been developed to estimate LE based on the Monin-Obukhov Similarity Theory (*MOST*) and the Penman-Monteith (*PM*) equation driven by satellite and meteorological observations (Wang and Dickinson, 2012). The traditional one- and two-source models (Kustas & Daughtry, 1990; Shuttleworth & Wallace, 1985), such as the Surface Energy Balance System (*SEBS*) (Su, 2002), the Surface Energy Balance Algorithm for Land (*SEBAL*) algorithm (Bastiaanssen et al., 1998), the Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (*METRIC*)-Model (Allen et al., 2007) and the Two-Source LE Model coupled with Atmosphere-Land Exchange Inverse (*ALEXI*) model (Anderson et al., 1997; Norman et al., 1995), use surface air temperature gradients ($T_s - T_a$) or time series of satellite-retrieved T_s to obtain sensible heat flux (H) and LE (Tang & Li, 2015). Yet, the use of T_s in the energy residual equation to estimate regional or global terrestrial LE will lead to greater than 50% errors because advection of H from the surrounding landscape influences the

calculation of H and LE at a given time and place (Gowda et al., 2008; Stewart et al., 1994; Zhang et al., 2010a, 2010b). To overcome this problem, Mu et al (2011) revised a beta version (Mu et al., 2007) developed from the Cleugh et al. (2007) version of the PM method to estimate global terrestrial LE . That algorithm considered the differences of surface resistance for different biomes and was updated to generate the Moderate Resolution Imaging Spectroradiometer (*MODIS*) LE product (*MOD16*) driven by *MODIS LAI*, albedo and land cover, and the Modern-Era Retrospective Analysis for Research and Applications (*MERRA*) data provided by the National Aeronautics and Space Administration (*NASA*) Global Modeling and Assimilation Office (*GMAO*) (Mu et al., 2011). However, the sensitivity of these PM algorithms to the parameterization of resistances and error propagation through complicated calculations will lead to lower accuracy compared with other LE algorithms using empirical formulation of the evaporative process (Ershadi et al., 2014; Fisher et al., 2009).

An alternative approach, the Priestley-Taylor (PT) algorithm, is a simplified PM method that avoids parameterizations of aerodynamic and surface resistance without decreasing the accuracy of the LE estimates (Fisher et al., 2008; Jin et al., 2011; Priestley and Taylor, 1972; Yao et al., 2013). The PT algorithm uses a coefficient multiplier (also named the PT parameter, α) to replace the atmospheric demand and surface resistance. In general, α can range from 0 (no water) to 1.26 (wet surface) and varies with soil moisture and plant condition in different regions (Brutsaert & Chen, 1995; Detto et al., 2006; Sumner & Jacobs, 2005). Currently two types of

algorithms have been developed to determine α for regional LE estimation using remote sensing and meteorological observations: (1) T_s - VI triangular methods which use the spatial variation of T_s (or day-night T_s difference, ΔT_s) and normalized difference vegetation index ($NDVI$) to interpolate α and EF for LE estimation (Jiang & Islam, 2001; Price, 1990; Tang et al., 2010; Wang et al., 2006), and (2) ecophysiological constraint methods that use the α of the potential LE to multiply ecophysiological constraints, such as LAI , T_a , soil moisture, and vegetation moisture, to estimate actual LE (Fisher et al., 2008; Jin et al., 2011; Miralles et al., 2011). T_s - VI triangular methods have been widely used to estimate regional LE because they only require T_s and $NDVI$ derived from remote sensing data without any auxiliary data. Yet these methods do not fully consider the impacts of T_s - VI on different land cover types that have different aerodynamic resistance (Carlson, 2007), and thus lack robustness at the global scale. Although the PT algorithms based on ecophysiological constraints (*i.e.*, Fisher et al., 2008) have higher performance when compared to PM methods due to their excellent representation of universal physical governing laws, as well as partitioning of total evaporation, these approaches are applied uniformly across the globe, thus ignoring the differences of ecosystem types to which further calibration and optimization could result in even better estimates (Ershadi et al., 2014; Fisher et al., 2008, 2009; Jin et al., 2011; Miralles et al., 2011; Yao et al., 2013).

In this study, to reduce uncertainties in global LE estimation using the universal empirical LE algorithms or the universal α parameterization of PT algorithms, we developed an optimized hybrid algorithm to determine the PT parameter for global

terrestrial LE estimation across multiple biomes by combining a simple empirical equation with physically based ecophysiological constraints (*i.e.*, $PT-JPL$: Fisher et al., 2008) calibrated to measurements from global eddy covariance, satellite and meteorological observations. The objectives of this study are to (1) describe this satellite-based hybrid algorithm for parameterization of the PT parameter to obtain the sum of the weighted ecophysiological constraints ($f(e)$); (2) evaluate the hybrid-algorithm and the corresponding PT method based on a series of cross-validations across multiple biomes using global long-term $FLUXNET$ measurements from 240 flux tower sites; and (3) revise the coefficients of the hybrid algorithm using $MODIS$ data and $MERRA$ meteorological data for estimating annual global terrestrial LE averaged over the period of 2003 to 2005 with a spatial resolution of 0.05° across multiple biomes.

2. Data

2.1 Data at eddy covariance flux tower sites

Ground-measurements of eddy covariance ($ECOR$) were used to validate and evaluate algorithm performance. Data from 240 $ECOR$ flux tower sites, including those from LathuileFlux, AsiaFlux, AmeriFlux, the Asian Automatic Weather Station Network (ANN) Project supported by the Global Energy and Water Cycle Experiment ($GEWEX$) Asian Monsoon Experiment ($GAME ANN$), the Coordinated Enhanced Observation Network of China ($CEOP$) and some individual principal investigators (PIs) of the $FLUXNET$ project were used in this study. These sites are mainly distributed in North America, Asia and Europe, with only 5 sites in Africa, 5 in

Australia and 7 in South America (Amazon region) (Fig.1). These sites covered 9 major global terrestrial biomes: cropland (*CRO*; 34 sites), savanna (*SAW*; 10 sites), shrubland (*SHR*; 14 sites), evergreen needleleaf forest (*ENF*; 64 sites), evergreen broadleaf forest (*EBF*; 16 sites), deciduous needleleaf forest (*DNF*; 6 sites), deciduous broadleaf forest (*DBF*; 28 sites), and grass and other types (*GRA*; 56 sites). The data include half-hourly or hourly incoming solar radiation (R_s), soil heat flux (G), R_n , T_a , vapor pressure deficit (VPD), relative humidity (RH), H and LE . Gaps in the data were filled using the method described in Reichstein et al. (2005) that utilizes both the co-variation of fluxes with meteorological variables and the temporal autocorrelation of fluxes. The half-hourly or hourly LE , H and meteorological variables were subsequently aggregated into daily and monthly means. If missing data was more than 25% of entire data at a given day, the value of this day was indicated as missing. Otherwise daily values were obtained by multiplying averaged hourly rate by 24 (hours). Similarly, monthly values were obtained by multiplying averaged daily rate by 30 or 31 (days). When missing data was more than 25% of entire month data, the monthly values were also indicated as missing. The data cover the period from 2000 through 2009, and each flux tower has at least one year's worth of data.

Because the *ECOR* method suffers an energy imbalance problem, where the measured available energy ($R_n - G$) is greater than the sum of the measured LE and H (Foken, 2008; Jung et al., 2010; Wilson et al., 2002), we corrected the measured LE based on the fixed Bowen ratio method proposed by Twine et al. (2000):

$$LE_c = \frac{LE_o}{R_c} \quad (1)$$

$$R_c = \frac{LE_o + H_o}{R_n - G} \quad (2)$$

where LE_c is the corrected latent heat flux, LE_o and H_o are the uncorrected latent heat flux and sensible heat flux, respectively. R_c is the energy closure ratio.

Fig. 1 HERE

2.2 Satellite and reanalysis datasets

To develop and revise this satellite-based hybrid algorithm for global terrestrial LE estimation, in this study we used a *MODIS* global 16-day *NDVI* product (*MOD13A2*) with a 1-km spatial resolution, which was downloaded from the Oak Ridge National Laboratory Distributed Active Center (*ORNL DAAC*) website (<http://daac.ornl.gov/MODIS/>). The daily *NDVI* values were temporally interpolated from the 16-day averages using linear interpolation. We only used the *NDVI* values of pixels that covered the flux tower sites and used the quality control (*QC*) flags to exclude the poor quality, cloud contaminated *NDVI*. We also used *MERRA* reanalysis meteorological data (R_n , T_a , RH and VPD) with spatial resolution of $1/2^\circ \times 2/3^\circ$ provided by the *NASA GMAO* (Global Modeling and Assimilation Office, 2004). Detailed information on the *MERRA* dataset can be downloaded from the website (<http://gmao.gsfc.nasa.gov/research/merra>). The *MERRA* data were spatially interpolated to 1km using the method described in Zhao et al. (2005) that exploits a cosine function and the four *GMAO-MERRA* cells to smooth sharp changes in a pixel.

To estimate global terrestrial LE at a spatial resolution of 0.05 degree from 2003 to 2005, we also used the method described in Zhao et al. (2005) to interpolate the *MERRA* data to 0.05 degrees. We also used the Collection 5 *MODIS NDVI*

(*MOD13C1: CMG*, 0.05°) product (Huete et al., 2002) and Collection 4 *MODIS* land cover (*MOD12C1: CMG*, 0.05°) product (Friedl et al., 2002) to drive the hybrid algorithm for global *LE* estimation across multiple biomes. We filled in the missing and unreliable *NDVI* at 0.05-degree spatial resolution using the method described by Zhao et al. (2005).

3. Methods

3.1 Hybrid algorithm-based Priestley-Taylor model logic

We developed an algorithm from the *PT* model of (Fisher et al., 2008; Priestley & Taylor, 1972):

$$LE = \phi \frac{\Delta}{\Delta + \gamma} f(e)(R_n - G) \quad (3)$$

where *LE* is the latent heat flux in W/m², ϕ is the *PT* coefficient for a wet surface condition (1.26) and represents the maximum value of α , Δ is the slope of the saturated vapor pressure curve (KPa °C⁻¹), γ is the psychrometric constant (KPa °C⁻¹), R_n and G are the surface net radiation and soil heat flux in W/m², respectively, and $f(e)$ is the sum of the weighted ecophysiological constraints to determine the *PT* parameter by multiplying ϕ , which can be calculated using atmospheric moisture and vegetation indices (Fisher et al., 2008; Yao et al., 2013). The value of $f(e)$ varies from 0 to 1. Accurate parameterization of $f(e)$ is a tough problem because it is difficult to characterize the dynamics of the *ET* process based on the limited data. Considering that energy, water and temperature are the three key potential constraints that drive soil evaporation and vegetation transpiration and that the *PT* model includes an energy term ($R_n - G$), we introduce a simple empirical linear combination of air

temperature and physical-based water parameters to estimate $f(e)$.

$$f(e) = a_0 + a_1 f(T_a) + a_2 f(m) \quad (4)$$

$$f(m) = b_0 + b_1 f(em) + b_2 f(tm) + b_3 f(ws) + b_4 f(im) \quad (5)$$

where a_i ($i=0, \dots, 2$) and b_i ($i=0, \dots, 4$) are empirical coefficients, $f(T_a)$ is the temperature constraint, and $f(m)$ is the moisture constraint, which can be considered to be a linear equation of unsaturated soil moisture constraint $f(em)$, vegetation transpiration moisture constraint $f(tm)$, saturated soil moisture constraint $f(ws)$ and canopy interception moisture constraint $f(im)$. In our *PT* algorithm, both $f(ws)$ and $f(im)$ represent the maximum *LE* with sufficient water conditions, namely,

$$f(ws) = 1 \quad (6)$$

$$f(im) = 1 \quad (7)$$

$f(T_a)$ for both surface soil and vegetation follows the empirical equation detailed by Wang et al. (2007):

$$f(T_a) = c_0 + c_1 T_a \quad (8)$$

where c_i ($i=0,1$) is the empirical coefficient. $f(em)$ is mainly controlled by soil moisture. In our algorithm, we chose RH^{VPD} as introduced by Fisher et al. (2008) to parameterize $f(em)$ based on the complementary hypothesis that surface moisture status is linked to the evaporative demand (*ED*) of the atmosphere, indicating that soil moisture is characterized by the adjacent atmospheric moisture (Bouchet, 1963; Fisher et al., 2008). Thus, $f(em)$ can be expressed as:

$$f(em) = d_0 + d_1 RH^{VPD} \quad (9)$$

where d_i ($i=0, 1$) is the empirical coefficient. $f(tm)$ is closely related to vegetation canopy conductance (g_s). According to previous studies, g_s mainly depends on photosynthetic leaf area, plant moisture, T_a and VPD (Jarvis 1976; Mu et al., 2007, 2011; Wang & Dickinson, 2012). In our algorithm, we used satellite-based $NDVI$ and VPD to parameterize $f(tm)$, because $NDVI$, which has no model-related errors, is sensitive to LAI , and $(e_1NDVI - e_2)VPD$ is used to reduce the maximum g_s when VPD is high enough to inhibit photosynthesis (Leuning, 1995; Misson et al., 2004; Mu et al., 2007; Xu & Baldocchi, 2003; Wang et al., 2010a, 2010b), such that:

$$f(tm) = e_0 + (e_1NDVI - e_2)VPD \quad (10)$$

where e_i ($i=0, \dots, 2$) is the empirical coefficient. Eq.(10) shows that $f(tm)$ is diagnosed by the $NDVI$ and VPD terms, and the temperature terms are directly included in $f(e)$. Combining Eqs. (3)-(10), we simplify these empirical coefficients and obtain the hybrid algorithm-based PT equation:

$$LE = \phi \frac{\Delta}{\Delta + \gamma} (R_n - G) [k_0 + k_1T_a + k_2RH^{VPD} + (k_3NDVI - k_4)VPD] \quad (11)$$

k_i ($i=0, \dots, 4$) are the empirical coefficient. For simplicity, we assumed that $f(sm) = RH^{VPD}$ and $f(vm) = (k_3NDVI - k_4)VPD$. We also estimated G based on a simple statistical method driven by fractional vegetation cover (f_c) and R_n (Halliwell & Rouse, 1987; Rouse, 1984; Yao et al., 2013; Zhang et al., 2009):

$$G = a_g(1 - f_c)R_n \quad (12)$$

$$f_c = \frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}} \quad (13)$$

where a_g is a constant (0.18). $NDVI_{\max}$ and $NDVI_{\min}$ are the maximum and minimum $NDVI$ during the study period and are set as invariant constants: 0.95 and 0.05, respectively (Tucker, 1979; Zhang et al., 2009). f_c will be replaced by one of the satellite products that are based on more sophisticated estimation algorithms (Liang, et al., 2012; Jia et al., 2014).

Advantages offered by the hybrid algorithm-based PT method over other complicated physical LE models are that 1) it is easy to operate for routine, long-term mapping of LE because it only requires R_n , T_a , $NDVI$, RH and VPD and avoids wind speed (WS) and soil moisture. Reliable soil moisture and WS measurements that are required to parameterize LE in many algorithms are unavailable at large scales (Gao & Dirmeyer, 2006; McVicar et al., 2012; Wagner et al., 2003); 2) it reduces the errors in the required forcing data by avoiding the use of the temperature or humidity differences and by overcoming use of the computational complexities of aerodynamic and surface resistance (Wang & Dickinson, 2012); and 3) it considers the differences in the coefficients of the Eq. (11) for different $PFTs$ to improve the accuracy of LE estimation.

3.2 Cross validation

The parameters of the Eq. (11) were calibrated by linear regression using the observed data (EC ground-measured data and $MODIS$ $NDVI$ product) collected from a sufficient number of representative flux towers. To validate the estimated $f(e)$ and LE accuracy, we evaluated the performance of the satellite-based hybrid algorithm and the corresponding PT model using a five-fold cross validations method, which

randomly stratified the data set into five groups with approximately equal numbers of samples (Jung et al., 2011). We independently validated the estimated LE for each of the five groups based on the calibrated coefficients of Eq.(11), using data from the remaining four groups. We performed the optimizations for the parameters in Eq. (11) for each PFT . The optimization is based on the least square method to minimize the difference between the estimated $f(e)$ using satellite and meteorological forcing data and the observed $f(e)$ inverted from Eq. (3) using ground-observed LE , T_a , R_n and G from flux tower sites. We also summarized the squared correlation coefficients (R^2), root mean square error ($RMSE$), bias and p values of the estimated $f(e)$ and LE and those derived from the flux tower data to demonstrate the relative predictive errors.

To evaluate the ability of our method to predict the spatio-temporal variations in LE , we used the observed and estimated data to test three categories of LE variability: (1) seasonal variation, (2) among-site variation, and (3) annual anomalies. We first performed a series of cross-validations of LE seasonal cycle by comparing the daily (monthly) estimated LE and the observed LE . To test the among-site variation, we validated the average values of the measured and predicted LE at each site over the entire period. To assess how well the model predicts long-term variations in LE , we averaged the measured and predicted LE into annual values at each site and removed the multiyear average from the annual values to acquire annual LE anomaly for each site. We chose flux tower sites that had at least three years' worth of data.

For comparison with LE estimates based on the other algorithms, we used a

simple holdout method that randomly divided the data set into two groups with approximately equal numbers of samples (Yao et al., 2014a). We validated daily *LE* using data from the first group based on the calibrated coefficients of Eq.(11) using data from the second group and we then validated daily *LE* using data from the second group based on the calibrated coefficients of Eq.(11) using data from the first group.

3.3 Comparison with other LE algorithms

3.3.1 MOD16 LE algorithm

A *MOD16* global *LE* retrieval algorithm is based on the well-established Penman-Monteith logic (Monteith, 1965) with modifications to account for parameters not readily available from space (Cleugh et al., 2007). The *MOD16* algorithm accounts for both surface energy partitioning and environmental constraints on *ET*, and includes canopy interception evaporation, evaporation from wet/moist soil surfaces, and transpiration through vegetation pores (stomata). Atmospheric relative humidity (*RH*) is used to quantify the proportion of wet soil and wet canopy components (Fisher et al., 2008). Proportional vegetation cover is derived from *MODIS* fractional absorbed photosynthetically active radiation (*FPAR*) (Los et al., 2000), and used to partition net radiation (R_n) between vegetation and soil surfaces. Leaf level stomatal conductance is determined by the mean daytime surface air vapor pressure deficit (*VPD*) and daily minimum air temperature (T_{min}), and further up-scaled to the non-wet canopy level using the *MODIS* leaf area index (*LAI*) product (*MOD15A2*). Using the complementary relationship hypothesis (Fisher et al., 2008), soil evaporation is estimated as the potential evaporation rate for wet soil surfaces

scaled down by RH and VPD for moist soil conditions. The daily LE calculation represents the 24 hour sum of LE from the daytime and nighttime (largely minimal) calculations. *MOD16* LE algorithm was validated at 46 flux tower sites and agreed with the LE measurements well (Mu et al., 2011). Considering that most LE occurs during daytime, our proposed PT algorithm in this study only estimated daytime LE and neglected nighttime LE . Therefore, we only used *MOD16* algorithm to estimate daytime LE .

3.3.2 PT-JPL LE algorithm

A Priestley-Taylor-based (*PT-JPL*) LE algorithm was introduced by Fisher et al. (2008), based on the PT equation to downscale potential LE to actual LE by adding both atmospheric (RH and VPD) and ecophysiological constraints ($FPAR$ and LAI). *PT-JPL* estimates LE by calculating the sum of the soil evaporation, the canopy transpiration and the canopy interception evaporation. The validation at the 39 global flux tower sites illustrates that the averaged $RMSE$ of the estimated and observed LE is 15.2 W/m^2 with an R^2 of 0.9 (Fisher et al., 2008, 2009). *PT-JPL* has been independently demonstrated as the highest performing physically based global remote sensing LE algorithm in multi-algorithm intercomparisons (Chen et al., 2014; Ershadi et al., 2014; Vinukollu et al., 2011).

4. Results

4.1 Optimization of the PT parameter

To parameterize the PT parameter, we used $f(e)$ to replace the original PT parameter because $f(e)$ is a suitable ecophysiological index for the temporal scaling.

To determine the factors that drive the variation of $f(e)$, we analyzed the variations of the combined variables from ground-measured T_a , RH , VPD and *MODIS NDVI* from all of the flux tower sites. Fig. 2 gives an example of the temporal variation of the 8-day $f(e)$ estimated directly from observations during January 2002-December 2006 at the Au-How site using Eq. (3) together with T_a , $f(sm)$ and $f(vm)$. Both $f(sm)$ and $f(vm)$ have an obvious seasonal pattern in this savanna that was similar to $f(e)$ and have high correlations with $f(e)$ at all of the flux tower sites. Although the variation of T_a also follows that of $f(e)$, T_a has a relatively lower correlation with $f(e)$ at all of the flux tower sites because $\Delta/(\Delta + \gamma)$ directly included T_a . Therefore, soil moisture and vegetation moisture were the largest contributors to the variations in $f(e)$.

Fig.2 HERE

Figs 3 and 4 show the correlations of monthly observed $f(e)$ directly inverted from observations using Eq. (3) with monthly $f(sm)$ and $f(vm)$ for different biomes, respectively. Generally speaking, variations in monthly $f(sm)$ explained 25% to 82% of the variance in monthly $f(e)$ at all sites. The correlation coefficients between $f(e)$ and $f(sm)$ vary from 0.56 ($p < 0.01$) at all *MF* sites to 0.87 ($p < 0.01$) at all *SAW* sites. The correlations between $f(e)$ and $f(sm)$ in both all *GRA* and *SAW* sites are higher than 0.78 ($p < 0.01$), yet $f(sm)$ was not always the best predictor of $f(e)$ in the *CRO* and forest (excluding *EBF*) ecosystems. Therefore, $f(sm)$ captures the variations in surface soil evaporation for different *PFTs* because surface soil moisture can sustain the transpiration of sparse vegetation (e.g., grass and savanna) and cannot

provide supply water for the transpiration of dense vegetation (*e.g.*, forests). As expected, $f(vm)$ also explains much of the variance of $f(e)$ in most obvious seasonal biomes, and $f(vm)$ is highly correlated with $f(e)$ for deciduous forests, shrub, crop and grass sites. For instance, the correlation coefficient between $f(vm)$ and $f(e)$ is 0.89 ($p<0.01$) at all *DNF* sites and 0.78 ($p<0.01$) at all *SHR* sites. Thus, $f(vm)$ characterizes the vegetation transpiration across multiple biomes by a combination of *NDVI* and *VPD* because *NDVI* is used to monitor the seasonal variation of vegetation growth and *VPD* reflects the negative effects of vegetation photosynthesis.

Fig. 3 HERE

Fig. 4 HERE

Table 1 shows the parameters of Eq. (11) for nine different biomes by linear regression based on the satellite-based *NDVI*, ground-measured T_a , *RH*, *VPD* and $f(e)$. Our proposed hybrid algorithm yields different values of $f(e)$ for each PFT. For example, in July, *GRA* and *CRO* had the largest estimated $f(e)$ (approximately 0.85), followed by *DNF*, *DBF*, *SAW*, *EBF*, *SHR*, while *ENF* and *MF* had the minimum $f(e)$. $f(vm)$ by integrating *NDVI* and *VPD* is highly correlated to *LE* in all biomes and $f(e)$ increased as a function of $f(vm)$ with vegetation growth. $f(sm)$ affected $f(e)$ significantly for non-forests, and *LE* for forests was not dependent on surface moisture.

Table 1 HERE

The sensitivity experiments used to determine the dependence of $f(e)$ on T_a , *RH*

and $NDVI$ are shown in Fig. 5. The $f(e)$ at different biomes vary by less than 0.3 with the increasing T_a from 5 to 30°C when other input variables are set as constants ($RH=0.7$; $NDVI=0.7$). In response to the same changes in T_a , the estimated $f(e)$ at the DNF sites varies the most compared with those at other biomes sites. Similarly, the estimated $f(e)$ varies by less than 0.5 for a 0.8 change in RH and $NDVI$ at most PFT sites. However, at MF sites, $f(e)$ increase by more than 0.5 for a 0.8 increase in RH and $NDVI$. Therefore, both RH and $NDVI$ have a significant influence on $f(e)$, and $f(e)$ is less sensitive to the error in T_a but cannot be neglected.

Fig. 5 HERE

4.2 Algorithm evaluation

4.2.1 Algorithm performance based on cross validation

We performed a series of cross validations to evaluate the performance of our satellite-based algorithm for monthly $f(e)$ at different $PFTs$. Fig. 6 shows the comparison of estimated and observed monthly $f(e)$ at nine biomes. It is clear that the performance varies with the biomes and criteria (bias, $RMSE$ and R^2). The $RMSE$ between estimated $f(e)$ and observed $f(e)$ are all less than 0.15, and the R^2 ranges from 0.61 to 0.88 (99% confidence). The hybrid algorithm has the highest performance, with an $RMSE$ of 0.07 and an R^2 of 0.86 ($p<0.01$) at the DNF sites, followed by at SAW , SHR , GRA , DBF , EBF , MF and CRO sites. However, the worst performances, with an R^2 of 0.55 ($p<0.01$), occur at the ENF sites. In general, the few samples at the DNF sites led to the relative higher accuracy of $f(e)$ estimation. Perhaps when there are equal numbers of samples at the different biomes, the

algorithm will have lower accuracy of $f(e)$ at dense forests sites due to the saturation effect of *NDVI*. We consider the overall performance of our algorithm at different *PFTs* is satisfying for estimating the *PT* parameter.

Fig.6 HERE

Estimated *LE* based on our *PT* model driven by tower-specific meteorology and *MODIS NDVI* product was also cross-validated. A comparison of the measured and estimated daily (monthly) *LE* at the site scale for each *PFT* demonstrates that our *PT* algorithm accurately estimates seasonal *LE* (Fig. 7). At the *PFT* level, the *RMSE* of the estimated monthly (daily) *LE* varies from 4.3 (11.5) W/m^2 for all *DNF* sites to 18.1 (20.9) W/m^2 for all *CRO* sites and the R^2 (99% confidence) varies from 0.80 (0.68) for all *SHR* sites to 0.96 (0.87) for all *DNF* sites. The seasonal variation of *LE* is the most robust feature using both daily and monthly *ECOR* data. In Fig.7 we can also observe a good ability of our *PT* algorithm to estimate the among-site variability, where the R^2 of the site-averaged estimated versus observed *LE* ranges from 0.78 ($p<0.01$) for all *GRA* sites to 0.96 ($p<0.01$) for all *DNF* sites and the *RMSE* varies from 2.1 W/m^2 for all *SHR* sites to 9.5 W/m^2 for all *SAW* sites. Overall, the estimated *LE* based on our algorithm displays a high accuracy according to the validation of seasonal and spatial variation in *LE*. Clearly, our algorithm is also satisfactory in reproducing the inter-annual variability at the site scale for each *PFT* with at least 3 years of data (Fig. 7). The R^2 between the measured and estimated annual *LE* anomaly is significantly below the confidence level of $p<0.05$ and is between 0.71 for all *ENF* sites and 0.94 for all *DNF* sites. The lowest *RMSE* is 2.1 W/m^2 at all *DNF* sites due to

the few samples, while the largest $RMSE$ is 5.8W/m^2 at all *EBF* sites due to the missing observed LE data caused by bad weather conditions in tropical ecosystems (Falge et al., 2001).

Fig. 7 HERE

4.2.2 Comparison with other LE algorithms

Because point-based validation with ground observation is typically a good method to evaluate algorithm performance (Vinukollu et al., 2011a; 2011b), the estimated daily LE at site scale using our *PT* algorithm were compared with those for the *MOD16* algorithm and the *PT-JPL* algorithm for each *PFT*. Table 2 shows the results of comparisons between the estimated LE using the three algorithms versus daily ground-observations from the first group using the second group data to calibrate the coefficients of our *PT* algorithm. For *CRO* and *GRA* sites, the average $RMSE$ of the estimated LE using our algorithm is less than 22W/m^2 , and the average R^2 is more than 0.75 ($p<0.01$), which show better performance than the *MOD16* algorithm and the *PT-JPL* algorithm. For all forests sites, the average $RMSE$ of the estimated LE using our *PT* algorithm is less than 24W/m^2 and is lower than for the *MOD16* algorithm and the *PT-JPL* algorithm together with slightly higher R^2 at the 99% level of confidence. For the *SHR* and *SAW* sites, the average $RMSE$ of the estimated LE using our *PT* algorithm is much lower and the average R^2 is more than 0.62 (95% confidence) when compared with the other two algorithms. Overall, the average $RMSE$ for our *PT* algorithm decreased by approximately 5W/m^2 for forests and *SHR* sites, and approximately 3W/m^2 for *CRO* and *SAW* sites, and approximately

2W/m² for *GRA* sites. The average R^2 increases by approximately 0.1 ($p<0.05$) at *SAW* and *CRO* sites and, by approximately 0.06 ($p<0.05$) at most forest, *SHR* and *GRA* sites. This improvement over *MOD16* and *PT-JPL* is expected given our calibration to *ECOR* data, with which we also used for validation.

Table 2 HERE

Table 3 HERE

Fig. 8 shows a time series for 8-day average *LE* measurements and tower-driven predictions for *PFTs*. In comparison to the *MOD16* algorithm and the *PT-JPL* algorithm, in this study our *PT* algorithm yielded seasonal *LE* variations that are closest to the ground-measured values. Table 3 presents the statistics of the comparisons of the three *LE* algorithms from the second group, using the first group data to calibrate the coefficients of our algorithm, and we draw the similar conclusion that our proposed *LE* algorithm presents better performance for quantifying the turbulent heat fluxes than that of the *MOD16* algorithm and the *PT-JPL* algorithm. Therefore, our *PT* algorithm is among those algorithms that provide a better fit to flux tower observations.

Fig. 8 HERE

4.3 Global implementation of the terrestrial LE estimation based on MERRA data

Based on Eq. (11) parameterized by the coefficients listed in Table 1, we estimated global terrestrial *LE* during 2000-2009 with a spatial resolution of 0.05° using *MERRA* meteorological data and *MODIS* products. Unfortunately, we found

that our *PT* algorithm tends to underestimate *LE* using *MERRA* data when compared to ground-measured *LE* due to the underestimated R_n from *MERRA* data (Fig. 9). To improve the accuracy of the estimated *LE* driven by *MERRA* data, we recalibrated the coefficients of Eq. (11) using the *MERRA* meteorological data, *MODIS* products and ground-measured *LE* collected at global-distributed flux tower sites. Table 4 lists the parameters of Eq. (11) for nine different biomes by linear regression based on the *MODIS*-derived *NDVI*, ground-measured $f(e)$, *MERRA*-derived T_a , *RH* and *VPD*. Cross-validations show that when using *MERRA* data as a substitute for tower-specific meteorology, our revised *PT* algorithm driven by *MERRA* data produced higher predictive errors at most flux towers due to the large errors of *MERRA* meteorological data. The average *RMSE* of the daily *LE* increased from 18.2W/m^2 using the original algorithm driven by specific-tower meteorology to 20.6W/m^2 using the revised algorithm driven by *MERRA* data (Fig. 10). The coefficient of determination (R^2) between the daily *LE* estimates and observations decreased from 0.84 using the original algorithm to 0.70 using the revised version. Predicted relative errors of *LE* for *MERRA*-based revised algorithm compared to the original version also slightly increased by 4% for validating among-sites variability and annual *LE* anomalies. Wang et al. (2010a) suggested that the relative error of the required *LE* simulation for analyzing spatiotemporal variation is typically less than 14% and the accuracy of our revised algorithm driven by *MERRA* data meets this requirement.

Table 4 HERE

Fig. 9 HERE

Fig.10 HERE

We evaluated the global spatial patterns of $f(e)$ and LE averaged from 2003 through 2005 using monthly *MERRA* gridded data. Tropical rainfall forests in the Amazon regions of South America, Congo basins of Africa and the Southeast Asia and European monsoonal temperate regions had the highest annual $f(e)$. Arid regions and the Arctic had the lowest annual $f(e)$ due to the contribution of low soil moisture and vegetation cover to decreasing LE . Global annual $f(e)$ varies from 0.22 in barren lands, 0.42 in *SHR*, 0.51 in *GRA*, 0.65 in *CRO*, 0.66 in *DBF*, to 0.73 in *EBF* (Fig.11).

Global annual LE is 41.7 W/m^2 over vegetated regions. The highest annual LE is found in the equatorial tropics and monsoonal subtropical regions due to the sufficient soil moisture and higher vegetation cover. Small LE occurs in cold and dry environments due to the lower temperature and precipitation. *EBF* has the largest average LE (90.9 W/m^2), followed by *SAW* (70.3 W/m^2), *DBF* (61.2 W/m^2), *CRO* (46.2 W/m^2), *MF* (37.3 W/m^2), *GRA* (31.9 W/m^2), *ENF* (27.5 W/m^2), *SHR* (19.6 W/m^2) and *DNF* (18.8 W/m^2) (Fig.12).

Fig. 11 HERE

Fig. 12 HERE

5. Discussion

5.1 Ecophysiological hypothesis for optimization of the PT parameter

The basis of *PT* models is the hypothesis that the energy terms coupled with the

ecophysiological constraints are the main controller of LE and determine the partition of the sensible and latent heat flux (Jarvis & Mcnaughton, 1986; Priestley & Taylor, 1972). In the satellite-based PT algorithms, ecophysiological constraints are recognized as the core regulators for downscaling potential LE to actual LE . For unsaturated soil and vegetation surfaces where there is limited supply of soil moisture, ecophysiological constraints and LE are affected significantly by available water and canopy structures (Baldocchi & Xu, 2007; Davies & Allen, 1973; Jin et al., 2011; Komatsu, 2003). $f(e)$ used in this study includes the variables ($f(sm)$ and $f(vm)$) for characterizing available water and vegetation information, all of which can be fully acquired from satellite data.

Several studies have suggested using satellite-derived soil moisture with a high spatial heterogeneity to parameterize the soil moisture constraint for estimating soil evaporation (Gokmen et al., 2012; Jin et al., 2012; Miralles et al., 2011). However, satellite-derived soil moisture only considers surface soil moisture from approximately the top 2-5 cm of the soil profile and neglects the moisture deeper within the soil profile (Anderson et al., 2007; Jarvis et al., 1976). In general, soil evaporation stems from the contributions of soil moisture from all of the different layers of the soil profile. In theory, by combining RH and VPD , $f(sm)$ used in this study couples the entire atmosphere boundary layer and soil evaporation to characterize the atmospheric evaporative demand and hydrological effects on soil moisture diffusion through different soil layers, even though $f(sm)$ may not explicitly represent the soil water deficit on daily scales when convection is frequent and strong

due to strong vertical mixing (Fisher et al., 2008; Salvucci & Gentine, 2013). Previous studies have used $f(sm)$ to calculate soil water deficit and neglected their differences in different biomes (Fisher et al., 2008; Mu et al., 2011). However, our algorithm accounts for their differences using $f(sm)$ multiplied with different coefficients. *VPD*-based algorithm maintains a physically realistic representation of soil evaporation and is operational to replace soil moisture-based methods, especially when soil moisture is not available.

In this study, the nonlinear algorithm of $f(vm)$, defined as a function of *NDVI* and *VPD*, represents an improvement for optimizing *PT* parameter because it expresses the canopy-level transpiration rate by coupling vegetation water supply with atmospheric evaporative demand. The decrease of *NDVI* and *LAI* respond to the rise in vegetation water stress and stomatal closure by altering their leaf density to adapt to the changing environment (Field et al., 1995; Gokmen et al., 2012). *NDVI* was chosen to substitute *LAI* because *LAI* will overestimate vegetation canopy conductance when *LAI* is higher than 3 (Glenn et al., 2007; Suyker & Verma, 2008). The $(e_1NDVI - e_2)VPD$ term considers the effect of causing $f(e)$ for different biomes to level off in tropic regions with low *VPD* and highly saturated *NDVI* values. Although $f(e)$ or *EF* are more linearly related to *NDVI* (Choudhury et al., 1994; Wang et al., 2007), our satellite-based hybrid algorithm to determine the *PT* parameter yields comparable results.

5.2 Algorithm performance analysis

Algorithm calibration and validation at 240 globally distributed *ECOR* flux

tower sites illustrates that the satellite-based hybrid algorithm for estimating $f(e)$ and LE was reliable and robust across multiple biomes and different climate regions. Fig.6 and Fig.7 demonstrate that the satellite-based hybrid algorithm yielded small errors of $f(e)$ and LE across multiple biomes based on the cross-validations. However, the hybrid algorithm still has relatively low R^2 and large $RMSEs$ for the estimated $f(e)$ and LE compared to ground-measured data at some irrigated crop sites. This suggests that irrigation and fertilization practices, and in general differences among crop types, may be more critical than canopy structure in determining PT model performance (Zhang et al., 2012). When excluding the observations of these irrigated crop sites, the hybrid algorithm performance greatly improved.

Under the same meteorological and ecological conditions, the hybrid algorithm and PT model had large inter-biome differences for predictive $f(e)$ and LE . For instance, the hybrid algorithm yielded the high $f(e)$ values (more than 0.75 under ideal conditions) and explained more than 80% of the $f(e)$ variability for GRA , non-irrigated crop, DNF and DBF sites (Fig.13). Many studies have demonstrated that these $PFTs$ present strong seasonal changes in vegetation leaf, chlorophyll content and red reflectance (Mu et al., 2007; Yebra et al., 2013; Yan et al., 2012; Yao et al., 2014a, 2014b). Satellite-based $NDVI$ responds strongly to variations in red reflectance, chlorophyll and LAI variations as vegetation leaf dries in many vegetation species. Our hybrid algorithm captures this seasonal cycle of vegetation to improve the accuracy of estimating $f(e)$ and LE by using $NDVI$ to parameterize $f(v_m)$. In contrast, the hybrid algorithm yielded the poor performances for $f(e)$ ($RMSE \geq 0.09$, $R^2 < 0.65$)

and LE ($RMSE \geq 17.5 \text{ W/m}^2$ and $R^2 < 0.80$) estimates for site-specific meteorology inputs for ENF and EBF sites. For tall ENF and EBF regions, vegetation seasonal variations are less evident, and $NDVI$ saturates and is contaminated by clouds, which reduces the ability of $f(e)$ to reliably capture satellite signals of vegetation transpiration (Huete et al., 2002). This hypothesis is supported by the previous study of Eugster et al. (2000), which reported that evergreen conifer forests have a canopy conductance that is half that of deciduous forests, which is consistent with our finding that our hybrid method yielded the lowest $f(e)$ for evergreen forests under the same meteorological and eco-physiological conditions (Fig. 13). Direct evidence of this interpretation is that the availability of $f(sm)$ to resolve changes in $f(e)$ and LE in this land functional type is limited, with an R^2 of 0.34 ($p < 0.05$) due to the lower bare soil exposure ratio caused by greater overlapping of leaves of different species competing for sunlight (Eugster et al., 2000).

Fig.13 HERE

A typical difference between our PT algorithm and other two algorithms ($PT-JPL$ and $MOD16$) is that our algorithm combines ground-observations and physically based ecophysiological constraints to parameterize $f(e)$ for each PFT . Although our algorithm uses a relatively simple and largely empirical equation of the LE process, it has lower uncertainties in the required forcing data and illustrates the improved performance compared to other two algorithms. Moreover, a resistance-based PM algorithm is not accurate to calculate canopy resistance in diverse vegetation, and the structure of the $PT-JPL$ algorithm by design ignores

classifications among *PFTs* (Ershadi et al., 2014; Fisher et al., 2009).

The accuracy of our algorithm is highly dependent on the accuracy of the *ECOR* *LE* ground-measurements, algorithm inputs errors (including *PFT* classification map), spatial scale mismatches among different datasets and algorithm inherent limitations. Although *ECOR* measurements are relatively accurate, they have an error of approximately 5-20% (Foken, 2008; Glenn et al., 2008) and the gap filling from days to months also leads to 5% errors for annual values of *LE* (Hui et al., 2004). Additionally, *ECOR* measurements have an energy imbalance problem, with $H+LE < R_n - G$ (Wilson et al., 2002), and the annual mean energy balance closure at more than 200 *FLUXNET* sites was approximately 0.8 (Beer et al., 2010). Although several reasons for this energy closure problem have been documented by a substantial body of literature (Foken, 2008; Twine et al., 2000; Wang and Dickinson, 2012) and we corrected it in this study, the errors produced by the correction and measurements are still unclear (Shuttleworth, 2007). Moreover, the biases of other ground-measured meteorological variables (*e.g.*, T_a , RH) also introduced point-based $f(e)$ and *LE* estimation errors. When global terrestrial *LE* was calculated, driven by the *MERRA* reanalysis dataset, the biases of the *MERRA* data influenced the accuracy of our algorithm, even though we performed a recalibrated using Eq (11). Recent studies have revealed substantial errors for *MERRA* data when compared to ground measurements (Zhao et al., 2006; Rienecker., 2011). In this study, we also found that *MERRA* data usually underestimated R_n at high values compared to the ground-measurements (Fig. 9). Our algorithm show significant differences in *LE*

estimation if the classification shifts or is wrong. Previous studies revealed that the accuracy of the *IGBP* layer of the *MODIS* Collection 5 Land Cover Type product (*MCD12Q1*) is estimated to be 74.8% globally (Bartholome and Belward, 2005; Friedl, et al. 2002; Hansen, et al. 2000). Thus, misclassification of the *MODIS* land cover product will also lead to the use of incorrect parameters in Eq.(11), resulting in less accurate *LE* estimates.

Typically, the footprints of the *ECOR* measurements are approximately several hundred meters (Baldocchi, 2008), and the resolutions of both *MODIS NDVI* (1km and 0.05 degree) and *MERRA* gridded data (1/2*2/3 degree) are greater than the footprints of the *ECOR* measurements (Rienecker., 2011). The *MODIS NDVI* and *MERRA* gridded meteorological data may not adequately capture vegetation and eco-physiological signals at the flux tower sites (Mu et al., 2011; Zhang et al., 2010a). Inaccurate representations of the field measurement footprint may result in algorithm errors for many flux tower sites. The structure of our algorithm will also reduce the accuracy of *LE* estimates because it ignores the effects of CO_2 and *WS*. High- CO_2 -induced partial stomatal closure causes an underestimation of daily *LE* when *NDVI* tends to increase (Idso and Brazel, 1984; Yao et al., 2013). Our algorithm excludes *WS* because *WS* is not globally observable. By quantifying the sensitivity of wind speed to evaporative demand, a recent study revealed that *WS* contributed substantially to declining evaporation rates (McVicar et al., 2012). For less than two decades, the effect of *WS* on *LE* may be negligible, but for several decades, this effect should be considered.

5.3 Global terrestrial LE estimation

Despite the existing errors, our proposed algorithm demonstrated its reliability for calculating annual *LE*, which was compared with other reanalysis, satellite and hydrological datasets. We estimated that the annual global terrestrial *LE* (excluding Greenland and Antarctica) was 41.7W/m^2 during 2003-2005, which is slight larger than the value of independent global estimates: 35.3W/m^2 from a *MODIS* product (Mu et al., 2011), 34.2W/m^2 from *GSWP* data (Dirmeyer et al., 2006) and 40.2W/m^2 based on the Atmospheric Water Balance (*AWB*) method (Mueller et al., 2011). However, recent studies have demonstrated that the global average *LE* derived from multiple algorithms varies from 34.1W/m^2 to 42.7W/m^2 , with an average of 36.9W/m^2 (Wang and Dickinson, 2012). Our estimated annual *LE* falls within the above range.

The global magnitude of *LE* for each *PFT* agreed, in general, with results documented in the literature (Giambelluca et al. 2009; Mu et al., 2011; Zhang et al., 2009, 2010a). We found that *EBF*, *SAW*, *DBF* and *CRO* have the largest annual average *LE*, greater than 45W/m^2 , and both *SHR* and *DNF* have the lowest annual average *LE*, less than 20W/m^2 , which are in good agreement in its representation of *AVHRR-LE* (Zhang et al., 2010) and *MODIS-LE* (Mu et al., 2011). Fig. 14 shows the *MODIS LE* product and our estimates aggregated for vegetation types. In addition, Frank and Inouye (1994) estimated annual *LE* at 94 sites covering 11 biomes based on approximately 20 years of meteorological records and found that the value of annual *LE* was approximately 15.7W/m^2 for tundra, 29.6W/m^2 for taiga, 45.7W/m^2 for broadleaf forests, 68.8W/m^2 for savannas and 106.1W/m^2 for wet tropical forests.

Giambelluca et al. (2009) used *ECOR* observations to document that the annual averaged *LE* is 64.1W/m^2 and 53.6W/m^2 for two tropical savanna sites in Brazil. These comparable results demonstrate the applicability of our algorithm to accurately estimate global terrestrial *LE*.

Fig. 14 HERE

6. Conclusions

We developed a satellite-based hybrid algorithm to calibrated to *ECOR* measurements to determine the *PT* parameter for global terrestrial *LE* estimation across multiple biomes by combining a simple empirical equation with physically based ecophysiological constraints to obtain the sum of the weighted ecophysiological constraints ($f(e)$) from global eddy covariance, satellite and meteorological observations. $f(e)$ considers the differences in coefficients among *PFTs* and it includes *VPD*-based soil moisture and *NDVI*-based vegetation factors. The parameters of the hybrid algorithm for nine different biomes are acquired by linear regression based on the satellite-based *NDVI*, ground-measured *LE*, T_a , *RH*, and *VPD*. It has a low sensitivity to errors in the input data.

A series of cross-validations based on 240 global *ECOR* observations show that the optimization at a *PFT* level performed well. The satellite-based hybrid algorithm had the highest performance, with an *RMSE* of 0.07 and an R^2 of 0.86 ($p<0.01$) at *DNF* sites, and the worst performances, with an R^2 of 0.55 ($p<0.01$), occurred at *ENF* sites. Cross-validations were also performed to evaluate the ability of our *PT* method to yield *LE* seasonal, spatial, and inter-annual variability. On average, the *RMSE* of

the estimated monthly (daily) LE varies from 4.3 (11.5) W/m^2 for all *DNF* sites to 18.1 (20.9) W/m^2 for all *CRO* sites, and the R^2 (99% confidence) varies from 0.80 (0.68) for all *SHR* sites to 0.96 (0.87) for all *DNF* sites. Performance was also good for predicting among-site variability, with an R^2 of more than 0.78. The validation of inter-annual variability at the site scale shows that the R^2 between the measured and estimated annual LE anomaly is between 0.71 for all *ENF* sites and 0.94 for all *DNF* sites. When compared with the *MOD16* and *PT-JPL* algorithms, which are not calibrated to site measurements unlike our algorithm, our LE algorithm performed better than them at the site scale.

We implemented the terrestrial LE estimation based on *MERRA* data by recalibrating the coefficients of the satellite-based hybrid algorithm using the *MERRA* meteorological data, *MODIS* products and ground-measured LE . The estimated seasonal, spatial, and inter-annual variability of LE agreed well with the tower measurements. Although the predicted relative errors of LE for the *MERRA*-based revised algorithm compared to the original version increased slightly by 4% for validating among-site variability and annual LE anomalies, the accuracy of our revised algorithm still met the requirement for analyzing global terrestrial LE changes. The annual average global terrestrial LE for 2003–2005 as estimated by our algorithm driven by *MERRA* data was approximately 41.7 W/m^2 , which is in good agreement with other studies. Our estimates provide information for comparing and calibrating climate and hydrological models in terms of their sensitivity to energy partition.

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Table 1. Coefficients derived from global plant functional type-based optimization of Eq. (11) using MODIS NDVI and tower-specific meteorology. DBF: deciduous broadleaf forest; DNF: deciduous needleleaf forest; EBF: evergreen broadleaf forest; ENF: evergreen needleleaf forest; MF: mixed forest; SAW: savannas and woody savannas; SHR: open shrubland and closed shrubland; CRO: cropland; GRA: grassland, urban and built-up, barren or sparsely vegetated.

Plant Functional Types	Coefficients for different PFTs				
	k_0	k_1	k_2	k_3	k_4
CRO	0.2093	0.0024	0.5558	0.1651	0.4860
GRA	0.2734	0.0070	0.4556	0.2329	0.4399
SAW	0.1749	0.0022	0.4972	0.1573	0.4279
SHR	0.2101	0.0061	0.3729	0.1595	0.3102
DNF	-0.2442	0.0119	0.7722	0.1474	0.5500
DBF	-0.0456	0.0114	0.5417	0.1510	0.4118
MF	0.4968	0.0110	0.0724	0.7139	0.7495
EBF	0.2740	0.0047	0.3820	0.1170	0.2190
ENF	0.1730	0.0091	0.3680	0.0656	0.0765
Average	0.1691	0.0073	0.4464	0.2122	0.4079

Table 2. A summary of the statistics (bias, the Root Mean Square Error, $RMSE$, and the square of the correlation coefficients, R^2) of the comparison between the ground-measured and the estimated average daily LE using the three LE algorithms driven by tower-specific meteorology of the first group. The second group was used as training data to calibrate the coefficients of our PT algorithm. The bias and $RMSE$ are in units of W/m^2 . PT -Hybrid stands for our PT algorithm.

$PFTs$	$Bias$			$RMSE$			R^2		
	$MOD16$	$PT-JPL$	$PT-Hybrid$	$MOD16$	$PT-JPL$	$PT-Hybrid$	$MOD16$	$PT-JPL$	$PT-Hybrid$
DBF	-10.2	9.8	5.4	28.7	27.1	21.6	0.61	0.73	0.79
DNF	-9.1	5.4	3.3	21.2	19.2	12.9	0.42	0.65	0.81
EBF	-6.3	18.7	2.8	27.6	34.3	23.4	0.57	0.58	0.69
ENF	-5.5	13.1	2.1	30.5	31.2	22.8	0.42	0.64	0.66
MF	-6.7	5.8	3.4	27.4	28.1	20.4	0.48	0.72	0.80
SAW	-8.2	11.3	5.2	25.9	22.3	19.7	0.47	0.53	0.71
SHR	-1.8	8.6	4.6	26.1	22.8	16.8	0.41	0.59	0.63
CRO	-12.6	-2.3	6.5	32.3	25.3	21.1	0.52	0.68	0.77
GRA	-9.2	1.8	4.3	26.9	19.8	18.7	0.50	0.70	0.76
Average	-7.7	8.0	4.2	27.4	25.6	19.7	0.50	0.64	0.74

Table 3. A summary of the statistics (bias, the Root Mean Square Error, $RMSE$, and the square of the correlation coefficients, R^2) of the comparison between the ground-measured and the estimated average daily LE using the three LE algorithms driven by tower-specific meteorology of the second group. The first group was used as training data to calibrate the coefficients of our PT algorithm. The bias and $RMSE$ are in units of W/m^2 . PT -Hybrid stands for our PT algorithm.

$PFTs$	$Bias$			$RMSE$			R^2		
	MOD16	PT-JPL	PT-Hybrid	MOD16	PT-JPL	PT-Hybrid	MOD16	PT-JPL	PT-Hybrid
DBF	-12.6	6.2	4.7	33.2	30.3	24.3	0.57	0.62	0.78
DNF	-7.5	9.2	7.2	26.3	27.8	19.4	0.45	0.49	0.59
EBF	-12.6	14.8	1.2	37.2	39.8	31.8	0.41	0.42	0.62
ENF	-5.3	7.4	2.8	28.1	23.8	20.7	0.45	0.59	0.79
MF	-1.7	10.2	4.6	27.3	27.1	21.9	0.51	0.65	0.81
SAW	-18.9	6.1	1.1	30.7	27.5	20.6	0.41	0.51	0.61
SHR	-2.2	9.3	1.2	26.6	23.8	18.1	0.41	0.52	0.59
CRO	-14.3	-1.8	3.8	34.8	30.8	29.5	0.42	0.51	0.63
GRA	-7.3	5.2	3.9	28.8	26.6	23.4	0.41	0.52	0.60
Average	-9.1	7.4	3.4	30.3	28.6	23.3	0.45	0.54	0.67

Table 4. Coefficients derived from global plant functional type-based optimization of Eq. (11) using MODIS NDVI and MERRA meteorological data.

<i>PFTs</i>	Coefficients for different PFTs				
	k_0	k_1	k_2	k_3	k_4
CRO	0.6695	0.0001	0.0676	0.2626	0.4966
GRA	0.2489	0.0039	0.3861	0.2310	0.6695
SAW	0.0263	0.0063	0.5900	0.1525	0.5625
SHR	0.1475	0.0063	0.4038	0.2400	0.6788
DNF	0.3941	0.0033	0.0001	0.3019	0.6172
DBF	0.5499	0.0078	0.0078	0.5473	0.8164
MF	0.5951	0.0081	0.0001	0.4246	0.4721
EBF	0.4698	0.0081	0.1053	0.1694	0.1891
ENF	0.4663	0.0080	0.1072	0.1642	0.2428
Average	0.3964	0.0058	0.1853	0.2771	0.5272

Figure captions

Fig.1. The spatial distribution of 240 eddy covariance flux tower sites used in this study.

Fig.2. An example of the time series of the 8-day $f(e)$, T_a , $f(sm)$ and $f(vm)$ derived from ground-measured data during January 2002-December 2006 at Au-How site. Here, $f(sm) = RH^{VPD}$, $f(vm) = (k_3 NDVI - k_4)VPD$. Both k_3 and k_4 of Eq.(11) were calibrated using by linear regression using the observed data collected from Au-How site.

Fig.3. Scatter plots of the observed monthly $f(e)$ versus $f(sm)$ at the site scale for each *PFT*. $f(e)$ is inverted from Eq.(3) using ground-measured R_n , LE , T_a and G collected from flux tower sites. $f(sm)$ is calculated using RH and VPD collected from flux tower sites.

Fig.4. Scatter plots of the observed monthly $f(e)$ versus $f(vm)$ at the site scale for each *PFT*. $f(e)$ is inverted from Eq.(3) using ground-measured R_n , LE , T_a and G collected from flux tower sites. $f(vm) = (k_3 NDVI - k_4)VPD$, which is calculated using MODIS NDVI and VPD collected from flux tower sites. Both k_3 and k_4 of Eq. (11) were calibrated using by linear regression using the observed data collected flux tower sites.

Fig. 5. Sensitivity of $f(e)$ to variations in the amounts of a) T_a ($RH=0.7$, $NDVI=0.7$), b) RH ($T_a =25^\circ\text{C}$, $NDVI=0.7$) and c) $NDVI$ ($T_a =25^\circ\text{C}$, $RH=0.7$). Other input variables are set as constants when one variable changes.

Fig. 6. Cross-validation of the estimated monthly $f(e)$ using the hybrid algorithm driven by tower-specific Meteorology versus ground-measured $f(e)$ for each *PFT*.

Fig. 7. The estimated LE (y axis, unit: W/m^2) using our *PT* algorithm driven by tower-specific Meteorology versus ground-measured LE (x axis, unit: W/m^2) for cross validation for daily LE , monthly LE , among-sites variability and annual LE anomalies.

Fig. 8. Example of a time series for the 8 day LE average as measured and estimated using three tower-driven algorithms for different *PFTs*. y axis represents LE , unit:

W/m^2 ; x axis represents time series of year. *PT*-Hybrid stands for our *PT* algorithm.

Fig.9. An example of a) comparison of daily *LE* observations at US-Wcr site and the corresponding estimated *LE* based on Eq. (11) with the coefficients listed in Table 1 driven by the *MERRA* dataset. b) comparison of daily R_n observations at US-Wcr site and the corresponding R_n derived from *MERRA* dataset.

Fig. 10. The estimated *LE* (y axis, unit: W/m^2) using our *PT* algorithm driven by *MERRA* meteorological data versus ground-measured *LE* (x axis, unit: W/m^2) for cross validation for daily *LE*, monthly *LE*, among-sites variability and annual *LE* anomalies.

Fig.11. Spatial distribution of annual global terrestrial $f(e)$ averaged for 2003-2005 at spatial resolution of 0.05° according to the satellite-based hybrid algorithm driven by MODIS NDVI and *MERRA* meteorology.

Fig.12. Spatial distribution of annual global terrestrial *LE* averaged for 2003-2005 at spatial resolution of 0.05° according to our *PT* algorithm driven by MODIS NDVI and *MERRA* meteorology.

Fig.13. Variability of $f(e)$ at multiple biomes using the same inputs ($T_a=25^\circ\text{C}$, $\text{RH}=0.7$ and $\text{NDVI}=0.7$).

Fig.14. Comparison of our *LE* estimates and MODIS-*LE* product at the various ecosystem types. *PT*-Hybrid stands for our *PT* algorithm.

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7.1

Figure 7.2

Figure 8

Figure 9

Figure 10.1

Figure 10.2

Figure 11

Figure 12

Figure 13

Figure 14