A continuous satellite-derived global record of land surface evapotranspiration from 1983 to 2006

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A continuous satellite-derived global record of land surface evapotranspiration from 1983 to 2006

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We applied a satellite remote sensing–based evapotranspiration (ET) algorithm to assess global terrestrial ET from 1983 to 2006. The algorithm quantifies canopy transpiration and soil evaporation using a modified Penman-Monteith approach with biome-specific canopy conductance determined from the normalized difference vegetation index (NDVI) and quantifies open water evaporation using a Priestley-Taylor approach. These algorithms were applied globally using advanced very high resolution radiometer (AVHRR) GIMMS NDVI, NCEP/NCAR Reanalysis (NNR) daily surface meteorology, and NASA/GEWEX Surface Radiation Budget Release-3.0 solar radiation inputs. We used observations from 34 FLUXNET tower sites to parameterize an NDVI-based canopy conductance model and then validated the global ET algorithm using measurements from 48 additional, independent flux towers. Two sets of monthly ET estimates at the tower level, driven by in situ meteorological measurements and meteorology interpolated from coarse resolution NNR meteorology reanalysis, agree favorably (root mean square error (RMSE) = 13.0–15.3 mm month−1; R2 = 0.80–0.84) with observed tower fluxes from globally representative land cover types. The global ET results capture observed spatial and temporal variations at the global scale and also compare favorably (RMSE = 186.3 mm yr−1; R2 = 0.80) with ET inferred from baseline–scale water balance calculations for 261 basins covering 61% of the global vegetated area. The results of this study provide a relatively long term global ET record with well-quantified accuracy for assessing ET climatologies, terrestrial water, and energy budgets and long-term water cycle changes.


1. Introduction

[2] Evapotranspiration (ET) is a major component of the global water cycle and represents a critical link between terrestrial water, carbon, and surface energy exchanges. The world has experienced persistent climatic warming attributed largely to human activities over the past century [Trenberth et al., 2007], and the warming is projected to continue [Meehl et al., 2007]. Recent climatic changes have altered the global water cycle and surface energy budget [Huntington, 2006; Trenberth et al., 2007]. To better understand these regional and global water balance changes, each term in the terrestrial water balance equation, \( \Delta S = P - ET - R \), must be accurately measured or quantified. Precipitation (P) and runoff (R) can be directly measured by in situ weather stations and stream gauge networks. However, ET is inherently difficult to measure and predict especially at large spatial scales. Recent advances in retrieval algorithms and satellite remote sensing technology now enable large-scale mapping and monitoring of ET [e.g., Cleugh et al., 2007; Fisher et al., 2008; Mu et al., 2007, 2009, 2007; Zhang et al., 2009], P [e.g., Hong et al., 2005; Hsu et al., 1992; Huffman et al., 2007; Joyce et al., 2004; Kummerow et al., 2001; Sorooshian et al., 2000], and water storage (\( \Delta S \)) [Tapley et al., 2004]. However, basin-scale water budget closure is rarely, if ever, achieved due to large and variable uncertainties and inconsistencies among the water budget terms and associated products [Pan and Wood, 2006; Sheffield et al., 2009; Ferguson et al., 2010]. Improved accuracy in quantifying the magnitude and variability of regional and global water and energy fluxes, closing the water budget worldwide and hence improving weather forecasting, climate, and water availability assessments are the ultimate goals of current water and energy cycle research.

[3] Remote sensing (RS), especially from polar-orbiting satellites, provides relatively frequent and spatially contiguous measurements for global monitoring of surface biophysical variables affecting ET, including albedo, vegetation type, and density. There are a multitude of RS-based ET products derived from simplified process models [e.g., Montiel, 1972; Norman et al., 1995; Priestley and Taylor, 1972] driven by RS inputs [Anderson et al., 2008; Cleugh et al., 2007; Fisher et al., 2008; Mu et al., 2007], thermal RS-based surface energy balance (SEB) approaches [Bastiaanssen et al., 1998; Kalma and Jupp, 1990; Su, 2002], and empirical, vegetation index–ET relationships, i.e., the triangle method or its derivatives [Gillies et al.,...
1997; Nemani and Running, 1989; Nishida et al., 2003; Q. Tang et al., 2009). Comprehensive reviews of the historical development and accuracies of in situ and RS-based ET estimation methods are provided elsewhere [e.g., Glenn et al., 2007; Kalma et al., 2008]. The various RS-based ET methods have different spatial scales and domains, temporal coverage, input requirements, and accuracies. However, there is currently no continuous, long-term (i.e., from the early 1980s) satellite-based global ET record available for global change studies.

[4] Cleugh et al. (2007) proposed a methodology that estimates 8 day evaporation at 1 km spatial resolution using gridded meteorological fields and the Penman-Monteith (PM) equation [Monteith, 1965], where the surface conductance term is a simple function of remotely sensed leaf area index (LAI) from the Moderate Resolution Imaging Spectroradiometer (MODIS). Mu et al. [2007] revised the surface conductance model of Cleugh et al. [2007] to produce a global ET algorithm by accounting for stomata response to temperature and atmospheric humidity deficit and introducing a separate soil evaporation term not explicitly considered by Cleugh et al. [2007]. This algorithm was further modified by incorporating surface meteorology retrievals from AMSR-E microwave remote sensing over the high latitudes [Mu et al., 2009] and is experiencing other ongoing improvements. Meanwhile, Leuning et al. [2008] developed a biophysical, six-parameter surface conductance model, which can be reduced to a two-parameter model, driven by LAI to replace Cleugh et al.’s empirical surface conductance model. The Leuning et al. model accounts for stomatal conductance sensitivity to atmospheric humidity deficit and light, and includes a simple term for soil evaporation; the ET results derived using optimized parameters showed improved performance relative to Cleugh et al.’s model in relation to measurements from 15 global flux station sites. In a companion study, Y. Zhang et al. [2008] optimized the parameters of this model using steady state water balance estimates (P–R) from gauged catchments in Australia and applied the model to estimate catchment-level evaporation. These studies show favorable ET accuracy at both site and catchment levels [Leuning et al., 2008; Y. Zhang et al., 2008]. However, this approach is sensitive to uncertainty in LAI inputs [Leuning et al., 2008]. It is also necessary to optimize the model parameters [Y. Zhang et al., 2008]; thus, additional parameter optimization is likely to be needed for global application of this approach. The Leuning et al. and Mu et al. models are also limited by global LAI availability and accuracy in the pre-MODIS era (i.e., before 2000). Alternatively, the normalized difference vegetation index (NDVI) is sensitive to photosynthetic leaf area and calculated directly from satellite sensor spectral reflectances. Unlike the downstream LAI product, there are no model-related errors in NDVI. The NOAA advanced very high resolution radiometer (AVHRR)-based NDVI record extends from 1981 to present and can be used for global long-term ET mapping since NDVI is sensitive to vegetation structure and photosynthetic canopy cover. The results of Cleugh et al. [2007], Mu et al. [2007], and Leuning et al. [2008] show that the PM equation is a biophysically sound and robust framework for estimating daily ET at regional to global scales using remotely sensed data.

[5] We developed a biome-specific, NDVI-based canopy conductance model that accounts for stomata response to temperature and atmospheric vapor pressure deficit and the unique physiological characteristics of different biomes [Zhang et al., 2009]. Canopy conductance is defined using empirical relationships between potential surface conductance ($g_0$) and NDVI and reduced by temperature and moisture constraint multipliers. The canopy conductance and NDVI functional relationships are derived for different biomes using regional flux tower measurements and then coupled with PM-based canopy and soil evaporation models, and a Priestly-Taylor (PT)-based open water evaporation model to determine the aggregated ET of a grid cell. This approach was successfully applied to produce a long-term (1983–2005) daily ET record for the pan-Arctic basin and Alaska [Zhang et al., 2009]. These results showed improved performance over Mu et al.’s global ET method in relation to tower based meteorology from 14 sites representing regionally dominant biomes. However, the northern biomes represent less than half of all global land cover types. Moreover, NDVI and canopy conductance relationships were only defined for four regionally dominant biomes due to sparse regional tower eddy covariance measurements.

[6] In this study, we extend our RS NDVI-based ET algorithm to the global domain and derive biome-specific NDVI-based canopy conductance functions for all major global biomes using surface energy fluxes and meteorology measurements from the global FLUXNET tower network [Baldocchi, 2008]. The objectives of this study are to (1) derive biome-specific NDVI-based canopy conductance functions for the major global biome types and correspondingly refine the RS NDVI-based ET algorithm for global applications and (2) generate a global long-term (1983–2006) daily ET record with well-quantified accuracy for studies on regional/global water balances changes.

2. Theory

2.1. ET Algorithm Logic

[7] We extended an NDVI-based ET algorithm developed for the northern high latitudes in the work of Zhang et al. [2009] to a global domain for this study. The core components of the ET algorithm are similar to those of Zhang et al. [2009], but with substantial algorithm modifications needed for global applications, including (1) deriving biome-specific canopy conductance versus NDVI functions for the major global biome types using daily eddy covariance and associated meteorological measurements from globally distributed tower sites, (2) replacing the calculation of soil heat flux and heat storage as a constant fraction of net radiation with more physically based equations, (3) calculating ET for mixed forest land cover types as a composite of component ET values from the distinct growth forms (e.g., deciduous versus evergreen) comprising this class rather than as a single biome type.

[8] In our ET algorithm, energy at the surface of the earth is governed by the surface energy balance equation,

$$R_n = H + LE + G,$$  \hspace{1cm} (1)

where $R_n$ (W m$^{-2}$) is the net radiation flux, $H$ (W m$^{-2}$) is the surface sensible heat flux, $LE$ (W m$^{-2}$) is the surface latent heat flux (LE), and $G$ is the sum of the soil heat flux and
heat storage in above-ground biomass for vegetated areas or heat storage in water bodies. \( R_n \) is calculated using
\[
R_n = R_{ns} - R_{nl} = (1 - \alpha)R_{sl} - R_{nl},
\]
where \( R_{ns} \) is net shortwave (i.e., solar) radiation, \( R_{sl} \) is incoming net longwave radiation, \( \alpha \) is surface albedo, and \( R_{nl} \) is outgoing net longwave radiation. \( R_{nl} \) is calculated using the method of Allen et al. [1998],
\[
R_{nl} = \frac{\sigma (T_{max,\ell} + T_{min,\ell})}{2} (0.34 - 0.14\sqrt{e_s}) \left(1.35 \frac{R_{sl} - 0.35}{R_{so}} \right),
\]
where \( \sigma \) is the Stefan–Boltzmann constant \( (4.903 \times 10^{-9} \text{ MJ K}^{-4} \text{ m}^{-2} \text{ d}^{-1}) \), \( T_{max,\ell} \) and \( T_{min,\ell} \) are the daily maximum and minimum air temperature in Kelvin, respectively, \( e_s \) (Pa) is the actual daily air water vapor pressure, and \( R_{so} \) (W m\(^{-2}\)) is clear-sky incoming shortwave radiation.

[9] In our algorithm, we first identified open water body and vegetated pixels using a remote sensing-derived global land cover classification. For vegetated areas, we used the PM equation with a biome-specific NDVI-based canopy conductance model to calculate vegetation transpiration and a modified PM equation to calculate soil evaporation. We used the PT method to calculate evaporation for water body pixels.

### 2.1.1. Evapotranspiration for Vegetated Areas

[10] ET for vegetated areas is partitioned into soil evaporation and canopy transpiration by partitioning available energy for ET using the fractional vegetation cover \( (f_c) \) derived from satellite observed NDVI. Detailed information about \( f_c \) is available elsewhere [e.g., Mu et al., 2007]. The available energy for ET \( (A: \text{ W} \text{ m}^{-2}) \) is determined as the difference between \( R_n \) and \( G \). For vegetated areas, \( G \) is calculated as a function of \( R_n \) and \( f_c \) according to Su et al. [2001],
\[
G = R_n \times \left[ \Gamma_c + (1 - f_c) \times (\Gamma_s - \Gamma_c) \right],
\]
where \( \Gamma_c \) and \( \Gamma_s \) are the ratios of \( G \) to \( R_n \) for full vegetation canopy and bare soil, respectively. Su et al. [2001] assumed \( \Gamma_c \) and \( \Gamma_s \) as global constants, while we regarded \( \Gamma_c \) and \( \Gamma_s \) as biome-specific constants in this study.

[11] The \( A \) term is then linearly partitioned into available energy components for the canopy \( (A_{\text{Canopy}}: \text{ W} \text{ m}^{-2}) \) and soil surface \( (A_{\text{Soil}}: \text{ W} \text{ m}^{-2}) \) using \( f_c \) such that
\[
A_{\text{Canopy}} = A \times f_c,
\]
\[
A_{\text{Soil}} = A \times (1 - f_c).
\]

[12] The PM equation is used to calculate vegetation transpiration as
\[
\lambda E_{\text{Canopy}} = \frac{\Delta A_{\text{Canopy}} + \rho C_P (e_{\text{sat}} - e_s) g_s}{\Delta + \gamma (1 + g_s / g_a)},
\]
where \( \lambda E_{\text{Canopy}} \) (W m\(^{-2}\)) is the latent heat flux of the canopy (i.e., \( LE_{\text{Canopy}} \)) and \( \lambda \) (J kg\(^{-1}\)) is the latent heat of vaporization; \( \Delta = d (e_{\text{sat}}) / dT \) (Pa K\(^{-1}\)) and is the slope of the curve relating saturated water vapor pressure \( (e_{\text{sat}}: \text{ Pa}) \) to air temperature \( (T: \text{ K}) \); \( e_{\text{sat}} - e \) is equal to the vapor pressure deficit \( (VPD: \text{ Pa}) \); \( \rho \) (kg m\(^{-3}\)) is the air density; \( C_P \) (J kg\(^{-1}\) K\(^{-1}\)) is the specific heat capacity of air; and \( g_a \) (m s\(^{-1}\)) is the aerodynamic conductance. The psychrometric constant is given by
\[
\gamma = (M_a / M_v) (C_P P_a / \lambda) \text{ where } M_a \text{ (kg mol}^{-1}\text{)}, \text{ } M_v \text{ (kg mol}^{-1}\text{)}, \text{ and } P_a \text{ (Pa)} \text{ are the molecular mass of dry air, the molecular mass of wet air, and the air pressure, respectively. The } g_s \text{ (m s}^{-1}\text{)} \text{ term in the original PM equation is the surface conductance. Since we use the PM equation to calculate canopy transpiration in this section, the } g_s \text{ term is identical to the canopy conductance } (g_c), \text{ where } g_s \text{ is calculated using a biome-specific NDVI-based Jarvis-Stewart-type canopy conductance model } [\text{Zhang et al., 2009}],
\]
\[
g_c = g_0 (NDVI) \times m(T_{day}) \times m(VPD),
\]
where \( g_0 \) (NDVI) is the biome-dependent potential (i.e., maximum) value of \( g_c \), which is a function of NDVI; \( T_{day} \) (°C) is the daytime average air temperature; \( m(T_{day}) \) is the temperature stress factor and function of \( T_{day} \); \( m(VPD) \) is a water/moisture stress factor and function of VPD. The temperature stress factor \( m(T_{day}) \) follows the equation detailed by June et al. [2004] with an optimum temperature \( T_{opt} \),
\[
m(T_{day}) = \begin{cases} 
0.01 & T_{day} \leq T_{close\_\text{min}} \\
\exp\left(-\frac{T_{day} - T_{opt}}{\beta}\right) & T_{close\_\text{min}} < T_{day} < T_{close\_\text{max}} \\
0.01 & T_{day} \geq T_{close\_\text{max}}
\end{cases}
\]
where \( T_{opt} \) (°C) is a biome-specific optimal air temperature for photosynthesis; \( T_{close\_\text{min}} \) (°C) and \( T_{close\_\text{max}} \) (°C) are the biome-specific minimum and maximum critical temperatures for stomatal closure and the effective cessation of plant photosynthesis; \( \beta \) (°C) is a biome-specific parameter and is the difference in temperature from \( T_{opt} \) at which temperature stress factor falls to 0.37 (i.e.,, \( e^{-1} \)). The \( m(\text{VPD}) \) term is calculated as,
\[
m(\text{VPD}) = \begin{cases} 
1.0 & \text{VPD} \leq \text{VPD}_{\text{open}} \\
\frac{\text{VPD}_{\text{close}} - \text{VPD}}{\text{VPD}_{\text{close}} - \text{VPD}_{\text{open}}} & \text{VPD}_{\text{open}} < \text{VPD} < \text{VPD}_{\text{close}} \\
0.1 & \text{VPD} \geq \text{VPD}_{\text{close}}
\end{cases}
\]
where \( \text{VPD}_{\text{open}} \) (Pa) is the biome-specific critical value of \( \text{VPD} \) at which the canopy stomata are completely open; \( \text{VPD}_{\text{close}} \) (Pa) is the biome-specific critical value of \( \text{VPD} \) at which canopy stomata are completely closed.

[13] Soil evaporation is calculated using the soil evaporation equation from Mu et al. [2007] and Zhang et al. [2009], which is a combination of an adjusted PM equation and the complementary relationship hypothesis [Bouchet, 1963; Fisher et al., 2008]. The soil evaporation equation and its auxiliary equations include,
\[
\lambda E_{\text{Soil}} = RH(\text{VPD}) \Delta A_{\text{Soil}} + \rho C_P \text{VPD} g_a \Delta + \gamma \times g_a / \text{Soil},
\]
where RH is the relative humidity of air with values between 0 and 1; RH(VPD) is a moisture constraint on soil evaporation [Fisher et al., 2008], which is an index of soil water deficit based on the complementary relationship of Bouc...
and aerodynamically rough surfaces following Monteith and Unsworth [2007]. Although the use of a constant \( g_0 \) can introduce uncertainty into the ET estimates, this simplification has been successfully applied for similar satellite-based ET mapping studies [e.g., Mu et al., 2007; Y. Zhang et al., 2008; Zhang et al., 2009]. By substituting \( g_0 \) in equation (18) for \( g_c \) in equation (8) and rearranging the equation, we derived the potential surface conductance as

\[
g_0 = \frac{g_c \Delta E_{\text{canopy}}}{[\Delta A_{\text{canopy}} + \rho C_T VPD g_4 - \Delta E_{\text{canopy}}(\Delta + \gamma)] \cdot m(T_{\text{day}}) \cdot m(VPD)}
\]

[19] We (1) calculated daily \( g_0 \) for the major global biome types using daily surface meteorology and LE measurements from selected representative flux towers within each biome; (2) sorted the \( g_0 \) series for each NDVI interval (interval size = 0.04) in numeric order and removed outliers falling below the 10th percentile and above the 90th percentile for \( g_0 \); (3) calculated average daily values of \( g_0 \) and NDVI for each NDVI interval with sufficient \(( \geq 10 \) \) samples; and (4) fitted the scatter plots of \( g_0 \) versus NDVI using sigmoid response functions for each biome type following Zhang et al. [2009],

\[
g_0(\text{NDVI}) = \frac{1}{b_1 + b_2 + \exp(-b_3 \times \text{NDVI})} + b_4.
\]

where \( b_1 \) (s m\(^{-1}\)), \( b_2 \) (s m\(^{-1}\)), \( b_3 \) (dimensionless), and \( b_4 \) (m s\(^{-1}\)) are empirical parameters. Considering the constraint \( g_0(0) = 0 \), the \( b_4 \) parameter is equal to \(-1/(b_1 + b_2)\). To analyze the uncertainty in the fitted relationship of \( g_0 \) versus NDVI, we applied an adaptive Markov chain Monte Carlo (MCMC) method [Haario et al., 2006] with a chain of length 6000 to produce the 99% posterior distribution of the fitted relationship of \( g_0 \) versus NDVI for each biome type.

2.3. Global Implementation of the ET Algorithm

[20] We applied the above ET algorithm with parameterized, biome-specific NDVI-derived canopy conductance models to calculate global ET at the pixel level. We chose the 8 km resolution of the GIMMS NDVI product as the final resolution of the global ET calculations. To adequately consider land cover heterogeneity within the 8 km grid cells, we calculated the fractional coverage of every vegetation type and open water body within each 8 km grid cell using the 500 m MODIS-IGBP Collection 5 global land cover product [Friedl et al., 2010] and applied the above ET algorithm to calculate ET for every vegetation and open water class within each grid cell. Finally, we used the land cover fractions as weights to sum the ET values of each land cover type within the 8 km grid cell to produce the 8 km area-average ET.

3. Data and Methods

3.1. Eddy Covariance Flux Towers

[21] We utilized tower eddy covariance and meteorological data from 82 tower sites of the FLUXNET data archive (http://www.fluxnet.ornl.gov/); these sites were split into separate algorithm development and parameterization (34 towers) and validation (48 towers) data sets representing the major global biome types (Figure 1). The flux tower site information is summarized in Tables 1 and 2. These sites are distributed across the world in all continents and global vegetation types (Figure 1 and Tables 1 and 2). The tower sites represent 10 of the 12 IGBP global vegetation types, including evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF), deciduous forest (DBF), mixed forest (MF), closed shrubland (CSH), open shrubland (OSH), grassland (GRS), cropland (CRP), woody savanna (WSV), and savanna (SV). Considering the geographically wide distribution of the ENF biome type and the impacts of
different climate zones on leaf longevity and associated biophysical functioning [Kikuzawa, 1995; Reich et al., 2007], we stratified the global ENF category into temperate ENF (TENF) and boreal/cold ENF (BENF) types according to a multyear average of frost-free days ($T_{\text{Frost-free}}$: days). Frost-free days are defined as those days with above-zero ($^\circ$C) daily minimum air temperature and are calculated from the NCEP/NCAR Reanalysis (NNR) surface meteorology. The ENF pixels are classified as TENF when $T_{\text{Frost-free}}$ exceeds 7 months (212 days); otherwise, the ENF pixels are classified as BENF.

The following criteria were used to select flux tower sites for this study in order of decreasing importance: (1) at least two sites must be available for each vegetation type; (2) the selected sites should have data covering at least two growing seasons; and (3) the vegetation types within the tower footprints must be the same as the dominant vegetation type of the overlying 8 km resolution grid cell. The 82 tower sites were divided into two data sets representing an algorithm development set with 34 sites and an algorithm validation set with 48 sites. The algorithm development set was used to derive the biome-specific NDVI-based canopy conductance functions, while the validation set was used for independent validation of the global ET algorithm.

### 3.2. Satellite and Meteorological Inputs

In this study, the satellite-based data inputs to the global ET algorithm include NDVI, land cover, tree cover continuous fields, and short-wave radiation terms, while the remaining daily surface meteorology inputs were obtained from the global NNR product [Kalnay et al., 1996; Kistler et al., 2001]. We derived a daily NDVI series for each 8 km pixel using temporal linear interpolation of adjacent monthly values of the 8 km semimonthly AVHRR GIMMS NDVI product [Pinzon et al., 2005; Tucker et al., 2005]. The daily linear interpolation approach is a relatively simple, but effective, means for producing daily time series of satellite-observed vegetation state variables including fraction of photosynthetically active radiation (FPAR) and LAI and has been successfully applied for vegetation based analyses of the AVHRR series [e.g., Kimball et al., 2006, 2007; Zhang et al., 2007].

The 500 m NASA MODIS Collection 5 IGBP global land cover classification (henceforth abbreviated as the 500 m MODIS-IGBP land cover) [Friedl et al., 2010] was used to determine the dominant land cover and fractional vegetation type within each 8 km AVHRR GIMMS grid cell. We then used the 1 km AVHRR Tree Cover Continuous Fields data [DeFries et al., 2000a, 2000b] to derive forest type (i.e., evergreen or deciduous) fractional cover of 8 km grid cells.
grid cells containing MF pixels distinguished by the 500 m MODIS-IGBP land cover classification.

[25] The daily net, incoming, and clear-sky incoming shortwave solar radiation terms ($R_{sw}$, $R_{swc}$, and $R_{swi}$) were derived from the NASA World Climate Research Programme/Global Energy and Water-Cycle Experiment (WCRP/GEWEX) Surface Radiation Budget (SRB) Release 3.0 data sets with 1.0° x 1.0° resolution using the Pinker/Laszlo shortwave algorithm [Pinker and Laszlo, 1992]. Daily meteorological data including maximum, minimum, and average air temperatures ($T_{max}$, $T_{min}$, and $T_{avg}$, °C) and air water vapor pressure ($e_v$, Pa) were derived from the National Centers for Environmental Prediction-National Center for Atmospheric Research (NCEP-NCAR) Reanalysis (NRR) [Kalnay et al., 1996; Kistler et al., 2001]. The $T_{max}$, $T_{min}$, and $T_{avg}$ variables were also used to calculate $T_{dew}$ and VPD. In addition, 1 km resolution USGS Global 30 Arc-Second (GTOPO30) DEM (http://eros.usgs.gov/products/elevation/gtopo30/gtopo30.html) information was used to calculate pixel-wise atmospheric pressure with corrections for deviations from STP (e.g., equation (15)) and to analyze topographic complexities around the 82 flux towers. The relatively coarse NASA SRB radiation and NNR meteorology data were interpolated to the 8 km resolution ET modeling grid and 1 km tower footprint spatial scales for the ET/LE estimates using bilinear interpolation.

### 3.3. Evaluation of ET Algorithm Performance

[26] To evaluate ET algorithm performance, we produced two sets of LE/ET estimates at the tower level using our ET algorithm. The two sets of estimates were derived from respective tower measured and reanalysis meteorology inputs spatially interpolated to the 1 km tower locations. We then compared the two sets of LE/ET estimates with measured values from the eddy covariance flux towers at daily and
monthly time scales. This process ensured that the tower level LE/ET results represented the dominant land cover class of the local tower footprint rather than the composite regional land cover attributes of the overlying 8 km resolution grid cell of the global LE/ET database. Previous research [e.g., K. Zhang et al., 2008] has shown that coarse NNR meteorology reanalysis can introduce considerable uncertainty in capturing local micrometeorology in some regions. We compared the two sets of model simulations to attribute LE/ET uncertainties between model logic error and errors due to the coarse scale reanalysis meteorology relative to tower observations. The final 8 km global LE/ET estimates are the composite values of every vegetation type and open water body delineated by the 500 m MODIS-IGBP land cover product within each 8 km grid cell. The tower-level LE/ET estimates driven by the NNR reanalysis are actually components of the final 8 km composite LE/ET falling over the tower footprints; thus, the validation of the tower-level estimates also serve as validation of the final 8 km LE/ET results. Three statistical variables were used to quantify algorithm performance, including mean residual difference (MR), root mean square error (RMSE), and simple correlation coefficient \( r \) between model estimates and tower measurements. The residuals are defined as the “true” values, namely, tower measurements minus model estimates. The MR is the mean value of the residuals and provides a way to quantify the bias of the estimates relative to the measurements, while the RMSE is used to describe the accuracy of the estimations. The \( r \) parameter is used to evaluate the strength of the relationships between the model results and tower observations.

[27] We verified the final global 8 km resolution ET calculations at the river basin level by comparing the model results with alternative ET estimates inferred from the long-term water balance: \( \Delta S = P - ET - R \). For periods of 5 years or more, the average change in basin water storage is negligible compared to precipitation, evaporation, and runoff [e.g., Hobbins et al., 2001]. Given the condition of \( \Delta S = 0 \), the multiyear average water balance can be written as \( ET = \overline{ET} - \overline{R} \). We denoted \( \overline{ET} \) as \( ET_{\text{infrared}} \) and the multiyear average basin-scale ET derived from the remote sensing ET products as \( ET_{8S} \) in this study. We chose 261 major global basins with relatively good records of stream flow discharge and precipitation to conduct the comparison. These basins cover 61% of global vegetated area, vary in drainage area from thousands to millions of square kilometers, and span the major global climate and vegetation zones. The observed stream flow data were compiled and provided by Dai et al. [2009]. The \( ET_{8S} \) and \( ET_{\text{infrared}} \) variables were compared for the same periods between 1983 and 2006 that vary with the discharge data availability of each basin. The precipitation data were obtained from the Global Precipitation Climatology Center (GPCC) monthly precipitation database [Rudolf and Schneider, 2005]. The GPCC precipitation data are provided at 0.5° resolution and produced from surface gauge network observations. The GPCC precipitation data were interpolated to the 8 km resolution ET modeling grid for basin-level water balance estimates using bilinear interpolation.

3.4. Uncertainty in Reanalysis Meteorology Inputs and Impacts on LE Estimation

[28] We used the root mean squared deviation (RMSD) metric to quantify differences between interpolated NNR and NASA/GEWEX SRB meteorology at the site level and tower-measured meteorology and between tower-driven and reanalysis-driven daily LE estimates. The RMSD statistic is defined as

\[
\text{RMSD} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_{i,j} - x_{j})^2},
\]

where \( n \) is the sample size; \( x_{i,j} \) is the measured value or measurement-driven estimate; and \( x_{j} \) is the reanalysis value or reanalysis-driven estimate.

[29] We first evaluated overall accuracies of the five major meteorological variables used to drive our ET algorithm from NNR meteorology and NASA/GEWEX SRB based net radiation inputs, including \( T_{\text{max}} \), \( T_{\text{avg}} \), \( T_{\text{min}} \), VPD and \( R_{n} \), in relation to available daily tower measurements from all tower sites. We then analyzed the impacts of uncertainties in these variables from the NNR meteorology and NASA/GEWEX SRB solar radiation on the accuracies of reanalysis-driven daily LE estimates relative to corresponding tower-driven daily LE estimates. The RMSD values for the five variables (i.e., RMSD(\( T_{\text{max}} \)), RMSD(\( T_{\text{avg}} \)), RMSD(\( T_{\text{min}} \)), RMSD(\\text{VPD}), and RMSD(\( R_{n} \))) at the 82 tower sites were calculated. The RMSD between the tower-driven and reanalysis-driven daily LE estimates (RMSD(LE)) were also calculated. The correlations of RMSD(LE) versus RMSD(\( T_{\text{max}} \)), RMSD(\( T_{\text{avg}} \)), RMSD(\( T_{\text{min}} \)), RMSD(\\text{VPD}), and RMSD(\( R_{n} \)) were then used to analyze the impacts of meteorology reanalysis uncertainties on the LE estimates.

[30] Finally, we calculated the standard deviation of DEM elevations within 100 km x 100 km windows centered over each of the 82 flux tower sites as a measure of topographic heterogeneity surrounding individual tower sites. We then compared these results with the RMSDs of the meteorological variables at the 82 sites to assess relations between topographic heterogeneity and the accuracy of NNR meteorology and NASA/GEWEX SRB solar radiation in representing local tower conditions.

4. Results

4.1. Retrieved Biome-Specific Potential Canopy Conductance Versus NDVI Functions

[31] Values of \( g_{0} \) derived from tower measured surface energy fluxes and meteorology from the 34 algorithm development sites are plotted in Figure 2 against satellite-observed NDVI values of pixels overlapping the respective tower footprints for the 10 global biome types, including the TENF and BENF land cover subgroups. For all biome types, \( g_{0} \) generally follows a sigmoid response curve with increasing NDVI that gradually levels off at higher NDVI values. The derived empirical parameters for the biome-specific \( g_{0} \) versus NDVI relationships and other parameters used are listed in Table 3. The NDVI is an effective surrogate for canopy density. The reduced slope of this relationship at higher NDVI levels reflects increasing shading of individual leaves and leaf boundary layer adjustments with increasing canopy density. Higher canopy density can increase leaf boundary layer thickness and correspondingly reduce leaf boundary layer and canopy conductance relative to lower canopy density under the same meteorological
Figure 2. Scatter plots of calculated average potential surface conductance values derived from tower measurements ($g_0$) versus corresponding NDVI values from the AVHRR GIMMS data set and empirical fitted relationships between $g_0$ and NDVI using sigmoid functions for TENF, BENF, EBF, DBF, CSH, OSH, WSV, SV, GRS, and CRP vegetation types. Error bars denote the standard deviations of $g_0$. Gray areas correspond to the 99% posterior limits of the fitting model uncertainty derived from an adaptive MCMC method [Haario et al., 2006].

Table 3. The Biome Properties Look-up Table (BPLUT) Used for the NDVI-Based Global ET Algorithms

<table>
<thead>
<tr>
<th>Parameters</th>
<th>BENF</th>
<th>TENF</th>
<th>EBF</th>
<th>DBF</th>
<th>CSH</th>
<th>OSH</th>
<th>WSV</th>
<th>SV</th>
<th>GRS</th>
<th>CRP</th>
<th>Sources</th>
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<tr>
<td>$T_{close_min}$ (°C)</td>
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<td>-8</td>
<td>-8</td>
<td>-6</td>
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<td>-8</td>
<td>1,2</td>
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<td>40</td>
<td>50</td>
<td>45</td>
<td>40</td>
<td>50</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>45</td>
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<td>4000</td>
<td>2800</td>
<td>3300</td>
<td>3700</td>
<td>3200</td>
<td>5000</td>
<td>3800</td>
<td>3800</td>
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<tr>
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<td>500</td>
<td>650</td>
<td>500</td>
<td>500</td>
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<td>0.01</td>
<td>0.005</td>
<td>0.002</td>
<td>0.001</td>
<td>0.005</td>
<td>0.005</td>
<td>3,5</td>
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<tr>
<td>$g_{st}$ (m s^{-1})</td>
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<td>0.004</td>
<td>0.006</td>
<td>0.002</td>
<td>0.001</td>
<td>0.012</td>
<td>0.0018</td>
<td>0.001</td>
<td>0.001</td>
<td>0.005</td>
<td>3</td>
</tr>
<tr>
<td>$g_{th}$ (m s^{-1})</td>
<td>0.08</td>
<td>0.08</td>
<td>0.01</td>
<td>0.01</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>6</td>
</tr>
<tr>
<td>$b_1$ (s m^{-1})</td>
<td>208.3</td>
<td>133.3</td>
<td>57.7</td>
<td>85.8</td>
<td>202.0</td>
<td>178.6</td>
<td>0.2</td>
<td>790.9</td>
<td>175</td>
<td>105</td>
<td>3</td>
</tr>
<tr>
<td>$b_2$ (s m^{-1})</td>
<td>8333.3</td>
<td>888.9</td>
<td>769.2</td>
<td>694.7</td>
<td>4040.4</td>
<td>178.6</td>
<td>240000</td>
<td>8181.8</td>
<td>2000</td>
<td>300</td>
<td>3</td>
</tr>
</tbody>
</table>

<sup>4</sup>The listed $b_1$, $b_2$, and $b_3$ values for the WSV biome are for the first segment of the fitted $g_0$ versus NDVI function when NDVI ≤ 0.64. When NDVI > 0.64, the $b_1$, $b_2$, $b_3$, and $b_4$ parameters are set to 57.1, 3333.3, 8, and -0.01035, respectively; 1: Zhao et al. [2008]; 2: Mu et al. [2007]; 3: this study; 4: Larcher [2003]; 5: Monteith and Unsworth [2007]; 6: Thornton [1998].
conditions. These effects provide a negative feedback for transpiration so that stomatal conductance has less effect on canopy water loss at higher NDVI and canopy density levels than would be expected from an analysis of individual leaves [Jarvis and McNaughton, 1986]. The error bars show that there is variability in $g_0$, which generally falls between 0.0005 and 0.002 m s\(^{-1}\). The SV, WSV, and CSH biomes have the lowest variability in $g_0$; EBF, DBF, and CRP biomes have the highest $g_0$ variability, and TENF, BENF, OSH and GRS biomes show intermediate $g_0$ variability. The fitted $g_0$ versus NDVI functions using the means of $g_0$ should not significantly affect ET estimates considering the generally low variability in $g_0$.

The derived $g_0$ versus NDVI relationships for the 10 biome types show clear differences among each other despite having similar functional shapes; these differences reflect variations in leaf traits and physiologies among the different biome types. The relationship between $g_0$ and NDVI for the TENF group shows an upward shift relative to the BENF group, indicating that climate influences leaf traits and physiological responses within the broader ENF biome type. The $g_0$ values generally vary between 0.001 and 0.012 m s\(^{-1}\) and are biome specific. For the same values of NDVI, $g_0$ values are highest for the EBF and DBF biome types followed by the CRP, GRS, TENF, and BENF types, while the CSH, OSH, WSV, and SV types have the lowest $g_0$ values. These results are similar to reported values of maximum stomatal conductance determined for 15 global flux towers by Leuning et al. [2008]. We applied sigmoid functions to describe the observed relationship between $g_0$ and NDVI in Figure 2. The fitted curves for the 10 biome types are also shown in Figure 2 and show generally favorable agreement with the tower observations. The fitted curves explain 81%, 55%, 77%, 55%, 54%, 24%, 86%, 31%, 77%, and 60% of the variation in $g_0$ for the BENF, TENF, EBF, DBF, CSH, OSH, WSV, SV, GRS, and CRP types, respectively. The derived $g_0$ posterior distributions of the $g_0$ versus NDVI relationships are generally narrow for each biome type (Figure 2). However, there are large uncertainties in these relationships at higher NDVI values (>0.80) for several biome types, including EBF, DBF, CSH, WSV, and GRS; this is due to less data and larger variations in the relationships between $g_0$ and NDVI at these higher canopy densities. The larger uncertainties in the fitted $g_0$ versus NDVI relationships at these higher NDVI levels may introduce larger uncertainties in the corresponding LE/ET calculations.

4.2. ET Algorithm Performance Relative to Tower Measurements

4.2.1. Development Tower Set Results

We produced two sets of daily LE estimates at the tower level. The first set was produced using tower-measured meteorology (hereafter called tower-driven results), while the second set was produced using daily NNR meteorology and NASA/GWEX SRB solar radiation inputs (hereinafter called reanalysis-driven results). We then compared these algorithm results with corresponding ET measurements in Figure 4 for representative tower sites from the algorithm development set. Each of the selected towers represents the longest measurement record for the respective biome type. There are some uncertainties in the model results at several sites. For example, both sets of model results at CAOBS tend to underestimate mid-season ET values. There are many low LE values in summer from the reanalysis-driven ET results at USBLO, which are caused by considerable overestimation of NNR VPD inputs for this period. Overall, both sets of model results generally agree well with tower observations and capture observed LE seasonality and interannual variability and associated differences among the global biomes represented.

4.2.2. Validation Tower Set Results

ET algorithm performance for the validation tower set was similar to the results from the algorithm development tower set (Figure 5), although the MR and RMSE statistics for the validation set have slightly wider distributions than the algorithm development set. The MR values of the tower-driven daily LE estimates fall within ±20 W m\(^{-2}\) for 44 sites and within ±30 W m\(^{-2}\) for the remaining four validation sites (Figure 5). The RMSE values of tower-driven LE estimates are below 45 W m\(^{-2}\) for all 48 validation sites, of which 45 sites have RMSE differences below 32 W m\(^{-2}\) (Figure 5). Correlation coefficients between tower meteorology based daily LE estimates and tower observations are generally higher than 0.6, while the lowest $r$ value is 0.24 for the USSO2 site (Figure 5).

The reanalysis-driven daily LE simulations have similar accuracies as the tower-driven results for most sites but markedly lower accuracies at some sites due to differences between reanalysis and local tower meteorology. Figure 6 shows the time series of modeled daily LE fluxes driven by tower measurements and reanalysis inputs with
corresponding tower LE measurements for representative tower sites from the validation set. Each of the selected towers represents one biome type with the longest record within the respective tower group. There are large differences between modeled and measured LE values at several sites. For the USNR1 site, there are many measured high LE values during winters in 1999, 2000, 2001, and 2002, but these patterns do not show in the following years, indicating that the large winter LE variations in the earlier years may be an artifact of measurement errors. Both tower-driven and reanalysis-driven results tend to overestimate LE during the early seasons at USKS2 but underestimate LE during the middle seasons at CAOAS. The low correlations between LE simulations and LE measurements at USSO2 are to some extent due to lack of variation in satellite-observed NDVI and small LE sample size for comparison. Moreover, this site is located in the California Mediterranean climate zone where plant transpiration can be greatly impacted by occasional precipitation and fog events that are not directly captured in our ET algorithms. Despite these uncertainties in the LE simulations, both sets of model results generally correspond well with the tower observations and capture observed LE seasonality and interannual variability and associated differences among the major global biomes represented.

For MF tower sites, LE/ET was computed as a weighted composite of all forest types within the tower footprint including ENF, EBF, DNF, and DBF, as deter-
Figure 4. Time series of daily measured and modeled latent heat flux (LE: W m⁻²) using the NDVI-based ET algorithm driven by tower-measured and NNR meteorology for the representative tower sites with the longest (3–15 years) records for their respective land cover classes from the algorithm development tower set. The r and RMSE statistics are also listed for the two sets of simulations for each site. All r values are significant with 99% confidence. The time series and statistics of modeled LE driven by tower-measured and NNR meteorology are marked in gray and black, respectively.
mined from satellite remote sensing–based tree cover continuous fields data. This method accounts for the effects of varying tree compositions on the aggregate functional response of mixed forest stands and was evaluated at 10 MF tower sites across the global domain, including 3, 2, and 5 sites in Europe, Asia, and North America, respectively (Table 2). The two sets of simulations driven by tower and reanalysis meteorology inputs at these MF tower sites show generally similar LE/ET accuracies as non MF tower sites, with higher correlation coefficients than some biome types (Figure 5).

4.2.3. Evaluation of Monthly ET Estimates

[19] On a monthly basis, the model ET results derived from both tower–measured and reanalysis meteorology inputs agree well with ET observations from the 82 tower sites, including both algorithm development and validation sets (Figure 7). The tower-driven results account for approximately 84% of the observed variation in monthly ET measurements with respective RMSE and MR values of 13.0 and −0.8 mm month⁻¹, while the reanalysis-derived results account for 80% of the variation in measured ET with respective RMSE and MR values of 15.3 and −3.0 mm month⁻¹. The local tower conditions were poorly represented by the coarse NNR meteorology at several sites, reducing the overall performance of reanalysis-driven results. The USSRM site located in Arizona’s arid area is the most obvious example. The coarse NNR meteorology poorly captures the air vapor pressure around this woody savanna site, resulting in substantial underestimates of ET and the flat distribution of the scatter points (solid triangles) in the lower left portion of Figure 7b. However, the reanalysis-driven results show similar performance relative to tower–driven results at most sites. Although the model results show small global biases for both algorithm development and validation sets, the high coefficients of determination (i.e., $R^2$), low RMSE, and MR differences for the two sets of monthly ET results indicate that the algorithm generally captures observed seasonal and inter-annual variations and site-to-site differences in ET.
4.3. Evaluation of ET at the Basin Level

The satellite-based global ET results were evaluated against inferred basin-scale average ET derived from observed discharge and gauge-based (GPCC) precipitation records for 261 global basins (Figure 8). Figure 8a shows the global distribution of selected basins and the relative difference (%) between ET\(_{RS}\) and ET\(_{Inferred}\) defined as \((ET_{RS} - ET_{Inferred}) \times 100 / ET_{Inferred}\). Figure 8b is the scatter plot of the relationship between ET\(_{RS}\) and ET\(_{Inferred}\); these results indicate that ET\(_{RS}\) and ET\(_{Inferred}\) are similar for most basins (RMSE = 186.3 mm yr\(^{-1}\); \(R^2 = 0.80\)). The relative difference between ET\(_{RS}\) and ET\(_{Inferred}\) falls within ±50%, ±20%, and ±10% for 95%, 68%, and 47% of the area covered by the 261 basins, respectively. The largest ET\(_{RS}\) and ET\(_{Inferred}\) difference occur in some northern high-latitude, subtropical and tropical basins (Figure 8a). ET\(_{RS}\) is much higher than ET\(_{Inferred}\) in some northern high-latitude basins including the Yukon, Mackenzie, Yenisei, Lena, Kolyma, Pechora, Indigirka, and Yana basins (Figure 8a). The mean ET\(_{RS}\) and ET\(_{Inferred}\) difference in these basins is approximately 100 mm yr\(^{-1}\). This systematic difference is at least partially attributable to the substantial underestimation of GPCC precipitation from snow and wind-related biases of gauge observations and the sparse weather station network density in the northern high latitudes [Yang et al., 2005]. Zhang et al. [2009] showed that the GPCC product underestimates precipitation by 7.15 mm month\(^{-1}\) in relation to bias-corrected observations in these regions [Yang et al., 2005]. The GPCC precipitation bias can contribute to an underestimation of 90 mm yr\(^{-1}\) in ET\(_{Inferred}\), which
approximates the average difference between $E_{T_{RS}}$ and $E_{T_{Inferred}}$ in these basins. $E_{T_{RS}}$ is lower than $E_{T_{Inferred}}$ in Western Africa and Indian subcontinent basins, indicating that the RS model may underestimate actual ET in these regions. However, uncertainty in the coarse GPCC precipitation and discharge measurements may also contribute to $E_{T_{RS}}$ and $E_{T_{Inferred}}$ differences in these regions. Although there are large differences between $E_{T_{RS}}$ and $E_{T_{Inferred}}$ in some basins, the generally favorable agreement in these results for most areas indicates that the RS-based ET product is relatively accurate on a global basis.

4.4. Reanalysis Meteorology Impacts on LE Estimation

Overall, the NNR temperature variables ($T_{max}$, $T_{avg}$, and $T_{min}$) show the highest correspondences with the tower

Figure 7. Comparisons between monthly modeled ET (mm month$^{-1}$) and tower measurements for the 82 tower sites; the simulations in Figure 7a are derived from tower-measured meteorology, while simulations in Figure 7b are derived from NNR meteorology and NASA/GEWEX SRB solar radiation inputs. These relationships are significant with 99% confidence.

Figure 8. Comparisons between multiyear (1983–2006) average RS-based ET ($E_{T_{RS}}$) and inferred ET ($E_{T_{Inferred}}$) from basin-scale water balance calculations for 261 major global basins: (a) difference (%) between $E_{T_{RS}}$ and $E_{T_{Inferred}}$ and (b) scatter plot of $E_{T_{RS}}$ versus $E_{T_{Inferred}}$. 
observations and explain 90% or more of variability in the observations, while the NNR VPD explains the lowest variability in the tower site observations (Table 4); the correspondence ($R^2$) between tower observations and NASA/GEWEX SRB results for $R_e$ is generally intermediate between these results. The error distributions for the temperature variables are also narrow, and the mean errors for these temperature variables are close to zero. Both NNR VPD and NASA/GEWEX SRB-based $R_e$ are generally overestimated relative to the observations and show considerable error distributions. The statistics in Table 4 suggest that the largest uncertainties in input meteorological parameters are from NNR VPD followed by SRB-based $R_e$ while the NNR temperature variables have the lowest uncertainties. These results are also consistent with previous studies [Zhang et al., 2007; K. Zhang et al., 2008].

4.5. Global ET Patterns

We applied the NDVI-based ET algorithm with daily NNR surface meteorology and NASA/GEWEX SRB solar radiation inputs to calculate daily ET globally at 8 km spatial resolution from 1983 to 2006. The multiyear (1983–2006) average annual ET is plotted in Figure 9 and shows strong regional variations and latitudinal gradients corresponding to global climate patterns. Tropical rainforests in South America, Africa, and Southeast Asia have the highest annual ET, while drier areas within temperate and subtropical regions and the Arctic have the lowest annual ET. Annual ET values for temperate and boreal forests are generally intermediate between these two extremes. The estimated ET over water bodies is generally much larger than for adjacent vegetated areas within the same climate zone due to lower surface resistance to evaporation over water relative to land. The global terrestrial average annual ET weighted by area is $539.3 \pm 9.1 \text{ mm yr}^{-1}$, which is about $0.60 \pm 0.02$ of the global average annual GPCC precipitation. The estimated global average ET to $P$ ratio is similar to values reported from previous studies [e.g., L.ovich and White, 1990; Alton et al., 2009]. The Evergreen Broadleaf Forest biome has the largest average ET of $1138 \pm 175 \text{ mm yr}^{-1}$ followed by Woody Savanna ($749 \pm 209 \text{ mm yr}^{-1}$), Deciduous Broadleaf Forest ($635 \pm 200 \text{ mm yr}^{-1}$), Savanna ($676 \pm 183 \text{ mm yr}^{-1}$), Permanent Wetland ($529 \pm 311 \text{ mm yr}^{-1}$), Cropland ($507 \pm 157 \text{ mm yr}^{-1}$), Mixed Forest ($361 \pm 124 \text{ mm yr}^{-1}$), Closed Shrubland ($352 \pm 166 \text{ mm yr}^{-1}$), Grassland ($311 \pm 193 \text{ mm yr}^{-1}$), Evergreen Needleleaf Forest ($294 \pm 81 \text{ mm yr}^{-1}$), Deciduous Needleleaf Forest ($243 \pm 29 \text{ mm yr}^{-1}$), and Open Shrubland ($202 \pm 83 \text{ mm yr}^{-1}$). Open water bodies cover about 3.4% of the global land area as inferred by the 500 m MODIS-IGBP land cover product, while mean annual ET from these water bodies is $906 \pm 561 \text{ mm yr}^{-1}$ and represents approximately 7% of total annual terrestrial ET.

The magnitudes and spatial patterns of the estimated global ET are generally consistent with the literature. The study of Bruinzeel [1990] indicated that annual ET ranges from 1310 to 1500 mm in humid tropical forests, Frank and Inouye [1994] used 19–25 year climate records to calculate annual ET at 94 sites representing 11 biomes and reported annual ET of 202 ± 34, 380 ± 43, 588 ± 47, 884 ± 71, and 1363 ± 77 mm yr$^{-1}$ for tundra (10 sites), taiga (11 sites), broadleaf forest (10 sites), savannah (4 sites), and wet tropical forest (10 sites), respectively. Measurements of water vapor fluxes from 1 September 2003 to 31 August 2004 in a 74 year mixed-wood boreal forest in Ontario, Canada, show an annual water loss of 480 ± 30 mm [Pejam et al., 2006]. Giansoldi et al. [2009] reported mean annual ET values of 823 and 689 mm for two tropical savanna sites in central Brazil using tower eddy covariance measurements. Eddy covariance measurements for a poplar plantation in Northern Italy revealed cumulative ET over three growing seasons (April–September) of 388, 471, and 484 mm for 2002, 2003, and 2004, respectively [Migliavacca et al., 2009].

The multiyear mean seasonal patterns of ET from 1983 to 2006 using the NDVI-based ET algorithm with daily NNR surface meteorology and NASA/GEWEX SRB solar radiation inputs shows distinct global seasonality (Figure 10). The tropical rain forest regions show yearround high ET values, while tropical dry forest and savanna regions show alternate wet and dry seasons. The temperate

Table 4. Statistics for the Comparison of Daily NNR Meteorological Variables and NASA/GEWEX SRB Net Radiation Relative to Daily Tower Observations

<table>
<thead>
<tr>
<th>Variables</th>
<th>MR</th>
<th>$Q_i$</th>
<th>$M$</th>
<th>$Q_3$</th>
<th>RMSE</th>
<th>$R^2$</th>
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<tbody>
<tr>
<td>$T_{max}$ (°C)</td>
<td>-0.08</td>
<td>-2.44</td>
<td>0.08</td>
<td>2.48</td>
<td>4.32</td>
<td>0.90</td>
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<td>$T_{avg}$ (°C)</td>
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<td>0.05</td>
<td>1.81</td>
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<td>$T_{min}$ (°C)</td>
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<td>-0.29</td>
<td>2.06</td>
<td>4.08</td>
<td>0.90</td>
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<tr>
<td>VPD (Pa)</td>
<td>-84.49</td>
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<td>-9.49</td>
<td>120.17</td>
<td>464.81</td>
<td>0.68</td>
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<td>$R_e$ (W m$^{-2}$)</td>
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<td>-20.47</td>
<td>-3.94</td>
<td>13.97</td>
<td>34.01</td>
<td>0.77</td>
</tr>
</tbody>
</table>

*The sample size for each variable is 97,655. The statistics include mean (MR), median ($M$), first quartile ($Q_1$), and third quartile ($Q_3$) of the errors defined as the measured values minus the reanalysis values, root mean squared error (RMSE), and coefficient of determination ($R^2$).
and boreal-Arctic regions have much higher seasonal variability than the tropics.

5. Discussion and Conclusions

[46] We extended an NDVI-based ET algorithm, originally developed for the northern high latitudes [Zhang et al., 2009], to the global domain by deriving biome-specific maximum canopy conductance functions for all major global biomes. The algorithm was modified using AVHRR GIMMS NDVI and corresponding tower eddy-covariance measurement derived canopy conductances from 34 globally distributed sites. The algorithm was applied using two sets of

Figure 9. Global map of multiyear (1983–2006) mean annual ET as derived from the AVHRR GIMMS NDVI record, NNR daily meteorology, and NASA SRB solar radiation inputs. Barren land (in gray) and ocean (in white) areas were excluded from the model calculations.

Figure 10. Multiyear (1983–2006) mean seasonality of global ET.
daily meteorology inputs, including in situ tower measurements and relatively coarse-resolution NNR and NASA/GEWEX SRB gridded global products. The model was validated using tower ET measurements at the 34 development sites and 48 additional, independent tower sites encompassing the major global biomes. The AVHRR NDVI versus corresponding tower measurement derived potential canopy conductance values follow sigmoid-type response curves for the major biome types but with distinct differences among different biomes that follow characteristic variations in climate and associated plant adaptations; these results indicate that the NDVI-based canopy conductance algorithm is robust and more biophysically based than alternative approaches that employ a constant, maximum canopy conductance parameterization for individual biomes. The two sets of LE/ET simulations at the tower level show generally favorable agreement with tower measurements at daily and monthly time scales, although the tower-driven results show generally better accuracy than the reanalysis-driven results. These results indicate that the ET algorithm provides a reasonably accurate measure of spatial patterns and daily to annual temporal dynamics in global ET and corresponding land-atmosphere water and latent energy exchanges. The global ET results capture observed spatial and temporal variations at the global scale and compare favorably with ET inferred from basin-scale water balance calculations for 261 basins covering 61% of the global vegetated area. Through this study, we constructed an ET climatology based on long-term satellite observations for each pixel of the global vegetated land area.

[47] Two potential sources of uncertainty in the ET calculations are linked to corresponding uncertainties in tower eddy flux measurements and satellite-observed NDVI used for model development and validation. First, we used the 8 km AVHRR GIMMS NDVI record to derive NDVI values at each tower site. The tower measurement footprints are typically about 1 km in size [Baldocchi, 2008] and much smaller than the resolution of the overlying GIMMS NDVI grid cell. The satellite derived NDVI may not adequately capture subgrid scale vegetation signals at these sites, especially in areas of complex topography or heterogeneous land cover; thus, model error for some tower sites may be attributed to inaccurate NDVI representation of tower footprint conditions. The ET algorithm performance may also be negatively impacted by uncertainty in tower eddy flux measurements and associated lack of energy balance closure due to complexity in wind patterns, footprint representation and sampling variability [Twine et al., 2000; Wilson et al., 2002]. Twine et al. [2000] reported that the discrepancy in energy balance closure is generally about 10%-30% when the eddy covariance method is used. These tower measurement uncertainties are within the range of accuracy of the algorithm ET calculations but may also introduce additional model error because tower LE measurements are used to derive biome-specific relationships between gs and NDVI. In addition, the ET algorithm in this study does not explicitly consider the impacts of precipitation events on surface conductances due to the limited availability of accurate global precipitation data, which may introduce ET estimation uncertainty.

[48] Despite the above uncertainties, the ET algorithm performs well across the observed range of global biomes, vegetation conditions, and climatic regimes as indicated by favorable agreement with LE/ET measurements from 82 diverse tower sites, annual ET values reported in the literature and basin scale ET estimates inferred from the regional water balance. The algorithm is also simple enough to apply with long-term global satellite NDVI records for evaluating regional ET anomalies and climatologies, drought, agricultural, and forest health monitoring and other applications. The results of this study also represent a systematic and continuous long-term (24 year) global record of ET/LE with well-quantified accuracy useful for global assessment of ET climatologies and climate change assessment of terrestrial water and energy cycle dynamics and interactions.

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