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## 1 **Evaluating European ECOSTRESS Hub Evapotranspiration Products Retrieved** 2 **from Three Structurally Contrasting SEB Models over Europe**

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### 20 **Key Points:**

- 21 • Evaporation products over Europe and Africa were generated using 3 different models  
22 (STIC, SEBS, and TSEB) in the European ECOSTRESS Hub
- 23 • Comparison at 19 eddy covariance sites revealed noteworthy model divergence with  
24 increasing aridity and vegetation sparseness
- 25 • A substantial overestimation of the official NASA ECOSTRESS ET product was found  
26 under high water limitations  
27

## 28 Abstract

29 The ECOSystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) is  
30 a scientific mission that collects high spatio-temporal resolution ( $\sim 70$  m, 1-5 days average revisit  
31 time) thermal images since its launch on 29 June 2018. As a predecessor of future missions, one  
32 of the main objectives of ECOSTRESS is to retrieve and understand the spatio-temporal variations  
33 in terrestrial evapotranspiration (ET) and its responses to soil water availability. In the European  
34 ECOSTRESS Hub (EEH), by taking advantage of land surface temperature retrievals, we  
35 generated ECOSTRESS ET products over Europe and Africa using three structurally contrasting  
36 models, namely Surface Energy Balance System (SEBS) and Two Source Energy Balance (TSEB)  
37 parametric models, as well as the non-parametric Surface Temperature Initiated Closure (STIC)  
38 model. A comprehensive evaluation of the EEH ET products was conducted with respect to flux  
39 measurements from 19 eddy covariance sites over 6 different biomes with diverse aridity levels.  
40 Results revealed comparable performances of STIC and SEBS (RMSE of  $\sim 70$  W m<sup>-2</sup>). However,  
41 the relatively complex TSEB model produced a higher RMSE of  $\sim 90$  W m<sup>-2</sup>. Comparison between  
42 STIC ET estimate and the operational ECOSTRESS ET product from NASA PT-JPL model  
43 showed a difference in RMSE between the two ET products around 50 W m<sup>-2</sup>. Substantial  
44 overestimation ( $>80$  W m<sup>-2</sup>) was noted in PT-JPL ET estimates over shrublands and savannas  
45 presumably due to the weak constraint of LST in the model. Overall, the EEH is promising to serve  
46 as a support to the Land Surface Temperature Monitoring (LSTM) mission.

## 47 1 Introduction

48 Evapotranspiration (ET) is an intrinsic component of climate in the land-atmosphere system and  
49 plays a critical role in affecting turbulence, cloud formation and convection at the local scale  
50 (Chen and Liu 2020; Fisher et al. 2017). As an important component of the water cycle in the  
51 terrestrial ecosystems, it quantifies the amount of water loss from the Earth surface to atmosphere  
52 (Chen and Liu 2020; Jasechko et al. 2013). ET consists of evaporation from soil (or water bodies)  
53 and wet vegetation and transpiration through pores in plant leaves. Through the stomatal  
54 conductance, transpiration is closely related to CO<sub>2</sub> exchange between leaf and atmosphere  
55 (Anderson et al. 2008). Thus, ET links the land surface water, energy, and carbon cycles (Anderson  
56 et al. 2008; Fisher et al. 2017; Mallick et al. 2021), and is a keystone variable in terrestrial  
57 ecosystem processes (Bai et al. 2022; Bayat et al. 2018; Kustas and Anderson 2009; Ryu et al.  
58 2011).

59 Thermal infrared (TIR) remote sensing has been widely used to obtain ET at large scales  
60 considering land surface temperature (LST) constrains the magnitude and variability of the surface  
61 energy balance (SEB) components and is immensely sensitive to evaporative cooling (Crago and  
62 Qualls 2014; Mallick et al. 2021; Mallick et al. 2014; Norman et al. 1995). ET products are  
63 generated from TIR observations of different sensors, including Landsat (Anderson et al. 2012;  
64 Anderson et al. 2021; Jaafar et al. 2022), Moderate resolution Imaging Spectroradiometer  
65 (MODIS) (Chen et al. 2019; Chen et al. 2021; Senay et al. 2013), Visible Infrared Imaging  
66 Radiometer Suite (VIIRS) onboard polar-orbiting satellites (Jaafar et al. 2022), and Advanced  
67 Baseline Imager (ABI) (Anderson et al. 2007; Fang et al. 2019) onboard Geostationary Operational  
68 Environmental Satellite (GOES). These ET data are harnessed in a variety of applications such as  
69 drought monitoring (Anderson et al. 2011; González-Dugo et al. 2021; Otkin et al. 2013), water  
70 resource management (Anderson et al. 2012), irrigation control (Allen et al. 2011), global change  
71 studies (Dai et al. 2004; Mao et al. 2015), and biodiversity assessments (Fisher et al. 2011).

72 However, there remains a gap in retrieving ET with concurrently high spatial and temporal  
73 resolutions at the global scale. For the polar-orbiting satellites, the Landsat ET product has a high  
74 spatial resolution (30 m via thermal sharpening) but coarse temporal resolution (16 days). MODIS  
75 and VIIRS have a daily temporal resolution but coarse spatial resolution ( $\geq 500$  m). For the  
76 geostationary satellites, the diurnal cycle can be captured by the sub-hourly observations, but the  
77 spatial resolution is above 1 km due to the orbit altitude and spatial coverage is limited to the  
78 continental scale. This constrains subsequent applications of ET products.

79 The ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS),  
80 positioned on the International Space Station (ISS) on 29 June 2018, is a pathfinder for the next  
81 generation TIR missions (Fisher et al. 2020; Hook et al. 2019; Hulley et al. 2021). It collects  
82 thermal images in five bands between 8 and 12.5  $\mu\text{m}$  with a high spatio-temporal resolution at  
83 varying times of the day. The spatial coverage is between  $\pm 52^\circ$  latitude over the globe. The pixel  
84 size after resampling at the nadir is  $\sim 70 \times 70$  m. The average revisit time is approximately 1-5  
85 days, depending on the latitude (Xiao et al. 2021). Over high latitude regions where the ISS orbital  
86 direction shifts, the observation frequency can reach several times in a single day. Therefore, the  
87 ECOSTRESS data provides an unprecedented opportunity for monitoring terrestrial ecosystems  
88 (Fisher et al. 2020; Liu et al. 2021; Xiao et al. 2021).

89 The European ECOSTRESS Hub (EEH) is a project funded by the European Space Agency (ESA),  
90 targeted at generating high spatio-temporal resolution LST and ET products over Europe and  
91 Africa from ECOSTRESS observations. Three structurally contrasting SEB models were selected  
92 to produce ET estimates, i.e., one-source Surface Energy Balance System (SEBS) and Two Source  
93 Energy Balance (TSEB) parametric models, and the one-source Surface Temperature Initiated  
94 Closure (STIC) analytical model. The EEH LST estimates were used as the driving force for ET  
95 retrieval from the three models, with the support of ancillary meteorological data and variables  
96 describing the surface conditions (e.g., albedo, vegetation coverage). The uniform forcing data  
97 describing the lower boundary conditions enables a fair comparison across a wide spectrum of  
98 energy and water availability scenarios among the three models with different parameterization  
99 schemes. EEH LST and ET products between August 2018 and December 2021 can be  
100 downloaded from the Food Security-TEP portal (<https://foodsecuritytep.net/>). More information  
101 about EEH can be found on the landing page (<http://isp-projects.private.list.lu/eeh/public/>).

102 In this paper, we aimed to evaluate the three ECOSTRESS ET products generated in EEH at the  
103 continental scale. A two-step evaluation strategy was adopted. First, the EEH ET products were  
104 compared with flux measurements from 19 eddy covariance sites over Europe between 2018 and  
105 2019. Then, the best performing EEH ET product was compared with the official National  
106 Aeronautics and Space Administration (NASA) ECOSTRESS ET product retrieved using the PT-  
107 JPL model. The purpose of this study is two-fold: 1) providing insights into ECOSTRESS ET  
108 products generated using SEB models with different structures and parameterizations schemes, 2)  
109 supporting ET retrieval for the future thermal missions like ESA's Land Surface Temperature  
110 Monitoring (LSTM) (Koetz et al. 2019), the Franco-Indian joint Thermal infraRed Imaging  
111 Satellite for High-resolution Natural resource Assessment (TRISHNA) (Lagouarde et al. 2018)  
112 and NASA's Surface Biology and Geology (SBG) (Cawse-Nicholson et al. 2021).

## 113 **2 ET models in EEH**

114 ET is intrinsically associated with the SEB equation, which is based on the partitioning of net  
115 available energy into sensible and latent heat fluxes. The SEB equation is written as follows

$$R_N = \lambda E + H + G \quad (1)$$

116 where  $R_N$  is the net radiation,  $H$  and  $\lambda E$  are sensible and latent heat fluxes ( $\text{W m}^{-2}$ ), respectively,  
 117 and  $G$  is the ground heat conduction flux. The segregation of net available energy ( $R_N - G$ ) into the  
 118 two different convective fluxes ( $H$  and  $\lambda E$ ) depends on the land surface moisture status,  
 119 atmospheric conditions in the lower boundary layer, and biophysical control of vegetation  
 120 (Anderson et al. 2008; Kustas and Anderson 2009; Mallick et al. 2014; Mallick et al. 2018a;  
 121 Mallick et al. 2018b).

122 Most thermal-based ET models calculate ET as a residual of SEB after estimating  $H$  or estimate  
 123 evaporative fraction first and derive ET from the net available energy. These models can be broadly  
 124 characterized as one-source and two-source models based on the conceptualization of the land  
 125 surface. In the one-source models, the vegetated surface is regarded as a ‘big leaf’ and the  
 126 evaporating front is assumed to be at the source/sink height, which is in the immediate vicinity of  
 127 the surface level. Whereas the two-source models assume that the vegetated surface consists of the  
 128 soil and vegetation components, and the energy fluxes are partitioned between these two  
 129 components.

## 130 2.1 STIC

131 The one-source STIC model was first proposed by Mallick et al. (2014). STIC is based on the  
 132 integration of radiometric temperature into the Penman-Monteith (PM) formulation to find the  
 133 analytical solution of the aerodynamic and surface conductances. To do so, STIC combines an  
 134 LST-driven water stress index with aerodynamic equations of  $H$  and  $\lambda E$  and a modified  
 135 complementary relationship advection-aridity hypothesis (Mallick et al. 2015). The latest version  
 136 of STIC (Bhattarai et al. 2018; Mallick et al. 2016) combines the Shuttleworth-Wallace sparse  
 137 canopy formulation model with the PM big-leaf model to calculate the vapour pressure at the  
 138 source/sink height (Shuttleworth and Wallace 1985).

### 139 2.1.1 State equations of STIC

140 The four state equations are at the core of STIC, which describe aerodynamic and surface  
 141 conductances ( $g_A$  and  $g_C$ ), aerodynamic temperature ( $T_0$ ), and evaporative fraction ( $F_E$ ):

$$g_A = \frac{\phi}{\rho c_p \left[ (T_0 - T_A) + \frac{e_0 - e_A}{\gamma} \right]} \quad (2)$$

$$g_C = g_A \frac{e_0 - e_A}{e_0^* - e_0} \quad (3)$$

$$T_0 = T_A + \left( \frac{e_0 - e_A}{\gamma} \right) \left( \frac{1 - F_E}{F_E} \right) \quad (4)$$

$$F_E = \frac{2\alpha s}{2s + 2\gamma + \gamma \frac{g_A}{g_C} (1 + M)} \quad (5)$$

142 where  $\Phi$  is the net available energy,  $\rho$  is the density of air ( $\text{kg m}^{-3}$ ),  $c_p$  is the specific heat of air at  
 143 constant pressure ( $\text{MJ kg}^{-1} \text{K}^{-1}$ ),  $\gamma$  is the psychrometric constant ( $\text{hPa K}^{-1}$ ),  $T_A$  is air temperature at

144 the reference height,  $e_0$  and  $e_0^*$  is the vapor pressure at the source/sink height,  $e_A$  is atmosphere  
 145 vapor pressure,  $\alpha$  is the Priestley-Taylor (PT) coefficient,  $s$  is the slope of saturation vapour  
 146 pressure versus temperature curve estimated at  $T_A$ ,  $M$  is the surface moisture availability (between  
 147 0 and 1), which is estimated from LST. Based on the four state equations, algebraic closure is not  
 148 possible due to the involvement of additional unknowns. Therefore, an iterative solution is adopted  
 149 to estimate the additional unknown variables ( $e_0^*$ ,  $e_0$ ,  $\alpha$  and  $M$ ).

150 2.1.2 Iterative solution of  $e_0^*$ ,  $e_0$ ,  $\alpha$  and  $M$  in STIC

151 From the aerodynamic equation of  $\lambda E$ ,  $e_0^*$  can be expressed as

$$e_0^* = e_A + \frac{\gamma \lambda E (g_A + g_C)}{\rho c_p g_A g_C} \quad (6)$$

152 Following Shuttleworth and Wallace (1985), the vapour pressure deficit ( $D_0 = e_0^* - e_0$ ) and vapour  
 153 pressure ( $e_0$ ) at the source/sink height are expressed as follows:

$$D_0 = D_A + \frac{s\phi - (s + \gamma)\lambda E}{\rho c_p g_A} \quad (7)$$

$$e_0 = e_0^* - D_0. \quad (8)$$

154 A physical equation of  $\alpha$  is expressed as

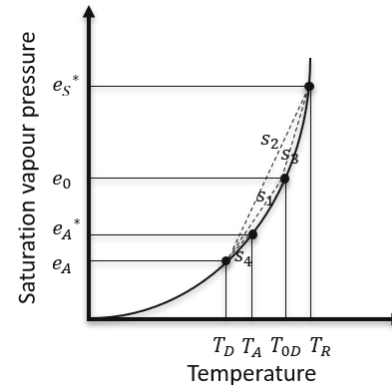
$$\alpha = \frac{\left[ 2s + 2\gamma + \gamma \frac{g_A}{g_C} (1 + M) \right] g_C (e_0^* - e_A)}{2s[\gamma(T_0 - T_A)(g_A + g_C) + g_C(e_0^* - e_A)]}. \quad (9)$$

155  $M$  is expressed as the ratio of the vapour pressure difference to the vapour pressure deficit between  
 156 the surface and atmosphere as follows

$$M = \frac{e_0 - e_A}{e_0^* - e_A} = \frac{e_0 - e_A}{k(e_s^* - e_A)} = \frac{s_1(T_{0D} - T_D)}{ks_2(T_R - T_D)} \quad (10)$$

157 where  $T_{0D}$  is the dew-point temperature at source/sink height and  $T_D$  is the air dew-point  
 158 temperature,  $T_R$  is the radiometric surface temperature,  $s_1$  and  $s_2$  are the psychrometric slopes of  
 159 the saturation vapour pressure and temperature between the  $(T_{0D} - T_D)$  vs.  $(e_0 - e_A)$  and  $(T_R - T_D)$   
 160 vs.  $(e_s^* - e_A)$ , and  $k$  is the ratio between  $(e_0^* - e_A)$  and  $(e_s^* - e_A)$ , as shown in Figure 1. Despite  $T_0$   
 161 driving the sensible heat flux, the comprehensive dry-wet signature of the underlying surface due  
 162 to soil moisture variations is directly reflected in  $T_R$ . Thus,  $T_R$  in the denominator is directly related  
 163 to the surface moisture availability ( $M$ ). In Equation 10,  $T_{0D}$  can be calculated as

$$T_{0D} = T_D + \frac{\gamma \lambda E}{\rho c_p g_A s_1}. \quad (11)$$



164  
165 **Figure 1.** Schematic representation of the exponential relationship between saturation vapor  
166 pressure versus temperature.

167 An iterative method is applied to solve the equations because the four state variables and  $e_0^*$ ,  $e_0$ ,  $\alpha$   
168 and  $M$  are entangled.

### 169 2.1.3 Initialization

170 An initial value of  $\alpha$  is assigned as 1.26 and initial estimates of  $e_0^*$ ,  $e_0$  are obtained from  $T_R$  and  $M$   
171 as

$$e_0^* = 6.13753e^{\frac{17.27T_R}{T_R+237.3}} \quad (12)$$

$$e_0 = e_A + M(e_0^* - e_A). \quad (13)$$

172  $M$  is initialized by assuming  $e_0^* = e_s^*$ , i.e.,  $k$  in Equation 10 equals 1, expressed as follows

$$M = \frac{s_1(T_{0D} - T_D)}{s_2(T_R - T_D)}. \quad (14)$$

173  $T_{0D}$  can be expressed as

$$T_{0D} = \frac{e_s^* - e_A - s_3T_R + s_1T_D}{s_1 - s_3}. \quad (15)$$

174 The slopes  $s_1$  and  $s_3$  can be expressed as

$$s = 4098 \frac{6.13753e^{\frac{17.27T}{T+237.3}}}{(T + 237.3)^2} \quad (16)$$

175 where  $T$  is set to  $T_D$  and  $T_R$  for  $s_1$  and  $s_3$ , respectively. With the initial estimates of  $e_0^*$ ,  $e_0$ ,  $\alpha$ , and  
176  $M$ ,  $g_A$ ,  $g_C$  and  $\lambda E$  can be calculated. Then  $e_0^*$ ,  $e_0$ ,  $\alpha$  and  $M$  are updated, and  $\lambda E$  is recalculated. The  
177 iteration continues until the convergence of  $\lambda E$  is achieved.

### 178 2.1.4 Hysteresis consideration

179 By considering the hysteresis between  $T_R$ ,  $D_A$ , and  $\lambda E$ , the surface moisture availability  $M$  can be  
180 expressed as

$$M = \frac{\gamma s_1(T_{0D} - T_D)}{s_3(T_R - T_{0D})s + \gamma s_4(T_A - T_D)} \quad (17)$$

181 Hysteresis occurs because the capacity of the soil and vegetation to supply moisture to the  
 182 atmosphere is larger in the morning than in the afternoon (Boegh et al. 1999). As such, two  
 183 equations are used for estimating  $M$  in STIC depending on the occurrence of hysteresis. It is  
 184 assumed that Equation 10 is used to indicate surface wetness that controls the evapotranspiration  
 185 from the upper few centimetres of the surface, whereas Equation 17 is used to indicate the root-  
 186 zone wetness that controls the evapotranspiration under strong hysteretic conditions between  $\lambda E$ ,  
 187  $R_N$ ,  $T_R$  and  $D_A$ .

188 2.1.5 Driving parameters for STIC

189 The input variables used for driving the STIC model are listed in Table 1. The LST and emissivity  
 190 are retrieved from the EEH L2 LST product. The land surface properties including albedo, and  
 191 land use land cover (LULC) data and fractional vegetation coverage (FVC) are obtained from the  
 192 Copernicus Global Land Service (CGLS, <https://land.copernicus.eu/global/index.html>). The  
 193 meteorological data are obtained from the ERA5 reanalysis data  
 194 (<https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset>). All these CGLS and ERA5 data  
 195 are spatially (bilinearly) and temporally (linearly) interpolated to match the ECOSTRESS LST  
 196 data.

197 **Table 1.** Input parameters for STIC, SEBS, and TSEB

Data	Purpose	Model	Source	Spatial resolution	Temporal resolution
LST	$R_N$ , $T_R$	STIC, SEBS, TSEB	ECOSTRESS	~70 m	daily
Emissivity	$R_N$	STIC, SEBS, TSEB	ECOSTRESS	~70 m	daily
Black sky and white sky albedo ( $a_{bs}$ , $a_{ws}$ )	$R_N$	STIC, SEBS	CGLS	1 km	10-day
FVC	surface condition	STIC, TSEB	CGLS	300 m	10-day
NDVI	surface condition	SEBS	CGLS	300 m	10-day
LAI	surface condition	TSEB	CGLS	300 m	10-day
LULC	surface condition	STIC, SEBS, TSEB	CGLS	100 m	annual
Shortwave direct radiation ( $R_{sdir}$ )	$R_N$	STIC, SEBS	ERA5	0.25°	1 hour
Shortwave global radiation ( $R_s$ )	$R_N$	STIC, SEBS, TSEB	ERA5	0.25°	1 hour
Air temperature ( $T_A$ )	lower boundary condition (2 m)	STIC, SEBS, TSEB	ERA5	0.25°	1 hour



Atmosphere vapour pressure ( $e_A$ ) or Dewpoint temperature ( $T_D$ )	lower boundary condition (2 m)	STIC, SEBS, TSEB	ERA5	0.25°	1 hour
Wind speed	lower boundary condition (10 m)	SEBS, TSEB	ERA5	0.25°	1 hour

198 **2.2 SEBS**

199 The one-source SEBS model was developed by Su (2002), which also includes sub-models for the  
 200 roughness length of heat as well as momentum transfer and a formulation for the determination of  
 201 the evaporative fraction on the basis of energy balance at limiting cases.

202 To derive the sensible and latent heat fluxes, the similarity theory is used. In the Atmospheric  
 203 Surface Layer (ASL) similarity relationship, the profiles of the mean wind speed  $u$  and the mean  
 204 temperature  $\theta_0 - \theta_a$  can be expressed as follows

$$u = \frac{u_*}{k} \left[ \ln \left( \frac{z - d_0}{z_{0m}} \right) - \Psi_m \left( \frac{z - d_0}{L} \right) + \Psi_m \left( \frac{z_{0m}}{L} \right) \right] \quad (18)$$

$$\theta_0 - \theta_a = \frac{H}{k u_* \rho c_p} \left[ \ln \left( \frac{z - d_0}{z_{0h}} \right) - \Psi_h \left( \frac{z - d_0}{L} \right) + \Psi_h \left( \frac{z_{0h}}{L} \right) \right] \quad (19)$$

205 where  $z$  is the height above the surface (m),  $u^* = (\tau_0/\rho)^{1/2}$  is the friction velocity ( $\text{m s}^{-1}$ ),  $\tau_0$  is the  
 206 surface shear stress ( $\text{kg m}^{-1} \text{s}^{-2}$ ),  $\rho$  is the density of air ( $\text{kg m}^{-3}$ ),  $k = 0.4$  is von Karman's constant,  
 207  $d_0$  is the zero plane displacement height (m),  $z_{0m}$  is the roughness height for momentum transfer  
 208 (m),  $\theta_0$  is the potential temperature at the surface ( $^{\circ}\text{C}$ ),  $\theta_a$  is the potential air temperature ( $^{\circ}\text{C}$ ) at  
 209 height  $z$ ,  $z_{0h}$  is the scalar roughness height for heat transfer (m),  $\Psi_m$  and  $\Psi_h$  are the stability  
 210 correction functions for momentum and sensible heat transfer respectively.  $L$  is the Obukhov  
 211 length, which is defined as follows.

$$L = - \frac{\rho c_p u_*^3 \theta_v}{k g H} \quad (20)$$

212 where  $g$  is the acceleration due to gravity ( $\text{m s}^{-2}$ ) and  $\theta_v$  is the potential virtual temperature near  
 213 the surface.

214 The friction velocity, the sensible heat flux and the Obukhov stability length are obtained by  
 215 solving the system of non-linear Eqs. 18-20. Derivation of the sensible heat flux using the above  
 216 equations requires only the wind speed and temperature at the reference height as well as the  
 217 surface temperature and is independent of other SEB terms.

218 The input parameters used for the SEBS model are listed in Table 1. Most of the input parameters  
 219 are the same as used for the STIC model, except for two additional parameters. The normalized  
 220 differential vegetation index (NDVI) data from CGLS are used in the retrieval of leaf area index  
 221 (LAI) and canopy height. The wind speed from the ERA5 data is used in the retrieval of  
 222 aerodynamic resistance.

223 2.3 TSEB

224 The TSEB model was first proposed by Norman et al. (1995) who represented the surface by a  
 225 combination of soil and vegetation components. Through the introduction of the TSEB model, the  
 226 problem of defining the extra resistance (caused by using the radiometric temperature instead of  
 227 aerodynamic temperature) in the calculation of sensible heat is bypassed.

228 Component radiometric temperatures are used to compute the surface energy balance fluxes for  
 229 the canopy and soil components of the combined land surface system:

$$R_{N,S} = H_S + \lambda E_S + G \quad (21)$$

$$R_{N,C} = H_C + \lambda E_C \quad (22)$$

230 where  $H_S$  and  $H_C$  are soil and canopy sensible heat fluxes, respectively.  $\lambda E_S$  and  $\lambda E_C$  are the soil  
 231 evaporation and canopy transpiration, respectively.  $G$  is the soil conduction heat flux,  $R_{N,S}$  and  $R_{N,C}$   
 232 are the net radiation for the soil and canopy components.

233 By using the series resistance network to account for the interactions between the soil and  
 234 vegetation canopy fluxes, the sensible heat fluxes can be expressed as follows:

$$H_S = \rho c_p \frac{T_S - T_{AC}}{R_S} \quad (23)$$

$$H_C = \rho c_p \frac{T_C - T_{AC}}{R_X} \quad (24)$$

235 where  $R_S$  and  $R_X$  are the aerodynamic resistance from soil surface and total boundary layer  
 236 aerodynamic resistance of the complete canopy leaves, respectively,  $T_{AC}$  is the momentum  
 237 aerodynamic temperature.

238 For the latent heat flux from the canopy, the Priestly-Taylor formula is used to initially estimate  
 239 a potential rate for  $\lambda E_C$

$$\lambda E_C = \alpha_{PT} f_G \frac{s}{s + \gamma} R_{N,C} \quad (25)$$

240 where  $\alpha_{PT}$  is the Priestly-Taylor constant, with the initial value set to 1.3 and a higher value (~2)  
 241 under well-watered partial canopy cover conditions in advective environments,  $f_G$  is the fraction  
 242 of green vegetation, with the initial value set to 1. Based on  $\lambda E_C$ , the initial canopy temperature  $T_C$   
 243 can be obtained as follows

$$T_C = T_a + \frac{R_{N,C} R_A}{\rho c_p} \left[ 1 - \alpha_{PT} f_G \frac{s}{s + \gamma} \right] \quad (26)$$

244 where  $R_A$  is the aerodynamic resistance to heat transfer (s/m). The soil component temperature can  
 245 be calculated based on the ensemble radiometric temperature  $T_R$  and  $T_C$ . Then the sensible and  
 246 latent heat fluxes of soil are calculated based on the energy balance.

247 Non-physical solutions, such as daytime condensation at the soil surface (i.e.,  $\lambda E_S < 0$ ), can be  
 248 obtained under conditions of moisture deficiency. This occurs because the initial value of  $\alpha_{PT}$  used  
 249 for the initiation of  $\lambda E_C$  can lead to an overestimation of transpiration in water deficit environments.  
 250 If this is encountered,  $\alpha_{PT}$  is iteratively reduced until  $\lambda E_S$  approaches 0.

251 The input parameters used for the TSEB model are listed in Table 1, which are almost the same as  
 252 used for SEBS. The canopy height is calculated using the FVC and LULC data by linear scaling  
 253 between a seasonal minimum and maximum canopy height value for each land surface type  
 254 (Massman 1997). The uniform driving variables for the three models facilitate a fair and thorough  
 255 comparison among the three different SEB models.

### 256 3 Evaluation method

257 To evaluate the three EEH ET products, 19 eddy covariance (EC) sites over Europe were selected  
 258 (Table 2) from the Integrated Carbon Observations System (ICOS) and European Fluxes Database  
 259 Cluster (EFDC). These sites cover six different biomes, including forest (deciduous broadleaf  
 260 forest, evergreen needleleaf forest and mixed forest), cropland, grassland, shrubland, wetland and  
 261 savanna. The instantaneous clear-sky ET estimates (in the form of latent heat flux) were compared  
 262 against half-hourly latent heat flux measurements closest to the ECOSTRESS overpass times  
 263 between 2018 and 2019 at the selected sites. A Bowen ratio SEB closure correction was applied  
 264 to the EC data before the comparison based on the measurements of four components in surface  
 265 radiation budget,  $\lambda E$ ,  $H$ , and  $G$  (Bhattarai et al. 2018). Some extracts were unable to provide all  
 266 the seven measurements required for the SEB closure correction and thus discarded. Moreover,  
 267 the extracts were also discarded if any of these seven measurements did not have a good quality  
 268 (indicated by the quality control flag). Considering the average footprint of the EC sites (Fisher et  
 269 al. 2020), subsets of  $3 \times 3$  pixels were extracted centred on the tower coordinates and the average  
 270 ET values were used in the comparison. To mitigate the uncertainties introduced due to cloud  
 271 contamination, only extracts surrounded by  $15 \times 15$  (approximately 1 km) cloud-free pixels (based  
 272 on the EEH cloud mask product) were considered for further evaluation. The evaluation was first  
 273 conducted over different land surface types, followed by an overall comparison by gathering the  
 274 samples at all the sites.

275 **Table 2.** List of the selected eddy covariance flux sites. The biomes are according to the IGBP  
 276 classification, and climate is according to the Köppen climate type. Biomes covered in this study  
 277 include deciduous broadleaf forest (DBF), evergreen needleleaf forest (ENF), mixed forest (MF),  
 278 savanna (SAV), cropland (CRO), grassland (GRA), shrubland (SHR) and wetland (WET). Climate  
 279 types include humid subtropical (Cfa), temperate oceanic (Cfb), hot-summer Mediterranean (Csa),  
 280 hot-summer humid continental (Dfa), warm-summer humid continental (Dfb), and subarctic (Dfc).  
 281 Mean annual precipitation (MAP) and aridity index (AI) indicate the aridity level at the sites. AI  
 282 is calculated as the ratio between precipitation and potential ET for 30 years and indicates the local  
 283 climatology.

Site ID	Biome	Climate	Latitude (°)	Longitude (°)	MAP (mm)	AI	Source
BE-Lcr	DBF	Cfb	51.11	3.85	861	0.93	ICOS
BE-Lon	CRO	Cfb	50.55	4.75	743	0.97	ICOS
BE-Maa	SHR	Cfb	50.98	5.63	839	0.93	ICOS
BE-Vie	MF	Cfb	50.31	6.00	1062	1.37	EFDC
CZ-Wet	WET	Dfa	49.03	14.77	604	0.74	EFDC
DE-Geb	CRO	Cfb	51.10	10.92	470	0.58	EFDC
DE-Gri	GRA	Dfb	50.95	13.51	872	0.91	ICOS
DE-Kli	CRO	Dfb	50.89	13.52	842	1.00	EFDC
DE-Rur	GRA	Cfb	50.62	6.30	1033	1.38	EFDC
DE-RuS	CRO	Dfb	50.87	6.45	698	0.82	ICOS
ES-LMI	SAV	Csa	39.94	-5.78	700	0.30	EFDC

ES-Abr	SAV	Csa	38.70	-6.79	400	0.32	EFDC
FR-Aur	CRO	Cfb	43.55	1.11	669	0.74	ICOS
FR-Bil	ENF	Cfb	44.49	-0.96	960	0.89	ICOS
FR-Hes	DBF	Cfb	48.67	7.07	820	0.89	EFDC
FR-LGt	WET	Cfb	47.32	2.28	700	0.73	ICOS
FR-Mej	GRA	Cfb	48.12	-1.80	722	0.79	ICOS
IT-Lsn	SHR	Cfa	45.74	12.75	1100	0.91	ICOS
IT-Tor	GRA	Dfc	45.84	7.58	945	1.42	ICOS

284 Three statistical metrics were used to assess the performances of ET products:

$$r = \frac{\sum_{i=1}^n (E_i - \bar{E})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^n (E_i - \bar{E})^2} \sqrt{\sum_{i=1}^n (O_i - \bar{O})^2}} \quad (27)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (E_i - O_i)^2}{n}} \quad (28)$$

$$bias = \frac{\sum_{i=1}^n (E_i - O_i)}{n} \quad (29)$$

285 where  $r$  is the Pearson's correlation coefficient,  $RMSE$  is root-mean-square error,  $bias$  is the mean  
 286 bias, between the model and measurements,  $n$  is the total number of data pairs.  $E_i$  and  $O_i$  are the  
 287 model estimated and measured latent heat fluxes and  $\bar{O}$  is the average of observed values and  $\bar{E}$  is  
 288 the average of estimated values. Additionally, the Kling-Gupta efficiency (KGE) is adopted to  
 289 provide a quantitative and objective assessment of the agreement between the measured latent heat  
 290 fluxes and ET estimates (Gupta et al. 2009). It is calculated as follows

$$KGE = 1 - \sqrt{(r - 1)^2 + \left(\frac{\sigma_s}{\sigma_0} - 1\right)^2 + \left(\frac{u_s}{u_0} - 1\right)^2} \quad (30)$$

291 where  $r$  is the Pearson correlation coefficient,  $\sigma_0$  and  $\sigma_s$  are the standard deviations of EC site  
 292 measurements and EEH estimates, respectively, and  $u_0$  and  $u_s$  are the averages of measurements  
 293 and estimates, respectively. The closer KGE is to 1, the more consistent the ET estimates are with  
 294 the flux measurements.

295 Furthermore, the best performing ET product among the three was compared with the operational  
 296 NASA ECOSTRESS ET product generated using the PT-JPL model (Fisher et al. 2020) at the  
 297 same EC sites. The three statistical metrics described in Equations 27-29 were also used in the  
 298 comparison.

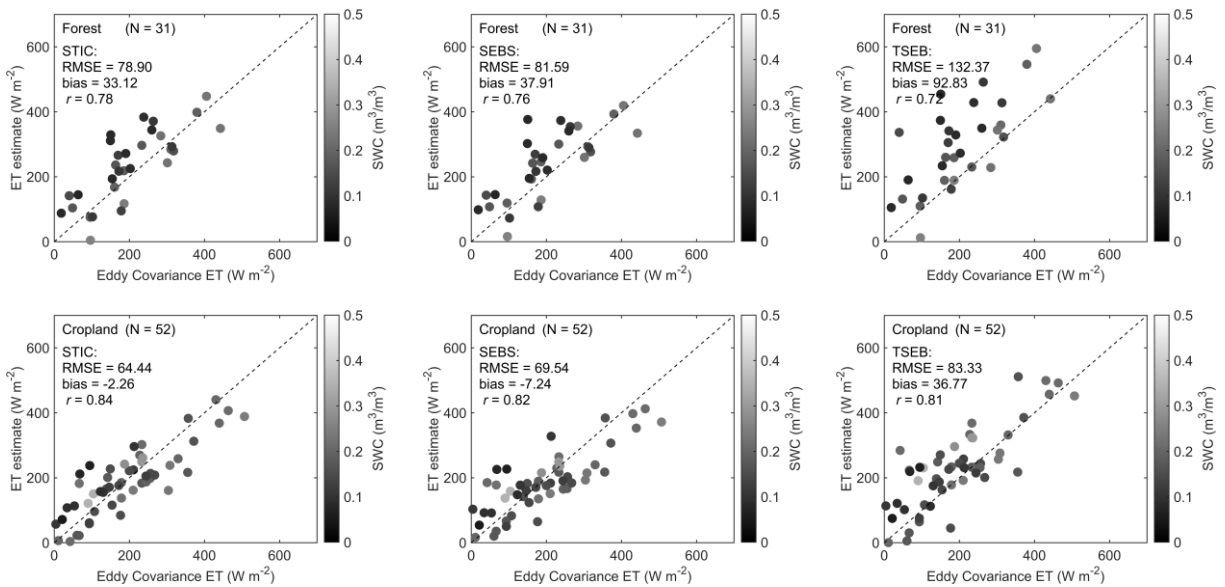
## 299 4 Results

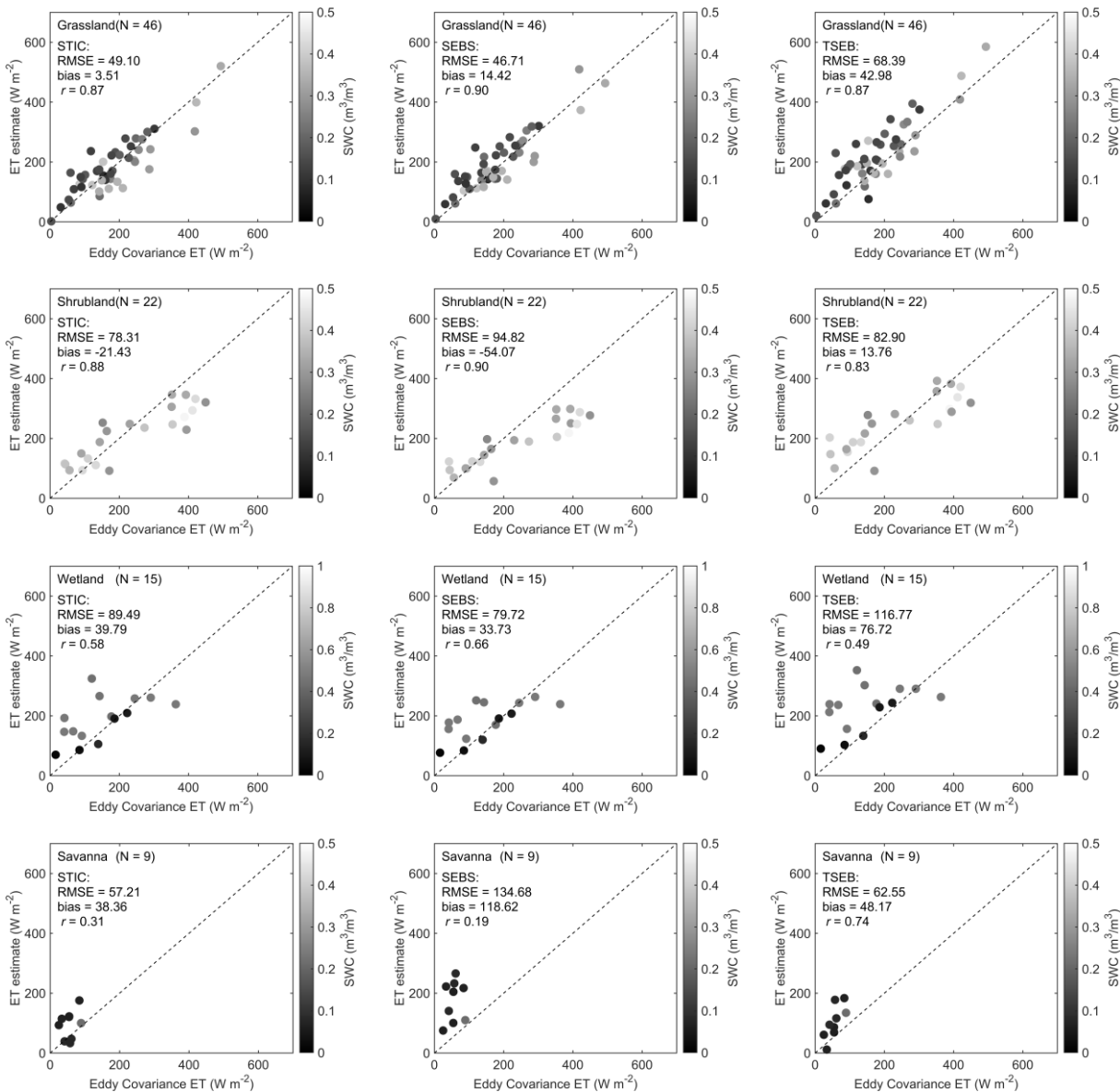
### 300 4.1 Model intercomparison

301 Comparison among the three EEH ET products over six different biomes (Figure 2) for a wide  
 302 range of soil water content (SWC) reveals that the STIC ET estimates produce the least statistical

303 errors over forest, cropland, shrubland and savanna (RMSE between 57.21 and 78.90  $W m^{-2}$ , bias  
 304 between -21.43 and 38.36  $W m^{-2}$ ). While the SEBS ET estimates have the highest consistency with  
 305 respect to EC measurements over grassland and wetland, the performance of SEBS is poor in  
 306 semiarid shrubland and savanna. SEBS shows the highest RMSE ( $\sim 135 W m^{-2}$ ) and bias ( $\sim 119 W$   
 307  $m^{-2}$ ) in these water-scare ecosystems among the three ET products. In contrast, TSEB ET estimates  
 308 have the maximum RMSE (between 68.39 and 132.37  $W m^{-2}$ ) and bias (between 36.77 and 92.83  
 309  $W m^{-2}$ ) over most of the land surface types except for shrubland and savanna (RMSE between 60  
 310 and 85  $W m^{-2}$ , bias between 10 and 50  $W m^{-2}$ ). The performances of STIC and TSEB are  
 311 comparable over shrubland and savanna, with differences of RMSE and bias within 10  $W m^{-2}$ .  
 312 Overall, ET estimates from STIC have consistent performances across different biomes. The SEBS  
 313 ET estimates perform reasonably well in radiation-controlled ecosystems, which is on the contrary  
 314 to the TSEB estimates.

315 All the models show relatively higher uncertainties in ET estimates over forest and wetland, where  
 316 RMSEs are approximately 80  $W m^{-2}$  and biases are above 30  $W m^{-2}$ . The large error in ET  
 317 estimates over forest is probably partly caused by the inconsistency between the meteorological  
 318 variables from the ERA5 reanalysis data and the actual conditions at the reference height above  
 319 the forest. On the contrary, due to the low canopy height and uniform landscape, the atmospheric  
 320 conditions are better depicted by the meteorological data over grassland and cropland, which leads  
 321 to a better ET estimation accuracy in these biomes. For the wetland, the high ET errors under high  
 322 SWC condition could be due to the presence of background water, which does not match the  
 323 conceptualized surface (soil-vegetation-atmosphere continuum) in the three SEB models. Over  
 324 savanna, the overestimation by all the models reflects the challenges in estimating ET over  
 325 semiarid complex landscapes with substantial water stress and low magnitude of ET.

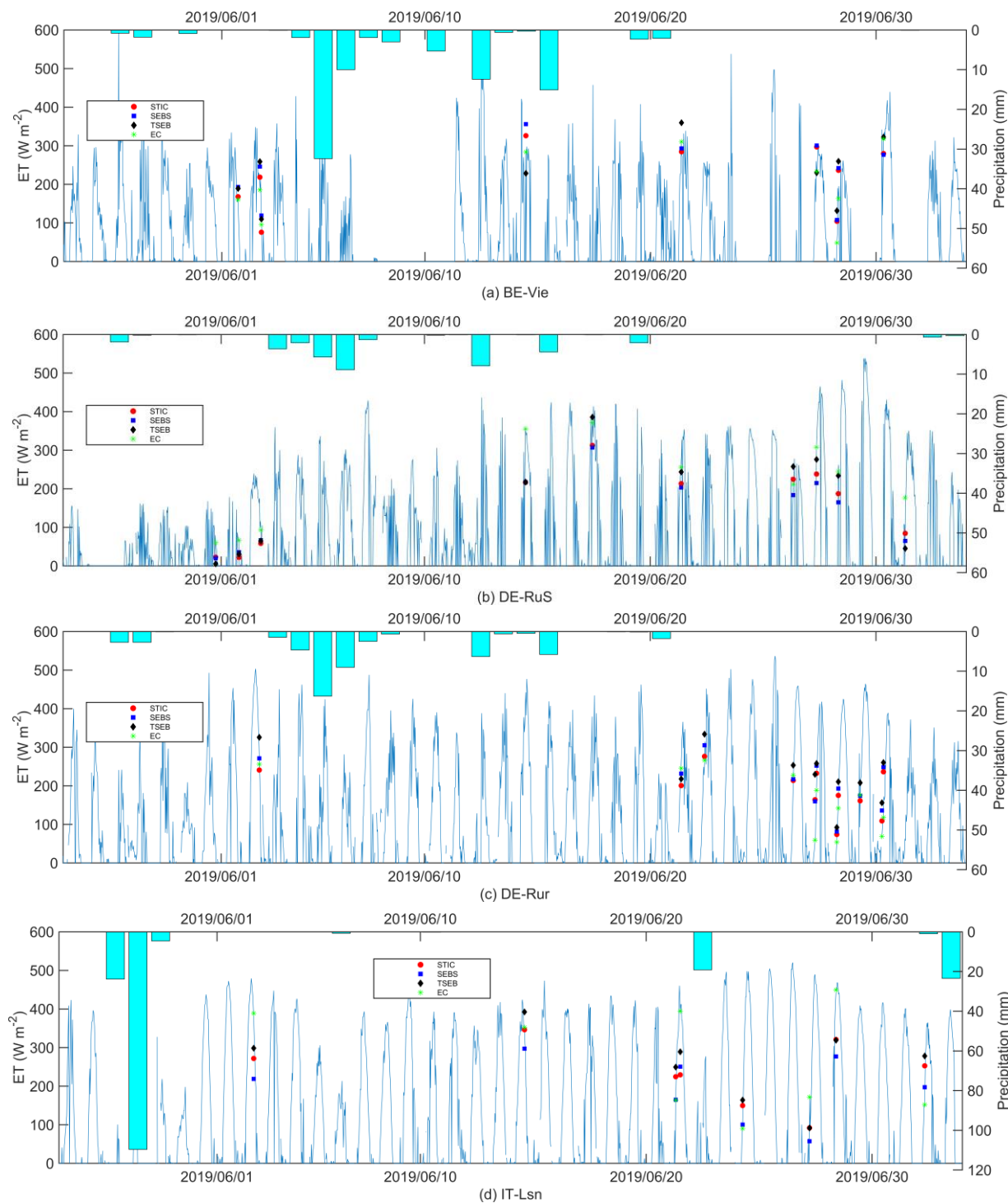


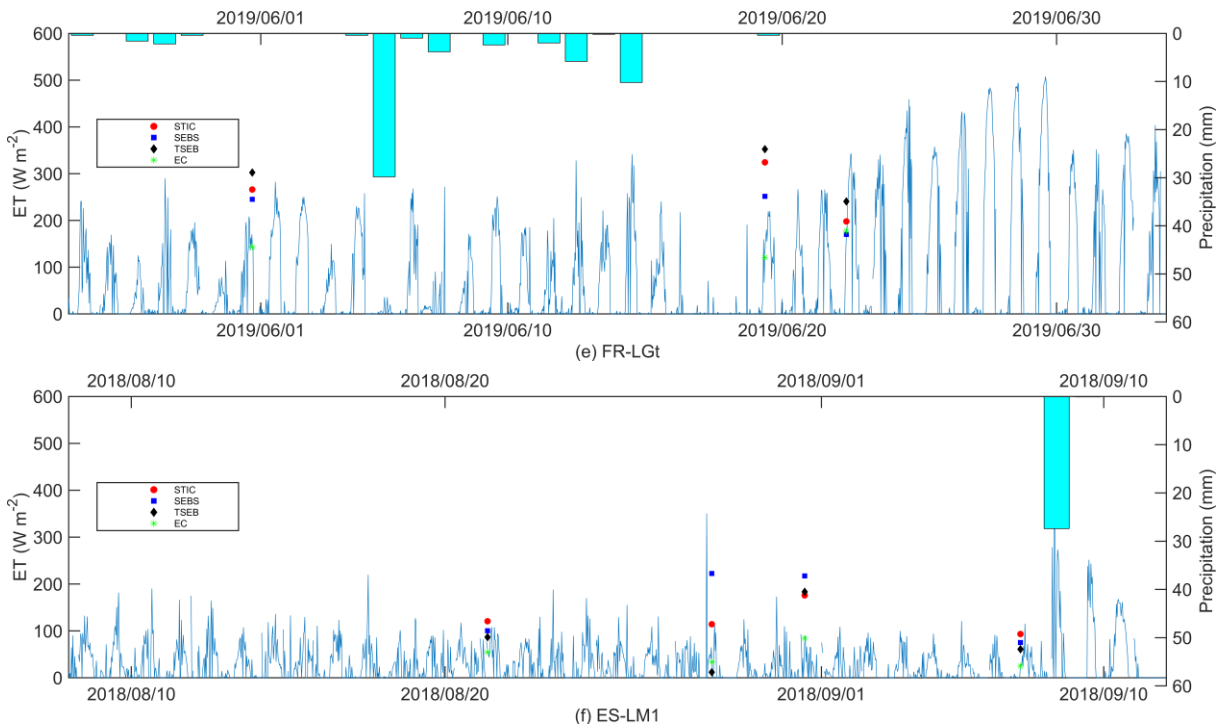


326 **Figure 2.** Comparison between the observed ET at EC sites and instantaneous ET estimates from  
 327 STIC, SEBS and TSEB for 6 biomes during the period 2018–2019. The colour bar represents the  
 328 soil water content (SWC) measurements from the EC sites.

329 The time series of EEH ET estimates at six representative biomes is shown in Figure 3. Overall,  
 330 the ET estimates capture the variation in EC flux measurements although the magnitude is different  
 331 on some days. The diurnal variation of ET is reasonably represented by the estimates (Figure 3(a)  
 332 and (c)). The lagged responses of ET to rainfall events are shown. In line with the better  
 333 performances over grassland and cropland in Figure 2, the EEH ET estimates are also closer to the

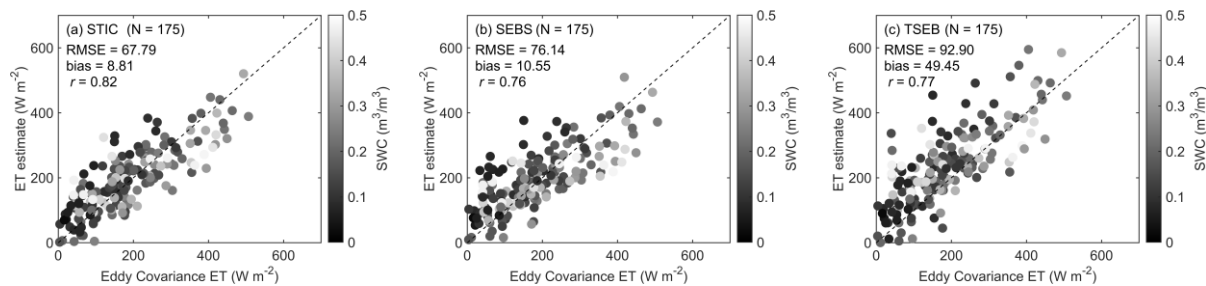
334 EC measurements over these two biomes as compared to the other four. The overestimation of the  
 335 EEH ET products over savanna is clearly embodied (Figure 3(f)).





336 **Figure 3.** Time series of the observed ET and EEH ET estimates from STIC, SEBS and TSEB at  
 337 six representative sites of different biomes (a) forest (BE-Vie), (b) cropland (DE-RuS), (c)  
 338 grassland (DE-Rur), (d) shrubland (IT-Lsn), (e) wetland (FR-LGt), and (f) savanna (ES-LM1).  
 339 The blue line represents the diurnal cycle of latent heat flux measurements at the EC sites. The bar  
 340 represents the daily precipitation obtained by accumulating the half-hourly measurements from the  
 341 EC sites.

342 Overall, the STIC ET estimates have the lowest statistical errors (Figure 4). The accuracy of SEBS  
 343 is similar, with an RMSE around  $70 \text{ W m}^{-2}$ , bias of  $\sim 10 \text{ W m}^{-2}$ , and correlation coefficient ( $r$ )  
 344 around 0.8. ET estimates from TSEB have a relatively larger RMSE ( $92.90 \text{ W m}^{-2}$ ) and bias ( $49.45$   
 345  $\text{W m}^{-2}$ ) although having a similar  $r$  (0.77) to the other two models.

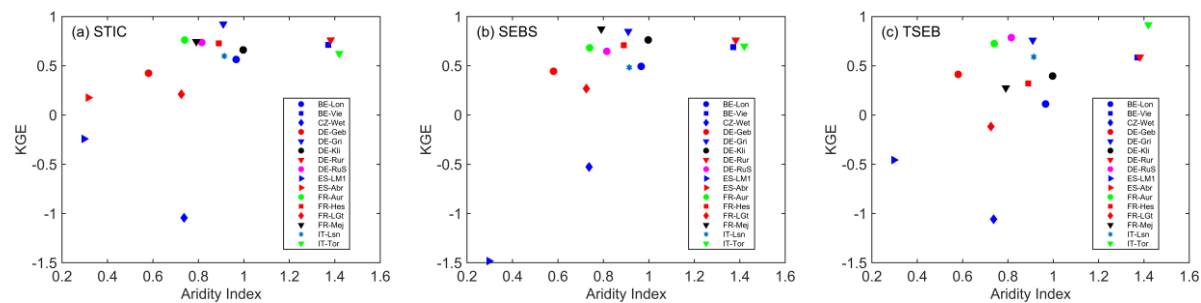


346 **Figure 4.** Comparison between the observed ET and EEH ET estimates at all the eddy covariance  
 347 sites for (a) STIC, (b) SEBS and (c) TSEB during the period between 2018 and 2019. The colour  
 348 bar represents the SWC measurements from the EC sites.

349 To understand the model performance under different aridity conditions, the relationship between  
 350 KGE and aridity index is shown in Figure 5. Aridity index is calculated as the ratio between  
 351 precipitation and potential ET for 30 years, which indicates the local climatology. Here, the Global



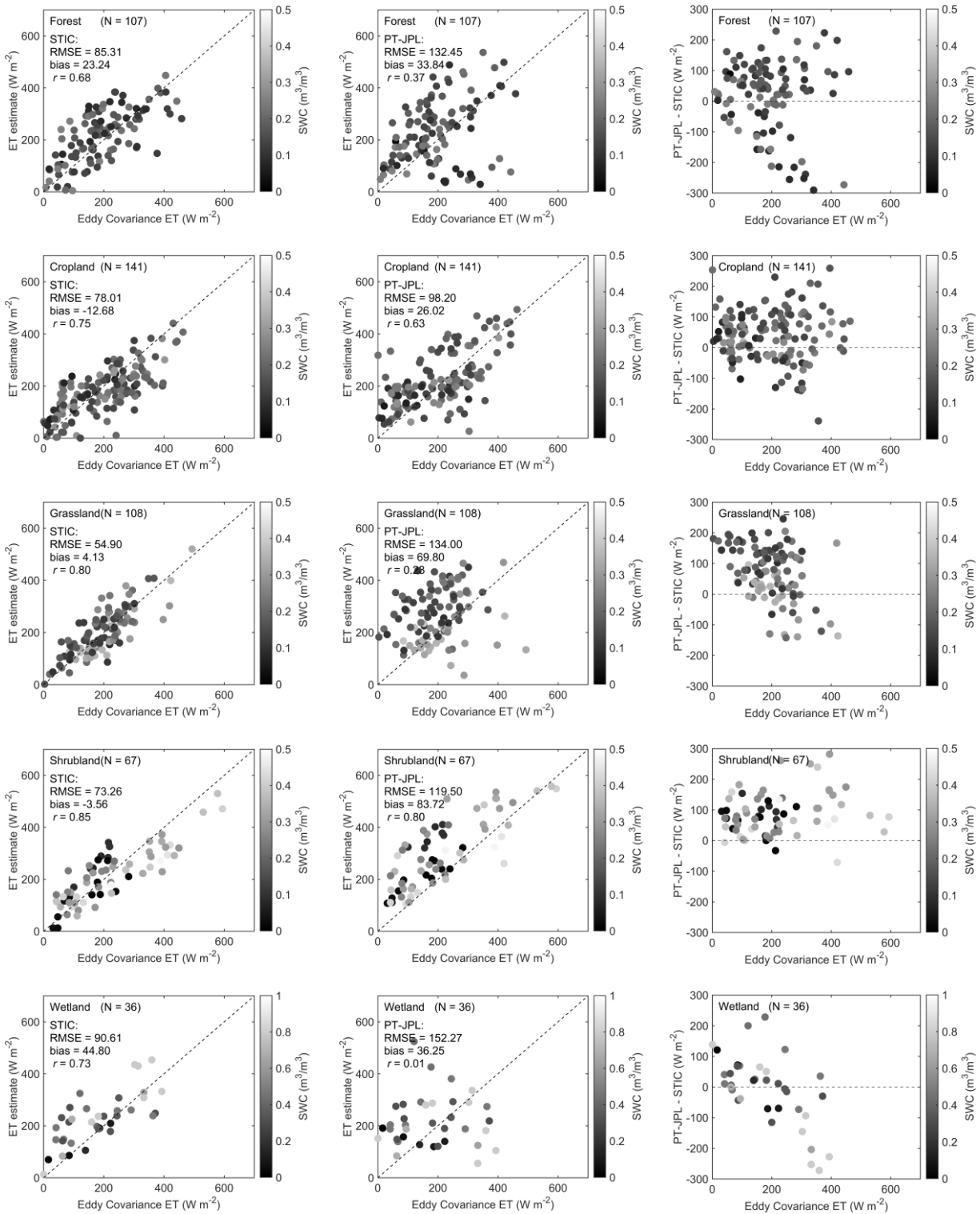
352 Aridity Index and Potential Evapotranspiration Climate Database v3 (Zomer and Trabucco 2022)  
 353 (Global-AI\_PET\_v3) at 1 km pixel scale was used to obtain the aridity indices at the EC sites. The  
 354 KGE for STIC at most of the sites are close to 1, indicating a good agreement between the ET  
 355 estimates and EC measurements. Only the two sites over wetland and two sites over savanna are  
 356 below 0.5, which is consistent with the large biases in these two biomes as found in Figure 2. It is  
 357 also clear that the accuracy of ET estimates improves when the sites have a humid climate (aridity  
 358 index >0.65) as compared to those with a semiarid (0.2-0.5) or dry subhumid (0.5-0.65) climate.  
 359 The SEBS estimates have a similar performance when the aridity index is above 0.5. Whereas  
 360 KEG is notably lower for SEBS under a semiarid climate. The KGE samples for TSEB are more  
 361 scattered, and the magnitudes of KGE at most of the sites are lower than STIC and SEBS.

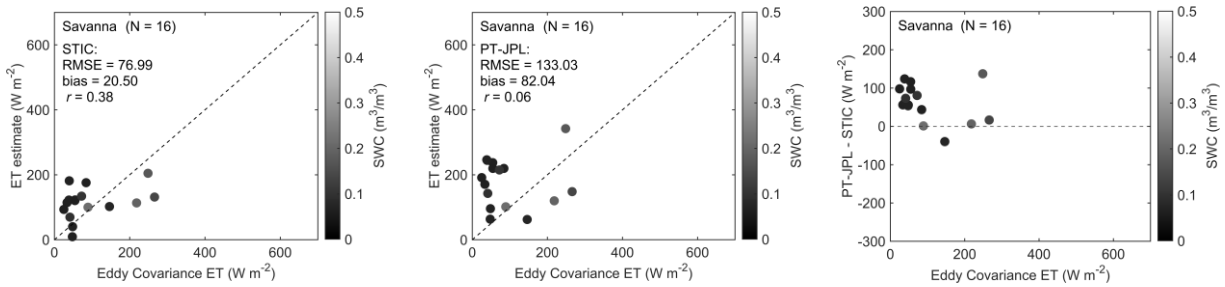


362 **Figure 5.** KGE at different aridity levels for various sites for (a) STIC, (b) SEBS and (c) TSEB  
 363 during the period between 2018 and 2019. Sites over the same land surface type are represented  
 364 using the same marker. The KEG at ES-Abr for SEBS (-5.07) and TSEB (-2.50) are not shown  
 365 due to the excessively low values. The higher the aridity index is, the more humid conditions are.

#### 366 4.2 Comparison between STIC and PT-JPL

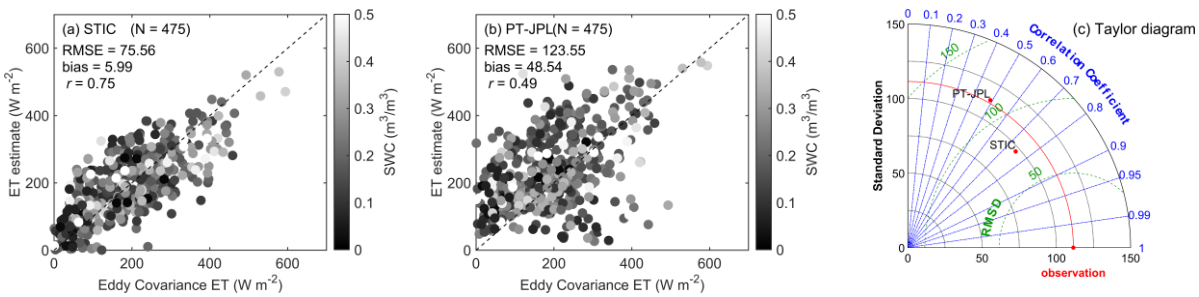
367 Given that the ET estimates from STIC showed the best agreement with the EC measurements,  
 368 STIC ET was compared with the official ECOSTRESS ET that was generated using the PT-JPL  
 369 model (Figure 6). The performance of STIC is pronouncedly better as compared to PT-JPL over  
 370 all the biome types. The differences in RMSE are  $\sim 50 \text{ W m}^{-2}$  in all the cases except over cropland  
 371 where the difference is around  $20 \text{ W m}^{-2}$ . The PT-JPL ET estimates are scattered, with most  
 372 samples above the 1:1 line. This is reflected in the large positive biases of PT-JPL estimates. The  
 373 overestimation of PT-JPL as compared to STIC in dry conditions (with low EC ET) is clearly  
 374 shown. In particular over shrubland and savanna, all the estimates from PT-JPL are greater than  
 375 from STIC. We infer that this is caused by the weak LST constraint in the PT-JPL model, which  
 376 makes the model insensitive to surface water stress. In the PT-JPL model, LST is just used in the  
 377 calculation of surface net radiation. Whereas in the STIC model, LST is embedded in the  
 378 calculation of surface soil moisture availability and thus directly linked to evaporative fraction  
 379 (Equation 5).





380 **Figure 6.** Comparison between the observed ET at EC sites and instantaneous ET estimates from  
 381 STIC and PT-JPL over 6 land surface types during the period between 2018–2020. The colour bar  
 382 represents the SWC measurements from the EC sites.

383 Overall, the PT-JPL model has a RMSE of  $123.55 \text{ W m}^{-2}$  and bias of  $48.54 \text{ W m}^{-2}$ , which are both  
 384  $\sim 50 \text{ W m}^{-2}$  higher than those of STIC. The PT-JPL ET estimates are scattered, in contrast to the  
 385 STIC estimates that are tightly and evenly distributed around the 1:1 line (Figure 7(a) and (b)).  
 386 The Taylor diagram further clarifies the closeness of STIC ET estimates to the ground ‘truth’  
 387 although the standard deviation of PT-JPL ET estimates is closer to that of the observations.



388 **Figure 7.** Comparison between the observed ET and instantaneous ET estimates at all the eddy  
 389 covariance sites for (a) STIC and (b) PT-JPL and (c) Taylor diagram during the period between  
 390 2018 and 2020.

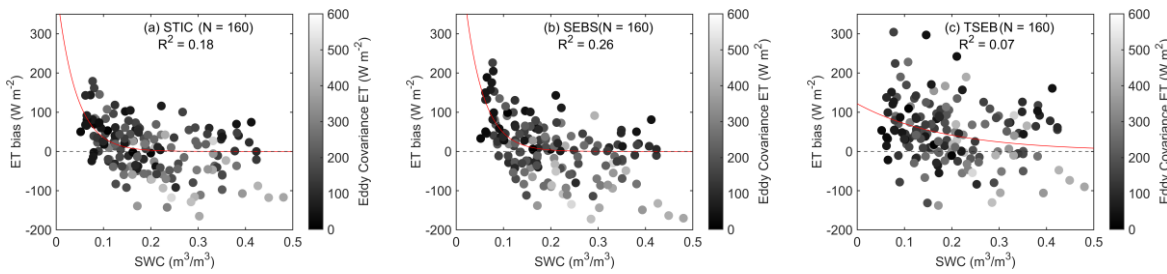
## 391 5 Discussion

### 392 5.1 Factors affecting model performances

393 Different impact factors influencing the model performances were investigated, including SWC  
 394 (Figure 8), vapor pressure deficit (VPD, Figure 9), viewing zenith angle (VZA, Figure 10), and  
 395 FVC (Figure 11), respectively.

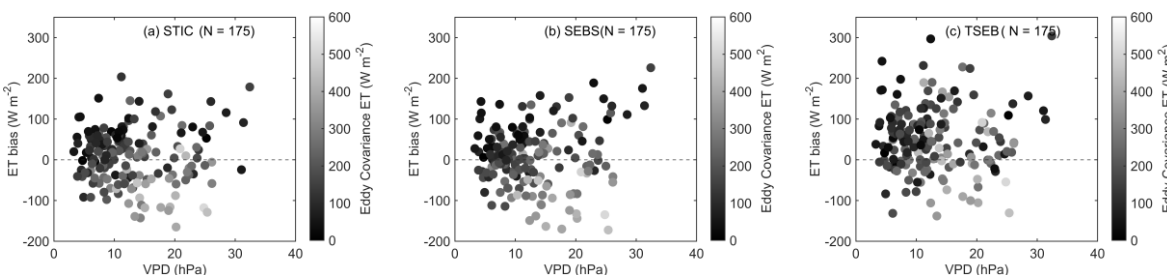
396 For all the models, the variation of ET bias with SWC is exponential (Figure 8). A sharp increase  
 397 in ET bias with progressive surface drying (decreasing SWC) is evident when SWC is below  $0.1 \text{ m}^3 \text{ m}^{-3}$ ,  
 398 which is also associated with low ET magnitude. This is particularly obvious for SEBS,  
 399 which showed a large overestimation under dry conditions. This reflects the challenges as well as  
 400 opportunities in enhancing the performances of ET models in water-scarce regions where the  
 401 coupling between the land surface and atmosphere is strong and evaporation is mainly driven by  
 402 soil water induced stomatal control (Mallick et al. 2022; Mallick et al. 2016). In contrast, when  
 403 SWC is above  $0.2 \text{ m}^3 \text{ m}^{-3}$ , the ET bias tends to diminish and approaches zero, although  
 404 underestimation is indicated when EC ET are high. Due to the scattered samples of TSEB

405 estimates, the relationship between ET bias and SWC is not so strong ( $R^2 = 0.07$ ) as found in STIC  
 406 and SEBS. However, the overall trends in ET bias versus SWC are similar in all the three models.



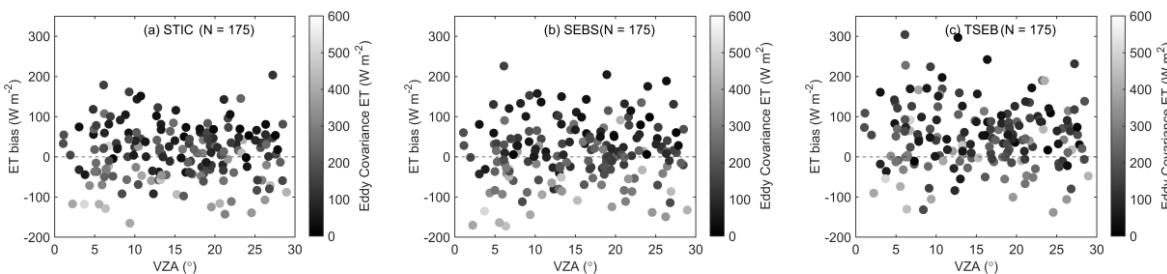
407 **Figure 8.** ET bias (ET estimate minus ground measurement) versus SWC for (a) STIC, (b) SEBS  
 408 and (c) TSEB during the period between 2018 and 2019. Samples at all the sites except for the  
 409 wetland sites are included. The wetland sites are excluded due to the high SWC and different  
 410 pattern between ET bias and SWC from the other land surface types.

411 Compared with SWC, the relationship between ET bias and VPD is not so strong although the bias  
 412 is generally larger when VPD is above 20 hPa (Figure 9). The increase of ET bias with VPD is  
 413 more noticeable for SEBS. This is consistent with the large uncertainty of SEBS that could not  
 414 adequately capture the low ET magnitudes over shrubland and savanna.



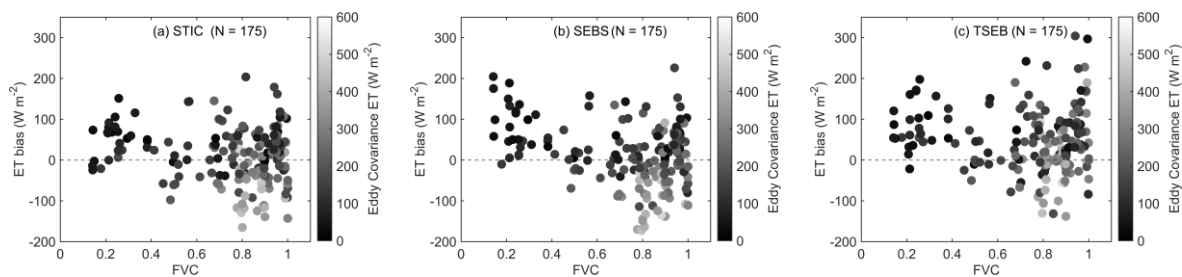
415 **Figure 9.** ET bias (ET estimate minus ground measurement) versus VPD for (a) STIC, (b) SEBS  
 416 and (c) TSEB during the period between 2018 and 2019.

417 No impact of VZA on ET bias is found for all the three models (Figure 10). The magnitude of ET  
 418 bias across different VZAs is close. We infer this is partly because the angular variation of thermal  
 419 radiation is not pronounced when VZA is below  $30^\circ$  (Ermida et al. 2018; Hu et al. 2019; Mwangi  
 420 et al. 2022). Moreover, the high spatial homogeneity at the EC sites (Fisher et al. 2020) is also an  
 421 important factor for the weak angular variation of thermal radiation.



422 **Figure 10.** ET bias (ET estimate minus ground measurement) versus VZA for (a) STIC, (b) SEBS  
 423 and (c) TSEB during the period between 2018 and 2019.

424 The overestimation of ET over sparsely vegetated surfaces ( $FVC < 0.5$ ) is notable for all the three  
 425 models (Figure 11). The ET bias of STIC is lower as compared to the other two models, with most  
 426 of the samples below  $100 \text{ W m}^{-2}$ . The ET bias of SEBS for  $FVC < 0.2$  is substantially higher than  
 427 STIC and TSEB, which is consistent with the high RMSE of SEBS ET estimates over shrubland  
 428 and savanna. This is also reported in previous studies (Bhattarai et al. 2018; Boulet et al. 2012;  
 429 Faivre et al. 2017), which is mostly associated with the underestimation of  $H$  due to uncertainties  
 430 in the estimation of  $kB^{-1}$  and  $z_{OM}$  when the difference between  $T_R$  and  $T_0$  is substantial. Chen et al.  
 431 (2013) proposed an improved roughness height parameterization by updating  $kB^{-1}$  of bare soil,  
 432 which showed a better performance than the original SEBS model by correcting for the  
 433 underestimation of  $H$ . However, it is beyond the scope of this study to compare the revised SEBS  
 434 model with the others in detail. For densely vegetated surfaces ( $FVC > 0.8$ ), the ET bias is evenly  
 435 distributed above and below the zero-bias line. However, the magnitude of bias is higher over  
 436 densely vegetated surfaces due to the relatively higher ET. For TSEB, high biases in ET are found  
 437 when  $FVC$  approaches unity. This high bias in TSEB is presumably due to the uncertainty in  
 438 fraction of green vegetation, which is also reflected in the large RMSE of TSEB ET over forests  
 439 in Figure 2. Given no attempt was made to change the pyTSEB version of Nieto et al. (2016), we  
 440 adopted the default value of fraction of green vegetation (=1) of pyTSEB in EEH. This can be  
 441 somehow problematic when vegetation senescence occurs. However, accurate retrievals of these  
 442 vegetation biophysical parameters are difficult to obtain at large spatial scales, especially for  
 443 ECOSTRESS that only has TIR observations, which could add additional challenges to TSEB.  
 444 Moreover, the PT-TSEB version with a single PT coefficient was used in the EEH. The PM-TSEB  
 445 version with tabulated minimum stomatal resistance might mitigate the large uncertainties of  
 446 TSEB over densely vegetated surfaces (Colaizzi et al. 2014).



447 **Figure 11.** ET bias (ET estimate minus ground measurement) versus FVC for (a) STIC, (b) SEBS  
 448 and (c) TSEB during the period between 2018 and 2019.

449 **5.2 Contrasting performances of ECOSTRESS ET products**

450 The STIC ET estimates showed consistent performances over different land surface types. This  
 451 could be attributed to the non-parameterized structure of this model. Different from the other  
 452 thermal based models, the aerodynamic and surface resistances in STIC are expressed through  
 453 physical equations without empirical parameterization of surface roughness and atmospheric  
 454 stability corrections. However, the calculation of aerodynamic resistance relies on wind speed in  
 455 SEBS and TSEB, which makes these models relatively more sensitive to uncertainties associated  
 456 with wind velocity. Moreover, the aerodynamic temperature is directly retrieved in STIC instead  
 457 of utilizing the radiometric temperature as a proxy and involving subsequent empirical corrections  
 458 as commonly conducted in one-source models (Mallick et al. 2022). As a result, the dependence  
 459 of ET estimates on additional inputs (e.g., wind speed and canopy height) is also eliminated in  
 460 STIC. LST is mainly used for depicting surface water availability in STIC rather than directly

461 calculating sensible heat flux. Considering the current validation datasets, the STIC model is  
462 relatively robust across varying biomes.

463 The SEBS ET estimates showed similar accuracy to the STIC estimates in all cases except for over  
464 sparsely vegetated surfaces (i.e., shrubland and savanna). This could be associated with empirical  
465 parameterizations of resistances to accommodate the inequality between radiometric temperature  
466 and aerodynamic temperature (Mallick et al. 2022; Trebs et al. 2021). Over sparse canopies, large  
467 uncertainties exist in the parameterization scheme. Bhattarai et al. (2018) and Trebs et al. (2021)  
468 reported that uncertainties in  $kB^{-1}$  greatly hindered the accuracy of ET estimates in the arid and  
469 semiarid ecosystems. Moreover, there is no universal methodology for calculating the heat  
470 roughness length, which varies with vegetation structure, surface water stress and climatic  
471 conditions (Kustas and Anderson 2009; Mallick et al. 2022). As such, the SEBS model should be  
472 used with caution in operational ET retrieval.

473 The TSEB ET estimates had larger uncertainties overall as compared to STIC and SEBS. Over  
474 forests, the RMSE and bias reached 132.37 and 92.83 W m<sup>-2</sup>, respectively. As reported by Yang  
475 et al. (2015), a major factor is the uncertainty in determining the initial P-T coefficient, which  
476 represents the aerodynamic forcing and vegetation controls on ET. We used the value of 1.26 in  
477 the model implementation. However, the P-T coefficient has strong spatial variations with surface  
478 dryness, VPD, wind speed and canopy biophysical properties. Thus, a deterministic P-T coefficient  
479 can lead to uncertainties at large scales. An adjustment of the initial P-T coefficient based on land  
480 surface type may mitigate the uncertainty in ET estimates (Andreu et al. 2018; Cristóbal et al.  
481 2020; Cristóbal et al. 2017; Guzinski et al. 2013). Also, the soil aerodynamic resistance  
482 parameterization and the associated empirical coefficients could be another reason (Li et al. 2019).  
483 Moreover, the determination of fraction of green vegetation was simplified in EEH and set to 1  
484 directly. This could also contribute to the large uncertainties of TSEB ET estimates considering  
485 the import role of canopy biophysical parameters in heat transfer (Kustas et al. 2016). A possible  
486 solution could be estimating  $f_G$  based on the empirical approach proposed by Fisher et al. (2008).  
487 In this case, additional input parameters are required such as fraction of absorbed  
488 photosynthetically active radiation (fAPAR), which will bring extra complexity in operational ET  
489 retrieval. Although the biophysical parameters (e.g., LAI and FVC) used in TSEB are the same as  
490 in STIC and SEBS, the TSEB ET estimates seem to be more susceptible to uncertainties in these  
491 biophysical inputs due to the model structure and partitioning of energy between soil and  
492 vegetation. Due to the absence of visible and shortwave infrared (VSWIR) bands in the  
493 ECOSTRESS observations, external biophysical parameters were used in the ET retrieval.  
494 However, the temporal and spatial mismatches between these biophysical parameters and the  
495 instantaneous ECOSTRESS LST estimates could have introduced errors into the TSEB ET results  
496 (Anderson et al. 2021).

497 The accuracy of PT-JPL ET estimates was substantially lower as compared to the STIC estimates  
498 over all the land surface types. This could be attributed to the following reasons. First, the  
499 ECOSTRESS LST is only used for calculating surface net radiation in PT-JPL ET retrieval. Net  
500 radiation has a weak dependence on LST and therefore the ET products generated using PT-JPL  
501 does not take full advantage of surface water stress information embodied in LST. Second, PT-  
502 JPL relies on atmospheric vapor pressure deficit instead of LST for constraining the ET  
503 components. Moreover, the determination of the P-T coefficient for different biomes is a challenge  
504 as well as a major source of uncertainties. Thus, a physically based formula is needed to estimate

505 the P-T coefficient for better interpolation of the aerodynamic forcing and soil-vegetation control  
506 in the SEB process.

### 507 5.3 Uncertainties and limitations in the current evaluation

508 Although we selected EC sites with good maintenance and only used good quality flux  
509 measurements, uncertainties could still exist in the measured fluxes, which may have influenced  
510 the evaluation results. Due to the unavailability of well-maintained EC sites over Africa, we only  
511 evaluated the EEH ET products over Europe. Also, sites in semiarid regions (e.g., over savanna)  
512 have limited sample numbers due to the sparse spatial coverage of ECOSTRESS over the Iberian  
513 Peninsula. Inclusion of more EC sites over Africa and semiarid regions in Europe would benefit a  
514 more thorough and comprehensive evaluation of EEH ET products in the future.

515 In the ECOSTRESS observations, only five thermal bands (three since May 2019 due to the loss  
516 of the two onboard Mass Storage Units) are available. Therefore, ancillary data related to land  
517 surface biophysical properties can only be obtained from external sources. In the case of EEH, we  
518 used the CGLS FVC, and albedo data generated from Sentinel-3/OLCI and PROBA-V. Therefore,  
519 discrepancies in spatial resolution and satellite overpass times cannot be avoided, which could  
520 impact the ET retrieval process. Moreover, cloud masking without the support of VSWIR bands  
521 is challenging and problematic. Although strict cloud screening was exercised in the evaluation,  
522 residuals from the cloud mask could still harm the accuracy of LST retrieval, thus impacting ET  
523 estimation. Fortunately, in the future thermal missions such as TRISHNA and LSTM, these  
524 problems will be minimized substantially with the measurement in VSWIR bands.  
525 Correspondingly, the accuracy of ET estimates can be envisaged to further improve.

526 Due to the issue with the sensor's radiometric calibration in Collection 1 ECOSTRESS data, a cold  
527 bias of ~1 K was found in the ECOSTRESS LST products (Hulley et al. 2021). This has been  
528 addressed in Collection 2 that will be released in 2022. Accordingly, we will reprocess the  
529 ECOSTRESS LST, and ET products based on the Collection 2 ECOSTRESS radiance data and  
530 extend the temporal coverage of EEH products to September 2023 in the Phase-2 of EEH. The 5-  
531 year time series of high spatio-temporal resolution ECOSTRESS products with improved accuracy  
532 is expected to greatly benefit the studies on terrestrial ecosystem processes.

## 533 6 Conclusion

534 TIR observations from ECOSTRESS onboard the ISS with high spatio-temporal resolution  
535 provide a good opportunity for generating LST and ET products at the field scale over the globe.  
536 In this study, we evaluated three ECOSTRESS ET products generated in the EEH project based  
537 on three structurally contrasting thermal-based SEB models (i.e., STIC, SEBS, and TSEB). The  
538 ET estimates were compared against latent heat flux measurements at 19 EC sites over Europe  
539 between 2018 and 2019. Furthermore, the best performing STIC ET estimates were compared with  
540 the NASA official ECOSTRESS ET products using the PT-JPL model at the same sites. Six  
541 different land surface types were encompassed in the evaluation, including forest, grassland,  
542 cropland, shrubland, wetland and savanna.

543 The results revealed that the STIC ET estimates had consistent performance over different land  
544 surface types with a relatively better accuracy as compared to the other two models, which is

545 directly linked to the analytical framework of STIC without resistance parameterizations. The  
546 SEBS estimates had similar performances to STIC except over shrubland and savanna where the  
547 uncertainties of SEBS ET were substantially higher than for the other two models. This is attributed  
548 to the large uncertainties in empirical parameterizations of resistances to accommodate the  
549 inequality between radiometric temperature and aerodynamic temperature in SEBS over sparsely  
550 vegetated surfaces. The performance of TSEB was particularly good in water-scarce ecosystems.  
551 However, large uncertainties were found in TSEB in radiation-controlled ecosystems. The setting  
552 of P-T coefficient, soil aerodynamic resistance parameterization, fraction of green vegetation  
553 values, and temporal and spatial mismatches between the input biophysical parameters and the  
554 instantaneous ECOSTRESS LST retrievals could account for the high uncertainties to some extent.

555 Compared with the PT-JPL estimates, the performance of STIC was substantially better over all  
556 the land surface types. The overall RMSE and bias were both  $\sim 50 \text{ W m}^{-2}$  higher in the PT-JPL  
557 estimates than those of STIC. The serious overestimation of PT-JPL ET estimates could be  
558 explained by the weak LST constraint in the model.

559 We conclude that the high spatio-temporal resolution EEH ET products provide an unprecedented  
560 opportunity for environmental and agricultural applications. The comprehensive evaluation among  
561 the EEH ET estimates driven by uniform forcing data provides insights into SEB models with  
562 different structures and contrasting parameterization schemes. Overall, the EEH is promising to  
563 serve as a support for the future thermal missions such as TRISHNA jointly collaborated by France  
564 and India, SBG from NASA and LSTM from ESA.

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