

Satellite-based Near-Real-Time Global Daily Terrestrial Evapotranspiration Estimates

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Abstract.

Accurate and timely global evapotranspiration (ET) data is crucial for agriculture, water resource management, and drought forecasting. Although numerous satellite-based ET products are available, few offer near-real-time data. For instance, products like NASA's ECOSTRESS and MOD16 face challenges such as uneven coverage and delays exceeding one week in data availability. In this study, we refined the Variation of the Standard Evapotranspiration Algorithm (VISEA) by fully integrating satellite-based data, including European Centre for Medium-Range Weather Forecasts ERA5-Land's shortwave radiation, which includes satellite remote sensing data within its assimilation system and MODIS's land surface data include surface reflectance, temperature/emissivity, land cover, vegetation indices, and albedo as inputs. It enables VISEA to provide near-real-time global daily ET estimates with a maximum delay of one week at a resolution of 0.05°. Its accuracy was assessed globally using observation data from 149 flux towers across 12 land cover types and comparing it with five other satellite-based ET products and GPCP precipitation data. The results indicate that VISEA provides comparable accuracy ET estimates to existing products, achieving a mean correlation coefficient (R) of about 0.6 and an RMSE of 1.4 mm day⁻¹. Furthermore, we demonstrated VISEA's utility in drought monitoring during a drought event in the Yangtze River Basin in 2022, in which the ET changes correlated with the precipitation. The near-real-time capability of VISEA is, thus, especially valuable in meteorological and hydrological applications for coordinating drought relief efforts. The VISEA ET dataset is available at <https://doi.org/10.11888/Terre.tpd.300782> (Huang, 2023a).

1 Introduction

Global terrestrial evapotranspiration (ET) is a vital component of the Earth water cycle and energy budget. It includes evaporation from the soil and water surfaces (some studies also consider evaporation from the intercepted precipitation in canopies) and plant transpiration (He et al., 2022; Wang et al., 2021a;

44 Zhang et al., 2021). Accurate and timely estimation of ET is essential for quantitatively assessing changes
45 in the water cycle under climate change, vigilant monitoring drought, and effectively managing and
46 allocating water resources (Aschonitis et al., 2022; Han et al., 2021; Su et al., 2020).

47 Near-real-time ET estimation from reanalysis data has been widely used to assess ET changes in the
48 global water cycle under different climate changes (Copernicus Climate Change Service, 2020). While
49 these datasets, such as ERA5 (Albergel et al., 2012; Jarlan et al., 2008; Miller et al., 1992) and CRA-40
50 (Liu et al., 2023; Zhao et al., 2019), offer near-real-time latent heat flux (ET in energy units) with a delay
51 of just six days, but they typically feature coarser spatial resolutions, often 0.25° or more. This level of
52 resolution may limit their effectiveness for detailed assessments of drought conditions and the
53 optimization of water resource allocation. On the other hand, obtaining highly accurate, near-real-time,
54 or real-time ET measurements through local eddy covariance or lysimeter methods can be very valuable
55 (Awada et al., 2022), but collecting large-scale ET data on a fine grid using this equipment is prohibitively
56 expensive (Barrios et al., 2015; Tang et al., 2009).

57 Satellite remote sensing-based ET estimates outperform reanalysis data by providing high spatial
58 resolution for detailed water utilization analysis, near-real-time data for prompt environmental response,
59 and global coverage for comprehensive water cycle studies. These ET estimates rely on direct
60 observations, enhancing accuracy, especially where ground data are sparse, and allowing for the dynamic
61 monitoring of land and vegetation changes.

62 The selected ET products discussed below have significantly contributed to estimating global ET
63 and have gained recognition within the scientific community. The MOD16 ET product, developed by Mu
64 et al. (2007, 2011), utilizes a Penman-Monteith-based approach and is driven by MODIS land cover,
65 albedo, fractional photosynthetically active radiation, leaf area index, and daily meteorological reanalysis
66 data from NASA's Global Modelling and Assimilation Office (GMAO) to estimate ET. The AVHRR ET
67 product, developed by Zhang et al. (2006, 2009), significantly advanced the study of the global water
68 cycle. It employed a modified Penman–Monteith approach over land, integrating biome-specific canopy
69 conductance determined by NDVI, and utilized a Priestley–Taylor approach over water surfaces. These
70 algorithms were driven by AVHRR Global Inventory Modeling and Mapping Studies (GIMMS) NDVI,
71 daily surface meteorology data from the National Centers for Environmental Prediction/National Center
72 for Atmospheric Research (NCEP/NCAR) reanalysis, and solar radiation from NASA/GEWEX Surface
73 Radiation Budget Release-3.0. The FLUXCOM framework has made a substantial contribution to
74 resolving the evapotranspiration paradox. It utilizes machine learning to integrate eddy covariance data
75 from the global FLUXNET tower network, surface meteorological data from the Climatic Research Unit
76 (CRU) reanalysis, and remote sensing data (Jung et al., 2009, 2010, 2019). Additionally, GLEAM,
77 developed by Miralles et al. (2011b) and Martens et al. (2017), is one of the best satellite-based ET
78 products using unique algorithmic approaches that have advanced the estimation of global ET which uses
79 meteorology data from ECMWF Reanalysis 5. Lastly, PML, developed by Zhang et al. (2019, 2022) is
80 the first to offer global ET coverage at a 500-meter resolution, demonstrating high accuracy compared to
81 local eddy covariance observations worldwide with MODIS satellite data and Global Land Data
82 Assimilation System Version 2.1 (GLDAS-2.1) data (Zhang et al., 2023).

83 However, these ET products cannot provide near-real-time data due to reliance on local ground-
84 based meteorology and land-surface/reanalysis models, which are time-consuming to obtain globally. For
85 example, MOD16 and PML use GMAO and GLDAS-2.1 data, respectively. While AVHRR ET depends
86 on AVHRR satellite data and NCEP/NCAR Reanalysis meteorology data, GLEAM ET uses MODIS
87 satellite data and ECMWF meteorology Reanalysis data. FLUXCOM relies on FLUXNET and the
88 Climatic Research Unit (CRU) reanalysis data, which are not updated in real-time. Recently, NASA's
89 ECOSystem Spaceborne Thermal Radiometer Experiment, mounted on the International Space Station
90 on the Space Station (ECOSTRESS), was designed to estimate global-scale ET (Fisher et al., 2019, 2020).
91 thermal infrared data at 70-meter resolution every 1 to 7 days. This results in uneven global coverage and
92 reduced data frequency, especially in regions like the Middle East, as noted by Anderson et al., 2021 and
93 Jaafar et al., 2022. In contrast, the VISEA model uses only MODIS land products and ERA5-Land
94 shortwave radiation, enabling near-real-time ET estimations.

95 The objective of this manuscript is twofold: 1) adapt the VISEA model for near real-time, global
96 application by replacing land-based solar radiation inputs with hourly shortwave radiation data from
97 ECMWF ERA5-Land's data assimilation system (Sabater, 2019); and 2) to globally validate the model
98 using a comprehensive set of datasets, including meteorological instrument data and eddy covariance
99 measurements from 149 FLUXNET flux towers (Pastorello et al., 2020). Additionally, multi-year ET
100 datasets from GLEAM (Martens et al., 2017; Miralles et al., 2011), FLUXCOM (Jung et al., 2009, 2010,
101 2018), AVHRR (Zhang et al., 2009, 2010), MOD16 (Mu et al., 2007, 2011), PML (Zhang et al., 2019,
102 2022) and precipitation data from the Global Precipitation Climatology Centre (GPCC) (Udo et al., 2011)
103 are also employed in the assessment.

104 **2. Methods**

105 **2.1 Description of the VISEA algorithm**

106 VISEA, short for the Variation of the Moderate Resolution Imaging Spectroradiometer Standard
107 Evapotranspiration Algorithm, is a modification of the MODIS standard Evapotranspiration (ET)
108 algorithm. The original MODIS algorithm, created by Mu et al. (2007 and 2011), is based on the Penman-
109 Monteith method. VISEA introduces two significant modifications. First, it employs the Vegetation (VI)-
110 Temperature (Ts) Triangle method, originally developed by Nishida et al. (2003), to estimate air
111 temperature. Second, VISEA incorporates hourly data on shortwave downward radiation from the ERA5-
112 Land dataset to calculate daily average energy. These two advancements enable VISEA to estimate large-
113 scale ET without needing local measurements as supplementary data.

114 Unlike energy budget-based ET algorithms, such as SEBS (Surface Energy Balance System),
115 METRIC (Mapping Evapotranspiration at high Resolution with Internalized Calibration), and ALEXI
116 (Atmosphere-Land Exchange Inverse), which calculate ET (latent heat flux) as the residual of the net
117 radiation by subtracting soil heat flux and sensible heat flux. VISEA estimates ET using the Penman-
118 Monteith equation, placing it in a different category of satellite-based global ET products currently in
119 use. VISEA is a two-source model, which means the ET in one grid cell was separated as the transpiration
120 from full vegetation cover and the evaporation from bare soil surface if energy transfer from the
121 vegetation to the soil surface was ignored (Nishida et al., 2003), i.e.,

122
$$ET = f_{veg}ET_{veg} + (1 - f_{veg})ET_{soil} \quad (1)$$

123 where the subscript "veg" means full vegetation cover and the subscript "soil" indicates the soil exposed
 124 to solar radiation (called bare soil); ET_{veg} is the transpiration from full vegetation cover area ($W m^{-2}$),
 125 ET_{soil} is the evaporation from bare soil ($W m^{-2}$), f_{veg} is the portion of the area with the vegetation cover,
 126 which can be calculated by Normalized Difference Vegetation Index (calculation details are provided in
 127 Appendix A, Tang et al., 2009).

128 The available energy Q ($W m^{-2}$), which is the sum of the latent heat flux and sensible heat flux (also
 129 known as the net radiation minus soil heat flux) is also separated into the available energy for vegetation
 130 transpiration, Q_{veg} ($W m^{-2}$) and Q_{soil} ($W m^{-2}$) for bare soil evaporation, which was expressed by Nishida
 131 et al. (2003) as:

132
$$Q = f_{veg}Q_{veg} + (1 - f_{veg})Q_{soil} \quad (2)$$

133 As satellites like Terra and Aqua only provide instantaneous snapshot observations of the Earth, a
 134 temporal scaling method is needed to convert instantaneous measurements into daily ET values. Nishida
 135 et al. (2003) used satellite-based noon time instantaneous evaporation fraction (EF), defined as the ratio
 136 of latent heat flux (ET) to available energy as daily EF ($EF = \frac{ET}{Q}$), multiplied the daily Q to calculated
 137 daily ET based on the assumption that EF is constant over a day:

138
$$ET = EF Q \quad (3)$$

139 In the next section, we will detail how VISEA calculates the daily EF , and Q in Eq. 3, daily air
 140 temperature and daily land surface temperature.

141 2.1.1 Daily evaporation fraction calculation

142 Combining Eq. 1, 2 and 3, we calculated the instantaneous evaporation fraction, EF^i as:

143
$$EF^i = f_{veg} \frac{Q_{veg}^i}{Q^i} EF_{veg}^i + (1 - f_{veg}) \frac{Q_{soil}^i}{Q^i} EF_{soil}^i \quad (4)$$

144 EF_{veg}^i and EF_{soil}^i are the instantaneous full vegetation coverage and bare soil EF , respectively. EF_{veg}^i can
 145 be expressed as a function of instantaneous parameters (Nishida et al., 2003):

146
$$EF_{veg}^i = \frac{\alpha \Delta^i}{\Delta^i + \gamma(1 + r_{cveg}^i / 2r_{aveg}^i)} \quad (5)$$

147 where α is the Priestley-Taylor parameter, which was set to 1.26 for wet surfaces (De Bruin, 1983); Δ^i is
 148 the instantaneous slope of the saturated vapor pressure, which is a function of the temperature ($Pa K^{-1}$);
 149 γ is the psychrometric constant ($Pa K^{-1}$); r_{cveg}^i is the instantaneous surface resistance of the vegetation
 150 canopy ($s m^{-1}$); r_{aveg}^i is the instantaneous aerodynamics resistance of the vegetation canopy ($s m^{-1}$).
 151 EF_{soil}^i was expressed by Nishida et al. (2003) as a function of the instantaneous soil temperature and the
 152 available energy based on the energy budget of the bare soil:

153
$$EF_{soil}^i = \frac{T_{soil\ max}^i - T_{soil}^i}{T_{soil\ max}^i - T_a^i} \frac{Q_{soil0}^i}{Q_{soil}^i} \quad (6)$$

154 where $T_{soil\ max}^i$ is the instantaneous maximum possible temperature at the surface reached when the land
 155 surface is dry (K), T_{soil}^i is the instantaneous temperature of the bare soil (K), T_a^i is the instantaneous air
 156 temperature, Q_{soil0}^i is the instantaneous available energy for bare soil when T_{soil}^i is equal to T_a^i ($W\ m^{-2}$).

157 As the assumption of noon time instantaneous evaporation fraction EF^i equals daily average
 158 evaporation fraction, EF^d , thus, $EF^i = EF^d$, caused a 10%-30% underestimation of daily ET (Huang
 159 et al., 2017; Yang et al., 2013), we introduced a decoupling parameter to covert EF^i into EF^d (Huang et
 160 al., 2021; Tang et al., 2017; Tang and Li, 2017). The superscript "d" means daily and "i" means
 161 instantaneous. This new decoupling parameter-based evaporation fraction is developed from Penman-
 162 Monteith and McNaughton-Jarvis mathematical equations:

163
$$EF^d = EF^i \frac{\Delta^d}{\Delta^d + \gamma} \frac{\Delta^{i+\gamma} \Omega^{*i} \Omega^d}{\Delta^i \Omega^{*d} \Omega^i} \quad (7)$$

164 where Ω is the decoupling factor that represents the relative contribution of radiative and aerodynamic
 165 terms to the overall evapotranspiration (Tang and Li, 2017), Ω_i^* is the value of the decoupling factor, Ω ,
 166 for wet surfaces. According to Pereira (2004), the calculation details of Ω and Ω^* are presented in
 167 Appendix B.

168 For full vegetation-covered areas, the decoupling parameter based daily EF_{veg}^d is expressed as:

169
$$EF_{veg}^d = \frac{\alpha \Delta^i}{\Delta^{i+\gamma} \left(1 + \frac{r_{c\ veg}^i}{2r_{a\ veg}^i}\right)} \left(\frac{\Delta^d}{\Delta^d + \gamma} \frac{\Delta^{i+\gamma} \Omega_{veg}^{*i} \Omega_{veg}^d}{\Delta^i \Omega_{veg}^{*d} \Omega_{veg}^i} \right) \quad (8)$$

170 where $r_{c\ veg}^i$ is the instantaneous canopy resistance ($s\ m^{-1}$), $r_{a\ veg}^i$ is the instantaneous aerodynamic
 171 resistance ($s\ m^{-1}$). Determining these resistances are presented in Appendix C. For bare soil, the
 172 decoupling parameter based daily EF_{soil}^d is calculated as:

173
$$EF_{soil}^d = \frac{T_{soil\ max}^i - T_{soil}^i}{T_{soil\ max}^i - T_a^i} \frac{Q_{soil0}^i}{Q_{soil}^i} \left(\frac{\Delta^d}{\Delta^d + \gamma} \frac{\Delta^{i+\gamma} \Omega_{soil}^{*i} \Omega_{soil}^d}{\Delta^i \Omega_{soil}^{*d} \Omega_{soil}^i} \right) \quad (9)$$

174 Thus, EF^d is expressed as:

175
$$EF^d = f_{veg} \frac{Q_{veg}^i}{Q^i} EF_{veg}^d + (1 - f_{veg}) \frac{Q_{soil}^i}{Q^i} EF_{soil}^d \quad (10)$$

176 The same energy balance equations are used for calculating both instantaneous values Q^i , Q_{veg}^i and Q_{soil}^i
 177 and daily values Q^d , Q_{veg}^d and Q_{soil}^d but with parameters adjusted for each timeframe. The details of the
 178 calculation for the daily values are outlined below.

179 **2.1.2 Daily calculation of available energy Q_{veg}^d and Q_{soil}^d**

180 We used an improved daily available energy Q ($W m^{-2}$) method (Huang et al., 2023b) for the
181 vegetation and the bare soil surface is calculated by the energy balance equation:

$$182 \quad R_n - G = Q \quad (11)$$

183 where R_n is the net radiation ($W m^{-2}$), which could be calculated by the land surface energy balance; G
184 is the soil heat flux ($W m^{-2}$), $G \approx 0$ on a daily basis (Fritschen and Gay, 1979; Nishida et al., 2003; Tang et
185 al., 2009),

$$186 \quad R_n^d = (1 - albedo^d)R_d^d - \varepsilon_s^d \sigma T_s^{d4} + (1 + Cloud^d)\varepsilon_a^d \sigma T_a^{d4} \quad (12)$$

187 where $albedo^d$ is the daily albedo of the soil surface; R_d^d is daily incoming shortwave radiation ($W m^{-2}$),
188 obtained from the ERA5_Land shortwave radiation (called ERA5_Rd); ε_s^d and ε_a^d are the daily
189 emissivity of land surface and atmosphere, σ is the Stefan-Boltzmann constant; T_a^d is the daily near-
190 surface air temperature (K); T_s^d is the daily surface temperature (K). The difference with the former study
191 by Huang et al. (2021) is that ε_s^d and ε_a^d were not set equal. Instead we calculated the ε_a^d using the method
192 of Brutsaert, (1975) and Wang and Dickinson(2013), as detailed in Appendix D and ε_s^d can be was
193 retrieved from MOD11C1.

194 We account for the influence of clouds by assuming a linear correlation between downward
195 longwave radiation and cloud coverage in the calculation of downward longwave radiation based on the
196 study of Huang et al. (2023b):

$$197 \quad Cloud^d = (1 - K_t) \quad (13)$$

198 where $Cloud^d$ is the daily clearness index and K_t is (Chang and Zhang, 2019; Goforth et al., 2002)

$$199 \quad K_t = \frac{R_a^d}{R_d^d} \quad (14)$$

200 where R_a^d is the daily extraterrestrial radiation calculated by the FAO (1998).

201 Q_{veg}^d can be calculated by assuming as $T_s^d = T_a^d$ according to the VI-Ts method which implies that
202 the minimum land surface temperature occurs in fully vegetated grid cells and is equivalent to T_a^d (Huang
203 et al., 2023b). According to the land surface energy budget, the daily available energy of vegetation
204 coverage area, Q_{veg}^d and bare soil Q_{soil}^d can be calculated following the study of Huang et al. (2023b):

$$205 \quad Q_{veg}^d = (1 - albedo^d)R_d^d + (1 + Cloud^d)\varepsilon_a^d \sigma T_a^{d4} - \varepsilon_s^d \sigma T_s^{d4} \quad (15)$$

$$206 \quad Q_{soil}^d = (1 - C_G)(1 - albedo^d)R_d^d + (1 + Cloud^d)\varepsilon_a^d \sigma T_a^{d4} - \varepsilon_s^d \sigma T_s^{d4} \quad (16)$$

207 The daily mean air temperature, T_a^d can be extended by a sin and cos function based on the
208 instantaneous air temperature T_a^i which was calculated using the linear correlation between vegetation

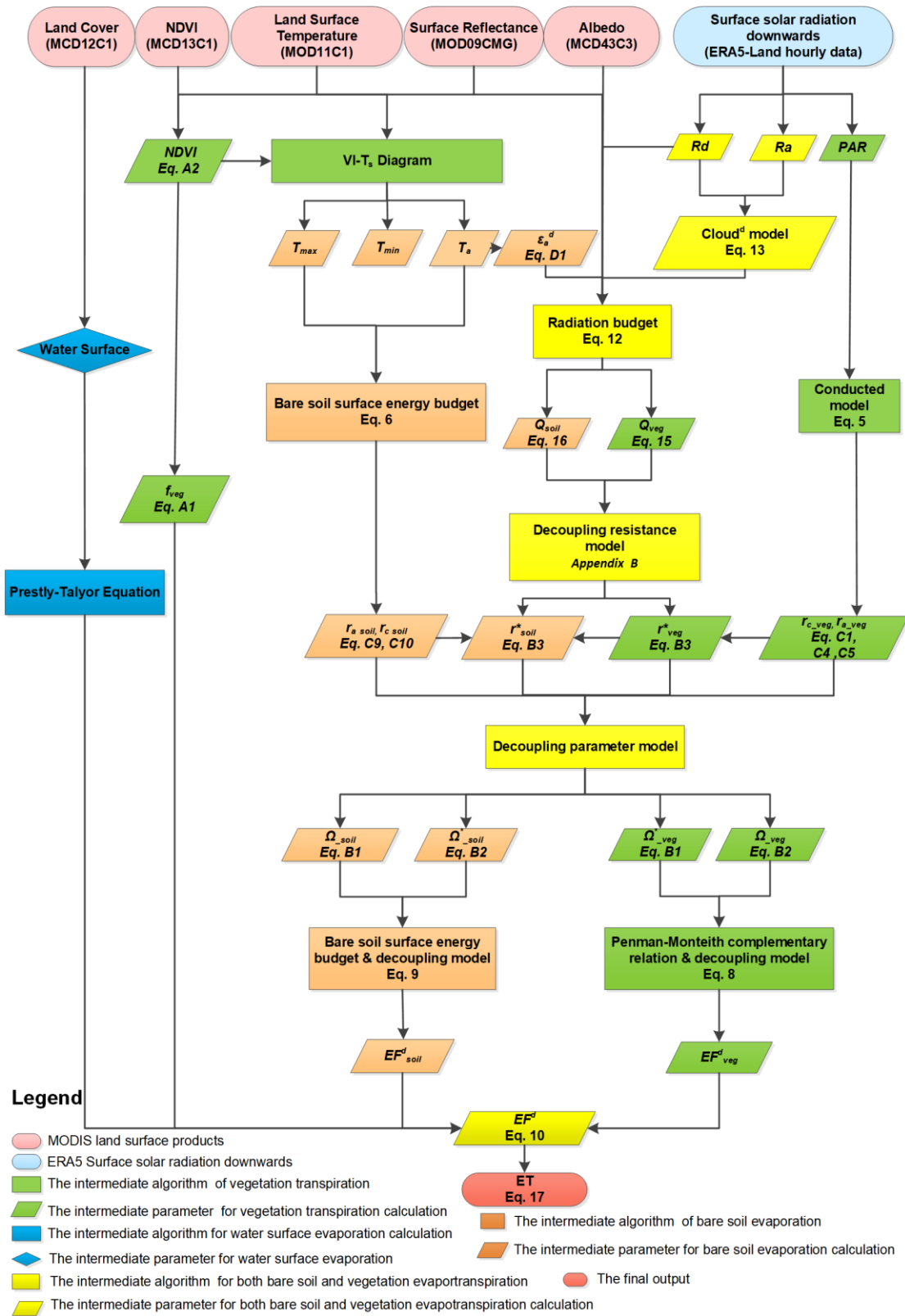
209 index (VI) and surface temperature (Ts) method. Thus, $(1 + Cloud^d)\epsilon_a^d\sigma T_a^{d4}$ is the daily downward
210 longwave radiation ($W m^{-2}$), and $\epsilon_s^d\sigma T_s^{d4}$ is the daily upward longwave radiation ($W m^{-2}$), where C_C is
211 an empirical coefficient ranging from 0.3 for a wet soil to 0.5 for a dry soil (Idso et al., 1975).

212 Q_{veg}^d and Q_{soil}^d are calculated by the energy balance equations, which are robust on both
213 instantaneous and daily scales. Thus instantaneous Q_{veg}^i and Q_{soil}^i are calculated by the same set of
214 equations Eq 17 and 18 by replacing the daily by the instantaneous parameters.

215 Following the study of Huang et al. (2023b), the daily ET^d can be calculated by the daily EF^d and
216 Q^d as:

$$217 \quad \quad \quad ET^d = EF^d Q^d \quad \quad \quad (17)$$

218 Figure 1 illustrates the workflow of VISEA. VISEA utilizes land cover data from the MOD12C1
219 IGBP land cover classification. When land cover in a MOD12C1 IGBP data grid cell is identified as a
220 water surface, VISEA then uses the Priestley-Taylor equation to compute water surface evaporation. This
221 process guarantees that the unique attributes of water surfaces are precisely reflected in VISEA ET
222 calculations.



223

224

225

226

Figure 1. Schematic of VISEA algorithm. The ovals in the top row are the databases, the square boxes are the algorithms, and parallelograms are the parameters. The numbers in the parenthesis are the equation to determine the parameters.

227 2.1.3 The calculation of daily air temperature, T_a^d and surface temperature, T_s^d

228 Daily air temperature, T_a^d is a critical parameter in the VISEA algorithm, used in calculations for
229 downward longwave radiation, daily aerodynamic resistance, and surface resistance. The key innovation
230 in calculating T_a^d , involves employing the VI-Ts method to estimate instantaneous air temperature, T_a^i
231 during the daytime (Huang et al., 2017; Nishida et al., 2003; Tang et al., 2009).

232 This VI-Ts method was developed based on the empirical linear relationship between the surface
233 temperature (Ts) and the Vegetation Index (VI). Surface temperature increases when the vegetation index
234 decreases, and conversely, surface temperature decreases when the vegetation index increases. In the
235 scatter plot, defined by VI (horizontal axis) and Ts (vertical axis) from the neighboring 5×5 grid cells,
236 we identify the "warm edge" (characterized by a low vegetation cover fraction and high Ts) and the "cold
237 edge" (marked by a high vegetation cover fraction and low Ts). The warm edge is automatically selected
238 as the hypotenuse of the triangle formed by these scatter points. Through simple interpolation, Ts
239 corresponding to any given vegetation condition within the range of the "warm edge" and "cold edge"
240 can be determined. The lowest Ts could be determined by the highest VI, and the highest Ts could be
241 determined by the lowest VI. Therefore, following Nishida et al. (2003), assuming that the lowest surface
242 temperature equals the air temperature (Ta), we can derive the daily air temperature.

243 For nighttime periods, it is assumed that air temperature is equivalent to the nighttime land surface
244 temperature provided by MOD11C1. These two temperature estimates are then extended into hourly air
245 temperature profiles using a sine-cosine fitting curve. The 24-hour average of T_a^i is used as T_a^d . Similarly,
246 T_s^d is calculated using MOD11C1 land surface temperature data for both daytime and nighttime. These
247 estimates are extended into hourly surface temperature profiles using a similar sine-cosine fitting curve,
248 and the daily average of T_s^d is determined (Huang et al., 2021).

249 This VI-Ts method allows for the estimation of T_a^i and $T_{soil\ max}^i$ without the need for additional
250 meteorological data. However, some studies have found that the VI-Ts method may not consistently
251 provide satisfactory results, especially in colder regions where vegetation thrives better under higher
252 temperatures.

253 2.2 Technical validation

254 The correlation coefficient, Root Mean Square Error (RMSE) and Nash-Sutcliffe efficiency
255 coefficient are used to evaluate our global daily ET estimates with eddy covariance measurements and
256 compared with the other five independent global ET products on a monthly scale.

257 The correlation coefficient R is calculated as:

$$258 \quad R = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \quad (18)$$

259 R is the correlation coefficient; X is the estimated variable; \bar{X} is the average of X; Y is the observed
260 variable; \bar{Y} is the average of Y.

261 The Root Mean Square Error (RMSE) is calculated as:

$$262 \quad RMSE = \sqrt{\frac{\sum_{i=1}^N (X_i - Y_i)^2}{N}} \quad (19)$$

263 For a more nuanced understanding of the Root Mean Square Error (RMSE), we have deconstructed
264 it into two distinct components: RMSEs (systematic RMSE) and RMSEu (unsystematic RMSE). This
265 breakdown allows a more detailed examination of the systematic and unsystematic sources contributing
266 to the overall error metric.

267 The systematic Root Mean Square Error (RMSEs) is calculated as:

$$268 \quad RMSEs = \sqrt{\frac{\sum_{i=1}^N (Z_i - Y_i)^2}{N}} \quad (20)$$

269 The unsystematic Root Mean Square Error (RMSEu) is calculated as:

$$270 \quad RMSEu = \sqrt{\frac{\sum_{i=1}^N (Z_i - X_i)^2}{N}} \quad (21)$$

271 Where $Z_i = a + bY_i$, where a and b are the least squares regression coefficients of the estimated variable
272 X_i and observed variable Y_i , N is the sample size (Norman et al., 1995).

273 The Nash-Sutcliffe efficiency coefficient (NSE)

$$274 \quad NSE = 1 - \frac{\sum (X_i - Y_i)^2}{\sum (Y_i - \bar{Y})^2} \quad (22)$$

275 The ratio of the standard deviations of X and Y

$$276 \quad Ratio = \frac{X_{Standard\ Deviation}}{Y_{Standard\ Deviation}} \quad (23)$$

277 The Bias of X and Y

$$278 \quad Bias = \bar{X} - \bar{Y} \quad (24)$$

279 **2.3 The gap-filling of MODIS data**

280 MODIS sensors on board of Terra and Aqua observe the Earth twice a day. However, there are
281 always data gaps in the MODIS land products because of cloud cover problems. In the VISEA algorithm,
282 we used the data from the neighboring days to fill the data gaps. The periods when MODIS Land
283 temperature data were missing, primarily due to cloud cover, accounted for approximately one-third of
284 the observation period. The accuracy of this gap-filling method is evaluated in Section 4.

285 3. Data

286 3.1 The input data

287 The input data including the MODIS land products: daily 0.05° surface reflectance (MOD09CMG),
288 land surface temperature/emissivity (MOD11C1) and albedo (MCD43C3), 8-day 0.05° vegetation
289 indices (MOD13C1) and yearly 0.05° land cover products (MCD12C1). We also used hourly downward
290 surface solar radiation from the Fifth Generation of the European Centre for Medium-Range Weather
291 Forecasts (ECMWF) Reanalysis (ERA5), “ERA5-Land hourly data from 1950 to present” data as energy
292 input of VISEA algorithm. The surface solar radiation data from ERA5-Land and land data products from
293 MODIS land products are both near-real-time datasets with a one-week delay, enabling VISEA to provide
294 global near-real-time ET estimations. Details of the input data, their download links, variable names, used
295 parameters, spatial and temporal resolution are given in Table 1.

296 **Table 1. The input of VISEA**

The input of VISEA			
Data source	Data name	Used parameter	Spatial/temporal resolution
MODIS Land Product	MOD11C1	Land Surface Temperature	0.05°/ daily
	MOD09CMG	Surface Reflectance	0.05°/daily
	MCD43C3	Albedo	0.05°/daily
	MOD13C1	NDVI	0.05°/16-day
	MCD12C1	Land Cover	0.05°/ yearly
ERA5-Land hourly data	Rd	Downward Surface Solar Radiation	0.1°/ hourly

297

298 3.2 The evaluation data

299 3.2.1 The flux tower measurements from FLUXNET

300 We evaluated the accuracy of the input ERA5-Land shortwave radiation, estimated daily net
301 radiation, air temperature, and ET by comparing them against measurements from FLUXNET2015
302 (Pastorello et al., 2020). FLUXNET consists of 212 globally distributed flux towers and it has
303 implemented quality control measures for energy closure and is considered reliable (Baldocchi et al.,
304 2001; Pastorello et al., 2020; Wang et al., 2022). The data from FLUXNET2015 can be obtained at
305 <https://fluxnet.org/data/download-data>. We selected data from 2001 to 2015 and excluded sites with zero
306 ERA5-Land downward shortwave radiation.

307 While there are records from 212 flux towers in our datasets, not all met the stringent inclusion
308 criteria. Each site needed to fulfill three specific requirements to be included in our analysis: (1)
309 availability of data for the period spanning from 2001 to 2015; (2) ERA5-Land downward shortwave
310 radiation greater than 0 within the 0.1° × 0.1° grid cell corresponding to the flux tower's location; (3)
311 conformity with MODIS land cover data (MOD12C1) at the 0.05° × 0.05° grid cell level, ensuring that
312 the flux tower was situated on land rather than over the ocean. Based on these criteria, we selected a

313 subset of 149 flux towers that met these stringent criteria. This approach ensures the reliability and
 314 relevance of our analysis. The distribution of these 149 flux towers is presented in Figure 2.
 315 Supplementary Table S1 shows the longitude, latitude, elevation, and land cover type (classified by the
 316 International Geosphere-Biosphere Programme, IGBP) of these sites. The 149 sites covered 12 IGBP
 317 land cover types: 18 croplands (CRO), 1 closed shrublands (CSH), 15 deciduous broadleaf forests (DBF),
 318 1 deciduous needle leaf forest (DNF), 10 evergreen broadleaf forests (EBF), 34 evergreen needle leaf
 319 forests (ENF), 30 grasslands (GRA), 5 mixed forests (MF), 8 open shrublands (OSH), 8 savannas (SAV),
 320 13 wetlands (WET), and 6 woody savannas (WSA).

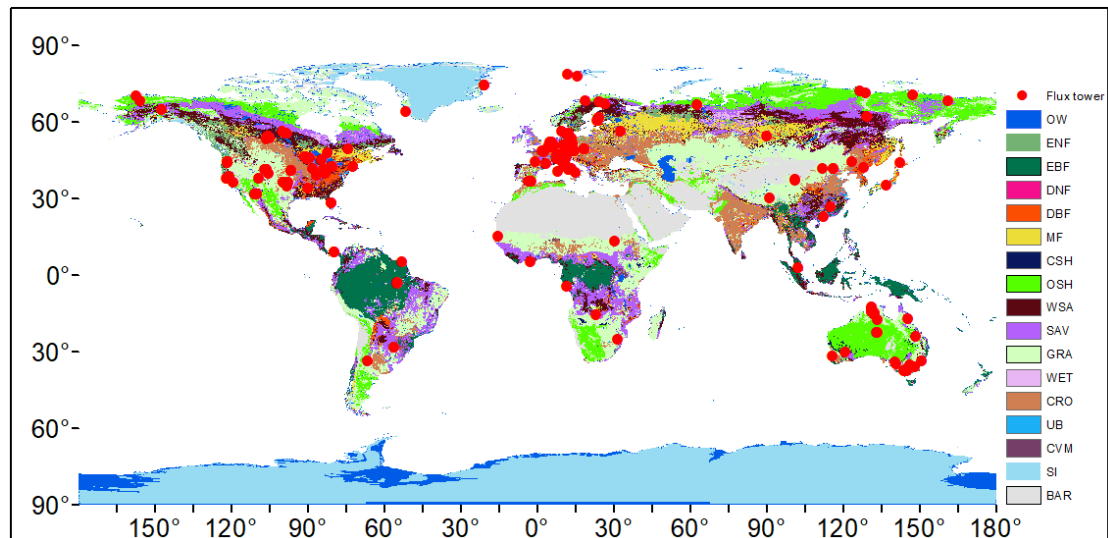
321 3.2.2 The other gridded ET and precipitation products

322 Five independent globally gridded ET products and one precipitation product were used to evaluate
 323 VISEA estimated ET. The five ET products include two MODIS-based ET products: MOD16 (Mu et al.,
 324 2007, 2011) and Penman-Monteith-Leuning Evapotranspiration V2 (PML) (Zhang et al., 2019, 2022),
 325 one AVHRR-based AVHRR ET (Zhang et al., 2009, 2010), one machine learning algorithm output, the
 326 FLUXCOM ET data (Jung et al., 2009, 2010, 2018, 2019) and one multiple-satellites data based Global
 327 Land Evaporation Amsterdam Model (GLEAM) ET (Martens et al., 2017; Miralles et al., 2011). The
 328 precipitation data was from the Global Precipitation Climatology Centre (GPCC), which is based on local
 329 measurements (Becker et al., 2013; Schneider et al., 2014, 2017) and Global Unified Gauge-Based
 330 Analysis of Daily Precipitation (GPC). Details of these five ET products and the precipitation data are
 331 given in Table 2. To maintain the consistency in temporal and spatial resolution for comparison purposes,
 332 we obtained monthly MOD16 and PML despite their original temporal resolution of 8 days. We used the
 333 $0.05^\circ \times 0.05^\circ$ version of MOD16, AVHRR ET and PML. Additionally, for multi-year scale comparisons,
 334 we confined our dataset to the timeframe between 2001 and 2020. This selection enabled us to utilize a
 335 diverse range of ET products, effectively minimizing the influence of temporal discrepancies on our
 336 comparative analysis. We also incorporated daily Evapotranspiration (ET) data from GLEAM and
 337 VISEA, alongside precipitation data from the Climate Prediction Center (CPC), from July 25th to August
 338 2nd, 2022. It allowed for near-real-time analysis of ET and precipitation during the Yangtze River drought
 339 incident within that interval, despite the datasets potentially encompassing more extensive periods.

340 **Table 2.** The five global girded ET products and one precipitation product used for comparison with our
 341 near-real-time global daily terrestrial ET estimates.

Product name	Spatial/Temporal resolution	Time period	Theory
GLEAM	0.25°/Monthly	2001-2022	Priestly-Taylor Equation
FLUXCOM	0.5°/Monthly	2001-2016	Machine Learning
MOD16	0.05°/Monthly	2001-2014	Penman-Monteith Equation
AVHRR	1°/Monthly	2001-2006	Improved Penman-Monteith Equation
PML	0.05°/8-day	2003-2018	Penman-Monteith Equation and A Diagnostic Biophysical Model
GPCC	0.25°/Monthly	2001-2019	In-situ Observations
GPC	0.5°/Daily	08/28/2022-09/01/2022	Global Unified Gauge-Based Analysis of Daily Precipitation

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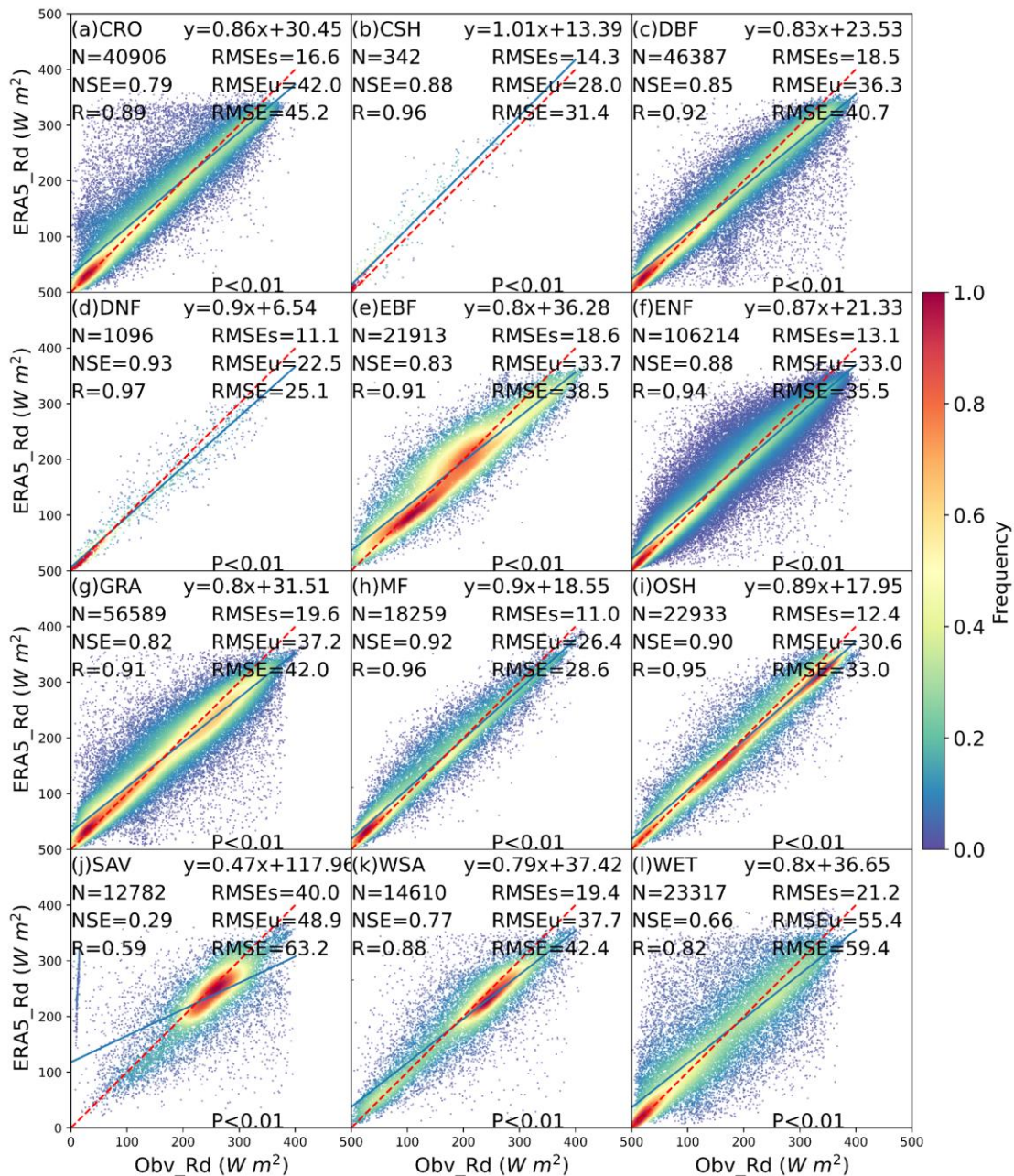
344 **Figure 2.** The distribution of 149 flux towers from FLUXNET in different IGBP land cover types,
 345 specifically OW (Water bodies), ENF (Evergreen needle leaf forests), EBF (Evergreen broadleaf forests),
 346 DNF (Deciduous needle leaf forests), DBF (Deciduous broadleaf forests), MF (Mixed forests), CSH
 347 (Closed shrublands), OSH (Open shrublands), WSA (Woody savannas), SAV (Savannas), GRA
 348 (Grasslands), WET (Permanent wetlands), CRO (Croplands), UB (Urban and built-up lands), CVM
 349 (Cropland/natural vegetation mosaics), SI (Snow and ice), BAR (Barren).

350 4. Results

351 To evaluate the performance of ERA5_Rd across different land cover initial categories, we
 352 juxtaposed downward solar radiation input data from ERA5-Land (ERA5_Rd) with measurements
 353 obtained from 149 flux towers (Obv_Rd) across diverse IGBP land cover types, as illustrated in Figure
 354 3. The results indicate a commendable agreement between ERA5_Rd and Obv_Rd measurements for the
 355 majority of land covers, with notable exceptions observed in savanna (SAV). Specifically, the mean
 356 Nash-Sutcliffe Efficiency (NSE) stands at 0.84, the mean correlation coefficient (R) at 0.92, and the mean
 357 Root Mean Square Error (RMSE) at 38.3 W m^{-2} .

358 Figure 3 shows that ERA5 input shortwave radiation generally agrees well with local measurements.
 359 ERA5_Rd exhibits optimal performance in DNF and MF, reflected by NSE and R values surpassing 0.9.
 360 In these land covers, the mean RMSEs stand at 11 W m^{-2} , mean RMSEu at 24.5 W m^{-2} , and mean RMSE
 361 at 26.9 W m^{-2} . However, its performance in SAV is notably subpar, characterized by an NSE of 0.29, an
 362 R of 0.59, highest RMSEs of 40 W m^{-2} , RMSEu of 48.9 W m^{-2} , and RMSE of 63.2 W m^{-2} . For ERA5_Rd,
 363 the mean RMSEs amount to 16 W m^{-2} , and the mean RMSEu is 34.8 W m^{-2} , suggesting that ERA5_Rd
 364 demonstrates high accuracy by effectively capturing the systematic variation in Obv_Rd, as indicated by
 365 its relatively low RMSEs and RMSEu close to RMSE (Willmott et al., 1981) in most land covers, except
 366 for SAV. Specifically, in Figure 3, Rd s derived from ERA5 exhibit very low P-values (<0.01).

367



368

369 **Figure 3.** The scatter plot of downward solar radiation from ERA5-Land (ERA5_Rd) compared with
 370 local instruments measurements (Obv_Rd) under 12 IGBP land cover types: CRO (Croplands), CSH
 371 (Closed shrublands), DBF (Deciduous broadleaf forests), DNF (Deciduous needle leaf forests), EBF
 372 (Evergreen broadleaf forests), ENF (Evergreen needle leaf forests), GRA (Grasslands), MF (Mixed
 373 forests), OSH (Open shrublands), SAV (Savannas), WSA (Woody savannas), WET (Permanent
 374 wetlands). The red dotted line is the 1:1 line. N is the number of data points, NSE is Nash-Sutcliffe
 375 Efficiency, R is correlation coefficients, RMSE is Root Mean Square Error, RMSEs is systematic RMSE,
 376 and RMSEu is unsystematic RMSE. The Frequency denotes the probability density estimated through
 377 the KDE method with a Gaussian kernel, and it is then scaled to ensure that the maximum value of the
 378 probability density function equals 1. P is the P-Value for the Correlation Coefficient.

379

380 Several factors come into play in understanding the disparities in performance in downward solar
 radiation of ERA5 (ERA5_Rd) across different land cover types. In regions characterized by denser

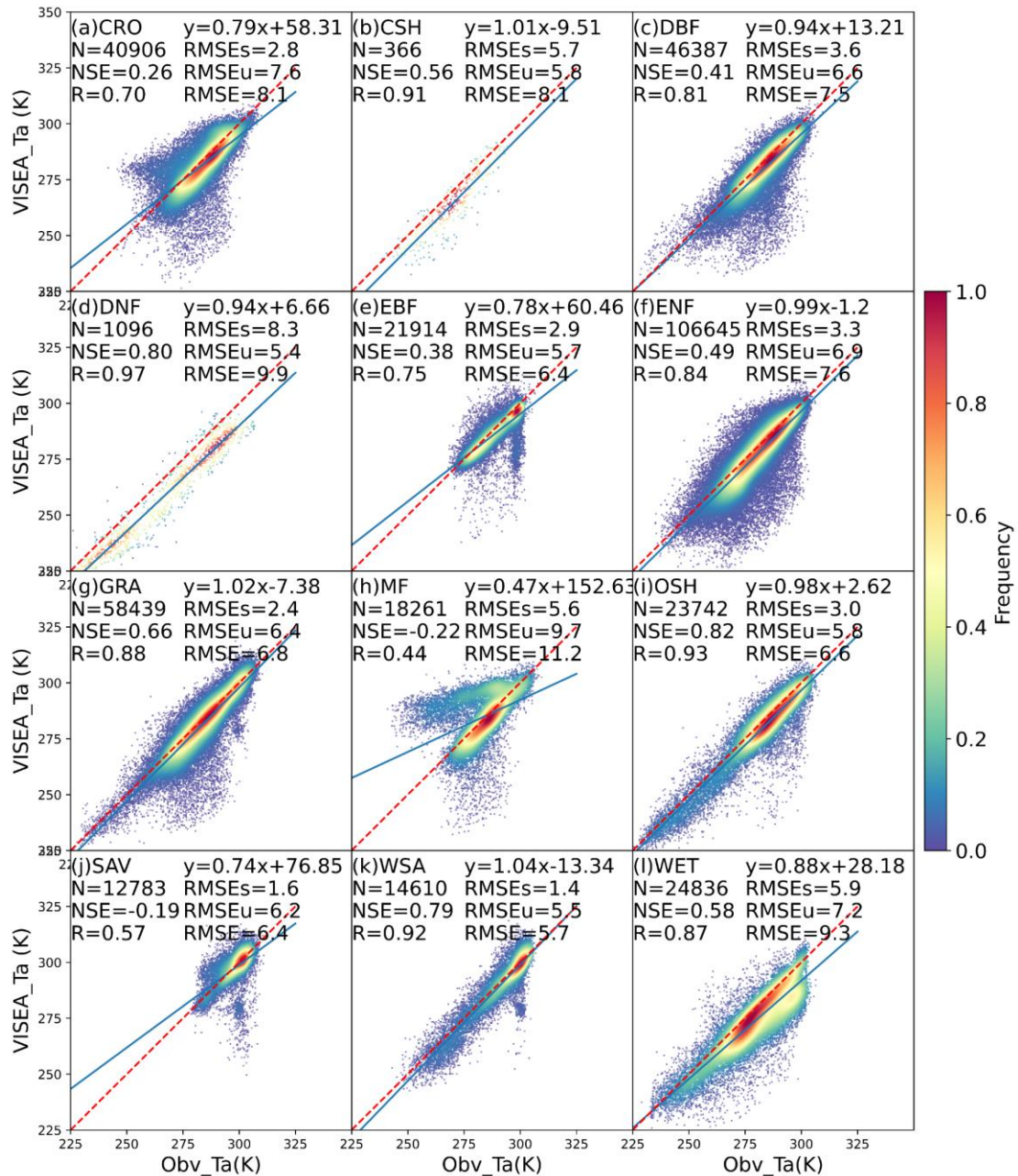
381 forests, such as DNF and MF, ERA5_Rd's good performance may be attributed to the lower density of
382 ground-based meteorology stations (DNF, N = 1096) and the relatively uniform subsurface and canopy
383 coverage in MF, facilitating a more accurate representation in the ERA5 radiative transfer model.
384 Conversely, savannas present unique challenges due to sparse vegetation and flat terrain, influencing
385 sunlight transmission dynamics (Yang and Friedl, 2003). Land-use changes, including farming and urban
386 development, further complicate the accuracy of sunlight transmission. Additionally, factors like aerosols
387 from natural or anthropogenic sources contribute to data variations (Naud et al., 2014; Wang et al.,
388 2021b). The inaccuracies in accounting for the rainy season, leading to increased cloud cover and rainfall
389 in savannas, contribute to ERA5_Rd's limitations (Jiang et al., 2020).

390 We chose to utilize 0.05° MODIS data for its detailed land surface information, daily time step, and
391 global coverage, which is essential for accurate and near-real-time ET calculations. Although ERA5 data
392 is at a coarser 0.1° resolution, it provides necessary atmospheric inputs that can be effectively interpolated
393 to match the MODIS resolution without significant loss of accuracy. As illustrated in Figures 3 and 4,
394 our tests confirm that this method achieves accurate ET despite the resolution differences.

395 Figure 4 depicts scatter plots illustrating the comparison between the estimated air temperature using
396 the VI-Ts method (VISEA_Ta) and local meteorological measurements (Obv_Ta). The analysis reveals
397 that VISEA_Ta generally aligns with Obv_Ta, exhibiting NSE values ranging from -0.22 (MF) to 0.82
398 (OSH), R values ranging from 0.44 (MF) to 0.97 (DNF), and RMSE values ranging from 5.7 K (WSA)
399 to 11.2 K (MF). Particularly noteworthy is VISEA_Ta's outstanding performance at OSH (NSE = 0.82,
400 R = 0.93, RMSE = 6.6 K), WSA (NSE = 0.79, R = 0.92, RMSE = 5.7 K) and GRA (NSE = 0.66, R =
401 0.88, RMSE = 6.8 K). Conversely, the least satisfactory performance is evident at MF (NSE = -0.22, R =
402 0.44, RMSE = 11.2 K), SAV (NSE = -0.19, R = 0.57, RMSE = 6.4 K), and CRO (NSE = 0.26, R =
403 0.70, RMSE = 8.1 K). The RMSEs are lower than RMSEu in most land cover sites, except in DNF.
404 Despite VISEA_Ta displaying a high NSE of 0.8 and R of 0.97 at DNF, it exhibits higher RMSEs (8.3
405 K) compared to RMSEu (5.4 K), indicating a systematic underestimation of VISEA_Ta at DNF.

406 As detailed in Section 2.4, the VI-Ts method relies on a negative correlation between vegetation
407 coverage (VI) and land surface temperature (Ts), ideally suited for cases with significant VI and Ts
408 differences. However, the assumed negative correlation breaks down for land cover types like DNF and
409 MF in temperate regions with distinct seasons and cool-to-cold climates. In these regions, the positive
410 correlation between VI and Ts, driven by vegetation growth proportional to rising Ts, results in the failure
411 of the VI-Ts method. The challenges persist in SAV, where the VI-Ts method encounters difficulties
412 during dry and wet seasons. In the dry season, the method falters due to the prevalence of bare soil,
413 resulting in VI values approaching zero and homogeneous high Ts values. Conversely, the wet season
414 presents challenges, with both VI and Ts exhibiting relatively high values and limited variances between
415 grid cells, ultimately undermining the accuracy of VISEA_Ta estimation.

416



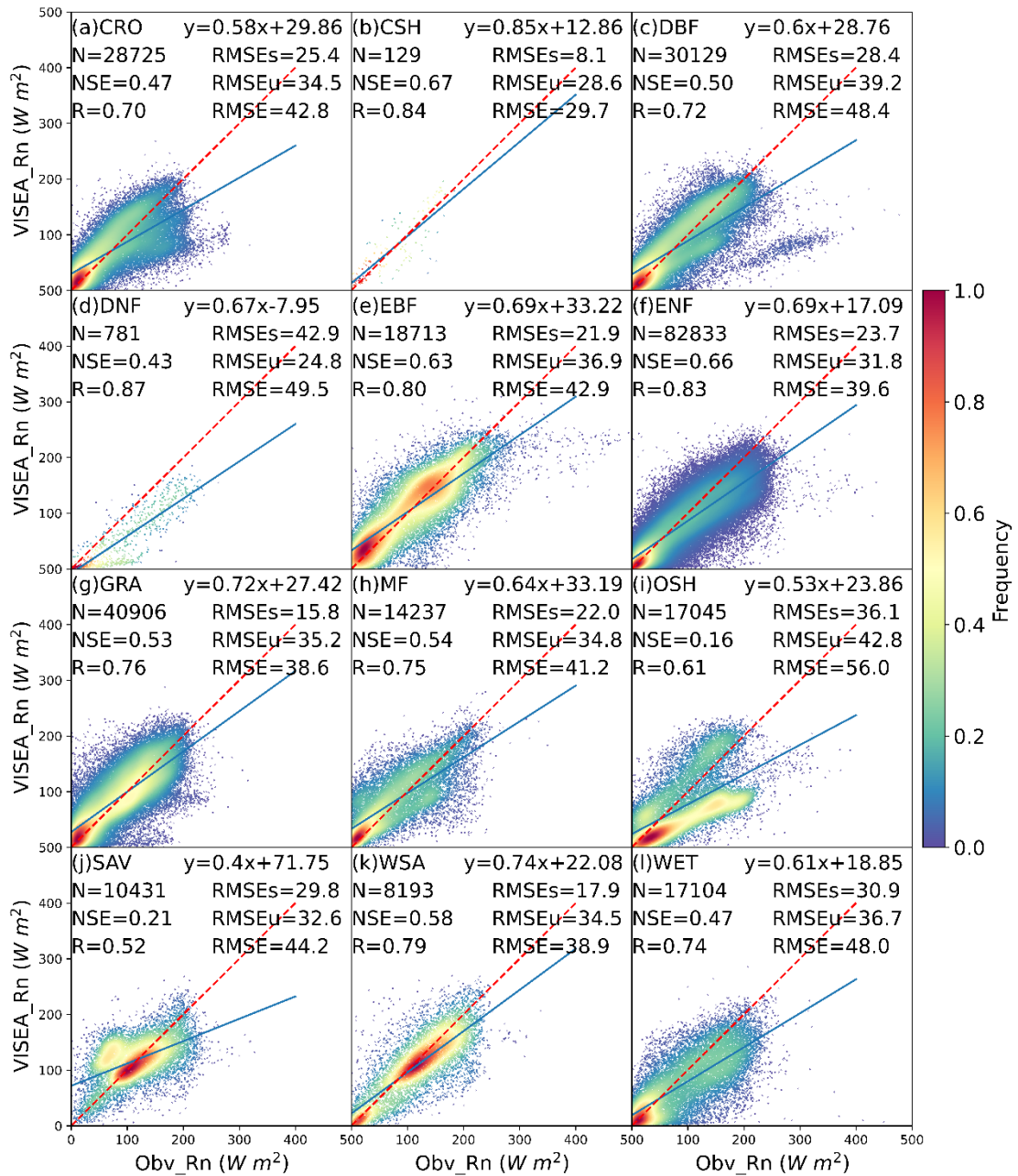
417

418 **Figure 4.** The scatter plot of daily air temperature simulated by VISEA (VISEA_Ta) compared with local
 419 instruments measurements (Obv_Ta) under 12 IGBP land cover types: CRO (Croplands), CSH (Closed
 420 shrublands), DBF (Deciduous broadleaf forests), DNF (Deciduous needle leaf forests), EBF (Evergreen
 421 broadleaf forests), ENF (Evergreen needle leaf forests), GRA (Grasslands), MF (Mixed forests), OSH
 422 (Open shrublands), SAV (Savannas), WSA (Woody savannas), WET (Permanent wetlands). The red
 423 dotted line is the 1:1 line. N is the number of data points, NSE is Nash-Sutcliffe Efficiency, R is
 424 correlation coefficients, RMSE is Root Mean Square Error, RMSEs is systematic RMSE, and RMSEu is
 425 unsystematic RMSE. The frequency denotes the probability density estimated through the Kernel Density
 426 Estimation, KDE method with a Gaussian kernel, and it is then scaled to ensure that the maximum value
 427 of the probability density function equals 1.

428 The simulated daily net radiation (VISEA_Rn) from VISEA is assessed against local meteorological
429 measurements (Obv_Rn) in Figure 5. In contrast to the satisfactory performance of ERA5_Rd in Figure
430 3, VISEA_Rn exhibits more notable discrepancies, characterized by significant underestimation
431 compared to Obv_Rn. This is reflected in the mean NSE of 0.49, mean R of 0.74, and mean RMSE of
432 43.3 W m⁻². Specifically, VISEA_Rn demonstrates good accuracy in certain land cover types, including
433 CHS with an NSE of 0.67, R of 0.84, and RMSE of 29.7 W m⁻², EBF with an NSE of 0.63, R of 0.8, and
434 RMSE of 42.9 W m⁻², and ENF with an NSE of 0.66, R of 0.83, and RMSE of 39.6 W m⁻². However, its
435 performance diminishes notably at OSH, where it records an NSE of 0.16, R of 0.61, and RMSE of 56
436 W m⁻², as well as in SAV, with an NSE of 0.21, R of 0.52, and RMSE of 44.2 W m⁻². While VISEA_Rn
437 appears to have lower accuracy compared to ERA5_Rd, in the majority of land cover types, the RMSEs
438 are smaller than RMSEu, with mean RMSEs of 25.2 W m⁻² and mean RMSEu of 34.3 W m⁻². Moreover,
439 the RMSEu of 43.3 W m⁻² is almost the same as the RMSE.

440 In the context of VISEA_Rn, a consistent pattern of approximately 30% underestimation in net
441 radiation across various land cover types raises noteworthy discussions. This systematic discrepancy
442 could be linked to the disparity in vegetation coverage between the observed sites' footprint and the mean
443 vegetation coverage of the 0.05° × 0.05° grid cell. Specifically, the lower albedo within the footprint,
444 compared to the grid cell's average albedo (as expressed by Eq. 14, contributes to the underestimation of
445 Obv_Rn. This is particularly evident in OSH, where the vegetation coverage within the footprint
446 significantly exceeds the mean vegetation coverage of the grid cell (<0.2 compared to >0.5). Factors such
447 as the bias in ERA5_Rd (refer to Fig. 3j) and VISEA_Ta (refer to Fig. 4j) contribute to the
448 underestimation of VISEA_Rn in SAV. Moreover, a substantial 50% underestimation in DNF results
449 from the underestimated VISEA_Ta (refer to Fig. 4d) leads to a subsequent underestimation of downward
450 long-wave radiation.

451

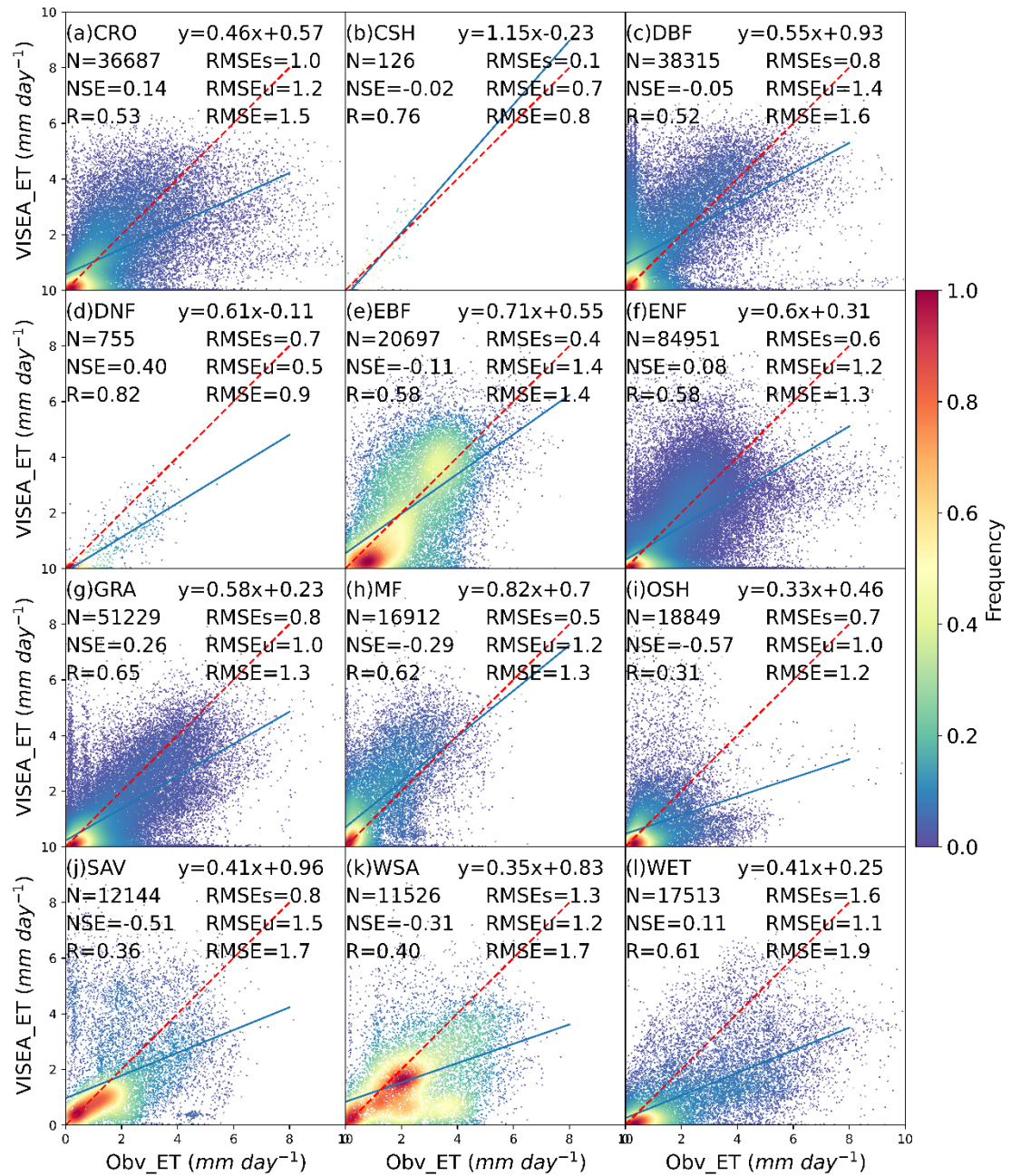


452

453 **Figure 5.** The scatter plot of daily net radiation simulated by VISEA (VISEA_Rn) compared with local
 454 instruments measurements (Obv_Rn) under 12 IGBP land cover types: CRO (Croplands), CSH (Closed
 455 shrublands), DBF (Deciduous broadleaf forests), DNF (Deciduous needle leaf forests), EBF (Evergreen
 456 broadleaf forests), ENF (Evergreen needle leaf forests), GRA (Grasslands), MF (Mixed forests), OSH
 457 (Open shrublands), SAV (Savannas), WSA (Woody savannas), WET (Permanent wetlands). The red
 458 dotted line is the 1:1 line. N is the number of data points, NSE is Nash-Sutcliffe Efficiency, R is
 459 correlation coefficients, RMSE is Root Mean Square Error, RMSEs is systematic RMSE, and RMSEu is
 460 unsystematic RMSE. The frequency denotes the probability density estimated through the Kernel Density
 461 Estimation, KDE method with a Gaussian kernel, and it is then scaled to ensure that the maximum value
 462 of the probability density function equals 1.

463 Figure 6 illustrates scatter plots of daily evapotranspiration (ET) simulated by VISEA (VISEA_ET)
464 against eddy covariance measurements obtained from 149 flux tower sites (Obv_ET) across 12 IGBP
465 land cover types. The scatter plots of VISEA_ET reveal a dispersed distribution, as evidenced by an
466 average NSE of -0.08, average R of 0.56, and average RMSE of 1.4 mm day⁻¹. Notably, VISEA_ET tends
467 to underestimate daily ET across most land cover types. Among the 12 land cover types, VISEA_ET
468 exhibits the highest accuracy in DNF, with an NSE of 0.4, an R of 0.82, and an RMSE of 0.9 mm day⁻¹.
469 It was closely followed by GRA, with NSE values of 0.26, R values of 0.65, and RMSE values of 1.3
470 mm day⁻¹. However, for CRO, ENF, and WET land cover types, the NSE values, although above 0, are
471 close to 0 (mean NSE of 0.11), with a mean R of 0.53 and a mean RMSE of 1.3 mm day⁻¹. In the remaining
472 land cover types, particularly in OSH and SAV, VISEA_ET appears to struggle in aligning with local
473 measurements, resulting in NSE values of -0.57 and -0.51, R values of 0.31 and 0.36, and RMSE values
474 of 1.2 mm day⁻¹ and 1.7 mm day⁻¹, respectively. As the evaluation of daily VISEA_ET with observed
475 ET, Obv_ET, at CRO and WET, the bias mainly comes from the bias in ERA5_Rd (the third highest
476 RMSE of 45.2 W m⁻² and second highest RMSE of 59.4 W m⁻²) (Fig. 3a and l). In ENF, the biases
477 primarily is caused by the disability of VISEA_ET to capture the Obv_ET under a cold climate, with low
478 net radiation estimation (Fig. 5f) and air temperature (Fig. 4f). For OSH, the bias mainly arises from the
479 poor estimation of VISEA_Rn, which has the lowest NSE of 0.16 and the highest RMSE of 56 W m⁻²
480 (Fig. 5i). The bias of VISEA_ET in SAV is a result of the combined biases in ERA5_Rd (the lowest NSE
481 and R of 0.29 and 0.59, respectively, and the highest RMSE of 63.2 W m⁻²), VISEA_Ta (the second
482 lowest NSE and R of -0.19 and 0.57, respectively).

483 The periods when MODIS land temperature data were missing, primarily due to cloud cover,
484 accounted for approximately one-third of the observation period. Using the gap-filling method (section
485 2.3), it can be observed that for most surfaces, the accuracy of VISEA was not significantly affected by
486 clouds, as evidenced by the figures below. The accuracy on cloudy days is slightly lower for some
487 surfaces compared to clear days. For example, in the case of DBF, the correlation coefficient R is 0.52
488 on both clear and cloudy days, and the RMSE is 1.4 mm day⁻¹ on both clear and cloudy days, indicating
489 a slight decrease in accuracy under cloudy conditions. Similarly, for ENF, the R value is 0.59 on clear
490 days and 0.56 on cloudy days. At the same time, the RMSE is 1.3 mm day⁻¹ on clear days and 1.4 mm
491 day⁻¹ on cloudy days, showing that although there is some impact, the overall performance of VISEA
492 remains robust across different weather conditions (Figures S4 and S5).



493

494 **Figure 6.** The scatter plot of daily ET simulated by VISEA (VISEA_ET) compared with local instruments
 495 measurements (Obsv_ET) under 12 IGBP land cover types: CRO (Croplands), CSH (Closed shrublands),
 496 DBF (Deciduous broadleaf forests), DNF (Deciduous needle leaf forests), EBF (Evergreen broadleaf
 497 forests), ENF (Evergreen needle leaf forests), GRA (Grasslands), MF (Mixed forests), OSH (Open
 498 shrublands), SAV (Savannas), WSA (Woody savannas), WET (Permanent wetlands). The red dotted line
 499 is the 1:1 line. N is the number of data points, NSE is Nash-Sutcliffe Efficiency, R is correlation
 500 coefficients, RMSE is Root Mean Square Error, RMSEs is systematic RMSE, and RMSEu is
 501 unsystematic RMSE. The frequency denotes the probability density estimated through the Kernel Density
 502 Estimation, KDE method with a Gaussian kernel, and it is then scaled to ensure that the maximum value
 503 of the probability density function equals 1.

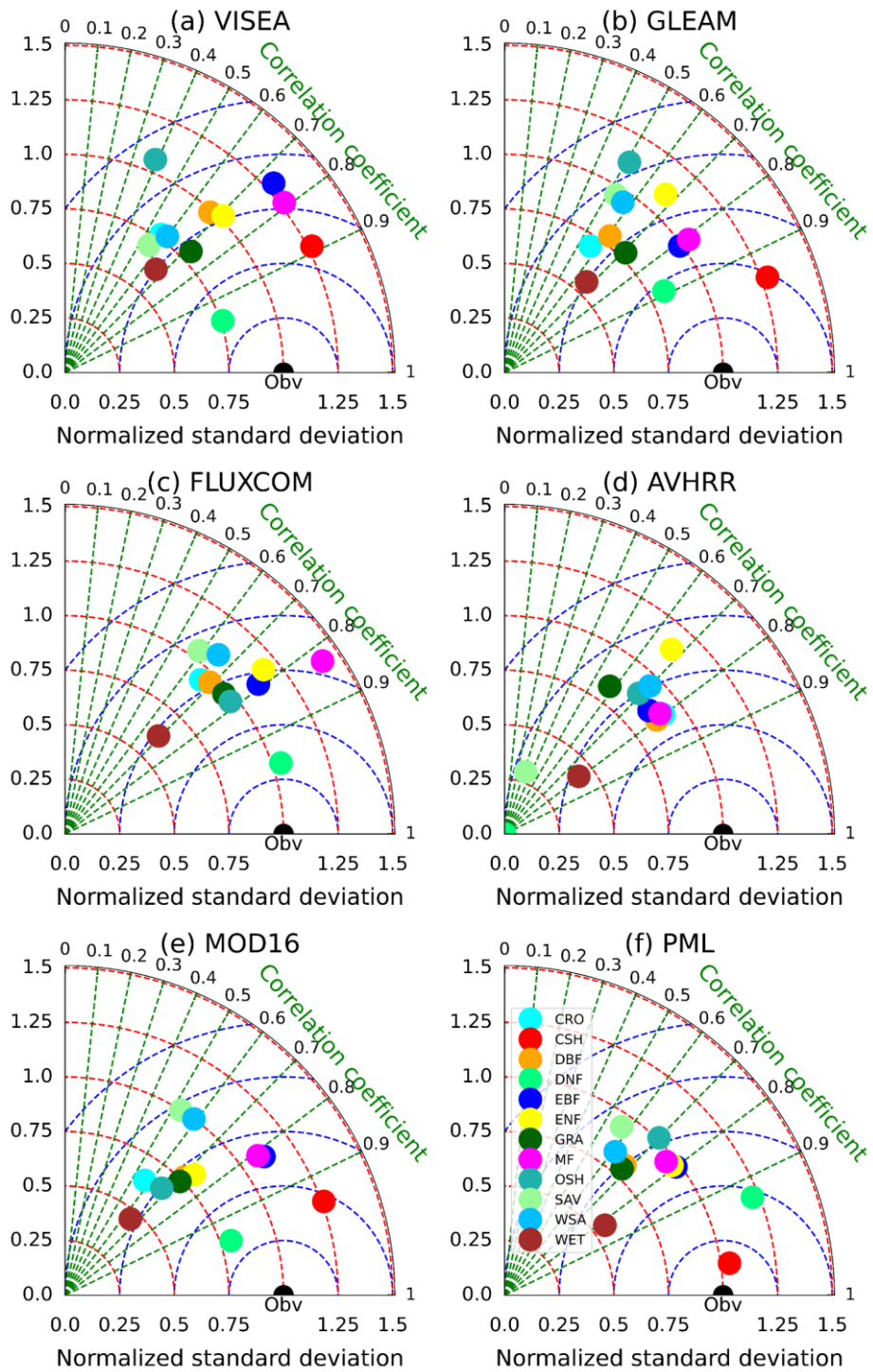
504 We also conducted the VISEA sensitivity to different radiation input data by comparing results
505 obtained using CERES and ERA5 datasets. Specifically, we analyzed the performance of the VISEA
506 model in simulating net radiation (Rn) and evapotranspiration (ET), comparing these simulations with
507 ground-based observational data. Figures S1 and 2 compare the downward shortwave radiation data from
508 CERES and ERA5 with ground-based observations of the 149 flux towers. The CERES shortwave
509 radiation data generally agree with the observational data, with a mean R of 0.89, a mean RMSE of 34.8
510 W m², and a mean NSE of 0.78. In contrast, the ERA5 shortwave radiation data mean R of 0.85, a mean
511 RMSE of 40.4 W m², and a mean NSE of 0.58 when compared with the ground-based observations,
512 indicating systematic bias and lower precision for the ERA5 net radiation compared with CERES. Figures
513 S2 and 5 compare the net radiation of the flux towers with that calculated by the VISEA model with
514 shortwave radiation of CERES and ERA5 as input data. For CERES data, the mean R is 0.74, the mean
515 RMSE is 34.3 W m² and the mean NSE is 0.64. The ERA5 data yield a mean R of 0.64, a mean RMSE
516 of 39.44 W m², and a mean NSE of 0.44. Finally, the ET calculated with the VISEA using the net radiation
517 of CERES and ERA5 as input is compared with ground-based data in Figures S3 and 6. Again, CERES
518 outperforms ERA5 as indicated by the statistical measures. The sensitivity analysis reveals that the
519 VISEA model's performance highly depends on the quality of the incident radiation data used as input.
520 The model shows better accuracy and consistency with CERES data than ERA5 data. Therefore, selecting
521 high-precision radiation data is crucial for improving the accuracy and reliability of VISEA model
522 simulations.

523 In Figure 7, we utilized Taylor diagrams (Taylor, 2001) to evaluate the performances of six global
524 gridded monthly ET products with simulated ET from VISEA (a), GLEAM (b), FLUXCOM (c), AVHRR
525 (d), MOD16 (e), and PML (f). Table 3 lists the statistical metrics, including correlation coefficient (CC),
526 bias, RMSE, RMSEu, RMSEs, and Nash-Sutcliffe Efficiency (NSE) across different vegetation types
527 and their mean values. The vegetation types include Croplands (CRO), Closed Shrublands (CSH),
528 Deciduous Broadleaf Forest (DBF), Deciduous Needleleaf Forest (DNF), Evergreen Broadleaf Forest
529 (EBF), Evergreen Needleleaf Forest (ENF), Grasslands (GRA), Mixed Forests (MF), Open Shrublands
530 (OSH), Savannas (SAV), Woody Savannas (WSA), Wetlands (WET), and an overall mean (MEAN).

531 VISEA, with a mean correlation coefficient (CC) of 0.69, indicates moderate correlation across
532 vegetation types but suffers from significant biases, notably in WET, with a mean bias of -9.56 mm
533 month⁻¹. It also has the highest mean Root Mean Square Error (RMSE) at 31.6 mm month⁻¹ and a mean
534 NSE of 0.25. MOD16 demonstrates a slightly better correlation with a mean CC of 0.72 and presents less
535 variation in bias, resulting in a marginally lower mean RMSE of 28.7 mm month⁻¹ and a higher mean
536 NSE of 0.36. AVHRR matches VISEA in mean CC at 0.69 but exhibits extreme biases, particularly in
537 SAV, and achieves a comparable mean RMSE of 26.3 mm month⁻¹. However, its mean NSE of 0.10 is
538 the lowest among the six products, suggesting its predictions are less reliable.

539 On the other hand, GLEAM, FLUXCOM, and PML show better agreements. GLEAM has a high
540 mean CC of 0.69 with the lowest bias at -0.82 mm month⁻¹, indicating consistent performance with a
541 mean RMSE of 29.6 mm month⁻¹ and a mean NSE of 0.31. FLUXCOM exhibits a higher mean CC of
542 0.76, suggesting better overall correlation, but with a higher mean bias of 6.2 mm month⁻¹, it hints at a

543 tendency towards overestimation. The mean RMSE is 30.0 mm month⁻¹, with a mean NSE of 0.22. PML
 544 outperforms the others, with the highest mean CC of 0.75 and the highest mean NSE of 0.49, indicating
 545 the strongest predictive accuracy. It also has the lowest mean RMSE at 26.0 mm month⁻¹.



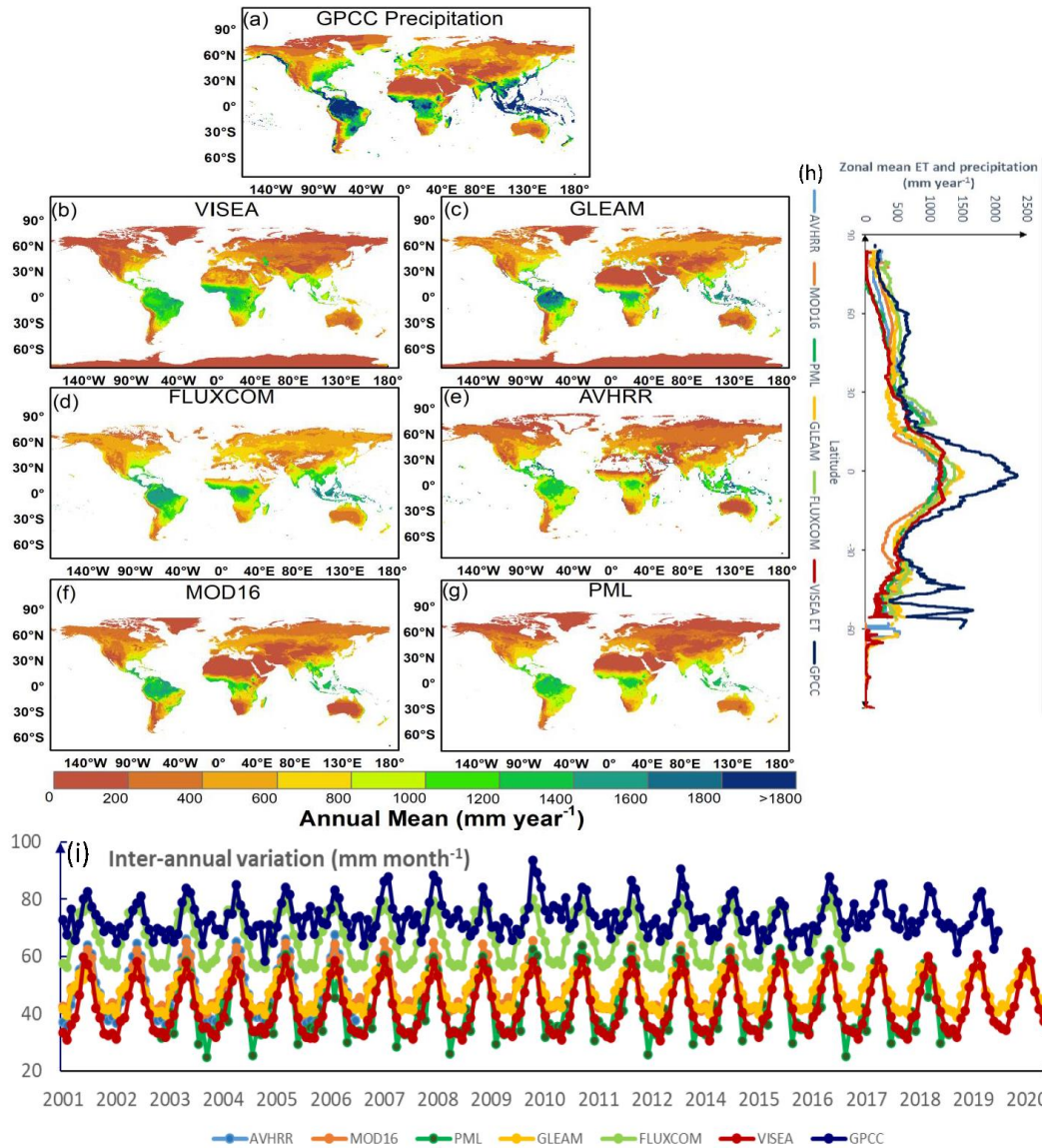
546
 547 **Figure 7.** Taylor Diagrams comparing monthly measurements of (a) VISEA, GLEAM (b), FLUXCOM
 548 (c), AVHRR (d), MOD16 (e), and PML (f) with 150 flux towers (labeled as Obv) in different IGBP land
 549 cover types. The diagrams display the Normalized Standard Deviation (represented by red circles),
 550 Correlation Coefficient (shown as green lines), and Centred Root-Mean-Square (depicted as blue circles).

551 **Table 3.** Statistical variables of six ET Products – CC (Correlation Coefficient), Ratio (the ratio of the
552 standard deviations of simulated ET and flux tower measurements), Bias, RMSE, RMSEu, RMSEs, and
553 NSE.

		CRO	CSH	DBF	DNF	EBF	ENF	GRA	MF	OSH	SAV	WSA	WET	MEAN
WISEA	CC	0.57	0.89	0.67	0.95	0.74	0.71	0.72	0.79	0.39	0.55	0.6	0.66	0.69
	Ratio	0.77	1.27	0.99	0.76	1.29	1.02	0.8	1.27	1.06	0.7	0.78	0.63	0.95
	Bias	-14.16	-1.27	3.9	-19.06	1.37	-11.15	-13.47	1.53	-6.83	-0.45	-23.14	-31.98	-9.56
	RMSE	39.4	12.5	34	22.1	30.4	29.3	32	23.3	30.4	32.5	41.2	51.6	31.56
	RMSEU	27.4	12.1	30.7	7.4	30.4	25.3	23.1	23.2	25.4	22.5	25.8	25.4	23.23
	RMSES	28.3	3.1	14.5	20.8	2.2	14.7	22.2	1.5	16.8	23.5	32.1	44.9	18.72
	NSE	0.18	0.64	0.34	0.45	0.24	0.3	0.41	0.38	-0.36	0.28	0.01	0.08	0.25
GLEAM	CC	0.56	0.94	0.61	0.89	0.81	0.67	0.71	0.81	0.51	0.53	0.57	0.67	0.69
	Ratio	0.7	1.28	0.79	0.82	0.99	1.1	0.78	1.04	1.12	0.96	0.95	0.56	0.92
	Bias	-6.13	12.52	5.8	-5.04	5.42	4.37	-1.16	10.51	5.62	-7.1	-16.73	-17.91	-0.82
	RMSE	37.2	15.4	34.2	14.7	21.8	30.3	29.6	21.4	28.6	37.1	40.9	44.4	29.63
	RMSEU	25.3	8	25.9	11.2	20.1	28.5	22.8	18	25.5	31.2	32.1	22.5	22.59
	RMSES	27.2	13.1	22.3	9.4	8.6	10.3	18.8	11.5	12.8	20	25.3	38.3	18.13
	NSE	0.27	0.35	0.33	0.75	0.61	0.25	0.5	0.47	-0.17	0.06	0.02	0.32	0.31
FLUXCOM	CC	0.66	0.98	0.69	0.95	0.79	0.77	0.75	0.83	0.78	0.59	0.65	0.69	0.76
	Ratio	0.94	1.76	0.96	1.04	1.12	1.18	0.97	1.42	0.97	1.04	1.08	0.62	1.09
	Bias	7.22	23.49	17.57	-2.26	6.29	7.08	6.91	21.02	10.04	0.74	-9.75	-14.04	6.19
	RMSE	35.8	27.9	36.7	9.9	25.2	27.7	30	31.9	19.8	35.5	37.8	41.7	29.99
	RMSEU	31	5.8	28.9	9.7	24.1	26.6	26.8	23.5	15.8	32.3	34.3	24.2	23.58
	RMSES	18	27.3	22.6	2.3	7.5	7.8	13.4	21.6	11.9	14.8	15.8	33.9	16.41
	NSE	0.32	-1.14	0.23	0.88	0.48	0.38	0.48	-0.17	0.43	0.14	0.17	0.4	0.22
AVHRR	CC	0.8	0	0.8	0	0.76	0.67	0.58	0.79	0.69	0.32	0.7	0.79	0.58
	Ratio	0.91	0	0.87	0	0.87	1.14	0.83	0.9	0.89	0.3	0.95	0.43	0.67
	Bias	-1.15	0	5.96	0	5.24	-1.72	-7.04	0.16	-2.41	-47.83	-0.42	-25.32	-6.21
	RMSE	23.6	0	26.1	0	23.3	31.1	36	18.8	22.1	54.7	33.2	46.6	26.29
	RMSEU	21.2	0	22	0	19.5	29.9	27.9	16.6	18.8	8	29.8	14.6	17.36
	RMSES	10.4	0	14.1	0	12.7	8.5	22.7	8.7	11.6	54.2	14.6	44.2	16.81
	NSE	0.63	0	0.61	0	0.54	0.22	0.24	0.62	0.43	-2.79	0.42	0.29	0.10
MOD16	CC	0.57	0.94	0.71	0.95	0.82	0.73	0.71	0.81	0.67	0.53	0.59	0.65	0.72
	Ratio	0.64	1.26	0.77	0.8	1.11	0.81	0.74	1.09	0.66	1	1	0.46	0.86
	Bias	-7.88	14.03	5.79	-4.07	7.17	-4.34	-5.05	4.09	-6.41	-16.01	-23.76	-21.07	-4.79
	RMSE	36.9	16.7	30.7	11.1	23.4	24.6	29.6	19.4	20.4	40.4	44.3	47.2	28.73
	RMSEU	23	8.4	23	7.4	22	19.5	21.7	18.7	12.8	32.4	33.3	18.8	20.08
	RMSES	28.8	14.4	20.3	8.2	7.8	15	20.2	5.2	15.9	24.2	29.1	43.3	19.37
	NSE	0.28	0.24	0.48	0.87	0.55	0.51	0.5	0.57	0.39	-0.12	-0.14	0.23	0.36
PML	CC	0.68	0.99	0.68	0.93	0.8	0.79	0.68	0.77	0.7	0.57	0.61	0.82	0.75
	Ratio	0.8	1.04	0.81	1.22	0.98	0.97	0.79	0.96	1.01	0.94	0.83	0.56	0.91
	Bias	-6.6	-3	3.39	0.47	-1.42	-5.43	-6.66	-0.59	6.48	-0.18	-16.04	-22.1	-4.31
	RMSE	33.2	4.1	31.5	13.3	21.9	23	31.7	19.8	21.1	34.5	37.5	40.5	26.01
	RMSEU	25.6	2.8	25.1	12.7	20.5	20.8	24.1	18.2	18.6	29.5	27.1	17.3	20.19
	RMSES	21.1	3.1	19	3.9	7.8	9.6	20.6	7.7	9.9	17.8	26	36.6	15.26
	NSE	0.42	0.95	0.44	0.79	0.61	0.57	0.43	0.55	0.33	0.19	0.16	0.43	0.49

554

555 Figure 8 illustrates the spatial distribution of the multi-year average (a-g), the zonal mean (h) and
556 inter-annual variation (i) of (a) GPCP (2001-2019), (b) VISEA (2001-2020), (c) GLEAM (2001-2020),
557 (d) FLUXCOM (2001-2016), (e) AVHRR (2001-2006), (f) MOD16 (2001-2014) and (g) PML (2003-
558 2018).



559

560 **Figure 8.** The spatial distribution of the multi-year average (a-g), the zonal mean (h) and inter-annual
 561 variation (i) of (a) GPCC precipitation (2001-2019), (b) VISEA (2001-2020), (c) GLEAM (2001-2020),
 562 (d) FLUXCOM (2001-2016), (e) AVHRR (2001-2006), (f) MOD16 (2001-2014) and (g) PML (2003-
 563 2018) ET data.

564 The VISEA ET product demonstrates consistent spatial distribution patterns among the six ET
 565 products across various years in terms of annual means (a-g) and latitude zonal means (h). These patterns
 566 closely align with the precipitation distribution data from GPCC. Furthermore, VISEA ET also exhibit
 567 similar spatial distributions compared to other ET products, particularly in the extremes of the
 568 distribution, below the 5th percentile and above the 95th percentile (Figure S6, S7). The highest ET values,
 569 approximately 1,500 mm year⁻¹, are predominantly in equatorial low-latitude regions with the
 570 corresponding high precipitation levels of approximately 2,500 mm year⁻¹. These regions include South
 571 America (Amazon Basin), Central Africa (Congo Basin), and Southeast Asia (encompassing Indonesia,
 572 Malaysia, parts of Thailand, and the Philippines), which have tropical rainforest climates. Remote sensing
 573 data support the ET estimates and align with findings from previous studies, such as Chen et al. (2021)

574 and Zhang et al. (2019), who reported that the multi-year average annual ET is nearly 1,500 and the
575 precipitation is approximately 2,500 mm year⁻¹. Also, Panagos et al. (2017) report similar multi-year
576 average annual ET and precipitation rates.

577 In this analysis, barren lands (BAR) such as the Sahara, Arabian, Gobi, and Kalahari deserts, along
578 with large areas of Australia, and snow and ice (SI) regions including significant parts of Canada, Russia,
579 and the Qinghai-Tibet Plateau in China, are characterized by notably low evapotranspiration (ET). These
580 regions typically experience less than 400 mm year⁻¹ of annual ET, paralleled by minimal yearly
581 precipitation ranging from 200 to 400 mm year⁻¹, according to GPCC data. Comparative ET rates for
582 other land cover types generally range from 400 to 1,400 mm year⁻¹, closely following the GPCC
583 precipitation amounts of 600 to 1,600 mm year⁻¹.

584 In regions experiencing moisture-limited evapotranspiration (ET), the scarcity of available water is
585 the primary constraint. Conversely, in areas where sufficient water is available, ET is energy-limited, and
586 factors such as cloud cover or shading restrict the absorption of solar radiation, affecting the
587 evapotranspiration rate. Panel (i) in Figure 8 illustrates inter-annual monthly variations over the past two
588 decades. It shows how VISEA and other satellite-based ET products, alongside GPCC precipitation data,
589 capture the rhythmic patterns of ET. These data reveal distinctive seasonal fluctuations and highlight the
590 significant inter-annual climate variability. Among these products, FLUXCOM consistently shows ET
591 values 10-20 mm month⁻¹ higher than those of other ET products. GLEAM and MOD16 exhibit similar
592 ET estimations, closely paralleling each other, as do PML and VISEA. Notably, after 2007, both GLEAM
593 and MOD16 reported higher ET estimations than PML and VISEA in November, December, January,
594 and February. For the same months, PML consistently records lower ET estimations than VISEA.

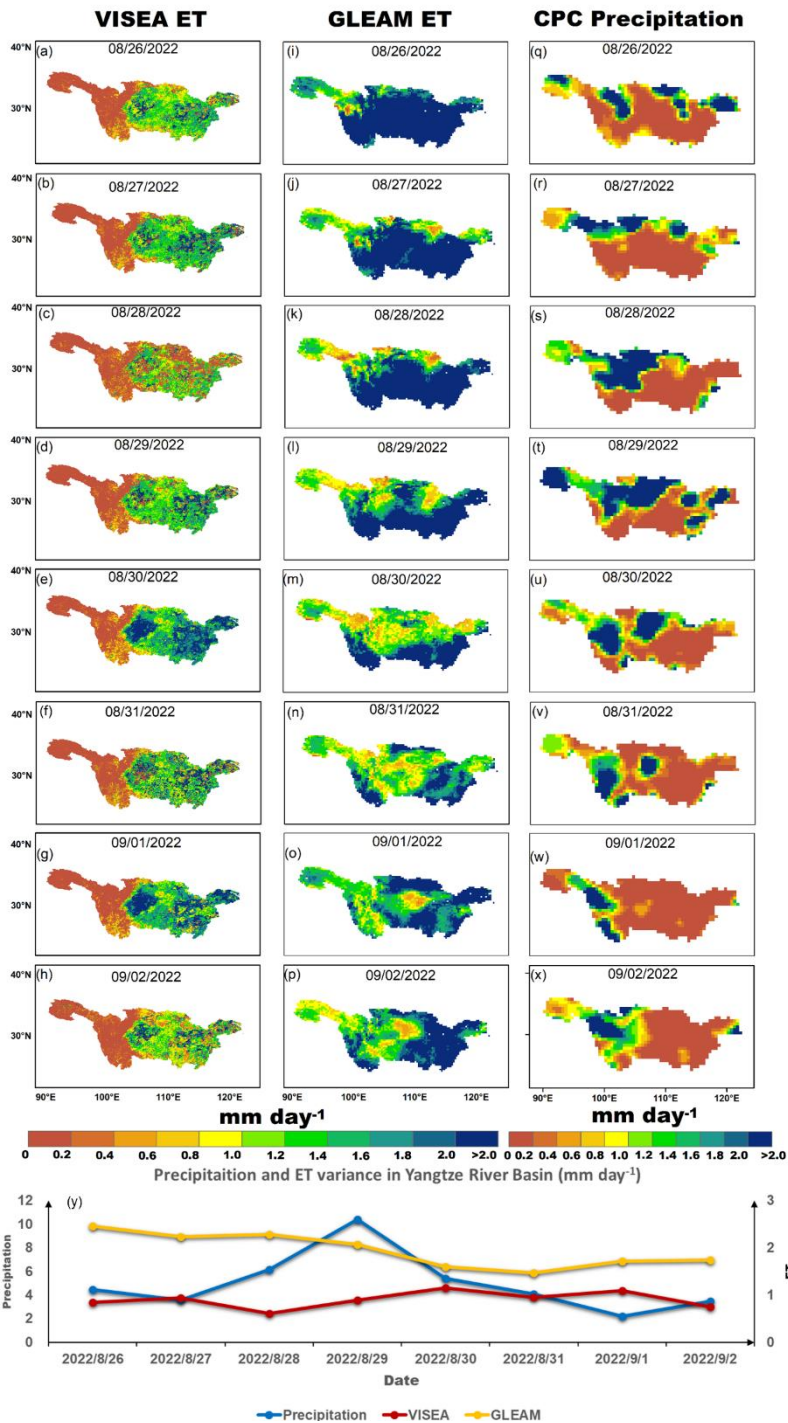
595 Analysis across the datasets reveals how ET estimates respond to extreme climate events, providing
596 insights into the variability and resilience of these models. For instance, during the 2011-2012 drought in
597 the Horn of Africa—one of the most severe droughts in recent decades—both ET estimations and GPCC
598 precipitation data showed significant declines. Similarly, the prolonged California drought from 2012 to
599 2016 also saw a considerable decrease in ET values, aligning with the reduced precipitation levels
600 captured by GPCC.

601 Regarding the inter-annual monthly variations, panel (i) shows the fluctuations in ET across
602 different years for the analyzed ET products and precipitation data. The graph reveals a rhythmic pattern
603 of ET across the years. VISEA and other ET products showed distinctive peaks and troughs
604 corresponding to seasonal changes and inter-annual climate variability. The ET products' data align
605 closely with the precipitation patterns reported by GPCC, highlighting the interconnectedness between
606 ET and precipitation as climatic variables. Notably, FLUXCOM consistently presents higher ET
607 estimations than the other products. GLEAM's ET estimations are also slightly higher during the winter,
608 indicating a trend of systematic overestimation in these products relative to the others in the dataset.

609 Figure 9 presents the daily ET from VISEA and GLEAM, alongside precipitation data from the
610 GPCC across the Yangtze River Basin from August 26th to September 2nd, 2022. During this period, a

611 significant drought was observed in the region, which began in July and showed signs of abating by late
612 August and early September, according to Zhang et al. (2023). VISEA ET illustrates the evolving drought
613 conditions, with notably low ET levels (below 1 mm day^{-1}) across the basin from August 26th to 28th, as
614 shown in panels (a-c). A marked increase in precipitation on August 29th, evident in panels (s) and (u),
615 correlates with an uptick in ET values (surpassing 1 mm day^{-1}) throughout the basin, visualized in panels
616 (d-f). Although GLEAM generally captures the fluctuations in ET—both decreases and increases—
617 during this period, it consistently reports much higher ET values than VISEA. The panel (y) graph in
618 Figure 9 shows the precipitation and the ET calculated by VISA E and GLEAM after an 11 mm rainfall
619 on August 29th. The ET of VISEA increased and the decreased, which is expected because ET and soil
620 moisture are positively correlated. The GLEAM does not follow the expected pattern shown in panel y.
621 This comprehensive analysis highlights the interdependence of precipitation and ET and underscores the
622 importance of considering soil moisture dynamics to fully understand the hydrological processes within
623 the Yangtze River Basin during extreme weather events.

624 Beyond precipitation, soil moisture is a critical regulator of ET, particularly during droughts and
625 their recovery phases. Acting as a buffer, soil moisture tempers ET rates during dry periods and amplifies
626 them after rainfall, as noted in late August. This buffering capacity results in a delay between precipitation
627 events and subsequent ET changes, which is key to understanding drought recovery dynamics. VISEA's
628 data accurately reflect these variations in precipitation, demonstrating its effectiveness in tracking daily
629 ET fluctuations and its reliability for near-real-time monitoring of ET during hydrological extremes.



630

631 **Figure 9.** Daily ET from VISEA (a-h), GLEAM (i-p), and CPC precipitation (q-x) distributions from
 632 August 26th to September 2nd in 2022, alongside daily mean ET and Precipitation variances in the Yangtze
 633 River Basin (y) during the same period.

634 **5. Discussion**

635 While global ET products (GLEAM, FLUXCOM, AVHRR, MOD 16 and PML ET) require at least
 636 2 weeks to generate global actual ET estimation, we developed VISEA, a satellite-based algorithm which
 637 is capable of generating near-real-time evapotranspiration on a daily time step with a resolution of 0.05°.

638 To assess its accuracy, we compared the calculated ET with data from 149 flux towers around the world
639 in various land use types.

640 Scale mismatch is a problem for many satellite-based ET products. The footprints of these flux towers
641 typically range from 100 to 200 meters, while the VISEA model outputs gridded cells at a resolution of
642 $0.05^\circ \times 0.05^\circ$ (nearly 25 km²). This discrepancy introduces errors, especially since flux towers require a
643 uniform fetch, which may not represent the larger gridded cell (Sun et al., 2023). To enhance the validity
644 of our assessments, we assessed monthly values and spatial patterns of our ET measurements with five
645 other satellite-based ET products named MOD16, AVHRR, GLEAM, FLUXCOM and PML (Figures 7
646 and 8).

647 The VISEA model uses gridded ERA5-Land shortwave downward radiation as its energy input.
648 Utilizing this input, along with MODIS land surface products, VISEA calculates gridded daily air
649 temperature and net radiation. These two important intermediate variables are essential for estimating
650 daily ET. The calculated ET generally matches local measurements and other model-calculated values
651 well, but we found significant biases (Figures 6 and 7). These biases largely arise from inaccuracies in
652 the input ERA5-Land shortwave radiation (Figure 3), improper application of the VI-Ts method (Figure
653 4), and uncertainties in daily net radiation (Figure 5). Next, we look further into the causes of the biases.

654 Incoming shortwave radiation from ERA5-Land is employed to derive the available energy for
655 vegetation coverage and bare soil (Eq. 15 and 16), which are the main parameters for calculating daily
656 ET (Eq. 17). While ERA5-Land is widely utilized as a reanalysis dataset, offering near-real-time land
657 variables by integrating model data with global observations based on physical laws. However, the
658 accuracy of shortwave radiation from ERA5-Land seems compromised in savannas (Figure 3) due to the
659 challenges associated with simulating radiation transmission under land-use changes and aerosol
660 pollution from natural or anthropogenic sources (Babar et al., 2019; Martens et al., 2020).

661 Air temperature is an important parameter in determining the daily evaporation fraction of bare soil
662 (Appendix B), canopy surface resistance, aerodynamic resistance of the bare soil (Appendix C),
663 atmospheric emissivity (Appendix D), and available energy for vegetation coverage and bare soil. Since
664 air temperature is not measured directly by satellites, many other ET products use therefore ground
665 observations, land models or reanalysis data. In contrast, VISEA derives the air temperature from the
666 negative linear relationship between vegetation index (VI) and surface temperature (Ts) using the VI-Ts
667 method (section 2.1.3). It gives very good results under grass land, open shrubland and woody savannas
668 landcover types, as shown in Figure 4. As previously explained, the VI-Ts method relies on the negative
669 linear correlation between the Vegetation Index (VI) and surface temperature (Ts) within a 5×5 grids'
670 window. Therefore, the variance of VI values across these grid cells and the strength of their negative
671 correlation are crucial for accurately calculating air temperature (Nishida et al., 2003). However, the VI-
672 Ts method is less effective in regions like dense forests, bare lands and deserts, where the vegetation
673 index and temperature data vary little across the 5×5 grids' window. Also, in regions with freezing
674 temperatures, the VI-Ts method does not perform well because warmer temperature is related to increased

675 vegetation, which is the opposite of warmer areas, where there is a positive correlation between the
676 vegetation index and surface temperature (Cui et al., 2021).

677 Another bias source of the VISEA model is the uncertainties of daily net radiation, notably
678 originating from input downward shortwave radiation from ERA5-Land (Figure 2) and VI-Ts estimated
679 air temperature (Figure 4). The energy budget equation (Eq. 14) and these two figures indicate that net
680 radiation shows more uncertainties than shortwave radiation and air temperature. At the same time,
681 assuming a linear relationship between cloud coverage (Eq. 15 and 16) and calculating downward
682 longwave radiation (Eq. 17 and 18) may be an oversimplification that could introduce uncertainties. Since
683 available energy for evapotranspiration (ET) depends on net radiation (Eq. 14), addressing these
684 uncertainties is crucial for enhancing overall model accuracy (Huang et al., 2023b). Future refinements
685 will contribute to a more precise daily net radiation estimation within the VISEA model.

686 The VISEA model calculates ET primarily based on vegetation coverage, utilizing it as an indirect
687 constraint to estimate evapotranspiration. However, this model does not directly incorporate variables
688 related to water availability, which is a critical factor in ET processes. In tropical regions, where solar
689 radiation is abundant (available energy), the model tends to overestimate ET due to its emphasis on
690 vegetation coverage without adequately accounting for the actual water available for evapotranspiration.
691 This methodology, while effectively capturing the effect of vegetation on ET under varied conditions,
692 can lead to overestimations in areas where energy availability significantly exceeds water availability,
693 typical of many tropical regions. Our analysis and subsequent discussion aim to highlight this
694 characteristic of the VISEA model, acknowledging its implications for ET estimations in such energy-
695 rich, water-variable environments.

696 While the VISEA model provides evapotranspiration (ET) globally, its best ET is between 60°N and
697 90°S, as evidenced by a Nash-Sutcliffe efficiency (NSE) of 0.4 and a correlation coefficient (R) of 0.9 in
698 Figure 6. VISEA model tends to underestimate ET in colder regions within the 60°N to 90°S latitude
699 range, such as the western territories of Canada. This underestimation is primarily due to the model's
700 inability to incorporate evaporation from frozen surfaces into its ET calculations. These discrepancies
701 arise from several factors: inaccuracies in the ERA5-Land shortwave radiation data (illustrated in Figure
702 3), the misapplication of the VI-Ts method (explained in Figure 4), and the uncertainties in daily net
703 radiation (depicted in Figure 5). Designed to amalgamate bare soil and full vegetation coverage, as shown
704 in Equation 1, the VISEA model encounters difficulties in accurately estimating ET at higher latitudes,
705 especially in conditions of reduced solar radiation. These challenges are predominantly linked to the
706 uncertainties associated with ERA5-Land shortwave radiation data, further compounded by increased
707 cloudiness levels in these regions, as highlighted by Babar et al. (2019). Such uncertainties substantially
708 impact the model's performance at higher latitudes, affecting its reliability in these conditions.
709 Nevertheless, VISEA's ET estimates compare favorably with other ET data products in cold regions
710 above 60°N, as indicated by the latitude zonal mean comparison in Figure 8.

711 The accuracy of the VISEA model could be enhanced by incorporating additional satellite and
712 climate data with higher resolution and improved accuracy. Moreover, the delay in providing ET data

713 could be reduced to three days or less by integrating real-time updated satellite and climate data. We
714 propose developing alternative methods for estimating air temperature and net radiation to enhance
715 accuracy. Additionally, incorporating variables such as soil moisture and water availability into the model
716 could further refine its precision. These improvements provide a roadmap for future research, aiming to
717 significantly enhance satellite-based near-real-time ET modeling.

718 **6. Conclusion**

719 Several satellite-based ET products have been developed, but few estimate near-real-time global
720 terrestrial evapotranspiration (ET). We have developed VISEA ET, which only uses satellite-based input
721 data and can provide near-real-time global daily terrestrial ET estimates at a 0.05° spatial resolution. The
722 accuracy of VISEA ET estimates is comparable to existing ET products sooner than existing products.
723 Our evaluations show that VISEA aligns well with measurements from 149 globally distributed tower
724 flux sites on daily and monthly scales. In addition, VISEA captures spatial patterns of evapotranspiration,
725 aligning with GPCP precipitation data across diverse geographical regions, particularly highlighting
726 elevated values in tropical rainforest regions and lower values in arid and semi-arid zones. ET estimates
727 are slightly too high in the Sahara and slightly too low in western Canada. Specifically, daily net radiation
728 and ET estimations of VISEA in Savannah and frozen surfaces need improvements. We plan to address
729 these issues in future developments. The near-real-time global daily terrestrial ET estimates provided by
730 VISEA are valuable for meteorology and hydrology applications, especially for coordinating relief efforts
731 during droughts.

732 **7. Code Availability**

733 Python code to synthesise the results and to generate the figures of VISEA results and the codes for
734 generating the global ET products can be obtained through the public repository at
735 <https://doi.org/10.6084/m9.figshare.24647721.v1> (Huang, 2023c). The VISEA code for calculating daily
736 ET is written in C and can be executed on Windows 10 using an Intel(R) Core (TM) i7-8565U CPU @
737 1.80GHz, 1.99 GHz, 16.0 GB RAM with Visual Studio 2019, or compatible platforms. Additionally, it
738 can run on high-performance computing servers equipped with an Intel(R) Xeon(R) CPU E5-2680 in a
739 CentOS environment. The system is scalable, supporting configurations ranging from 20 nodes and 656
740 CPUs down to fewer nodes and CPUs as required.

741 **8. Data Availability**

742 The VISEA ET data can be obtained from <https://doi.org/10.11888/Terre.tpd.300782> (Huang,
743 2023a). We are committed to continuously updating this dataset, ensuring that the latest ET data will be
744 consistently and promptly made available.

745 **8.1 Input data**

746 MOD11C1 can be obtained at <https://e4ftl01.cr.usgs.gov/MOLT/MOD11C1.061/>. MOD09CMG
747 can be obtained at <https://e4ftl01.cr.usgs.gov/MOLT/MOD09CMG.061/>. MCD43C3 can be obtained at
748 <https://e4ftl01.cr.usgs.gov/MOTA/MCD43C3.061/>. MOD13C1 can be obtained at
749 <https://e4ftl01.cr.usgs.gov/MOLT/MOD13C1.061/>. MCD12C1 can be obtained at
750 <https://e4ftl01.cr.usgs.gov/MOLT/MOD21C1.061/>. ERA5-Land shortwave radiation data can be
751 obtained at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=form>.

752 **8.2 Evaluation data**

753 FLUXNET2015 flux towers data (FLUXNET2015: CC-BY-4.0 33) can be obtained at
754 <https://fluxnet.org/data/download-data/>. The GLEAM 3.8a ET dataset was obtained from
755 <https://www.gleam.eu/#downloads> (an email is required to receive a password for the SFTP). The
756 FLUXCOM ET dataset was freely available (CC4.0 BY licence) from [https://www.fluxcom.org/EF-](https://www.fluxcom.org/EF-Download/)
757 [Download/](https://www.fluxcom.org/EF-Download/) the Data Portal (an email is required to receive a password for the FTP). MOD16 ET with
758 the resolution of 0.05° was freely downloaded from
759 [http://files.nts.govt.edu/data/NTSG_Products/MOD16/MOD16A2_MONTHLY.MERRA_GMAO_1k](http://files.nts.govt.edu/data/NTSG_Products/MOD16/MOD16A2_MONTHLY.MERRA_GMAO_1kmALB/Previous/)
760 [mALB/Previous/](http://files.nts.govt.edu/data/NTSG_Products/MOD16/MOD16A2_MONTHLY.MERRA_GMAO_1kmALB/Previous/). Additionally, the AVHRR ET dataset with 1° was sourced from
761 http://files.nts.govt.edu/data/ET_global_monthly_ORIG/Global_1DegResolution/ASCIIFormat/.
762 Lastly, the PML ET dataset was obtained from [https://www.tpdc.ac.cn/zh-hans/data/48c16a8d-d307-](https://www.tpdc.ac.cn/zh-hans/data/48c16a8d-d307-4973-abab-972e9449627c)
763 [4973-abab 972e9449627c](https://www.tpdc.ac.cn/zh-hans/data/48c16a8d-d307-4973-abab-972e9449627c).

764 The precipitation from Global Precipitation Climatology Centre (GPCC) data was as obtained at
765 [https://cds.climate.copernicus.eu/cdsapp#!/dataset/insitu-gridded-observations-global-and-](https://cds.climate.copernicus.eu/cdsapp#!/dataset/insitu-gridded-observations-global-and-regional?tab=form)
766 [regional?tab=form](https://cds.climate.copernicus.eu/cdsapp#!/dataset/insitu-gridded-observations-global-and-regional?tab=form). The precipitation from Global Unified Gauge-Based Analysis of Daily Precipitation
767 (CPC) was obtained at https://downloads.psl.noaa.gov/Datasets/cpc_global_precip/precip.2022.nc

768 Other data that supports the analysis and conclusions of this work is available at
769 [https://figshare.com/articles/dataset/Satellite-based_Near-Real](https://figshare.com/articles/dataset/Satellite-based_Near-Real_Time_Global_Daily_Terrestrial_Evapotranspiration_Estimates/24669306)
770 [Time_Global_Daily_Terrestrial_Evapotranspiration_Estimates/24669306](https://figshare.com/articles/dataset/Satellite-based_Near-Real_Time_Global_Daily_Terrestrial_Evapotranspiration_Estimates/24669306) (Huang, 2023d).

771

772 **Appendix**

773 **Appendix A. Determining the vegetation fraction calculation:**

774
$$f_{veg} = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (A1)$$

775 where the $NDVI$ is the Normalized Difference Vegetation Index and can be calculated as:

776
$$NDVI = \frac{R_{nir} - R_{red}}{R_{nir} + R_{red}} \quad (A2)$$

777 where $NDVI_{min}$ is the $NDVI$ of the bare soil without plants and $NDVI_{max}$ is the $NDVI$ of the full
778 vegetation cover, R_{nir} is the near-infrared reflectance and R_{red} is the red reflectance. The daily
779 reflectance R_{nir} and R_{red} were measured by MODIS reflectance data MOD09CMG (Fig. 1). Based on
780 Tang et al. (2009), we set $NDVI_{min} = 0.22$ and $NDVI_{max} = 0.83$. Missing observation for the daily
781 MOD09CMG calculated $NDVI$ data was filled with the 16-day averaged $NDVI$ values in the
782 MOD13Q1 data product (Fig. 1).

783

784 **Appendix B. Determining of decoupling factor:**

785 Ω_i^* is the value of the decoupling factor, Ω , for wet surface. According to Pereira (2004), Ω and Ω^*
786 can be expressed as:

787

788

789
$$\Omega = \frac{1}{1 + \frac{\gamma}{\Delta + \gamma} \frac{r_c}{r_a}} \quad (\text{B1})$$

790

$$\Omega^* = \frac{1}{1 + \frac{\gamma}{\Delta + \gamma} \frac{r^*}{r_a}} \quad (\text{B2})$$

791

$$r^* = \frac{(\Delta + \gamma) \rho C_p VPD}{\Delta \gamma (R_n - G)} \quad (\text{B3})$$

792 where r_c is the surface resistance (s m^{-1}); r_a is the aerodynamic resistance (s m^{-1}); the calculation details
793 of instantaneous and daily r_c and r_a for vegetation and soil. r^* is the critical surface resistance when the
794 actual evapotranspiration equals the potential evaporation (called equilibrium evapotranspiration, s m^{-1});
795 ρ is the air density (kg m^{-3}); C_p is the specific heat of the air ($\text{J kg}^{-1} \text{K}^{-1}$); VPD is the vapor pressure deficit
796 of the air (Pa). Δ is the slope of the saturated vapor pressure (Pa K^{-1}).

797

798 **Appendix C. Determining the resistances of vegetation canopy and bare soil surface**

799 The canopy surface resistance of the vegetation, denoted as $r_{c\ veg}$ ($s\ m^{-1}$), was determined using the
800 relationship established by Jarvis et al. (1976), is equivalent to:

801
$$\frac{1}{r_{c\ veg}} = \frac{f_1(T_a)f_2(PAR)f_3(VPD)f_4(\varphi)f_5(CO_2)}{r_{cMIN}} + \frac{1}{r_{cuticle}} \quad (C1)$$

802 The minimum resistance r_{cMIN} ($s\ m^{-1}$) is defined as 33 ($s\ m^{-1}$) for cropland and 50 ($s\ m^{-1}$) for forest
803 as determined by Tang et al. (2009); the canopy resistance related to diffusion through the cuticle layer
804 of leaves $r_{cuticle}$ is set at 100,000 ($s\ m^{-1}$) in the Biome-BGC model is according to White et al. (2000).
805 The relationships involving air temperature T_a , $f_1(T_a)$ and photosynthetic active radiation PAR , $f_2(PAR)$
806 expressed by the functions provided Jarvis et al. (1976):

807
$$f_1(T_a) = \left(\frac{T_a - T_n}{T_o - T_n} \right) \left(\frac{T_x - T_a}{T_x - T_o} \right)^{\frac{T_x - T_o}{T_o - T_n}} \quad (C2)$$

808
809 The minimum, optimal, and maximum temperatures for stomatal activity are denoted as T_n , T_o and
810 T_x , respectively. As per Tang et al. (2009), T_n is set to 275.85 K, T_o to 304.25 K, and T_x to 318.45 K. The
811 expression for the function $f_2(PAR)$ is provided below:

812
$$f_2(PAR) = \frac{PAR}{PAR + A} \quad (C3)$$

813 where PAR is photosynthetic active radiation per unit area and time ($\mu\ mol\ m^{-2}\ s^{-1}$) calculated by
814 incoming solar radiation multiplied by 2.05 (White et al., 2000); A is a parameter related to photon
815 absorption efficiency at low light intensity, which was set to $152\ \mu\ mol\ m^{-2}\ s^{-1}$ 20; Nishida³² found that
816 in Eq. D1 the following functions can be omitted without great loss of accuracy: the functions depending
817 on vapor pressure deficit, $f_3(VPD)$, leaf water potential $f_4(\varphi)$ and carbon dioxide vapor pressure,
818 $f_5(CO_2)$.

819 The photosynthetic active radiation per unit area and time (PAR), measured in $\mu\ mol\ m^{-2}\ s^{-1}$, is
820 computed by multiplying incoming solar radiation by 2.05, as outlined by White et al. (2000). The
821 parameter A , associated with photon absorption efficiency at low light intensity, is established at $152\ \mu\ mol\ m^{-2}\ s^{-1}$.
822 Nishida et al. (2003) observed that, in Eq. D1, the functions tied to vapor pressure deficit
823 $f_3(VPD)$, leaf water potential $f_4(\varphi)$, and carbon dioxide vapor pressure $f_5(CO_2)$ can be omitted without
824 significant loss of accuracy. Tang et al. (2009) employed this canopy resistance approach to estimate
825 evapotranspiration (ET) at a 500-meter resolution in the Kalam river basin. The evaluation of their results
826 indicated that the simplification of these calculations did not significantly impact the final accuracy of
827 ET estimates. Additionally, Huang et al. (2017) evaluated this method for 0.05° ET assessments across
828 China. In this study, we follow the methodologies originally developed by Tang et al. (2009) and Nishida
829 (2003), with the goal of enhancing the VISEA model to accurately estimate daily scale evaporation
830 fraction and net radiation. These efforts build on earlier work by Huang et al. (2017, 2021 and 2023b)

831 that introduced vapor pressure deficit (VPD) and leaf water potential in calculating canopy resistance.
 832 However, comparative analyses between VISEA and other models, such as PML and MOD16—
 833 particularly PML, which integrates VPD as a limiting factor in estimating GPP and ET—show that
 834 VISEA maintains accuracy without significant biases. It is important to note that none of the ET models
 835 in our comparison directly incorporate leaf water potential into their canopy resistance calculations. We
 836 are committed to addressing these gaps in our future studies.

837 The aerodynamic resistance of the canopy, denoted as $r_{a\ veg}$ ($s\ m^{-1}$), is computed for forest cover,
 838 grassland, and cropland using the empirical formulae presented by Nishida et al. (2003) for both
 839 instantaneous and daily values.

$$840 \quad \frac{1}{r_{a\ veg\ (forest)}} = 0.008U_{50m} \quad (C4)$$

841 The wind speed at a height of 50 meters above the canopy (U_{50m}) is used to determine the
 842 aerodynamic resistance for grassland and cropland, as follows:

$$843 \quad \frac{1}{r_{a\ veg\ (grassland\ \&\ cropland)}} = 0.003U_{1m} \quad (C5)$$

844 where U_{1m} is the wind speed 1m above the canopy ($m\ s^{-1}$). The wind speed as a function of the
 845 height z , $U(z)$ can be calculated by the logarithm profile of wind. A recent study found that the velocity
 846 log law does not apply to a stratified atmospheric boundary layer (Cheng et al., 2011). Thus D4 and D5
 847 are valid under neutral boundary layer conditions. Since $r_{a\ veg}$ is calculated differently for forests (Eq.
 848 D4) and grasslands/croplands (Eq. D5), we used the land cover classes from the yearly International
 849 Geosphere-Biosphere Programme (IGBP) (MCD12C1) to identify the land cover and choice the different
 850 equation of $r_{a\ veg}$. U_{50m} and U_{1m} were calculated by the logarithm profile of wind:

$$851 \quad U(z) = U_{shear} \ln \left[\frac{(z-d)}{z_0} \right] / k \quad (C6)$$

852 where U_{shear} is the shear velocity ($m\ s^{-1}$); z is the height (m); d is the surface displacement (m); z_0
 853 is the roughness length, we followed Nishida et al. (2003), set as 0.005 m for bare soil and 0.01 m for
 854 grassland; k is the von Kármán's constant and set as 0.4 following Nishida (Nishida et al., 2003). The
 855 shear velocity U_{shear} was calculated as:

$$856 \quad U_{shear} = U_{1m\ soil} \frac{0.4}{\ln \left(\frac{1}{0.005} \right)} \quad (C7)$$

857 where the $U_{1m\ soil}$ is the wind speed of bare soil at 1 m height ($m\ s^{-1}$), it was calculated as:

$$858 \quad U_{1m\ soil} = 1/0.0015\ r_{a\ soil} \quad (C8)$$

859 The Vegetation Index-surface Temperature (VI-T_s) diagram (Nishida et al., 2003) can be utilized to
 860 compute the instantaneous air temperature. This is achieved by utilizing MODIS instantaneous surface
 861 temperature/emissivity data (MOD11C1) and daily-calculated NDVI as input parameters.

862 The aerodynamic resistance of the bare soil, denoted as $r_{a\ soil}$ ($s\ m^{-1}$), was determined by Nishida
 863 et al. (2003). This calculation assumes that the maximum surface temperature of bare soil $T_{soil\ max}$ (K)
 864 happens when the sum of latent heat flux and sensible heat flux of the bare soil, referred to as the available
 865 energy of bare soil Q_{soil} ($W\ m^{-2}$), is utilized as the sensible heat flux, while the latent heat flux is set to
 866 zero.

$$867 \quad r_{a\ soil} = \frac{\rho C_p (T_{soil\ max} - T_a)}{Q_{soil}} \quad (C9)$$

868 $r_{a\ soil}$ is the aerodynamic resistance of the bare soil, ($s\ m^{-1}$), ρ is the air density, $kg\ m^{-3}$; C_p is the
 869 specific heat of the air, ($J\ kg^{-1}\ K^{-1}$); T_a is the air temperature (K), Q_{soil} is the available energy of bare soil
 870 ($W\ m^{-2}$).

871 To compute the canopy surface resistance of bare soil, denoted as $r_{c\ soil}$ ($s\ m^{-1}$), we adhere to the
 872 methodologies outlined in the works of Griend and Owe (1994) and Mu et al. (2007):

$$873 \quad r_{c\ soil} = r_{tot} - r_{a\ soil} \quad (C10)$$

$$874 \quad r_{tot} = \frac{1.0}{\left(\frac{T_a}{293.15}\right)^{1.75} \frac{101300}{P}} * 107.0 \quad (C11)$$

875 The total aerodynamic resistance r_{tot} ($s\ m^{-1}$) is composed of the aerodynamic resistance over the
 876 bare soil $r_{a\ soil}$ ($s\ m^{-1}$), with atmospheric pressure P set at 101,300 Pa.

877

878 **Appendix D. The calculation of atmospheric emissivity for clear sky**

879 As per Brutsaert (1975), the atmospheric emissivity ε_a^d for clear sky under standard humidity and
 880 temperature conditions is

881
$$\varepsilon_a^d = 1.24 \times (e_a^d/T_a^d)^{1/7} \quad (D1)$$

882 where e_a^d represents the daily water vapor pressure (kPa). To calculate e_a^d , it is necessary to
 883 compute the slope of the saturated vapor (Δ) as:

884
$$\Delta = \frac{4098 [0.6108 \exp[\frac{17.27T_a}{(T_a+237.3)}]]}{(T_a+237.3)^2} \quad (D2)$$

885 VPD is the vapor pressure deficit of the air (kPa), which is expressed as:

886
$$VPD = e^0(T_a) - e_a \quad (D3)$$

887
$$e^0(T_a) = 0.6108 \exp \left[\frac{17.27T_a}{(T_a+237.3)} \right] \quad (D4)$$

888
$$e_a = e^0(T_{dew}) \quad (D5)$$

889
$$e^0(T_{dew}) = 0.6108 \exp \left[\frac{17.27T_{dew}}{T_{dew}+237.3} \right] \quad (D6)$$

890 The expression within parentheses denotes the independent variable, where, $e^0(T_a)$ represents the
 891 saturation vapor pressure (kPa) at the air temperature T_a (°C); e_a is the actual vapor pressure (kPa);
 892 $e^0(T_{dew})$ is the saturation vapor pressure (kPa) at the dew point temperature T_{dew} (°C). For forest, water
 893 surface, and cropland T_{dew} is set to the minimum air temperature during the day. In arid regions such as
 894 bare soil and non-irrigated grassland, T_{dew} may be 2-3 °C lower than T_{min} . Therefore, 2 °C is subtracted
 895 is subtracted from T_{min} in arid and semiarid areas to derive T_{dew} . While these simplifications might
 896 introduce a bias in the final calculated ET value, our initial results indicate that the effect is negligible.

897

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902 **Author contributions**

903 L. H. had the original idea and drafted the paper with help from Y. L.; J. M. C. Q. T., T. S., W. C.
904 and W. S. participated in the discussion and the many manuscript revisions.

905 **Competing interests**

906 The authors declare no competing interests.

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