



Estimation of Evapotranspiration and Its Components across China Based on a Modified Priestley–Taylor Algorithm Using Monthly Multi-Layer Soil Moisture Data

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Abstract: Although soil moisture (SM) is an important constraint factor of evapotranspiration (ET), the majority of the satellite-driven ET models do not include SM observations, especially the SM at different depths, since its spatial and temporal distribution is difficult to obtain. Based on monthly three-layer SM data at a 0.25° spatial resolution determined from multi-sources, we updated the original Priestley Taylor-Jet Propulsion Laboratory (PT-JPL) algorithm to the Priestley Taylor-Soil Moisture Evapotranspiration (PT-SM ET) algorithm by incorporating SM control into soil evaporation $(E_{\rm s})$ and canopy transpiration (*T*). Both algorithms were evaluated using 17 eddy covariance towers across different biomes of China. The PT-SM ET model shows increased R^2 , NSE and reduced RMSE, Bias, with more improvements occurring in water-limited regions. SM incorporation into T enhanced ET estimates by increasing R² and NSE by 4% and 18%, respectively, and RMSE and Bias were respectively reduced by 34% and 7 mm. Moreover, we applied the two ET algorithms to the whole of China and found larger increases in T and E_s in the central, northeastern, and southern regions of China when using the PT-SM algorithm compared with the original algorithm. Additionally, the estimated mean annual ET increased from the northwest to the southeast. The SM constraint resulted in higher transpiration estimate and lower evaporation estimate. $E_{\rm s}$ was greatest in the northwest arid region, interception was a large fraction in some rainforests, and T was dominant in most other regions. Further improvements in the estimation of ET components at high spatial and temporal resolution are likely to lead to a better understanding of the water movement through the soil-plant-atmosphere continuum.

Keywords: evapotranspiration; Priestley–Taylor algorithm; soil moisture; evaporation; transpiration; China

1. Introduction

Understanding water and heat exchange information of the soil–plant–atmosphere continuum (SPAC) is imperative to better manage more restricted water resources in the future. As one of the most important connecting terms in SPAC [1], evapotranspiration (*ET*), which consists of evaporation from wet surfaces (*E*) and transpiration through plants (*T*), is critical for both the energy budget and water balance in the earth–atmospheric system. Normally, vegetation *T* is a physiological process that is closely associated with CO₂ assimilation and has a great influence on the gross productivity of terrestrial ecosystems, while evaporation from wet canopy surfaces (*E*_i) or soil (*E*_s) is often regarded as a wasteful loss of water and does not directly contribute to the ecosystem productivity [2,3]. Therefore, *ET* partitioning is of prime importance for the water resources and forests management



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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). and the agriculture practice. Over the past five decades, much effort has been devoted to the development of techniques and algorithms for *ET* or its components estimation, as documented by a substantial body of literatures [4–7]. However, estimates of *ET* or its components are still a major challenge for the complex climatic and underlying conditions.

In general, ET partitioning methods can be grouped into two categories: (1) Field measurements (i.e., micro-lysimeter, Bowen ratio, isotopes, sap flow, and the eddy covariance (EC) technique, etc.) [8–13] and (2) models such as remote sensing-based physical models, land surface models (i.e., the Shuttleworth-Wallace model, the energy and water balance model, the soil-water-energy and transpiration model, and the two-source energy balance model, etc.) [14–18]. Due to the difficulty of using relatively few scattered point measurements to infer regional variability [19], remote sensing-based ET models have become a dominant means for providing spatially distributed regional ET information on land surface, as they have greatly improved the large-scale observation of soil and vegetation dynamics [20]. Among the remote sensing-based ET models, the physical models, such as the Penman–Monteith (PM) ET algorithm and Priestley Taylor–Jet Propulsion Laboratory (PT-JPL) ET algorithm, focusing on the dynamics of the ET process, have been widely used [20–24]. Particularly, the PT-JPL algorithm, a simplified version of the more theoretical PM ET algorithm that avoids the computational complexities of aerodynamic resistance, has outperformed many ET models [17,25]. Although the PT-JPL ET algorithm utilizes eco-physiological and atmospheric constraints to regulate the potential ET flux to an actual ET flux, such as the other ET remote sensing algorithms, it also lacks soil moisture (SM) control.

SM can not only control the conversion of incident radiation into sensible and latent heat fluxes but also determine the distribution of rainfall in infiltration, runoff, and evaporation [26]. Up until now, only a few studies have been conducted to estimate ET components using SM observations, mainly since the accurate values of SM observation are difficult to obtain. Instead, previous studies usually use the land surface temperature and vegetation index, which can serve as proxy indicators of the surface moisture status over a range in spatial scales [27], to estimate plant T and E_s [28,29]. Along with the constant development of remote sensing techniques on SM (e.g., the global Soil Moisture Climate Change Initiative project, SMCCI, 1978; Soil Moisture and Ocean Salinity, SMOS, 2009; Soil Moisture Active Passive, SMAP, 2015), SM data have become increasingly available in recent years [30,31]. Within this context, Purdy et al. (2018) incorporated the launch of the SMAP satellite-derived surface SM control on the PT-JPL ET algorithm to estimate E_s and canopy T [24]. Walker et al. (2019) presented a modified ET model using a surface actual water vapor pressure parameter, which was estimated by incorporating the SM from SMAP products [32]. It is important to note that the SMAP mission was first launched in January 2015, and the length of SM observations is relatively short. Indeed, the increasing accuracy and a variety of spatial scales of *SM* datasets will provide much assistance in *ET* estimates. However, many of these remote sensing techniques can only provide SM estimates for the surface [27,33–37], which cannot satisfy the transpiration water requirements for the vegetation with deeper roots, such as trees and shrubs. Therefore, in order to investigate the SM effect on vegetation T estimation, effective SM data from the deeper sources should first be obtained.

Various adaptations of *SM* normalized by soil properties to compute the relative extractable water (*REW*) have been applied to limit E_s or *T* [24,29], while *SM* under the canopy is just one of numerous environmental variables that constrains the photosynthesis and/or canopy evaporative demand [4,20,38,39]. Moreover, the estimation accuracy of vegetation *T* not only relies on the quality of environmental variables, such as temperature, vapor pressure, radiation, and *SM* data, but also relates to the plant types, canopy heights, and aboveground biomass [23,24,40]. However, the impact of environmental variables and plant and soil types on soil water availability is difficult to quantify and subject to much uncertainty. Recently, the availability of high-quality meteorological forcing datasets and observations of vegetation characteristics and canopy heights, as well as *SM*-observing

satellites, together with data assimilation techniques, provides us the opportunity to gather further information on plant sensitivity to environmental conditions [24,32]. Nonetheless, accurate documentation of the spatial and temporal distribution of multi-layer *SM* and quantification of the effect of the environmental conditions on vegetation *T* are important in the *ET* and its components' estimates.

Overall, to the best of our knowledge, there is a scarcity of studies incorporating *SM* of multi-layers into the physically and remote sensing-based *ET* algorithm, as well as of those focusing on the role of *SM* in different *ET* components estimates. The primary objective of this study is to estimate *ET* components at monthly scale based on a modified PT-JPL *ET* algorithm by incorporating the *SM* constraints. To this end, *SM* data of multi-layers are integrated from observation and remote sensing products. As a case study, both the original PT-JPL *ET* algorithm and the modified algorithm (here-after called PT-SM) are evaluated using the observed *ET* from 17 eddy covariance sites across different land covers in China. Ultimately, we also apply the new PT-SM model to the whole of China using *SM* data at different depths, and the individual component contribution to the mean annual *ET* is investigated.

2. Materials and Methods

2.1. PT-JPL Algorithm

Potential evapotranspiration (*PET*, in mm) is defined in terms of the radiation- and temperature-based Priestley–Taylor (PT) equilibrium equation:

$$PET = \alpha \frac{\Delta}{\lambda(\Delta + \gamma)} (R_n - G) \tag{1}$$

where α is the PT coefficient of 1.26, Δ is the slope of the saturated vapor pressure curve (kPa °C⁻¹), γ is the psychrometric constant (~0.066 kPa °C⁻¹), λ is the latent heat of vaporization (kPa °C⁻¹), R_n is the net radiation at the surface (MJ m⁻²), and *G* is the ground heat flux (MJ m⁻²).

Subsequently, Fisher et al. (2008) developed a modified PT model (i.e., the PT-JPL model) to scale the *PET* down to the actual *ET* using eco-physiological constraints and soil evaporation partitioning, which are driven by atmospheric moisture (vapor pressure deficit and relative humidity, *VPD* and *RH*) and vegetation indices (normalized and soil adjusted vegetation indices, *NDVIs*, and the enhanced vegetation index, *EVI*) [37]. The PT-JPL algorithm estimate *ET* at the monthly scale is defined as follows:

$$ET = E_s + E_i + T \tag{2}$$

$$E_s = [f_{wet} + (1 - f_{wet})f_{sm}] \alpha \frac{\Delta}{\lambda(\Delta + \gamma)} R_{ns}$$
(3)

$$E_i = f_{wet} \alpha \frac{\Delta}{\lambda(\Delta + \gamma)} R_{nc} \tag{4}$$

$$T = (1 - f_{wet}) f_C f_T f_M \alpha \frac{\Delta}{\lambda(\Delta + \gamma)} R_{nc}$$
(5)

where f_{wet} is the relative surface wetness (RH^4) ; f_{sm} is a soil moisture constraint $(RH_{min}^{VPD_{min}/\beta}, Where <math>VPD_{min}$ is calculated by T_{max} and RH_{min}); f_C is the green canopy fraction (f_{APAR}/f_{IPAR}) with f_{APAR} being the fraction of absorbed photosynthetically active radiation (PAR) absorbed by green vegetation cover $(m_1EVI + b_1)$ and f_{IPAR} the fraction of intercepted PAR $(m_2NDVI + b_2)$; f_T is a plant temperature constraint $(\exp(-((T_{max} - T_{opt})/T_{opt})^2))$; f_M is a plant moisture constraint (the ratio between f_{APAR} and $f_{APARmax}$); T_{max} is the maximum air temperature; and T_{opt} is T_{max} at max $(R_nT_{max}EVI/VPD)$. R_{ns} is the net radiation at the soil surface calculated as:

$$R_{ns} = R_n \exp(-k_{R_n} LAI) \tag{6}$$

where $k_{R_n} = 0.60$, and *LAI* is the leaf area index; R_{nc} is the canopy net radiation $(R_n - R_{ns})$.

2.2. PT-SM Algorithm

In the PT-JPL model, the soil water deficit index, f_{sm} (RH_{min} ^{VPD_{min}/ β) is employed to constrain the rate of evaporation from the soil surface according to the Bouchet's complementary hypothesis that the surface moisture status is linked to the evaporative demand of the atmosphere [37]. In the original PT algorithm, the *REW* is usually used as an index that normalizes the impact based on the soil moisture and soil properties [41]. Note that E_s is driven by moisture within the top few centimeters of the soil profile. Therefore, with the aid of observed surface soil moisture (*SM*, m³ m⁻³), the scalar f_{REW} can be calculated from the following equation:}

$$f_{REW} = \frac{SM_1 - SM_{1wp}}{SM_{1fc} - SM_{1wp}}$$
(7)

where SM_1 is the 0–5 cm soil moisture (m³ m⁻³); SM_{1fc} and SM_{1wp} are the soil field capacity and soil moisture at the wilting point, respectively. Therefore, the new E_s equation is conducted by replacing f_{sm} with f_{REW} :

$$E_s = [f_{wet} + (1 - f_{wet})f_{REW}] \alpha \frac{\Delta}{\lambda(\Delta + \gamma)} R_{ns}$$
(8)

In the original PT-JPL formulation, the plant moisture stress is inferred from the deviation from maximum greenness (f_M), which is calculated by normalizing phenological parameters by the maximum observed value per pixel. Actually, at the monthly scale, the latent responses from vegetation to soil moisture deficits can also affect the vegetation T to some extent, especially for arid and semi-arid regions [23]. To evaluate the influences of plant access on atmospheric demand and of deeper water storage intensification or mitigating vegetation sensitivity on water availability, the transpiration response curve to soil water availability can be drawn (the relation between transpiration stress and soil moisture conforms to the exponential form), and the results indicate that higher canopy heights show less sensitivity to soil water availability [24,42]. Furthermore, the root system developed in different vegetations is different. Generally, the depth of root system is related to plant species, but it is also related to the climate [24]. For example, in the subtropical region, there is plenty of rain, tree species can get enough water from the surface soil, so they should not grow deeper into the soil. Therefore, in this study, vegetation is divided into four categories, forest, shrub, grass, and crop, and a new eco-physiological scalar is formulated as follows:

$$f_{TRM} = max \left[\left(1 - RH^{4(1 - SRH_k)(1 - RH)} \right) f_M + \left(RH^{4(1 - SRH_k)(1 - RH)} \right) f_{TREW} \right]$$
(9)

where SRH_k is the soil relative humidity at *k*-layer. Three layers (0–5, 5–20, and 20–100 cm) are used in this study, k = 1, 2, 3 for frost and shrub covers, and k = 1, 2 for grass and crop covers. While the transpiration constraint f_{TREW} is supposed to be related to the type and height of vegetation, and the climate condition, which can be calculated by:

$$f_{TREW} = 1 - \left(\frac{SM_{kCR} - SM_k}{SM_{kCR} - SM_{kwp}}\right)^{CH_{scalar} \times VT_{scalar} \times CL_{scalar}}$$
(10)

where SM_{kCR} is the critical *k*-layer soil moisture at which soil water availability limits *ET*; $CH_{scalar} = \sqrt{CH}$ is a canopy height (*CH*) scalar set to range from 1 to 5, and the square root is formed from Martens et al. (2017) [40]; VT_{scalar} is a vegetation type (*VT*) scalar that represents the impact of vegetation sensitivity on soil water availability; and CL_{scalar} is a climate (*CL*) scalar, e.g., the deep-rooted tree species can gradually change into the shallow-rooted species in the subtropical environment. Both the vegetation type and

climate scalars are set to 0–1, which are determined by comparing the modeled *ET* series to the observations.

Thus, the algorithm of vegetation transpiration can be described as follows:

$$T = (1 - f_{wet}) f_C f_T f_{TRM} \alpha \frac{\Delta}{\lambda(\Delta + \gamma)} R_{nc}$$
(11)

2.3. Evaluation

Eddy covariance (EC) observations of latent heat flux (*LE*) across different land cover types are often used for *ET* model evaluation. The performances of PT-JPL and PT-SM algorithms for estimating monthly *ET* were evaluated by comparing the simulated monthly *ET* series against *ET* values observed by EC sites. Four statistics, namely the coefficient of determination (R^2), the Nash–Sutcliffe Efficiency (*NSE*), the root mean square error (*RMSE*), and the amount of system deviation (Bias), were used to evaluate the performances of these two PT models. The four statistics are defined in the forms of

$$R^{2} = \frac{\left(\sum_{i=1}^{n} \left(ET_{sim,i} - \overline{ET_{sim,i}}\right) \left(ET_{obs,i} - \overline{ET_{obs,i}}\right)\right)^{2}}{\sum_{i=1}^{n} \left(ET_{sim,i} - \overline{ET_{sim,i}}\right)^{2} \sum_{i=1}^{n} \left(ET_{obs,i} - \overline{ET_{obs,i}}\right)^{2}}$$
(12)

$$NSE = 1 - \frac{\sum_{i=1}^{n} (ET_{sim,i} - ET_{obs,i})^{2}}{\sum_{i=1}^{n} (ET_{obs,i} - \overline{ET_{obs,i}})^{2}}$$
(13)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (ET_{sim,i} - ET_{obs,i})^2}{n}}$$
(14)

$$Bias = \frac{\sum_{i=1}^{n} (ET_{sim,i} - ET_{obs,i})}{n}$$
(15)

with $\overline{ET_{obs,i}} = \sum_{i=1}^{n} ET_{obs,i}/n$ as the average of the observed ET_i , where *n* is the number of time-steps.

2.4. Eddy Covariance (EC) Flux Data

Ranging from 3.8 to 53.6°N and from 73.6 to 135.1°E (Figure 1), China is the third largest national territorial area in the world with a total area of over 9.73 million km². With such a large area, China is characterized by a complex climate and diverse land cover types and soil types (Figure 1B,C). Ground-measured *LE* data of 17 eddy covariance sites from China FLUX, USCCC, WATER, and Asia flux, distributed in different land cover types of China, were collected to validate the PT-JPL and PT-SM algorithms (Figure 1A and Table 1). The land cover types of the flux towers include croplands (Crop; four sites), deciduous needle leaf forests (DNF; one site), evergreen broadleaf forests (EBF; two sites), open shrubland (OSH; one site), evergreen needle leaf forests (ENF; one site), grasslands (GRA; seven sites), and mixed forests (MF; one site). Our analysis is based on EC site data during the period of 2003–2011 (see Table 1). It has been noted that the sum of sensible heat (*H*) and *LE* as measured by the EC method is generally less than the available energy [43]. Therefore, the original ground-measured *LE* was corrected using the method put forward by Twine et al. (2000) and Jung et al. (2010) [19,44].

2.5. Observed Meteorological and Hydrological Data

A high spatial-temporal resolution (with a daily temporal resolution and a spatial resolution of 0.1°), gridded, near-surface meteorological dataset from the China Meteorological Forcing Dataset (CMFD) was used in this study. The dataset was made through fusion of remote sensing products, reanalysis of the dataset, and in situ observations at weather stations [45]. Monthly precipitation, relative humidity, radiation, and maximum



and minimum temperatures at a spatial resolution of 0.25° during the 2003–2015 period were calculated and resampled.

Figure 1. (A) Locations of the study area, 17 eddy covariance sites and 577 meteorological stations. (B) Land cover classification and (C) soil classification from the International Geosphere–Biosphere Programme (IGBP) used in this study.

Tower	SITE_NAME	IGBP	LAT (°N)	LON (°E)	Time Period	NETWORK
CN-Din	Dinghushan	EBF	23.17	112.54	2004-2005	ChinaFLUX
CN-Qia	Qianyanzhou	ENF	26.74	115.06	2003-2005	ChinaFLUX
XSBN	Xishuangbanna	EBF	21.90	101.27	2003-2005	ChinaFLUX
CN-Cha	Changbaishan	MF	42.40	128.10	2003-2005	ChinaFLUX
DX	Daxing	Crop	39.62	116.43	2008-2010	WATER
MY	Miyun	Crop	40.63	117.32	2008-2010	WATER
QH	Qinghai	GRÂ	37.60	101.33	2002–2004	Asiaflux

Table 1. Description of 17 eddy covariance sites used in this study.

Tower	SITE_NAME	IGBP	LAT (°N)	LON (°E)	Time Period	NETWORK
CN-Ha2	Haibei Shrubland	OSH	37.61	101.33	2003-2005	ChinaFLUX
YC	Yucheng	Crop	36.96	116.63	2003-2005	ChinaFLUX
GT-1	Guantao	Crop	36.52	115.13	2008-2010	WATER
AR	Arou	GRÂ	38.09	100.52	2009-2011	WATER
CN-Du2	Duolun_grassland (D01)	GRA	42.05	116.28	2006-2008	USCCC
CN-Cng	Changling	GRA	44.59	123.51	2007-2010	USCCC
CN-Dan	Dangxiong	GRA	30.50	91.07	2003-2005	ChinaFLUX
CN-Sw2	Siziwang Grazed (SZWG)	GRA	41.79	111.90	2011	USCCC
GT-2	Guantan	DNF	38.53	100.25	2010-2011	WATER
NMG	Neimenggu	GRA	44.13	116.30	2004-2005	ChinaFLUX

Table 1. Cont.

2.6. Remote Sensing NDVI, EVI, and LAI Data

The time series of *EVI* and *NDVI* were acquired from moderate resolution imaging spectroradiometer (MODIS) products (MOD13A3), which provide 1 km spatial and monthly temporal resolutions. We used an average of four surrounding pixels around the EC flux sites to acquire the *EVI* and *NDVI* values. The *LAI* and *FPAR* products, potential factors influencing total *ET* segmentation, were extracted from MCD15A2H at 500 m spatial and 8-day temporal resolution. The 8-day temporal *EVI*, *NDVI*, *LAI*, and *FPAR* records were integrated into a monthly scale.

2.7. Canopy Height and Soil Moisture Data

Observations of canopy height were used to model plant sensitivity to water content at different depths. These canopy height (*CH*) and soil relative humidity (*SRH*) datasets of 376 agricultural gas stations spanning from 2003 to 2015 on the China meteorological data network (http://data.cma.cn (accessed on 11 June 2021)) were selected. Since the datasets only include the *CH* and *SRH* data of the cropland, the *CH* from the Geoscience Laser Altimeter System (GLAS) on the Ice, Cloud, and Land Elevation Satellite [46] and soil moisture obtained from the outputs of the GLDAS-2 Noah Land Surface Model (LSM) L4 model [47], which here-after is referred to as LDAS-derived *SM*, were employed to enrich the basic study data. Considering the different spatial–temporal resolution of each *SM* data product (see Table 2), in this study, using the multiple linear regression and trapezoidal method [48], monthly *SM* data from 2003 to 2015 of three layers (0–5, 5–20, and 20–100 cm) were reconstructed through integrating the observed precipitation, farmland *SRH* observation, *SM* dataset from Yang et al. (2020) [49], GRACE-derived ΔTWS [50], and GLDAS *SM* outputs at different depths (0–10, 10–40, and 40–100 cm).

The multiple linear regression used in our study is in terms of

$$SM_{\text{reconstructed}} = a_1 \times P + a_2 \times \Delta TWS + a_3 \times SM_{\text{LDAS}} + a_4 \times SRH$$
(16)

where *SM* is the soil moisture; *SRH* is the soil relative humidity, $SRH = SM/SM_{\text{field moisture}}$ _{capacity} × 100%. During January 2002–December 2011, we define $SM_{\text{reconstructed}} = SM_{\text{ITPLDAS}}$, then the coefficients (a_1 , a_2 , a_3 , and a_4) are estimated, and $SM_{\text{reconstructed}}$ during January 2012–December 2015 are calculated. Note that the relationship between *SRH* observations and products was transplanted to the neighbored grid where there was a lack of observations.

The trapezoidal method [51] used in this study can be described as:

$$\hat{S} = \left[2.5\hat{\theta}_1 + \sum_{i=2}^k \hat{\theta}_k\right] \Delta z \tag{17}$$

where the subscript of $\hat{\theta}$ refers to the soil layer (from *i* = 1 to *k*); *k* corresponds to the final depth of measurement; and Δz is the depth interval between two successive measurements.

Data	Designation	Time-Period	Reso Tempor	lution al Spatial	Source		
Total precipitation (mm)	Р	January 2003–December 2015	monthly	$0.1 imes 0.1^\circ$	China Meteorological Forcing Dataset		
GRACE-derived land water storage changes (cm)	ΔTWS	January 2003–December 2015	monthly	$1.0 imes 1.0^{\circ}$	GRACE satellite images		
Soil relative humidity (%)	SRH	January 2003–December 2015	10-days	stationly	China Meteorological Forcing Dataset		
GLDAS-2 Noah Land Surface Model (LSM) L4 model outputs (kg m ⁻²)	SM	January 2003–December 2015	monthly	$0.25 imes 0.25^{\circ}$	GLDAS-2		
Soil- Moisture_from_ITPLDAS	SM	January 2002–December 2011	daily	$0.25 imes 0.25^{\circ}$	National Tibetan Plateau/Third Pole Environment Data Center		

Table 2. Overview of the data used to reconstruct soil moisture in the study.

3. Results

3.1. Spatial Distribution Characteristics of Soil Moisture

The estimation and prediction of SM, especially the root zone SM, have gained the interest of researchers [52,53]. Overall, many kinds of methods, including land surface modeling and the data assimilation technique, have been applied to estimate the multilayer SM. In this study, the monthly SM data from 2003 to 2015 of three layers (0–5, 5–20, and 20-100 cm) were reconstructed from multi-sources. Particularly, SM data collected at three observational networks (i.e., Ngari, Maqu, and Naqu; detailed information can be found in Yang et al. (2020)) across the Tibetan Plateau were employed to validate the reconstructed SM dataset [49]. Due to the lack of observation from deeper soils, Figure 2 only shows the comparison of the LDAS-derived and reconstructed monthly SM with the observed ones in the three layers of Naqu and surface layer of Ngari and Maqu. Both the observed station-averaged SM and its standard deviation are given in this figure. Only the LDAS-derived *SM* at a depth of 5 cm in the Ngari network is higher than the in situ data, as the LDAS-derived SM in the Magu and Nagu networks are lower than the in situ data. This phenomenon might be due to the fact that the LDAS-derived SM only denoted liquid water and did not account for soil ice. In general, the reconstructed SM is much closer to the observation in all three networks. However, the Ngari network still exhibits underestimation in summer (Figure 2A), and the Naqu network exhibits a minor amount of overestimation in summer (Figure 2C).

Spatial distributions of the reconstructed *SM* of 0–5, 5–20, and 20–100 cm averaged over 2003–2015 are respectively plotted in Figure 3. For all depths, the *SM* values range from 0.007 to 0.600, with the high values (over 0.4) distributed in northeast China and the southern part of China. In contrast, the SM values are relatively small in northwest China, the upper and middle reaches of the Yellow River, and western part of the Tibetan Plateau. From Figure 3A–C, we can also see that the *SM* values of individual depth are different, for example, the *SM* values of 0–5 cm in depth in southwest China are higher than those of 5–20 and 20–100 cm in depth. This region belongs to the tropical rainforest climate, the forest coverage is high, and the surface layer of soil has a strong capacity of water fixation [54]. A significant positive correlation between *SM* and *P* in eastern China has been identified in many previous studies [55,56]. Despite this, the relation between *SM* and *P* is a complex non-local process, and it is still unclear whether it represents the discovery of relevant phenomena or the explanation of the possible mechanism.



Figure 2. Temporal variability of observed station-averaged soil moisture and its standard deviation, LDAS–derived soil moisture, and reconstructed soil moisture at (**A**) 5–cm depth in the Ngari network; (**B**) 5–cm depth in the Maqu network; (**C**) 5–cm depth in the Naqu network; (**D**) 10–cm depth in the Naqu network; (**E**) 20–cm depth in the Naqu network; (**F**) 40–cm depth in the Naqu network.



Figure 3. Spatial distribution of the reconstructed (**A**) 0–5 cm, (**B**) 5–20 cm, and (**C**) 20–100 cm soil moisture, respectively averaged over 2003–2015.

3.2. Comparison of Algorithm Parameters

The differences between the parameters of the PT-JPL algorithm and PT-SM algorithm lie in the core of the performances of these two algorithms. Therefore, before we evaluate the performances of the PT-JPL algorithm and PT-SM algorithm at EC sites and hydrological catchments, the model parameters, including soil moisture constraint on soil evaporation f_{sm} , f_{REW} , soil water availability constraint on transpiration f_M , and f_{TRM} are firstly examined and compared. As a typical site with different underlying surfaces, Figure 4 shows the variation plot between f_{sm} and f_{REW} , f_M and f_{TRM} calculated from the reconstructed SM data at the CN-Qia (forest) flux tower, CN-Ha2 (shrub) flux tower, CN-Du2 (grass) flux tower, and YC (crop) flux tower. It can be seen that for all biomes, almost all of the f_{TRM} values are larger than the f_{M} values, and the values of f_{REW} are larger than those of f_{sm} , especially in the values values. Comparatively, the values of f_{REW} are much larger than those of f_{sm} for the forest and the shrub biomes, while those of f_{TRM} are much larger than those of $f_{\rm M}$ for the forest and the crop land cover types. This result is reasonable, as several studies have shown that in comparison with shorter vegetation, taller vegetation is less sensitive to soil water deficits since the deeper root can absorb water from deep soil or groundwater, where there is a delay in response to drought [23,57]. For instance, Figure 4G,H indicates that for the crop biome, the f_{REW} series closely follows f_{sm} , while in the peak values, the values of $f_{\rm REW}$ are larger than those of $f_{\rm sm}$. For $f_{\rm TRM}$, it can also be clearly seen that the new soil water availability constraints on transpiration are always higher than the original $f_{\rm M}$, especially at the $f_{\rm M}$ valley values (mostly occurring in the period from October to next March). Moreover, f_{TRM} being considerably higher could be due to the fact that Yucheng tower is an agricultural experiment station that monitors areas in which wheat and corn crops are mainly planted in winter and summer, respectively.



Figure 4. Comparisons of smoothed f_{sm} and relative extractable water (f_{REW}), f_M and new soil water availability constraint on transpiration (f_{TRM}) during 2003.1–2015.12 at (**A**,**B**) CN–Qia (forest) flux tower, (**C**,**D**) CN–Ha2 (shrub) flux tower, (**E**,**F**) CN–Du2 (grass) flux tower, and (**G**,**H**) YC (crop) flux tower.

3.3. Comparison of Incorporating Soil Moisture into Soil Evaporation and Transpiration

Since the algorithm models individual ET components, we can separately quantify the added value from incorporating SM into soil E and canopy T. Consequently, we evaluated the updated PT-SM algorithm with SM incorporation into soil E (PT_Es), the updated algorithm with SM incorporation into T (PT_T), and the updated algorithm with SM incorporation into both soil *E* and *T* (PT-SM) compared with the original PT-JPL model. Comparisons among the four EC sites, i.e., CN-Qia (forest) flux tower, CN-Ha2 (shrub) flux tower, CN-Du2 (grass) flux tower, and YC (crop) flux tower, are shown in Figure 5. It can be clearly seen that incorporating explicit SM can improve estimates of monthly ET series. Especially at the Yucheng EC site, the updated PT-SM algorithm shows greater R^2 and NSE (PT-JPL: 0.93 and 0.85; PT_Es: 0.95 and 0.91; PT_T: 0.91 and 0.98; PT-SM: 0.98 and 0.98, respectively), lower RMSE and Bias (PT-JPL: 11.29 and -8.09; PT_Es: 9.50 and -6.01; PT_T: 5.20 and -1.07; PT-SM: 5.02 and 1.17, respectively), and larger slopes (PT_Es: 0.840, PT_T: 0.941, PT-SM: 0.970) closer to 1.0 when compared with the PT-JPL model (PT-JPL: 0.821) (Figure 5D and Table 3). At the Yucheng EC site, by only replacing soil evaporation E_s , R^2 and NSE increased by 2% and 7%, respectively, and RMSE and Bias decreased by 16% and 2 mm, respectively. By only replacing canopy T, R^2 and NSE increased by 4% and 15%, respectively, and RMSE and Bias decreased by 54% and 7 mm, respectively. According to our results, the performance of the updated PT-SM algorithm with SM incorporation into both E_s and canopy T considerably improved (i.e., R^2 and NSE increased by 5% and 15%, respectively, and RMSE and Bias decreased by 56% and 9 mm, respectively; Table 3) when compared with the original PT-JPL-modelled ET. Moreover, observations between 60 and 120 mm are better represented by the updated model with a scatter closer to the 1:1 line from raised underestimation in *ET* (see Figure 5).

Table 3. Quantitative measures of original PT-JPL model, updated algorithm PT-SM with soil moisture incorporation into soil evaporation (PT_Es), updated algorithm with soil moisture incorporation into transpiration (PT_T), and updated PT-SM ET performance at monthly time-steps for 17 flux sites.

	Tower		Р	F-JPL			P	Γ_Es			Р	T_T			РТ	-SM	
		R^2	NSE	RMSE	Bias	R^2	NSE	RMSE	Bias	R^2	NSE	RMSE	Bias	R^2	NSE	RMSE	Bias
	CN-Din	0.87	0.54	12.68	-10.33	0.89	0.65	9.85	-5.68	0.90	0.89	6.58	-3.52	0.94	0.93	4.76	-1.10
	CN-Qia	0.96	0.96	6.30	-2.29	0.96	0.96	5.77	-0.17	0.96	0.94	7.38	4.43	0.96	0.91	8.87	6.40
	XSBN	0.90	0.78	7.98	-5.76	0.90	0.88	6.65	-1.45	0.90	0.89	5.13	1.89	0.93	0.92	4.82	1.59
	CN-Cha	0.98	0.91	8.50	-6.28	0.98	0.92	6.57	-3.18	0.98	0.94	5.27	1.58	0.98	0.97	4.87	2.46
	DX	0.93	0.89	10.33	-6.47	0.93	0.91	9.85	-2.30	0.94	0.93	8.42	-1.05	0.95	0.95	7.03	0.14
	MY	0.95	0.94	8.41	-3.00	0.95	0.95	7.57	-1.05	0.96	0.96	7.80	-0.62	0.97	0.96	7.00	1.33
	QH	0.98	0.93	7.77	-5.26	0.98	0.94	6.57	-3.61	0.97	0.95	5.29	-0.81	0.98	0.97	4.86	1.17
	CN-Ha2	0.98	0.90	10.20	-7.68	0.99	0.95	7.15	-5.10	0.99	0.99	3.48	0.66	0.99	0.98	4.59	2.90
	YC	0.93	0.85	11.29	-8.09	0.95	0.91	9.50	-6.01	0.97	0.98	5.20	-1.07	0.98	0.98	5.02	1.17
	GT-1	0.87	0.77	6.34	-3.05	0.89	0.82	4.51	-1.99	0.96	0.95	4.46	0.71	0.99	0.98	4.41	1.90
	AR	0.86	0.79	13.01	-7.70	0.90	0.84	8.17	-5.46	0.97	0.94	7.83	0.88	0.98	0.97	6.96	2.35
	CN-Du2	0.91	0.82	7.29	-5.15	0.93	0.86	5.32	-3.54	0.99	0.99	3.06	0.75	0.98	0.96	5.42	3.77
	CN-Cng	0.93	0.73	12.20	-9.23	0.96	0.80	11.45	-6.57	0.95	0.87	9.54	1.80	0.95	0.91	7.93	3.71
	CN-Dan	0.91	0.69	17.48	-8.69	0.93	0.76	10.87	-5.67	0.96	0.95	7.81	-2.64	0.98	0.97	6.92	2.03
	CN-Sw2	0.90	0.72	6.93	-4.72	0.94	0.83	5.41	-3.25	0.98	0.96	4.03	1.52	0.99	0.96	3.40	2.68
	GT-2	0.92	0.82	7.12	-3.48	0.93	0.90	6.57	-1.58	0.97	0.95	6.18	2.85	0.98	0.95	5.81	4.57
	NMG	0.94	0.76	7.41	-5.67	0.95	0.83	5.44	-2.57	0.96	0.95	4.97	1.55	0.96	0.95	4.58	2.03
Change	PET/P < 1.7					0	6	-16	3	1	12	-29	6	2	14	-31	8
rate	PET/P > 1.7					3	9	-23	2	7	23	-39	7	8	25	-40	9
(%)	All towers					2	7	-20	3	4	18	-34	7	5	20	-36	8

Among all of the EC towers, we noted that, by only replacing soil evaporation E_s , the R^2 and NSE increased by 2% and 7%, respectively, and the *RMSE* and Bias decreased by 20% and 3 mm, respectively. By only replacing canopy *T*, R^2 and *NSE* increased by 4% and 18%, respectively, and *RMSE* and Bias decreased by 34% and 7 mm, respectively (see Table 3). The improvement to the updated PT-SM algorithm is more obvious at the EC towers in the arid area (*PET/P* > 1.7) than that at the EC towers in the humid regions (*PET/P* < 1.7), with the R^2 and *NSE* being increased by 8% and 25%, respectively, and *RMSE* and Bias being decreased by 40% and 9 mm, respectively. In addition, both Figure 5 and Table 3 show that this improvement is strongly dependent on the simulation accuracy of vegetation *T*; the



result also confirms that our approach of incorporating the soil moisture constraints into a simple algorithm can provide good estimates of *ET* series at different land cover regions.

Figure 5. Comparisons of monthly evapotranspiration (*ET*) from observation, original PT–JPL algorithm (PT–JPL), updated algorithm with soil moisture incorporation into soil evaporation (PT_Es), updated algorithm with soil moisture incorporation into transpiration (PT_T), and updated PT-SM algorithm; and scatter plot of ET model without and with soil moisture incorporation into the updated algorithm at (**A**) CN–Qia (forest) flux tower, (**B**) CN–Ha2 (shrub) flux tower, (**C**) CN–Du2 (grass) flux tower, and (**D**) YC (crop) flux tower.

3.4. Model Evaluation with In Situ Forcing

Both the PT-JPL and PT-SM algorithms were executed for in situ evaluation. The in situ modeled *ET* from both the PT-JPL and PT-SM show good consistency with the observations (Figure 6, Table 3). We noted a site-wide average improvement in R^2 , *NSE*, *RMSE*, and absolute Bias as a result of the model improvements. Sites are ordered from

wet to dry (left to right; top to bottom) based on the aridity index (PET/P). The PT-SM algorithm demonstrates greater performance than that of the original PT model at waterlimited sites (Table 3). On average, the PT-SM algorithm shows an apparent decrease in *RMSE* and absolute Bias (36% and 8 mm, respectively), a weak increase in R^2 (5%), and a large increase in *NSE* (20%) when compared with the original PT-JPL model. An interesting feature is that the more overall statistical improvements are observed at CN-Cng and YC sites, two sites that both have relatively dry conditions (PET/P = 2.38 and 1.82, respectively; Figure 6M,I) and a large fraction of *ET* comes from soil evaporation. It can also be seen that at YC, AR, and CN-Cng sites, the PT-SM model demonstrates considerable improvements to the model estimation of *ET* during the seasonal dry term (Figure 6).

Compared with the observed 17 EC sites' monthly *ET* series, the R^2 and *NSE* of the PT-JPL monthly *ET* series are 0.94 and 0.90, respectively, and the *RMSE* and Bias are 10.05 and -6.34, respectively (Figure 7A). The R^2 and *NSE* of the PT-SM monthly *ET* series are 0.97 and 0.96, respectively, and the *RMSE* and Bias are 5.90 and 2.13, respectively, when compared with the observed *ET* (Figure 7B). Among all of the land covers (biomes), both models represent the observed monthly *ET* series well, especially at the EC sites across the MF and Crop biomes. Only at the EC sites in the GRA land cover type, the two models represent the observed monthly *ET* series not so well. Comparing Figure 7B to Figure 7A, we can see that the PT-SM model provides much better improvements than those of the original PT-JPL model at the EC sites across the EBF and GRA land cover types. This phenomenon illustrates that at the EBF and GRA land cover regions, the PT *ET* model, considering the soil water availability constraint on transpiration, is better at reflecting the monthly *ET* series.

3.5. Evapotranspiration Partitioning

As an important component of ET, the interception evaporation (E_i) of vegetation plays a vital role in water resources at both global and regional scales [23,57,58]. The ratios of canopy interception evaporation-to-precipitation (E_i/P) values of different land covers are notably different, with the averages for all biomes ranging from 0.11 to 0.27, but all values are below 0.30 (Figure 8 and Table 4). The average E_i/P for the ENF land cover is higher than that of other types, and the OSH biome has the lowest value (0.11). This may be related to different raining conditions and LAIs across land cover types. The E_i/P variation in the Crop biome is larger than that of other biomes, with values ranging from 0.11 to 0.27 and an average across the four Crop sites of 0.18. Research on the E_i/P ratio has attracted much attention. Under Mediterranean climate conditions, Llorens and Domingo (2007) discovered that for an annual rainfall of 90–800 mm, the mean relative interception was approximately 18% for trees and 31.6% for shrubs [59]. Miralles et al. (2010) reviewed 42 studies from different periods and found average E_i/P values for the EBF biome of 0.17 with ranges from 0.08 to 0.29, and the ENF biome average was 0.23 with ranges from 0.16 to 0.42 [57]. Gu et al. (2018) obtained the E_i/P from 11 terrestrial biomes based on 75 eddy covariance towers and found average E_i/P values for the Crop biome of 0.12 with ranges from 0.06 to 0.16, and the GRA biome average was 0.13 with ranges from 0.02 to 0.17 [58]. Compared with these previous studies, the overall variation is relatively consistent, but the E_i/P of the individual biome is somewhat different, which is most likely due to the fact that the EC sites used in this study are relatively few in number (e.g., Crop: 11 sites in Gu et al. (2018) vs. four sites in our study; GRA: 12 sites in Gu et al. (2018) vs. seven sites in our study) [58]. Overall, we found that the E_i/P variation in the land covers was large, ranging from 0.11 to 0.27, with an average of 0.16 among 17 sites (see Figure 8A), which is relatively reasonable compared with those of other similar studies (shown in Table 4). The canopy interception evaporation-to-evapotranspiration (E_i/ET) ratios across different land cover types are shown in Figure 8B. The average E_i/ET values across biomes range from 0.11 (OSH biome) to 0.32 (GRA biome). Large variations are noted within each land cover type, with the GRA biome having the greatest range (0.19–0.32) followed by the EBF biome (ranges of 0.20–0.28, respectively).



Figure 6. In situ model performance across 17 eddy covariance sites ((A): CN–Din; (B): CN–Qia; (C): XSBN; (D): CN–Cha; (E): DX; (F): MY; (G): QH; (H): CN–Ha2; (I): YC; (J): GT–1; (K): AR; (L): CN–Du2; (M): CN–Cng; (N): CN–Dan; (O): CN–Sw2; (P): GT–2; (Q): NMG) distributed across China.



Figure 7. Observed evapotranspiration (ET) at eddy covariance sites vs. (**A**) PT–JPL ET and (**B**) PT–SM ET. The solid line is the 1:1 line and the short dashed line is the trend line for ET series of all land cover types of the 17 EC sites.



Figure 8. Ratio of (**A**) canopy interception evaporation to precipitation (E_i/P) varies across different land covers; (**B**) canopy evaporation to total evapotranspiration (E_i/ET); (**C**) vegetation transpiration to total evapotranspiration (T/ET); and (**D**) soil evaporation to total evapotranspiration (E_s/ET). Boxes mark the 75th and 25th percentiles and the solid lines and crosses in the boxes refer to the average and median values, respectively.

Figure 8C demonstrates that the average T/ET values across biomes range from 0.37 (GRA biome) to 0.65 (EBF biome). Large variations are noted within the GRA biome (ranges of 0.37–0.48). The average T/ET values for the Crop biome of 0.53 range from 0.49 to 0.55, and the EBF biome average of 0.63 has a range from 0.61 to 0.65 (Figure 9C). Overall, our estimated T/ET values are much lower than the 0.80–0.90 global values that Jasechko et al. (2013) found using isotope approaches, but similar with the results of Gu et al. (2018) [58,60], that used 75 eddy covariance towers across a wide range of biomes. Previous studies [6,13,16] also indicate that a large variability occurs in T/ET, which is partly due to different ET measurements, model structures, and inconsistent spatial and temporal resolutions of forcing data.

Landcover	Current Study	Interception Ratio Literature
Crop	0.18	0.17 (Vinukollu et al. 2011); 0.12 (Gu et al. 2018)
DNF	0.14	0.12 (Vinukollu et al. 2011); 0.23 (Miralles et al. 2010)
EBF	0.15	0.14 (Vinukollu et al. 2011); 0.17 (Miralles et al. 2010);
	0.15	0.16 (Gu et al. 2018)
ENIE	0.10	0.19 (Vinukollu et al. 2011); 0.23 (Miralles et al. 2010);
EINF	0.19	0.12 (Gu et al. 2018)
GRA	0.16	0.14 (Vinukollu et al. 2011); 0.13 (Gu et al. 2018)
MF	0.19	0.19 (Vinukollu et al. 2011); 0.13 (Gu et al. 2018)
OSH	0.11	0.09 (Gu et al. 2018)

Table 4. Annual ratios (average) of canopy evaporation losses to the total precipitation based on land cover types.



Figure 9. (**A**) Mean annual PT–SM evapotranspiration (ET); (**B**) canopy interception evaporation (Ei); (**C**) vegetation transpiration (T); and (**D**) soil evaporation (Es) of multiyear (2003–2015) in China.

The soil evaporation-to-evapotranspiration ratios across different biomes are shown in Figure 8D. The average E_s/ET values across biomes range from 0.11 (EBF biome) to 0.49 (OSH biome). The largest variation was noted for the GRA biome, having a greatest range of 0.27–0.39, followed by the Crop biome (range of 0.26–0.35). Our estimated E_s/ET values are within the range of previously reported values.

3.6. Spatial Distributions of Mean Annual Evapotranspiration and Its Components

We applied the verified PT-SM algorithm to the whole of China for the period of 2003–2015 at a spatial resolution of 0.25° using CMFD meteorological data, MODIS products, and integrated *SM* datasets as described in Sections 3.2–3.4. Figure 9 shows the maps of mean annual *ET*, E_i , *T*, and E_s over the period of 2003–2015. The mean annual *ET* distribution presented an intricate spatial structure with relatively high *ET* values in the southern China and low values located in the northwest. In most regions of the Xinjiang, Tibet, Qinghai, and Inner Mongolia provinces, the *ET* values are lower than 200 mm/year. In contrast, in the south of the Yangtze River and the Huai River, the *ET* values are higher than 800 mm/year. Generally, the mean annual *ET* increased from the northwest to the

southeast (Figure 9A). Almost all of the E_i values in Xinjiang, Qinghai, and Inner Mongolia provinces are lower than 50 mm/year, especially in the northwestern part of China (barren lands) (Figure 9B). Similarly, *T* values of the northwestern part are lower than 100 mm/year, while only in the upper of Huai River basin, the Pearl River basin, central China, the southwest and southeast parts of China are the values of *T* higher than 600 mm/year. Notably, in the south region of Yunnan province, the *T* values are larger than 800 mm/year (Figure 9C). Furthermore, E_s values lower than 100 mm/year were found in the arid and desert regions of the northwest part of China, while in some parts of southern China, the E_s values are higher than 400 mm/year (see Figure 9D).

4. Discussion

4.1. Soil Water Availability Constraint on Evaporation and Transpiration

Many previous studies have tried to estimate soil moisture by measurements, such as time domain reflectometry soil moisture probes [61], hydrologic models [62], remote sensing techniques [63] or statistical learning tools such as support vector machines [64]. Unfortunately, most of these studies only paid attention to the *SM* at the surface. For vegetation with deeper roots, the transpiration water requirements also need the *SM* at the root zone. However, although the estimation of *SM* at the root zone has drawn great attention [53,65], its retrieval is difficult for spatial heterogeneity. Consequently, in this study, the multiple linear regression model and trapezoidal method were employed to estimate the *SM* of both the surface and root zone. The simulated *SM* performs the observation well (see Figure 2), and it was noted that the observation-driven model *SM* displays superior strength with coupling precipitation, soil relative humidity, ΔTWS , and GLDAS soil moisture outputs. These results further confirmed that for most regions, *SM* is closely related to precipitation and terrestrial water storage change, which is consistent with the findings of previous studies [34,53,65].

The performances of the updated PT-SM algorithm with the *SM* constraint separately on E_s and *T* are different (see Table 3). Overall, it was observed that the updated PT-SM algorithm with the *SM* constraint on *T* (PT_T) performs the observation better than the PT-SM algorithm with the *SM* constraint on E_s (PT_Es), and the PT-SM model showed increased R^2 and *NSE* and reduced *RMSE* and Bias, with the greatest improvements occurring in water-limited regions. With the aid of SMAP-derived surface soil moisture data, Purdy et al. (2018) indicated that the performance of the updated PT-SM algorithm with the soil moisture constraint on E_s has improved performance on *T* across the 14 Ameriflux EC sites distributed across the US [24]. This result is different with our study, a difference that may have resulted from the difference in f_{REW} and f_{TRM} estimates. In particular, some studies also demonstrated that SMAP might underestimate *SM* for the low biases in the Global Modeling and Assimilation Office surface temperature [39]. While Purdy et al. (2018) estimated the *ET* components with SMAP-derived soil moisture at a single depth (5 cm), in our study, *SM* data of three layers (0–5, 5–20, and 20–100 cm) were employed to estimate the *ET* components, which is a possible explanation of the difference.

Figure 10 is plotted to investigate the spatial difference of E_s and T estimation by the PT-JPL algorithm and PT-SM algorithm. In contrast to the T estimated in July 2003 by the PT-JPL algorithm (Figure 10A), the estimated T results of the PT-SM algorithm showed higher values, especially in the central, southern, and northeastern parts of China (see Figure 10B), regions showing higher *SM* values (see Figure 3) and *LAIs* [66]. For E_s estimation, the large differences also occurred in the northeastern, southern, and central parts of China (Figure 10C,D). The results further illustrate that estimation of *ET* components can only be improved by adequate soil moisture.



Figure 10. Comparisons of vegetation transpiration (*T*) from the original PT–JPL algorithm (PT–JPL) (**A**) and updated PT–SM algorithm (**B**); comparisons of soil evaporation (E_s) from the PT–JPL model (**C**) and PT–SM model (**D**) in July, 2003 across China.

4.2. Contribution of Each ET Component to the Total ET

We also evaluated the contribution of each ET component to the total ET by different algorithms for the whole of China. Figure 11 shows that the PT-SM algorithm considering SM estimated a higher T/ET value than those of the original PT-JPL model (64.9% vs. 53.7%) and lower E_i/ET and E_s/ET values (21.2% vs. 15.4%; 25.1% vs. 19.7%). Overall, the average estimates of the T/ET value in our study are somewhat lower than previous studies' results, although the T/ET value was improved by incorporating SM of multilayers into the original PT-JPL model. In essence, there are two possible reasons behind this phenomenon: (1) In terms of the site scale, E_i of vegetation has rarely been separately considered by previous studies, as usually, only E_s and T are observed, and, therefore, the T/ET estimates would be higher; (2) different research scales, monitoring techniques or algorithms may also contribute to the variability-for instance, the isotope-based approach constrained by hydrologic decoupling always overestimates T/ET [60]. Additionally, the PT-SM E_s/ET and E_i/ET values of our study are larger than the similarly reported fractions from the GLEAM model by 7–15% and 11–12%, respectively [23,57], but similar with E_s/ET , T/ET, and E_i/ET at 23 \pm 1.7%, 54 \pm 1.6%, and 21 \pm 0.8% of total ET, respectively, as reported in Purdy et al. (2018). It is worth noting that all of these studies focus on the global scale.

Figure 11C reveals the spatial patterns of dominant *ET* components. It can be seen that the bare soil evaporation is dominated across almost the entire arid area of northwest China, especially in the arid and semi-arid regions, while in some warmer and wet regions, such as southeastern of Tibet, the interception loss is the main component. In contrast, transpiration typically takes up most of the remaining regions (especially the forested terrain), while in some areas in southern China (often rainforests), the total interception loss is generally the dominant component. These findings are consistent with the partitioning obtained from other datasets [6,24]. Nonetheless, this phenomenon is a comprehensive reflection of climate, water absorption capacity of vegetation, growth status, soil moisture, etc.



Figure 11. Evapotranspiration (*ET*) components expressed as a percentage of total ET from (**A**) the original PT–JPL algorithm (PT–JPL) and (**B**) updated PT–SM algorithm across China. Yellow indicates soil evaporation (E_s), blue indicates vegetation transpiration (*T*), and red indicates canopy interception evaporation (E_i). Below, (**C**) the spatial distribution of the dominant percent contribution to total *ET* from components as E_s , *T*, and E_i .

4.3. Inter-Annual Variability of ET for 2003–2015

It can be seen that the whole of China is characterized by complex spatial patterns in *ET* and its change in components (Figure 12). For the total *ET*, more than half of the entire area of China show upward trends, while the other half show downward trends. Additionally, the largest upward trend of the annual *ET* series is recognized at the Qinghai–Tibet Plateau with a value of 3.35 mm/y, while the largest downward trend (i.e., -2.88 mm/y) can be found at the southeastern part of China (Figure 12A). Moreover, based on a modified Priestley–Taylor algorithm, Yao et al. (2013) found that the *LE* decreased over large areas in central China, northwest China, and Inner Mongolia while increasing in the northeast, north, and south regions of China during the period of 2001–2010 by driving monthly MODIS products [29]. These two results are different partly due to the different study periods, and another reason could be the difference in data and methods used. By employing the ensembles of remote sensing-based physical models and machine learning algorithms, overall increasing trends (0.62 and 0.38 mm/y, respectively) in global terrestrial *ET* during the period of 1982–2011 were evaluated by Pan et al. (2020) [17]. A further investigation into the control factors of *ET* variations showed that anthropogenic Earth greening was the dominating factor, which has also been reported by previous studies [1,67]. By contrast, drought and reducing solar radiation caused by substantial increases in aerosol optical depth (AOD) were usually identified as the main possible factors of *ET* reduction [68,69].



Figure 12. Annual trend slopes of (**A**) PT–SM evapotranspiration (*ET*); (**B**) canopy evaporation (E_i); (**C**) vegetation transpiration (*T*); and (**D**) soil evaporation (E_s) during 2003–2015.

The ET components are not only influenced by vegetation cover and growth period but also by environmental factors, such as climate conditions, topography, and soil characteristics [70]. However, the control degree of different influencing factors on individual ET components varies with energy and water conditions. E_i across northwest China indicates upward trends, and this may be a result of the afforestation and grassland projection over the past two decades. For almost the whole southeastern part of China, E_i shows downward trends with the largest downward trend (i.e., -2.57 mm/y) being found in central China (Figure 12B), this result is relatively reasonable due to the development of modern agricultural technology, a large number of agricultural water-saving technologies have been implemented in the southeast region, the water use efficiency was increased, and the unnecessary evaporation dissipation was reduced [71]. As for the vegetation T, most areas presented upward trends, except small areas in the northeastern and southeastern parts of the country, and the larger upward trends of annual T series were recognized at the Tibetan Plateau, with a value over 2.00 mm/y (Figure 12C). Unlike the general paradox regarding whether or not the growing-season precipitation amount or the precipitation pattern is the main reason for vegetation T change [6,72], increased NDVI and LAI as a result of large-scale afforestation and agricultural intensification have been widely

identified to play the most important role in the increase in vegetation T [17,58,73]. E_s across China (with the exception of the southeastern region) presented downward trends. Furthermore, the changing trends were mostly less than 3.00 mm/y (Figure 12D). Similar to E_i , E_s also represents the ineffective water consumption that does not directly contribute to production. Although the slopes of the trends were different, all of the values of ET and its components have been found to show increasing trends with increasing precipitation by Gu et al. (2018) [58]. Meanwhile, the variation of f_{REW} (relative extractable water) has the most significant impact on the E_s simulation in arid areas with low vegetation [74]. Nevertheless, such E_s reduction may be due to the decrease in solar radiation or drought. Additionally, many studies noted that the sensibility of ET components changes in relation to different climatic environments, biomasses, soil properties, plant types, and canopy heights [7,23,75]. Therefore, the reasons for the distinction of the performances of the updated PT-SM algorithm with a soil moisture constraint on E_s and T separately are complex and warrant further investigation.

5. Conclusions

By incorporating soil moisture into the widely used PT-JPL *ET* algorithm, in this study, *ET* and its components series at a spatial scale of $0.25 \times 0.25^{\circ}$ were estimated. For this purpose, *SM* data at three layers (0–5, 5–20, and 20–100 cm) were firstly reconstructed by the multiple linear regression model and trapezoidal method, integrating the datasets of humidity observations relative to farmland soil, observed precipitation, GRACE solutions, and *SM* datasets obtained from the LDAS-2 outputs and Yang et al. (2020). High *SM* values generally occurred in the southeastern part of China, while low values were distributed in the northwestern part of the country. Meanwhile, the two algorithms' parameters in the update PT-SM *ET* algorithm (f_{REW} and f_{TRM}) were compared with the parameters in the original PT-JPL algorithm (f_{sm} and f_{M}). The values of parameters in the updated PT-SM *ET* algorithm (i.e., f_{REW} and f_{TRM}) were observed to be larger than those of the original PT-JPL algorithm (i.e., f_{sm} and f_{M}), especially in the peak or valley values.

The updated algorithm (i.e., PT-SM) model shows increased R² and NSE and reduced RMSE and Bias, with the greatest improvements occurring in water-limited regions. SM incorporation into E_s can improve ET estimates by increasing R^2 and NSE by 2% and 7%, respectively; RMSE and Bias were reduced by 20% and 3 mm, respectively; while SM incorporation into T improved ET estimates by increasing R^2 and NSE by 4% and 18%, respectively. RMSE and Bias were reduced by 34% and 7 mm, respectively. These updated PT-SM ET estimates distinctly show a reduced error and provide a rich dataset to evaluate land surface models, vegetation or anthropogenic perturbation response to changes in water availability. The mean annual ET distribution presented an intricate spatial structure with relatively high ET values in the southeast of China and low values in the northwestern part. As a whole, the soil moisture constraint resulted in a higher transpiration estimate and lower evaporation estimate. These results can provide more accurate water consumption data for regional water resource management and planning. In the future, a high spatial-temporal resolution ET is expected to be obtained. Therefore, the critical variables determining the model's ability to simulate ET components, vegetation, surface, and root-zone soil moisture at high spatial-temporal resolution, are urgently needed.

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