



Research papers

Estimation of high-resolution terrestrial evapotranspiration from Landsat data using a simple Taylor skill fusion method



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ABSTRACT

Estimation of high-resolution terrestrial evapotranspiration (*ET*) from Landsat data is important in many climatic, hydrologic, and agricultural applications, as it can help bridging the gap between existing coarse-resolution *ET* products and point-based field measurements. However, there is large uncertainty among existing *ET* products from Landsat that limit their application. This study presents a simple Taylor skill fusion (*STS*) method that merges five Landsat-based *ET* products and directly measured *ET* from eddy covariance (*EC*) to improve the global estimation of terrestrial *ET*. The *STS* method uses a weighted average of the individual *ET* products and weights are determined by their Taylor skill scores (*S*). The validation with site-scale measurements at 206 *EC* flux towers showed large differences and uncertainties among the five *ET* products. The merged *ET* product exhibited the best performance with a decrease in the averaged root-mean-square error (*RMSE*) by 2–5 W/m² when compared to the individual products. To evaluate the reliability of the *STS* method at the regional scale, the weights of the *STS* method for these

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five *ET* products were determined using *EC* ground-measurements. An example of regional *ET* mapping demonstrates that the *STS*-merged *ET* can effectively integrate the individual Landsat *ET* products. Our proposed method provides an improved high-resolution *ET* product for identifying agricultural crop water consumption and providing a diagnostic assessment for global land surface models.

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1. Introduction

The latent heat of evapotranspiration (*ET*), which is the sum of the heat flux from the earth's surface to the atmosphere for soil evaporation, vegetation transpiration and evaporation of water intercepted by plant canopies, plays an important role in many geophysical applications (e.g., climatic forecasting, crop yield forecasting and agricultural water resource management) (Jiménez et al., 2011; Kool et al., 2014; Liang et al., 2010; Wang and Dickinson, 2012; Zhang et al., 2009). *ET* exhibits strong heterogeneity across the land surface due to complex environmental controls and biophysical feedback processes (Kalma et al., 2008; Mallick et al., 2009; Yao et al., 2014; Yuan et al., 2010). Large-scale networks of direct biosphere-atmosphere measurements with the eddy covariance (*EC*) method have been widely used for site-scale studies. However, such local *ET* observations cannot represent *ET* at regional to global scales (Baldocchi et al., 2001; Choi et al., 2009; Kustas and Anderson, 2009; Liu et al., 2016; Xu et al., 2011; Xu et al., 2016; Yao et al., 2015).

Remote sensing has provided us with an effective way to obtain spatially and temporally continuous *ET* data at a regional scale. Currently, there are various moderate spatial resolution satellite-based *ET* products available, such as the Moderate Resolution Imaging Spectroradiometer (*MODIS*) product (*MOD16*), which has 1 km and 8 day of spatial and temporal resolution, respectively (Mu et al., 2007, 2011) or the *EUMETSAT* Satellite Application Facility on Land Surface Analysis (*LSA-SAF*) product (*LSA-SAF MSG*) (Ghilain et al., 2011, 2012) with 5 km spatial resolution and daily temporal resolution. However, validation results with direct measurements indicate that the *MOD16* and *LSA-SAF MSG ET* products tend to consist of uncertainties at most *FLUXNET* flux tower sites (Chen et al., 2014; Hu et al., 2015; Kim et al., 2012). Other *ET* products (including reanalysis and data assimilation datasets), such as the European Centre for Medium-Range Weather Forecasts (*ECMWF*) *ERA-40* reanalysis (Uppala et al., 2005) and the Global Land Data Assimilation System (*GLDAS*) datasets, have high temporal resolution (daily) but rather coarse spatial resolution ($\geq 0.5^\circ$) (Kumar et al., 2006; Rodell et al., 2004). This relative coarse spatial resolution of global *ET* products limits the representation of the heterogeneous terrestrial biosphere.

The Landsat multispectral data record from the Thematic Mapper (*TM*) and the Enhanced Thematic Mapper Plus (*ETM+*) are valuable data sources for producing *ET* product at rather high spatial resolution (~ 30 m) (Ju and Roy, 2008). They can also bridge the gap between existing coarse-resolution *ET* products and point-based field measurements and be used to validate coarse-resolution data. Various Landsat-based *ET* algorithms, roughly classified as *VNIR* (visible and near infrared)-based remote sensing methods and *TIR* (thermal infrared)-based remote sensing methods, have been developed to estimate regional *ET* (Kalma et al., 2008; Li et al., 2009). *VNIR*-based remote sensing methods include some empirical/statistical models (Glenn et al., 2008; Jung et al., 2010; Wang et al., 2007; Wang and Liang, 2008) and Penman-Monteith (*PM*)/Priestley-Taylor (*PT*) methods (Fisher et al., 2008; Jin et al., 2011; Mu et al., 2007, 2011; Priestley and Taylor, 1972; Yao et al., 2013), which usually use remotely sensed normalized difference vegetation index (*NDVI*) or leaf area index (*LAI*) to estimate *ET*. *TIR*-based remote sensing methods, such as the Mapping

Evapotranspiration with Internalized Calibration (Allen et al., 2007), the two-source model (Anderson et al., 1997; Kustas and Norman, 1999; Norman et al., 1995), Surface Energy Balance System (Su, 2002), Surface Energy Balance Algorithm for Land (Bastiaanssen et al., 1998), and the surface temperature versus vegetation index triangle/trapezoid space (Jiang and Islam, 1999; Long and Singh, 2012; Tang et al., 2010; Zhang et al., 2005), calculate *ET* as the residual of surface energy balance (*SEB*) or *PT* method from *TIR*-derived land surface temperatures (*LST*). Although these methods provide reasonable *ET* estimates for Landsat data, they still have large uncertainties in regional *ET* simulations because of different model structures and environmental variables employed (Chen et al., 2014; Choi et al., 2009; Liaquat and Choi, 2015; Liu et al., 2011; Liu et al., 2013).

This issue has been partially resolved by several data fusion methods, such as Bayesian model averaging (*BMA*) and empirical orthogonal function (*EOF*), which merge multiple *ET* products to improve regional *ET* estimation (Feng et al., 2016; Yao et al., 2014, 2016; Zhu et al., 2016). For example, Yao et al. (2014) used the *BMA* method by merging five *ET* products to enhance daily *ET* estimates with smaller root mean square errors (*RMSEs*) than those of the individual products. Zhu et al. (2016) also documented that the *BMA* method by merging four *ET* models across north China has the advantage of generating more skillful and reliable predictions than the simple model averaging (*SMA*) scheme. Similarly, Feng et al. (2016) reported that the *EOF* fusion method was capable of integrating the two satellite-based *ET* datasets with improved consistency and reduced uncertainties. However, the complex structures of these fusion methods, which affect their computational efficiency for calculating the weightings for individual datasets, can limit their wide application.

To reduce the complexity of the fusion method and to generate global *ET* products with high spatial resolution, in this study we developed a simple Taylor skill fusion (*STS*) method by merging five Landsat-based *ET* products produced by the individual algorithms and *FLUXNET* eddy covariance (*EC*) observations to improve terrestrial *ET* estimation. The objectives of this study are threefold: (1) to evaluate five Landsat-based *ET* datasets derived from five classic *ET* algorithms using global long-term *FLUXNET* measurements from 206 flux tower sites; (2) to apply and validate the *STS* method for five Landsat-based *ET* datasets to improve terrestrial *ET* estimation; and (3) give an example of mapping terrestrial *ET* using the *STS* method and Landsat data.

2. Data

2.1. Landsat-based *ET* products

We produced the individual Landsat-based *ET* products using five classic *ET* algorithms. We only used five traditional Landsat-based *ET* products derived from *VNIR*-based remote sensing methods in this article because there are some disadvantages when applying *TIR*-based remote sensing methods to *ET* estimations at the global scale (Hope et al., 2005; Su, 2002). The forcing data includes Landsat *NDVI* data with 30 m spatial resolution and daily Modern Era Retrospective Analysis for Research and Applications (*MERRA*) meteorological data with $1/2 \times 2/3$ degree spatial resolu-

tion. All coarse resolution MERRA data were spatially interpolated into 30 m using the method described by Zhao et al. (2005). Theoretically, this spatial interpolation method improves the accuracy of meteorological data for each 30 m pixel because it uses a cosine function and the four MERRA cells surrounding a given pixel to remove sharp changes from one side of a MERRA boundary to the other (Zhao et al., 2005). The individual ET products (Table 1) are briefly described below.

2.1.1. RS-PM ET product

The RS-PM ET product was produced based on a revised remote sensing-based PM (RS-PM) algorithm (Monteith, 1965) modified from the Mu et al. (2007) algorithm (Appendix A). The input variables include daily surface net radiation (R_n), relative humidity (RH), air temperature (T_a), and vapor pressure (e) from MERRA data and LAI derived from Landsat NDVI data. The RS-PM ET product has 30 m spatial resolution. The product has a 16-day temporal resolution inherited from the Landsat data in the same time and filled values with -9999 are assigned for cloudy pixels. The product is global in coverage spanning 1998–2010 and future years are produced periodically.

2.1.2. SW ET product

The Shuttleworth-Wallace dual-source (SW) model (Shuttleworth and Wallace, 1985) was adopted to generate the SW ET product. The SW model accounts separately for the energy balance for vegetation and soil components of a soil-vegetation canopy unity (Hu and Jia, 2015; Sellers et al., 1992; Shuttleworth and Wallace, 1985) (Appendix A). The SW ET product requires R_n , RH, T_a , e , and wind speed (WS) from MERRA data and LAI derived from Landsat NDVI data. The SW ET product has global coverage during the period of 1995–2009 at 30 m spatial resolution and 16-day temporal resolution. The ET values for cloudy pixels are also set as -9999.

2.1.3. PT-JPL ET product

The PT-JPL ET product was produced using a novel PT algorithm developed by Fisher et al. (2008). This algorithm (PT-JPL) considers the effects of both atmosphere and ecophysiology to derive constraints representing vegetation conductance without using any ground-based observed data (Appendix A). The input variables are R_n , RH, T_a , e , and vegetation parameters (NDVI, LAI and absorbed photosynthetically active radiation (FPAR)) derived from Landsat NDVI data. The PT-JPL ET product is available from 1998 to 2010 globally and with 16-day temporal and at 30 m spatial resolution.

2.1.4. MS-PT ET product

The MS-PT ET product was generated based on the modified satellite-based PT (MS-PT) model developed by Yao et al. (2013) and this model uses the apparent thermal inertia (ATI) derived from diurnal air temperature range (DT) to parameterize surface soil moisture (SM) constraints (Appendix A). The MS-PT ET product

only requires R_n , T_a , DT from MERRA data and NDVI from Landsat data as inputs. The MS-PT ET product is generated at the same spatial resolution, temporal resolution, coverage period, and filling values as the PT-JPL ET product for the period of 1997–2009.

2.1.5. SIM ET product

A simple hybrid ET (SIM) formulation presented by Wang and Liang (2008) is used in this study to generate the SIM ET product; further, the SIM algorithm partitions the R_n by introducing T_a , NDVI, DT and prior parameters (Appendix A). The SIM ET product is also available at 30 m spatial and 16-day temporal resolution over the global land surface from 1998 to 2009. The data processing step includes MERRA interpolation to the target grid size of 30 m.

2.2. Eddy covariance data

Five Landsat-based ET products and the STS fusion method were evaluated and validated using a large data set of ground-measured flux data. The data from 206 EC flux tower sites were provided by AmeriFlux, ChinaFlux, LathuilleFlux, AsiaFlux, Arid/Semi-arid experimental observation synergy network of China, Chinese ecosystem research network (CERN), Asian Automatic Weather Station Network (ANN), Swiss FluxNet and several individual principal investigators (PIs) of FLUXNET network. These EC flux tower sites are mainly located in Europe, North America, and Asia, with three sites in Australia, four sites in South America and three sites in Africa (Fig. 1). The sites cover 10 global plant functional types (PFTs): deciduous broadleaf forest (DBF, 28 sites), deciduous needleleaf forest (DNF, 2 sites), evergreen broadleaf forest (EBF, 13 sites), evergreen needleleaf forest (ENF, 54 sites), mixed forest (MIF, 10 sites), cropland (CRO, 31 sites), grassland (GRA, 36 sites), savanna (woody savanna and savanna) (SAW, 8 sites), shrubland (open, closed) (SHR, 13 sites) and wetland (WET, 11 sites). These EC flux tower sites were separated into two separate subsets for the merging algorithm calibration (103 sites) and validation (103 sites), each representing major global PFTs. These EC data covered the period of 2000–2009 (each tower to varying extent) and cover at least one growing season.

The half-hourly and hourly EC measurements (ET; sensible heat flux, H) were processed based on a method of gap filling and quality control that used both the covariance of surface fluxes with meteorological parameters and the temporal variations in surface fluxes (Reichstein et al., 2005). These turbulent fluxes were complemented by measurements of R_n and soil heat flux (G). If less than 30% of the total data are missing, the daily values for R_n , ET, H and G were calculated the averages of the ground-measurements. Else, the daily value was set as invalid value (-9999). Because turbulent EC measurements are susceptible to incomplete energy balance closure (Leuning et al., 2012), we corrected the daily ET using the method proposed by Twine et al. (2000).

$$ET_c = (R_n - G)/(H_u + ET_u) \times ET_u \quad (1)$$

Table 1
Summary of the Landsat ET products generated in this study for 2000–2009.

| ET products | Spatial resolution | Temporal resolution | Time Period | Algorithms | Forcing Inputs of the ET products | |
|-------------|--------------------|---------------------|-------------|--|-----------------------------------|---------|
| | | | | | MERRA | Landsat |
| RS-PM | 30 m | 16-day | 1998–2010 | Remote sensing-based Penman-Monteith algorithm | R_n , RH, T_a , e | NDVI |
| SW | 30 m | 16-day | 1995–2009 | Shuttleworth-Wallace dual-source model | R_n , RH, T_a , e , WS | NDVI |
| PT-JPL | 30 m | 16-day | 1998–2010 | Priestley-Taylor algorithm of Jet Propulsion Laboratory, Caltech | R_n , RH, T_a , e | NDVI |
| MS-PT | 30 m | 16-day | 1997–2009 | Modified satellite-based Priestley-Taylor algorithm | R_n , T_a , DT | NDVI |
| SIM | 30 m | 16-day | 1998–2009 | Simple hybrid algorithm | R_n , T_a , DT | NDVI |

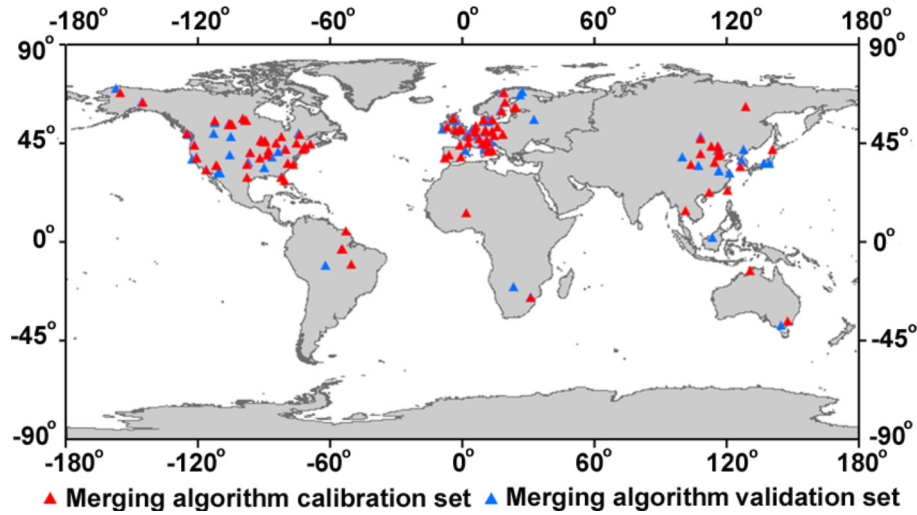


Fig. 1. Locations of the flux tower sites used to merge *ET* algorithm calibration (103 sites) and validation (103 sites).

Accordingly, ET_c is the corrected *ET*, and H_u and ET_u are the uncorrected *H* and *ET*, respectively.

3. Methods

3.1. Simple Taylor skill fusion method

A simple Taylor skill fusion (*STS*) method is developed to merge the five Landsat-based *ET* products into a single *ET* product. The *STS* fusion method uses a weighted average of all the Landsat-based *ET* products and the weights are determined by their Taylor skill scores (*S*) (Taylor, 2001). The *S* value of each *ET* product is calculated using the direct *EC* ground-measurements for reference. The weights for all *ET* products sum up to one and the weights are proportional to the *S* values of the five *ET* products. Thus, the weights can be expressed as:

$$W_i = S_i / \sum_{i=1}^n S_i \quad (2)$$

$$S_i = \frac{4(1 + R_i)^4}{(\delta_i + 1/\delta_i)^2(1 + R_{\max})^4} \quad (3)$$

where W_i is the weight for *ET* product *i*, S_i is the Taylor skill score of *ET* product *i* and n is the number of *ET* products ($n = 5$ in this study). R_i is the correlation coefficient between the estimated *ET* for product *i* and the *EC* ground-measured *ET*. R_{\max} is the maximum correlation coefficient that is set to 1.0 in this study. δ_i is the ratio of the standard deviation of the estimated *ET* for product *i* to the standard deviation of the corresponding *EC* ground-measured *ET*. *S* varies from zero (least skillful) to one (most skillful). The *STS* method ensures that the merged *ET* product has the maximal R^2 and minimal error variance.

3.2. Assessment methods

R^2 , *S*, the root-mean-square error (*RMSE*) and the bias are used to assess the performance of the *STS* method and the individual *ET* products. R^2 measures the agreement between satellite-based estimated and ground-measured *ET*. *RMSE* characterizes the closeness of the estimation and observations and is calculated as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^N (E_j - O_j)^2} \quad (4)$$

Where N is the number of samples, E_j is the estimated *ET* for sample j and O_j is the *EC* ground-measured *ET* for sample j . The bias is also a metric to evaluate the predictive skill and it reflects the difference between the average of the estimation and observations.

$$Bias = \frac{1}{N} \sum_{j=1}^N (E_j - O_j) \quad (5)$$

4. Results and discussion

4.1. Validation of Landsat-based *ET* products

To assess the accuracy of the five Landsat-based *ET* products, the estimated *ET* from five Landsat-based *ET* products were directly compared with *EC* ground-measurements at all 206 flux tower sites for different *PFTs*. At the site scale, large differences were found in the five Landsat-based *ET* products among different *PFTs* (Fig. 2). For both *DBF* and *MIF* sites, the *RS-PM* *ET* product has the largest *S* (>0.74) and R^2 (>0.73 , $p < 0.01$) compared to the other four *ET* products, whereas the *MS-PT* *ET* product has the smallest *RMSE* (29.4 W/m^2 for *DBF* and 20.4 W/m^2 for *MIF*) and bias ($<8 \text{ W/m}^2$). For both *ENF* and *WET* sites, the *SW* *ET* product exhibits highest *S* (0.48 for *ENF* and 0.62 for *WET*) and the smallest *RMSE* (30.1 W/m^2 and 22.3 W/m^2). For all of the *SAW* sites, both *RS-PM* and *SW* *ET* products have the highest accuracy with an average *S* of 0.68 and average *RMSE* of approximately 20 W/m^2 . The *MS-PT* *ET* product exhibits the highest *S* (>0.57) with an *RMSE* of less than 25.5 W/m^2 , and R^2 (>0.65) with a confidence level of $p < 0.05$ for both *EBF* and *CRO* sites. For *GRA* and *SHR* sites, the *SIM* *ET* product with the low *RMSE* of less than 26.3 W/m^2 presents the highest *S* (>0.59) and R^2 (>0.58 , $p < 0.05$) compared to others. Most *ET* products (excluding *SW* *ET* product) have the highest *S* and (more than 0.68) and R^2 (more than 0.66 , $p < 0.05$) with the lowest average *RMSEs*, less than 22 W/m^2 for all of the *DNF* sites, compared to those for the other land cover types. This may be caused by a few samples for only 2 *DNF* sites artificially to highlight the good performance of these *ET* products. When we selected equal samples for all of the land cover types, most *ET* products still provide better fits to the flux tower observations for *DNF* sites. According to the *S* values, the accuracies of both *MS-PT* and *SIM* *ET* products are the highest for all *ENF* sites. Although the *PT-JPL* *ET* product does not result in the highest *S*, it still has good accuracy for the variety of vegetation types. Moreover, we found that none of the individual

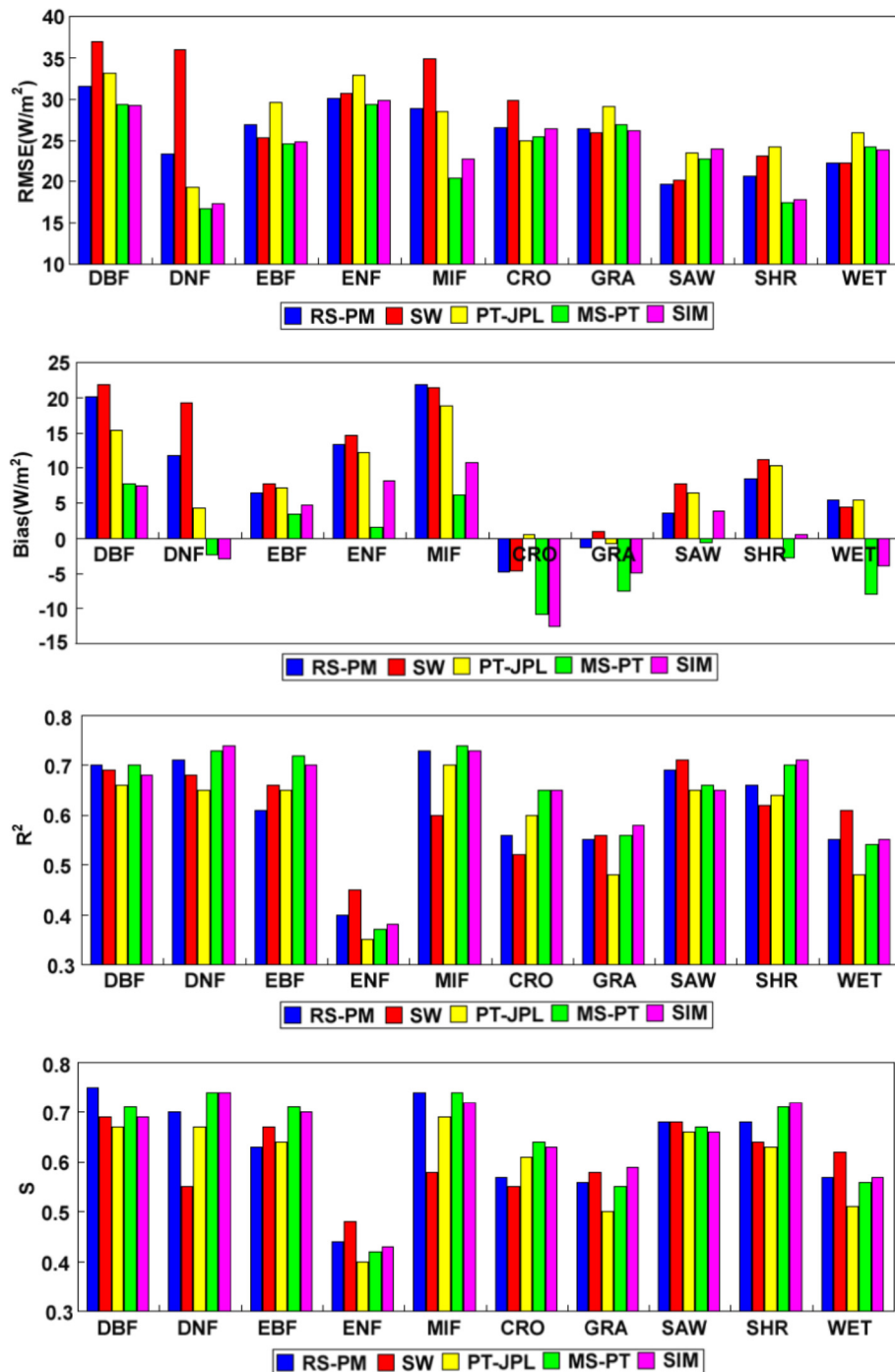


Fig. 2. Bar graphs of the statistics (*RMSE*, *Bias*, R^2 and *S*) of the comparison between daily *ET* from multiple Landsat-based *ET* products (including merged *ET* product) and ground-measurements at all 206 flux tower sites for different land cover types. *DBF*: deciduous broadleaf forest, *DNF*: deciduous needleleaf forest, *EBF*: evergreen broadleaf forest, *ENF*: evergreen needleleaf forest, *MIF*: mixed forest, *CRO*: cropland, *GRA*: grassland, *SAW*: woody savanna and savanna, *SHR*: open and closed shrubland, and *WET*: wetland.

Landsat-based *ET* dataset provides the most accurate *ET* estimate for all land cover types.

Overall, the five Landsat-based *ET* products account for 52–57% of *ET* variability over all *EC* measurements (Fig. 3). Both *MS-PT* and *SIM* *ET* products have the highest *S* of 0.59, followed by *RS-PM*, *SW* and *PT-JPL* with *S* values ranging from 0.55 to 0.58. This indicates that different algorithm parameterizations affect the accuracy of different *ET* products. The highest accuracy of both *MS-PT* and *SIM* *ET* products may be a result from the lower uncertainties in the required in the lower number of forcing data (Wang and

Liang, 2008; Yao et al., 2013). In addition, the algorithm for the *SIM* *ET* product is strongly related to the regression coefficients because it was calibrated over the Southern Great Plains (*SGP*) area of the United States. Therefore, the *SIM* *ET* product estimated from this algorithm provides a better fit to flux tower observations. In contrast, the *ET* products (e.g. *RS-PM* and *SW*) are produced using resistance-based methods. The surface resistance parameterization schemes of these methods are complex, which also affected the accuracy of these *ET* products (Ershadi et al., 2014; Zhu et al., 2016). All five Landsat-based products slightly underestimate *ET*

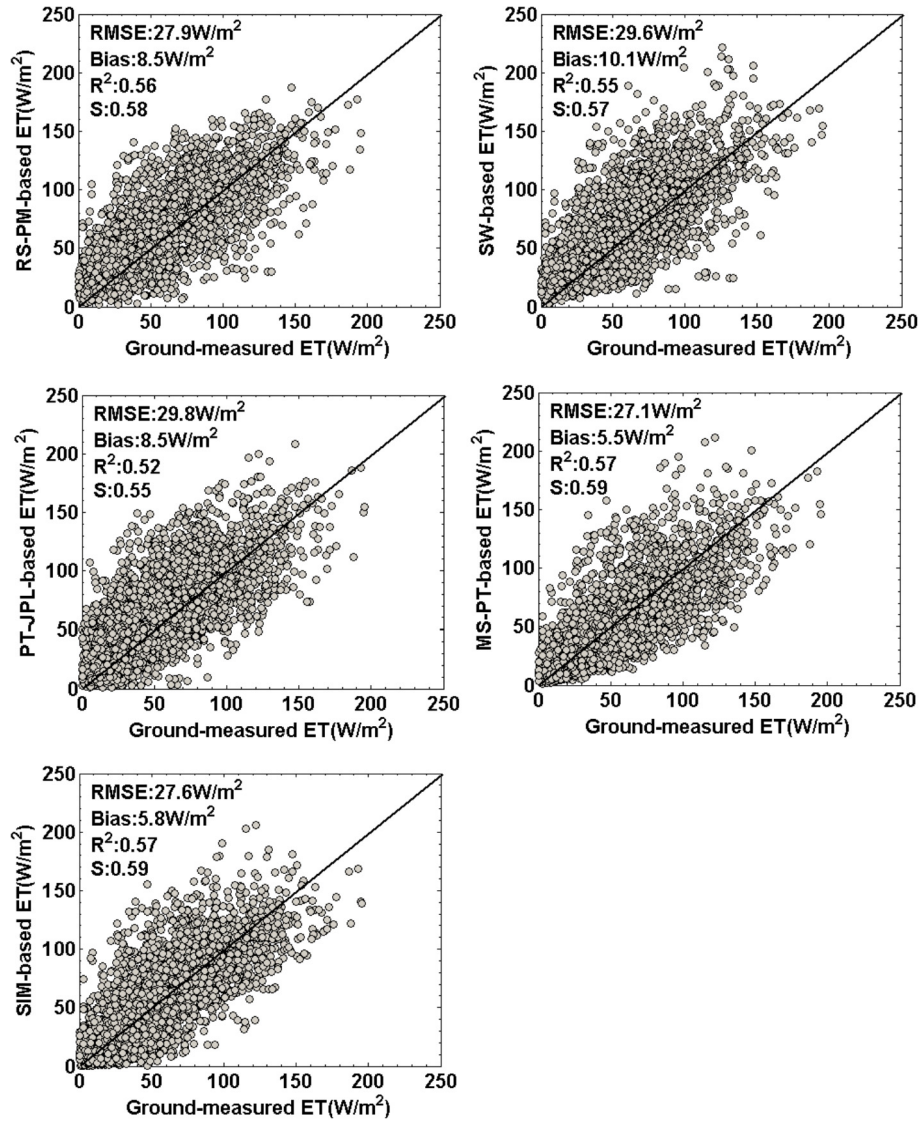


Fig. 3. Scatterplots of the daily ET from multiple Landsat-based ET products and ground-measurements at all 206 flux tower sites.

compared to the measurements, which can be explained by the fact that the algorithms for producing these products are originally developed based on the MODIS data.

4.2. Merging of the Landsat-based ET products

4.2.1. Calibration against tower measurements

To merge five Landsat-based ET products according to the STS method, the data collected at the 103 merging algorithm calibration sites were considered as calibration data to determine weights for the individual ET products. Fig. 4 presents the weights for the five Landsat-based ET products based on EC ground-measurements. Both MS-PT and SIM ET products have the highest weight of 20.5%, followed by RS-PM (20.2%) and SW (19.5%) ET products. In contrast, the weight for PT-JPL ET products is only 19.3%, indicating its contribution to the merged ET estimates is the smallest than for those of the other products. Although previous studies showed that the PT-JPL algorithm driven by the MODIS vegetation variables had the best performance compared to the PM algorithm (Ershadi, et al., 2014; Yao et al., 2013), our result illustrates that the PT-JPL algorithm driven by the Landsat vegetation variables has the worst performance compared to other four algo-

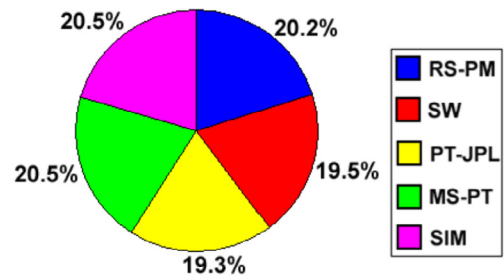


Fig. 4. Weights for five Landsat-based ET products at the 103 calibration tower sites.

gorithms (RS-PM, SW, MS-PT and SIM). This may be caused by the spectral reflectance difference between Landsat and MODIS data, which resulted in the difference between Landsat and MODIS vegetation variables (e.g. NDVI) (Jia, et al., 2012).

The statistical summaries of the STS method performance for the 103 calibration sites among different land cover types are plotted in Fig. 5. One can notice that the STS-based ET estimation for different land cover types have higher S and lower RMSEs

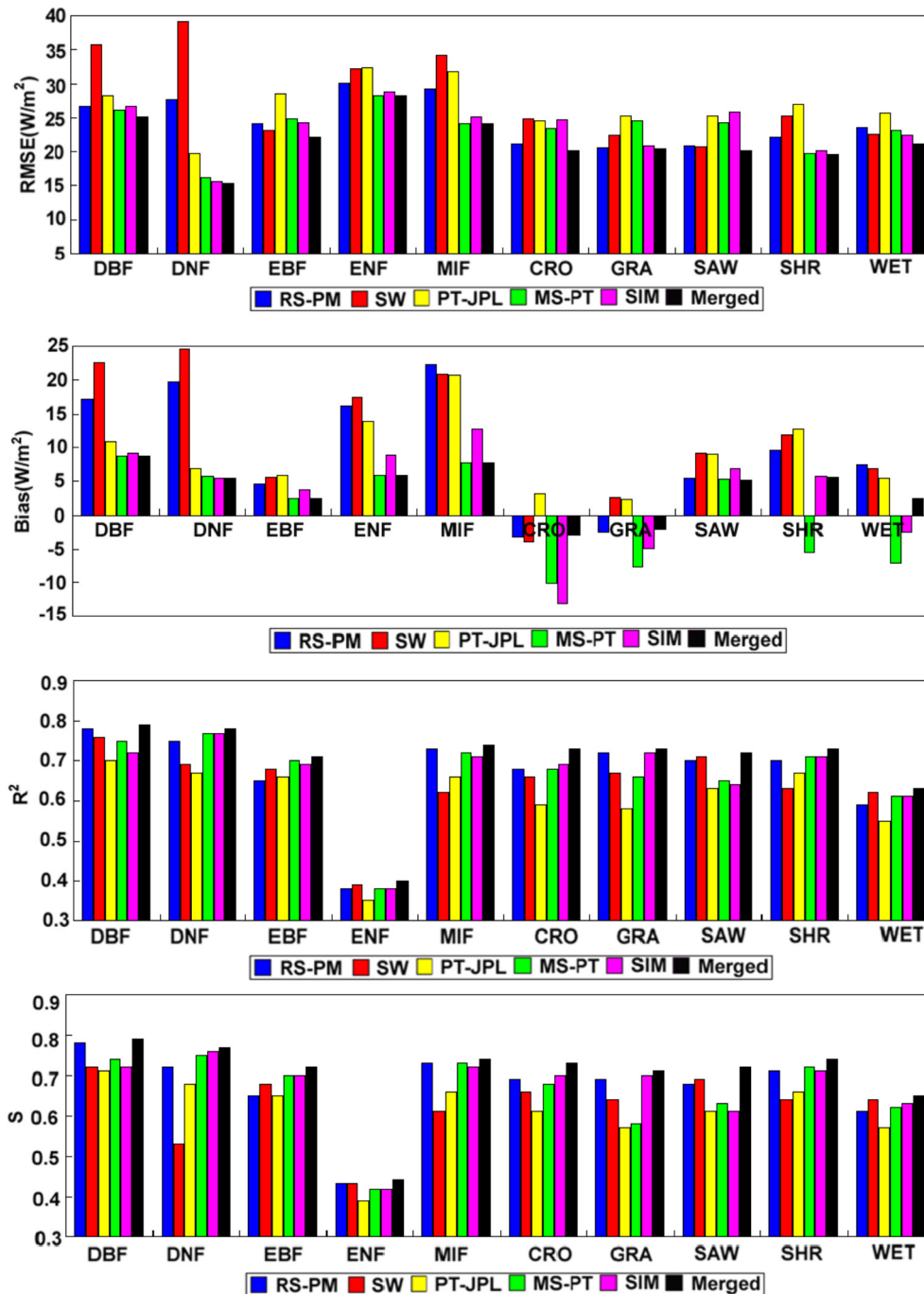


Fig. 5. Same as Fig. 2 but for the 103 calibration tower sites. The merged ET was calculated using the weights for five Landsat-based ET products at the 103 calibration tower sites.

compared to the individual Landsat-based ET products at the site scale. For 27 ENF calibration sites, the STS method has a higher S of 0.47 and R^2 of 0.43 ($p < 0.05$) and a lower $RMSE$ of 23.8 W/m^2 than individual ET products, though it presents the worst performance than those at other land cover types. For 6 WET calibration sites, the STS method shows better performance than single ET products, with lower $RMSEs$ of 22.4 W/m^2 and higher S of 0.68. Similarly, the $RMSEs$ of the STS -based ET estimation versus EC ground-measurements at 70 other calibration sites are all less than 25 W/m^2 and the S values are all more than 0.7. Fig. 6 compares daily ET observations at all 103 calibration sites and ET estimates for the different ET products. The results show that the merged

ET product has the best performance with the highest S of 0.66 and the lowest $RMSE$ of 23.8 W/m^2 , compared to the other products. This indicates that a reasonable choice of fusion method is feasible to improve the accuracy of Landsat-based ET estimation by combining EC ground-measurements and multiple ET products.

4.2.2. Validation against EC measurements

The performance of the STS method for the validation tower set is similar to the results from the merging algorithm calibration tower set (Fig. 7), though the S and R^2 statistics for the partial validation set (e.g. DBF , ENF) are slightly smaller than the merging algorithm calibration set. The $RMSE$ of the merged daily ET for dif-

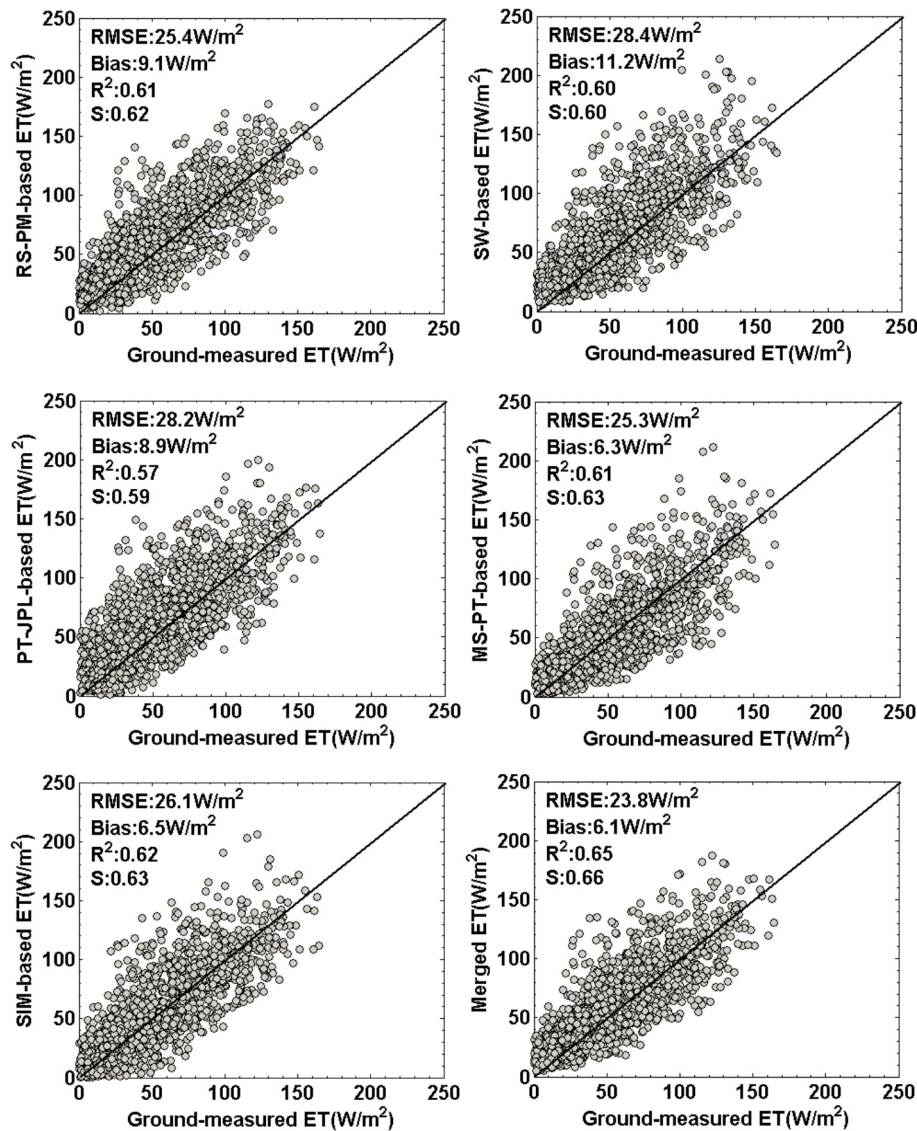


Fig. 6. Scatterplots of the daily ET from multiple Landsat-based ET products (including merged ET product) and ground-measurements at the 103 calibration tower sites.

ferent land cover types varies from 11.2 W/m^2 to 32.4 W/m^2 , the R^2 varies from 0.45 to 0.86, and the S is greater than 0.7 (excluding ENF and WET). The merged ET decreases the RMSE by $\sim 2 \text{ W/m}^2$ for forests, cropland and grassland sites and $\sim 3 \text{ W/m}^2$ for other sites, and increases the S by approximately 0.03 and increased the R^2 by more than 0.02 ($p < 0.05$).

Fig. 8 illustrates a time series for clear-sky daily ground-measurements and estimated ET from multiple datasets for different land cover types. In comparison to the single Landsat-based ET products, the merged ET based on the STS fusion method produces seasonal ET variations that are closest to the ground-observed values. Overall, the S (R^2) and RMSE of the merged ET were approximately 5% higher and 8% lower than those of the best Landsat-based ET product, respectively (Fig. 9). The STS fusion method reduced the errors of the estimated ET by adjusting the weights of the single products through incorporation of EC ground-measurements.

4.2.3. Implementation of merging the ET products

To merge the five Landsat-based ET products to generate a new ET dataset, we obtained the weights of the STS method using five ET

products and all EC ground-measurements. Fig. 10 demonstrates the weights of different Landsat-based ET products when merging the ET, which is similar to the weights from the merging algorithm calibration tower subset. One notices that the relative contributions differ considerably for five Landsat-based ET products. The greatest contributors to the merged ET are both MS-PT and SIM, contributing 20.5%, followed by RS-PM (20.1%), SW (19.8%) and PT-JPL (19.1%).

Fig. 11 shows scatter plots of a comparison between daily merged and ground-measured ET using ground observation data at all 206 flux tower sites. The RMSE of the merged ET at the site scale is 25.1 W/m^2 , the bias is 5.4 W/m^2 , the S is 0.61 and the R^2 is 0.60 ($p < 0.05$). In comparison to the other five Landsat-based ET products, the merged ET product yields the highest accuracy (Fig. 3). Fig. 12 illustrates that the error histograms for the single Landsat-based ET products are more biased compared to the EC observations, whereas the merged ET using the STS method is more centered around zero. A substantial number of previous studies reported that the errors of the estimated ET from remotely sensed data is approximately 15–30% (Jung et al., 2010; Wang and Dickinson, 2012; Yao et al., 2014) and the overall error of the

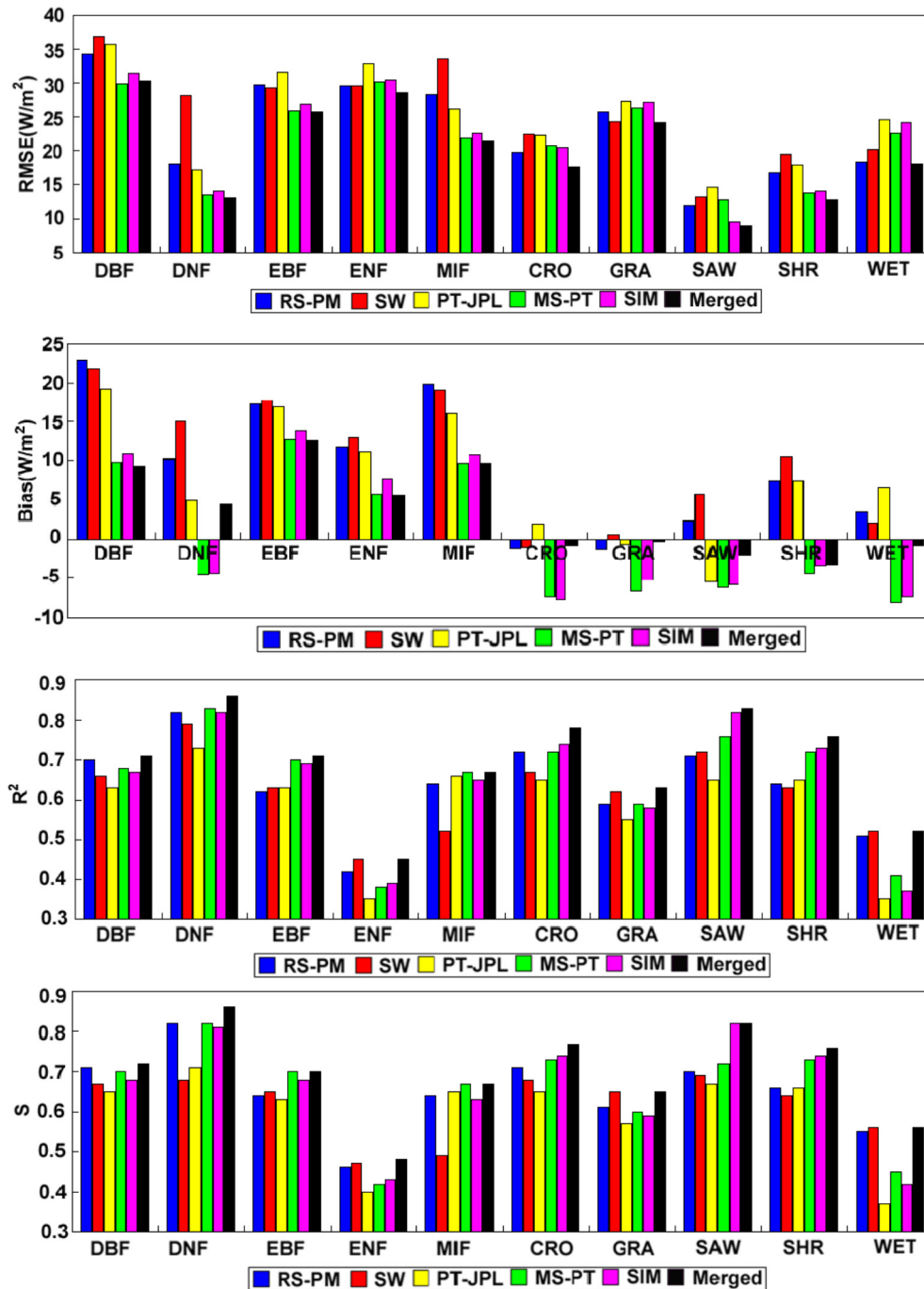


Fig. 7. Same as Fig. 2 but for the 103 validation tower sites for different land cover types. The merged *ET* was calculated using the weights for five Landsat-based *ET* products at the 103 calibration tower sites.

merged *ET* based on the *STS* method is approximately 10%. Therefore, the accuracy of the merged *ET* in this study can be applied to produce global terrestrial Landsat-based *ET* product.

4.3. A case study of mapping regional *ET*

To map the regional *ET* from the Landsat-based *ET* products, we selected an example from the Landsat data of a 1.4 by 1.2 km region (33.77°N–33.88°N and 117.94°E–118.09°E) that mainly included cropland to map daily *ET* (Fig. 13). Fig. 13 also shows the corresponding spatial patterns in *NDVI* for August 12, 2005,

along with the associated frequency histogram. High vegetation cover fraction occurred on August 12 owing to rapid crop growth.

In Fig. 14, the spatial pattern of *ET* from each product is illustrated along with a histogram showing the frequency distribution of values within the simulation domain. The maps of *ET* are strongly positively correlated with the *NDVI* (R^2 of more than 0.91), which may be explained by the fact that higher vegetation transpiration where there is a higher vegetation fractional cover. In terms of overall magnitude and spatial pattern, there are obvious differences among the multiple Landsat-based *ET* products. In general, the merged *ET* has an intermediate *ET* value with a his-

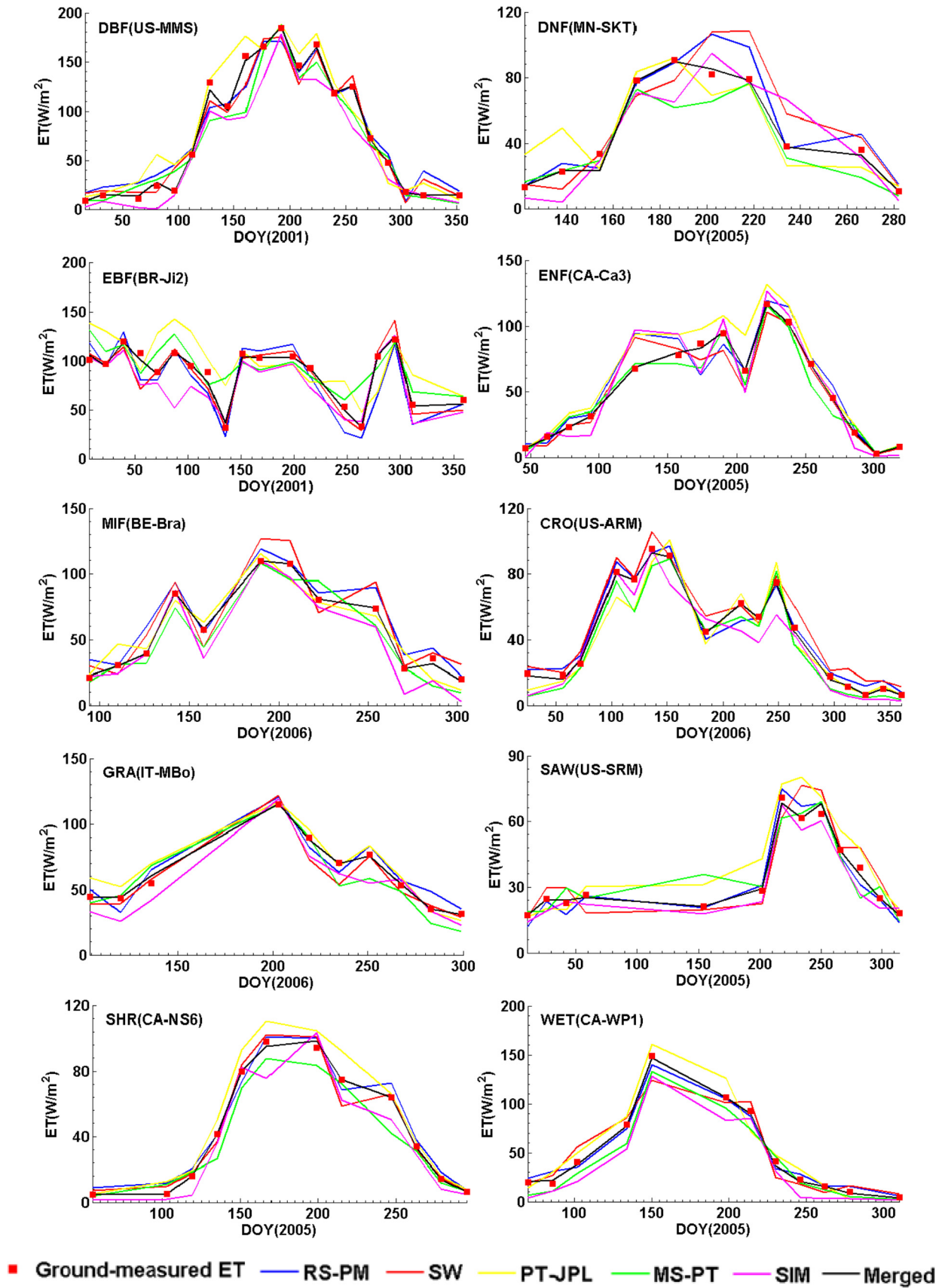


Fig. 8. Example of a time series for daily ET as ground-measured and estimated using different Landsat-based ET products (including merged ET product) at ten validation sites. The merged ET was calculated using the weights for five Landsat-based ET products at the 103 calibration tower sites.

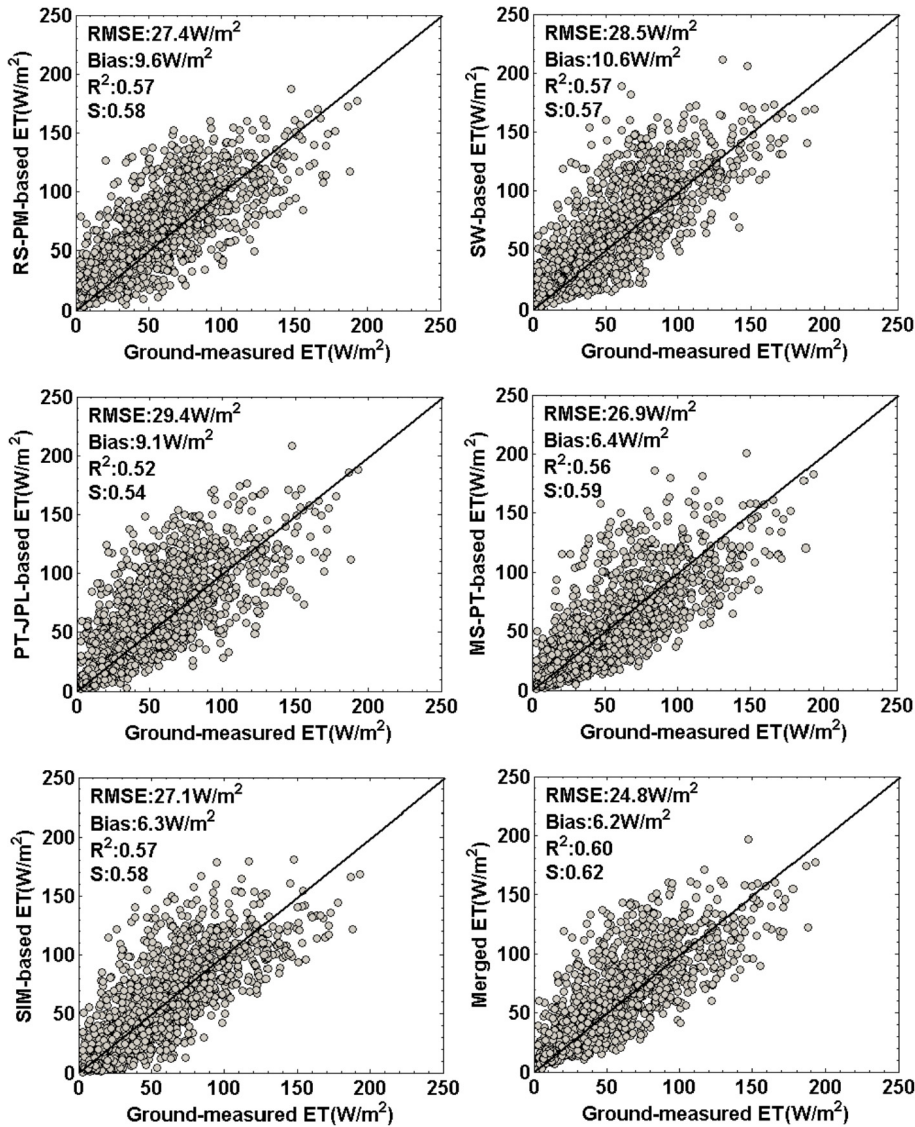


Fig. 9. Same as Fig. 6 but for the 103 validation tower sites. The merged ET was calculated using the weights for five Landsat-based ET products at the 103 calibration tower sites.

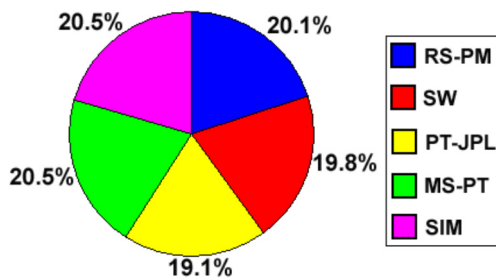


Fig. 10. Weights for five Landsat-based ET products at all 206 flux tower sites.

togram of spanning a full range from 60 to 82 W/m^2 , which is slightly smaller than the RS-PM, PT-JPL and SW ET products whereas slightly larger than both MS-PT and SIM ET products. The difference in spatial pattern of these ET products was mainly caused by the different physical structures of ET algorithms, such as the physical parameterizations of the SW algorithm, affecting its coupling with land surface and atmosphere (Dirmeyer et al., 2013).

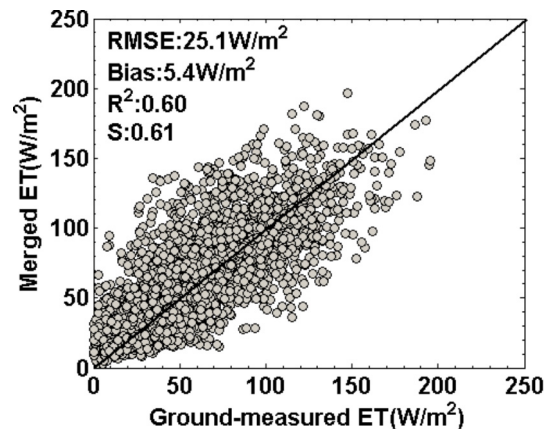


Fig. 11. Scatterplots of the daily ET from the merged ET products and ground-measurements at all 206 flux tower sites. The merged ET was calculated using the weights for five Landsat-based ET products at all 206 flux tower sites.

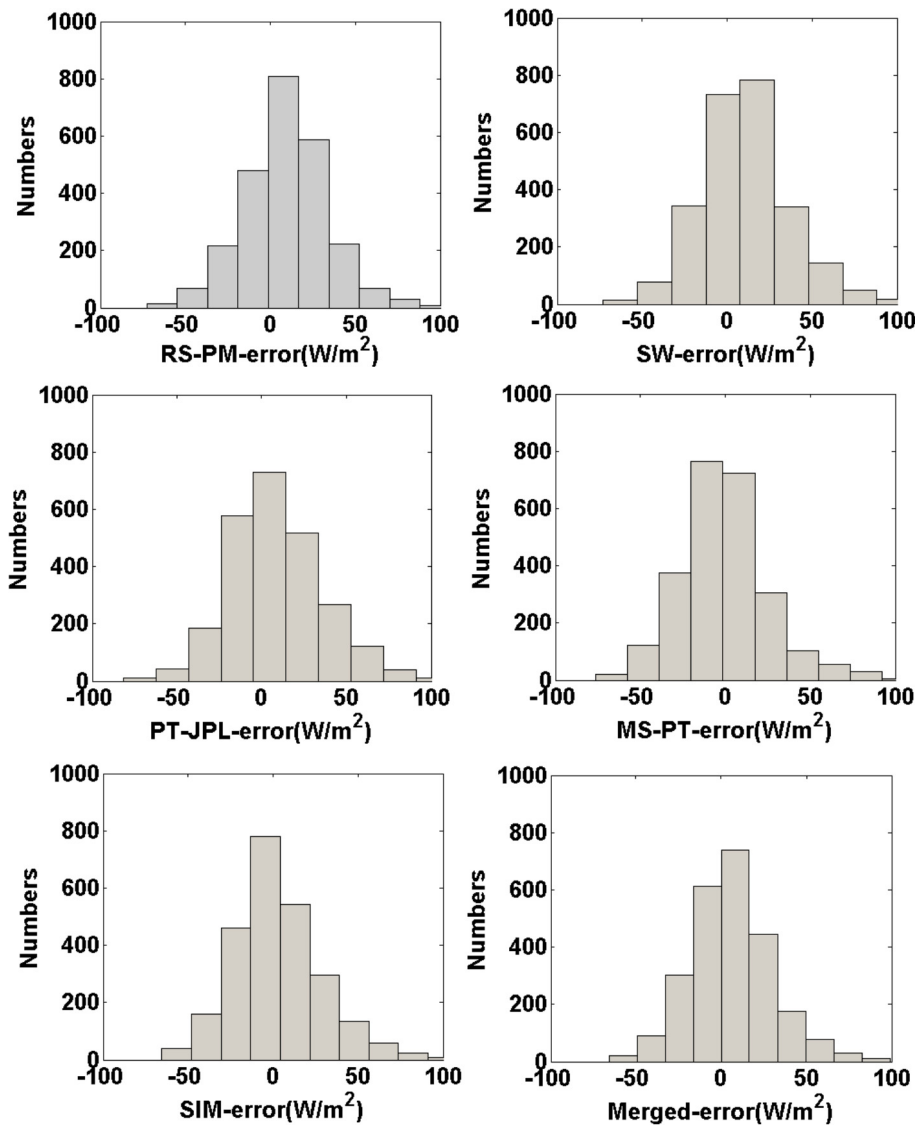


Fig. 12. Error histograms for daily *ET* derived from five Landsat-based *ET* products, and the merged *ET* product for all 206 flux tower sites.

4.4. Discussion

4.4.1. Uncertainties of the merged *ET* estimates

4.4.1.1. *Input errors.* The varied accuracies of the merged *ET* product were affected by the input errors of the *STS* fusion method, which refers to the errors from the individual Landsat-based *ET* products and *EC* ground-measurements. The individual Landsat-based *ET* products are estimated using the meteorological variables from *MERRA* data and vegetation parameters derived from Landsat data. Previous studies showed that no single reanalysis dataset is superior to others in terms of meteorological variables (T_a , RH , e and WS) to estimate land surface energy budgets (Shi and Liang, 2014; Wang and Zeng, 2012; Zhu et al., 2012). Recent studies revealed large bias for *MERRA* data when compared to ground-measurements (Rienecker et al., 2011; Zhao et al., 2006). Yao et al. (2015) found that daily R_n from *MERRA* tended to underestimate at high values compared to ground-measurements. In addition, there also exist large biases in the vegetation parameters (e.g. *LAI*) retrieved from Landsat data (Ganguly et al., 2012). Eklundh et al. (2003) reported that Landsat data can only explain 50–80% of the variation in *LAI* for coniferous forests. Thus, the

uncertainty from the individual and merged *ET* products could be inherited through errors from both *MERRA* and Landsat data inputs.

The errors of the *EC* ground-measurements determine the accuracy of the merged *ET* product because ground-measured *ET* is considered as the “true” value for calibrating the individual products. Although *EC* measurements are relatively accurate for *ET* acquisition, approximately 5–20% still exist (Foken, 2008). Moreover, there could be inaccuracies in interpreting their values owing to the energy imbalance in the *EC* method (Mahr, 2010). Foken (2008) pointed out that the *EC* method can only capture small eddies and ignore large eddies in the lower boundary layer, which influence the energy imbalance. Although we used the method proposed by Twine et al. (2000) to correct the *ET*, currently no agreements or protocols have been reached for the causes and corrections of energy imbalance from eddy covariance measurement (Leuning et al., 2012; Wohlfahrt et al., 2009). These corrections still cause large errors of *EC* measurements (Finnigan et al., 2003; Twine et al., 2000). Thus, input errors of the *EC* measurements and error propagation through calculations, including *EC* data correction, gridded interpolation and different data fusion, all contribute to the uncertainties of the merged *ET* product.

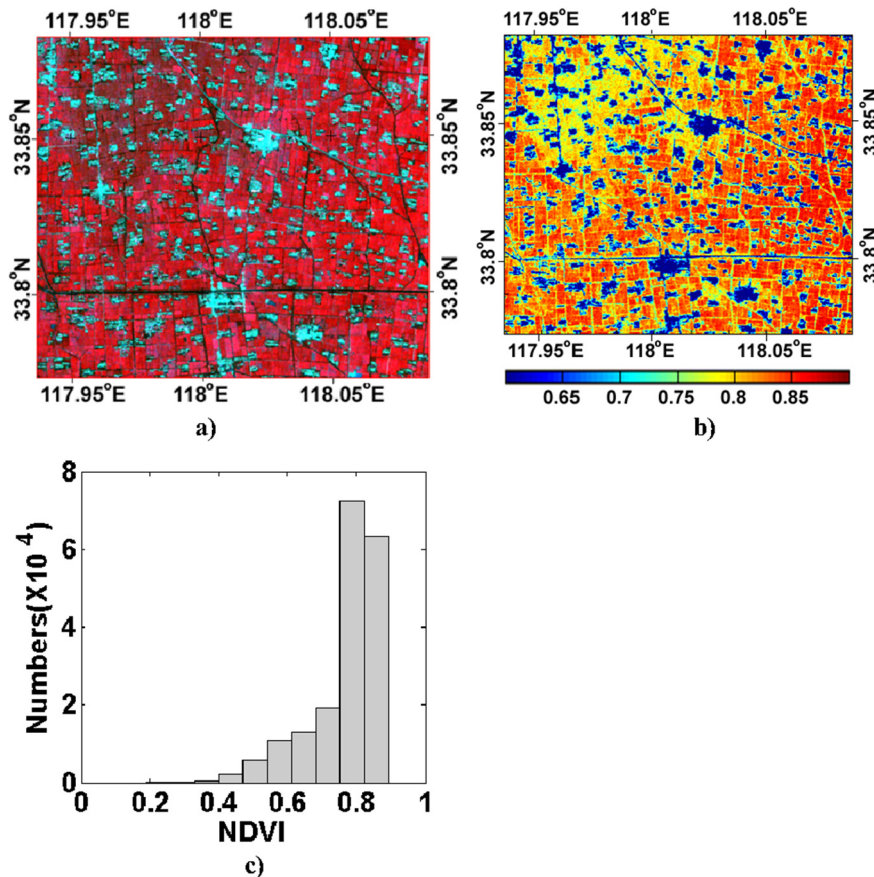


Fig. 13. (a) An example of a partial region of Landsat imagery with a false-color composite on August 12, 2005; (b) NDVI maps for August 12, 2005, and (c) frequency histograms for NDVI on August 12, 2005.

4.4.1.2. Scaling effects. The error of the merged *ET* product introduced by the spatial mismatch between the flux tower site footprints and the individual Landsat-based *ET* pixel footprints is an important issue. The footprint of the flux tower site is approximately several hundred meters while the spatial resolution of the individual Landsat-based *ET* products is only 30 m (Baldocchi, 2008; McCabe and Wood, 2006). Directly using *EC* ground-measured *ET* as “true” value to merge the individual Landsat-based *ET* products would lead to large uncertainties in the merged *ET* estimates.

To investigate the impact of the resample scale of the individual Landsat-based *ET* products to the accuracy of the merged *ET*, we averaged the daily *ET* from different Landsat-based *ET* products by use of a 30–570 m window. Compared with the original *ET* estimates at 30 m, a substantial drop in *ET* estimation errors occurred when products were aggregated to slightly coarser resolutions (Fig. 15). With an increase in window size, a rise in estimation errors appeared owing to the surface heterogeneity in *ET*. When spatial resolution arrived at 450 m, which is much larger than that of *TM* (30 m), the individual and merged *ET* products had the smallest *RMSE*. This supports the expectation that differences in the resample scales owing to the higher surface heterogeneity directly influences the accuracy of the merged *ET*.

4.4.1.3. Fusion method. In the case of high-level data fusion for terrestrial *ET*, the *STS* method constrains the error of the fused *ET* by introducing *EC* ground-measurements to adjust the weights for the individual Landsat-based *ET* products. To quantify the errors of the different fusion methods, experiments with the same inputs have been performed for different fusion models, including Multiple Linear Regression (*MLR*), Simple Model Averaging (*SMA*), Baye-

sian Model Averaging (*BMA*) (Raftery et al., 1997), Supported Vector Machine (*SVM*) (Vapnik, 1999), Multivariate Adaptive Regression Splines model (*MARS*) (Friedman, 1991), Random Forest Regression (*RFR*) (Breiman, 2001) and the *STS* method. The results of the leave-one-out cross-validation illustrated that the largest absolute differences in *RMSE* and *R*² of *ET* between the *STS* method and other fusion methods are relatively low, by approximately 1.0 W/m² and 0.02 respectively (Table 2). Further, the *STS* produced comparable accuracy but reduced the complexity of the fusion algorithm to improve computational efficiency when compared with other advanced fusion methods, indicating that the *STS* method can effectively achieve the goal of *ET* products integration in this study.

Although the *STS* method might have the statistical significance to a certain degree, it obviously lacks of physical mechanism. The *STS* method only considers the combinations of different algorithms or datasets and it does not improve the satellite-based retrieval algorithm itself in essence (Taylor, 2001; Yao et al., 2014). Therefore, the performance of the *STS* method is highly dependent on the weightings for individual datasets, which was calibrated using the data from a lot of flux tower sites. Our next step is to develop a novel physical-based fusion algorithm by combining the residual of surface energy balance method and the water balance equation to produce *ET* product for regional application.

4.4.2. Implications for agricultural water consumption and global models assessment

Quantifying *ET* using Landsat data is critical for mapping regional-scale *ET* at relatively high spatial resolution, acknowledging agricultural and watershed water management (Anderson

et al., 2008). The merged *ET* product in this study was estimated using Landsat *NDVI* without *LST*. *NDVI* change relatively slowly when compared with surface moisture conditions characterized in the *LST*, and sampling frequency may be less of an issue (Anderson et al., 2012). Thus, these *VNIR*-based methods to *ET* mapping have some practical advantages over *TIR*-based methods (Glenn et al., 2011). However, *NDVI* offers no information about bare soil evaporation after crops have senesced (Anderson et al., 2008). Fortunately, meteorological relative humidity (*RH*) and diurnal air temperature range (*DT*) can effectively characterize the soil water deficit (Fisher et al., 2008; Wang and Liang, 2008). Recent studies indicate *RH* was superior to other water stress metrics (including soil water content and *VPD*) in regional *ET* estimation (Yan and Shugart, 2010). In particular, for the period of the main winter wheat growing season, *ET* derived by *VNIR*-based methods demonstrated their reliability to characterize agricultural moisture conditions at a regional scale (Zhang et al., 2016). This

suggests that the merged *ET* in this study can be used to identify climatically sensitive agricultural systems and provide a diagnostic assessment of agricultural crop water consumption.

Accurate estimates of global terrestrial *ET* will be important for understanding global energy, water and carbon cycles. However, current both coarse-resolution global *ET* products estimated by remote sensing or global climate models (*GCMs*) have not been well validated owing to the sparse ground-measurements, complicated surface characteristics and the spatial mismatch between the flux tower site footprints and the coarse-resolution global *ET* products footprints (Anderson et al., 2012; Yebra et al., 2013; Yan et al., 2012). Like *TIR*-derived *ET* products, the merged *ET* product with high spatial resolution provides a reference dataset for evaluating and validating coarse-resolution global *ET* products (e.g., *GCMs*) because it provides a bridge between the tower flux footprint scale (several decades and hundreds meters) and the grid scale of coarse-resolution global *ET* products with several hundred kilome-

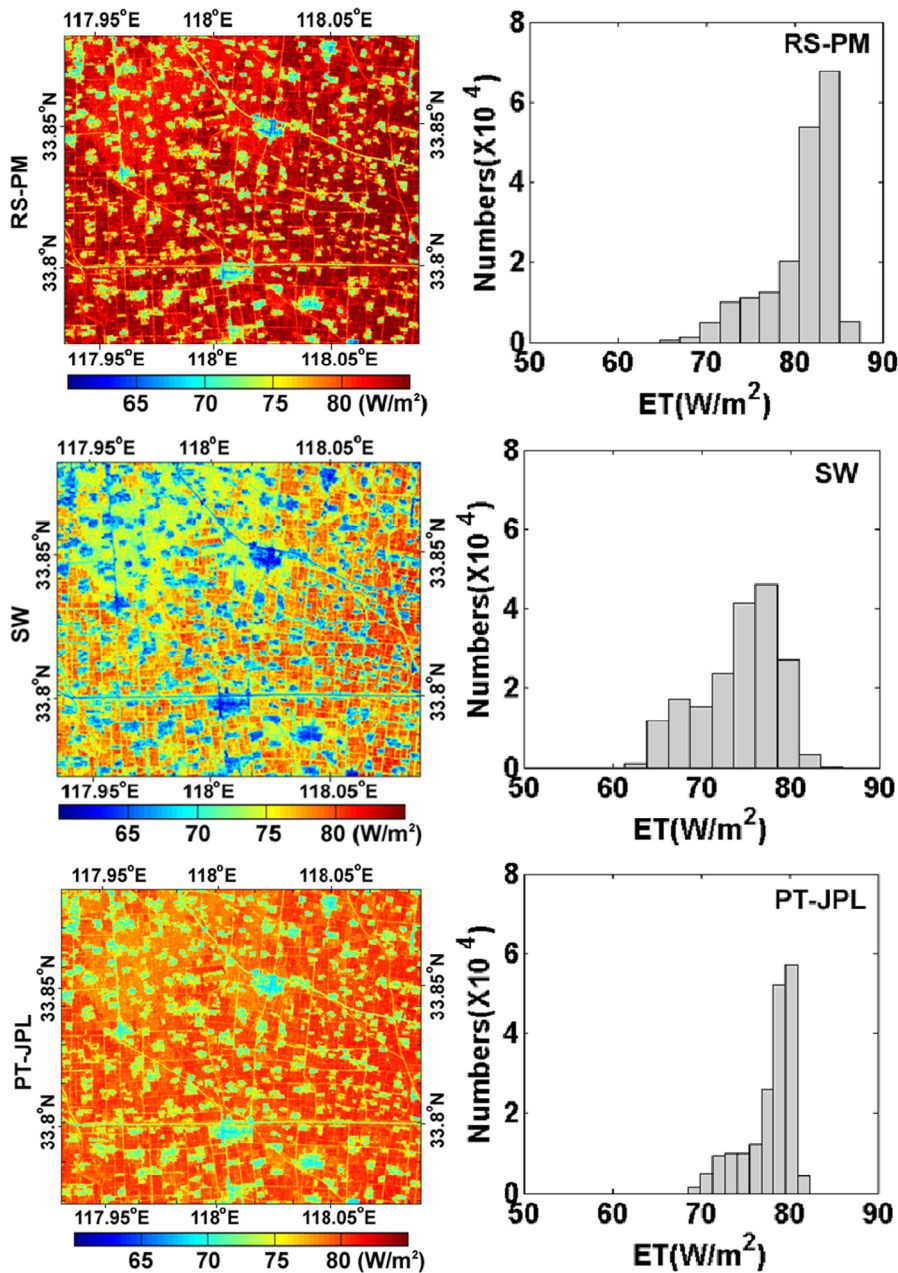


Fig. 14. Daily *ET* maps of a partial region shown in Fig. 13 with frequency histograms from five Landsat-based *ET* products, and the merged *ET* product for August 12, 2005.

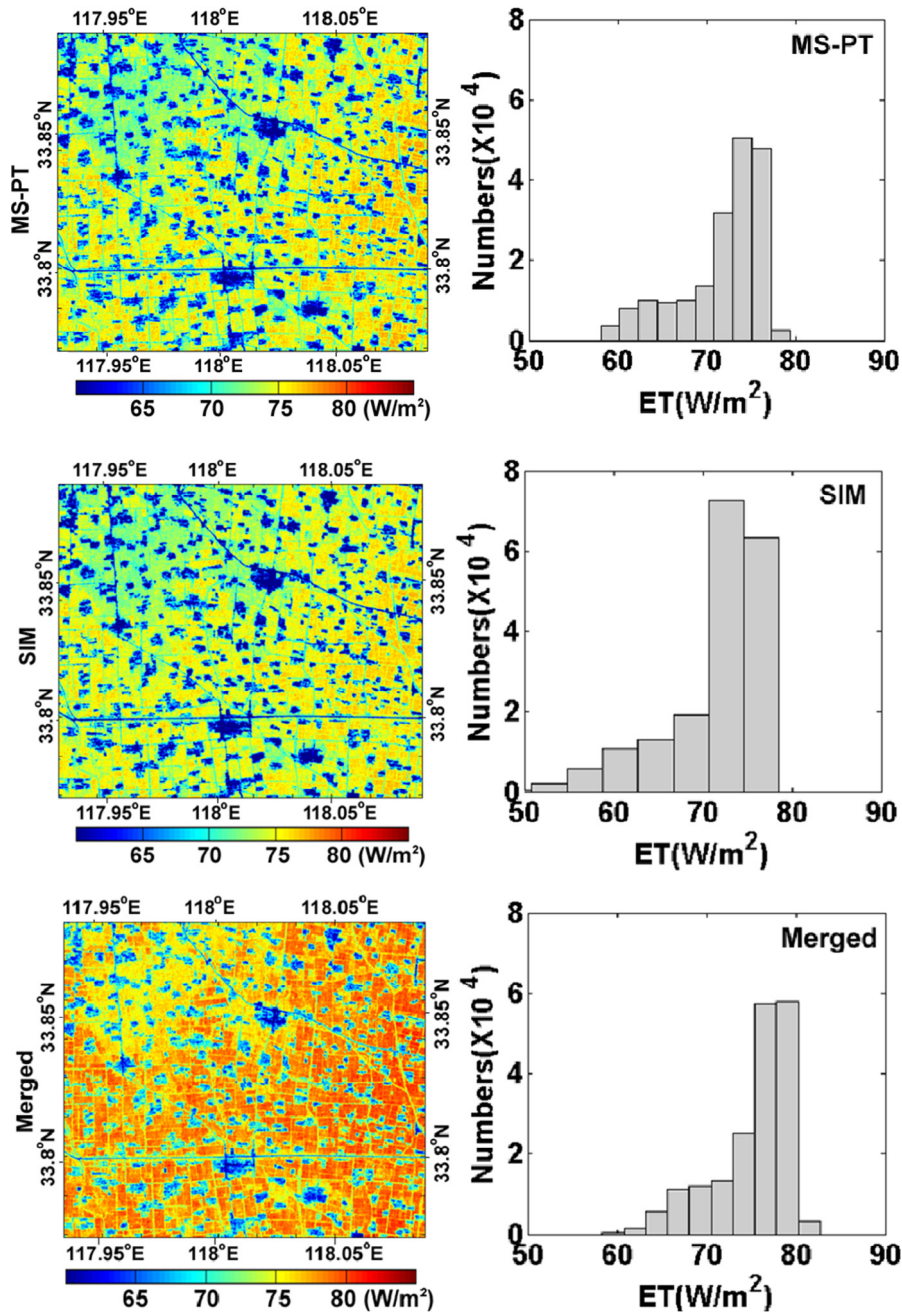


Fig. 14 (continued)

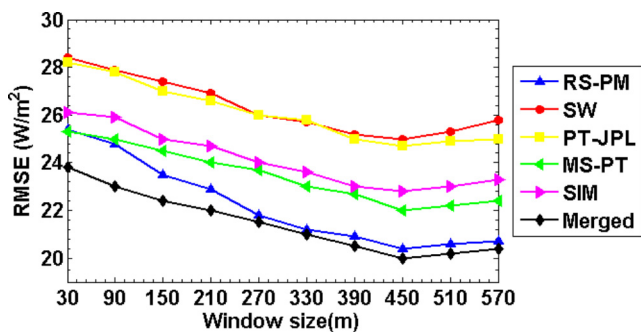


Fig. 15. Change of RMSE of estimating daily ET from five Landsat-based ET products, and the merged ET product with spatial resolutions at the 103 validation tower sites. The merged ET was calculated using the weights for five Landsat-based ET products at the 103 calibration tower sites.

Table 2

Comparison of the cross validation results of daily ET from multiple Landsat-based ET products and fused products. S represents the Taylor skill scores.

| ET Products | RMSE | R ² | S |
|-------------|------|----------------|------|
| STS | 25.4 | 0.60 | 0.61 |
| MLR | 26.2 | 0.59 | 0.60 |
| SMA | 26.9 | 0.58 | 0.59 |
| BMA | 24.9 | 0.61 | 0.62 |
| SVM | 24.2 | 0.63 | 0.63 |
| MARS | 24.4 | 0.62 | 0.62 |
| BFR | 24.1 | 0.64 | 0.64 |
| RS-PM | 27.9 | 0.56 | 0.58 |
| SW | 29.6 | 0.55 | 0.57 |
| PT-JPL | 29.8 | 0.52 | 0.55 |
| MS-PT | 27.1 | 0.57 | 0.59 |
| SIM | 27.6 | 0.57 | 0.59 |

ters. Further studies should focus on spatial upscaling of the merged *ET* product in this study to evaluate the different coarse-resolution global *ET* products.

5. Conclusions

We described a simple Taylor skill (*STS*) fusion method that merged five Landsat-based *ET* products produced by individual algorithms and *FLUXNET* eddy covariance (*EC*) observations for improving terrestrial *ET* estimation. These five Landsat-based *ET* products were also evaluated based on the globally distributed *FLUXNET EC* observations. We found that at the site scale, large differences were found in the five Landsat-based *ET* products among different plant functional types.

According to the *STS* method, weights for the individual *ET* products were calibrated based on the data collected at the 103 merging algorithm calibration sites and the results show that the merged *ET* product has the best performance compared to the individual products. The performance of the *STS* method for the validation tower subset was similar to the results from the merging algorithm calibration tower subset, though the *S* and *R*² statistics for the partial validation set are slightly smaller than the merging algorithm calibration set.

The weights of the *STS* method using five *ET* products and all *EC* ground-measurements were used to map the regional *ET*. An example of regional *ET* mapping shows that the *STS*-merged *ET* provides valuable insights for agricultural *ET* estimation. Uncertainties of the *STS*-merged *ET* are also discussed. The merged *ET* product presented in this study provides the bridge between the tower flux footprint scale and the grid scale of coarse-resolution global *ET* products. However, the *STS* method obviously lacks of physical mechanism. Our next step is to develop a novel physical-based fusion algorithm by combining the residual of surface energy balance method and the water balance equation to produce *ET* product for regional application.

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Appendix A. Algorithms for Landsat-based ET products

A.1. RS-PM algorithm

The revised remote sensing-based *PM* (*RS-PM*) algorithm is developed based on the Mu et al. (2011) algorithm, which is revised from the *PM* equation and it can be computed as follows:

$$ET = \frac{\Delta(R_n - G) + \rho C_p VPD/r_a}{\Delta + \gamma(1 + r_s/r_a)} \quad (A1)$$

where Δ is the slope of the saturation water vapor pressure curve (P_a/K); γ is the psychrometric constant (P_a/K); ρ is the density of the air (k/gm^3); *VPD* is the vapor pressure deficit (P_a); r_a is the aerodynamic resistance (s/m) and r_s is the surface resistance (s/m). r_a calculation is described in Mu et al. (2011). For calculating r_s , Mu et al. (2011) calculated the temperature and moisture constraints for stomatal conductance using different parameters among various ecosystem types. In this study, we revised the temperature constraint (m_T) with an optimum air temperature (T_{opt}) set at 25 °C (Fisher et al., 2008; Yao et al., 2013; Yuan et al., 2010).

$$m_T = \exp \left[- \left(\frac{T_a - T_{opt}}{T_{opt}} \right)^2 \right] \quad (A2)$$

We also revised the moisture constraint (Mu et al., 2007) (m_{VPD}) by setting VPD_{close} and VPD_{open} as 650 Pa and 2900 Pa for all ecosystem types, respectively.

$$m_{VPD} = \begin{cases} 1.0 & VPD \leq VPD_{open} \\ \frac{VPD_{close} - VPD}{VPD_{close} - VPD_{open}} & VPD_{open} < VPD < VPD_{close} \\ 0.1 & VPD \geq VPD_{close} \end{cases} \quad (A3)$$

where *close* refers to nearly complete inhibition and *open* refers to no inhibition to transpiration. Yuan et al. (2010) also found that it is possible to set invariant model parameters across different ecosystem types to reduce the effects of misclassification of land cover types.

A.2. SW algorithm

The Shuttleworth-Wallace (*SW*) algorithm is designed by combining two *PM* models for soil evaporation and vegetation transpiration (Shuttleworth and Wallace, 1985). The *SW* algorithm can be written as:

$$ET = C_s PM_s + C_v PM_v \quad (A4)$$

$$PM_s = \frac{\Delta(R_n - G) + (\rho C_p VPD - \Delta r_{ac} R_{nc}) / (r_{aa} + r_{as})}{\Delta + \gamma[1 + r_{ss} / (r_{aa} + r_{as})]} \quad (A5)$$

$$PM_v = \frac{\Delta(R_n - G) + [\rho C_p VPD - \Delta r_{ac} (R_{ns} - G)] / (r_{aa} + r_{ac})}{\Delta + \gamma[1 + r_{sc} / (r_{aa} + r_{ac})]} \quad (A6)$$

$$C_s = \frac{1}{1 + [R_s R_a / (R_c (R_s + R_a))]} \quad (A7)$$

$$C_v = \frac{1}{1 + [R_c R_a / (R_s (R_c + R_a))]} \quad (A8)$$

$$R_a = (\Delta + \gamma) r_{aa} \quad (A9)$$

$$R_s = (\Delta + \gamma)r_{as} + r_{ss}\gamma \quad (\text{A10})$$

$$R_c = (\Delta + \gamma)r_{ac} + r_{sc}\gamma \quad (\text{A11})$$

where C_s and C_v (dimensionless) are the surface resistance coefficients for soil and vegetation, respectively. PM_s and PM_v are variables related to describe evaporation from soil and transpiration from vegetation, respectively. R_{ns} and R_{nc} are R_n into soil and vegetation, respectively. r_{aa} is aerodynamic resistances from vegetation canopy height to reference height. r_{as} and r_{ac} are aerodynamic resistances from the soil surface to canopy height and leaf to canopy height, respectively. r_{ss} and r_{sc} are the surface resistance for soil and vegetation, respectively. In general, r_{ss} is calculated using a function of the top layer of soil moisture (Sellers et al., 1992). In this study, we used RH^{VPD} to replace soil moisture to calculate r_{ss} because RH^{VPD} can be used to characterize soil moisture constraints for soil evaporation (Fisher et al., 2008) and it can be expressed as:

$$r_{ss} = \exp(8.206 - 4.255RH^{VPD}) \quad (\text{A12})$$

A.3. PT-JPL algorithm

Based on the Priestley-Taylor algorithm, Fisher et al. (2008) developed the PT-JPL algorithm by downscaling potential ET (PET) to actual ET and it is written as:

$$ET = ET_s + ET_c + ET_i \quad (\text{A13})$$

$$ET_s = \alpha[f_{wet} + (1 - f_{wet})f_{sm}] \frac{\Delta}{\Delta + \gamma} (R_{ns} - G) \quad (\text{A14})$$

$$ET_c = \alpha(1 - f_{wet})f_g f_T f_M \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (\text{A15})$$

$$ET_i = \alpha f_{wet} \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (\text{A16})$$

Where ET_s refers to soil evaporation, ET_c refers to vegetation transpiration and ET_i refers to the canopy interception evaporation. α is the PT coefficient (1.26). f_{wet} is the wet surface fraction (RH^4). f_{sm} is the soil moisture constraint (RH^{VPD}). f_g is the green canopy fraction (f_{APAR}/f_{IPAR}). f_T is the plant temperature constraint (m_T) and f_M is the plant moisture constraint ($f_{APAR}/f_{APARmax}$). f_{APAR} is the absorbed photosynthetically active radiation (PAR) and f_{IPAR} is the intercepted PAR.

A.4. MS-PT algorithm

The modified satellite-based PT (MS-PT) algorithm developed by Yao et al. (2013) estimates ET by calculating the sum of the unsaturated soil evaporation (ET_{ds}), the saturated wet soil surface evaporation (ET_{ws}), the canopy transpiration (ET_v), and the canopy interception evaporation (ET_{ic}). The total ET can be expressed as:

$$ET = ET_{ds} + ET_{ws} + ET_v + ET_{ic} \quad (\text{A17})$$

$$ET_{ds} = \alpha(1 - f_{wet})f_{sm} \frac{\Delta}{\Delta + \gamma} (R_{ns} - G) \quad (\text{A18})$$

$$ET_{ws} = \alpha f_{wet} \frac{\Delta}{\Delta + \gamma} (R_{ns} - G) \quad (\text{A19})$$

$$ET_v = \alpha(1 - f_{wet})f_g f_T \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (\text{A20})$$

$$ET_{ic} = \alpha f_{wet} \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (\text{A21})$$

$$f_{sm} = \left(\frac{1}{DT} \right)^{DT/DT_{max}} \quad (\text{A22})$$

$$f_{wet} = f_{sm}^4 \quad (\text{A23})$$

$$f_c = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (\text{A24})$$

where DT_{max} is the maximum diurnal air temperature range (40 °C) and f_c is vegetation cover fraction. $NDVI_{min}$ and $NDVI_{max}$ were the minimum and maximum NDVI during the study period, set as constants of 0.05 and 0.95 (Zhang et al., 2009) in this algorithm, respectively.

A.5. SIM algorithm

The simple hybrid ET (SIM) formulation was developed by Wang and Liang (2008) based on satellite determination of surface net radiation, vegetation index, temperature, and DT and the SIM algorithm can be written as:

$$ET = R_n(a_0 + a_1NDVI + a_2T_a - a_3DT) \quad (\text{A25})$$

where $a_0 = 0.1440$, $a_1 = 0.6495$, $a_2 = 0.0090$ and $a_3 = 0.0163$. These coefficients were calibrated using the ground measurements at the Southern Great Plains (SGP) sites in the United States from January 2002 to May 2005. Considering the SGP sites cover the variety of land cover that includes grass, rangeland, pastures, crop fields, forests, and mixed cover-including vegetation and bare soil-and that their locations also differ considerably from each other, it can be used to estimate global terrestrial ET (Wang and Liang, 2008).

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