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Accepted Version

Bezerra, U. A., Cunha, J., Valente, F., Nóbrega, R. L. B., Andrade, J. M., Moura, M. S.B., Verhoef, A. ORCID: <https://orcid.org/0000-0002-9498-6696>, Perez-Marin, A. M. and Galvão, C. O. (2023) STEEP: a remotely-sensed energy balance model for evapotranspiration estimation in seasonally dry tropical forests. *Agricultural and Forest Meteorology*, 333. 109408. ISSN 0168-1923 doi: 10.1016/j.agrformet.2023.109408 Available at <https://reading-pure-test.eprints-hosting.org/111295/>

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To link to this article DOI: <http://dx.doi.org/10.1016/j.agrformet.2023.109408>

Publisher: Elsevier

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1 **STEEP: a remotely-sensed energy balance model for evapotranspiration estimation in** 2 **seasonally dry tropical forests**

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15 **Highlights**

- 16 • STEEP is a RS-based SEB model from a one-source bulk transfer equation for SDTF.
- 17 • STEEP includes improved representations of phenology and soil moisture for SDTF.
- 18 • STEEP is tested against eddy covariance data from the largest SDTF in South America.
- 19 • STEEP exhibits satisfactory metrics and outperforms SEBAL, MOD16, and PMLv2.

20 **Abstract**

21 Improvement of evapotranspiration (ET) estimates using remote sensing (RS) products based on
22 multispectral and thermal sensors has been a breakthrough in hydrological research. In large-scale
23 applications, methods that use the approach of RS-based surface energy balance (SEB) models
24 often rely on oversimplifications. The use of these models for Seasonally Dry Tropical Forests
25 (SDTF) has been challenging due to incompatibilities between the assumptions underlying those
26 models and the specificities of this environment, such as the highly contrasting phenological phases
27 or ET being mainly controlled by soil–water availability. We developed a RS-based SEB model from
28 a one-source bulk transfer equation, called Seasonal Tropical Ecosystem Energy Partitioning
29 (STEEP). Our model uses the plant area index to represent the woody structure of the plants in
30 calculating the moment roughness length. We included the parameter kB^{-1} and its correction using
31 RS soil moisture in the calculation of the aerodynamic resistance for heat transfer.

32 Besides, λET caused by remaining water availability in endmembers pixels was quantified using the
33 Priestley-Taylor equation. We implemented the algorithm on Google Earth Engine, using freely
34 available data. To evaluate our model, we used eddy covariance data from four sites in the Caatinga,
35 the largest SDTF in South America, in the Brazilian semiarid region. Our results show that STEEP
36 increased the accuracy of ET estimates without requiring any additional climatological information.
37 This improvement is more pronounced during the dry season, which, in general, ET for these SDTF
38 is overestimated by traditional SEB models, such as the Surface Energy Balance Algorithms for Land
39 (SEBAL). The STEEP model had similar or superior behavior and performance statistics relative to
40 global ET products (MOD16 and PMLv2). This work contributes to an improved understanding of the
41 drivers and modulators of the energy and water balances at local and regional scales in SDTF.
42 Keywords: Sensible heat flux, Aerodynamic resistance for heat transfer, Surface energy balance,
43 Caatinga, Google Earth Engine

44

45 **1. Introduction**

46 Quantifying evapotranspiration (ET) is one of the largest research challenges in hydrology
47 because ET is driven by a complex combination of atmospheric, vegetation, edaphic, and terrain
48 characteristics (Wang et al., 2016; Bhattarai et al., 2017). The traditional techniques to quantify ET,
49 e.g. Bowen ratio or eddy covariance system (EC), are limited to areas up to ~ 10 km² (Allen et al.,
50 2011; Anapalli et al., 2016; Mcshane et al., 2017; Mallick et al., 2018; Chu et al., 2021). Over the
51 past decades, models based on satellite remote sensing (RS) data have been increasingly
52 developed and applied to estimate ET for multiple temporal and spatial scales (Anderson et al., 2011;
53 Chen and Liu, 2020). RS-based surface energy balance (SEB) models estimate ET in terms of
54 energy per unit area (e.g. W/m²), i.e. by latent heat flux, λET , where λ is the latent heat of vaporization
55 of water (Shuttleworth, 2012; Barraza et al., 2017; Trebs et al., 2021). SEB models obtain λET by
56 subtracting the soil heat (G) and sensible heat (H) fluxes from the net radiation (R_n). Estimates of R_n
57 obtained with RS data have been improving, and this flux can nowadays be estimated with
58 acceptable precision (Allen et al., 2011; Ferreira et al., 2020). The $G:R_n$ ratio can be predicted with
59 reasonable accuracy through the use of empirical relationships with soil, vegetation, and temperature
60 characteristics (Bastiaanssen, 1995; Murray and Verhoef, 2007; Allen et al., 2011; Danelichen et al.,

61 2014). Challenges in estimating λET as a residual of the energy balance are mostly associated with
62 the uncertainties in H (Gokmen et al., 2012; Paul et al., 2014; Mohan et al., 2020a, Mohan et al.,
63 2020b; Costa-Filho et al., 2021). The bulk heat transfer calculation that is used to compute H involves
64 variables related to the temperature gradient and to the aerodynamic resistance for heat transfer
65 (rah). If any of these variables are poorly estimated, the performance of SEB models will be reduced
66 (Verhoef et al., 1997a, b; Su et al., 2001; Gokmen et al., 2012; Costa-Filho et al., 2021; Liu et al.,
67 2021; Trebs et al., 2021).

68 The difference between the aerodynamic surface temperature and air temperature (dT)
69 drives H . However, the lack of techniques to measure the aerodynamic surface temperature required
70 strategies to use the radiometric land surface temperature (LST) as an alternative. Bastiaanssen et
71 al. (1998), when creating the Surface Energy Balance Algorithms for Land (SEBAL), proposed that
72 dT can be estimated with a linear relationship on LST. This requires identifying areas with contrasting
73 extreme conditions in terms of cover and humidity, e.g., dry bare and well-watered soil surfaces,
74 commonly known as hot/dry and cold/wet endmembers, respectively. The sensible heat transfer
75 equation in conjunction with the surface energy balance in hot/dry and cold/wet endmembers allows
76 one to obtain the coefficients of the linear relationship between dT and LST. Bastiaanssen et al.
77 (1998) proposed the selection of endmembers by assuming that H in the cold/wet endmember and
78 λET in the hot/dry endmember are zero. However, these assumptions are not necessarily valid
79 (Singh and Irmak, 2011; Singh et al., 2012). The cold/wet endmember refers to an area with a well-
80 irrigated crop surface having ground fully covered by vegetation, so it can be assumed that a non-
81 negligible amount of sensible heat can still be generated by such a surface. Similarly, for the hot/dry
82 endmember, an area dominated by bare soil, there may be a λET resulting from antecedent rainfall
83 events, hereafter referred to as remaining λET . Some studies have quantified H and λET in hot/dry
84 and cold/wet endmembers (Trezza, 2006; Allen et al., 2007; Singh and Irmak, 2011); they have
85 shown that this quantification produces a better approximation of daily ET.

86 Based on the Monin-Obukhov similarity theory, rah is defined as a function of the momentum
87 ($z0m$) and heat ($z0h$) roughness lengths. Theoretically, the sum of the zero plane displacement
88 height ($d0$) together with $z0h$ defines the level of the effective source of sensible heat (Thom, 1972;
89 Chehbouni et al., 1996; Gokmen et al., 2012) and, therefore, $z0h$ constitutes one of the most crucial

90 parameters for the accurate calculation of H (Verhoef et al., 1997a; Su et al., 2001). However, as
91 z_0h cannot be measured directly, it is commonly calculated via the dimensionless parameter kB^{-1}
92 formulated to express the excess resistance of heat transfer compared to momentum transfer (Owen
93 and Thomson, 1963). In RS-based SEB models, oversimplifications are present in the calculation of
94 rah , e.g. different land use types are represented by the same values for z_0h (Bastiaanssen et al.,
95 2005; Allen et al., 2007) and kB^{-1} (Bastiaanssen et al., 1998), or the values for the aerodynamic
96 parameters are kept constant in time and space. However, these parameters should not be
97 considered constant, nor set to zero, because this can lead to large inaccuracies in the estimates of
98 H (Verhoef et al., 1997a) and, consequently, of λET (Liu et al., 2007; Paul et al., 2014; Liu et al.,
99 2021). Studies have shown that kB^{-1} typically ranges from 1 to 12, depending on the dominant
100 surface coverage (Kustas et al., 1989a; Troufleau et al., 1997; Verhoef et al., 1997a; Lhomme et al.,
101 2000; Su et al., 2001). Studies confirm that if appropriate values of kB^{-1} are used, H can be accurately
102 estimated using LST via the bulk transfer method (Stewart et al., 1994; Su et al., 2001; Jia et al.,
103 2003; Paul et al., 2013).

104 Another problem with RS-based SEB models is that these methods are imprecise when
105 applied to non-agricultural environments, such as forests, deserts, sparse savannahs or rangelands,
106 and riparian systems, because of the heterogeneous nature of the vegetation, terrain, soils, and
107 water availability in these environments. This causes the flux estimates obtained with the SEB
108 methods, and the underlying aerodynamic parameters, to be highly variable (Allen et al., 2011;
109 Gokmen et al., 2012; Barraza et al., 2017; Chen and Liu, 2020; Costa-Filho et al., 2021). This is
110 especially true in Seasonally Dry Tropical Forests (SDTF) regions, where there is a large spatio-
111 temporal variation in vegetation density, in vegetation structural parameters such as canopy height,
112 crown shape and branching, and water availability. SDTF are an important tropical biome and one
113 of the most threatened ecoregions of the world (Moro et al., 2015; Pennington et al., 2018). SDTF
114 are broadly defined as forest formations in tropical regions characterised by marked seasonality in
115 rainfall distribution, resulting in a prolonged dry season that usually lasts five or six months
116 (Pennington et al., 2009; Paloschi et al., 2020). The most extensive contiguous areas of SDTF are
117 in the neotropics, comprising more than 60% of the remaining global stands of this vegetation (Miles
118 et al., 2006; Queiroz et al., 2017). The physiognomies exhibited by SDTF are heterogeneous, with

119 vegetation ranging from tall forests with closed canopies to scrublands rich in succulents and thorn-
120 bearing plants (Moro et al., 2015; Paloschi et al., 2020). SDTF foliage patterns are adapted to the
121 intense climate and water seasonality, which is highly dependent on interannual climate variability
122 (Alberton et al., 2017; Medeiros et al., 2022). The vegetation drops most leaves during the dry
123 season, and the first rainfall events trigger a rapid leaf growth in the wet season (Alberton et al.,
124 2017; Paloschi et al., 2020; Medeiros et al., 2022). SDTF are being rapidly degraded (12% between
125 1980 and 2000), highlighting an urgent priority for their conservation (Moro et al., 2015; Maia et al.,
126 2020). The risks faced by SDTF mainly stem from anthropogenic disturbance effects, which range
127 from local habitat loss to global climate change, leading to biodiversity loss and reductions in biomass
128 (Allen et al., 2017; Maia et al., 2020).

129 Application of SEB models to estimate evapotranspiration over SDTF has been challenging
130 due to the incompatibility between the existing assumptions of the models and the specificities of
131 these forests. Precipitation seasonality is the primary phenological regulator of SDTF (Moro et al.,
132 2016; Campos et al., 2019; Paloschi et al., 2020), and land-cover patterns show distinct intra- and
133 inter-annual spectral responses (Cunha et al., 2020; Andrade et al., 2021; Medeiros et al., 2022).
134 Therefore, biophysical remotely-sensed variables, such as Normalized Difference Vegetation Index
135 (NDVI) and surface albedo, which are usually used to select the endmembers, exhibit high spatial
136 and temporal variability in SDTF, which causes ET estimates from the SEB models to lack fidelity
137 (Silva et al., 2019). Selection of suitable roughness parameters such as z_{0m} , d_0 , and kB^{-1} is
138 important for the correct quantification of the energy balance in SDTF. However, these parameters
139 are more challenging to obtain in SDTF than for evergreen forests, as in addition to vegetation height,
140 other characteristics such as plant density, above-ground plant structure and the strong seasonality
141 of phenology (Alberton et al., 2017; Miranda et al., 2020; Paloschi et al., 2020) have a considerable
142 effect on the turbulent transfer in these forests. Another key issue is how to verify the results of SEB
143 methods due to the scarcity, in many regions, of terrestrial observations and the uneven
144 spatiotemporal distribution of monitoring data. SEB models may not satisfactorily represent ET in
145 regions with sparse vegetation and high climatic seasonality, such as SDTF (Senkondo et al., 2019;
146 Laipelt et al., 2021; Melo et al., 2021). The main reason is that these methods have generally been
147 evaluated and/or parameterized using sites located in other ecosystems and climates in North

148 America, Europe, Australia, East Asia, and in agricultural regions that have characteristics quite
149 distinct from SDTF (Melo et al., 2021). Therefore, a better quantification of ET, especially in regions
150 with high climatic seasonality, will help to design better water management policies that will be able
151 to deal with the effects of climate variability, land use/cover and climate changes (Lima et al., 2021).

152 We hypothesise that a SEB model that improves or considers estimates of rah via $z0m$ and
153 kB^{-1} will improve H and ET for STDF. To test this assumption, we introduce a novel calibration-free
154 SEB model based upon a one-source bulk transfer equation, herein referred to as Seasonal Tropical
155 Ecosystem Energy Partitioning (STEEP). The STEEP model aims to improve H and ET estimates
156 for STDF by incorporating the woody structure of plants through the Plant Area Index (PAI), and soil
157 moisture obtained by remote sensing to help represent the seasonality of the aerodynamic and
158 surface variables that drive the energy fluxes. To obtain the coefficients of the linear relationship
159 between dT and LST its coefficients, we computed H by the surface energy balance, and the
160 remaining λET through the principle of the Priestley-Taylor equation in the hot/dry and cold/wet
161 endmembers. STEEP is designed to take advantage of the extensive free database available on the
162 Google Earth Engine (GEE) cloud computing environment. STEEP is herein evaluated at the field
163 scale against four flux towers in the Caatinga, the largest continuous SDTF in the Americas.
164 Additionally, the model was compared with SEBAL and two consolidated global ET products: MOD16
165 (Mu et al., 2011; Running et al., 2017) and PMLv2 (Zhang et al., 2019).

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167 **2. Methodology**

168 2.1 Study areas and respective data

169 The study concerns the Brazilian Caatinga, located between the Equator and the Tropic of
170 Capricorn (about 3 and 18° south), in the Brazilian semiarid region. It covers an area of about
171 850,000 km² (Silva et al., 2017a; Andrade et al., 2021; Brazil MMA, 2021). The climate in the
172 Caatinga is characterized by high air temperatures (around 26–30° C) and high potential
173 evapotranspiration (1,500–2,000 mm/year) coupled with low annual rainfall (300–800 mm/year,
174 normally concentrated in 3–6 months) with high intra- and inter-annual variability in space and time,
175 and a long dry season which sometimes lasts up to 11 months in some areas of Caatinga (Moro et
176 al., 2016; Miranda et al., 2018; Paloschi et al., 2020). The Caatinga vegetation has at least thirteen

177 physiognomies ranging from woods to sparse thorny shrubs, morphologically adapted to resist water
178 stress and high air temperatures (Araújo et al., 2009; Silva et al., 2017a; Marques et al., 2020;
179 Miranda et al., 2020), and it has been identified as one of the most biodiverse SDTF regions globally
180 (Pennington et al., 2006; Santos et al., 2014; Koch et al., 2017). Still, the Caatinga and other SDTF
181 are among the least studied ecoregions compared to tropical forests and savannas (Santos et al.,
182 2012; Koch et al., 2017; Tomasella et al., 2018; Borges et al., 2020). Only 1% of the Brazilian
183 Caatinga area is legally protected (Koch et al., 2017).

184 We used data from four sites located in the Caatinga (Fig. 1 and Table 1). The surrounding
185 areas of each of our study sites — which exceeds these EC towers footprints — are homogeneously
186 covered by Caatinga vegetation (Fig. S1). Located on crystalline terrain (Fig. 1a), these Caatinga
187 sites have soils with highly variable properties, ranging from fertile (those with a clayey texture) to
188 poor (those soils that are sandier). However, most soils of the SDTF are typically shallow and stony
189 (i.e. Entisols, Alfisols, and Ultisols; WRB, 2006), retaining water only for a short period between
190 rainfall events and after the rainy season (Moro et al., 2015; Queiroz et al., 2017). The wet and (dry)
191 seasons from the sites Petrolina (PTN) are concentrated in Jan–Apr (May–Dec; Souza et al., 2015);
192 Serra Negra do Norte (SNN) in Jan–May (June–Dec; Marques et al., 2020); Serra Talhada (SET) in
193 Nov–Apr (May–Oct; Silva et al., 2017b) and Campina Grande (CGR) in Mar–July (Aug–Feb; Oliveira
194 et al., 2021). The climate of the four observation sites is semi-arid, type BSh (Fig. 1b) according to
195 the Köppen climate classification (Alvares et al., 2013).

196 Eddy covariance data, covering several periods from 2011 to 2020 (Fig. 1c), were used to
197 evaluate the modelled ET and H . The four sites were instrumented with five flux towers equipped
198 with three-dimensional ultrasonic anemometers (CSAT3, Campbell Scientific Inc., Logan, UT, USA
199 in all the sites except CGR 2020) and open-path infrared gas analysers (LI-7500, LI-COR Inc.,
200 Lincoln, NE, USA, in the PTN site, or EC150, Campbell Scientific Inc., Logan, UT, USA, in the SET,
201 SNN, and CGR 2014 sites). In the more recent experiment (CGR 2020), the flux tower was equipped
202 with an IRGASON (Campbell Scientific Inc., Logan, UT, USA) that integrates the two sensors in just
203 one instrument. ET data for the PTN, SNN, and SET sites have been previously described; they
204 underwent standard procedures to ensure their quality and were published by Melo et al. (2021).
205 Observations at the CGR site were collected through two micrometeorological towers, located in a

206 dense Caatinga area within the Brazilian National Institute of Semiarid (INSA) experimental area, a
207 300 ha forest reserve with different stages of regeneration. The first tower (height of 7 m) was active
208 between the years of 2014 and 2017, as described in Oliveira et al. (2021). The second tower (height
209 of 15 m) is part of the Caatinga Observatory (OCA) and includes an EC system that has been
210 collecting data since 2020. The OCA is a laboratory maintained by the Federal University of Campina
211 Grande and INSA. H data for the PTN, SNN and CGR sites have been obtained from the respective
212 principal investigators, while data for the SET site have been obtained from the AmeriFlux network
213 (Antonino, 2019). For the retrieval of λET and H , LoggerNet software (Campbell Scientific, Inc.,
214 Logan, UT, USA) was used in order to transform 10 Hz raw data into 30 min binaries. Afterwards,
215 EdiRe software (Campbell Scientific Inc., Logan, UT, USA) was used to process the high-frequency
216 data, averaging every 30 min. The data from the EC flow towers in CGR have previously gone
217 through standard procedures to ensure their quality. Detailed information on data processing, quality
218 control, and post-processing can be found in Campos et al. (2019) and Cabral et al. (2020). The raw
219 data from the CGR flux tower were processed by Easy-flux data processing software (Campbell
220 Scientific Inc., Logan, UT, USA). In addition, data for any day with rainfall greater than 0.5 mm were
221 removed. The daily ET was calculated using the daily average λET .

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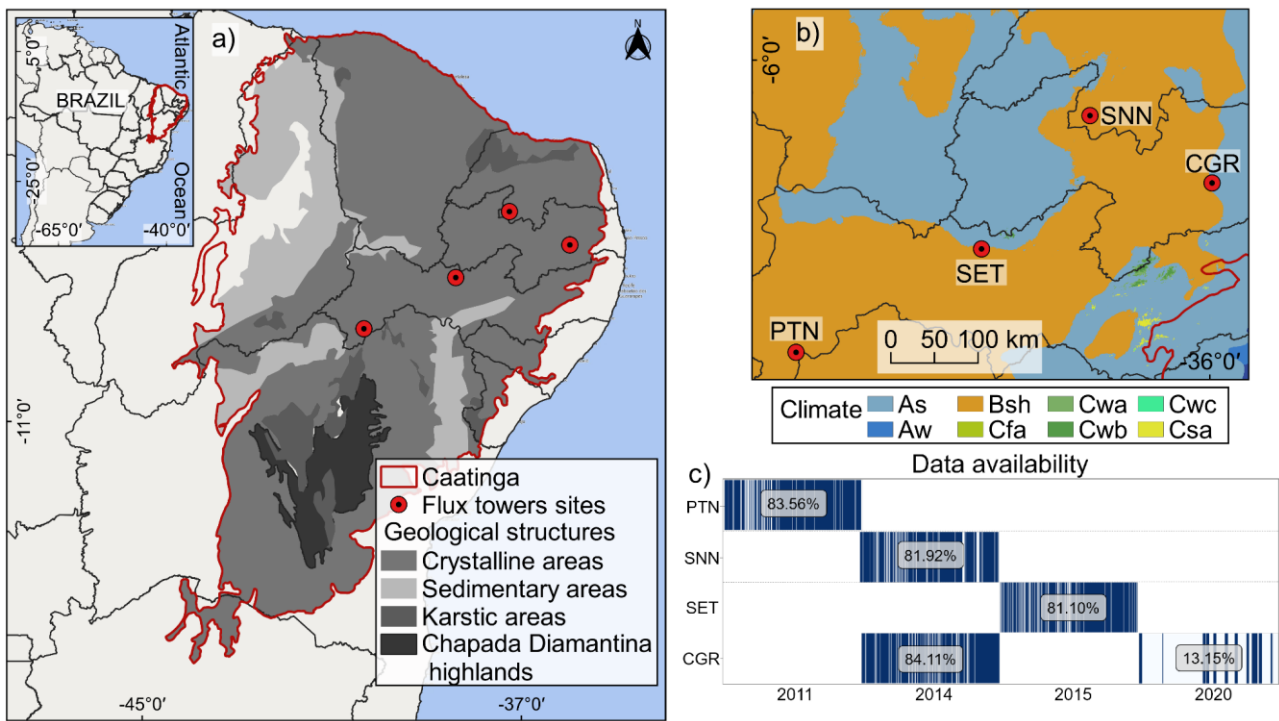
227

228 Table 1. List of EC-equipped flux tower observation sites in the study area.

Sites	State of Brazil	Mean annual of rainfall (mm) ¹	Site average elevation (m)	Main tree species	Location (Lon;Lat)	Data availability	Wet / Dry Seasons	Main reference
Petrolina (PTN)	Pernambuco	428.6	395	<i>Commiphora leptophloeos</i> , <i>Schinopsis brasiliensis</i> , <i>Mimosa tenuiflora</i> , <i>Cenostigma microphyllum</i> , <i>Sapium glandulosum</i>	-40.3212; -9.0465	Jan–Dec 2011	Jan-Apr / May-Dec	Souza et al. (2015)
Serra Negra do Norte (SNN)	Rio Grande do Norte	629.5	205	<i>Caesalpinia pyramidalis</i> , <i>Aspidosperma pyriformis</i> , <i>Anadenanthera colubrina</i> , <i>Croton blanchetianus</i>	-37.2514; -6.5783	Jan–Dec 2014	Jan-May / June-Dec	Marques et al. (2020)
Serra Talhada (SET)	Pernambuco	648	465	<i>Mimosa hostilis</i> , <i>Mimosa verrucosa</i> , <i>Croton sonderianus</i> , <i>Anadenanthera macrocarpa</i> , <i>Spondias tuberosa</i>	-38.3842; -7.9682	Jan–Dec 2015	Nov-Apr / May-Oct	Silva et al. (2017b)
Campina Grande (CGR)	Paraíba	777	490	<i>Croton blanchetianus</i> , <i>Mimosa ophthalmocentra</i> , <i>Poincianella pyramidalis</i> , <i>Allophylus quercifolius</i> , <i>Mimosa sp.</i> ²	-35.9750; -7.2798	Jan–Dec 2014	Mar-July / Aug-Feb	Oliveira et al. (2021)
Campina Grande (CGR)	Paraíba	777	490	<i>Croton blanchetianus</i> , <i>Mimosa ophthalmocentra</i> , <i>Poincianella pyramidalis</i> , <i>Allophylus quercifolius</i> , <i>Mimosa sp.</i> ²	-35.9763; -7.2805	Jan–Dec 2020	Mar-July / Aug-Feb	This study

229 ¹ Rainfall Data Sources: Brazilian National Institute of Meteorology (INMET) and Pernambuco State Agency for Water and Climate (APAC).

230 ² Barbosa et al. (2020).



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Fig. 1. Location of flux tower observation sites in Caatinga. a) Geographical overview of the

Caatinga (Moro et al., 2015), b) Köppen's climate classification map: Tropical zone with dry summer

(As), Tropical zone with dry winter (Aw), Dry zone semi-arid low latitude and altitude (Bsh), Humid

subtropical zone without dry season and with hot summer (Cfa), Humid subtropical zone with dry

winter and hot summer (Cwa), Humid subtropical zone with dry winter and temperate summer

(Cwb), Humid subtropical zone with dry winter and short and cool summer (Cwc), Humid

subtropical zone with dry summer and hot (Csa), according to Alvares et al. (2013) and c) Data

availability on the observation sites after procedures to ensure their quality.

2.2 The Seasonal Tropical Ecosystem Energy Partitioning (STEEP) model

SEB models have been applied in many parts of the world (Mohan et al., 2020a). The one-

source SEB models that are most commonly found in the literature are SEBAL (Bastiaanssen et al.,

1998), Surface Energy Balance System (SEBS; Su, 2002), Mapping EvapoTranspiration at high

Resolution with Internal Calibration (METRIC; Allen et al., 2007), and Operational Simplified Surface

Energy Balance (SSEBop; Senay et al., 2013). As in other SEB models, STEEP performs the energy

balance at the time of satellite overpass (instantaneous) to obtain λET as the surface energy balance

residual. The computation of R_n and G , necessary to get λET , followed the procedures described in

Ferreira et al. (2020) and Bastiaanssen et al. (2002), respectively, but with input data from the

249 Moderate-Resolution Imaging Spectroradiometer (MODIS) sensor. H was calculated following the
250 methods described in Table 2: using rah and dT , both traditionally applied in SEB models, but also
251 focusing on peculiarities of SDTF that have never been considered in other SEB models. In this
252 proposed version, rah was described according to Verhoef et al. (1997a) and Paul et al. (2013),
253 which requires, among other parameters/variables, the momentum roughness length ($z0m$), the zero
254 plane displacement height ($d0$), the dimensionless parameter kB^{-1} , and the atmospheric stability
255 corrections (Paulson, 1970). $z0m$ is influenced by a range of plant structural properties, e.g.
256 vegetation height, breadth and vegetation drag coefficients, and spacing (or density). $z0m$ is
257 commonly computed as a function of Leaf Area Index (LAI; Verhoef et al., 1997b; Liu et al., 2021).
258 However, most SDTF plants spend a substantial part of the year without leaves; under these
259 conditions, $z0m$ should be derived from information on dimensions of trunks, stems, and branches.
260 Since LAI is only related to leaf cover quantity and variability, it cannot represent the woody plant
261 structure without leaves (Miranda et al., 2020). Therefore, the Plant Area Index (PAI), which is the
262 total above-ground plant area, i.e. leaves and woody structures, was used to represent plant
263 structures in the computation of $z0m$ and $d0$.

264 To incorporate the conditions of water variability in the forest system in the calculation of
265 sensible heat we applied the procedure described in Gokmen et al. (2012) that corrects the kB^{-1}
266 equation presented in Su et al. (2001), incorporating soil moisture obtained by remote sensing. The
267 canopy conductance profiles are the link between soil moisture and sensible/latent heat flux. The
268 source of sensible/latent heat moves vertically throughout the canopy as a function of plant water
269 stress (Gokmen et al., 2012; Bonan et al., 2021), which affects heat roughness length, and, therefore,
270 kB^{-1} and rah . Thus, when there is a reduction in soil moisture, there is also a reduction in the value
271 of rah and, consequently, an increase of H and a decrease in λET . Furthermore, to calculate dT , we
272 used the linear relationship on LST, using the assumption of extreme contrast in terms of cover and
273 soil wetness (hot/dry and cold/wet endmembers) to determine the linear relationship coefficients.
274 However, in the hot/dry and cold/wet endmembers pixels, H was computed by the surface energy
275 balance (Allen et al., 2007), and the remaining λET was incorporated through the Priestley-Taylor
276 (1972) equation and plant physiological constraints following the approach in Singh and Irmak (2011)
277 and French et al. (2015). PAI and soil moisture time series used in our study can be seen in Fig. S2.

278 The references for the methods and equations adopted to formulate the STEEP model can be found
 279 in Table 2 and Appendix A, respectively. For illustration purposes, Table 2 also shows the references
 280 for the methods for one of the most widely used RS SEB models, the SEBAL model.

281 Table 2. References for the methods used in the STEEP and SEBAL models to obtain the sensible
 282 heat flux.

Variable/Parameter	STEPP	SEBAL
Aerodynamic resistance for heat transfer (rah)	Verhoef et al., 1997a; Paul et al., 2013	Bastiaanssen et al., 2002; Laipelt et al., 2021
Roughness length for momentum transfer ($z0m$)	Verhoef et al., 1997b; Paul et al., 2013, replacing LAI with PAI	Bastiaanssen et al., 2002; Laipelt et al., 2021
Zero plane displacement height ($d0$)	Verhoef et al., 1997b; Paul et al., 2013	-
Plant Area Index (PAI)	Miranda et al., 2020	-
Parameter kB^{-1}	Su et al., 2001	uses $z0h$ with constant value (0.1); Bastiaanssen et al., 2002
Correction of soil moisture by remote sensing in kB^{-1}	Gokmen et al., 2012	-
Calculation of the H and the remaining λET in endmembers pixels	Allen et al., 2007; Singh and Irmak, 2011; French et al., 2015	Calculation of the H in the hot/dry endmember only; Bastiaanssen et al., 2002

283

284 2.3 Algorithm implementation and processing

285 We implemented STEEP on the Google Earth Engine (GEE) cloud computing environment
 286 (Gorelick et al., 2017) using the Python API (version 3.6). Statistical analyses to evaluate the
 287 performance of the models were also conducted in Python and implemented in the Jupyter
 288 programming environment. The Python package geemap (Wu, 2020) enabled the integration of
 289 Python with the GEE environment, and the hydrostats package (Roberts et al., 2018) was used for
 290 the statistical evaluation of the performance of the models.

291 We designed the application of the model to take advantage of the data available on GEE
 292 (Table 3). The remote sensing datasets were derived from MODIS sensor products, the Shuttle
 293 Radar Topography Mission (SRTM; Farr et al., 2007), and the Global Forest Canopy Height product
 294 provided vegetation height (Potapov et al., 2021). The climate data necessary to run the model, i.e.
 295 wind speed, air temperature, relative humidity, shortwave radiation, and net thermal radiation at the
 296 surface, were sourced from the ERA5-Land reanalysis product (Muñoz Sabater, 2019). For data

297 regarding soil moisture, we used the Global Land Data Assimilation System (GLDAS) product
 298 (Rodell et al., 2004). CHIRPS precipitation product (Funk et al., 2015) was used to estimate the daily
 299 rainfall amount at the sites evaluated.

300 Table 3. Description of the datasets available on the GEE platform used in the research.

Product	GEE ID	Bands/variables	Time coverage	Spatial resolution	Temporal resolution
MCD43A4.006	MODIS/006/ MCD43A4	B1–B7	Feb 2000– present	0.5 km	1 day
MOD09GA.006	MODIS/006/ MOD09GA	SolarZenith	Feb 2000– present	1 km	1 day
MOD11A1.006	MODIS/006/ MOD11A1	LST_Day_1km; Emis_31, Emis_32	Mar 2000– present	1 km	1 day
SRTM	USGS/SRT MGL1_003	Elevation	Feb 2000	0.03 km	-
ERA5-Land	ECMWF/ER A5_LAND/H OURLY	dewpoint_temperature_2m, temperature_2m, u_component_of_wind_10, v_component_of_wind_10m, surface_net_solar_radiation _hourly, surface_net_thermal_radiati on_hourly	Jan 1981– present	0.1°	1 h
GLDAS	NASA/GLDA S/V021/NOA H/G025/T3H	SoilMoi0_10cm_inst	Jan 2000– present	0.25°	3 h
Global Forest Canopy Height, 2019	users/potapo vpeter/GEDI _V27	-	Apr 2019	0.03 km	-
CHIRPS	UCSB- CHG/CHIRP S/DAILY	Precipitation	Jan 1981– present	0.05°	1 day
MOD16A2.006	MODIS/006/ MOD16A2	ET	Jan 2001– present	0.5 km	8 days
PML_V2	projects/pml _evapotrans piration/PML /OUTPUT/P ML_V2_8da y_v016	Es, Ec, Ei	Feb 2000– present	0.5 km	8 days

301
 302 The presence of clouds or instrumental malfunctioning of orbital sensors can cause gaps in
 303 data. To reduce the loss of information due to missing data, we chose to use the MODIS MCD43A4

304 reflectance product. By combining reflectance data from MODIS sensors aboard the AQUA and
 305 TERRA satellites and modelling the anisotropic scattering characteristics using sixteen-day quality
 306 observations, the MCD43A4 product represents the daily dynamics of the Earth's surface without
 307 missing data (Schaaf and Wang, 2015). Daily surface reflectance data from the MCD43A4 product
 308 were used to obtain the surface albedo and vegetation indices (NDVI and PAI) needed to run STEEP.
 309 Thus, the surface albedo data and the vegetation indices show a low percentage of missing data.
 310 To compose the LST time series, we used data from MOD11A1, and to fill its missing data, a filter
 311 with the average value for a monthly window was applied. This procedure is similar to the method
 312 proposed by Zhao et al. (2005) and it is also used by the MOD16 algorithm to generate the
 313 continuous global ET (Mu et al., 2011).

314 Following the approach in comparable studies, STEEP algorithm processing was conducted
 315 with automatic selection of endmembers pixels (Bhattarai et al., 2017; Silva et al., 2019; Laipelt et
 316 al., 2021). Like Silva et al. (2019), we used the biophysical variables NDVI, surface albedo and LST
 317 to automate selection of the endmembers, but we applied different criteria. For the hot/dry
 318 endmember selection, the first step consisted of selecting those pixels whose surface albedo values
 319 are between the 50 and 75% quantiles, and with NDVI values greater than 0.1 and less than the
 320 15% quantile. After this first selection, a refinement is applied by selecting only those pixels from this
 321 first set that have LST values between the 85 and 97% quantiles. Using the set of pixels that met
 322 these criteria, the median values of R_n , G , LST and rah were calculated to establish a single value
 323 for each variable and describe the characteristics of the hot pixel. We applied a similar procedure to
 324 select the cold/wet endmember but with different limits (Table 4). The procedure for finding
 325 endmembers was conducted daily. To execute the model and conduct the selection of endmembers,
 326 we used an area of interest (AOI), also known as domain size. AOI was defined as a square area
 327 with 1000-km sides within the Caatinga domain and centred on the tower coordinates of each site.
 328 Cheng et al. (2021), for example, applied the SEBAL using MODIS data in China and used an AOI
 329 of 1200-km x 1200-km.

330 Table 4. Methodology used for the selection of endmembers pixels.

Endmembers

	Hot/dry pixel	Cold/wet pixel
Step 1	Q50% < surface albedo < Q75% and 0.10 < NDVI < Q15%	Q25% < surface albedo < Q50% and NDVI > Q97%
Step 2	of the pixels of the 1st Step, select pixels with Q85% < LST < Q97%	of the pixels of the 1st Step, select pixels with LST < Q20%
Step 3	Of the set of pixels that met the previous steps, the median values of R_n , G , LST and rah were calculated to establish a single value for each variable and describe the characteristics of endmembers	

331 Q = quantile.

332 2.4 Analysis of the algorithms' performance

333 We used SEBAL as a reference RS SEB model for comparison with STEEP. SEBAL is one
334 of the most applied SEB models since the algorithm uses a minimal number of in situ measurements
335 compared to similar models, e.g. METRIC and SSEBop, and is considered a suitable choice for
336 evapotranspiration estimates over cropped areas and in the context of water resource management
337 (Kayser et al., 2022). Applications with SEBAL have been conducted in the Caatinga as in the studies
338 of Teixeira et al. (2009), Santos et al. (2020), Costa et al. (2021), and Lima et al. (2021).
339 Implementations of the SEBAL algorithm are popular on several computing platforms, e.g. GRASS-
340 Python (Lima et al., 2021); Google Earth Engine (Laipelt et al., 2021); Python (Mhawej et al., 2020),
341 following the formulations described in Bastiaanssen et al. (1998) and Bastiaanssen et al. (2002).
342 The SEBAL version implemented in this work followed those presented by Bastiaanssen et al.
343 (2002), Costa et al. (2021) and Laipelt et al. (2021). The remote sensing datasets and endmembers
344 pixels selection for SEBAL were the same as described in STEEP.

345 ET and H estimates from STEEP and SEBAL were evaluated against the eddy covariance
346 measurements of the corresponding tower. Here, the modelled values were extracted for the pixel
347 representing the EC tower for each observation site. The footprint fetches for PTN, SET, SNN is less
348 than 500 m (Silva et al., 2017b; Campos et al., 2019; Santos, et al., 2020). We assume a similar
349 footprint for CGR due to its similarity in terms of wind characteristics and terrain slope compared to
350 the other sites. Moreover, the surrounding areas of each of our study sites (Fig. S1) — which exceeds
351 these EC towers footprints — are homogeneously covered by Caatinga vegetation. We evaluated
352 daily ET values, and instantaneous hourly H values more specifically with the modelled/measured H

353 value at 11:00 am local time (GMT-3), considering this is the closest time to the satellite's overpass.
354 Additionally, the STEEP model was compared with two consolidated global ET products available
355 on GEE: MODIS Global Terrestrial Evapotranspiration A2 version 6 (MOD16; Mu et al., 2011;
356 Running et al., 2017) and Penman-Monteith-Leuning model version 2 global evaporation (PMLv2;
357 Zhang et al., 2019); both products have a pixel resolution of 500 m (Table 3). The algorithm used in
358 MOD16 is based on the Penman-Monteith equation and driven by MODIS remote sensing data with
359 Modern-Era Retrospective analysis for Research and Applications (MERRA; Mu et al., 2011). In
360 MOD16 ET is the sum of soil evaporation (E_s), canopy transpiration (T_c) and wet-canopy evaporation
361 (E_c) and is provided as eight-day *cumulative* values. More details about MOD16 can be found in Mu
362 et al. (2011) and Running et al. (2017). The global PMLv2 product involves a biophysical model
363 based on the Penman-Monteith-Leuning equation which also uses MODIS remote sensing data, but
364 with meteorological reanalysis data from GLDAS as model inputs. As in MOD16, ET in PMLv2 is
365 also the sum of E_s , T_c and E_c but is provided as eight-day *average* values. To make MOD16 and
366 PMLv2 values compatible, ET of PMLv2 was multiplied by eight. Details about PMLv2 can be found
367 in Gan et al. (2018) and Zhang et al. (2019). We accumulated the daily ET measured at the
368 observation sites, i.e. derived from EC data, and ET modelled with STEEP for the same eight-day
369 time periods to make them compatible with the temporal resolution of the MOD16 and PMLv2
370 datasets. The average of the measured daily values over each eight-day time period (even if there
371 were missing values within this period) was multiplied by eight to calculate the observed 8-day ET.
372 To match the time steps of STEEP and MOD16/PMLv2 ET values, the 8-day average of the
373 evaporative fraction (EF) was multiplied by the daily net radiation over those 8 days, assuming that
374 EF can be considered constant in each of these periods. Then the ET was summed over the 8-day
375 interval. Finally, we also compared the modelled ET (by STEEP and the two global products) with
376 the observed ET, only in the 8-day periods when no field-observed data was missing. However, with
377 this criterion the number of observations dropped dramatically.

378 The STEEP and SEBAL models and global ET products were evaluated with five performance
379 metrics (Table 5). A combination of performance metrics is often used to assess the overall
380 performance of models because a single metric provides only a projection of a certain aspect of the
381 error characteristics (Chai and Draxler, 2014). Root mean square error (*RMSE*) is commonly used

382 to express the accuracy of the results with the advantage that it presents error values in the same
383 units of the variable analysed; optimal values are close to zero (Hallak and Pereira Filho, 2011).
384 Coefficient of determination (R^2) represents the quality of the linear trend between observed and
385 simulated data and ranges from 0 to 1; high values indicate better model performance. Nash–
386 Sutcliffe efficiency (NSE) indicates the accuracy of the model output compared to the average of the
387 referred data ($NSE = 1$ is the optimal value; Nash and Sutcliffe, 1970). Concordance correlation
388 coefficient (ρc) is a measure that evaluates how well bivariate data falls on the 1:1 line. ρc measures
389 both precision and accuracy. It ranges from -1 to +1 similar to Pearson's correlation coefficient, with
390 perfect agreement at +1 (Lin, 1989; Liao and Lewis, 2000; Akoglu, 2018). Percentage bias ($PBIAS$)
391 measures the average relative difference between observed and estimated values, with an optimal
392 value of 0 (Gupta et al., 1999). Additionally, we evaluate STEEP's model structure by extracting
393 model's performance metrics after excluding it from its main implementations individually (Table 2)
394 and by two-by-two combinations of zOm , rah and $r\lambda ET$. We run the control version of the SEB model,
395 i.e. SEBAL in our case, while incorporating one or two improvements in the model and keeping the
396 remaining parts of the algorithm the same as the reference SEB model.

397 Table 5. Performance metrics used to evaluate ET and H in this study.

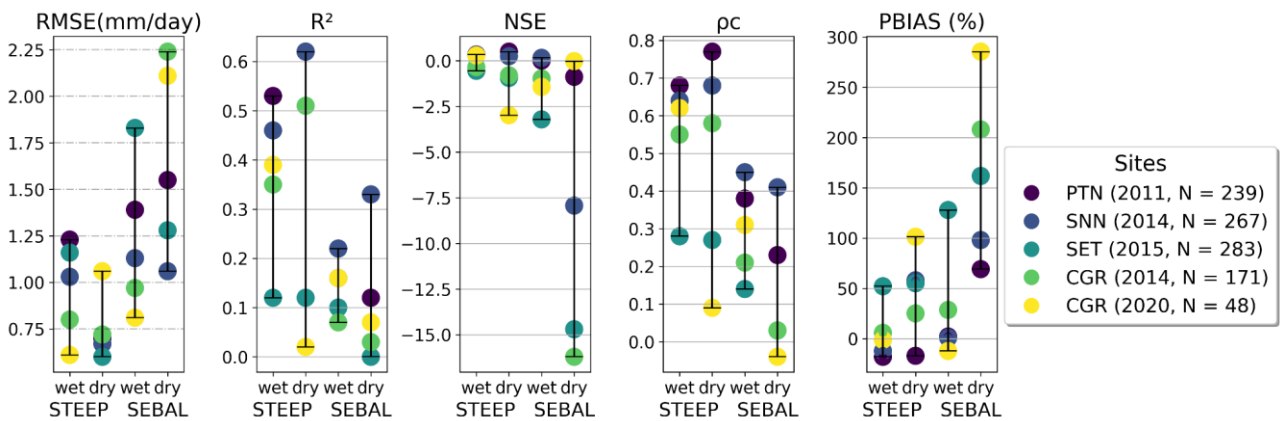
Performance metric	Equation	Range (Perfect value)
Root mean square error ($RMSE$)	$RMSE = \sqrt{\frac{\sum_{i=1}^N (M_i - O_i)^2}{N}}$	$[0, +\infty [(0)$
Coefficient of determination (R^2)	$R^2 = \frac{[\sum_{i=1}^N (O_i - \bar{O})(M_i - \bar{M})]^2}{\sum_{i=1}^N (O_i - \bar{O})^2 \cdot \sum_{i=1}^N (M_i - \bar{M})^2}$	$[0, 1] (1)$
Nash–Sutcliffe efficiency (NSE)	$NSE = 1 - \frac{\sum_{i=1}^N (M_i - O_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2}$	$] -\infty, 1] (1)$
Concordance correlation coefficient (ρc)	$\rho c = \frac{2 \sum_{i=1}^N (O_i - \bar{O})(M_i - \bar{M})}{\sum_{i=1}^N (O_i - \bar{O})^2 + \sum_{i=1}^N (M_i - \bar{M})^2 + (N - 1)(\bar{O} - \bar{M})^2}$	$[-1, 1] (1)$
Percentage bias ($PBIAS$)	$PBIAS = \frac{\sum_{i=1}^N (M_i - O_i) \cdot 100}{\sum_{i=1}^N O_i}$	$] -\infty, +\infty [(0)$

398 where: N sample size; O observed value; M modelled value; \bar{O} observed mean; \bar{M} modelled mean.

399 3. Results and discussion

400 3.1 Comparison of STEEP and SEBAL models results with observed (EC) values

401 The performance statistics of daily ET by STEEP and SEBAL in wet and dry seasons for the
 402 evaluated sites are shown in Fig. 2. In general, STEEP exhibited a better performance than SEBAL.
 403 Although the better statistical metrics of STEEP were in the dry season, in the wet season, they were
 404 also superior compared to SEBAL. Specifically, in the dry season, STEEP exhibited a *RMSE*
 405 between 0.6 and 1.06 mm/day, while SEBAL this was between 1.06 and 2.24 mm/day. The maximum
 406 value of R^2 in STEEP was 0.62 (sites PTN and SNN), whereas SEBAL achieved only 0.33. The *NSE*
 407 metric was the worst among the five analysed in SEBAL: values lower than -7.5 occurred in three of
 408 the five sites. Although in STEEP, PTN and SNN sites *NSE* had values higher than 0 (0.55 and 0.25,
 409 respectively) the other sites also had negative values, reaching up to -2.5. In terms of ρ_c , values
 410 ranged from 0.09 to 0.77 in STEEP and from -0.04 to 0.41 in SEBAL. It is also possible to see the
 411 reduction that STEEP has brought to ET modelling in terms of *PBIAS* when compared to SEBAL.
 412



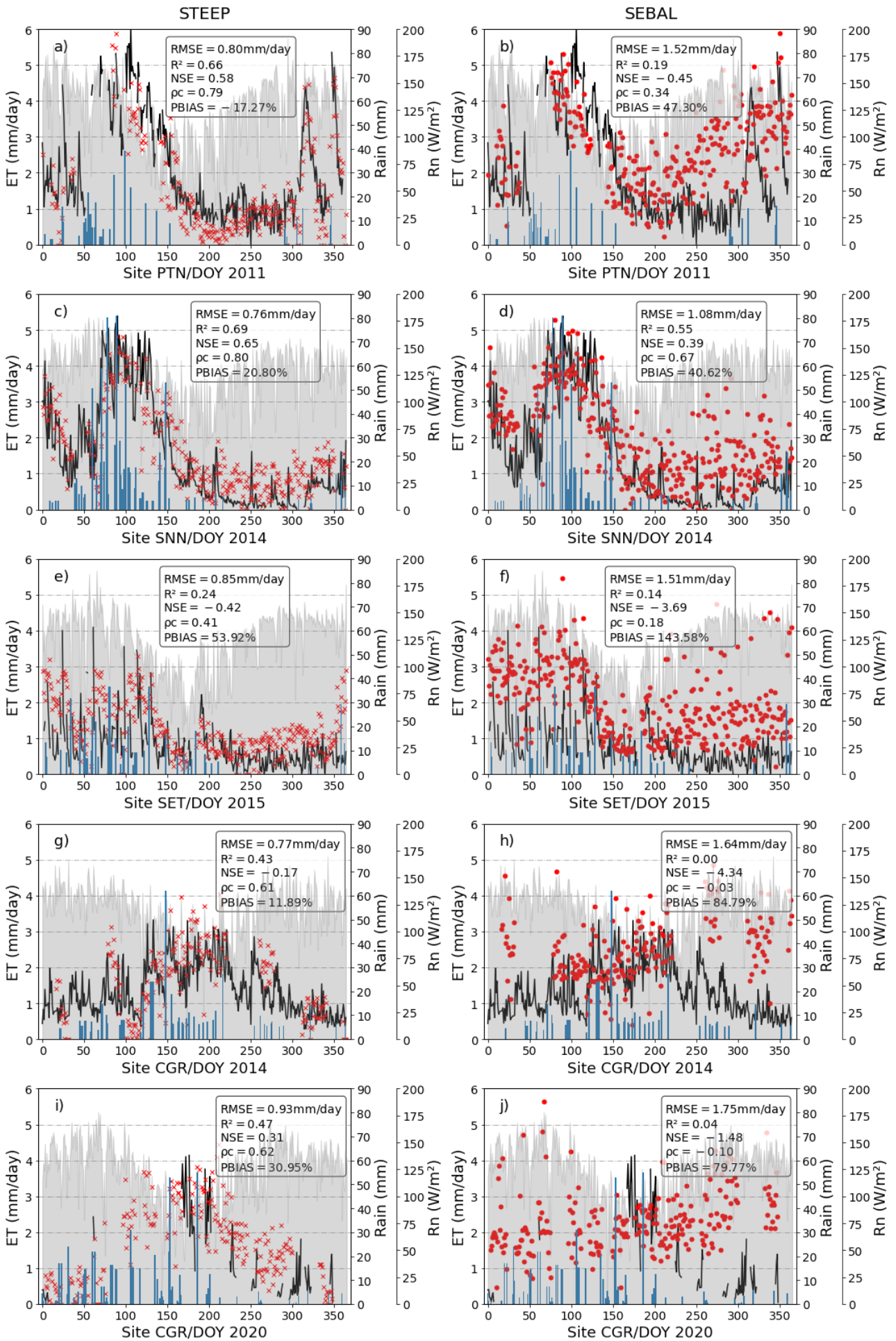
413
 414 Fig. 2. Results of the performance statistics of daily ET in wet and dry seasons for evaluated sites.

415 Globally, without discriminating between wet and dry seasons, STEEP exhibited better
 416 statistical performance than SEBAL at all the evaluated sites (Fig. 3). While STEEP exhibited a
 417 *RMSE* between 0.75 and 0.94 mm/day, the *RMSE* for SEBAL was between 1.08 and 1.75 mm/day.
 418 In terms of R^2 , the values were between 0.24 to 0.69 for STEEP, and were below 0.2 for SEBAL for
 419 all sites except in SNN (0.55). Similarly, *NSE* and ρ_c values were higher for STEEP compared to
 420 SEBAL. For STEEP, all sites had *NSE* and ρ_c values above -0.42 and 0.41, respectively, whereas
 421 all sites except SNN had values below these limits for SEBAL. Both models overestimated ET
 422 ($PBIAS > 0$), with the exception of the STEEP estimates for the PTN site. The highest overestimation
 423 by the STEEP model was less than 60%, whereas in SEBAL it was greater than 140%.

424 SEBAL metrics concerning the modelled ET were similar to those found in other studies.
425 Laipelt et al. (2021) found R^2 ranging from 0.18 to 0.87 when applying SEBAL and comparing it with
426 data from ten EC towers located in different Brazilian biomes (Amazon, Cerrado, Pantanal, and
427 Pampa). Cheng et al. (2021) obtained R^2 of 0.53–0.77 and $RMSE$ of 0.89–1.02 mm/day when
428 comparing estimates from SEBAL and EC towers on different land covers in China. Costa et al.
429 (2021), when applying SEBAL in the Caatinga, found R^2 and NSE values of 0.57 and 0.36,
430 respectively. Santos et al. (2020) modelled ET with SEBAL at the SNN site for the 2014–2016 period
431 and obtained R^2 and $RMSE$ values of 0.28 and 1.43 mm/day, respectively. For this site, we obtained
432 R^2 and $RMSE$ of 0.55 and 1.08 mm/day, respectively, for the year 2014 using SEBAL.

433 STEEP exhibited a greater seasonal accuracy compared to SEBAL (Fig. 3), as evidenced by
434 the goodness-of-fit between simulated and observed values expressed by the NSE indicator. STEEP
435 estimates followed the same temporal evolution as the observed values. STEEP satisfactorily
436 captured both minimum and maximum ET values, including after rainfall events, this is particularly
437 evident in Fig. 3a, where the two observed ET peaks in late 2011 — between DOY 300 and 360 —
438 in the PTN site were captured nicely by STEEP. This improved performance can be explained
439 because soil moisture is incorporated in the STEEP algorithm. In semi-arid regions and particularly
440 in the SDTF, besides the availability of energy, evapotranspiration is highly dependent on the soil–
441 water availability (Lima et al., 2012; Carvalho et al., 2018; Mutti et al., 2019; Paloschi et al., 2020).
442 In rainy months, low daily ET rates are often observed due to the reduced levels of incoming radiation
443 caused by high cloud cover (Mutti et al., 2019; Paloschi et al., 2020). Towards the end of the wet
444 period, when the available energy increases, the daily ET values also increase as a result of the high
445 soil water availability from previous precipitation events (Allen et al., 2011; Marques et al., 2020). In
446 the transition period from the rainy to the dry season, the leaves do not fall immediately (see Table
447 1, main tree species). Instead, leaf-shedding depends on the environmental conditions in each
448 location, including the rainy season duration, and species composition (Lima and Rodal, 2010; Lima
449 et al., 2012; Miranda et al., 2020; Paloschi et al., 2020; Queiroz et al., 2020; Medeiros et al., 2022).
450 The remaining water available in the soil or previously accumulated in plant tissues is sufficient for
451 the Caatinga vegetation to maintain its leaves, for short periods, at levels similar to the rainy season
452 (Barbosa et al., 2006; Mutti et al., 2019). However, in the dry season, when soil moisture reaches its

453 lowest levels, the Caatinga vegetation enters a state of dormancy that is accompanied by leaf drop
454 and a drastic reduction of photosynthetic activity (and hence of transpiration) as a strategy to cope
455 with the lack of available soil moisture (Dombroski et al., 2011; Paloschi et al., 2020). This resilience
456 mechanism is typical of xerophytic and/or deciduous species such as those found in the Caatinga
457 (Lima et al., 2012; Mutti et al., 2019; Paloschi et al., 2020), and explains the low rates of ET in the
458 dry season. In contrast, in SEBAL, which does not consider water availability, it was observed that
459 the daily ET followed the course of the daily net radiation throughout the year, especially in the dry
460 period of each of the experimental sites. This is in agreement with the results of Kayser et al. (2022),
461 who pointed out that estimates with SEBAL can be seasonally accurate in locations where the main
462 driver of ET is the available energy. Our results highlight that SEB models such as SEBAL, which
463 are formulated to be mainly dependent on energy availability and do not consider soil and plant water
464 availability, may not satisfactorily represent ET in semi-arid vegetation such as that found in the
465 SDTF (Gokmen et al., 2012; Paul et al., 2014; Melo et al., 2021).

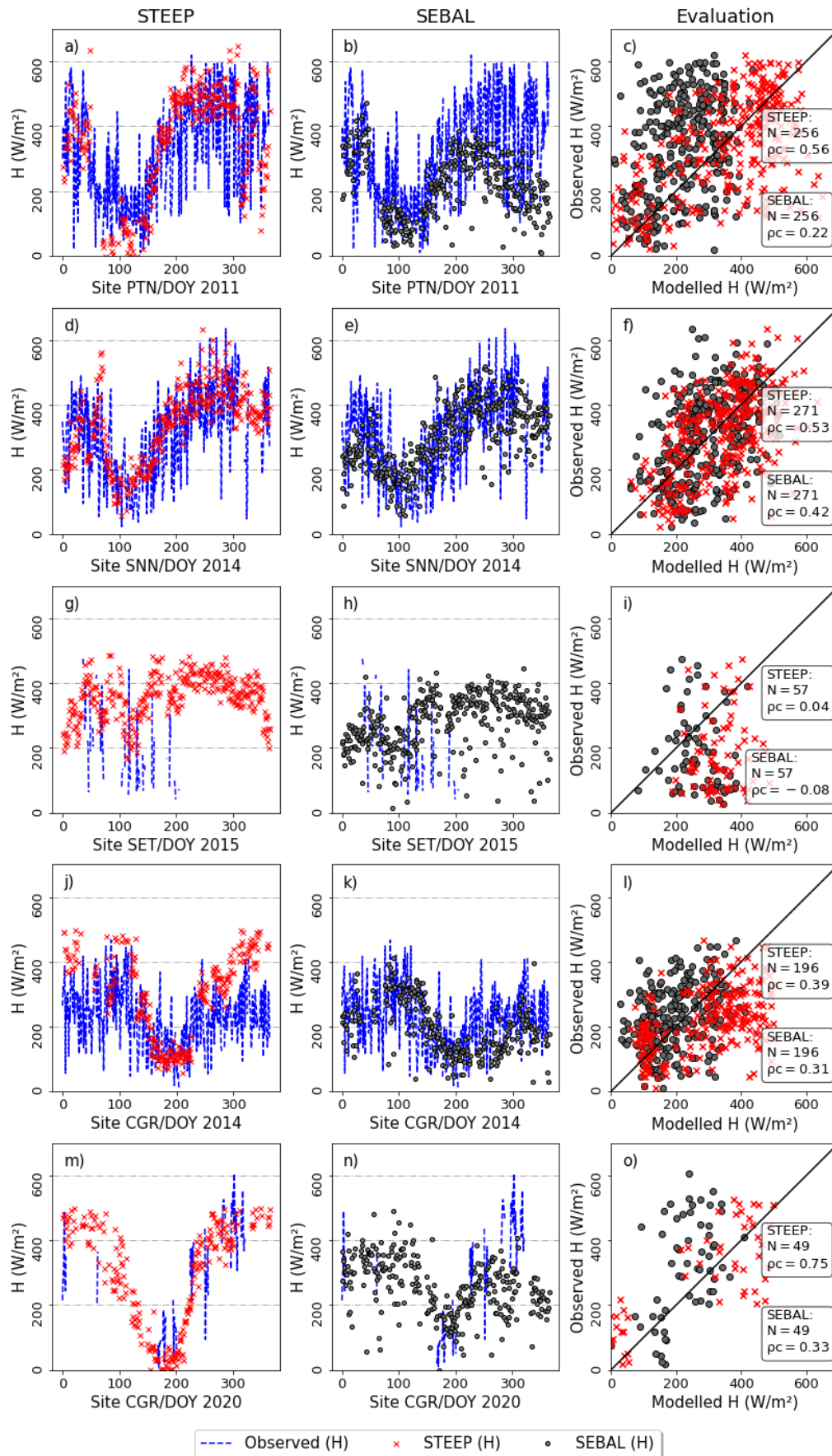


— Observed ET × STEEP • SEBAL ■ RAIN - CHIRPS ■ Daily net radiation

467 Fig. 3. Observed and modelled daily evapotranspiration (ET, mm/day) for the different
468 experimental sites: a) and b) PTN 2011, c) and d) SNN 2014, e) and f) SET 2015, g) and h) CGR
469 2014, i) and j) CGR 2020. The black lines represent observed ET; the red crosses and points are
470 STEEP and SEBAL estimates, respectively; the blue bars represent CHIRPS daily rainfall; the gray
471 region represents daily net radiation from ERA5-land.

472 The core of the STEEP and SEBAL algorithms is based on finding λET as the residual of the
473 energy balance; however, they differ with regards to the approach used to calculate H . In the STEEP
474 model, the seasonal variation of H fitted the observed values of the instantaneous measurements at
475 11:00 am (local time) better than SEBAL, for all the sites (Fig. 4). Our results show that an
476 improvement in H leads to a correspondent in ET estimates. This is contrary to the findings of Faivre
477 et al. (2017), who used the same formulation for kB^{-1} applied in our study, but included four different
478 methods to compute $z0m$. While STEEP estimates of H exhibited ρc values over 0.5 for three of the
479 five sites, SEBAL H estimates exhibited ρc values below 0.5 for all sites. When wet and dry seasons
480 data are analysed separately (Fig. 5), the same trend is observed in the results: in general, the
481 STEEP model presents better statistical metrics than SEBAL.

482



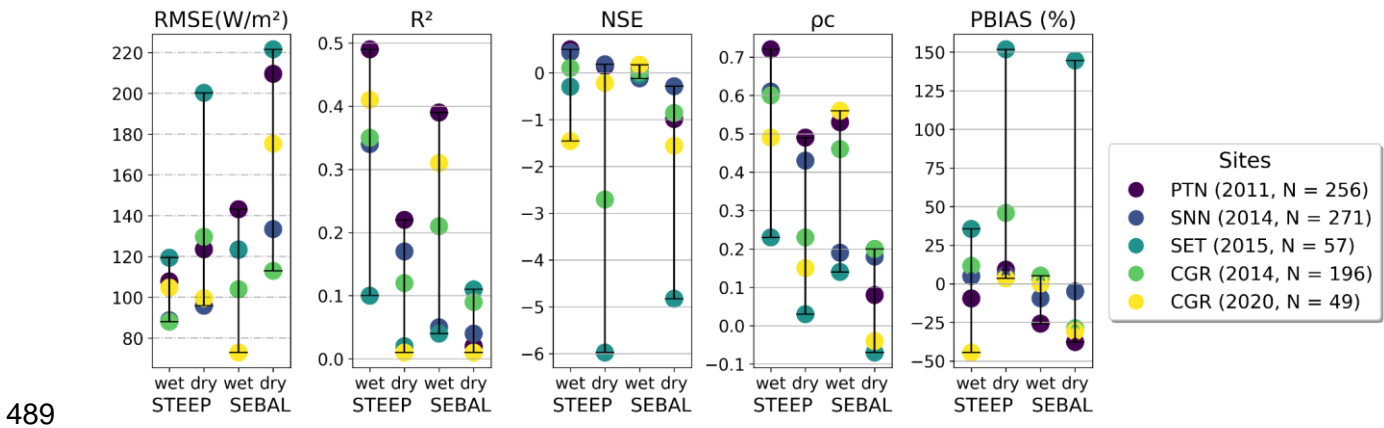
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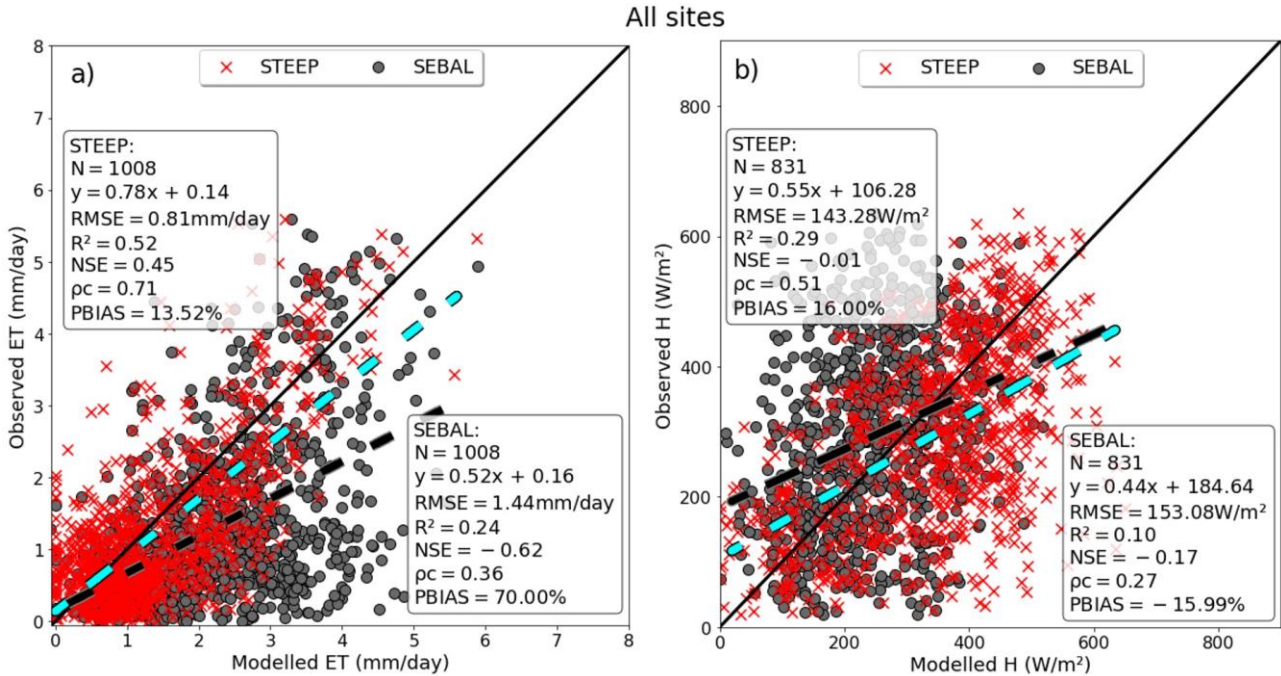
Fig. 4. Observed and modelled instantaneous sensible heat flux (H , at 11:00 am, W/m^2) for the different experimental sites: a), b) and c) PTN 2011, d), e) and f) SNN 2014, g), h) and i) SET

486 2015, j), k) and l) CGR 2014, m), n) and o) CGR 2020. The blue line represents the observed
 487 values; the red crosses and grey points correspond to the STEEP and SEBAL estimates,
 488 respectively. The black line is the 1:1 line.



489
 490 Fig. 5. Results of the performance statistics of instantaneous sensible heat flux (H , at 11:00 am,
 491 W/m^2) in wet and dry seasons, for the evaluated sites.

492 Evaluation of the STEAP and SEBAL daily ET and instantaneous H for all experimental sites
 493 (Fig. 6) indicates that both models lack a high performance for H estimates, although the use of
 494 STEAP resulted in better statistical measures than when SEBAL was employed (Fig. 6b). This
 495 substantiates previous findings (Gokmen et al., 2012; Paul et al., 2014; Trebs et al., 2021), that have
 496 shown the tendency of underestimation (overestimation) of H (ET) at water-limited sites. It can be
 497 seen that the overestimation of H by the STEAP model, compared to SEBAL, produced modelled
 498 ET values that were closer to the EC measurements (see Fig. 3 and 4). We ascribe the poor
 499 performance of H in the models relative to observed data to the continuous H oscillations throughout
 500 the day (Campos et al., 2019; Lima et al., 2021). As we compare an instantaneous H estimate
 501 (STEAP or SEBAL) to the 30-min H average measurement (EC), it is expected that modelled H
 502 performs worse than daily ET for the same site and period. Furthermore, for sites with fewer
 503 observations of H (SET 2015 and CGR 2020), especially in the dry season, the metrics showed that
 504 STEAP did not perform as well, for each season, as other sites with more data available. Still, these
 505 limited data were sufficient to show that STEAP outperformed SEBAL in estimating H .

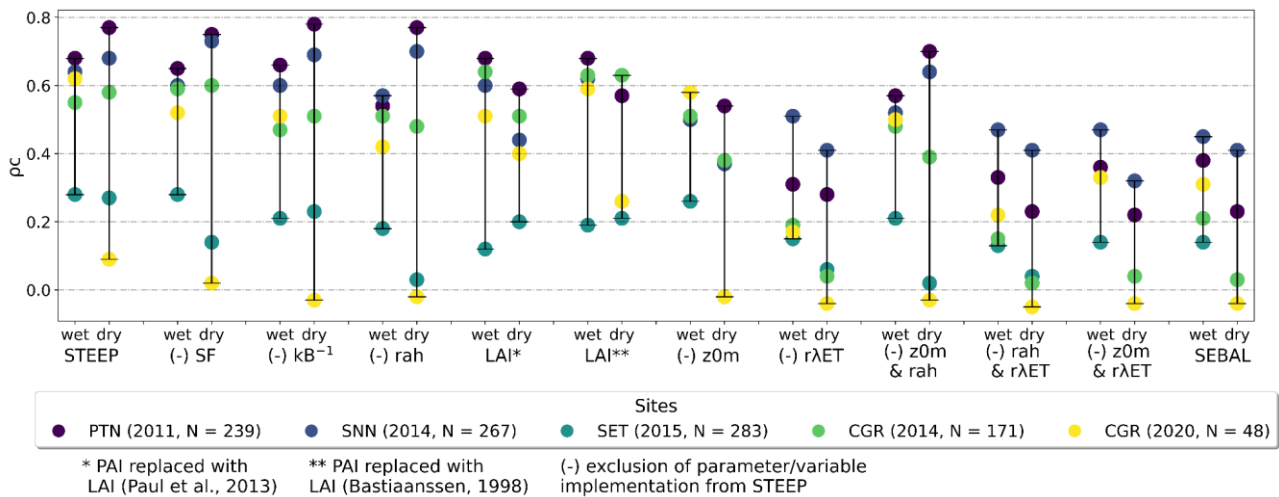


507

508 Fig. 6. Evaluation of observed and modelled: (a) daily evapotranspiration (ET, mm/day) and (b)
 509 instantaneous sensible heat flux (H , at 11:00 am, W/m²) for all experimental sites. STEEP (red
 510 crosses) and SEBAL (black points). The black line is the 1:1 line; the cyan (black) dashed line is
 511 the fitted linear regression between observed and STEEP (SEBAL) model values.

512 We attribute the better performance of STEEP over SEBAL for the Brazilian Caatinga to at
 513 least three reasons, shown in order of impact of model implementation on its performance (Fig. 7
 514 and Table S1). First, by quantifying the remaining λET in the endmembers pixels through the
 515 Priestley-Taylor equation, a more reliable estimate of H in the endmembers pixels can be obtained,
 516 as was also evidenced by Singh and Irmak (2011). This process is critical for the subsequent
 517 numerical calculation of H in SEB models that use dT , as its accuracy is closely related to quantifying
 518 the energy balance at the hot and cold endmembers (Trezza, 2006; Allen et al., 2007; Singh and
 519 Irmak, 2011; Singh et al., 2012). Secondly, roughness characteristics near the surface where the
 520 heat fluxes originate are parameterised by $z0m$, which depends on several factors, such as wind
 521 direction, height and type of the vegetation cover (Kustas et al., 1989b). Estimation of $z0m$ only with
 522 an exponential relationship, as a function of vegetation indices, may be an oversimplification (Kustas
 523 et al., 1989a; Paul et al., 2013). In our study, $z0m$ and $d0$ are calculated with the equations and
 524 coefficients proposed in Raupach (1994) and Verhoef et al. (1997b), and using PAI because this

525 index better represents the intra-annual phenological changes in the Caatinga (Miranda et al., 2020).
 526 This procedure considers the characteristics of SDTF, such as seasonality of phenology and
 527 vegetation height, that considerably affect the quantification of turbulent transfer (Liu et al., 2021).
 528 Third, our study uses the equation described in Verhoef et al. (1997a) and Paul et al. (2013) to
 529 estimate *rah*, which considers the differences between heat and momentum transfer, unlike the
 530 original equation employed in other SEB models e.g. SEBAL or METRIC that only considers *z0m*
 531 and sets *z0h* = 0.1 when computing this resistance. Furthermore, we account for the kB^{-1} parameter
 532 that varies in space and time and incorporates the soil moisture content obtained by RS (Su et al.,
 533 2001; Gokmen et al., 2012). ET estimation is best represented with a spatially varying kB^{-1} values,
 534 as pointed out by the studies of Gokmen et al. (2012) and Paul et al. (2014). Long et al. (2011) report
 535 that the introduction of these fixed values (*z0h* or kB^{-1}) has a significant impact on the magnitudes of
 536 the estimates of H. Furthermore, Mallick et al. (2018) and Trebs et al. (2021) indicate that the
 537 parameterization of *rah* can influence the estimation of ET, especially in SEB models that are largely
 538 dependent on *rah*. Our results show that including just one or two of the refinements had only partial
 539 performance gains (Fig. 7 and Table S1). In contrast, all the proposed STEEP improvements when
 540 implemented together resulted in the best performance metrics for all sites.

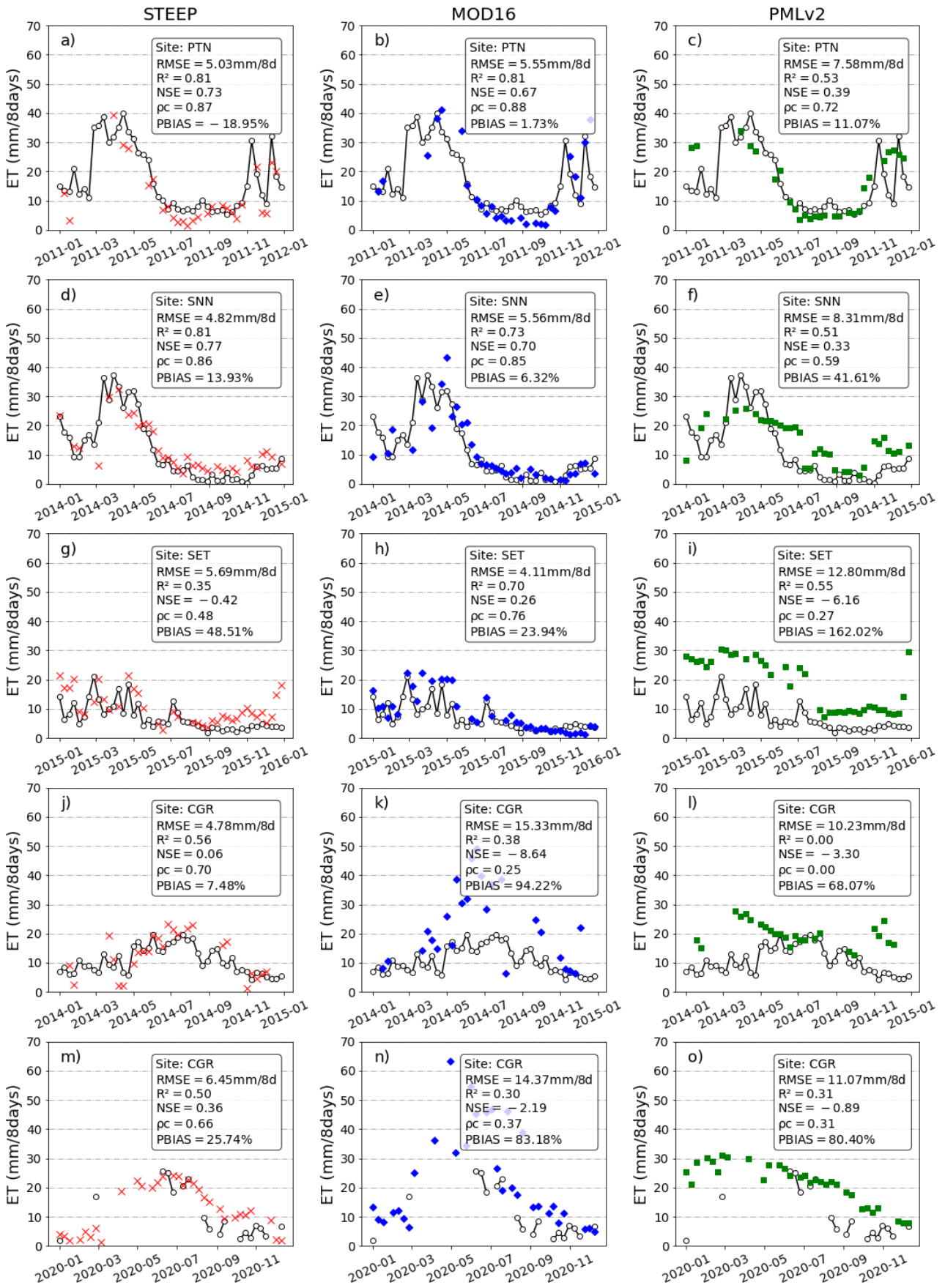


542 Fig. 7. Change of the concordance correlation coefficient (ρ_c) by the exclusion/modification of one
 543 or two parameters/variables implemented in the STEEP model, in the wet and dry seasons: scale
 544 factor soil moisture correction (SF), the parameter kB^{-1} , the aerodynamic resistance for heat
 545 transfer (*rah*), PAI replace with LAI (determined by two different methods), the roughness length for
 546 momentum transport (*z0m*) and the residual latent heat flux in the end members pixels (*rλET*).

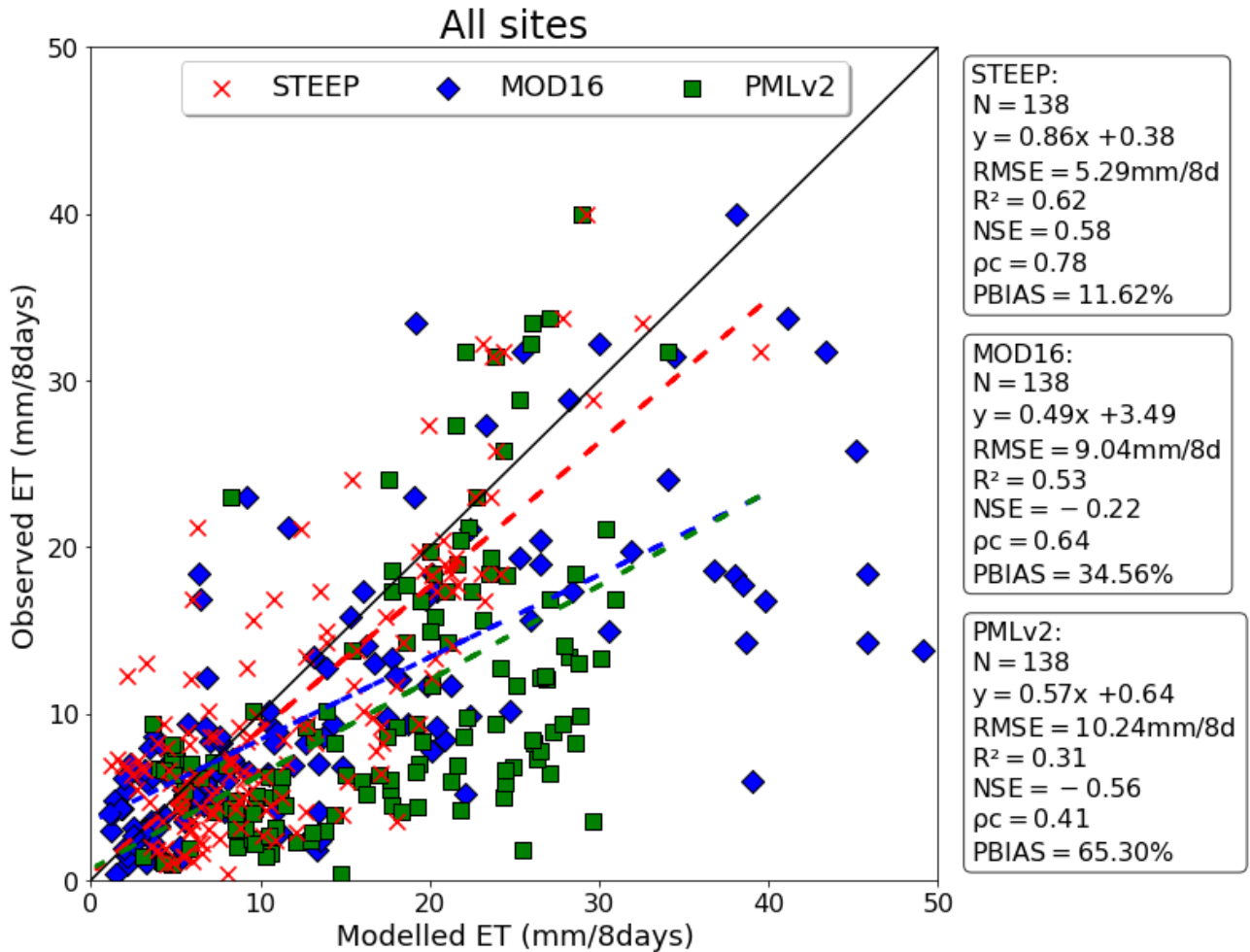
547 3.2 Comparison of STEEP model estimates with global evapotranspiration products

548 The comparison of ET estimates by STEEP, MOD16 and PMLv2 with the observed values
549 at the different sites (Fig. 8) reveals that the ET estimates by STEEP and global products adequately
550 followed the seasonality of the values, with a better fit for STEEP and MOD16. In general, the
551 evaluation at the different sites shows that the *RMSE* of STEEP was not higher than 6.45 mm/8
552 days, while the ET products' maximum *RMSE* was close to 15 mm/8 days. It is noted that the lowest
553 *RMSE* value found (4.11 mm/8 days) was for MOD16 at the SET site. Regarding R^2 values, 80% of
554 the evaluations with STEEP were equal to or greater than 0.50. For MOD16, 60% of the R^2 values
555 were equal to or greater than 0.70, while for PMLv2, no site had R^2 values that exceeded 0.55. The
556 best *NSE* value produced by STEEP was 0.77, while with MOD16, it was 0.70, both at the SNN site,
557 while PMLv2 did not exceed 0.39 (PTN site). Regarding ρ_c , the percentages of ET evaluations that
558 obtained values equal to or greater than 0.70 were 60% for STEEP and MOD16, and only 20% for
559 PMLv2 (site PTN). The overestimations (*PBIAS*) with STEEP were not higher than 50%, and not
560 higher than 95% with MOD16. For PMLv2 the overestimations did not exceed 80%, except for the
561 SET site that obtained a *PBIAS* approx. 160%. We highlight the good performance of MOD16 for
562 the SET, SNN, and especially the PTN sites, with very good performance metrics and seasonal
563 behaviour, capturing ET values in dry periods very well. The evaluation results of STEEP, MOD16
564 and PMLv2 for all observation sites combined are shown in Fig. 9. Noteworthy is the better
565 performance of STEEP over MOD16 and PMLv2, with *RMSE* of < 6 mm/8 days, R^2 and *NSE* greater
566 than or close to 0.60, ρ_c of > 0.75 and an average overestimation < 12%. Analysis with the dataset
567 considering only the 8-day time periods without missing field-observed data, i.e. periods with valid
568 ET measurements during eight consecutive days (Fig. S3) did not change the results overall,
569 confirming STEEP's dominance compared to the two standard products evaluated.

570



572 Fig. 8. Temporal evolution of ET from STEEP, MOD16 and PMLv2 for the different observation
 573 sites, and their individual performance statistics. a), b) and c) PTN 2011; d), e) and f) SNN 2014; g)
 574 h) and i) SET 2015; j), k) and l) CGR 2014; m), n) and o) CGR 2020. Black lines correspond to
 575 observed ET while data points refer to estimates by the STEEP model (red crosses), MOD16 (blue
 576 diamonds) and PMLv2 (green squares) products.



577
 578 Fig. 9. Evaluation of evapotranspiration (ET, mm/8 days) observed and modelled with STEEP (red
 579 crosses), MOD16 (blue diamonds) and PMLv2 (green squares) for all experimental sites. The
 580 black line is the 1:1 line; dashed lines are the fitted linear regressions of observed versus modelled
 581 values by the STEEP model (red), MOD16 (blue) and PMLv2 (green) products. $N = 138$ is the total
 582 number of eight-day periods with at least one day of EC data measured in at least one of the five
 583 experimental sites of Caatinga where all the ET models (STEEP, MOD16 and PMLv2) outputs
 584 were available.

585 The explanation of the differences between STEEP and the MOD16 and PMLv2 products is
586 two-fold. Firstly, the way ET is obtained differs between STEEP and the other products. While
587 STEEP and other SEB single-source models estimate ET as a combined single process, i.e. soil
588 evaporation and transpiration estimates are provided as a lumped sum (Sahnoun et al., 2021), and
589 interception loss is not taken into account, MOD16 and PMLv2 discriminate the ET components, i.e.
590 soil evaporation, transpiration, and wet canopy evaporation (Mu et al., 2011; Zhang et al., 2019).
591 With this in mind it is remarkable that STEEP performs better than the other, widely used, multiple-
592 source ET products. Secondly, the input data sets and their uses are different. The driving
593 meteorological data for STEEP are from ERA5-Land, while in MOD16, they are from MERRA and in
594 PMLv2 are provided by GLDAS (Mu et al., 2011; Zhang et al., 2019). In addition, the meteorological
595 elements used are different among the ET products. MOD16 requires air temperature, atmospheric
596 pressure, relative humidity, and downward shortwave radiation. In addition to these elements,
597 PMLv2 also requires precipitation, downward longwave radiation, and wind speed (Mu et al., 2011;
598 Zhang et al., 2019; Yin et al., 2020; Chen et al., 2022). Although both ET products use the same
599 land cover data (MOD12Q1), only MOD16 integrates it into its algorithm. In MOD16, the land cover
600 type defines biome delimitation for the characterization of leaf stomatal conductance, vapour
601 pressure deficit (VPD) and other related factors, while PMLv2 only uses land cover to construct a
602 mask of the land area (Chen et al., 2022). The sources and use of LAI in these two products are also
603 different. LAI is used to increase leaf conductance in MOD16, while it is used to divide the total
604 available energy into canopy uptake and soil uptake in PMLv2 (Mu et al., 2011; Zhang et al., 2019;
605 Chen et al., 2022). Although MOD16 uses EC data from 46 distributed sites for validation (Mu et al.,
606 2011) and PMLv2 uses EC data from 95 distributed sites and ten plant functional types for calibration
607 (Zhang et al., 2019; Yin et al., 2020), none of the products had observation sites in SDTF.

608 The uncertainties associated with field measurements of ET can also influence the evaluation
609 of the model products. It is generally accepted that EC flux towers provide reliable local, i.e. for areas
610 of relatively limited spatial extensions, ca. 10 km², ET measurements (Mu et al., 2011; Chu et al.,
611 2021; Salazar-Martínez et al., 2022). However, generally flux tower data have a lack of energy
612 balance closure, that is the difference between net radiation and ground heat flux is sometimes
613 greater than the sum of the turbulent latent and sensible heat fluxes, an error that can be in the of

614 10–30% range (Wilson et al., 2002; Foken, 2008; Allen et al., 2011). This gap can result from
615 instrument errors, weather and surface conditions, e.g. those that result in advection, and gap-filling
616 methods (Mu et al., 2011). In addition, the complex and heterogeneous canopy structure, the
617 stochastic nature of turbulence (Hollinger and Richardson, 2005) and adverse weather conditions,
618 e.g. rainy and stormy days, tower sensors recording abnormal values, can affect ET measurements
619 obtained by EC systems (Ramoelo et al., 2014).

620 3.3 Sources of error and further research for STEEP

621 In its current configuration, STEEP has some limitations that should be noted. Meteorological
622 reanalysis provides only large-scale averages and can misrepresent local meteorological conditions;
623 hence, it suffers from biases, especially over heterogeneous surfaces (Rasp et al., 2018). However,
624 despite moderate accuracy and biases at regional scales, ground-based assimilation and reanalysis
625 data have become important sources of meteorological inputs for ET estimates (Mu et al., 2011;
626 Zhang et al., 2019; Allam et al., 2021; Senay et al., 2022). Laipelt et al. (2020) and Kayser et al.
627 (2022) showed that global reanalysis data when used as meteorological inputs had modest effects
628 only on the accuracy of SEBAL for estimating ET. In our study, ERA5-Land exhibited relatively high
629 and satisfactory agreement with micrometeorological data measured at each site (Fig. S4). Also,
630 although gap-filling was used in the present study to improve the availability of LST data, this
631 procedure should be used with caution. In addition, care should be taken when using the MCD43A4
632 reflectance product, because in its composition there is also gap-filling. For example, on some cloudy
633 days, the estimates of vegetation indices, surface albedo, and LST may have introduced
634 inaccuracies in the STEEP (and in SEBAL) model calculation process due to these gap-filling
635 methods. Regarding the selection of endmembers pixels, although the temporal evolution of the
636 selected pixels in this study seems plausible, their representativeness of the actual conditions may
637 be debatable, especially considering the considerable extent of the AOI. The computational capacity
638 and the effectiveness of GEE for running SEB models should be commended. Although other studies
639 have demonstrated GEE's strength (Laipelt et al., 2021; Jaafar et al., 2022; Senay et al., 2022), this
640 platform has some limitations when it comes to the number of iterations, e.g. a convergence
641 threshold cannot be set to stop the within-loop iterations of H calculations; instead a fixed number of

642 iterations needs to be defined. Still, the availability of the several necessary datasets within one
643 platform greatly facilitates the run of STEEP and other SEB models.

644 One of the main focuses of this study is to provide a one-source model capable of
645 representing ET in environments that are mainly governed by soil–water availability, such as those
646 represented by SDTF, in a parsimonious way. Based on our findings we deem this main aim to be
647 achieved due to the relative simplicity of the STEEP model and its low data demand. The improved
648 performance of STEEP was the result of improvement of existing and physically meaningful
649 parameters (z_{0m} and kB^{-1}), rather than by introducing additional empirical parameters, thereby
650 satisfying the principle of equifinality (see Beven and Freer, 2001). To explore further the potential
651 and accuracy of STEEP, more research is needed to analyse the impact that the improved H
652 approach has on ET of different land covers at longer time scales. Despite the promising overall
653 results, additional efforts are required on modelling H in SDTF regions. Although we have shown
654 that STEEP outperforms other models in simulating either H or ET, we acknowledge that there is still
655 room for model improvement. Given that the STEEP model was formulated to be a calibration-free
656 model, it may be possible to improve H estimates by, for example, optimising coefficients associated
657 to soil moisture (see Eq A.12) and applying dynamic values to q_{pt} (see Eq A.25) varying seasonally.
658 Another potential improvement for instantaneous H estimates can be achieved by accounting for
659 biomass heat storage (BHS; Swenson et al., 2019) in STEEP. Meier et al. (2019) have shown that
660 considering BHS can enable land surface models to capture the diurnal asymmetry of the
661 temperature impact on energy fluxes and, consequently, provide improved sub-hourly H . Improving
662 the quantification of regional ET via RS-based SEB models has a great potential to provide a more
663 accurate estimate of the energy and water fluxes in SDTF regions, and will contribute to a better
664 understanding of the water cycle, its uses, and the interrelationships with ecosystem functioning.

665 **4. Conclusions**

666 Our work developed a calibration-free model (STEPP) with an improved approach for
667 estimating the latent and sensible heat fluxes by remote sensing for SDTF. In summary, the main
668 conclusions are:

- 669 • The estimates of H by STEEP allowed ET estimates to be closer to the observed field
670 values than those obtained by SEBAL. Based on all the performance metrics used to

671 analyse the models, STEEP was superior to SEBAL. STEEP showed *RMSE* less than
672 1mm/day, *R*² between 0.24 and 0.69, *NSE* between -0.17 and 0.65, *ρ*_c between 0.41
673 and 0.80 and *PBIAS* between -17% to 54%. Also noteworthy is how well STEEP captured
674 the seasonal course of observed ET.

675 • Compared with ET data from the global MOD16 and PMLv2 products, the STEEP model
676 simulated a similar but generally superior seasonal evolution and its performance metrics
677 were also better. Considering all observation sites simultaneously, at the eight-day scale,
678 STEEP showed superior performance with *RMSE* less than 6 mm/8 days, *R*² and *NSE*
679 equal to or greater than 0.60, *ρ*_c greater than 0.75, and an overestimation of < 12%.

680 Thus, we conclude that STEEP, a one-source model that incorporated the seasonality of the
681 aerodynamic and surface variables, was well-heelled in representing ET in environments that are
682 mainly governed by soil–water availability. All the same, there is a need to evaluate the newly
683 developed STEEP model performance for different land covers, climate, and for longer time series
684 than those considered during the modelling process in this study.

685 **Acknowledgements**

686 The Coordenação de Aperfeiçoamento de Pessoal de Nível Superior-Brazil (CAPES)-Finance Code
687 001, provided scholarships to the first and fifth authors. This work was funded by the Brazilian
688 National Council for Scientific and Technological Development (CNPq), grant 409341/2021-5, by the
689 Paraíba Scientific Foundation (FAPESQ), under grants 010/2021 and 403/2021, and by São Paulo
690 Scientific Foundation (FAPESP), grant 2015/24461-2. CEF is a research unit funded by Fundação
691 para a Ciência e a Tecnologia I.P. (FCT), Portugal (UIDB/00239/2020). MSBM, AV and RLBN
692 acknowledge support by the Newton/NERC/FAPESP Nordeste project (NE/N012526/1 ICL 652 and
693 NE/N012488/1 UoR). RLBN acknowledges support from the European Research Council under the
694 European Union's Horizon 2020 research and innovation programme (grant agreement No: 787203
695 REALM). MSBM thanks to Fundação de Amparo à Ciência e Tecnologia do Estado de Pernambuco
696 (FACEPE) for funding this through the Project FACEPE APQ 0062-1.07/15 (Caatinga-FLUX). MSBM
697 and AMPM acknowledge to the National Observatory of Water and Carbon Dynamics in the Caatinga
698 Biome (INCT: NOWCBCB) supported by FACEPE (grant: APQ-0498-3.07/17 ONDACBC), CNPq
699 (grant: 465764/2014-2), and CAPES (grants: 88887.136369/2017-00).

700 **Data Availability Statement**

701 ET data for the PTN, SNN, and SET sites were published by Melo et al. (2021), and are available at
702 <https://doi.org/10.5281/zenodo.5549321>. ET data for the CGR site; H data for the PTN, SNN, CGR
703 sites, and the code used for the formulation of the STEEP model presented in this study can be
704 accessed at <https://doi.org/10.5281/zenodo.7109043> and
705 https://github.com/ulissesaalencar/ET_SDTF, respectively. H data for the SET site is publicly
706 available for download at <https://ameriflux.lbl.gov/>.

707 **Supplementary material**

708 Table S1. Performance statistics by the exclusion/modification of one or two parameters/variables
709 implemented in the STEEP model, in the wet and dry seasons: scale factor soil moisture correction
710 (SF), the parameter kB^{-1} , the aerodynamic resistance for heat transfer (rah), PAI replace with LAI
711 (determined by two different methods), the roughness length for momentum transport (z_0m), the
712 residual latent heat flux in the end members pixels ($r\lambda ET$), and of the SEBAL model.

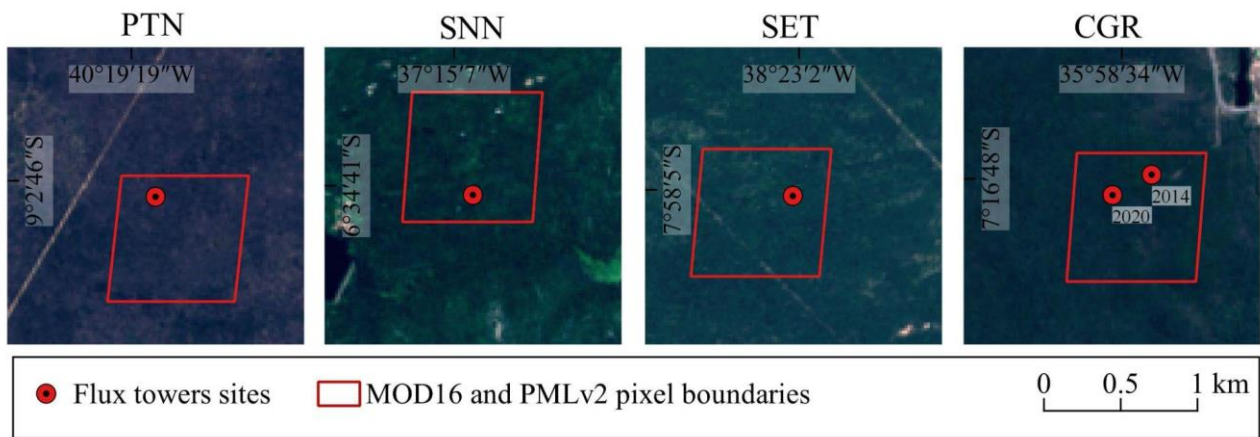
		Performance statistics									
Site		RMSE		R^2		NSE		ρ_c		PBIAS	
		wet	dry	wet	dry	wet	dry	wet	dry	wet	dry
PTN (N = 239; 2011)	STEEP	1.23	0.7	0.53	0.62	0.34	0.5	0.68	0.77	-18.01	-17.01
	(-) SF	1.38	0.69	0.56	0.58	0.16	0.52	0.65	0.75	-26.39	-7.99
	(-) kB-1	1.39	0.67	0.54	0.62	0.14	0.55	0.66	0.78	-23.37	-8.23
	(-) rah	1.61	0.66	0.42	0.6	-0.22	0.55	0.54	0.77	-32.42	-6.56
	LAI*	1.37	1.08	0.57	0.59	0.19	-0.18	0.68	0.59	-24.24	-56.26
	LAI**	1.27	0.91	0.54	0.34	0.28	0.17	0.68	0.57	-19.73	-11.95
	(-) z0m	1.48	0.88	0.36	0.3	0.01	0.21	0.5	0.54	-25.94	7.55
	(-) rλET	1.5	1.6	0.12	0.19	-0.15	-1.54	0.31	0.28	14.75	75.96
	(-) z0m & rah	1.51	0.72	0.44	0.51	-0.04	0.48	0.57	0.7	-28.85	4.4
	(-)rah & rλET	1.47	1.66	0.13	0.15	-0.11	-1.81	0.33	0.23	12.99	81.63
	(-) z0m & rλET	1.42	1.45	0.14	0.09	-0.31	-0.04	0.36	0.22	0.73	57.29
	SEBAL	1.39	1.55	0.16	0.12	0.01	-1.43	0.38	0.23	2.12	69.2
	SNN (N = 267; 2014)	STEEP	1.03	0.6	0.46	0.62	0.32	0.25	0.64	0.68	-12.17
(-) SF		1.07	0.58	0.47	0.64	0.29	0.44	0.6	0.73	-17.2	42.77
(-) kB-1		1.12	0.67	0.44	0.59	0.21	0.24	0.6	0.69	-17.86	50.26
(-) rah		1.19	0.6	0.49	0.62	0.19	0.41	0.57	0.7	-25.47	47.33
LAI*		1.38	0.8	0.54	0.3	-0.21	-0.07	0.6	0.44	-29.33	-58.36
LAI**		1.19	0.98	0.52	0.09	0.07	-0.6	0.62	0.26	23.77	55.02
(-) z0m		1.14	0.83	0.41	0.23	0.24	-0.16	0.5	0.37	-19.01	60.45
(-) rλET		1.16	1.18	0.32	0.43	0.18	-1.33	0.51	0.41	12.96	122.85
(-) z0m & rah		1.19	0.63	0.52	0.57	0.17	0.34	0.52	0.64	-26.49	50.69
(-)rah & rλET		1.13	1.14	0.25	0.37	0.16	-1.19	0.47	0.41	6.43	111.65
(-) z0m & rλET		1.13	1.03	0.24	0.17	0.16	-0.79	0.47	0.32	-5.86	79.17
SEBAL		1.13	1.06	0.22	0.33	0.16	-0.88	0.45	0.41	0.91	98.12
SET (N = 283; 2015)		STEEP	1.16	0.6	0.12	0.12	-0.55	-0.94	0.28	0.27	52.19

	(-) <i>SF</i>	1.04	0.61	0.11	0.02	-0.25	-0.99	0.28	0.14	36.58	38.26	
	(-) <i>kB-1</i>	1.13	0.58	0.06	0.07	-0.49	-0.86	0.21	0.23	36.71	40.83	
	(-) <i>rah</i>	1.06	0.56	0.04	0	-0.43	-1.03	0.18	0.03	21.82	39.71	
	<i>LAI*</i>	1.3	0.68	0.03	0.09	-0.98	-1.51	0.12	0.2	-62.3	-75.32	
	<i>LAI**</i>	1.15	0.6	0.04	0.05	-0.53	-0.97	0.19	0.21	-6.83	-29.78	
	(-) <i>z0m</i>	1.09	0.75	0.1	0	-0.36	-2.74	0.26	-0.02	42.62	80.96	
	(-) <i>rλET</i>	2.11	1.37	0.15	0.04	-4.18	-9.27	0.15	0.06	151.66	190.07	
	(-) <i>z0m & rah</i>	1.06	0.58	0.05	0	-0.3	-1.24	0.21	0.02	21.6	51.96	
	(-) <i>rah & rλET</i>	1.99	1.37	0.11	0.01	-3.99	-9.27	0.13	0.04	143.27	183.22	
	(-) <i>z0m & rλET</i>	1.66	1.16	0.07	0.01	-2.47	-6.31	0.14	0.04	104.32	134.34	
	SEBAL	1.83	1.28	0.1	0	-3.21	-7.93	0.14	0.03	128	161.89	
	STEEP	0.8	0.72	0.35	0.51	-0.35	-0.8	0.55	0.58	5.85	25.16	
CGR (N = 171; 2014)	(-) <i>SF</i>	0.7	0.67	0.36	0.52	-0.02	-0.53	0.59	0.6	6.57	30.14	
	(-) <i>kB-1</i>	0.78	0.8	0.25	0.44	-0.28	-1.18	0.47	0.51	15.04	38.9	
	(-) <i>rah</i>	0.71	0.78	0.28	0.46	-0.06	-1.07	0.51	0.48	-8.54	54.63	
	<i>LAI*</i>	0.76	0.83	0.49	0.61	-0.23	-1.35	0.64	0.51	-7.64	-62.39	
	<i>LAI**</i>	0.75	0.68	0.46	0.58	-0.18	-0.57	0.63	0.63	-9.25	-26.31	
	(-) <i>z0m</i>	0.71	0.83	0.28	0.35	-0.05	-1.35	0.51	0.38	-11.12	62.72	
	(-) <i>rλET</i>	1.15	2.32	0.09	0.07	-1.77	-17.48	0.19	0.04	46.68	217.84	
	(-) <i>z0m & rah</i>	0.69	0.84	0.24	0.44	-0.01	-1.43	0.48	0.39	3.9	68.9	
	(-) <i>rah & rλET</i>	1.14	2.44	0.05	0.03	-1.72	-19.4	0.15	0.02	43.77	229.58	
	(-) <i>z0m & rλET</i>	0.85	1.97	0.11	0.04	-0.51	-12.27	0.33	0.04	9.18	175.39	
	SEBAL	0.97	2.24	0.07	0.03	-0.97	-14.7	0.21	0.03	28.63	208.13	
	STEEP	0.61	1.06	0.39	0.02	0.29	-2.98	0.62	0.09	-1.19	101.37	
	CGR (N = 48; 2020)	(-) <i>SF</i>	0.82	1.03	0.3	0	-0.29	-2.76	0.52	0.02	-6.52	106.36
		(-) <i>kB-1</i>	0.83	1.26	0.29	0	-0.3	-4.63	0.51	-0.03	-5.31	135.98
(-) <i>rah</i>		1.11	1.13	0.25	0	-1.2	-3.55	0.42	-0.02	-15.37	133.29	
<i>LAI*</i>		0.85	1.02	0.29	0.01	-0.38	-0.99	-3.06	0.4	-4.71	31.63	
<i>LAI**</i>		0.67	0.76	0.36	0.07	0.14	-1.03	0.59	0.26	-3.58	2.87	

(-) $z0m$	0.69	1.03	0.41	0	0.15	-2.73	0.58	-0.02	-12.29	106.1
(-) $r\lambda ET$	0.99	2.25	0.03	0.06	-0.52	-16.98	0.17	-0.04	6.37	312.54
(-) $z0m$ & rah	1.04	1.13	0.34	0.01	-0.74	-3.52	0.5	-0.03	-16.56	134.92
(-) rah & $r\lambda ET$	0.89	2.38	0.05	0.14	-0.24	-19.08	0.22	-0.05	1.07	330.94
(-) $z0m$ & $r\lambda ET$	0.83	1.77	0.18	0.02	-0.6	-10.14	0.33	-0.04	-14.15	216.81
SEBAL	0.81	2.11	0.16	0.07	-0.02	-0.02	0.31	-0.04	-12.25	285.53

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715 $z0m$ = roughness length for momentum transfer; rah = aerodynamic resistance for heat transfer; $r\lambda ET$ = remaining λET in the endmembers pixels.

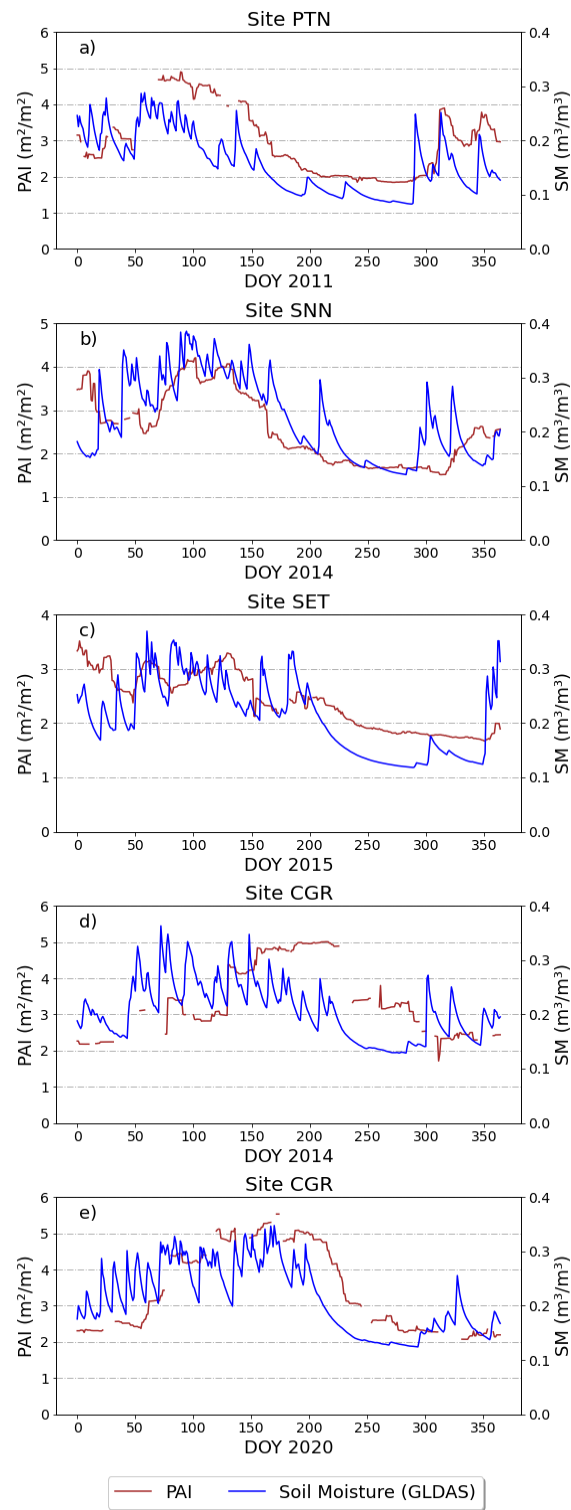


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717 Fig. S1. Location of the flux towers sites and MOD16 and PMLv2 pixel boundaries. True colour
 718 composite (bands 4, 3, and 2) of Harmonized Sentinel-2 MSI acquired via Google Earth Engine.

719 Scene acquired of PTN (12/06/2021); SNN and SET (25/05/2021); CGR (29/07/2021).

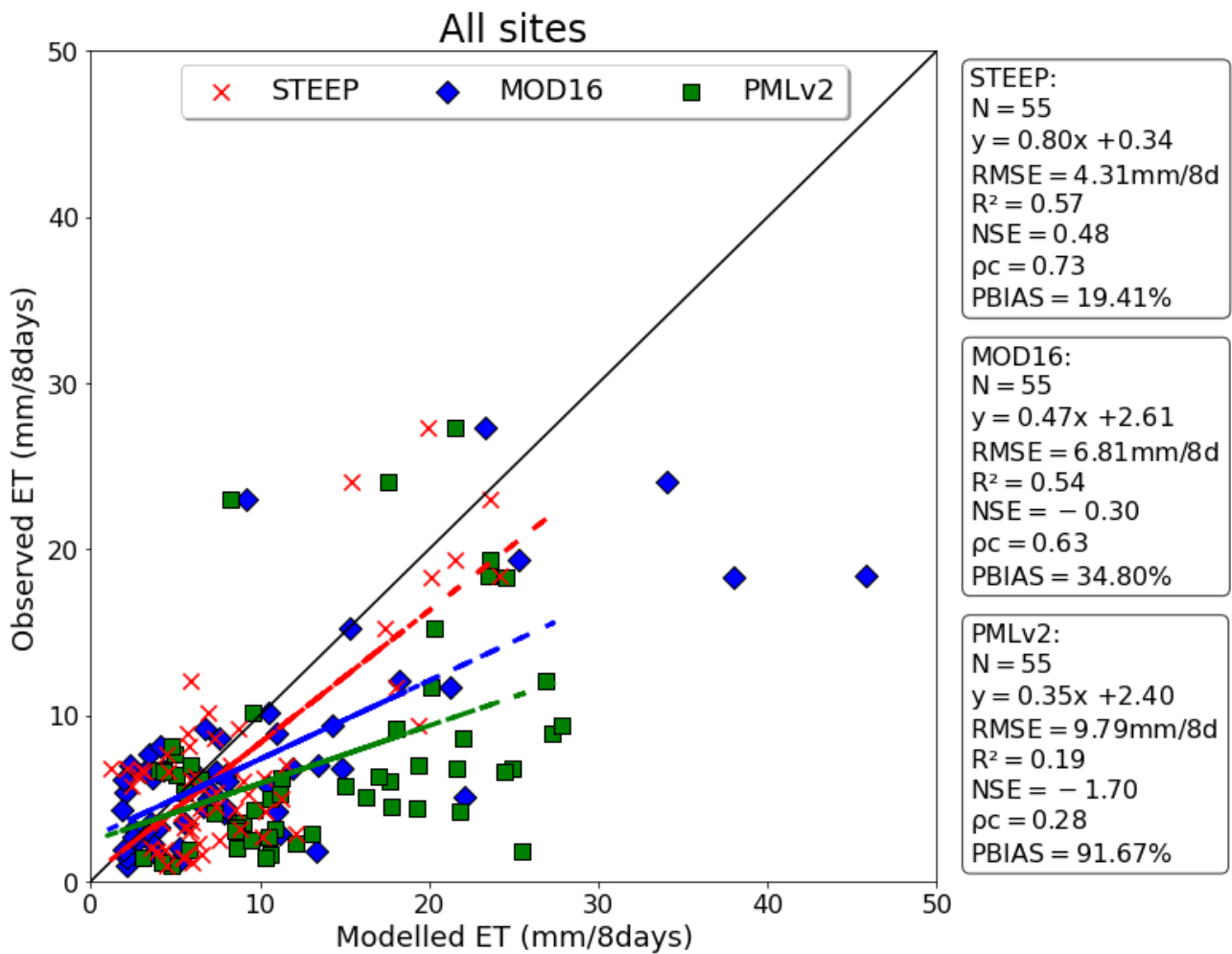
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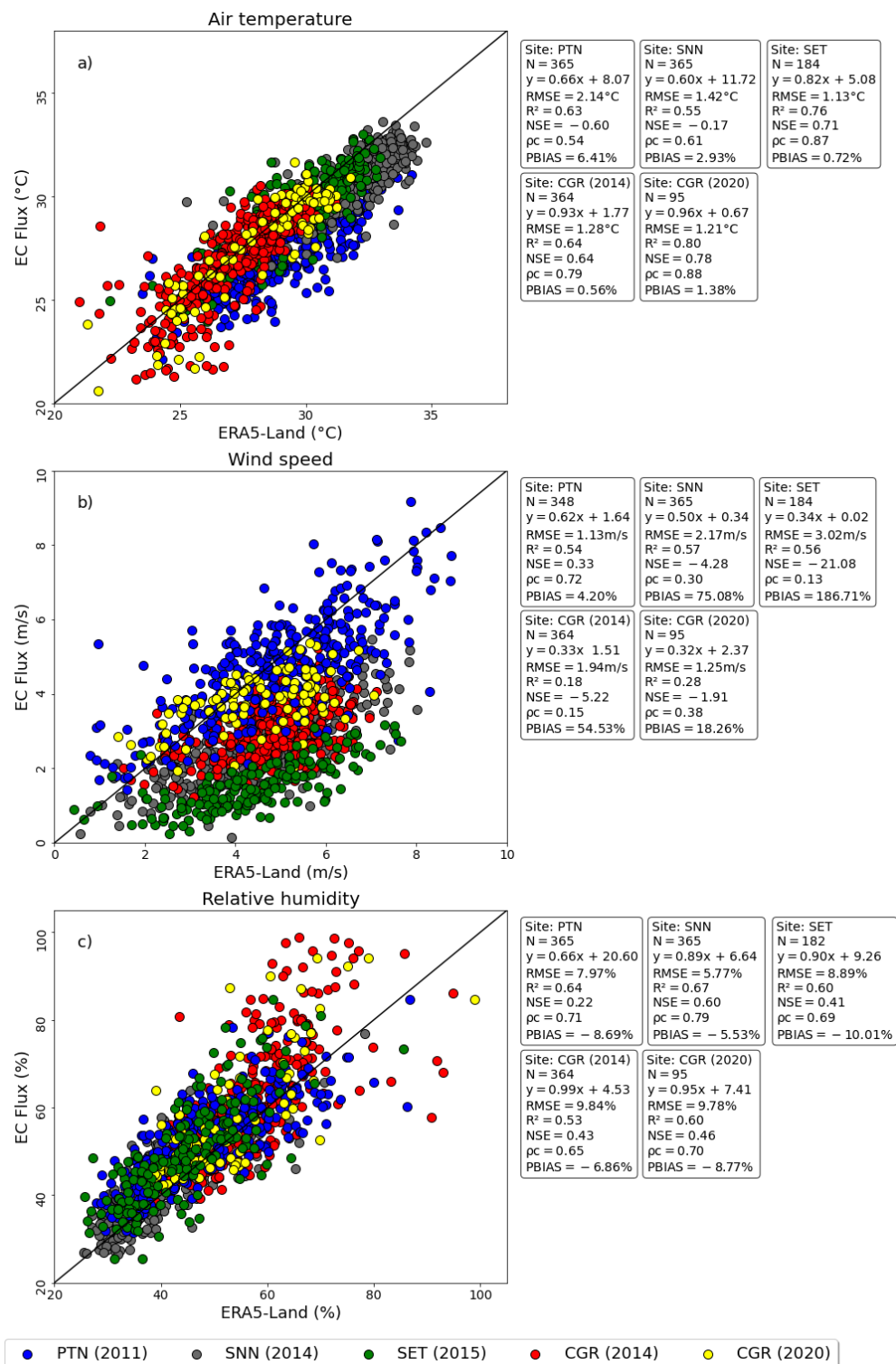
Fig. S2. PAI and soil moisture time series for the different observation sites.



723

724 Fig. S3. Evaluation of evapotranspiration (ET, mm/8 days) observed and modelled with STEEP
 725 (red crosses), MOD16 (blue diamonds) and PMLv2 (green squares) for all experimental sites
 726 considering only the 55 periods where the field-observed data had eight consecutive days. The
 727 black line is the 1:1 line; dashed lines are the fitted linear regressions of observed or modelled
 728 values by the STEEP model (red), MOD16 (blue) and PMLv2 (green) products.

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Fig. S4. Comparison between ERA5-Land reanalysis dataset and local observational meteorological measurements from the flux tower at the closest time from the satellite overpass. Micrometeorological sensors installed at the flux towers are up to 16 m in distance from the land surface, and ERA5-Land variables have different reference elevation (e.g. 2 m for air temperature and 10 m to wind speed).

737 **Appendix A – Equations adopted to formulate the STEEP model**

738 Latent heat flux (λET) was modeled using Eq. (A.1):

$$\lambda ET = R_n - G - H \quad (\text{A.1})$$

739 where R_n is net radiation, G is soil heat flux, and H is sensible heat flux. All variables are expressed
740 in energy units (e.g., W/m^2).

741 Net radiation (R_n) was modeled based on the radiation budget indicated by Allen et al. (2007) and
742 Ferreira et al. (2020) by Eq. (A.2):

$$R_n = R_{S\downarrow} \times (1 - \alpha) + \varepsilon_s \times R_{L\downarrow} - R_{L\uparrow} \quad (\text{A.2})$$

743 where $R_{S\downarrow}$ is incident shortwave radiation (W/m^2) estimated following Allen et al. (2007), α is surface
744 albedo (dimensionless), estimated following Trezza et al. (2013), $R_{L\downarrow}$ is longwave radiation from the
745 atmosphere (W/m^2) estimated following Ferreira et al. (2020) with atmospheric emissivity from
746 Duarte et al. (2006); $R_{L\uparrow}$ is emitted longwave radiation (W/m^2) following Ferreira et al. (2020) with ε_s
747 the surface emissivity (dimensionless), estimated following Long et al. (2010).

748 Soil heat flux (G), expressed as a ratio of net radiation, was estimated following the model by
749 Bastiaanssen et al. (1998):

$$\frac{G}{R_n} = [(LST - 273.15) \times (0.0038 + 0.0074 \times \alpha) \times (1 - 0.98 \times NDVI^4)] \quad (\text{A.3})$$

750 where LST is the surface temperature (K) and $NDVI$ is the Normalized Difference Vegetation Index
751 (dimensionless), estimated following Rouse et al. (1973).

752 Sensible heat flux (H) was modeled using:

$$H = \frac{\rho \times c_p \times dT}{rah} \quad (\text{A.4})$$

753 where ρ is the air density (kg/m^3), c_p refers to the specific heat of air at constant pressure (J/kg/K),
754 dT is the temperature gradient (K), and rah is the aerodynamic resistance for heat transfer (s/m).

755

756 Aerodynamic resistance to heat transport was estimated based on the classical equation given in
757 Paul et al. (2013), see also Verhoef et al. (1997a):

$$rah = \frac{1}{k \times u^*} \times \left[\ln \left(\frac{z_{ref} - d0}{z0m} \right) - \psi_h \right] + \frac{1}{k \times u^*} \times kB_{umd}^{-1} \quad (A.5)$$

758 where k is the von Kármán constant taken as 0.41, u^* is the friction velocity (m/s), z_{ref} is the
 759 reference height (m), $d0$ is zero plane displacement height (m), $z0m$ is roughness length for
 760 momentum transfer (m), ψ_h is the atmospheric stability correction function for heat transfer (m), as
 761 calculated following Paulson (1970), kB_{umd}^{-1} is the dimensionless parameter formulated to express
 762 the excess resistance of heat transfer compared to momentum transfer, corrected for soil moisture
 763 derived from remote sensing.

764 The friction velocity was computed according to Verhoef et al. (1997b) and Paul et al. (2013):

$$u^* = k \times u \left[\ln \left(\frac{z_{ref} - d0}{z0m} \right) - \psi_m \right]^{-1} \quad (A.6)$$

765 where u is the wind speed (m/s) at a known height z_{ref} , ψ_m is the atmospheric stability correction
 766 function for momentum transfer (m), as calculated following Paulson (1970).

767 Roughness length for momentum transport was estimated, based on the studies by Verhoef et al.
 768 (1997b):

$$z0m = (HGHT - d0) \times \exp(-k \times \gamma + PSICORR) \quad (A.7)$$

769 where $HGHT$ is the height of the vegetation (m), $PSICORR$ is taken as 0.2 and γ is the inverse of the
 770 square root of the bulk surface drag coefficient at the roughness canopy height (Raupach, 1992).

771 Zero plane displacement height ($d0$) was obtained following Raupach (1994) from:

$$d0 = HGHT \times \left[\left(1 - \frac{1}{\sqrt{CD1 \times PAI}} \right) + \left(\frac{\exp^{-\sqrt{CD1 \times PAI}}}{\sqrt{CD1 \times PAI}} \right) \right] \quad (A.8)$$

772 where $CD1$ is taken as 20.6 and PAI is the Plant Area Index.

773 γ was following Verhoef et al. (1997b):

$$\gamma = \left(CD + CR \times \frac{PAI}{2} \right)^{-0.5} \quad (A.9)$$

774 if $\gamma < 3.33$, γ is set to 3.33. Following Verhoef et al. (1997), CD and CR are taken as 0.01 and 0.35,
 775 respectively.

776 Plant Area Index was calculated according to Miranda et al. (2020) as:

$$PAI = 10.1 \times (\rho_{NIR} - \sqrt{\rho_{RED}}) + 3.1 \quad (A.10)$$

777 where ρ_{NIR} is the near infrared band reflectance, and ρ_{RED} is the red band reflectance. If $PAI < 0$, $d0$
 778 is set to 0.

779 The dimensionless parameter kB_{umd}^{-1} is corrected by soil moisture by remote sensing following the
 780 equations provided by Gokmen et al. (2012):

$$kB_{umd}^{-1} = SF \times kB^{-1} \quad (A.11)$$

781 where SF is a scaling factor, represented by a sigmoid function:

$$SF = \left[c + \frac{1}{1 + \exp(d - e \times SM_{rel})} \right] \quad (A.12)$$

782 Here, c , d , e are the sigmoid function coefficients, for which we adopted values of 0.3, 2.5, and 4,
 783 respectively, following Gokmen et al. (2012). SM_{rel} is the relative soil moisture, obtained from:

$$SM_{rel} = \frac{SM - SM_{min}}{SM_{max} - SM_{min}} \quad (A.13)$$

784 where SM is the actual soil moisture content, in our case obtained with the GLDAS reanalysis
 785 product, and SM_{min} and SM_{max} are the minimum and maximum soil moisture. The SM_{min} and SM_{max}
 786 values were obtained using the annual time series analysis of the soil moisture data.

787 kB^{-1} was calculated according to Su et al. (2001):

$$kB^{-1} = \frac{k \times Cd}{4 \times Ct \times \frac{u^*}{u(h)} \times \left(1 - \exp\left(\frac{-nec}{2}\right) \right)} \times f_c^2 + \frac{k \times \frac{u^*}{u(h)} \times \frac{z0m}{h}}{C_t^*} \times f_c^2 \times f_s^2 + kB_s^{-1} \times f_s^2 \quad (A.14)$$

788 where $kB_s^{-1} = 2.46(Re^*)^{0.25} - 2$, Cd is the drag coefficient of the foliage elements taken as 0.2, Ct
 789 is the heat transfer coefficient of the leaf with value 0.01.

790 The ratio $\frac{u^*}{u(h)}$ is parameterized as:

$$\frac{u^*}{u(h)} = c1 - c2 \times \exp(-c3 \times Cd \times PAI) \quad (A.15)$$

791 where $c1 = 0.320$, $c2 = 0.264$, $c3 = 15.1$.

792 nec is the extinction coefficient of the wind speed profile within the canopy given by:

$$nec = \frac{Cd \times PAI}{\frac{2u^{*2}}{u(h)^2}} \quad (A.16)$$

793 C_t^* is heat transfer coefficient of the soil given by:

$$C_t^* = Pr^{-2/3} \times (Re)^{-1/2} \quad (A.17)$$

794 where Pr is the Prandtl number with a value 0.71, and Re is the Reynolds number calculated as:

$$Re = \frac{u^* \times 0.009}{\nu}, \quad \nu = 1.461 \times 10^{-5} \quad (A.18)$$

795 where ν is the kinematic viscosity (m²/s).

796 In Eq. A.14 f_c is the fractional canopy cover calculated according to Eq. (A19), and f_s is its
797 complement.

$$f_c = 1 - \left[\frac{NDVI - NDVI_{max}}{NDVI_{min} - NDVI_{max}} \right]^{0.4631} \quad (A.19)$$

798 where $NDVI_{max}$ and $NDVI_{min}$ are maximum and minimum NDVI values, respectively. $NDVI_{max}$ and
799 $NDVI_{min}$ values were obtained using the annual time series analysis of the NDVI.

800 dT in Eq. (A4) was estimated daily with a linear relationship on the surface temperature
801 (Bastiaanssen et al., 1998) as:

$$dT = a + b \times LST \quad (A.20)$$

802 To find the coefficients a and b in Eq. (A20) requires that hot and cold endmembers pixels are
803 established. The coefficients were found as:

$$b = \frac{(dT_{hot} - dT_{cold})}{(LST_{hot} - LST_{cold})} \quad (A.21)$$

$$a = dT_{cold} - b \times LST_{cold} \quad (A.22)$$

$$dT_{hot/cold} = \frac{H_{hot/cold} \times rah_{hot/cold}}{\rho \times c_p} \quad (A.23)$$

$$H_{hot/cold} = Rn_{hot/cold} - G_{hot/cold} - \lambda ET_{hot/cold} \quad (A.24)$$

804 where $dT_{hot/cold}$ are dT values for the hot/dry and cold/wet endmember pixels, respectively,
 805 $Rn_{hot/cold}$, $G_{hot/cold}$, $LST_{hot/cold}$, $rah_{hot/cold}$ are the median values extracted on the endmember
 806 pixels of each variable. The selection of endmember pixels is detailed in section 2.3.

807 $\lambda ET_{hot/cold}$ is the term incorporated in the computation of H in the endmember pixels given by the
 808 Priestley-Taylor (1972) equation, according to Singh and Irmak (2011) and French et al. (2015):

$$\lambda ET_{hot/cold} = (Rn_{hot/cold} - G_{hot/cold}) \times f_c \times \alpha_{pt} \times \left[\frac{\Delta}{\Delta + \gamma_c} \right] \quad (A.25)$$

809 where α_{pt} is the empirical Priestley-Taylor coefficient, nominally set to 1.26, but here adjusted
 810 according to local conditions, i.e. we adopted the α_{pt} values (0.55 for hot/dry and 1.75 for cold/wet
 811 pixels) based on Ai and Yang (2016). Δ is the slope of the saturation vapor pressure-air temperature
 812 curve (kPa/°C) and γ_c is the psychrometric constant (kPa/°C).

813 The actual daily evapotranspiration (mm/day) was obtained by means of the following relationship:

$$ET_{24h} = \frac{86400}{(2.501 - 0.00236 \times T_a) \times 10^6} \times \frac{\lambda ET}{Rn - G} \times Rn_{24h} \quad (A.26)$$

814 where T_a is the mean daily air temperature (°C), λET is derived from Eq. A1, and Rn_{24h} corresponds
 815 to the daily net radiation (W/m²); in this study both driving variables were obtained with data from the
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