ABSTRACT

FANG, YUAN. Modeling Evapotranspiration by Land Cover Types with Global Eddy Flux and MODIS Data. (Under the direction of Dr. Ge Sun.)

Ecosystem evapotranspiration (ET) is a major component of terrestrial water-balances. Although ET is a key variable that links hydrological and biological processes in most ecosystem models, it is one of the most difficult hydrologic variables to quantify at fine scales. Changes in land use, land cover and climate directly affect ET and thus the entire hydrologic and biogeochemical cycles. I conducted a synthesis study by using global flux data (254 sites and 7 years) collected by the global eddy covariance network (FLUXNET), and by integrating modeling techniques with remote sensing (Moderate Resolution Imaging Spectroradiometer) products. This study explored the key factors (i.e., radiation, wind speed, leaf area index, soil water content, vapor pressure deficit) controlling ET for different land cover types (shrubland, cropland, deciduous forest, evergreen forest, grassland, mixed forest and savannas) and created individual ET regression models with various combinations of variables using continental U.S. (AmeriFlux) and global datasets (FLUXNET), respectively. Our study found that the most significant variables affecting ET variedby land cover type. The AmeriFlux data analysis showed that the leaf area index (LAI) and net radiation (Rn)explained most of the variability of observed ET for shrubland and grassland. In contrast, potential evapotranspiration (PET) as estimated by a temperature-based methodwas a key control for observedET ofdeciduous forest, evergreen forest and mixed forest. This study suggests that the ET processes for different ecosystems were controlled by different environmental variables, thus different ecosystems may have different response to projected future climate change. The improved ET models from this study may be useful in evaluating the impacts of climate change and land use change on water resources at regional to continental scales.

Modeling Evapotranspiration by Land Cover Types with Global Eddy Flux and MODIS Data

by
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BIOGRAPHY

Yuan Fang was born on August 18, 1988 in Anhui Province, P. R. China. She received her Bachelor degree from Anhui Agricultural University, China in July 2010. In August 2010, she was admitted to North Carolina State University to continue her Master of Science studies.

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1. INTRODUCTION

Evapotranspiration (ET) is a term describing the transport of water into the atmosphere from surfaces, including land (e.g. soil, rock and paved surface) and water(e.g. streams, ponds and open-water swamps), and from vegetation(Hewlett 1982). Evapotranspiration is a key variable in the ecosystem water balance (Jung *et al.* 2010) that could directly affect precipitation, soil water content and temperature of an area(Koster *et al.* 2004). On a global scale, evapotranspiration represents more than 60 percent of annual precipitation inputs (Vörösmarty *et al.* 1998) and more than 70 percent of the annual precipitation for the entire United States (Brooks *et al.* 1997). Clearly, ETis the primary individual component of terrestrial hydrological cycle (Baumgartner *et al.* 1975).

ET relates to climate change because it is sensitive to environmental variables such as temperature and precipitation. Climate change and land use change affect the hydrological cycle and water resources through altering ET processes.ET is also tightly correlated with net ecosystem exchange due to water use in photosynthesis and soil moisture effects on ecosystem respiration processes. Water availability limits leaf area index and then impacts carbon sequestration over the long-term across different vegetation covers (Law *et al.* 2002). Since different vegetation developmentis controlled differently by the environment via complex physiological processes (e.g., photosynthesis, carbon and water cycles) , it's essential to quantify evapotranspiration accurately for modeling ecosystem processesby land cover types(Sun *et al.* 2011a). Although ET is a key variable that impacts the behavior and dynamics of ecosystem(Baldocchi *et al.* 2000), ET is one of the most difficult water budget

components to quantify. Developing new measurements and modeling techniques to accurately quantify ecosystem ET is an important aspect of hydrometeorology for understanding the interactions of land and atmospheric processes in global change studies(Shuttleworth 2012).

1.1 ET quantification

There are many ways to quantify ET at different scales.ET estimate methods are broadly grouped into three categories: (1) field-based measurements including the eddy covariance method that this study focuses on; (2) remote sensing methods; and (3) mathematical modeling. A comparison of the strengths and weaknesses is described in Table 1.

Table 1.A comparison of major evapotranspiration quantification methods

	Methods	Strengths	Weaknesses	Sources
Field measurements	Catchment water balance	Easy to measure, low cost	Only long-term average is reliable	(Bosch et al. 1982; Wilson et al.2001)
	Sap flow	Allow routine unsupervised measurement accurately at single plant scale	Large scale measurement errors are determined by the sample size and variability of samples	(Smith et al. 1996; Wilson et al.2001; Domec et al. 2012; Vinukollu et al. 1998)
	Eddy covariance	Measuring fluxes continuously, offering high temporal resolution data	High cost in instrumentation, gap filling required, energy imbalance problems	(Baldocchi et al. 1988; Wilson et al.2001, 2002; Twine et al. 2000)
	Bowen Ratio	Low cost, works for both crops and natural vegetation	Relies on several assumptions, errors associated with low gradients	(Bowen 1926; Heilman et al. 1989)
Remote sensing	Remote sensing	Provide spatial, continuous and temporal scale high resolution data	Uncertainties due to errors generated by measurement of sparse canopies, data mostly from clear sky conditions	(Kustas et al. 1996; Justice et al. 1998; Shuttleworth 2008; Mu et al. 2007,2010)
Modeling	Theoretical models (e.g. Penman, Priestley-Taylor, Shuttleworth)	Widely used, long-term accepted, low cost	Require site-specific parameters, not easy to apply on large scale	(Priestley et al. 1972; Monteith 1965; Shuttleworth et al. 1985; Penman 1948; Vörösmarty et al. 1998; Fisher et al. 2005)
	Empirical models	Required less input variables, low cost	Uncertainty for extrapolating to novel conditions	(Sun et al. 2011a; Dunn et al. 1995; Liu et al. 2010)

All of these methods have been commonly used to estimate ET at present. Each technique may be appropriate for certain scales and has its own particular assumptions. The major ET quantification methods are introduced in more detailin the following sections.

1.1.1 Field measurements

Direct ecosystem scale ET measurement techniques include catchment water balance (Bosch *et al.* 1982), sap flow (Smith *et al.* 1996), eddy covariance (Baldocchi *et al.* 1988) and Bowen Ratio (Bowen 1926)methods.Remote sensing techniquesallowmonitoring ET at a large scale (Kustas *et al.* 1996).According to Wilson *et al.*(2001)who compared multiple methodologies of measuring ET, each method has its limitations. For example, the watershed water balance method, which istypically applicable to long-term average ET estimates,has errors when change in soil moisture is ignored. In this method, ET would be overestimated or underestimated when ET is computed as the residual of precipitation and runoff. Sap flow measurements provide a powerful tool for quantifying plant water use and physiological responses of plants to environmental conditions(Domec *et al.* 2012). However, this method would be not dependable for misdistribution of tree stands and inappropriate sample size of measurement and structural scalars (Vinukollu *et al.* 1998). The eddy covariance method measures fluxes continuously, offering high temporal resolution data series but it is limited by costly instruments and gap filling issues. Besides, eddy covariance method may underestimate ET due to lacking of energy balance closure. A20% underestimate of energy flux is not uncommon(Wilson *et al.* 2002). Because of the energy conservation discrepancy, in the current study, I have to correct ET to maintaincompleteclosure, i.e. artificially making

available energy flux (net radiation- soil heat fluxes) equal to the sum of sensible heat and latent heat fluxes(Twine *et al.* 2000).For the Bowen Ratio method, ET is derived from the ratio of sensible heat to latent heat which is calculated from of air temperature, humidity gradients, net radiation, and soil heatflux. It is relatively inexpensive but relies on several assumptions such asan extensive fetch over a homogeneous surface(Heilman *et al.* 1989).

1.1.2 Remote sensing method

Remote sensing has been widely used to estimate ET (Ray *et al.* 2001; Song *et al.* 2011). This method has been regarded as a flexible technology to obtain large scale and real time ecological variables such as evapotranspiration, leaf area index, etc. MODIS (Moderate Resolution Image Spectroradiometer) global products (Mu *et al.* 2007; Mu *et al.* 2010) have provided spatially continuous and temporal scale data such as evapotranspiration, at a high resolution for modeling and analysis(Justice *et al.* 1998). However, estimation errors exist due to uncertainties in the modeling effective surface emissivity and effective aerodynamic exchange resistance, and sparse canopies and thick cloudsalso make the remote sensing method less reliable(Shuttleworth 2008).

1.1.3 Modeling

Due to the high cost of measuring ET, mathematical modeling has been widely used to estimate ET. The Penman-Monteith equation (Monteith 1965)(Equation1) has been widely used for many decades to model ET at the leaf level. This model has been regarded as the best way to describe the environmental controls on ET processes.

$$ET = \frac{\Delta R_n + \rho_a C_p (VPD) g_a}{(\Delta + \gamma\left(1 + \frac{g_a}{g_s}\right))\lambda_v} \quad (1)$$

Where:
ET= Water volume evapotranspired ($m^3 s^{-1} m^{-2}$)
Δ=Rate of change of saturation specific humidity with air temperature (PaK^{-1})
R_n= Net radiation ($W\ m^{-2}$)
ρ_a= Dry air density (kgm^{-3})
C_p= Specific heat capacity of air ($J\ kg^{-1}K^{-1}$)
VPD= Vapor pressure deficit (Pa)
g_a= Atmospheric conductance ($m\ s^{-1}$)
g_s= Stomatal conductance ($m\ s^{-1}$)
γ= Psychrometric constant ($\gamma \approx 66\ Pa\ K^{-1}$)
λ_v= Latent heat of vaporization (i.e. energy required per unit mass of water vaporized) ($J\ g^{-1}$)

From the Penman-Monteith equation (Equation1),one can see that radiation, vapor pressure deficit, conductance of air and stomataaffect ET rate. The study of Collatz *et al.*(1991) indicated that the stomatal conductance of a leaf boundary layer can have a significant influence on the response of latent heat flux, and as a consequence, temperature, humidity and available water for energy exchange in proximity to the leaf surface can in turn affect stomatal conductance.

Although the Penman-Monteith model provides a solid basis for estimating ET, its application remains difficult. So potential evapotranspiration (PET) based methods are commonly used as an indirect method to estimate actual ET. Potential evapotranspiration is defined as the actual ET that would occur if there were ample soil water available(Linsley 1958). PET has been traditionally estimated using terms for local meteorological data and/or vegetation characteristics, and then actual ET can be estimated based on the limitation of soil

water to the ET processes(Stannard 1993; Ward *et al.* 2004). Soil water limitations to actual ET through stomatal conductance are indicated in process-based ET models (such as Penman-Monteith equation). Due to the simple concept and ease of estimation, PET is often compared with Precipitation (P) in agricultural irrigation scheduling (Allen *et al.* 1998).

The primary PET models used in water balance and terrestrial ecosystem modeling include the reference surface methods by Penman (1948) and Hamon (1963) and surface-dependent methods by Priestley *et al.*(1972), Monteith (1965) and Shuttleworth *et al.*(1985). The reference surface methods are defined as ET that occurs from a "reference crop", which refers to a specific well-watered, short, grass cover. In contrast, the surface-dependent methods of ET are measured at several designated land surfaces. The condition is only limited by albedo for the Priestley and Taylor method; other methods depend on surface roughness height, zero-plane displacement, maximum stomatal conductance, leaf area index, canopy radiation extinction, and albedo (Vörösmarty et al. 1998). According to the study of Fisher *et al.*(2005) and Vörösmarty (1998), the method developed by Shuttleworth-Wallace (1985) performed better than others when compared to measured ET.

Estimates of the conductance of stomata and air to derive transpiration from plant surfacesareneeded to estimate ET using the Penman-Monteith (PM) equation. However, this process-based model is difficult to use in practice because it requires parameters and climatic variables that are generally not available on a large spatial scale(Allen *et al.* 1994).So numerous less data intensive models including PM-Mu (Mu et al. 2007), SEBS (Su 1999)

and PT-Fi (Fisher *et al.* 2008) were developed for global ET evaluation (Vinukollu*et at.* 1998).

Empirical models require fewer environmental variables and are easy to use for hydrologic modeling, especially for large areas. For example, using ET data collected from 13 sites using various methods (Table1), Sun *et al.*(2011a) developed an empirical model for estimating monthly ecosystem evapotranspiration.

$$ET = 11.94 + 4.76LAI + ET_o(0.032LAI + 0.0026P + 0.15) \quad (2)$$

Where LAI is leaf area index, P is precipitation, R^2=0.85, RMSE=15 ($mm\ month^{-1}$), *n*=222

ET_o isthe FAO (Food and Agriculture Organization) reference ET representing a hypothetical short grass with a height of 0.12 meter, a surface resistance of 70 sm^{-1}, and albedo of 0.23 at the condition of no water stress (Allen *et al.* 1994). Furthermore, Sun *et al.*(2011b) provide another form of the ET model using Hamon's method to estimate PET instead of the FAO reference ET method in Equation2. Since a single model could not capture the spatial variability in ET, a specific ET equation for forested regions at high latitudes (e.g. >40 °N) dominated by winter precipitation in the northeastern U.S was applied as following:

$$ET = 0.4 * PET + 7.87 * LAI + 0.00169 * PET * P \quad (3)$$

Where R^2=0.85, RMSE=14.5 ($mm\ month^{-1}$), *n*=147.

For other regions,

$$ET = 0.174 * P + 0.502 * PET + 5.31 * LAI + 0.0222 * PET * LAI \quad (4)$$

Where R^2=0.85, RMSE=14.0 ($mm\ month^{-1}$), *n*=147.

1.2 Environmental controls on ET and empirical ET modeling

As described in thePenman-Monteith equation, at the leaf level, net radiation, air temperature and vapor pressure deficit are all important variables that affect ET rates. In addition, stomatal conductance and atmospheric conductance are essential.Stomatal conductance and leaf-level ET differ significantly among species(Ford *et al.* 2011). At the ecosystem level, ET is determined by canopy conductance. Since canopy conductance is closely related to leaf area index (LAI) at an ecosystem scale, LAI that influences the plant biomass becomes a key control of ET.Determining how leaf phenology affects ET may help us understand seasonal environmental controls (Mackay *et al.* 2007).There is no doubt that different plant species respond to environmental controls in rather different ways depending onage, neighbors, soil microbial communities and soil resources(Körner 1995), making the mechanism of vegetation in water exchange more complicated. Cheng *et al.*(2011)concluded that susceptibility of plants to climate change is one of the most important factors influencing ET at interannual scales.Because of the knowledge gap about the role of plant properties in ET processes, the empirical ET models described by Sun *et al.* (2011a, 2011b)failed to consider the influence of vegetation types. It is therefore necessary for us to explore ET

estimates based on different land cover types and to create models applicable at regional scales.

Both empirical ET data and models show that vegetation cover influencessurface energy and moisture balance at multiple scales(Dunn *et al.* 1995; Liu *et al.* 2010). ETvaries across different vegetation cover typesunder similar climatic and meteorological conditions (Liu *et al.*2010). Alteration in land use/land cover and climate change affect ET because of different combinations of environmental control for different ecosystems types. For example, in central Asian desert shrubland, which has low precipitation and high temperature in summer, solar radiation explains 60% at a maximum of ET (Li *et al.* 2011). In contrast, evapotranspiration is highly related with LAI (R^2 =0.96) for forests in northern Wisconsin (Sun *et al.* 2008). Further, analysis of climate and vegetation influences on ET conducted by Brümmer *et al.*(2012) found significant variation in correlations between ET and other factors (precipitation, vapor pressure deficit, radiation, etc.)by different vegetation types. Vegetation as a critical component of the global energy cycle, has reciprocal effects with environmental variables(Ter Braak 1987). Thus, ET modelsthat can characterize different vegetation types would contribute significantly to understanding the relationships between land use change and climate change (Wallace 1995).

1.3 Objectives

Although the types of empirical ET models developed by Sun et al. (2011a, 2011b) were useful for quantifying ET at the regional scale, these models did not completely describe environmental controls on ET on a short temporal scale. Improvements to these models were needed by examining global eddy flux data and byincorporating environmental controls on ET processesbased on different land cover types. The objectives of this study were to (1) examine environmental controls of ET at a monthly time scale by combining ET measurements from the global eddy flux network and associated remote sensing data, and (2) create a new set of ET models by separating land cover types, and separating regions when necessary. The goal was to improvethe previous ET models(Sun *et al.* 2011a, 2011b).

2. METHODS

Daily water flux measurements derived using the eddy covariance method were acquired for this studyfrom the FLUXNET (Baldocchi *et al.* 2001; Valentini *et al.* 2000; http://www.eosdis.ornl.gov/FLUXNET) and AmeriFlux(Hargrove 2003; Yang *et al.* 2007;http://public.ornl.gov/ameriflux/) programs (Figure1). For each eddy flux tower site from FLUXNET network (Figure2), I builta database consisting of ET, PET, soil water content (SWC), vapor pressure deficit (VPD), precipitation (P), wind speed (WS) and net radiation (Rn), scaling daily data to monthly values, to this, I added monthly LAI derived from 8-day LAI,extracted from MODIS products using positions of each site. After processing quality assessment and quality control of the data, I developed regression models of ET using different combinations of variables separated by land cover type (Figure1).

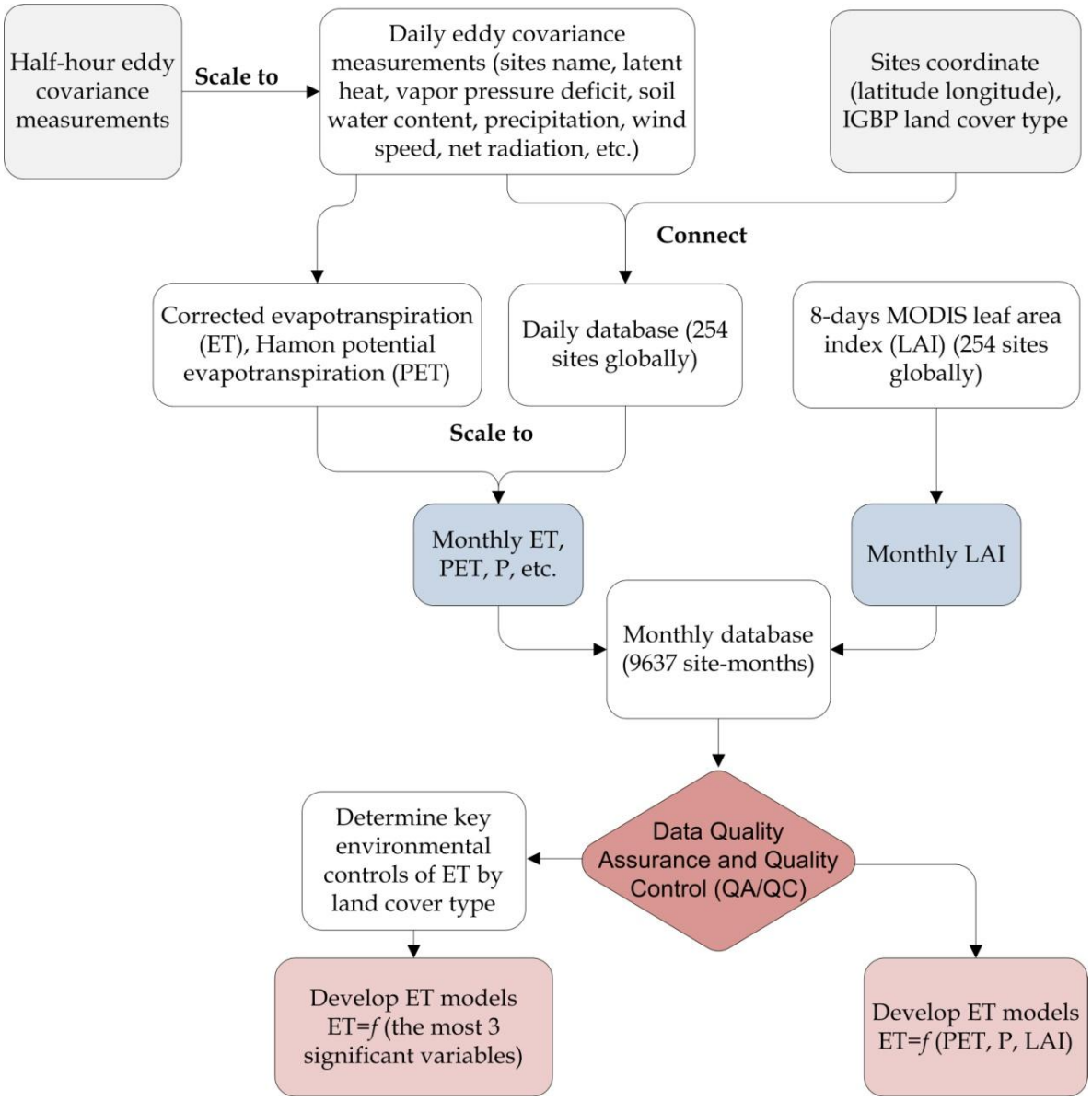


Figure 1. An overview of research methods for database development and analysis

Determining the controlling factors for ET was an essential step before developing ET models. Given the diversity of ecosystem types and data quality, I examined

thecontinental U.S.datasets from AmeriFlux and the global flux data (FLUXNET), separately. I also usedglobal remote sensing products from MODIS (Moderate Resolution Imaging Spectroradiometer), which provides data onvarious environmental variables, such as evapotranspiration, leaf area index, gross primary production and land cover at a resolution ranging from250m to 1000m.

I first determined the most significant environmental variables that control ET, and then developed a series of ET models that can be used readily at the regional scale. In particular, I focused on three environmental controls: PET, precipitation (P) and Leaf Area Index (LAI). I also explored the most significant variables that varied for different land cover types due to climatic variability. A series of ET models were developed so users had the choice to fit these to different objectives.

2.1 Daily FLUXNETdatabase

The eddy flux network provided water and carbon flux data and associated environmental variables measured for multiple years. I generated a database that included all variables for ET analysis and model building.

I built a daily database that includedlatent heat flux (LEin $MJ/m^2/day$), temperature (Ta in ℃), vapor pressure deficit (VPD in 100 Pa), soil water content (SWC in m^3/m^3), precipitation (Pin mm/day), wind speed (WS in m/s), net radiation (Rnin $MJ/m^2/day$), sensible heat flux (H in $MJ/m^2/day$) and soil heat flux (G in $Mj/m^2/day$). I associated these data with International Geosphere-Biosphere Programme(IGBP)global vegetation classification,

latitude and longitude scaled from half-hour eddy covariance measurements at FLUXNET sites (Figure2). The daily database consisted of 254 sites, among which 74 sites are from theAmeriFlux network (Figure3) operated in the United States (more details in Appendix). Sites spanned different climate and geomorphic regions, ranging from the northern hemisphere to southern hemisphere (Figure2). Flux towers selected operated on five continents and their latitudinal distribution ranged from 70 degrees north to 30 degrees south. The range of annual precipitation was from 27.52 mm to 5974 mm, and annual mean temperature was from -13.39 ℃ to 26.73℃.

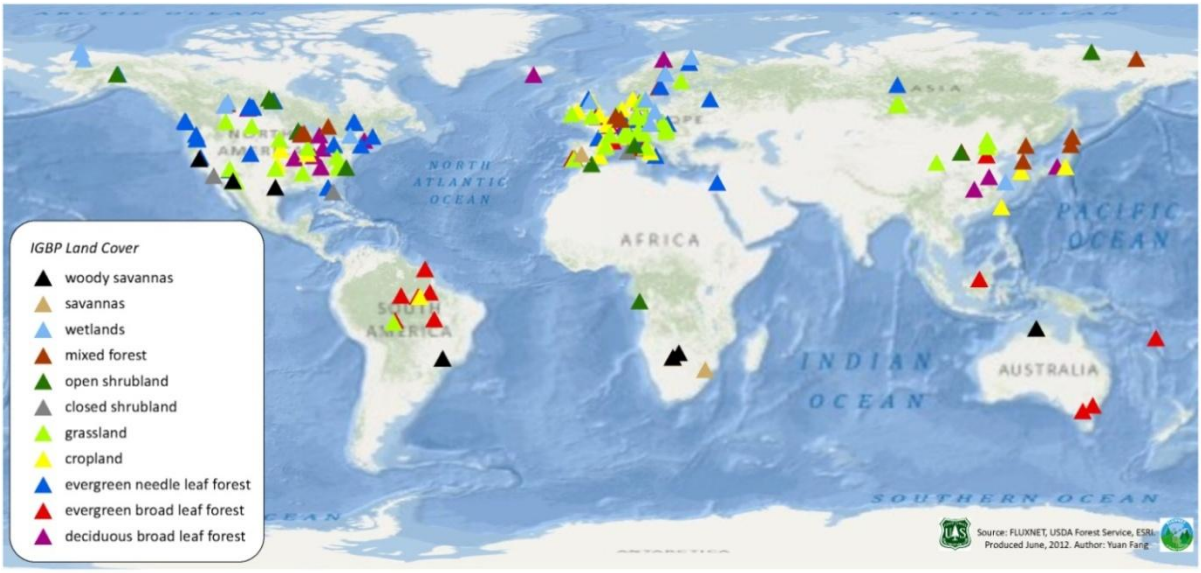


Figure 2. FLUXNET sites used in this study with IGBP land cover type

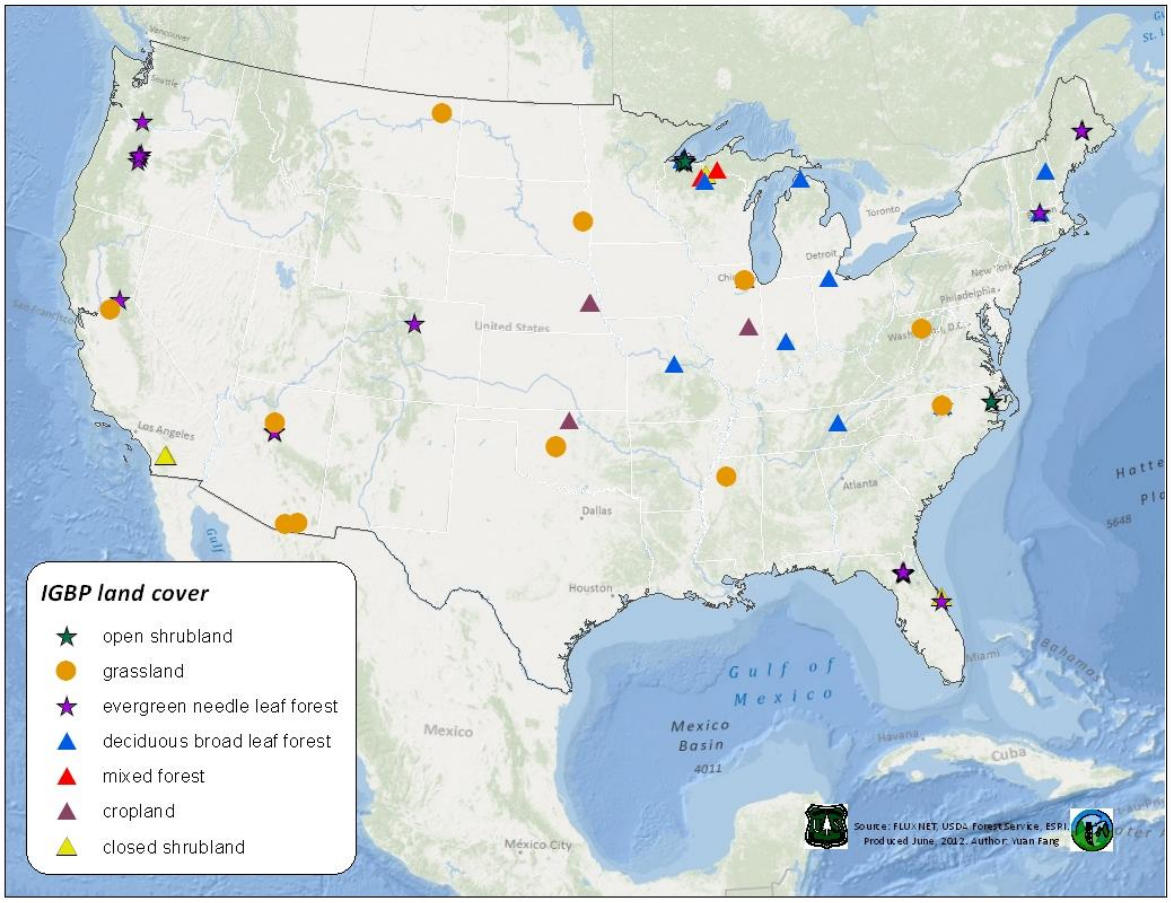


Figure 3.AmeriFlux sites used in this study with IGBP land cover type

2.2 Evapotranspiration (ET)

The flux data bases report daily latent heat fluxes that were scaled from half-hour measurements. Latent heat flux represented energy absorbed for evapotranspiration without a change in temperature. ET was calculated from latent heat flux as:

$$ET = LE \times \frac{1000}{4.18*597} \tag{5}$$

Energy balance closure (a formula requiring the sum of latent heat flux (LE) and sensible heat flux (H) to be equivalent to the difference between net radiation (R_n) and soil heat flux (G) and heat storage (S)) has been widely used in eddy covariance detection (Mahrt 1998). The energy balance at the land surface can be written as:

$$R_n - G - S = H + LE \tag{6}$$

According to the research ofWilson *et al.*(2002), the latent heat fluxhas been underestimated about 20% due to lack of energy balance closure. In other words, the right hand side of Equation 6 is often less than the left side, indicating ET values derived from latent heatwere ambiguous. Previous study pointed out that the incomplete energy closure problem was mainly caused by inaccuraciesin quantifying available energy (e.g. there is still some confusion as to how G should be calculated); lack of understanding of energy processing (e.g.S is often neglected) (Mayocchi *et al.* 1995); the source area of turbulent fluxes was constantly changing in contrast to the residual side (Schmid 1997); and large nonstationarity of the turbulent flux and flux sampling errors (Mahrt, 1998).

I corrected reported daily ET for the incomplete energy balance closure problem of eddy-covariance measurements using the method developed byTwine et al. (2000). This method redistributed the energy imbalance, i.e. the residual of available energy (Rn-G) and the sum of latent heat and sensible heat (H+LE), back to both LE and H by maintaining the Bowen Ratio (H/LE). So,

$$CorET = ET \times \frac{R_n - G}{H + LE} \quad (7)$$

Where
$CorET$= daily corrected evapotranspiration (mm)
R_n=daily net radiation (MJ/m^2)
G = daily soil heat flux (MJ/m^2)
H = daily sensible heat flux (MJ/m^2)
LE= daily latent heat flux (MJ/m^2)

2.3 Potential evapotranspiration (PET)

Potential evapotranspiration (PET) is an essential variable in developingET models in this study.Hamon's (1961)PET method was used in this study due to its simplicity and wide use (Vörösmarty*et al.* 1998;Lu *et al.* 2003).Hamon (1961)developed an equation estimating daily ET based on air temperature and day length.

I calculated daily potential evapotranspiration using Hamon's equations(Hamon 1961):

$$PET = 0.1651 \times DAY \times \frac{216.7 \times e_s}{t_a + 273.3} \quad (8)$$

$$e_s = 6.108 \times e^{\frac{17.2694 \times t_a}{t_a + 273.3}} \quad (9)$$

$$DAY = 2 \times \cos^{-1}\left(-1 \times \tan(lat \times 0.0175) \times \tan\left(0.4093 \times \sin\left(\frac{2 * 3.1415 * DoY}{365.0}\right) - 1.405\right)\right) \quad (10)$$

Where
PET = daily potential evapotranspiration (mm)
DAY = day length which depends upon latitude (hours)
e_s= saturation vapor pressure at the given temperature
t_a= temperature (℃)
DoY=day of year ranging between 1 and 366

Equation 9calculates saturation vapor pressure from air temperature(Murray 1967).

2.4 Leaf area index (LAI)

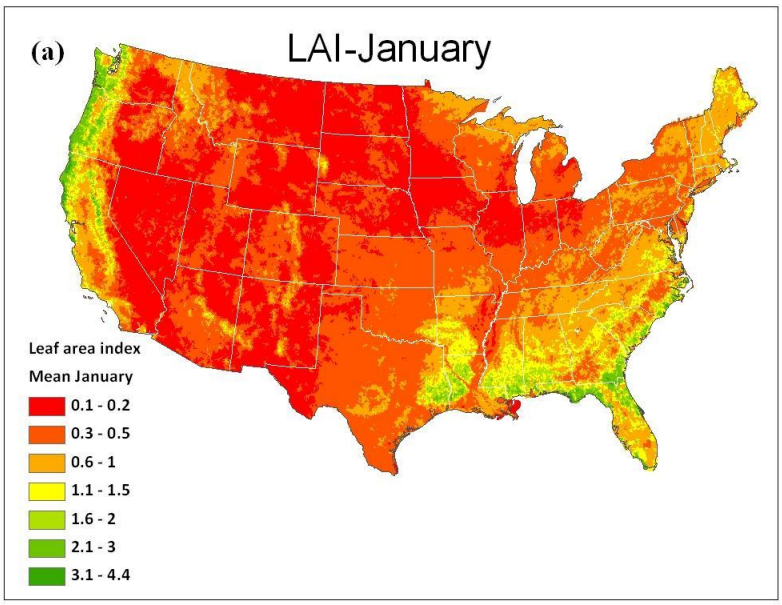
Leaf area index (LAI)is a key variable for understanding the ET process and its modeling. The eddy covariance database did not provide complete information on LAI for each site, so I created my own database of LAI using MODIS global products.I downloaded LAI data based on the coordinates for each eddy flux tower site.

Leaf area index (projected leaf surface per unit ground area, m^2/m^2) is an essential factor that representsdifferent biomes and ranges of ecological and climate conditions(Asner *et al.* 2003). LAIhas been widely used in understanding ecosystem processes and building ET models(Cramer *et al.* 1999). The development of remote sensing techniques made LAI measurements available over large range of areas and short time intervals(Asrar *et al.* 1983; Running 1984; Running *et al.* 1989).

I extracted leaf area index (2000-2006, 254sites) using 8-day GeoTIFF data from products of the Moderate Resolution Imaging Spectroradiometer (MODIS) 1-km LAI global fields and converted them to monthly leaf area index. First, I downloaded the 8-day data for each sites based on latitude and longitude and sorted files into separate folders by year.

Secondly, I converted IMAGE data into GRID format and multiplied bya scale factor of 0.1 to get a true value of leaf area index (Mu *et al.* 2011). Next, I integrated 8-day values to get monthly values and extracted them from GRID data. I repeated the procedure for 254 sites and reported the monthly leaf area index for 7 years.

LAI values varied greatly in space and time as demonstrated in an example (Figure4). In January, the continental average LAI values ranged from 0.1 to 4.4; in contrast, the value of LAI could reach as high as 6.3 in August in the growing season(Figure4). Figure5describes monthly LAI over three years for the Duke Forest site, NC.



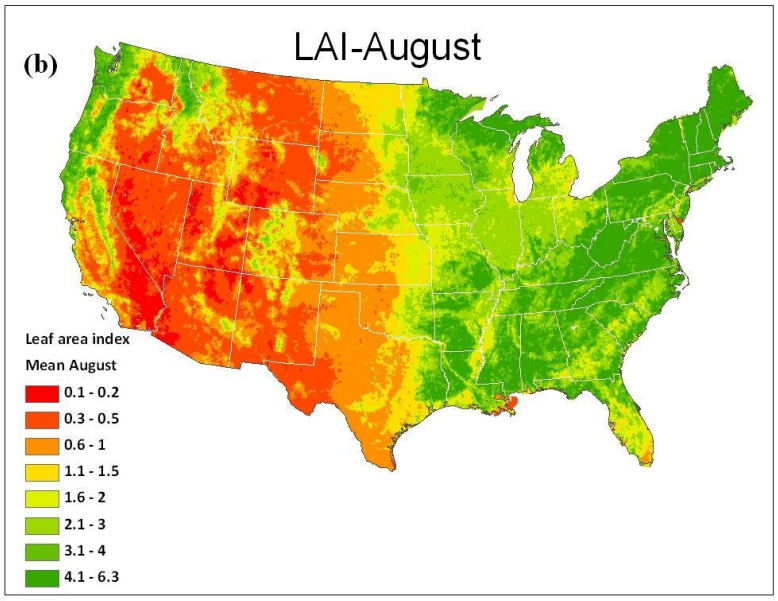


Figure 4.An example of monthly meanLAI (2000-2006) for (a) January, and (b) August inthe continental U.S.

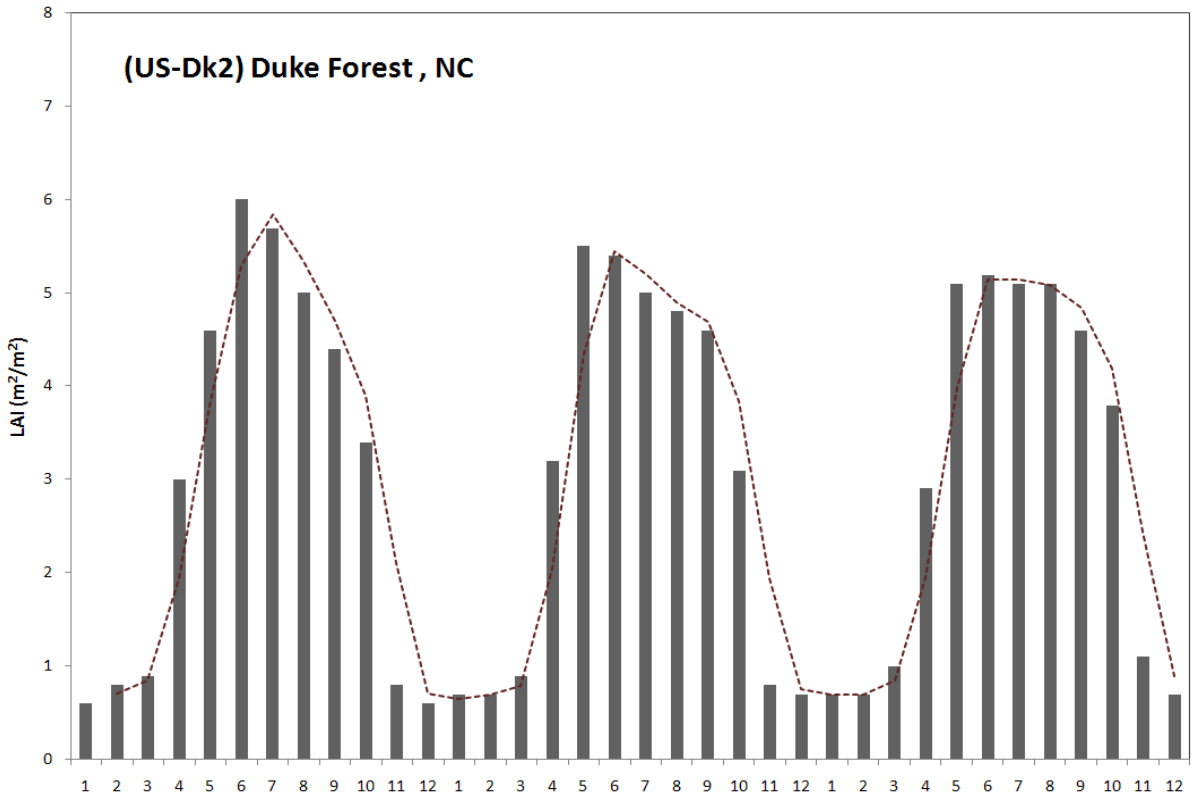


Figure 5.An example to show monthlyLAI (2003-2005) derived from MODIS for Duke Forest located in Durham, NC (latitude 35.9736, longitude -79.1004). This site was classified as deciduous forest by IGBP land cover classification system.

2.5 Monthly environmental database

I combined all data for monthly corrected ET, monthly P, monthly LAI and other monthly environmental variables (e.g., mean soil water content, vapor pressure deficit, etc)that were measured using eddy covariance methods, and potential evapotranspiration, as described above. PET was calculated by Equations 8, 9, and 10.Iassociatedall these variables with land cover types based on the IGBP land cover classification. The database spanned 7 years (2000- 2006) and included 9637 site-months records.

2.6 Data Quality Assurance and Quality Control

Data reported from FLUXNET were well known for uncertaintiesthatare normally caused by measurement errors and misunderstanding of computing methods(Hollinger *et al.* 2005). I removed data points which obviously should be excluded from the analysis.For example, negative values of soil water content, potential evapotranspiration and vapor pressure deficit would not be realistic. In addition, I also filtered the monthly data that were scaled from insufficient daily records (i.e. number of daily records of one month<15 days).To decrease the bias caused by missing data, I used the product of mean daily value of a variable in a month and 30 days (i.e. monthly value= mean daily value×30) to be the monthly value of that variable when the number of daily records of one monthwas greater than15 (days) but less than 30 (days). I also limited ET to be less than 300 (mm) per month to address the problem of unusually large ET values existing in the database. The details are: (a)Set to null values for daily net radiation>100(MJ/m^2) or daily latent heat>25 (MJ/m^2) or daily sensible heat flux>25(MJ/m^2) or daily soil water content <0 (m^3/m^3) or daily precipitation <0 (mm) or potential evapotranspiration<0 (mm) or evapotranspiration<0 (mm) or vapor pressure deficit<0(hPa).(b)Set to nullvalues formonthly evapotranspiration >300 (mm). (c)Set to null values for daily records of one month <15 (days). (d)Filter the data for sites used in our study. The details of sites used in model development are shown in Appendix A.

2.7 Monthly evapotranspiration model development

Investigating the responses of vegetation to environmental variables helps us understand mechanisms controlling evapotranspiration and energy exchange (Law *et al.* 2012). I used the data from sites representing different biomes to develop regression models of monthly ET consisting of different variable combinations (PET, P, and LAI; or, three of the most significant variables) for each land cover.I created ET modelsthat only included variables of PET, P and LAI because my objective was to produce a model that needed as few climate variables as possible. However, the most significant variables for ET varied from land cover to land cover. Thus, I identified significant variables for each land cover type using stepwise regressionin SAS(SAS Institute Inc., 2008) and createdET models using three of the most significant variables, so that the ET models could predict ET as precisely as possible.

In addition to what I discussed above, I assumed it would also be critical to develop two series of ET models, for ET prediction at both the global scale (FLUXNET) and the continental U.S scale (AmeriFlux), by land cover type.In other words, I developed ET models with two different combinations of variables using global data and U.S data separately (Figure6).

IdevelopedET models for different land cover types using the SAS 9.2 software (SAS Institute Inc., 2008), and created general regression models using three independent variables of PET, LAI and P, or three the most significant variables selected by stepwise

regression.According to the IGBP landcover classification system, the FLUXNET included seven land cover types: shrubland (including closed shrubland and open shrubland), cropland, grassland, deciduous forest (deciduous broad leaf forest), evergreen forest (including evergreen needle leaf forest and evergreen broad leaf forest), mixed forest and savannas (including savannas and woody savannas). For the U.S, I developed models for six land cover types since no land cover type forsavannas existed in U.S.

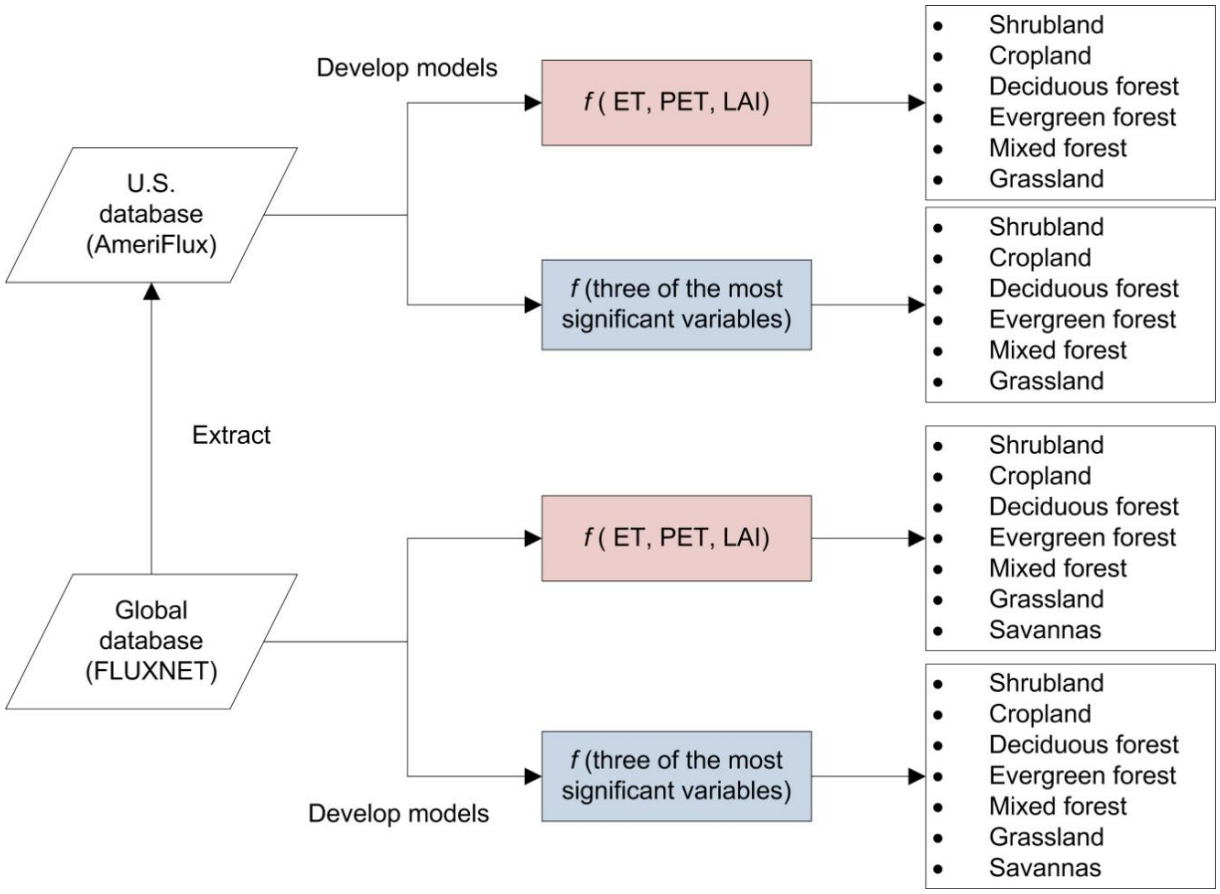


Figure 6.Workflow of monthly ET model development. I created two series of monthly ET models: regression models using ET, PET and LAI as the independent variables, and regression models using three of the most significant variables. The two series of monthly ET model were derived fromAmeriFlux and FLUXNET.

3. RESULTS

3.1 Key environmental controlling variables for different land cover types.

3.1.1 Key environmental controls generated by continental U.S. data

It appeared that the most significant variables explaining variability in ET were different among different ecosystems (Table2). Interestingly, PET was the best predictor for all forests while LAI was best for ecosystem with a low LAI (grasslands). Net radiation, instead of LAI, was most influential for croplands.

Table 2. The most significantly variables contributing to ET with partial R-square values and sample sizes of different land cover types developed from continental U.S. data (AmeriFlux).

Land cover type	Partial R-square of significant variables							n
	PET	LAI	Rn	P	SWC	VPD	Ta	
Shrubland	N/A	0.60	0.19	0.02	0.01	N/A	N/A	182
Cropland	N/A	0.08	0.75	0.01	0.01	N/A	N/A	291
Grassland	N/A	0.73	0.07	N/A	0.07	0.01	N/A	98
Deciduous forest	0.84	0.02	0.01	N/A	N/A	0.06	N/A	154
Evergreen forest	0.55	N/A	0.08	N/A	N/A	0.12	0.01	395
Mixed forest	0.95	N/A	N/A	N/A	N/A	0.01	N/A	52

For shrubland, LAI and Rn explained 78 % of the variability in ET (Table 2). For cropland, the variables Rn, LAI and P were the major controls of ET ($p<0.0001$), explaining 75 %, 8 % and 1 % of ET, separately. The correlation betweenRn and ET was as high as 0.79,

but in a non-linear relationship (Figure8). For deciduous forest, PET, VPD and LAI explained 84 %, 6 % and 1 % of ET. For evergreen forest, I could see that potential ET and vapor pressure deficit were highly correlated ($p<0.0001$) with ET, VPD and Rn. PET, VPD and Rn contributed 55 %, 12 % and 8 %, respectively. Precipitation and LAI did not contribute much to the coefficient of determination (R^2) between predicted ET and measured ET; this may explain the reason for a low R^2(0.67) in the evergreen forest ET prediction. Variables that affected grassland ET were LAI, SWC and Rn (explaining 74 %, 7 % and 7 % of the variability). Soil water content was the second most important factor correlated with ET after leaf area index. For mixed forest, PET was largely determining ET (R^2=0.95); however, sample sizes for mixed forests were far fewer than other land cover types.

The relationships between ET and individual environmental factors were rather complex (Figure 7). The slopes of linear relationships between ET and P (Figure7) indicated that grassland (95% confidence interval of slope = (0.57, 0.81)) evapotranspired the largest fraction of monthly precipitation. Cropland (95% confidence interval of slope = (0.04, 0.11)) and decidous forest (95% confidence interval of slope = (0.16, 0.49))were the second highest, and evergreen forests (95% confidence interval of slope = (0.04, 0.11)) did not evapotranspire as large precetange of precipitation as expected (Table 3). Moreover, evapotranspiration of evergreen forest was lower than other land cover types except mixed forest at the same LAI (95% confidence interval of slope= (0.04, 0.11) (Table 3)).It was possible that evergreen forest could conserve more water resources relative to other ecosystem types. I also could conclude that, cropland and grassland have higher ET than

other land cover at the same LAI. For croplands, Rn and ET were highly correlated in a non-linear fashion (Figure 7).

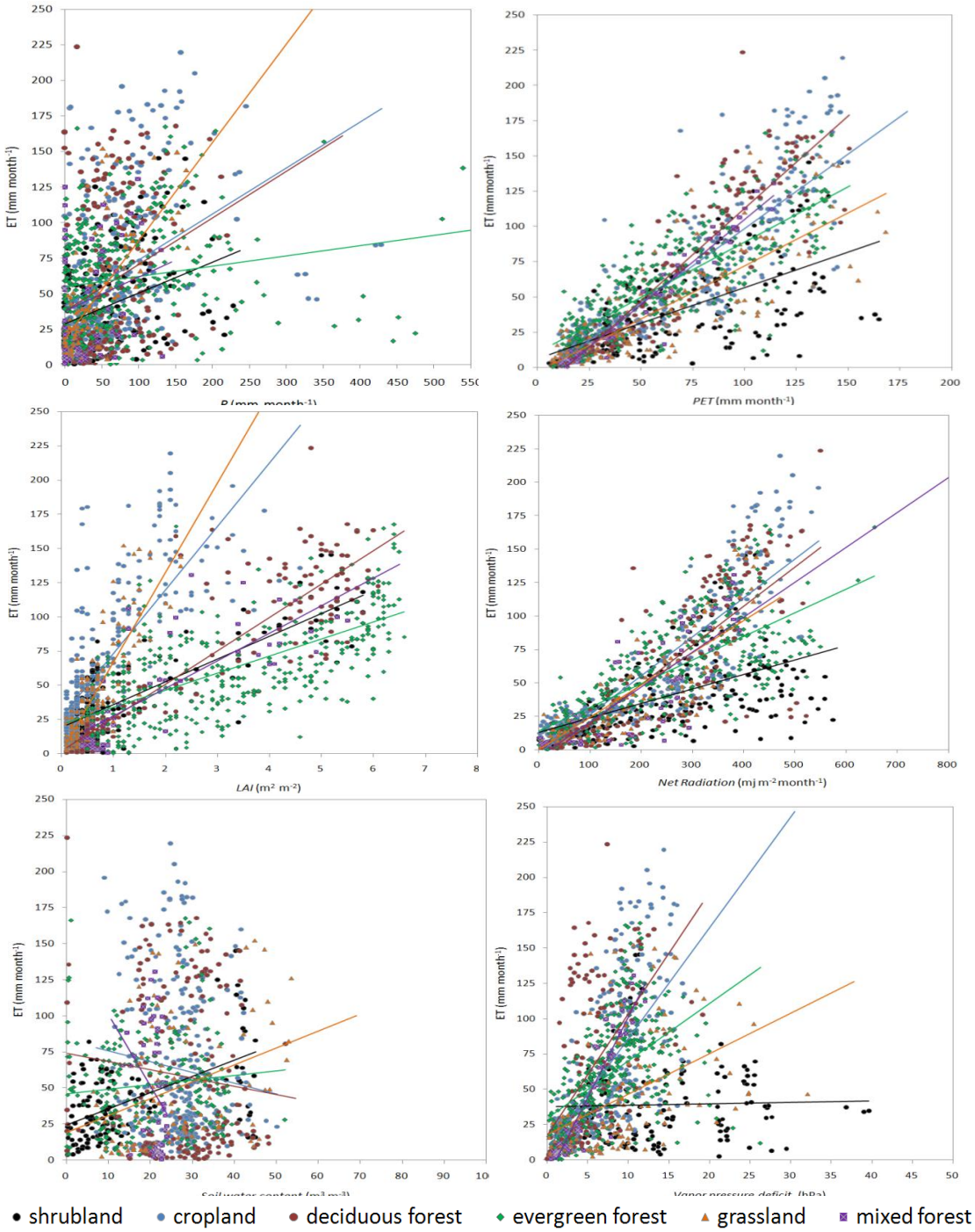


Figure 7.Relationship between monthly actual evapotranspiration (ET) and environmental variables:monthly precipitation (P), potential evapotranspiration (PET), leaf area index (LAI), net radiation (Rn) , soil water content (SWC) and vapor pressure deficit (VPD) based on AmeriFlux dataset. Lines shown are trend lines of each land cover type (AmeriFlux).

Table 3. 95% confidence limits of slope for monthly precipitation (P), potential evapotranspiration (PET), leaf area index (LAI), net radiation (Rn) , soil water content (SWC) and vapor pressure deficit (VPD) based on the AmeriFlux dataset. Dependent variable is ET.

Land cover	95% confidence limits of slope					
	P	PET	LAI	Rn	SWC	VPD
Shrubland	(0.14, 0.30)	(0.41, 0.59)	(14.80, 18.50)	(0.09, 0.13)	(0.81, 1.44)	(-0.50, 0.71)
Cropland	(0.24, 0.41)	(0.99, 1.13)	(42.09, 50.61)	(0.27, 0.31)	(-1.59, 0.08)	(6.84, 8.85)
Deciduous forest	(0.16, 0.49)	(1.23, 1.39)	(22.74, 26.06)	(0.26, 0.32)	(-1.33, 0.19)	(6.72, 10.40)
Evergreen forest	(0.04, 0.11)	(0.73, 0.84)	(11.04, 13.85)	(0.16, 0.19)	(-0.06, 0.69)	(3.38, 4.73)
Grassland	(0.57, 0.81)	(0.65, 0.85)	(58.36, 72.44)	(0.21, 0.27)	(0.48, 1.86)	(1.83, 3.88)
Mixed forest	(0.04, 0.61)	(1.11, 1.25)	(17.07, 25.39)	(0.21, 0.30)	(-6.40, 1.49)	(10.02, 12.35)

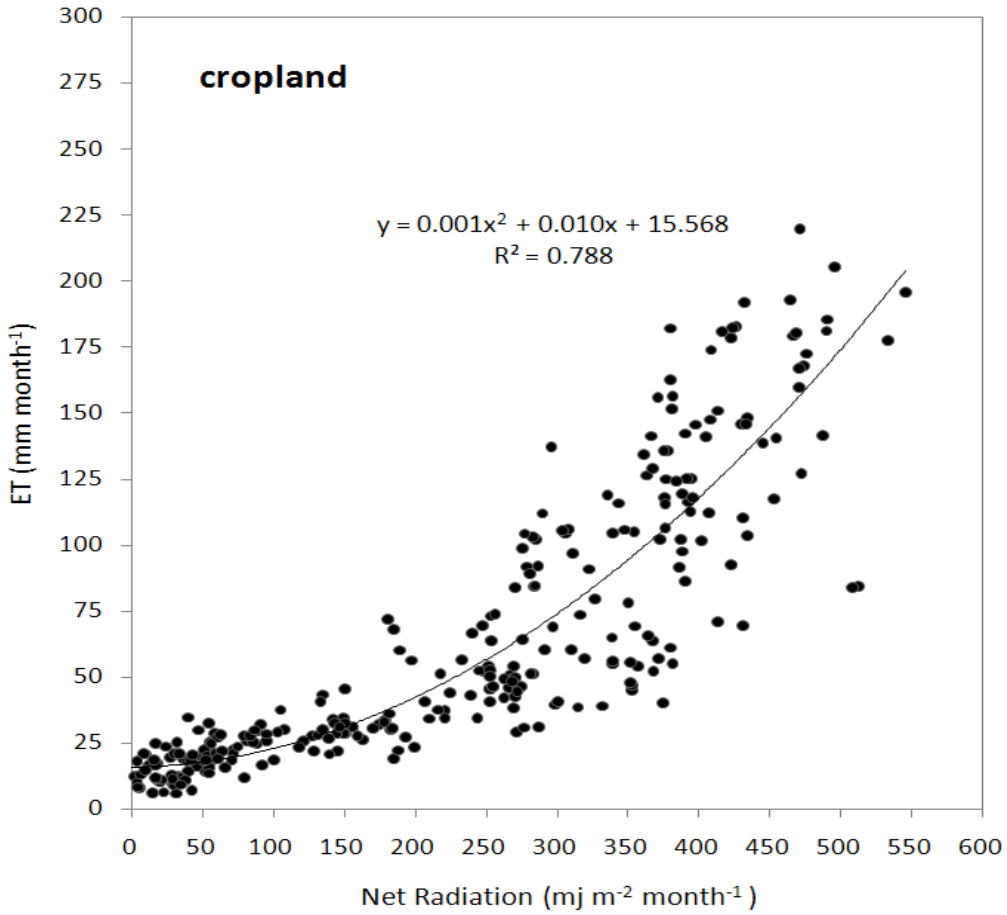


Figure 8. ET correlated with net radiation (Rn) of cropland

3.1.2 Key environmental controls determined by FLUXNET data

Compared with key environmental controls developed fromAmeriFlux, some differences were found using FLUXNET data. For shrubland, croplands, deciduous forest and mixed forest, the major controls were determined to be the same. However, for grasslands, Rn, instead of LAI, was the most influential variable. For mixed forests, Rn, instead of PET or temperature, was the best predictor for ET. There were few eddy flux

research sites for Savanna ecosystems. The limited data suggested that several environmental variables (LAI, Rn, VPD) controlled ET in savannas.

Table 4. The most significantly variables contributing to variability in ET with their partial R-square values,by land cover type, developed from global data (FLUXNET)

Land cover type	Partial R-square of significant variables							n
	PET	LAI	Rn	P	SWC	VPD	Ta	
Shrubland	N/A	0.60	0.19	0.02	0.01	N/A	N/A	193
Cropland	0.003	0.06	0.75	0.006	N/A	N/A	N/A	653
Grassland	0.01	N/A	0.77	0.03	0.01	N/A	N/A	803
Deciduous forest	0.75	N/A	0.02	N/A	0.003	0.08	N/A	692
Evergreen forest	N/A	N/A	0.62	0.006	N/A	0.02	0.06	1623
Mixed forest	0.95	N/A	N/A	N/A	N/A	N/A	N/A	254
Savannas	0.05	0.50	0.16	N/A	N/A	0.19	N/A	36

Similar to the relationships between environmental factors and ET found in the AmeriFlux data, PET, Rn, and LAI were linearly correlated to ET (Figure 9). Soil water conditions as represented by monthly P and SWC, were not good predictors for forest ET. ET was highly correlated with LAI for shrubland and savannas, suggesting plant biomass can be used as a good indicatorof water use for these types of ecosystems. In contrast, Rn was the key control for ET in cropland, grassland, and evergreen forest, indicating the importance of light in ET processes for these ecosystems.

The slopes of the linear relationships between ET and P (Figure9) indicated that shrubland (95% confidence interval of slope = (0.15, 0.30)), cropland (95% confidence

interval of slope = (0.12, 0.21)), and grassland (95% confidence interval of slope = (0.14, 0.22)) evapotranspired alarger fraction of monthly precipitation than any of the forest types (Table 5).

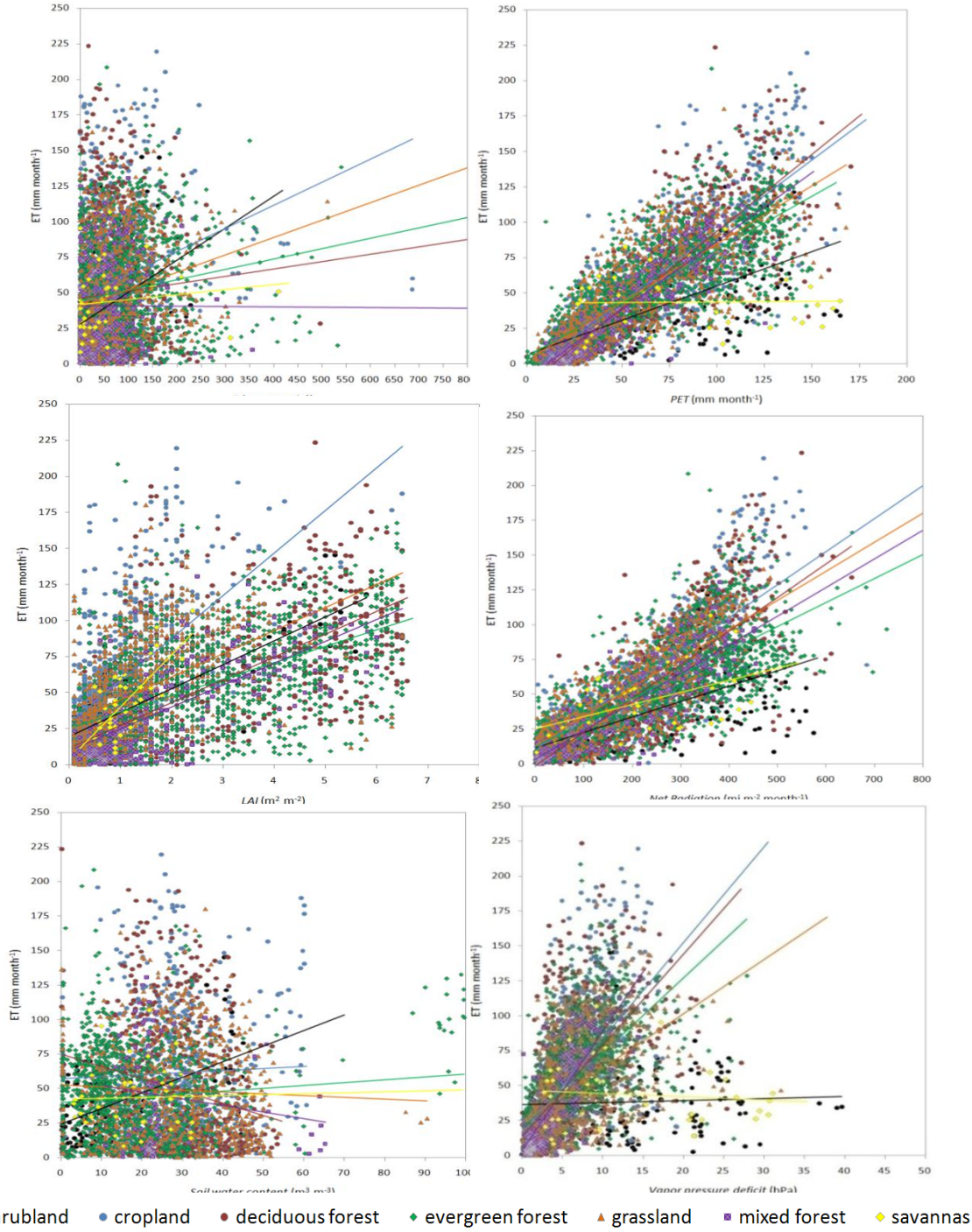


Figure 9. Relationship between monthly actural evapotranspiration (ET) and environmental variable: monthly precipitation (P), potential evapotranspiration (PET), leaf area index (LAI), net radiation (Rn) , soil water content (SWC) and vapor pressure deficit (VPD) based on FLUXNET dataset. Lines shown are trend lines of each land cover type.

Table 5. 95% confidence limits of slope for monthly precipitation (P), potential evapotranspiration (PET), leaf area index (LAI), net radiation (Rn) , soil water content (SWC) and vapor pressure deficit (VPD) based on FLUXNET dataset. Dependent variable is ET.

Land cover	95% confidence limits of slope					
	P	PET	LAI	Rn	SWC	VPD
Shrubland	(0.15,0.30)	(0.40,0.57)	(14.79,18.38)	(0.09,0.13)	(0.81,1.44)	(-0.43,0.72)
Cropland	(0.12,0.21)	(0.95,1.05)	(26.44,32.54)	(0.22,0.25)	(-0.24,0.53)	(6.16,7.59)
Deciduous forest	(-0.01,0.12)	(1.04,1.13)	(14.61,17.03)	(0.23,0.25)	(-1.24,-0.54)	(5.91,7.10)
Evergreen forest	(0.05,0.09)	(0.73,0.78)	(10.55,12.13)	(0.17,0.18)	(0.09,0.32)	(5.08,5.64)
Grassland	(0.14,0.22)	(0.78,0.86)	(13.23,16.94)	(0.19,0.21)	(-0.22,0.19)	(3.13,4.01)
Mixed forest	(-0.04,0.12)	(0.90,1.01)	(13.57,17.30)	(0.19,0.22)	(-0.94,0.35)	(7.85,9.44)
Savannas	(-0.06,0.13)	(-0.17,0.18)	(23.62,48.58)	(0.03,0.14)	(-0.80,0.94)	(-1.05,0.58)

3.2 Monthly ET models

From the above analysis and previous work (Sun *et al.* 2001; 2011b), it appears that PET, LAI, Rn, and P are key variables in developing general predictive models at the monthly scale. However, because Rn and VPD were not readily available for regional applications, this study provides two sets of ET models so the user has choices under various situations of data availability.

3.2.1 Monthly ET models developed from U.S data(AmeriFlux)

When pooling all data, the regression model derived from AmeriFlux was:

$$ET = -2.20 + 1.22PET - 5.14VPD + 0.07Rn \quad (11)$$

R^2=0.80, n=1173, $RMSE$=18.6 mm month^{-1}

When only PET, LAI, and P were considered, the monthly ET model took the form of:

$$ET = -6.51 + 0.76PET + 5.44LAI + 0.07P \quad (12)$$

R^2=0.72, n=1247, $RMSE$=19.9 mm month^{-1}

A comparison between measured ET and predicted ET values derived from the regression model (12) resulted in an overall RMSE of19.9 mm month^{-1} (Figure 10).

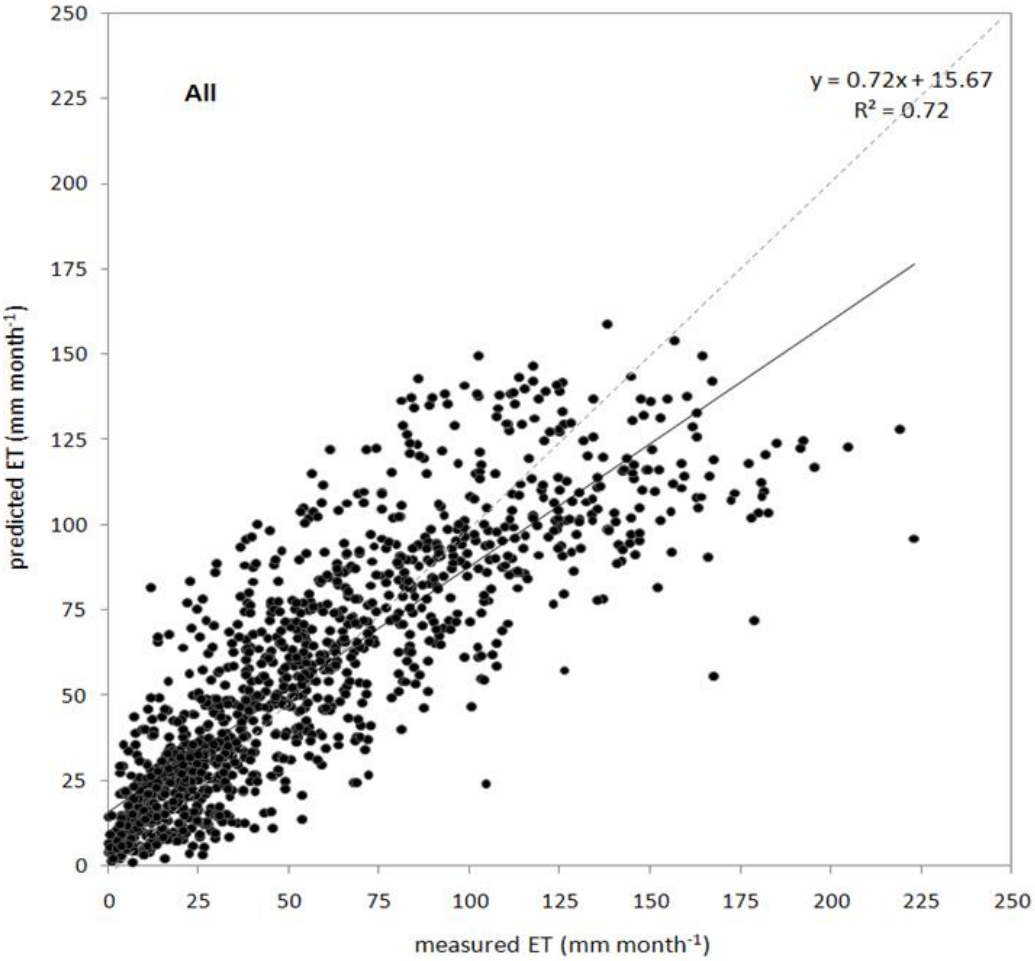


Figure 10.Predicted and measured monthly evapotranspiration (ET). Predicted ET was calculated by Equation 12 which was developed using data fromAmeriFlux. The solid lineis theregression line.The dashed line is the 1:1line.

Table 6.ET modelsusing the most significant variables for different land cover types developed using data fromAmeriFlux

Land cover type	Model	RMSE	R^2	n
Shrubland	ET=-5.78+13.22*LAI+0.10*Rn+0.11*P	11.2	0.86	182
Cropland	ET=-2.69+0.20*Rn+21.69*LAI+0.07*P	19.9	0.81	291
Grassland	ET=-24.55+34.65*LAI+0.67*SWC+0.15*Rn	15.7	0.83	98
Deciduous Forest	ET=-12.12+1.30*PET-4.76*VPD+7.71*LAI	15.6	0.91	154
Evergreen Forest	ET=7.56+0.84*PET-3.51*VPD+0.10*Rn	15.7	0.74	395
Mixed Forest	ET=-13.09+1.63*PET-4.58*VPD	8.3	0.96	52

Table 7.ET models using PET, P and LAI for different land cover types developed using data fromAmeriFlux

Land cover type	Model	RMSE	R^2	n
Shrubland	ET=-3.64+0.40*PET+0.09* P +11.05*LAI	12.7	0.80	182
Cropland	ET=-3.93+0.74* PET +0.06* P +17.78*LAI	21.1	0.78	294
Grassland	ET=-4.29+0.26*PET+0.19*P+38.78*LAI	17.1	0.79	123
Deciduous Forest	ET=-13.80+0.83*PET+10.38*LAI	18.1	0.88	187
Evergreen Forest	ET=5.34+0.65* PET +0.04*P +3.43*LAI	16.9	0.67	394
Mixed Forest	ET=-13.69+1.11* PET +1.81*LAI	8.8	0.95	51

All variables were highly significantly ($p<0.0001$) except for precipitation (P) in models for deciduous forest and mixed forest ($p>0.05$). TheR^2 of measured ET and predicted ET derived from regression models by land cover ranged from 0.67 to 0.95(Figure12).

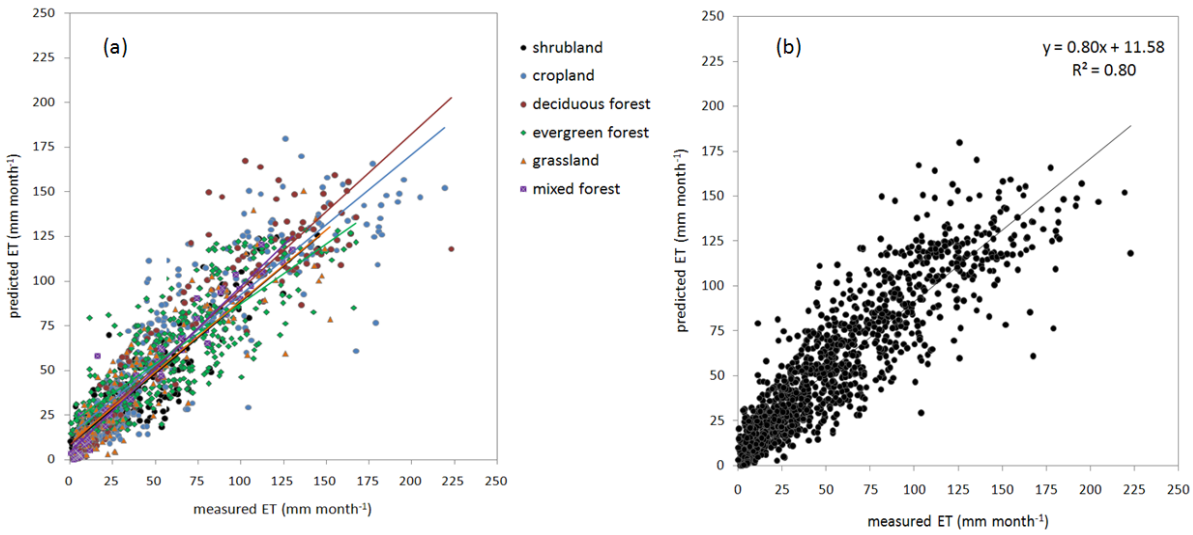


Figure 11.Predicted and measured monthly evapotranspiration (ET). Predicted ET was calculated using different equations for each land cover type. Lines shown areregression linesfor each model. (a) The relations between measured ET and predicted ET by land cover. (b) An overall comparison of measured ET and predicted ET by land cover type. The value of R^2 also reflected the how well ET was likely to be predicted by the models as a whole for all biome types.

A comparison of ET predicted by multiple models (Table7) and a single model (Equation12) suggested ET models separating bylandcover type would improve prediction. The R^2value of predicted ET and actual ET increased from 0.72 when data were lumped, to 0.80 when six individual models by land cover type were developed.

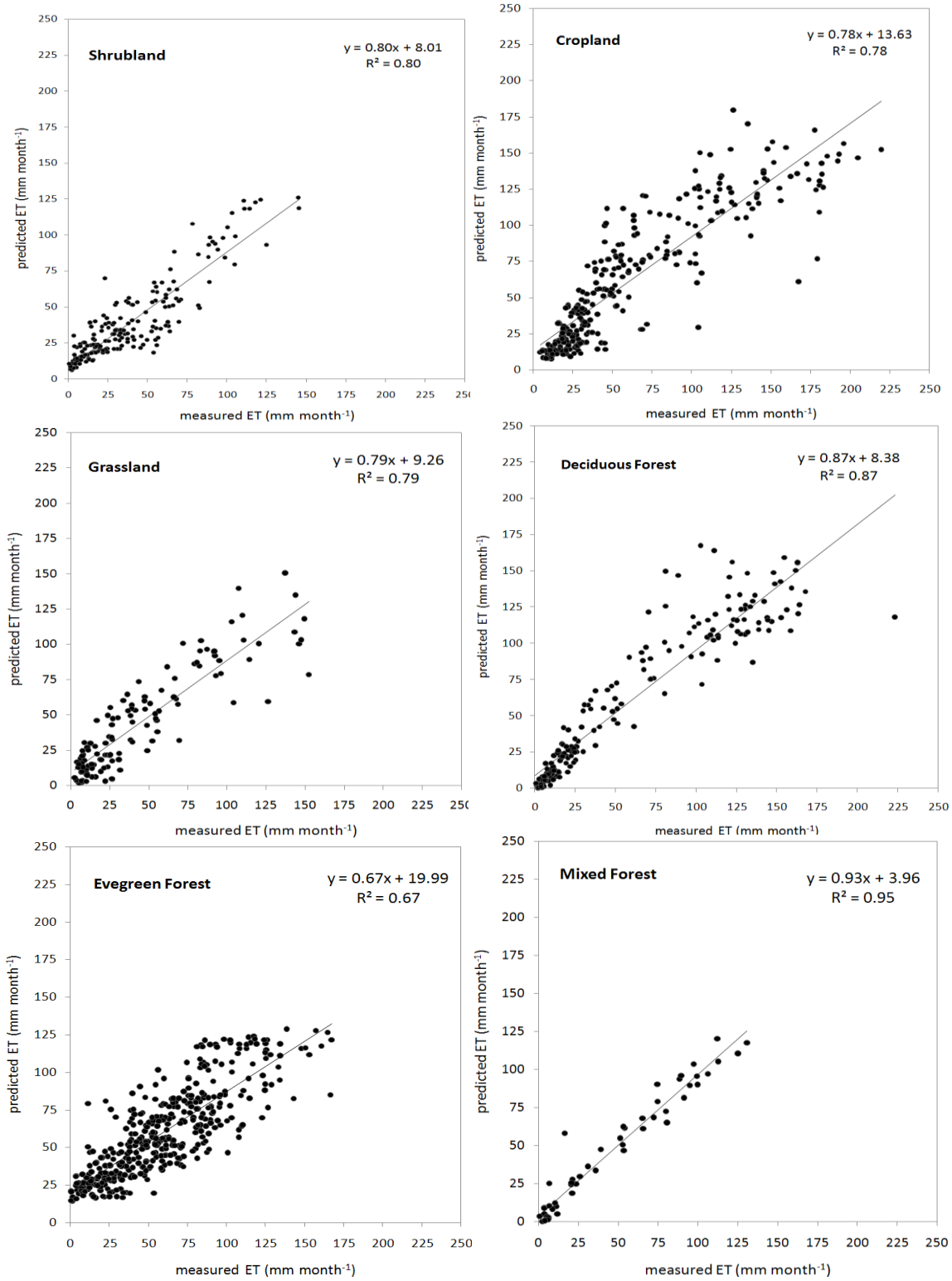


Figure 12. Measured and predicted ET derived from models (Table 7) developed by land cover types for the continental U.S. Lines shown were modeled means.

For deciduous forest and mixed forest, precipitation did not contribute significantly to ET models. One explanation for the insensitvity of ET to P may be that these forests have been rarely under water stress at the monthly scale. Therefore, I also developed regression models that consisted of the most significant variables for different land cover types (Table6).

1.3.2.1 Sub-models for ET prediction in western area of U.S.

After exploring the correlations between different environmental variables forall eddy flux sites, I found that the models developed had different accuracy for different climate regions. It appeared that the dry regions have unique ET processes that meant generalized models did not apply well.

For shrubland, monthly ET values ranged from less than 1 mm month^{-1}to 145 mm month^{-1}, reflecting the biophysical controls of leaf area index relative to precipitation (Table2, Figure 7). I also found that ET for many site-months was lower than PET within a narrow range of ET (0-50 mm month^{-1}). The predicted ET was linearly correlated with measured ET (R^2=0.80) for most of the sites. For example, the site US-Los was the Lost Creek tower in northern Wisconsin. (The site was covered with deciduous broadleaf vegetation , fully snow covered in winter and humid, warm in summer.) After ploting evapotranspiration, precipitation, potential evapotranspiration and leaf area index from 2001 to 2006 (Figure13a), I found that ET was highly correlated to PET. US-Los had 680mm average annual precipitation that could provide adequate water for ET, at least in growing seasons.

In contrast, at the Sky Oaks site in San Diego, CA (US-SO4) which had 482mm average annual precipitation from 2004-2006 (Figure13b), the water stresses in dry summers lead to a low monthly ET. The general model of shrubland underestimated ET for the western U.S. illustratedby comparing the predicted ET with USGS ET. ThereforeI derived a monthly ET model for the western area of the continental U.S..

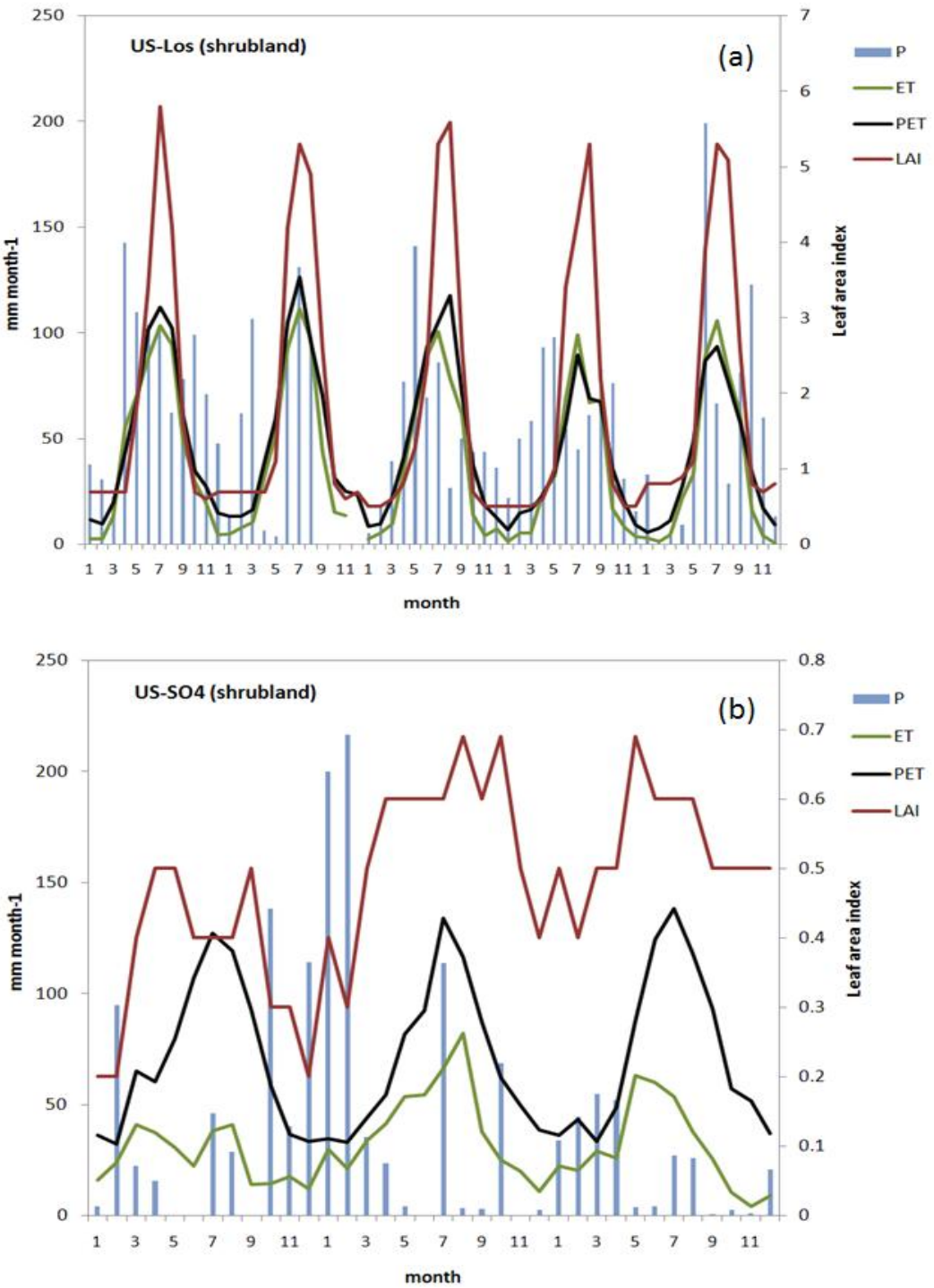


Figure 13. Variation of monthly P, PET, ET and LAI measured at sites in (a) Northern Wisconsin during the period of 2001 - 2006 and (b) San Diego during the period of 2004 - 2006. The dominated land cover type of the two sites wasshrubland

I also developed models ofthe western continental U.S. (dry regions) for the land cover types of evergreen forest, grassland and shrubland(Table 8).

Table 8. Additional models for dry area of continentalU.S

Land cover type	Model	RMSE	R^2	n
Shrubland	ET=-16.786+0.212*PET+0.110*P+65.075*LAI	9.3	0.54	96
Evergreen Forest	ET=4.041+0.953*PET+0.005*P+0.075*LAI	16.3	0.65	207
Grassland	ET=17.232-0.209*PET+0.004*PET*P+0.418*PET*LAI-0.082*P*LAI	15.7	0.68	340

I used just the data from the western part of the continental U.S to develop models for dry regions to improve the prediction accuracy for these low precipitation regions. For shrubland, I used data from sites in California (116 site-months) that had 493mm annual precipitation (in contrast to other sites such as 796mm for Wisconsin and 1074 mm for North Carolina) to develop models for dry regions. For evergreen forest, I extracted the data from California, Oregon, Arizona and Colorado (207 site-months) in which vegetation was mainly dominated by ponderosa pine, and created models for the western U.S region which had a low LAI for evergreen forest(1.69 m^2/m^2 monthly average compared to 2.90 m^2/m^2 monthly average for all regions). For grassland, I useddata from Oklahoma, Arizona, Montana, California, and South Dakota (344 site-months) and did model development for all of the western continental U.S. which has 483mm annual precipitation (in contrast to 1263mm annual precipitation of other regions of grassland).

I could use the models in Table6to estimate ET in the western region of the continental U.S for the land cover type of shrubland, evergreen forest and grassland specifically. To be consistent, I defined the western region to be the range of 95° W to 125° W, from eastern Texas to the West Coast, including the statesof California, Oregon, Arizona, Colorado, Oklahoma, Texas, etc.

3.2.2 Monthly ET models developed from global data (FLUXNET)

When pooling all data, the regression model derived from FLUXNET was:

$$ET = 0.42 + 0.74PET - 2.73VPD + 0.10Rn \quad (13)$$

R^2=0.73, n=4615, $RMSE$=17.0 mm month^{-1}

When only PET, LAI, and P were considered, the monthly ET model took the form of:

$$ET = -4.79 + 0.75PET + 3.92LAI + 0.04P \quad (14)$$

R^2=0.68, n=4265, $RMSE$=18.1 mm month^{-1}

A comparison between measured ET and predicted ET values derived from the regression model (14) resulted in an overall RMSE18.1 mm month^{-1} (Figure 14).

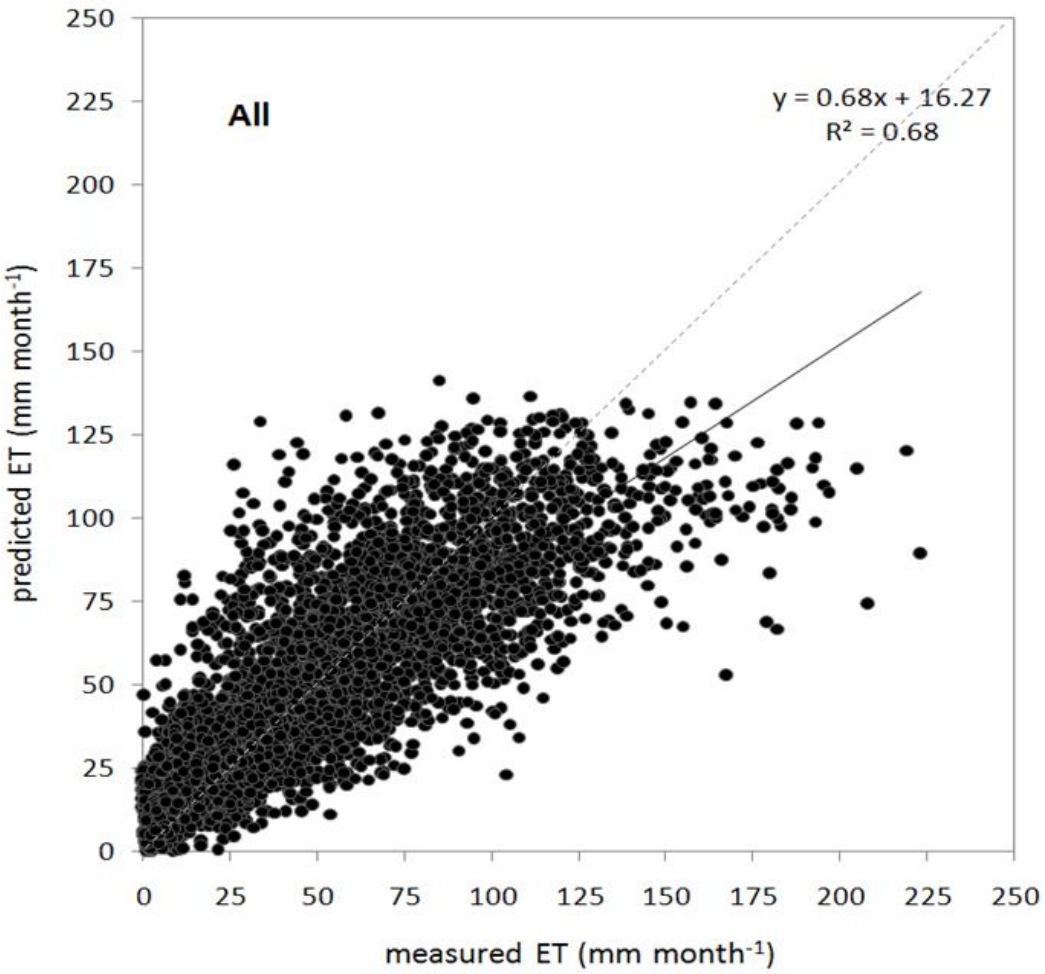


Figure 14. Predicted and measured monthly evapotranspiration (ET). Predicted ET was calculated byEquation(14) which was developed using data globally. The solid lineis the regression line.The dashed line is the 1:1 line.

The monthly ET models consisted of three of the most significant variables (Table4)are listed in Table9by land cover classification.For mixed forest, PETwas the only signifcant predictor variable ($p<0.0001$) of ET. Thus the monthly ET model of mixed forest only had one variable of PET. Even so, the precision of the ET model was high based on the high R^2 (0.79).

Table 9.ET models using the most significant variables for different land cover types developed using data fromFLUXNET.

Land cover type	Model	RMSE	R^2	n
Shrubland	ET=-4.59+13.02*LAI+0.10*Rn+0.11*P	11.2	0.85	193
Cropland	ET=0.87+0.19*Rn+13.99*LAI+0.06*P	20.2	0.72	649
Grassland	ET=-0.87+0.20*Rn+0.10*P+0.24*SWC	15.7	0.73	562
Deciduous Forest	ET=-17.80+1.24*PET-5.22*VPD+0.11*Rn	15.9	0.83	628
Evergreen Forest	ET=14.21+0.11*Rn+1.73*Ta-0.81*VPD	15.2	0.73	1919
Mixed Forest	ET=-8.763+0.95*PET	13.1	0.79	259
Savannas	ET=16.91+9.96*LAI+0.022*Rn-2.38*VPD	8.4	0.85	36

I also developed ET models based on PET, LAI and P variables only (Table10).All variables were highly significant($p<0.0001$) except for P in models of deciduous forest and mixed forest ($p>0.05$). The R^2 of measured ET and predicted ET derived by regression models of different land cover typeswerefrom 0.66 to 0.80 (Figure15).

Table 10.ET models using PET, P and LAI for different land cover types developed using data fromFLUXNET.

Land cover type	Model	RMSE	R^2	n
Shrubland	ET= -3.11+0.39*PET+0.09*P+11.127*LAI	12.5	0.80	193
Cropland	ET= -8.15+0.86*PET+0.01*P+9.54*LAI	20.9	0.70	653
Grassland	ET= -1.36+0.70*PET+0.04*P+6.56*LAI	16.8	0.66	803
Deciduous Forest	ET= -14.98+0.96*PET+3.08*LAI	20.0	0.74	692
Evergreen Forest	ET= -0.10+0.68*PET+0.04*P+3.27*LAI	15.6	0.71	1623
Mixed Forest	ET= -9.57+0.87*PET+2.46*LAI	13.2	0.79	254
Savannas	ET= -25.66+0.18*PET+0.10*P+44.63*LAI	11.1	0.68	36

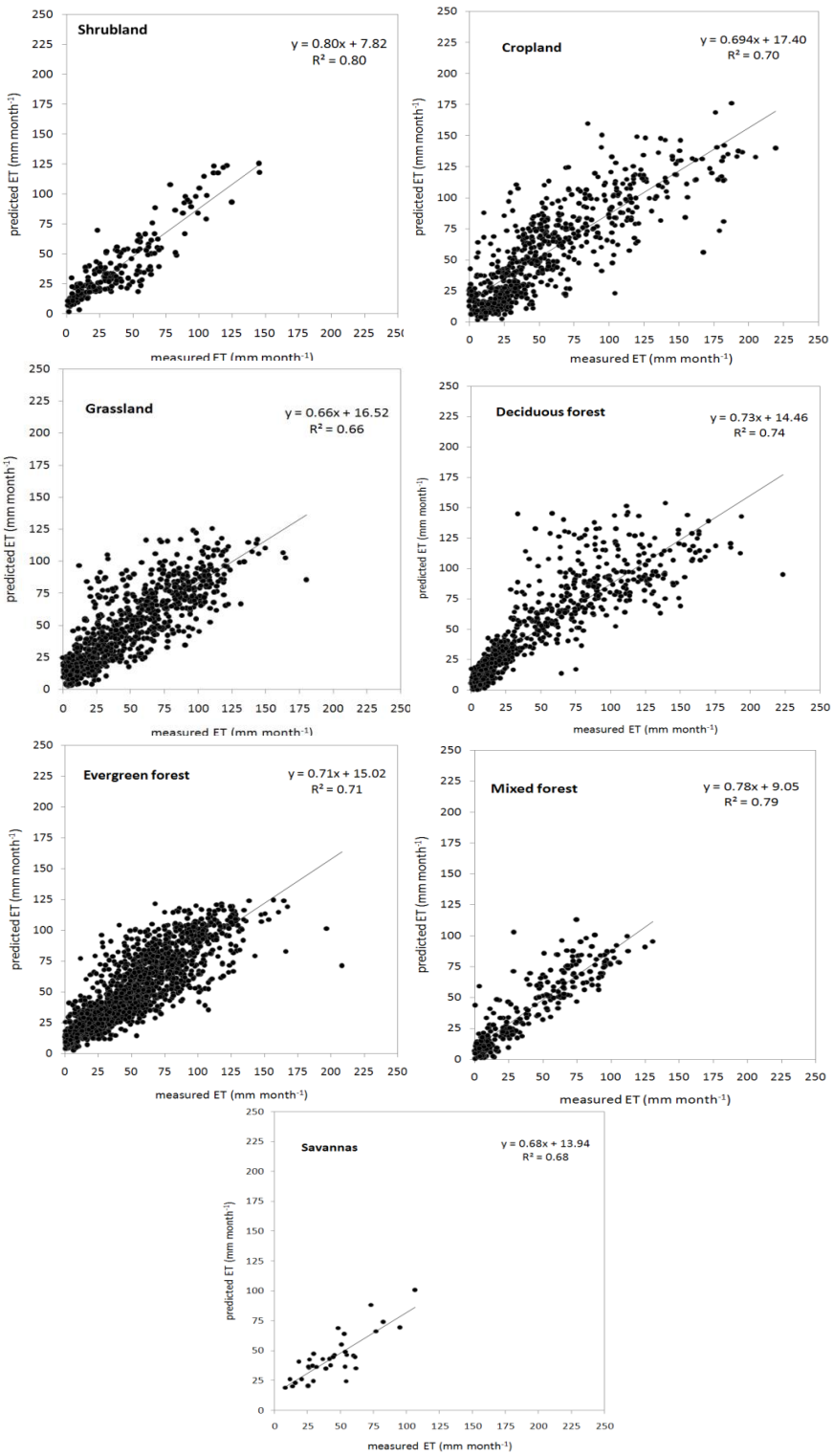


Figure 15. Measured and predicted ET derived from models(Table8) developed by land cover type globally. Lines shown are modeled means.

4. DISCUSSION

4.1 Relationship between ET and environmental variables

The global synthesis studyof ET for multiple vegetation types showed that ecosystem ET is mainly controlled by energy availability as represented by variables such as PET,Rn,vegetation dynamics, and LAI. Precipitation andsoil water content provide additional control of ET.

Itis well known that precipitation is the major source of water for plants. Theoretically, ET should be determined by P in the system, especially under water stress. In semiarid regions, ET was more correlated with P rather than net radiation and temperature (Nagler *et al.* 2007). In contrast, other variables such as LAI could replace the most significant position of P to ET in humid areas. In this study, I found that P was not the predominated predictor variable for deciduous forest and mixed forest in the U.S. By comparing the relations between P and ET by land cover type, I also found that for grassland the ratio of ET to Pwas much higher than that of evergreen and deciduous forest overall (Figure7,9; Table 3, 5). This finding agreed with the conclusionsbyWilliams *et al.*(2012) that grassland evaporated 9% more annual precipitation than forest,on average. The ET/P rate of cropland was lower than grassland, but higher than evergreen forest (Figure7,9; Table 3, 5).In croplands, ET washighly connected with soil water content (SWC) and precipitation (P) could be stored at the top 10cm of soil to meet the water need of plants at a period (Kurc *et al.* 2004).A study by Seneviratne *et al.* (2010)on soil water coupling with other climate variables

suggested that SWC limited ET due to soil moisture supply limitations. ET would be restricted by SWC when soil was too dry.

Underestimation errors may occur when using our model without considering SWC under extreme dry conditions.Nagler et al. (2007) considered interannual lags of precipitation in their study to account for effects of soil water storage on ET. During model development in this study,I also tried to use variablesfor total precipitation of the previous month and precipitation of the current month to account for lagging effects on ET. However, improvements by this method were not always achievable. The complexity of ecosystems monitored by the eddy flux network made general modeling challenging. LAI and PET were the critical controls to ET. ET had a positive correlation with LAI since more leaves mean more ET surfaces and water use.However, LAI was found to increase with an increase in precipitationwith a finite upper limit (Grier *et al.* 1977). In agreement with previous discussion, the variables of LAI, P and PET were therefore tightly coupled and closely linked to ET.

This study improved ET models previously developed by Sun *et al.* (2011a, 2011b) by accounting for land cover types. These findings suggest that different ecosystems may have different ET controls.Specific circumstances, such as the dry region,had unique vegetation and climate. Sub-models (Table8)worked best for ET predictionsin the western dry region of the continental U.S from longitude west 125° to west 95° (Arizona, California, Alabama, Organ, Colorado, etc). The sites used to develop the sub-models are given in

appendices(B, C, D, E, F, G), the sitesin boldare what I used to develop models for the western dry region. The sites with * represent missing ET data.

4.2 Water use ofET by land cover

In this study, I found that ET varied significantly by land cover type. I explored the water use of vegetation by comparing ET, PET, P and LAI of different land cover types. The months of July and August are always the peak growing season for vegetation in the northern hemisphere. A close look at these two months provides a contrast in maximum water use among land cover types (Figure 16). I plotted the mean monthly ET, P, PET and LAI of July and August for each land cover (Figure16). The average monthly ET was higher than average monthly P for all land cover during July and August. This indicated precipitation during these months could not satisfy the water requirement for ET and that soil water content may become the significant control for ET. Cropland had the highest mean monthly ET (142 mm) which was far beyond the monthly precipitation, so that may be due to irrigation in the summer. For cropland, deciduous forest and mixed forest, the mean monthly ET rates were even higher than mean monthly PET, indicating that these land covers need more water than "well-watered" grass lands. It was apparent that PET was not the highest ET achievable despite its definition. Cropland, deciduous forest and mixed forest evapotranspired more water than grassland under the condition of no water stress. Thus, grassland may not be the best reference vegetation cover type selected to calculate PET. Cropland or plantation forest has the potential to be used in estimating PET instead.As expected, for grasslands and shrublands that were distributed in the arid regions with low P, ET rates were lower than PET

during July and August, the peak growing seasons. On a per unit LAI basis, croplands with a mean LAI of 2.1, had the highest ET in July and August. Suprisingly, croplands lost more water than forests that had much higher LAI in the peak growing seasons.

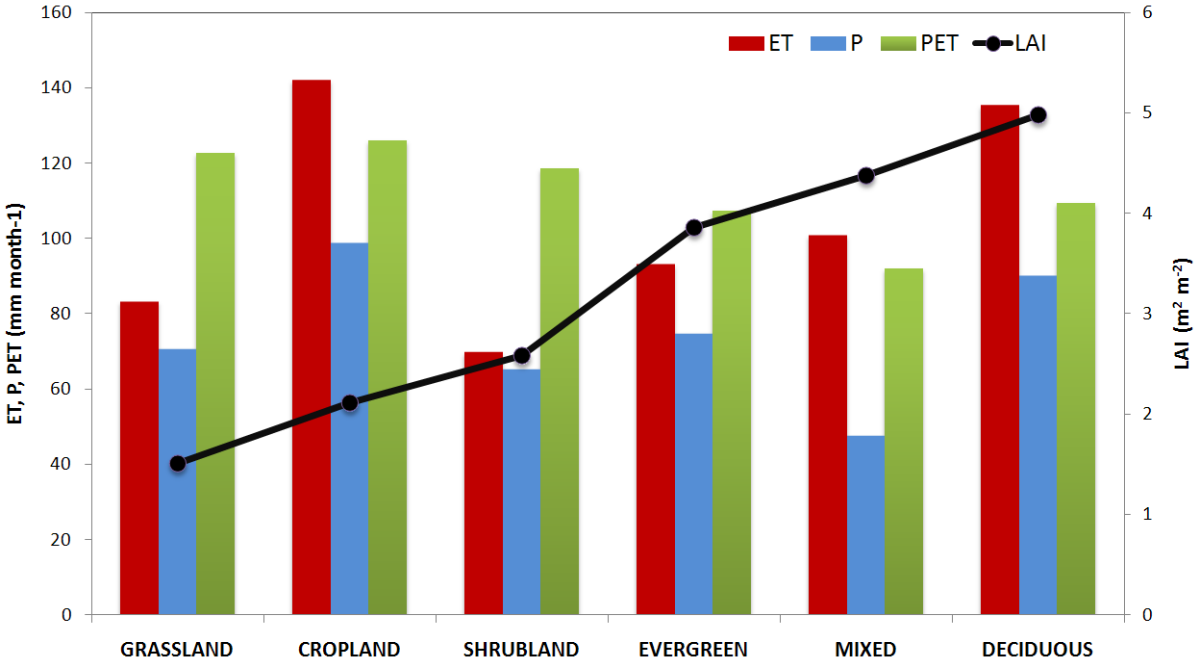


Figure 16.Mean monthly ET (evapotranspiration), P (precipitation), PET (potential evapotranspiration), and LAI (leaf area index) of July and August generated from AmeriFluxdata.

4.3 Limitation of the ET models developed by this study

For regional monthly ET prediction purposes in the U.S., the accuracy of the ET models with three input variables (PET, LAI, and P) is sufficient as judged by model summary statistics (R^2 =0.67 - 0.95; RMSE=8.3-19.9). However, estimation errors existed due to climatic peculiarities and large variability in climate across the U.S. continent. For example, the site of US-Blo (Blodgett Forest in California) had a warm and dry summer climate, and was dominated by ponderosa pine. The site had low precipitation in summer, but was wet in winter (Figure 17). In contrast, the other evergreen forest sites always had low precipitation in winter and high precipitation in the summer. Thus, ET was highly correlated with PET, LAI and P, seasonally. The generalized model,therefore,underestimated ET for the summer and overestimated ETfor the winterat the US-Blo site. Additionally, other errors and uncertainties of measurements may also contribute to estimation errors of the ET models as discussed later.

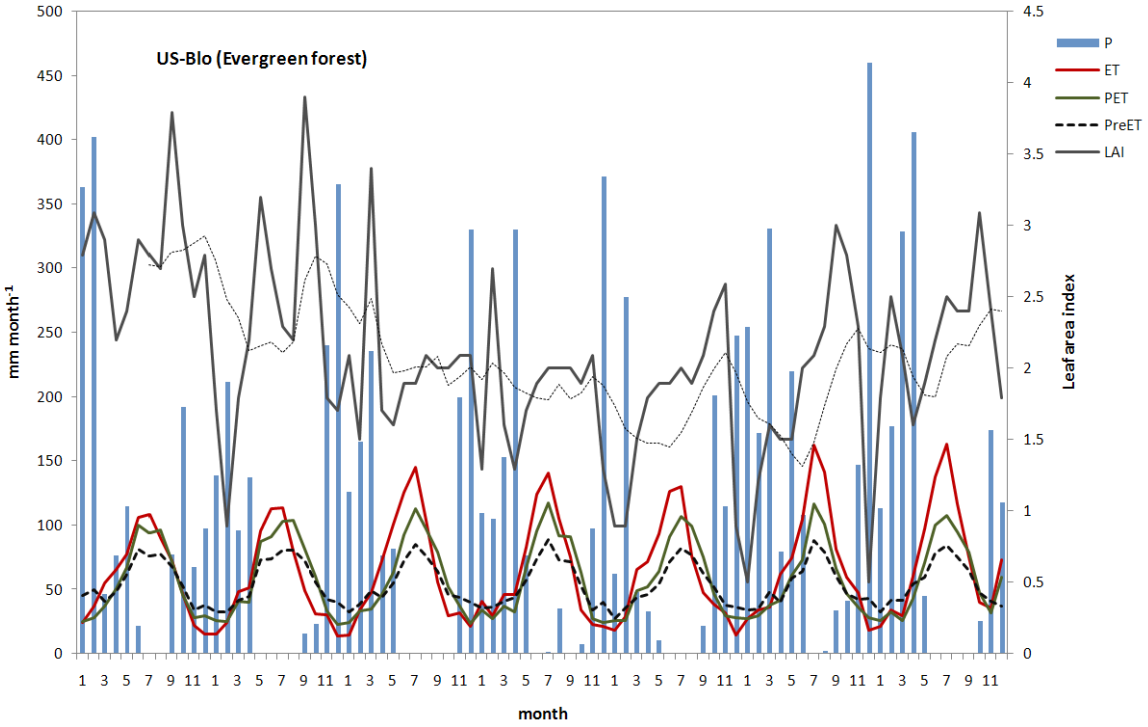


Figure 17. Variation of monthly P, PET, ET and LAI measured at Blodgett Forest in California (latitude 38.89, longitude -120.63)during the period of 2000-2006. The dominated land cover type is evergreen forest.

4.4 Uncertainties of ET and LAI

Daily ET was derived from latent heat flux (LE) measurements. It had biases that came from errors insurface temperature measurements(Kalma *et al.* 1990). Along with the inevitable measurement errors, unknown disturbances (i.e. the influence of animals) and instrument failures, ET estimation becamea inaccurate science (Allen 2008).

Aside from systematic errors associated with eddy covariance methods and remote sensing technique, due to possible bias in our model and data (including PET and LAI extraction), some data were removed from the databases (e.g. when correcting ET by energy closure ratio, ET would be null when energy closure ratio was null value). Energy imbalance

problems might have caused ET estimation errors. For example, the energy closure was found to range from 62% at Beijing poplars site to 110% at the Inner Mongolia grassland site in the study of Sun *et al.* (2011a). Wilson *et al.* (2012) concluded that around 20% of a general lack of closure exists in all measured vegetation types and variety of climate conditions and there was about 10% absolute uncertainty in energy balance measurement caused by incomplete closure problem for the eddy covariance method (Twine *et al.*2000). In our study, the energy closure ranged from 87% to 89% (i.e. 88±1%) at the 95% confidence interval for the worldwide eddy flux data (6725 site-months). This is consistent with Twine *et al.* (2000) and Wilson (2012)'s conclusions. The general phenomena of incomplete energy balance closure at FLUXNET sites causes underestimation of sensible heat and latent heat flux, and then underestimated ET at the mean value of 12% in our study. The correction methods to remedy energy closure errors could not guarantee that ET estimates were correct since the method assumes theof H/LE ratio remained constant

As an essential input to our model, LAI which derived from Moderate Resolution Imaging Spectroradiometer(MODIS), had a relatively high resolution (1km^2) but still was considered too coarse to represent the site level LAI. Quite often, ground-based measurements of forest LAI were much higher than MODIS LAI. Furthermore, fluctuations of monthly LAI were rather unrealistic in some cases. For example, at the Blodgett Forest site in California, LAI fell abruptly by around 1 (m^2/m^2) in September, 2001, but rose back to a higher value the next month.This abnormal phenomenonhappened in an evergreen forest.

Previous research byCohen *et al.*(2006)also found that daily MODIS LAI fluctuatedunrealistically. The large fluctuations were caused by clouds and snow affecting

the reflectance of vegetation. This type of problem existed in the current study even though I scaled LAI from daily to monthlyvalues which reduced the error to some extent. The misclassification of vegetation types also increased the errors of estimation when computing LAI by different biomes (Pandya *et al.* 2006). In addition, MODIS LAI had 1km^2 resolution which was greater than the size of the fetch of eddy flux measurements. For example, the grassland site of US-DK1 waslocated at theDuke Forest open field whichwas a grassy field adjacent to a forest.LAIfor this site was reported as high as 5.5 in the summer, apparently an over-estimation when compared to similar grasslands that had an average LAI of less than1.0. Such measurement errors could result in a great uncertainty in ET model building.

5. CONCLUSIONS

This study concluded that the key environmental controls for different ecosystem varied greatly. The analysis of AmeriFlux data showed that LAI and Rn explained most of the variability of observed ET for shrubland, cropland and grassland. In contrast, PET as estimated by a temperature-based method was a key control for observed ET of deciduous forest, evergreen forest and mixed forest.Monthly ET could be well explained by PET, LAI and P. The two series of empirical ET models developed from this study have the potential to be used for ET estimation at regional scales, which could be used to quantify actual ET and the accuracy of predicted ET could be as high as possible depending on the available data. The simpler ET models that consistof three variables (PET, P and LAI) might meet the requirements of users who do not have information onsoil water content, radiation and vapor humidity. Otherwise, ET models developed usingthe three most significant variables for ET

may fulfill the expectation of forecasting monthly ET.Furthermore, the improved ET models from this study may be useful in evaluating the impacts of climate change and land use change on water resources at a continental scale.

The approaches of this study combined methods of eddy covariance (FLUXNET) and remote sensing (MODIS). This multiple-ecosystem study showed the general relationships among terrestrial water loss, energy, and water availability and indicated intricate relationships among precipitation, availability of evaporative energy and vegetation dynamics at a finer temporal scale (i.e. monthly)- a scale that most regional-scale hydrological models use for global change studies. In addition, our study improved the previous predictive ET model (Sun *et al.* 2011) by including more eddy flux sites (254 global, 74 U.S.) and refinedthe monthly ET model into several sub-models by land cover type. This synthesis study contributed to improvement in ET models because it employed a large amount of data and created a series of ET models by land cover type. It included both global monthly ET models (developed from FLUXNET data) and U.S. monthly ET models (developed from AmeriFlux data), as well as sub-models for western dry areas of the U.S.,particularly.

The advantage of the models developed by this studywas convenienceof use for estimating ET at regional scales. Depending on data availability, users may have choices. The simple ET models only requiredthree variables (PET, P and LAI) which can be derived from networks of weather stations and remote sensing products, or from databases created by climate change projects.Future studies should evaluate the ET models by comparing

modeling results with other ET products, such as MODIS ET and ET estimates based on sapflow and watershed-balance methods in different regions with different regimes.

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APPENDICES

Appendix A. Sites used in the study of the world monthly ET model.

Land cover	Sites used in this study	Site-month	Sites removed
Shrubland	CA-NS6 CA-NS7 CG-Tch CN-Ku2 ES-LJu RU-Cok US-Los US-NC1 US-SO2 US-SO3 US-SO4 US-Wi6 US-Wi7	193	IT-Noe IT-Pia
Cropland	BE-Lon BR-Sa2 CH-Oe2 CN-Du1 DE-Geb DE-Kli DK-Fou DK-Ris FR-Aur FR-Gri FR-Lam IE-Ca1 IT-BCi IT-Cas JP-Mas KR-Hnm NL-Ca2 NL-Lan NL-Lut NL-Mol UK-ESa UK-Her US-Bo1 US-Bo2 US-IB1 US-Ne1 US-Ne2 US-Ne3 ES-ES2	653	ES-ES2(2004) US-ARM
Deciduous Forest	CA-Oas CN-Anh CN-Hny DE-Hai DK-Sor FR-Fon FR-Hes IT-Col IT-Non IT-PT1 IT-Ro1 IT-Ro2 IT-Vig JP-Tak SE-Abi SE-St1 UK-Ham UK-PL3 US-Bar US-Dk2 US-Ha1 US-LPH US-MMS US-MOz US-Oho US-UMB US-WCr US-Wi1 US-Wi8	692	
Evergreen Forest	AU-Tum AU-Wac BR-Ban BR-Cax BR-Ji2 BR-Ma2 BR-Sa1 BR-Sa3 CA-Ca1 CA-Ca2 CA-Ca3 CA-Man CA-NS1 CA-NS2 CA-NS3 CA-NS4 CA-NS5 CA-Obs CA-Ojp CA-Qcu CA-Qfo CA-SF1 CA-SF2 CA-SF3 CA-SJ1 CA-SJ2 CA-SJ3 CA-TP1 CA-TP2 CA-TP3 CA-TP4 CN-Bed CZ-BK1 DE-Har DE-Tha DE-Wet ES-ES1 FI-Hyy FI-Sod FR-LBr FR-Pue ID-Pag IL-Yat IT-Bon IT-Cpz IT-Lav IT-Lec IT-Ren IT-SRo NL-Loo PT-Esp RU-Fyo RU-Zot SE-Fla SE-Nor SE-Sk1 SE-Sk2 SK-Tat UK-Gri US-Blo US-Dk3 US-Fmf US-Fuf US-Ha2 US-Ho1 US-Ho2 US-KS1 US-Me1 US-Me2 US-Me3 US-Me4 US-NC2 US-NR1 US-SP1 US-SP2 US-SP3 US-Wi0 US-Wi2 US-Wi4 US-Wi5 US-Wi9 US-Wrc VU-Coc	1623	CA-SJ1 UK-Gri FR-Pue IT-Cpz US-SP1 IL-Yat US-Blo
Grassland	AT-Neu CA-Let CH-Oe1 CN-Du2 CN-HaM CN-Xi1 CN-Xi2 CZ-BK2 DE-Gri DE-Meh DK-Lva ES-VDA FI-Sii FR-Lq1 FR-Lq2 HU-Bug HU-Mat IE-Dri IT-Amp IT-Be2 IT-LMa IT-Mal IT-MBo NL-Ca1 NL-Haa NL-Hor RU-Ha1 RU-Ha2 RU-Ha3 UK-EBu UK-Tad US-ARb US-ARc US-Dk1 US-FPe US-Fwf US-Goo US-IB2	803	US-Bkg US-FPe (2001 2003 2004 2005.6 2005.7 2006) US-Var US-CaV US-Wkg US-Aud
Mixed Forest	BE-Bra BE-Jal BE-Vie CA-Gro CA-WP1 CN-Cha JP-Tef RU-Che US-PFa US-Syv	254	JP-Tom KR-Kw1
Savannas	ES-LMa ZA-Kru	36	BW-Ghg AU-Fog

Appendix B. Sites used in the study of U.S monthly ET model of shrubland.

(Sitesin boldare what we used to develop models for western dry region. The site with * had no data of ET available)

Shrubland

Site	Site code	Plant community and dominant species	Latitude	longitude	Climate	Observation period
Lost Creek (Wisconsin)	US-Los	willow shrub wetland	46.08	-89.97	Snow fully humid warm summer	2001-2005
Clearcut (North Carolina)	US-NC1	Loblolly pine seedlings surrounded by a dense groundcover composed of dogfennel and roundleaf greenbrier along the margins of the plantation.	35.81	-76.71	Warm temperate fully humid with hot summer	2005-2006
Sky Oaks- Old Stand(California)	**US-SO2**	Chamise-dominated chaparral	33.37	-116.62	Warm temperate with dry, hot summer	2004-2006
Sky Oaks- Young Stand(California)	**US-SO3**	Chamise-dominated chaparral	33.37	-116.62	Warm temperate with dry, hot summer	2001, 2003-2006
Sky Oaks(California)	**US-SO4**	Chamise-dominated chaparral	33.38	-116.64	Warm temperate with dry, hot summer	2004-2006
Pine barrens (Wisconsin)	US-Wi6	dominated by jack pines, red oaks, prairie willows, and various herbs such as lowbush blueberry and sweet ferns	46.62	-91.29	Snow fully humid warm summer	2002
Wisconsin Red pine clearcut (Wisconsin)	US-Wi7*	Red pine clearcut	46.64	-91.06	Snow fully humid warm summer	2005

Appendix C. Sites used in the study of U.S monthly ET model of cropland.

Cropland

Site	Site code	Plant community and dominant species	Latitude	longitude	Climate	Observation period
ARM Southern Great Plains site (Oklahoma)	US-ARM*	Agricultural: wheat, corn, and soybean periodic rotation	36.6	-97.48	Warm temperate fully humid with hot summer	2003-2006
Bondville (Illinois)	US-Bo1	Annual rotation between corn and soybeans	40	-88.29	Snow with fully humid hot summer	2000-2006
Bondville (companion site) (Illinois)	US-Bo2	Annual rotation between Corn-2004, Soybeans- 2005 planted with opposite crop in corn/soybean rotation to US-Bo1	40	-88.29	Snow with fully humid hot summer	2004-2006
Fermi National Accelerator Laboratory - (Agricultural site) (Illinois)	US-IB1	Corn/Soybean rotation	41.85	-88.22	Snow with fully humid hot summer	2005-2006
Mead - irrigated continuous maize site (Nebraska)	US-Ne1	Agriculture (continuous maize)	41.16	-96.47	Snow with fully humid hot summer	2001-2005
Mead - irrigated maize-soybean rotation site(Nebraska)	US-Ne2	Agriculture (maize-soybean rotation)	41.16	-96.47	Snow with fully humid hot summer	2001-2005
Mead - rainfed maize-soybean rotation site(Nebraska)	US-Ne3	Agriculture (maize-soybean rotation)	41.17	-96.43	Snow with fully humid hot summer	2001-2005

Appendix D. Sites used in the study of U.S monthly ET model of deciduous forest.

Deciduous Forest

Site	Site code	Plant community and dominant species	Latitude	longitude	Climate	Observation period
Morgan Monroe State Forest (Indiana)	US-MMS	Mixed hardwood deciduous forest, a secondary successional broadleaf forest within the maple-beech to oak hickory transition zone of the eastern deciduous forest.	39.32	-86.41	Warm temperate fully humid with hot summer	2002-2004
Missouri Ozark Site (Missouri)	US-MOz	Oak hickory forest	38.74	-92.2	Warm temperate fully humid with hot summer	2004-2006
Oak Openings (Ohio)	US-Oho	managed oak woodland	41.55	-83.84	Snow with fully humid hot summer	2004-2005
Willow Creek (Wisconsin)	US-WCr	Mature sugar maple-aspen-yellow birch forests, common type of second stage growth following old-growth hemlock-hardwood forests in northern Wisconsin	45.8	-90.07	Snow fully humid warm summer	2000-2006
Intermediate hardwood (Wisconsin)	US-Wi1	Naturally regenerated mixed hardwood	46.73	-91.23	Snow fully humid warm summer	2003
Young hardwood clearcut (Wisconsin)	US-Wi8	Naturally regenerated mixed hardwood	46.72	-91.25	Snow fully humid warm summer	2002
Bartlett Experimental Forest (New Hampshire)	US-Bar*	Temperate northern hardwood forest	44.06	-71.28	Snow fully humid warm summer	2004-2005

Duke Forest Hardwoods (North Carolina)	US-Dk2*	Mature oak-hickory dominated hardwood forest	35.97	-79.1	Warm temperate fully humid with hot summer	2003-2005
Harvard Forest EMS Tower (Massachusetts)	US-Ha1*	Temperate deciduous forest	42.53	-72.17	Snow fully humid warm summer	2000-2006
Little Prospect Hill (Massachusetts)	US-LPH*	Temperate deciduous forest	42.54	-72.18	Snow fully humid warm summer	2002-2005
Morgan Monroe State Forest (Indiana)	US-MMS	Mixed hardwood deciduous forest	39.32	-86.41	Warm temperate fully humid with hot summer	2002-2004
Univ. of Mich. Biological Station (Michigan)	US-UMB*	Deciduous broadleaf forest	45.55	-84.71	Snow fully humid warm summer	2000-2003

Appendix E. Sites used in the study of U.S monthly ET model of evergreen forest.

Evergreen Forest

Site	Site code	Plant community and dominant species	Latitude	longitude	Climate	Observation period
Blodgett Forest (California)	**US-Blo***	Mixed evergreen coniferous forest dominated by ponderosa pine	38.89	-120.63	Warm temperate with dry, warm summer	2000-2006
Duke Forest Loblolly Pine (North Carolina)	US-Dk3*	The uniform age overstory is almost solely composed of loblolly pines with an understory of 26 different hardwood species.	35.97	-79.09	Warm temperate fully humid with hot summer	2001-2005
Flagstaff - Managed Forest (Arizona)	**US-Fmf**	ponderosa pine forest	35.14	-111.72	Warm temperate with dry, warm summer	2005-2006
Flagstaff - Unmanaged Forest (Arizona)	**US-Fuf**	ponderosa pine forest	35.08	-111.76	Warm temperate with dry, warm summer	2005-2006 (incomplete data from January to June in 2005)
Harvard Forest Hemlock Site (Massachusetts)	US-Ha2*	Temperate coniferous forest	42.53	-72.17	Snow fully humid warm summer	2004
Howland Forest (Main Tower) (Maine)	US-Ho1*	The natural stands in this boreal--northern hardwood transitional forest consist of hemlock-spruce-fir, aspen-birch, and hemlock-hardwood mixtures.	45.2	-68.74	Snow fully humid warm summer	2000-2004
Howland Forest (West Tower) (Maine)	US-Ho2*	Evergreen Needleleaf Forest	45.2	-68.74	Snow fully humid warm summer	2000-2004

Kennedy Space Center (slash pine) (Florida)	US-KS1	Managed Slash Pine Flatwoods	28.45	-80.67	Warm temperate fully humid with hot summer	2002 November, December
MetoliusEyerly Burn (Oregon)	US-Me1	After fire in early July 2002, the live vegetation is constrained to the understory with a significant portion occupied by forbs and grasses. More common species to the understories of ponderosa pine forests in central Oregon have begun to regrow, including antelope bitterbrush and greenleaf manzanita.	44.57	-121.5	Warm temperate with dry, warm summer	2004-2005 Incomplete data from August to December in 2005)
Metolius Intermediate Pine (Oregon)	**US-Me2**	Evergreen Needleleaf Forest	44.45	-121.55	Warm temperate with dry, warm summer	2003-2005
Metolius Second Young Pine (Oregon)	**US-Me3**	Overstory is young ponderosa pine. Understory is dominated by grasses (~70%) and antelope bitterbrush and greenleaf manzanita (~30%).	44.31	-121.6	Warm temperate with dry, warm summer	2004-2005
Metolius Old Pine (Oregon)	**US-Me4**	Overstory is composed of 100% ponderosa pine occurring primarily in one of two distinct age classes: 1) mixed-age stand (~87 years); 2) old stand (~156 years). The understory is relatively sparse, decreasing with older stand ages.	44.49	-121.62	Warm temperate with dry, warm summer	2000
Loblolly Plantation (North Carolina)	US-NC2	In the immediate vicinity of the tower, vegetation is nearly 100% Loblolly pine with a few red cedars along small indentations in the plantation terrain.	35.8	-76.66	Warm temperate fully humid with hot summer	2005-2006
Niwot Ridge (Colorado)	**US-NR1**	Subalpine mixed coniferous forest with very little understory and a canopy gap fraction of 17%	40.03	-105.54	Snow fully humid cool summer	2000-2003
Austin Cary (Florida)	US-SP1*	95% pine uplands and 5% cypress wetlands, characterized by a mixture of longleaf pine and slash pine with a dense shrub understory.	29.73	-82.21	Warm temperate fully humid with hot summer	2000, 2001, 2005

Mize (Florida)	US-SP2	100% pine uplands, characterized by an overstory composed solely of slash pines with a moderately dense shrub understory.	29.76	-82.24	Warm temperate fully humid with hot summer	2000-2004
Donaldson (Florida)	US-SP3	100% pine uplands, characterized by an overstory composed solely of slash pines with a moderately dense shrub understory.	29.75	-82.16	Warm temperate fully humid with hot summer	2000-2004
Young red pine (Wisconsin)	US-Wi0*	Red pine plantation	46.61	-91.08	Snow fully humid warm summer	2002
Intermediate red pine (Wisconsin)	US-Wi2	Red pine plantation	46.68	-91.15	Snow fully humid warm summer	2003
Mature red pine (Wisconsin)	US-Wi4	Red pine plantation	46.73	-91.16	Snow fully humid warm summer	2003
Mixed young jack pine (Wisconsin)	US-Wi5*	Naturally regenerated jack pine and hardwood	46.65	-91.08	Snow fully humid warm summer	2004
Young Jack pine (Wisconsin)	US-Wi9*	Jack Pine plantation	46.61	-91.08	Snow fully humid warm summer	2004-2005
Wind River Crane Site (Washington)	US-Wrc	The Douglas-fir and western hemlock transitional overstory lies between the Western Hemlock Zone and the Pacific Silver Fir Zone, with an understory dominated by vine maple, salal, and Oregon grape.	45.82	-121.95	Warm temperate with dry, warm summer	2000-2002, 2004-2006

Appendix F. Sites used in the study of U.S monthly ET model of grassland.

Grassland

Site	Site code	Plant community and dominant species	Latitude	longitude	Climate	Observation period
ARM Southern Great Plains burn site (Oklahoma)	**US-ARb**	Re-emergent C4 and C3 grasses with minor amounts of forbs	35.54	-98.04	Warm temperate fully humid with hot summer	2005-2006
ARM Southern Great Plains control site (Oklahoma)	**US-ARc**	C4 and C3 grasses with minor amounts of forbs	35.54	-98.04	Warm temperate fully humid with hot summer	2005-2006
Audubon Research Ranch (Arizona)	**US-Aud***	desert grassland	31.59	-110.51	Arid Steppe cold	2002-2006
Brookings (South Dakota)	**US-Bkg**	Range Grassland	44.34	-96.83	Snow with fully humid hot summer	2005-2006
Canaan Valley (West Virginia)	US-CaV*	temperate grassland	39.06	-79.42	Warm temperate fully humid with warm summer	2004-2005
Duke Forest Open Field (North Carolina)	US-Dk1*	The stand is dominated by the C3 grass, tall fescue, with minor amounts of forbs, herbs, and grasses.	35.97	-79.09	Warm temperate fully humid with hot summer	2002-2005
Fort Peck (Montana)	**US-FPe**	Grassland	48.3	-105.1	Arid Steppe cold	2000, 2002, 2005

Flagstaff – Wildfire (Arizona)	**US-Fwf**	ponderosa pine forest burned by a wildfire 12 years ago (1996), now the vegetation includes only herbaceous species and a few shrubs	35.44	-111.77	Warm temperate with dry, warm summer	2005-2006
Goodwin Creek (Mississippi)	US-Goo*	Dominantly short grasses with scattered trees and shrubs	34.25	-89.87	Warm temperate fully humid with hot summer	2002-2006
Fermi National Accelerator Laboratory - (Prairie site) (Illinois)	US-IB2*	Tall grass prairie: C4 grasses and forbs	41.84	-88.24	Snow with fully humid hot summer	2004-2006
Vaira Ranch (California)	**US-Var***	Grazed C3 grassland opening in a region of oak/grass savanna	38.41	-120.95	Warm temperate with dry, hot summer	2001-2006
Walnut Gulch Kendall Grasslands (Arizona)	**US-Wkg***	warm season C4 grassland (bouteloua) with a few shrubs interspersed	31.73	-109.94	Arid Steppe cold	2004-2006

Appendix G. Sites used in the study of U.S monthly ET model of mixed forest.

Mixed Forest						
Site	Site code	Plant community and dominant species	Latitude	longitude	Climate	Observation period
Park Falls (Wisconsin)	US-PFa*	Species of trees found in the upland regions include aspen, balsam fir, sugar maple, red maple, basswood, red pine, paper birch, yellow birch, and white spruce. Recent clear-cuts are dominated by dense aspen, while older stands tend to be dominated by sugar maple or red pine. Wetlands comprise about 40% of the surrounding landscape and include alder, cedar, tamarack, and black spruce stands.	45.94	-90.27	Snow fully humid warm summer	2000, 2003
Sylvania Wilderness Area (Michigan)	US-Syv	Old-growth hemlock-hardwood forest	46.24	-89.34	Snow fully humid warm summer	2002-2006