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

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Abstract

Improvement of evapotranspiration (ET) estimates using remote sensing (RS) products based on multispectral and thermal sensors has been a breakthrough in hydrological research. In large-scale applications, methods that use the approach of RS-based surface energy balance (SEB) models often rely on oversimplifications of the aerodynamic resistances. The use of these SEB models for Seasonally Dry Tropical Forests (SDTF) has been challenging due to incompatibilities between the assumptions underlying those models and the specificities of this environment, such as the highly contrasting phenological phases or ET is mainly controlled by soil–water availability. We developed a RS-based SEB model from a one-source bulk transfer equation, called STEEP. Our model uses the Plant Area Index to represent the woody structure of the plants in calculating the moment roughness length. In the aerodynamic resistance for heat transfer, the parameter kB^{-1} was included, correcting it with RS soil moisture. Besides, the remaining λET in endmembers pixels was quantified

using the Priestley-Taylor equation. We implemented the STEEP algorithm on the Google Earth Engine platform, using worldwide free data. Four sites with eddy covariance data located in the Caatinga, the largest SDTF in South America, in the Brazilian semiarid region, were used to evaluate the STEEP model. Our results show that STEEP based on the specific characteristics of the SDTF increased the accuracy of ET estimates without requiring any additional climatological information. This improvement is more pronounced during the dry season, which in general, ET for these SDTF is overestimated by traditional SEB models, as happened in our research with the SEBAL. The STEEP model had similar or superior behaviour and performance statistics relative to global ET products (MOD16 and PMLv2). This work contributes to an improved understanding of the drivers and modulators of the energy and water balances at local and regional scales in SDTF.
Keywords: Sensible heat flux, Aerodynamic resistance for heat transfer, Surface energy balance, Caatinga, Google earth engine

1. Introduction

Quantifying evapotranspiration (ET) is one of the largest research challenges in hydrology because ET is driven by a complex combination of atmospheric, vegetation, edaphic and terrain characteristics (Wang et al., 2016; Bhattarai et al., 2017). The traditional techniques to quantify ET, e.g. Bowen ratio or eddy covariance system (EC), are limited to areas up to ~1 km² (Allen et al., 2011; Anapalli et al., 2016; Mcshane et al., 2017). Over the past decades, models based on satellite remote sensing (RS) data have been increasingly developed and applied to estimate ET for multiple temporal and spatial scales (Anderson et al., 2011; Chen and Liu, 2020). RS-based surface energy balance (SEB) models estimate ET in terms of energy per unit area (W/m²), i.e. by latent heat flux, λET, where λ is the latent heat of vaporization of water (Shuttleworth, 2012; Barraza et al., 2017). SEB models obtain λET by subtracting the soil heat (G) and sensible heat (H) fluxes from the net radiation (R_n). Estimates of R_n obtained with RS data have been improving, and this flux can nowadays be estimated with acceptable precision (Allen et al., 2011; Ferreira et al., 2020). The $G:R_n$ ratio can be predicted with reasonable accuracy through the use of empirical relationships with soil, vegetation, and temperature characteristics (Bastiaanssen, 1995; Murray and Verhoef, 2007; Allen et al., 2011; Danelichen et al., 2014). Challenges in estimating λET as a residual of the energy balance are mostly associated with the uncertainties in *H* (Gokmen et al., 2012; Paul et al., 2014; Mohan et al., 2020a, b; Costa-Filho et al., 2021). The bulk heat transfer calculation that is used to compute *H* involves variables related to the temperature gradient and to the aerodynamic resistance for heat transfer (*rah*). If any of these variables are poorly estimated, the performance of SEB models will be reduced (Verhoef et al., 1997a, b; Su et al., 2001; Gokmen et al., 2012; Costa-Filho et al., 2021; Liu et al., 2021).

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

Based on the Monin-Obukhov similarity theory, *rah* is defined as a function of the momentum (*z0m*) and heat (*z0h*) roughness lengths. Theoretically, the sum of the zero plane displacement height (*d0*) together with *z0h* defines the level of the effective source of sensible heat (Thom, 1972; Chehbouni et al., 1996; Gokmen et al., 2012) and, therefore, *z0h* constitutes one of the most crucial parameters for the accurate calculation of *H* (Verhoef et al., 1997a; Su et al., 2001). However, as *z0h* cannot be measured directly, it is commonly calculated via the dimensionless parameter kB^{-1} formulated to express the excess resistance of heat transfer compared to momentum transfer (Owen and Thomson, 1963). In RS-based SEB models, oversimplifications are present in the calculation of *rah*, e.g. different land use types are represented by the same values for *z0h* (Bastiaanssen et al., 2005; Allen et al., 2007) kB^{-1} (Bastiaanssen et al., 1998), or the values for the aerodynamic parameters are kept constant in time and space. However, these parameters should not be considered constant, nor set to zero, as this can lead to large inaccuracies in the estimates of *H* (Verhoef et al., 1997a) and, consequently, of *λET* (Liu et al., 2007; Paul et al., 2014; Liu et al., 2021). Studies have shown that kB^{-1} typically ranges from 1 to 12, depending on the dominant surface coverage (Kustas et al., 1989; Troufleau et al., 1997; Verhoef et al., 1997a; Lhomme et al., 2000; Su et al., 2001). Studies illustrate that if an appropriate value of kB^{-1} is used, *H* can be accurately estimated using LST via the bulk transfer method (Stewart et al., 1994; Su et al., 2001; Jia et al., 2003; Paul et al., 2013).

Another problem with RS-based SEB models is that these methods are imprecise when applied to non-agricultural environments, such as forests, deserts, sparse savannahs or rangelands and riparian systems, because of the heterogeneous nature of the vegetation, terrain, soils, and water availability in these environments. This causes the flux estimates obtained with the SEB method, and the underlying aerodynamic parameters, to be highly variable (Allen et al., 2011; Gokmen et al., 2012; Barraza et al., 2017; Chen and Liu, 2020; Costa-Filho et al., 2021). This is especially true in Seasonally Dry Tropical Forests (SDTF) regions, where there is a large spatio-temporal variation in vegetation density, in vegetation structural parameters such as canopy height, crown shape and branching, and water availability. SDTF are an important tropical biome and one of the most threatened ecoregions of the world (Moro et al., 2015; Pennington et al., 2018). SDTF are broadly defined as forest formations in tropical regions characterised by marked seasonality in rainfall distribution, resulting in a prolonged dry season that usually lasts five or six months (Pennington et al., 2009; Paloschi et al., 2020). The most extensive contiguous areas of SDTF are in the neotropics, comprising more than 60% of the remaining global stands of this vegetation (Miles et al., 2006; Queiroz et al., 2017). The physiognomies exhibited by SDTF are heterogeneous, with vegetation ranging from tall forests with closed canopies to scrublands rich in succulents and thornbearing plants (Moro et al., 2015; Paloschi et al., 2020). SDTF foliage patterns are adapted to the intense climate and water seasonality, which is highly dependent on interannual climate variability (Alberton et al., 2017; Medeiros et al., 2022). The vegetation drops most leaves during the dry season, and the first rainfall events trigger a rapid leaf growth in the wet season (Alberton et al., 2017; Paloschi et al., 2020; Medeiros et al., 2022). SDTF are being rapidly degraded (12% between 1980 and 2000), highlighting an urgent priority for their conservation (Moro et al., 2015; Maia et al., 2020). The risks faced by SDTF mainly stem from anthropogenic disturbance effects, which range from local habitat loss to global climate change, leading to biodiversity loss and reductions in biomass (Allen et al., 2017; Maia et al., 2020).

Application of SEB models to estimate evapotranspiration over SDTF has been challenging due to the incompatibility between the existing assumptions of the models and the specificities of these forests. Precipitation seasonality is the primary phenological regulator of SDTF (Moro et al., 2016; Campos et al., 2019; Paloschi et al., 2020), and land-cover patterns show distinct intra- and inter-annual spectral responses (Cunha et al., 2020; Andrade et al., 2021; Medeiros et al., 2022). Therefore, biophysical remotely-sensed variables, such as Normalized Difference Vegetation Index (NDVI) and surface albedo, which are usually used to select the endmembers, exhibit high spatial and temporal variability in SDTF, which causes ET estimates from the SEB models to lack fidelity (Silva et al., 2019). Selection of suitable roughness parameters such as *z0m*, *d0*, and kB^{-1} is important for the correct quantification of the energy balance in SDTF. However, these parameters are more challenging to obtain in SDTF than for evergreen forests, as in addition to vegetation height, other characteristics such as plant density, above-ground plant structure and the strong seasonality of phenology (Alberton et al., 2017; Miranda et al., 2020; Paloschi et al., 2020) have a considerable effect on the turbulent transfer in these forests. Another key issue is how to verify the results of SEB methods due to the scarcity, in many regions, of terrestrial observations and the uneven spatiotemporal distribution of monitoring data. SEB models may not satisfactorily represent ET in regions with sparse vegetation and high climatic seasonality, such as SDTF (Senkondo et al., 2019; Laipelt et al., 2021; Melo et al., 2021). The main reason is that these methods have generally been evaluated and/or parameterized using sites located in other ecosystems and climates in North America, Europe, Australia, East Asia, and in agricultural regions that have characteristics quite distinct from SDTF (Melo et al., 2021). Therefore, a better quantification of ET, especially in regions with high climatic seasonality, will help to design better water management policies that will be able to deal with the effects of climate variability, land use/cover and climate changes (Lima et al., 2021).

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

2. Methodology

2.1 Study areas and respective data

The study concerns the Brazilian Caatinga, the largest continuous SDTF in the Americas, located between the Equator and the Tropic of Capricorn (about 3° and 18° south), in the Brazilian semiarid region. It covers an area of about 850,000 km² (Silva et al., 2017a; Andrade et al., 2021; Brazil MMA, 2021). The climate in the Caatinga is characterized by high air temperatures (around 26° to 30° C) and high potential evapotranspiration (1,500 to 2,000 mm/year) coupled with low annual rainfall (300 to 800 mm/year, normally concentrated in 3–6 months) with high intra- and inter-annual variability in space and time, and a long dry season which sometimes lasts up to 11 months in some areas of Caatinga (Moro et al., 2016; Miranda et al., 2018; Paloschi et al., 2020). The Caatinga vegetation has at least thirteen physiognomies ranging from woods to sparse thorny shrubs, morphologically adapted to resist water stress and high air temperatures (Araújo et al., 2009; Silva et al., 2017a; Marques et al., 2020; Miranda et al., 2020), and it has been identified as one of the most biodiverse SDTF regions globally (Pennington et al., 2006; Santos et al., 2014; Koch et al., 2017). Still, the Caatinga and other SDTF are among the least studied ecoregions compared to tropical forests and savannas (Santos et al., 2012; Koch et al., 2017; Tomasella et al., 2018; Borges et al., 2020). Only 1% of the Brazilian Caatinga area is legally protected (Koch et al., 2017).

We used data from four sites located in the Caatinga (Fig. 1 and Table 1). Located on crystalline terrain (Fig. 1a), these Caatinga sites have soils with highly variable properties, ranging from fertile (those with a clayey texture) to poor (those soils that are sandier). However, most soils of the SDTF are typically shallow and stony (i.e. Entisols, Alfisols, and Ultisols; WRB, 2006), retaining water only for a short period between rainfall events and after the rainy season (Moro et al., 2015; Queiroz et al., 2017). The climate of the four observation sites is semi-arid, type BSh (Fig. 1b) according to the Köppen climate classification (Alvares et al., 2013).

Eddy covariance data, covering several periods from 2011 to 2020 (Fig. 1c), were used to evaluate the modelled ET and *H*. The four sites were instrumented with flux towers equipped with three-dimensional ultrasonic anemometers (CSAT3, Campbell Scientific Inc., Logan, UT, USA) and open-path infrared gas analyzers (LI-7500, LI-COR Inc., Lincoln, NE, USA, in the PTN site, or EC150, Campbell Scientific Inc., Logan, UT, USA, in the other three sites). ET data for the PTN, SNN and SET sites have been previously described; they underwent standard procedures to ensure their quality and were published by Melo et al. (2021). Observations at the CGR site were collected through two micrometeorological towers, located in a dense Caatinga area within the Brazilian National Institute of Semiarid (INSA) experimental area, a 300 ha forest reserve with different stages of regeneration. The first tower (height of 7 m) was active between the years of 2014 and 2017, as described in Oliveira et al. (2021). The second tower (height of 15 m) is part of the Caatinga Observatory (OCA) and includes an EC system that has been collecting data since 2020. The OCA is a laboratory maintained by the Federal University of Campina Grande and INSA. *H* data for the PTN, SNN and CGR sites have been obtained from the respective principal investigators, while data for the SET site have been obtained from the AmeriFlux network (Antonino, 2019). For the retrieval of *λET* and *H*, we used the LoggerNet software (Campbell Scientific, Inc., Logan, UT, USA) in order to transform 10 Hz raw data into 30 min binaries. Afterwards, EdiRe software was used to process the high-frequency data, averaging every 30 min. Detailed information on data processing, quality control, and post-processing can be found in Campos et al. (2019) and Cabral et al. (2020). In addition, data for any day with rain greater than 0.5 mm was removed. The daily ET was calculated using the daily average *λET*.

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)	Location (Lon;Lat)	Data availability	Main reference
Petrolina (PTN)	Pernambuco	428.6	395	-40.3212; -9.0465	Jan–Dec 2011	Souza et al. (2015)
Serra Negra do Norte (SNN)	Rio Grande do Norte	629.5	205	-37.2514; -6.5783	Jan–Dec 2014	Marques et al. (2020)
Serra Talhada (SET)	Pernambuco	648	465	-38.3842; -7.9682	Jan–Dec 2015	Silva et al. (2017b)
Campina Grande (CGR)	Paraíba	777	490	-35.9763; -7.2805	Jan–Dec 2014	Oliveira et al. (2021)
Campina Grande (CGR)	Paraíba	777	490	-35.9763; -7.2805	Jan–Dec 2020	This study

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

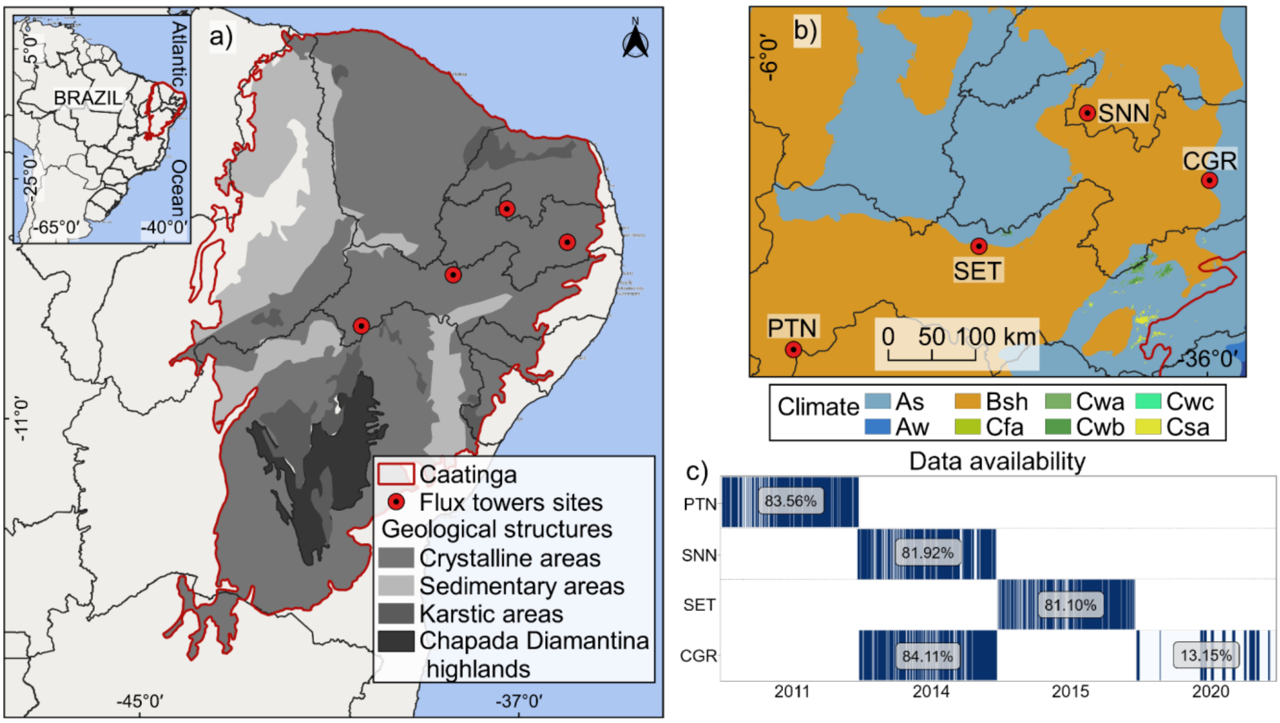


Figure 1. Location of flux tower observation sites in Caatinga. a) Geographical overview of the Caatinga (Moro et al., 2015), b) Köppen's climate classification map according to Alvares et al. (2013) and c) Data availability on the observation sites.

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

To incorporate the conditions of water variability in the forest system in the calculation of sensible heat we applied the procedure described in Gokmen et al. (2012) that corrects the kB^{-1}

equation presented in Su et al. (2001), incorporating soil moisture obtained by remote sensing. The decrease of kB^{-1} with a rise in plant water stress is based on general plant physiological observations related to vertical canopy stomatal conductance profiles, which affects the exchange of sensible and latent heat between the canopy and the atmosphere. Thus, when there is a reduction in soil moisture, there is also a reduction in the value of *rah* and, consequently, an increase of *H* and a decrease in *λET*. Furthermore, to calculate *dT*, we used the linear relationship on LST, using the assumption of extreme contrast in terms of cover and soil wetness (hot/dry and cold/wet endmembers) to determine the linear relationship coefficients. However, in the hot/dry and cold/wet endmembers pixels, *H* was computed by the surface energy balance (Allen et al., 2007), and the remaining *λET* was incorporated through the Priestley-Taylor (1972) equation and plant physiological constraints following the approach in Singh and Irmak (2011) and French et al. (2015). The references for the methods and equations adopted to formulate the STEEP model can be found in Table 2 and Appendix A, respectively. For illustration purposes, Table 2 also shows the references for the methods for one of the most widely used RS SEB models, the SEBAL model.

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

Variable/Parameter	STEEP	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

2.3 Algorithm implementation and processing

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

We designed the application of the model to take advantage of the data available on GEE (Table 3). The remote sensing datasets were derived from MODIS sensor products, the Shuttle Radar Topography Mission (SRTM; Farr et al., 2007), and the Global Forest Canopy Height product provided vegetation height (Potapov et al., 2021). The climate data necessary to run the model, i.e., wind speed, air temperature, relative humidity, shortwave radiation, and net thermal radiation at the surface, were sourced from the ERA5-Land reanalysis product (Muñoz Sabater, 2019). For data regarding soil moisture, we used the Global Land Data Assimilation System (GLDAS) product (Rodell et al., 2004). CHIRPS precipitation product (Funk et al., 2015) was used to estimate the daily rainfall amount at the sites evaluated.

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/SRTMGL1_003	Elevation	Feb 2000	0.03 km	-
ERA5-Land	ECMWF/ERA5_LAND/HOURLY	dewpoint_temperature_2m, temperature_2m, u_component_of_wind_10, v_component_of_wind_10m, surface_net_solar_radiation_hourly, surface_net_thermal_radiation_hourly	Jan 1981–present	0.1°	1 hour

GLDAS	NASA/GLDAS/V021/NOAH/G025/T3H	SoilMoi0_10cm_inst	Jan 2000–present	0.25°	3 hours
Global Forest Canopy Height, 2019	users/potapovpeter/GEDI_V27	-	Apr 2019	0.03 km	-
CHIRPS	UCSB-CHG/CHIRPS/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_evapotranspiration/PML/OUTPUT/PML_V2_8day_v016	Es, Ec, Ei	Feb 2000–present	0.5 km	8 days

The presence of clouds or instrumental malfunctioning of orbital sensors can cause gaps in data. To reduce the loss of information due to missing data, we chose to use the MODIS MCD43A4 reflectance product. By combining reflectance data from MODIS sensors aboard the AQUA and TERRA satellites and modelling the anisotropic scattering characteristics using sixteen-day quality observations, the MCD43A4 product represents the daily dynamics of the Earth's surface without missing data (Schaaf and Wang, 2015). Daily surface reflectance data from the MCD43A4 product were used to obtain the surface albedo and vegetation indices needed to run STEEP. Thus, the surface albedo data and the vegetation indices show a low percentage of missing data. To compose the LST time series, we used data from MOD11A1, and to fill its missing data, a filter with the average value for a monthly window was applied. This procedure is similar to the method proposed by Zhao et al. (2005) and it is also used by the MOD16 algorithm to generate the continuous global ET (Mu et al., 2011).

Following the approach in comparable studies, STEEP algorithm processing was conducted with automatic selection of endmembers pixels (Bhattarai et al., 2017; Silva et al., 2019; Laipelt et al., 2021). Like Silva et al. (2019), we used the biophysical variables NDVI, surface albedo and LST to automate selection of the endmembers, but we applied different criteria. For the hot/dry endmember selection, the first step consisted of selecting those pixels whose surface albedo values are between the 50 and 75% quantiles, and with NDVI values greater than 0.1 and less than the

15% quantile. After this first selection, a refinement is applied by selecting only those pixels from this first set that have LST values between the 85 and 97% quantiles. Using the set of pixels that met these criteria, 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 the hot pixel. We applied a similar procedure to select the cold/wet endmember but with different limits (Table 4). The procedure for finding endmembers was conducted daily. To execute the model and conduct the selection of endmembers, we used an area of interest (AOI), also known as domain size. AOI was defined as a square area with 1000-km sides within the Caatinga domain and centred on the tower coordinates of each site. Cheng et al. (2021), for example, applied the SEBAL using MODIS data in China and used an AOI of 1200-km x 1200-km.

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	

Q = quantile.

2.4 Analysis of the algorithms' performance

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

(2002), Costa et al. (2021) and Laipelt et al. (2021). The remote sensing datasets and endmembers pixels selection for SEBAL were the same as described in STEEP.

ET and *H* estimates from STEEP and SEBAL were evaluated against the eddy covariance measurements of the corresponding tower. Here, the modelled values were extracted for the pixel representing the EC tower for each observation site. We did not compute the footprint of the observation sites to determine the size of the influence of each measurement due to the spatial resolution of MODIS products being 0.5 km or greater (Biggs et al., 2016). We evaluated daily ET values, and instantaneous hourly *H* values more specifically with the modelled/measured *H* value at 11:00 am local time (GMT-3), considering this is the closest time to the satellite's overpass. Additionally, the STEEP model was compared with two consolidated global ET products available on GEE: MODIS Global Terrestrial Evapotranspiration A2 version 6 (MOD16; Mu et al., 2011; Running et al., 2017) and Penman-Monteith-Leuning model version 2 global evaporation (PMLv2; Zhang et al., 2019); both products have a pixel resolution of 500 m (Table 3). The algorithm used in MOD16 is based on the Penman-Monteith equation and driven by MODIS remote sensing data with Modern-Era Retrospective analysis for Research and Applications (MERRA; Mu et al., 2011). In MOD16 ET is the sum of soil evaporation (Es), canopy transpiration (Tc) and wet-canopy evaporation (Ec) and is provided as eight-day *cumulative* values. More details about MOD16 can be found in Mu et al. (2011) and Running et al. (2017). The global PMLv2 product involves a biophysical model based on the Penman-Monteith-Leuning equation which also uses MODIS remote sensing data, but with meteorological reanalysis data from GLDAS as model inputs. As in MOD16, ET in PMLv2 is also the sum of Es, Tc and Ec but is provided as eight-day *average* values. To make MOD16 and PMLv2 values compatible, ET of PMLv2 was multiplied by eight. Details about PMLv2 can be found in Gan et al. (2018) and Zhang et al. (2019). We accumulated the daily ET measured at the observation sites, i.e. derived from EC data, and ET modelled with STEEP for the same eight-day time periods to make them compatible with the temporal resolution of the MOD16 and PMLv2 datasets. The average of the measured daily values over each eight-day time period (even if there were missing values within this period) was multiplied by eight to calculate the observed 8-day ET. To match the time steps of STEEP and MOD16/PMLv2 ET values, the 8-day average of the evaporative fraction (EF) was multiplied by the daily net radiation over those 8 days, assuming that

EF can be considered constant in each of these periods. Then the ET was summed over the 8-day interval. Finally, we also compared the modelled ET (by STEEP and the two global products) with the observed ET, only in the 8-day periods when no field-observed data was missing. However, with this criterion the number of observations dropped dramatically.

The STEEP and SEBAL models and global ET products were evaluated with five performance metrics (Table 5). A combination of performance metrics is often used to assess the overall performance of models because a single metric provides only a projection of a certain aspect of the error characteristics (Chai and Draxler, 2014). Root mean square error (*RMSE*) is commonly used to express the accuracy of the results with the advantage that it presents error values in the same units of the variable analysed; optimal values are close to zero (Hallak and Pereira Filho, 2011). Coefficient of determination (R^2) represents the quality of the linear trend between observed and simulated data and ranges from 0 to 1; high values indicate better model performance. Nash–Sutcliffe efficiency (*NSE*) indicates the accuracy of the model output compared to the average of the referred data (*NSE* = 1 is the optimal value; Nash and Sutcliffe, 1970). Concordance correlation coefficient (ρc) is a measure that evaluates how well bivariate data falls on the 1:1 line. ρc measures both precision and accuracy. It ranges from -1 to +1 similar to Pearson's correlation coefficient, with perfect agreement at +1 (Lin, 1989; Liao and Lewis, 2000; Akoglu, 2018). Percentage bias (*PBIAS*) measures the average relative difference between observed and estimated values, with an optimal value of 0 (Gupta et al., 1999).

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, +∞ [(0)
Coefficient of determination (R^2)	$R^2 = \frac{\left[\sum_{i=1}^{N}(O_i - \bar{O})(M_i - \bar{M})\right]^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2 \cdot \sum_{i=1}^{N}(M_i - \bar{M})^2}$	[0, 1] (1)
Nash–Sutcliffe efficiency (*NSE*)	$NSE = 1 - \frac{\sum_{i=1}^{N}(M_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2}$	]-∞, 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*)	$PBIAS = \frac{\sum_{i=1}^{N}(M_i - O_i) \cdot 100}{\sum_{i=1}^{N} O_i}$	]-∞, +∞ [(0)

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

3. Results and discussion

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

STEEP exhibited better statistical performance than SEBAL at all the evaluated sites (Fig. 2). While STEEP exhibited a *RMSE* between 0.75 and 0.94 mm/day, the *RMSE* for SEBAL was between 1.08 and 1.75 mm/day. In terms of R^2, the values were between 0.24 to 0.69 for STEEP, and were below 0.2 for SEBAL for all sites except in SNN (0.55). Similarly, *NSE* and *ρc* values were higher for STEEP compared to SEBAL. For STEEP, all sites had *NSE* and *ρc* values above -0.42 and 0.41, respectively, whereas all sites except SNN had values below these limits for SEBAL. Both models overestimated ET (*PBIAS* > 0), with the exception of the STEEP estimates for the PTN site. The highest overestimation by the STEEP model was less than 60%, whereas in SEBAL it was greater than 140%.

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

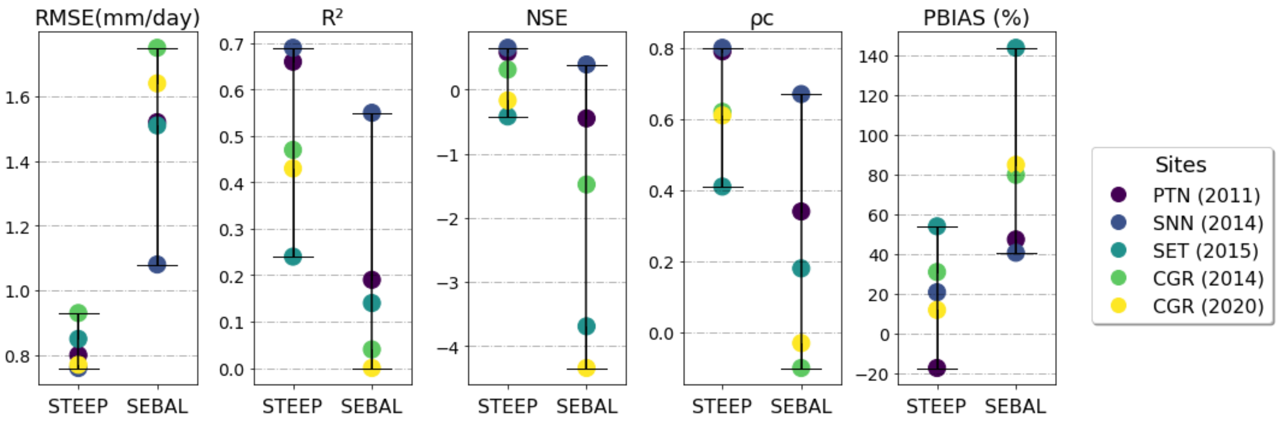
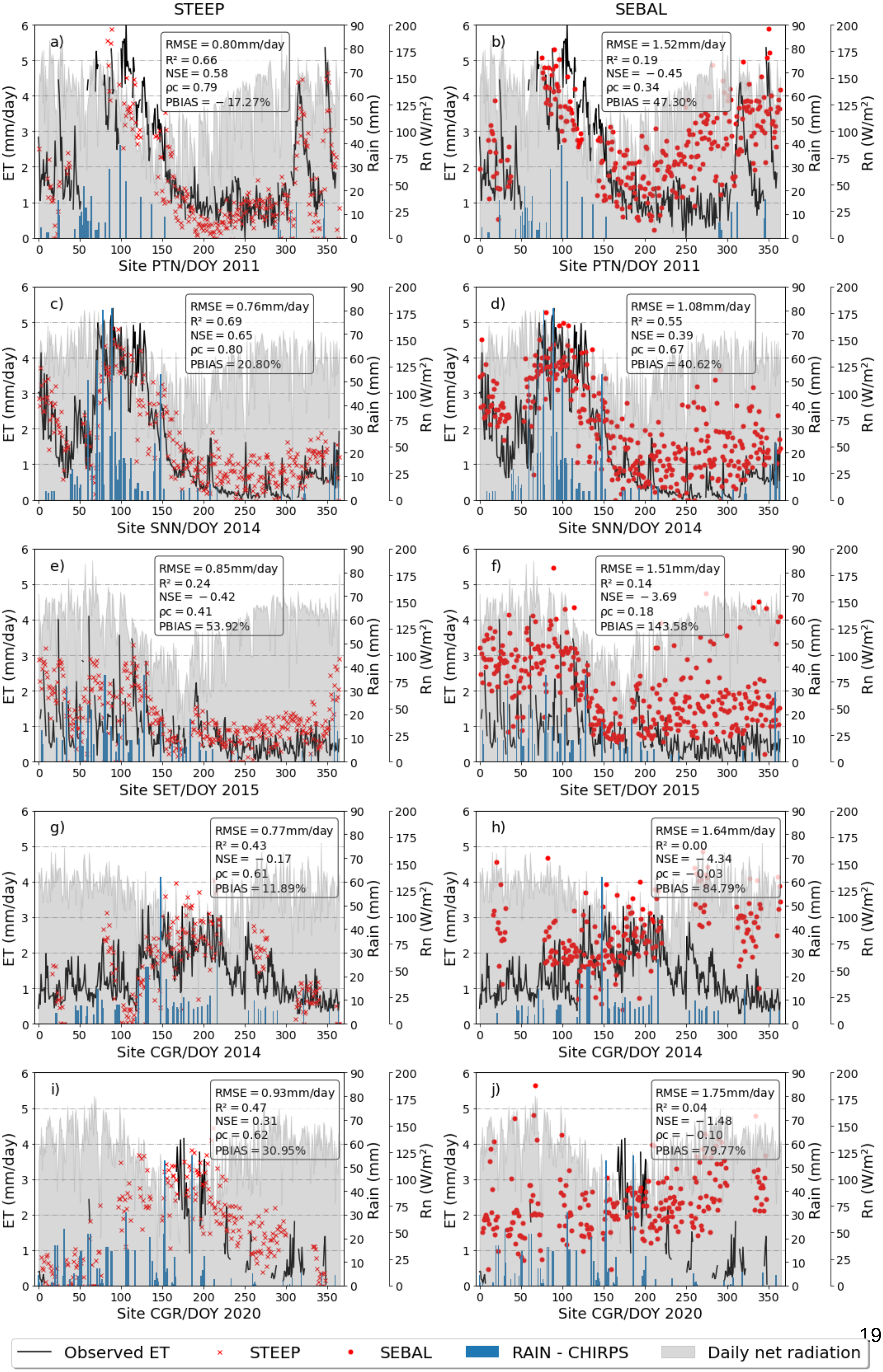


Figure 2. Results of the performance statistics of daily ET for evaluated sites.

STEEP exhibited a greater seasonal accuracy compared to SEBAL (Fig. 3), as evidenced by the goodness-of-fit between simulated and observed values expressed by the *NSE* indicator (Fig. 2). STEEP estimates followed the same temporal evolution as the observed values. STEEP satisfactorily captured both minimum and maximum ET values, including after rainfall events, this is particularly evident in Fig. 3a, where the two observed ET peaks in late 2011 — between DOY 300 and 360 — in the PTN site were captured nicely by STEEP. This improved performance can be explained because soil moisture is incorporated in the STEEP algorithm. In semi-arid regions and particularly in the SDTF, besides the availability of energy, evapotranspiration is highly dependent on the soil–water availability (Lima et al., 2012; Carvalho et al., 2018; Mutti et al., 2019; Paloschi et al., 2020). In rainy months, low daily ET rates are often observed due to the reduced levels of incoming radiation caused by high cloud cover (Mutti et al., 2019; Paloschi et al., 2020). Towards the end of the wet period, when the available energy increases, the daily ET values also increase as a result of the high soil water availability from previous precipitation events (Allen et al., 2011; Marques et al., 2020). In the transition period from the rainy to the dry season, the leaves do not fall immediately. Instead, leaf-shedding depends on the environmental conditions in each location, including the rainy season duration, and species composition (Lima and Rodal, 2010; Lima et al., 2012; Miranda et al., 2020; Paloschi et al., 2020; Queiroz et al., 2020; Medeiros et al., 2022). The remaining water available in the soil or previously accumulated in plant tissues is sufficient for the Caatinga vegetation to maintain its leaves, for short periods, at levels similar to the rainy season (Barbosa et al., 2006; Mutti et al., 2019). However, in the dry season, when soil moisture reaches its lowest levels, the Caatinga vegetation enters a state of dormancy that is accompanied by leaf drop and a drastic reduction of photosynthetic activity (and hence of transpiration) as a strategy to cope with the lack of available soil moisture (Dombroski et al., 2011; Paloschi et al., 2020). This resilience mechanism is typical of xerophytic and/or deciduous species such as those found in the Caatinga (Lima et al., 2012; Mutti et al., 2019; Paloschi et al., 2020), and explains the low rates of ET in the dry season. In contrast, in SEBAL, which does not consider water availability, it was observed that the daily ET followed the course of the daily net radiation throughout the year, especially in the dry period of each of the experimental sites. This is in agreement with the results of Kayser et al. (2022), who pointed out that estimates with SEBAL can be seasonally accurate in locations where the main driver of ET is the available energy. Our results highlight that SEB models such as SEBAL, which are formulated to be mainly dependent on energy availability and do not consider soil and plant water availability, may not satisfactorily represent ET in semi-arid vegetation such as that found in the SDTF (Gokmen et al., 2012; Paul et al., 2014; Melo et al., 2021).



STEEP
SEBAL
a)
RMSE = 0.80mm/day
R² = 0.66
NSE = 0.58
ρc = 0.79
PBIAS = −17.27%
b)
RMSE = 1.52mm/day
R² = 0.19
NSE = −0.45
ρc = 0.34
PBIAS = 47.30%
Site PTN/DOY 2011
c)
RMSE = 0.76mm/day
R² = 0.69
NSE = 0.65
ρc = 0.80
PBIAS = 20.80%
d)
RMSE = 1.08mm/day
R² = 0.55
NSE = 0.39
ρc = 0.67
PBIAS = 40.62%
Site SNN/DOY 2014
e)
RMSE = 0.85mm/day
R² = 0.24
NSE = −0.42
ρc = 0.41
PBIAS = 53.92%
f)
RMSE = 1.51mm/day
R² = 0.14
NSE = −3.69
ρc = 0.18
PBIAS = 143.58%
Site SET/DOY 2015
g)
RMSE = 0.77mm/day
R² = 0.43
NSE = −0.17
ρc = 0.61
PBIAS = 11.89%
h)
RMSE = 1.64mm/day
R² = 0.00
NSE = −4.34
ρc = −0.03
PBIAS = 84.79%
Site CGR/DOY 2014
i)
RMSE = 0.93mm/day
R² = 0.47
NSE = 0.31
ρc = 0.62
PBIAS = 30.95%
j)
RMSE = 1.75mm/day
R² = 0.04
NSE = −1.48
ρc = −0.10
PBIAS = 79.77%
Site CGR/DOY 2020
ET (mm/day)
Rain (mm)
Rn (W/m²)
Observed ET
STEEP
SEBAL
RAIN - CHIRPS
Daily net radiation

426

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

The core of the STEEP and SEBAL algorithms is based on finding λET as the residual of the energy balance; however, they differ with regards to the approach used to calculate *H*. In the STEEP model, the seasonal variation of *H* fitted the observed values of the instantaneous measurements at 11:00 am (local time) better than SEBAL, for all the sites (Fig. 4). While STEEP estimates of *H* exhibited ρc values over 0.5 for three of the five sites, SEBAL *H* estimates exhibited ρc values below 0.5 for all sites.

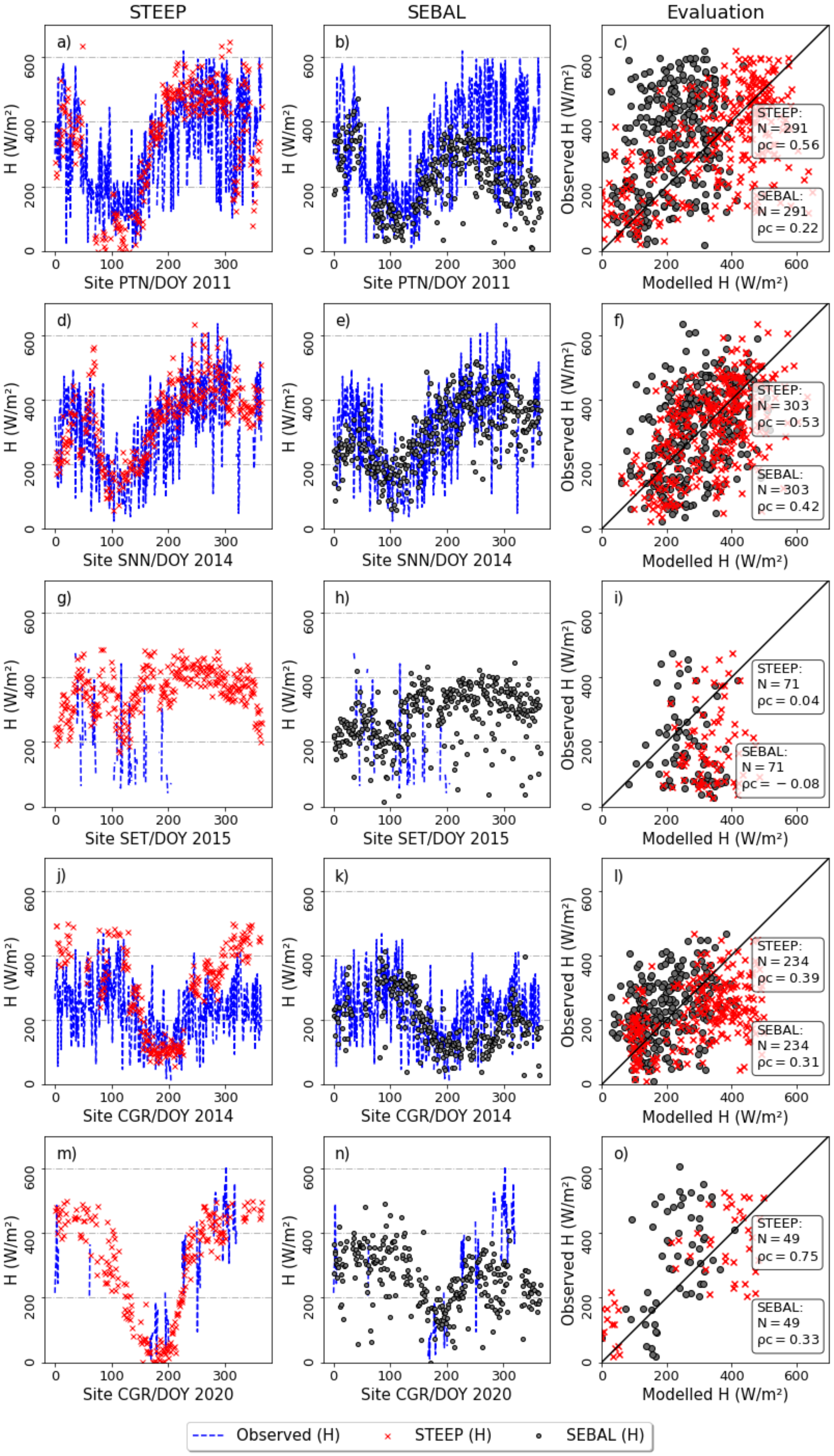


Figure 4. Observed and modelled instantaneous sensible heat flux (*H*, at 11:00 am, W/m^2) for the different experimental sites: a), b) and c) PTN 2011, d), e) and f) SNN 2014, g), h) and i) SET

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

Evaluation of the STEEP and SEBAL daily ET and instantaneous *H* for all experimental sites (Fig. 5) indicates that both models lack a high performance for *H* estimates, although the use of STEEP resulted in better statistical measures than when SEBAL was employed (Fig. 5b). It can be seen that the overestimation of *H* by the STEEP model, compared to SEBAL, produced modelled ET values that were closer to the EC measurements. This may indicate that either R_n was overestimated or *G* underestimated in the RS SEB methods, or that there was a lack of energy balance closure in the EC measurements.

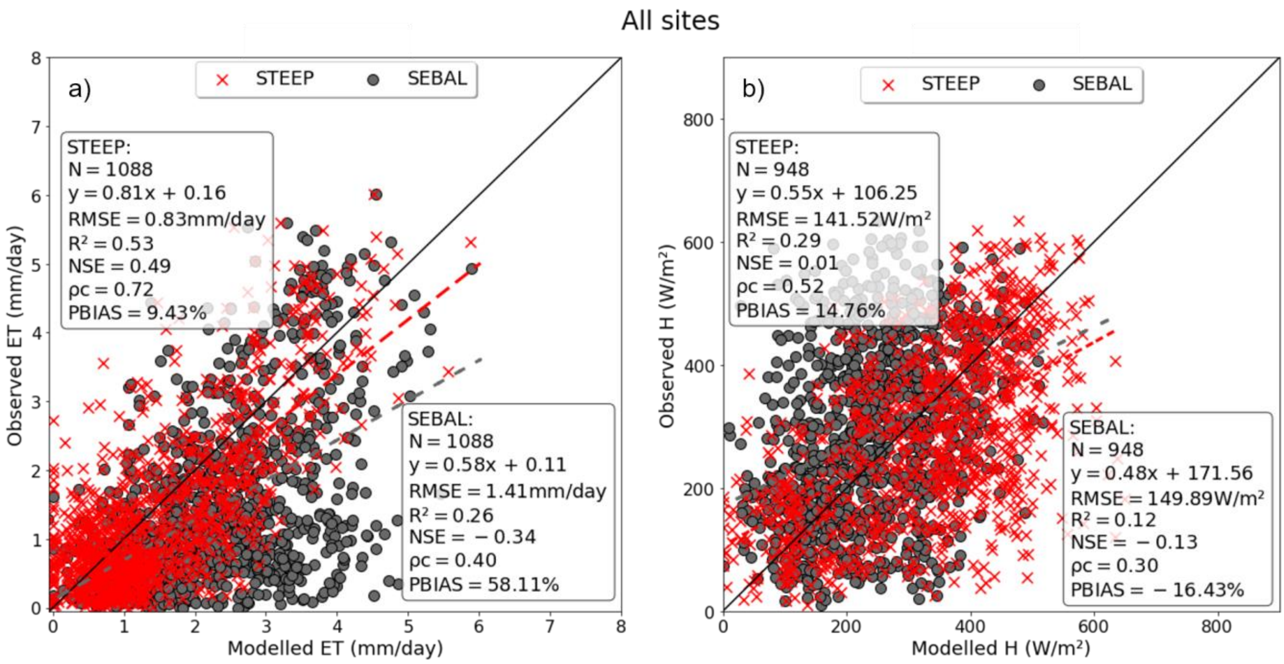


Figure 5. Evaluation of observed and modelled: (a) daily evapotranspiration (ET, mm/day) and b) instantaneous sensible heat flux (*H*, at 11:00 am, W/m^2) for all experimental sites. STEEP (red crosses) and SEBAL (black points). The black line is the 1:1 line; the red (gray) dashed line is the fitted linear regression between observed and STEEP (SEBAL) model values.

We attribute the better performance of STEEP over SEBAL for the Brazilian Caatinga to at least three reasons. First, roughness characteristics near the surface where the heat fluxes originate are parameterised by *z0m*, which depends on several factors, such as wind direction, height and type of the vegetation cover (Kustas et al., 1989). Estimation of *z0m* only with an exponential relationship, as a function of vegetation indices, may be an oversimplification (Kustas et al., 1989; Paul et al., 2013). In our study, *z0m* and *d0* are calculated using PAI instead of LAI and with the equations proposed in Verhoef et al. (1997b). This procedure considers the characteristics of SDTF, such as seasonality of phenology and vegetation height, that considerably affect the quantification of turbulent transfer (Liu et al., 2021). Secondly, our study uses the equation described in Verhoef et al. (1997a) and Paul et al. (2013) to estimate *rah*, which considers the differences between heat and momentum transfer, unlike the original equation employed in other SEB models e.g. SEBAL or METRIC that only considers *z0m* and *z0h* = 0.1 when computing this resistance. Furthermore, we account for the kB^{-1} parameter that varies in space and time and incorporates the soil moisture content obtained by RS (Su et al., 2001; Gokmen et al., 2012). ET estimation is best represented with a spatially varying kB^{-1} value, as pointed out by the studies of Gokmen et al. (2012) and Paul et al. (2014). Third, by quantifying the remaining λET in the endmembers pixels through the Priestley-Taylor equation, a more reliable estimate of *H* in the endmembers pixels can be obtained, as was also evidenced by Singh and Irmak (2011). This process is critical for the subsequent numerical calculation of *H* in SEB models that use the *dT*, as its accuracy is closely related to quantifying the energy balance at the hot and cold endmembers (Trezza, 2006; Allen et al., 2007; Singh and Irmak, 2011; Singh et al., 2012).

The impact on the performance metrics of each proposed refinement of the STEEP model (methods for *z0m*, *rah* and remaining λET in the endmembers pixels), and of their two by two combinations were analysed. We run the control version of the SEB model (SEBAL in our case) while incorporating one or two improvements in the model and keeping the remaining parts of the algorithm the same as the reference SEB model. The results (Table S1) show that including just one or two of the refinements had only partial performance gains. In contrast, all the proposed STEEP improvements implemented together resulted in the best performance metrics for all sites.

3.2 Comparison of STEEP model estimates with global evapotranspiration products

The comparison of ET estimates by STEEP, MOD16 and PMLv2 with the observed values at the different sites (Fig. 6) reveals that the ET estimates by STEEP and global products adequately followed the seasonality of the values, with a better fit for STEEP and MOD16. In general, the evaluation at the different sites shows that the *RMSE* of STEEP was not higher than 6.45 mm/8 days, while the ET products' maximum *RMSE* was close to 15 mm/8 days. It is noted that the lowest *RMSE* value found (4.11 mm/8 days) was for MOD16 at the SET site. Regarding R^2 values, 80% of the evaluations with STEEP were equal to or greater than 0.50. For MOD16, 60% of the R^2 values were equal to or greater than 0.70, while for PMLv2, no site had R^2 values that exceeded 0.55. The best *NSE* value produced by STEEP was 0.77, while with MOD16, it was 0.70, both at the SNN site, while PMLv2 did not exceed 0.39 (PTN site). Regarding ρc, the percentages of ET evaluations that obtained values equal to or greater than 0.70 were 60% for STEEP and MOD16, and only 20% for PMLv2 (site PTN). The overestimations (*PBIAS*) with STEEP were not higher than 50%, and not higher than 95% with MOD16. For PMLv2 the overestimations did not exceed 80%, except for the SET site that obtained a *PBIAS* of 150%. We highlight the good performance of MOD16 for the SET, SNN, and especially the PTN sites, with very good performance metrics and seasonal behaviour, capturing ET values in dry periods very well. The evaluation results of STEEP, MOD16 and PMLv2 for all observation sites combined are shown in Fig. 7. Noteworthy is the better performance of STEEP over MOD16 and PMLv2, with *RMSE* < 6 mm/8 days, R^2 and *NSE* greater than or close to 0.60, $\rho c > 0.75$ and an average overestimation < 12%. Analysis with the dataset considering only the 8-day time periods without missing field-observed data, i.e. periods with valid ET measurements during eight consecutive days (Fig. S1) did not change the results overall, confirming STEEP's dominance compared to the two standard products evaluated.

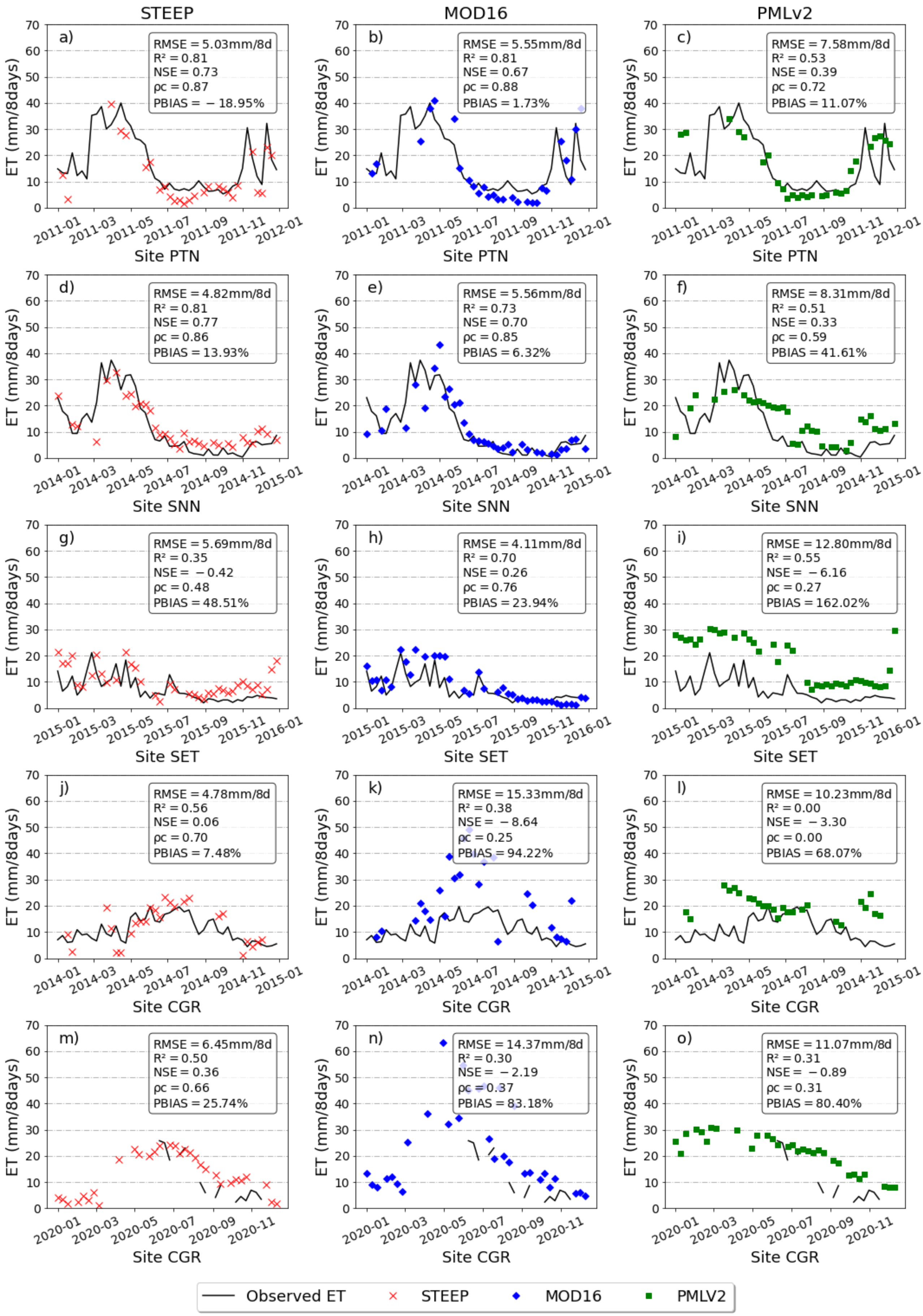

STEEP
MOD16
PMLv2
ET (mm/8days)
a)
RMSE = 5.03mm/8d
R² = 0.81
NSE = 0.73
ρc = 0.87
PBIAS = − 18.95%
Site PTN
b)
RMSE = 5.55mm/8d
R² = 0.81
NSE = 0.67
ρc = 0.88
PBIAS = 1.73%
Site PTN
c)
RMSE = 7.58mm/8d
R² = 0.53
NSE = 0.39
ρc = 0.72
PBIAS = 11.07%
Site PTN
d)
RMSE = 4.82mm/8d
R² = 0.81
NSE = 0.77
ρc = 0.86
PBIAS = 13.93%
Site SNN
e)
RMSE = 5.56mm/8d
R² = 0.73
NSE = 0.70
ρc = 0.85
PBIAS = 6.32%
Site SNN
f)
RMSE = 8.31mm/8d
R² = 0.51
NSE = 0.33
ρc = 0.59
PBIAS = 41.61%
Site SNN
g)
RMSE = 5.69mm/8d
R² = 0.35
NSE = − 0.42
ρc = 0.48
PBIAS = 48.51%
Site SET
h)
RMSE = 4.11mm/8d
R² = 0.70
NSE = 0.26
ρc = 0.76
PBIAS = 23.94%
Site SET
i)
RMSE = 12.80mm/8d
R² = 0.55
NSE = − 6.16
ρc = 0.27
PBIAS = 162.02%
Site SET
j)
RMSE = 4.78mm/8d
R² = 0.56
NSE = 0.06
ρc = 0.70
PBIAS = 7.48%
Site CGR
k)
RMSE = 15.33mm/8d
R² = 0.38
NSE = − 8.64
ρc = 0.25
PBIAS = 94.22%
Site CGR
l)
RMSE = 10.23mm/8d
R² = 0.00
NSE = − 3.30
ρc = 0.00
PBIAS = 68.07%
Site CGR
m)
RMSE = 6.45mm/8d
R² = 0.50
NSE = 0.36
ρc = 0.66
PBIAS = 25.74%
Site CGR
n)
RMSE = 14.37mm/8d
R² = 0.30
NSE = − 2.19
ρc = 0.37
PBIAS = 83.18%
Site CGR
o)
RMSE = 11.07mm/8d
R² = 0.31
NSE = − 0.89
ρc = 0.31
PBIAS = 80.40%
Site CGR
Observed ET
STEEP
MOD16
PMLV2

Figure 6. Temporal evolution of ET from STEEP, MOD16 and PMLv2 for the different observation sites, and their individual performance statistics. a), b) and c) PTN 2011; d), e) and f) SNN 2014; g) h) and i) SET 2015; j), k) and l) CGR 2014; m), n) and o) CGR 2020. Black lines correspond to observed ET while data points refer to estimates by the STEEP model (red crosses), MOD16 (blue diamonds) and PMLv2 (green squares) products.

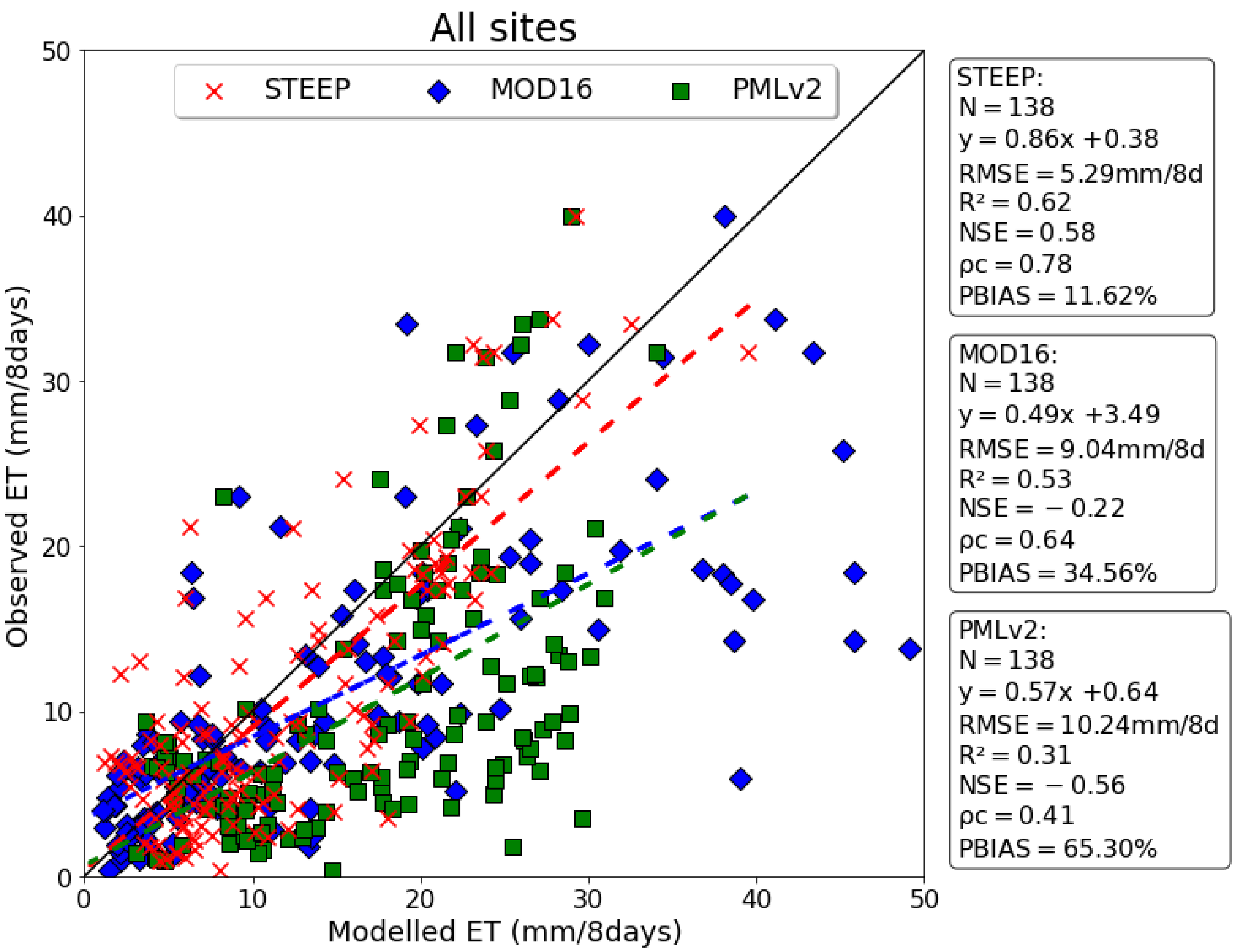


Figure 7. Evaluation of evapotranspiration (ET, mm/8days) observed and modelled with STEEP (red crosses), MOD16 (blue diamonds) and PMLv2 (green squares) for all experimental sites. The black line is the 1:1 line; dashed lines are the fitted linear regressions of observed versus modelled values by the STEEP model (red), MOD16 (blue) and PMLv2 (green) products.

The explanation of the differences between STEEP and the MOD16 and PMLv2 products is two-fold. Firstly, the way ET is obtained differs between STEEP and the other products. While STEEP and other SEB single-source models estimate ET as a combined singular process, i.e., there is no distinction between soil evaporation and transpiration (Sahnoun et al., 2021) and interception loss is not taken into account, MOD16 and PMLv2 discriminate the components of soil evaporation, canopy transpiration, and wet canopy evaporation (Mu et al., 2011; Zhang et al., 2019). With this in mind it is remarkable that STEEP performs better than the other, widely used, multiple-source ET products. Secondly, the input data sets and their uses are different. The driving meteorological data for STEEP are from ERA5-Land, while in MOD16, they are from MERRA and in PMLv2 are provided by GLDAS (Mu et al., 2011; Zhang et al., 2019). In addition, the meteorological elements used are different among the ET products. MOD16 requires air temperature, atmospheric pressure, relative humidity, and downward shortwave radiation. In addition to these elements, PMLv2 also requires precipitation, downward longwave radiation, and wind speed (Mu et al., 2011; Zhang et al., 2019; Yin et al., 2020; Chen et al., 2022). Although both ET products use the same land cover data (MOD12Q1), only MOD16 integrates it into its algorithm. In MOD16, the land cover type defines biome delimitation for the characterization of leaf stomatal conductance, vapour pressure deficit (VPD) and other related factors, while PMLv2 only uses land cover to construct a mask of the land area (Chen et al., 2022). The sources and use of LAI in these two products are also different. LAI is used to increase leaf conductance in MOD16, while it is used to divide the total available energy into canopy uptake and soil uptake in PMLv2 (Mu et al., 2011; Zhang et al., 2019; Chen et al., 2022). Although MOD16 uses EC data from 46 distributed sites for validation (Mu et al., 2011) and PMLv2 uses EC data from 95 distributed sites and ten plant functional types for calibration (Zhang et al., 2019; Yin et al., 2020), none of the products had observation sites in SDTF.

The uncertainties associated with field measurements of ET can also influence the evaluation of the model products. It is generally accepted that EC flux towers provide reliable local, i.e. for areas of relatively limited spatial extensions, ca. 1 km^2, ET measurements (Mu et al., 2011; Salazar-Martínez et al., 2022). However, generally flux tower data have a lack of energy balance closure, that is the difference between net radiation and ground heat flux is sometimes greater than the sum of the turbulent latent and sensible heat fluxes, an error that can be in the range of 10–30% (Wilson et al., 2002; Foken, 2008; Allen et al., 2011). This gap can result from instrument errors, weather and surface conditions, e.g. those that result in advection, and gap-filling methods (Mu et al., 2011). Although the data from the EC flux towers have been filtered to minimise errors due to lack of SEB closure, their influence cannot be neglected. In addition, the complex and heterogeneous canopy structure, the stochastic nature of turbulence (Hollinger and Richardson, 2005) and adverse weather conditions, e.g. rainy and stormy days, tower sensors recording abnormal values, can affect ET measurements obtained by EC systems (Ramoelo et al., 2014).

3.3 Sources of error and further research for STEEP

In its current configuration, STEEP has some limitations that should be noted. Meteorological reanalysis provides only large-scale averages and can misrepresent local meteorological conditions; hence, it suffers from biases, especially over heterogeneous surfaces (Rasp et al., 2018; Laipelt et al., 2020). However, despite moderate accuracy and biases at regional scales, ground-based assimilation and reanalysis data have become important sources of meteorological inputs for ET estimates (Mu et al., 2011; Zhang et al., 2019; Allam et al., 2021; Senay et al., 2022). Laipelt et al. (2020) and Kayser et al. (2022) observed that the use of ground measurements or global reanalysis data as meteorological inputs had modest effects only on the accuracy of SEBAL to estimate ET. Also, although gap-filling was used in the present study to improve the availability of LST data, this procedure should be used with caution. In addition, care should be taken when using the MCD43A4 reflectance product, because in its composition there is also gap-filling. For example, on some cloudy days, the estimates of vegetation indices, surface albedo and LST may have introduced inaccuracies in the STEEP (and in SEBAL) model calculation process due to these gap-filling methods. Regarding the selection of endmembers pixels, although the temporal evolution of the selected pixels in this study seems plausible, their representativeness of the actual conditions may be debatable, especially considering the considerable extent of the AOI. The computational capacity and the effectiveness of GEE for running SEB models should be commended. Although other studies have demonstrated GEE's strength (Laipelt et al., 2021; Jaafar et al., 2022; Senay et al., 2022), this platform has some limitations when it comes to the number of iterations, e.g. a convergence threshold cannot be set to stop the within-loop iterations of H calculations; instead a fixed number of iterations needs to be defined. Still, the availability of the several necessary datasets within one platform greatly facilitates the run of STEEP and other SEB models.

One of the main focuses of this study is to provide a one-source model capable of representing ET in environments that are mainly governed by soil–water availability, such as those represented by SDTF, in a parsimonious way. Based on our findings we deem this main aim to be achieved due to the relative simplicity of the STEEP model and its low data demand. The improved performance of STEEP was the result of improvement of existing and physically meaningful parameters (*z0m* and kB^{-1}), rather than by introducing additional empirical parameters, thereby satisfying the principle of equifinality (see Beven and Freer, 2001). To explore further the potential and accuracy of STEEP, more research is needed to analyse the impact that the improved *H* approach has on ET of different land covers at longer time scales. Improving the quantification of regional ET via RS-based SEB models has a great potential to provide a more accurate estimate of the energy and water fluxes in SDTF regions, and will contribute to a better understanding of the water cycle, its uses, and the interrelationships with ecosystem functioning.

4. Conclusions

Our work provides an improved approach for estimating the latent and sensible heat fluxes by remote sensing for land covers that experience seasonally varying severely reduced water availability. We tested it for four SDTF sites. The STEEP model focuses on the special features of the SDTF: the Plant Area Index is used to take into account the woody structure of the plants in calculating the momentum roughness length. In the equations to calculate the aerodynamic resistance for sensible heat transfer (using the bulk heat transfer equation), the parameter kB^{-1} was included, and it was allowed to vary in time as a function of corrected soil moisture, obtained by remote sensing. Finally, the remaining λET in endmembers pixels was quantified using the Priestley-Taylor equation. STEEP estimates for *H* and ET were evaluated at four observation sites equipped with EC systems in the Caatinga, the largest continuous SDTF in the Americas. The metrics of STEEP for instantaneous estimates of *H* and daily estimates of ET were compared with estimates from the SEBAL model, and ET at the eight-day scale with the widely used global products MOD16 and PMLv2.

In summary, the main conclusions are:

- The estimates of *H* by STEEP allowed ET estimates to be closer to the observed field values than those obtained by SEBAL. Based on all the performance metrics used to analyse the models, STEEP was superior to SEBAL. STEEP showed *RMSE* less than 1mm/day, R^2 between 0.24 and 0.69, *NSE* between -0.17 and 0.65, ρc between 0.41

and 0.80 and *PBIAS* between -17% to 54%. Also noteworthy is how well STEEP captured the seasonal course of observed ET.

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

Thus, we conclude that STEEP, a one-source model that incorporated the seasonality of the aerodynamic and surface variables, was well-heeled in representing ET in environments that are mainly governed by soil–water availability. All the same, there is a need to evaluate the newly developed STEEP model performance for different land covers, climate, and for a longer time series not considered during the modelling process in this study.

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Data Availability Statement

ET data for the PTN, SNN, and SET sites were published by Melo et al. (2021), and are available at https://doi.org/10.5281/zenodo.5549321. ET data for the CGR site; H data for the PTN, SNN, CGR sites, and the script used for the formulation STEEP model presented in this study can be accessed at https://doi.org/10.5281/zenodo.7109044. H data for the SET site is publicly available for download at https://ameriflux.lbl.gov/.

References

Akoglu, H. (2018). User's guide to correlation coefficients. Turkish journal of emergency medicine, 18(3), 91-93. doi: 10.1016/j.tjem.2018.08.001

Alberton, B., Torres, R. da S., Cancian, L. F., Borges, B. D., Almeida, J., Mariano, G. C., … Morellato, L. P. C. (2017). Introducing digital cameras to monitor plant phenology in the tropics: applications for conservation. Perspectives in Ecology and Conservation, 15(2), 82–90. doi:10.1016/j.pecon.2017.06.004

Allam, M., Mhawej, M., Meng, Q., Faour, G., Abunnasr, Y., Fadel, A., & Xinli, H. (2021). Monthly 10-m evapotranspiration rates retrieved by SEBALI with Sentinel-2 and MODIS LST data. Agricultural Water Management, 243, 106432. doi:10.1016/j.agwat.2020.106432

Allen, R. G., Tasumi, M., & Trezza, R. (2007). Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC)—Model. Journal of Irrigation and Drainage Engineering, 133(4), 380–394. doi:10.1061/(asce)0733-9437(2007)133:4(380)

Allen, K., Dupuy, J. M., Gei, M. G., Hulshof, C., Medvigy, D., Pizano, C., … Powers, J. S. (2017). Will seasonally dry tropical forests be sensitive or resistant to future changes in rainfall regimes? Environmental Research Letters, 12(2), 023001. doi:10.1088/1748-9326/aa5968

Allen, R. G., Pereira, L. S., Howell, T. A., & Jensen, M. E. (2011). Evapotranspiration information reporting: I. Factors governing measurement accuracy. Agricultural Water Management, 98(6), 899–920. doi:10.1016/j.agwat.2010.12.015

Alvares, C. A., Stape, J. L., Sentelhas, P. C., Gonçalves, J. D. M., & Sparovek, G. (2013). Köppen's climate classification map for Brazil. Meteorologische Zeitschrift, 22(6), 711-728. doi:10.1127/0941-2948/2013/0507

Anapalli, S. S., Ahuja, L. R., Gowda, P. H., Ma, L., Marek, G., Evett, S. R., & Howell, T. A. (2016). Simulation of crop evapotranspiration and crop coefficients with data in weighing lysimeters. Agricultural Water Management, 177, 274–283. doi:10.1016/j.agwat.2016.08.009

Andrade, J., Cunha, J., Silva, J., Rufino, I., & Galvão, C. (2021). Evaluating single and multi-date Landsat classifications of land-cover in a seasonally dry tropical forest. Remote Sensing Applications: Society and Environment, 22, 100515. doi:10.1016/j.rsase.2021.100515

Anderson, M. C., Kustas, W. P., Norman, J. M., Hain, C. R., Mecikalski, J. R., Schultz, L., … Gao, F. (2011). Mapping daily evapotranspiration at field to continental scales using geostationary and polar orbiting satellite imagery. Hydrology and Earth System Sciences, 15(1), 223–239. doi:10.5194/hess-15-223-2011

Antonino, A. C. D. (2019), AmeriFlux BASE BR-CST Caatinga Serra Talhada, Ver. 1-5, AmeriFlux AMP, (Dataset). https://doi.org/10.17190/AMF/1562386

Araújo, J. C., & González Piedra, J. I. (2009). Comparative hydrology: analysis of a semiarid and a humid tropical watershed. Hydrological Processes, 23(8), 1169–1178. doi:10.1002/hyp.7232

Barbosa, H. A., Huete, A. R., & Baethgen, W. E. (2006). A 20-year study of NDVI variability over the Northeast Region of Brazil. Journal of Arid Environments, 67(2), 288–307. doi:10.1016/j.jaridenv.2006.02.022

Barraza, V., Restrepo-Coupe, N., Huete, A., Grings, F., Beringer, J., Cleverly, J., & Eamus, D. (2017). Estimation of latent heat flux over savannah vegetation across the North Australian Tropical Transect from multiple sensors and global meteorological data. Agricultural and Forest Meteorology, 232, 689-703. doi:10.1016/j.agrformet.2016.10.013

Bastiaanssen, W. G. M. (1995). Regionalization of surface flux densities and moisture indicators in composite terrain: A remote sensing approach under clear skies in Mediterranean climates. Wageningen University and Research.

Bastiaanssen, W. G. M., Menenti, M., Feddes, R. A., & Holtslag, A. A. M. (1998). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. Journal of Hydrology, 212-213, 198–212. doi:10.1016/s0022-1694(98)00253-4

Bastiaanssen, W. G. M., Ahmad, M.-D., & Chemin, Y. (2002). Satellite surveillance of evaporative depletion across the Indus Basin. Water Resources Research, 38(12), 9–1–9–9. doi:10.1029/2001wr000386

Bastiaanssen, W. G. M., Noordman, E. J. M., Pelgrum, H., Davids, G., Thoreson, B. P., & Allen, R. G. (2005). SEBAL Model with Remotely Sensed Data to Improve Water-Resources Management under Actual Field Conditions. Journal of Irrigation and Drainage Engineering, 131(1), 85–93. doi:10.1061/(asce)0733-9437(2005)131:1(85)

Beven, K., & Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. Journal of Hydrology, 249(1–4), 11–29. doi:10.1016/s0022-1694(01)00421-8

Bhattarai, N., Quackenbush, L. J., Im, J., & Shaw, S. B. (2017). A new optimized algorithm for automating endmember pixel selection in the SEBAL and METRIC models. Remote Sensing of Environment, 196, 178–192. doi:10.1016/j.rse.2017.05.009.

Biggs, T. W., Marshall, M., & Messina, A. (2016). Mapping daily and seasonal evapotranspiration from irrigated crops using global climate grids and satellite imagery: Automation and methods comparison. Water Resources Research, 52(9), 7311–7326. doi:10.1002/2016wr019107

Borges, C. K., dos Santos, C. A. C., Carneiro, R. G., da Silva, L. L., de Oliveira, G., Mariano, D., … de S. Medeiros, S. (2020). Seasonal variation of surface radiation and energy balances over two contrasting areas of the seasonally dry tropical forest (Caatinga) in the Brazilian semi-arid. Environmental Monitoring and Assessment, 192(8). doi:10.1007/s10661-020-08484-y

Brazil, Ministério do Meio Ambiente. Caatinga. https://antigo.mma.gov.br/biomas/caatinga.html. Acessed date: 25 March 2021.

Cabral, O. M. R., Freitas, H. C., Cuadra, S. V., de Andrade, C. A., Ramos, N. P., Grutzmacher, P., … Rossi, P. (2020). The sustainability of a sugarcane plantation in Brazil assessed by the eddy covariance fluxes of greenhouse gases. Agricultural and Forest Meteorology, 282-283, 107864. doi:10.1016/j.agrformet.2019.107864

Campos, S., Mendes, K. R., da Silva, L. L., Mutti, P. R., Medeiros, S. S., Amorim, L. B., … Bezerra, B. G. (2019). Closure and partitioning of the energy balance in a preserved area of a Brazilian seasonally dry tropical forest. Agricultural and Forest Meteorology, 271, 398–412. doi:10.1016/j.agrformet.2019.03.018

Carvalho, H. F. D. S., de Moura, M. S., da Silva, T. G., & Rodrigues, C. T. (2018). Controlling factors of ‘Caatinga’and sugarcane evapotranspiration in the Sub-middle São Francisco Valley. Revista Brasileira de Engenharia Agrícola e Ambiental, 22, 225-230. doi:10.1590/1807-1929/agriambi.v22n4p225-230

Chai, T., & Draxler, R. R. (2014). Root mean square error (*RMSE*) or mean absolute error (MAE)? – Arguments against avoiding *RMSE* in the literature. Geoscientific Model Development, 7(3), 1247–1250. doi:10.5194/gmd-7-1247-2014

Chehbouni, A., Seen, D. L., Njoku, E. G., & Monteny, B. M. (1996). Examination of the difference between radiative and aerodynamic surface temperatures over sparsely vegetated surfaces. Remote Sensing of Environment, 58(2), 177-186. doi: 10.1016/S0034-4257(96)00037-5

Chen, J. M., & Liu, J. (2020). Evolution of evapotranspiration models using thermal and shortwave remote sensing data. Remote Sensing of Environment, 237, 111594. doi:10.1016/j.rse.2019.111594

Chen, H., Gnanamoorthy, P., Chen, Y., Mansaray, L. R., Song, Q., Liao, K., … Sun, C. (2022). Assessment and Inter-Comparison of Multi-Source High Spatial Resolution Evapotranspiration Products over Lancang–Mekong River Basin, Southeast Asia. Remote Sensing, 14(3), 479. doi:10.3390/rs14030479

Cheng, M., Jiao, X., Li, B., Yu, X., Shao, M., & Jin, X. (2021). Long time series of daily evapotranspiration in China based on the SEBAL model and multisource images and validation. Earth System Science Data, 13(8), 3995–4017. doi:10.5194/essd-13-3995-2021

Costa, J. A.; Navarro-Hevia, J., Costa, C. A. G., & de Araújo, J. C. (2021). Temporal dynamics of evapotranspiration in semiarid native forests in Brazil and Spain using remote sensing. Hydrological Processes, 35(3). doi:10.1002/hyp.14070

Costa-Filho, E., Chávez, J. L., Zhang, H., & Andales, A. A. (2021). An optimized surface aerodynamic temperature approach to estimate maize sensible heat flux and evapotranspiration. Agricultural and Forest Meteorology, 311, 108683. doi:10.1016/j.agrformet.2021.108683

Cunha, J., Nóbrega, R. L. B., Rufino, I., Erasmi, S., Galvão, C., & Valente, F. (2020). Surface albedo as a proxy for land-cover clearing in seasonally dry forests: Evidence from the Brazilian Caatinga. Remote Sensing of Environment, 238, 111250. doi:10.1016/j.rse.2019.111250

Danelichen, V. H. de M., Biudes, M. S., Souza, M. C., Machado, N. G., Silva, B. B. da, & Nogueira, J. de S. (2014). Estimation of soil heat flux in a neotropical Wetland region using remote sensing techniques. Revista Brasileira de Meteorologia, 29(4), 469–482. doi:10.1590/0102-778620120568

Dombroski, J. L. D., Praxedes, S. C., de Freitas, R. M. O., & Pontes, F. M. (2011). Water relations of Caatinga trees in the dry season. South African Journal of Botany, 77(2), 430–434. doi:10.1016/j.sajb.2010.11.001

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., ... & Alsdorf, D. (2007). The shuttle radar topography mission. Reviews of geophysics, 45(2). doi:10.1029/2005RG000183

Ferreira, T. R., Silva, B. B. D., Moura, M. S. B. D., Verhoef, A., & Nóbrega, R. L. B. (2020). The use of remote sensing for reliable estimation of net radiation and its components: a case study for contrasting land covers in an agricultural hotspot of the Brazilian semiarid region. Agricultural and Forest Meteorology, 291, 108052. doi:10.1016/j.agrformet.2020.108052

Foken, T. (2008). The energy balance closure problem: An overview. Ecological Applications, 18(6), 1351-1367.doi:10.1890/06-0922.1

French, A. N., Hunsaker, D. J., & Thorp, K. R. (2015). Remote sensing of evapotranspiration over cotton using the TSEB and METRIC energy balance models. Remote Sensing of Environment, 158, 281–294. doi:10.1016/j.rse.2014.11.003

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., ... & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific data, 2(1), 1-21. doi:10.1038/sdata.2015.66

Gan, R., Zhang, Y., Shi, H., Yang, Y., Eamus, D., Cheng, L., … Yu, Q. (2018). Use of satellite leaf area index estimating evapotranspiration and gross assimilation for Australian ecosystems. Ecohydrology, 11(5), e1974. doi:10.1002/eco.1974

Gokmen, M., Vekerdy, Z., Verhoef, A., Verhoef, W., Batelaan, O., & van der Tol, C. (2012). Integration of soil moisture in SEBS for improving evapotranspiration estimation under water stress conditions. Remote Sensing of Environment, 121, 261–274. doi:10.1016/j.rse.2012.02.003

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. doi:10.1016/j.rse.2017.06.031

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. Journal of hydrologic engineering, 4(2), 135-143. doi:10.1061/(ASCE)1084-0699(1999)4:2(135)

Hallak, R., & Pereira Filho, A. J. (2011). Metodologia para análise de desempenho de simulações de sistemas convectivos na região metropolitana de São Paulo com o modelo ARPS: sensibilidade a variações com os esquemas de advecção e assimilação de dados. Revista Brasileira de Meteorologia, 26, 591-608.doi:10.1590/S0102-77862011000400009

Hollinger, D. Y., & Richardson, A. D. (2005). Uncertainty in eddy covariance measurements and its application to physiological models. Tree Physiology, 25(7), 873–885. doi:10.1093/treephys/25.7.873

Jaafar, H., Mourad, R., & Schull, M. (2022). A global 30-m ET model (HSEB) using harmonized Landsat and Sentinel-2, MODIS and VIIRS: Comparison to ECOSTRESS ET and LST. Remote Sensing of Environment, 274, 112995. doi:10.1016/j.rse.2022.112995

Jia, L., Su, Z., van den Hurk, B., Menenti, M., Moene, A., De Bruin, H. A. ., … Cuesta, A. (2003). Estimation of sensible heat flux using the Surface Energy Balance System (SEBS) and ATSR measurements. Physics and Chemistry of the Earth, Parts A/B/C, 28(1-3), 75–88. doi:10.1016/s1474-7065(03)00009-3

Kayser, R. H., Ruhoff, A., Laipelt, L., de Mello Kich, E., Roberti, D. R., de Arruda Souza, V., ... & Neale, C. M. U. (2022). Assessing geeSEBAL automated calibration and meteorological reanalysis uncertainties to estimate evapotranspiration in subtropical humid climates. Agricultural and Forest Meteorology, 314, 108775. doi:10.1016/j.agrformet.2021.108775

Koch, R., Almeida-Cortez, J. S., & Kleinschmit, B. (2017). Revealing areas of high nature conservation importance in a seasonally dry tropical forest in Brazil: Combination of modelled plant diversity hot spots and threat patterns. Journal for Nature Conservation, 35, 24–39. doi:10.1016/j.jnc.2016.11.004

Kustas, W., Choudhury, B. Moran, M. Reginato, R. ., Jackson, R. ., Gay, L. ., & Weaver, H. . (1989). Determination of sensible heat flux over sparse canopy using thermal infrared data. Agricultural and Forest Meteorology, 44(3-4), 197–216. doi:10.1016/0168-1923(89)90017-8

Kustas, W. P., Choudhury, B. J., Kunkel, K. E., & Gay, L. W. (1989). Estimate of the aerodynamic roughness parameters over an incomplete canopy cover of cotton. Agricultural and Forest Meteorology, 46(1-2), 91-105. doi:10.1016/0168-1923(89)90114-7

Laipelt, L., Ruhoff, A. L., Fleischmann, A. S., Kayser, R. H. B., Kich, E. de M., da Rocha, H. R., & Neale, C. M. U. (2020). Assessment of an Automated Calibration of the SEBAL Algorithm to Estimate Dry-Season Surface-Energy Partitioning in a Forest–Savanna Transition in Brazil. Remote Sensing, 12(7), 1108. doi:10.3390/rs12071108

Laipelt, L., Henrique Bloedow Kayser, R., Santos Fleischmann, A., Ruhoff, A., Bastiaanssen, W., Erickson, T. A., & Melton, F. (2021). Long-term monitoring of evapotranspiration using the SEBAL algorithm and Google Earth Engine cloud computing. ISPRS Journal of Photogrammetry and Remote Sensing, 178, 81–96. doi:10.1016/j.isprsjprs.2021.05.018

Lhomme, J. P., Chehbouni, A., & Monteny, B. (2000). Sensible Heat Flux-Radiometric Surface Temperature Relationship Over Sparse Vegetation: Parameterizing B-1. Boundary-Layer Meteorology, 97(3), 431–457. doi:10.1023/a:1002786402695

Lima, A. L. A., & Rodal, M. J. N. (2010). Phenology and wood density of plants growing in the semi-arid region of northeastern Brazil. Journal of Arid Environments, 74(11), 1363–1373. doi:10.1016/j.jaridenv.2010.05.009

Lima, A. L. A., Sá Barretto Sampaio, E. V., Castro, C. C., Rodal, M. J. N., Antonino, A. C. D., & de Melo, A. L. (2012). Do the phenology and functional stem attributes of woody species allow for the identification of functional groups in the semiarid region of Brazil? Trees, 26(5), 1605–1616. doi:10.1007/s00468-012-0735-2

Lima, C. E. S. de, Costa, V. S. de O., Galvíncio, J. D., Silva, R. M. da, & Santos, C. A. G. (2021). Assessment of automated evapotranspiration estimates obtained using the GP-SEBAL algorithm for dry forest vegetation (Caatinga) and agricultural areas in the Brazilian semiarid region. Agricultural Water Management, 250, 106863. doi:10.1016/j.agwat.2021.106863

Liao, J. J., & Lewis, J. W. (2000). A note on concordance correlation coefficient. PDA journal of pharmaceutical science and technology, 54(1), 23-26.

Lin, L. K. (1989). A Concordance Correlation Coefficient to Evaluate Reproducibility. Biometrics, 45(1), 255–268. https://doi.org/10.2307/2532051

Liu, S., Lu, L., Mao, D., & Jia, L. (2007). Evaluating parameterizations of aerodynamic resistance to heat transfer using field measurements. Hydrology and Earth System Sciences, 11(2), 769–783. doi:10.5194/hess-11-769-2007

Liu, Y., Guo, W., Huang, H., Ge, J., & Qiu, B. (2021). Estimating global aerodynamic parameters in 1982–2017 using remote-sensing data and a turbulent transfer model. Remote Sensing of Environment, 260, 112428. doi:10.1016/j.rse.2021.112428

Long, D., Gao, Y., & Singh, V. P. (2010). Estimation of daily average net radiation from MODIS data and DEM over the Baiyangdian watershed in North China for clear sky days. Journal of Hydrology, 388(3–4), 217–233. doi:10.1016/j.jhydrol.2010.04.042

Maia, V. A., de Souza, C. R., de Aguiar-Campos, N., Fagundes, N. C. A., Santos, A. B. M., de Paula, G. G. P., … dos Santos, R. M. (2020). Interactions between climate and soil shape tree community assembly and above-ground woody biomass of tropical dry forests. Forest Ecology and Management, 474, 118348. doi:10.1016/j.foreco.2020.118348

Marques, T. V., Mendes, K., Mutti, P., Medeiros, S., Silva, L., Perez-Marin, A. M., … Bezerra, B. (2020). Environmental and biophysical controls of evapotranspiration from Seasonally Dry Tropical Forests (Caatinga) in the Brazilian Semiarid. Agricultural and Forest Meteorology, 287, 107957. doi:10.1016/j.agrformet.2020.107957

McShane, R. R., Driscoll, K. P., & Sando, R. (2017). A review of surface energy balance models for estimating actual evapotranspiration with remote sensing at high spatiotemporal resolution over large extents. Scientific Investigations Report. doi:10.3133/sir20175087

Medeiros, R., Andrade, J., Ramos, D., Moura, M., Pérez-Marin, A., dos Santos, C., … Cunha, J. (2022). Remote Sensing Phenology of the Brazilian Caatinga and Its Environmental Drivers. Remote Sensing, 14(11), 2637. doi:10.3390/rs14112637

Melo, D. C. D., Anache, J. A. A., Borges, V. P., Miralles, D. G., Martens, B., Fisher, J. B., … Wendland, E. (2021). Are Remote Sensing Evapotranspiration Models Reliable Across South American Ecoregions? Water Resources Research, 57(11). doi:10.1029/2020wr028752

Mhawej, M., Caiserman, A., Nasrallah, A., Dawi, A., Bachour, R., & Faour, G. (2020). Automated evapotranspiration retrieval model with missing soil-related datasets: The proposal of SEBALI. Agricultural Water Management, 229, 105938. doi:10.1016/j.agwat.2019.105938

Miles, L., Newton, A. C., DeFries, R. S., Ravilious, C., May, I., Blyth, S., … Gordon, J. E. (2006). A global overview of the conservation status of tropical dry forests. Journal of Biogeography, 33(3), 491–505. doi:10.1111/j.1365-2699.2005.01424.x

Miranda, R. Q., Nóbrega, R. L. B., Moura, M. S. B., Raghavan, S., & Galvíncio, J. D. (2020). Realistic and simplified models of plant and leaf area indices for a seasonally dry tropical forest. International Journal of Applied Earth Observation and Geoinformation, 85, 101992. doi:10.1016/j.jag.2019.101992

Miranda, R. D. Q., Galvincio, J. D., Morais, Y. C. B., MOURA, M. S. B. D., Jones, C. A., & Srinivasan, R. (2018). Dry forest deforestation dynamics in Brazil’s Pontal Basin. Revista Caatinga, 31, 385-395. doi:10.1590/1983-21252018v31n215rc

Mohan, M. M. P., Kanchirapuzha, R., & Varma, M. R. R. (2020a). Review of approaches for the estimation of sensible heat flux in remote sensing-based evapotranspiration models. Journal of Applied Remote Sensing, 14(04). doi:10.1117/1.jrs.14.041501

Mohan, M. P.; Kanchirapuzha, R., & Varma, M. R. R. (2020b). Integration of soil moisture as an auxiliary parameter for the anchor pixel selection process in SEBAL using Landsat 8 and Sentinel-1A images. International Journal of Remote Sensing, 41(3), 1214-1231.

Moro, M. F., Silva, I. A., Araújo, F. S. de, Nic Lughadha, E., Meagher, T. R., & Martins, F. R. (2015). The Role of Edaphic Environment and Climate in Structuring Phylogenetic Pattern in Seasonally Dry Tropical Plant Communities. PLOS ONE, 10(3), e0119166. doi:10.1371/journal.pone.0119166

Moro, M. F., Nic Lughadha, E., de Araújo, F. S., & Martins, F. R. (2016). A Phytogeographical Metaanalysis of the Semiarid Caatinga Domain in Brazil. The Botanical Review, 82(2), 91–148. doi:10.1007/s12229-016-9164-z

Mu, Q., Zhao, M., & Running, S. W. (2011). Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sensing of Environment, 115(8), 1781–1800. doi:10.1016/j.rse.2011.02.019

Muñoz Sabater, J., (2019): ERA5-Land hourly data from 1981 to present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). (Accessed on 23-Feb-2022), doi:10.24381/cds.e2161bac

Mutti, P. R., da Silva, L. L., Medeiros, S. de S., Dubreuil, V., Mendes, K. R., Marques, T. V., … Bezerra, B. G. (2019). Basin scale rainfall-evapotranspiration dynamics in a tropical semiarid environment during dry and wet years. International Journal of Applied Earth Observation and Geoinformation, 75, 29–43. doi:10.1016/j.jag.2018.10.007

Murray, T., and Verhoef, A. (2007) Moving towards a more mechanistic approach in the determination of soil heat flux from remote measurements. II. Diurnal shape of soil heat flux. Agricultural and Forest Meteorology, 147: 88-97.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I - A discussion of principles. Journal of Hydrology, 10(3), 282–290. doi:10.1016/0022-1694(70)90255-6

Oliveira, M. L., Santos, C. A. C., Oliveira, G., Perez-Marin, A. M., & Santos, C. A. G. (2021). Effects of human-induced land degradation on water and carbon fluxes in two different Brazilian dryland soil covers. Science of The Total Environment, 792, 148458. doi:10.1016/j.scitotenv.2021.148458

Owen, P. R., & Thomson, W. R. (1963). Heat transfer across rough surfaces. Journal of Fluid Mechanics, 15(3), 321–334. doi:10.1017/s0022112063000288

Paloschi, R. A., Ramos, D. M., Ventura, D. J., Souza, R., Souza, E., Morellato, L. P. C., … Borma, L. D. S. (2020). Environmental Drivers of Water Use for Caatinga Woody Plant Species: Combining Remote Sensing Phenology and Sap Flow Measurements. Remote Sensing, 13(1), 75. doi:10.3390/rs13010075

Paul, G., Gowda, P. H., Vara Prasad, P. V., Howell, T. A., Staggenborg, S. A., & Neale, C. M. U. (2013). Lysimetric evaluation of SEBAL using high resolution airborne imagery from BEAREX08. Advances in Water Resources, 59, 157–168. doi:10.1016/j.advwatres.2013.06.003

Paul, G., Gowda, P. H., Vara Prasad, P. V., Howell, T. A., Aiken, R. M., & Neale, C. M. U. (2014). Investigating the influence of roughness length for heat transport (zoh) on the performance of SEBAL in semi-arid irrigated and dryland agricultural systems. Journal of Hydrology, 509, 231–244. doi:10.1016/j.jhydrol.2013.11.040

Paulson, C. A. (1970). The mathematical representation of wind speed and temperature profiles in the unstable atmospheric surface layer. Journal of Applied Meteorology and Climatology, 9(6), 857-861. doi:10.1175/1520-0450(1970)009%3C0857:tmrows%3E2.0.co;2

Pennington, R. T., Lewis, G. P., & Ratter, J. A. (Eds.). (2006). An Overview of the Plant Diversity, Biogeography and Conservation of Neotropical Savannas and Seasonally Dry Forests. Neotropical Savannas and Seasonally Dry Forests, 1–29. doi:10.1201/9781420004496-1

Pennington, R. T., Lavin, M., & Oliveira-Filho, A. (2009). Woody Plant Diversity, Evolution, and Ecology in the Tropics: Perspectives from Seasonally Dry Tropical Forests. Annual Review of Ecology, Evolution, and Systematics, 40(1), 437–457. doi:10.1146/annurev.ecolsys.110308.120327

Pennington, R. T., Lehmann, C. E. R., & Rowland, L. M. (2018). Tropical savannas and dry forests. Current Biology, 28(9), R541–R545. doi:10.1016/j.cub.2018.03.014

Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., … Hofton, M. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. Remote Sensing of Environment, 253, 112165. doi:10.1016/j.rse.2020.112165

Priestley, C. H. B., & Taylor, R. J. (1972). On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters. Monthly Weather Review, 100(2), 81–92. doi:10.1175/1520-0493(1972)100<0081:otaosh>2.3.co;2

Queiroz, L. P., Cardoso, D., Fernandes, M. F., & Moro, M. F. (2017). Diversity and Evolution of Flowering Plants of the Caatinga Domain. Caatinga, 23–63. doi:10.1007/978-3-319-68339-3_2

Queiroz, M. G. D., Silva, T. G. F. D., Souza, C. A. A. D., Jardim, A. M. D. R. F., Araújo Júnior, G. D. N., Souza, L. S. B. D., & Moura, M. S. B. D. (2020). Composition of Caatinga species under anthropic disturbance and its correlation with rainfall partitioning. Floresta e Ambiente, 28. doi:10.1590/2179-8087-FLORAM-2019-0044

Ramoelo, A., Majozi, N., Mathieu, R., Jovanovic, N., Nickless, A., & Dzikiti, S. (2014). Validation of Global Evapotranspiration Product (MOD16) using Flux Tower Data in the African Savanna, South Africa. Remote Sensing, 6(8), 7406–7423. doi:10.3390/rs6087406

Rasp, S., Pritchard, M. S., & Gentine, P. (2018). Deep learning to represent subgrid processes in climate models. Proceedings of the National Academy of Sciences, 115(39), 9684–9689. doi:10.1073/pnas.1810286115

Roberts, W., Williams, G. P., Jackson, E., Nelson, E. J., & Ames, D. P. (2018). Hydrostats: A Python Package for Characterizing Errors between Observed and Predicted Time Series. Hydrology, 5(4), 66. doi:10.3390/hydrology5040066

Rodell, M., Houser, P. R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., … Toll, D. (2004). The Global Land Data Assimilation System. Bulletin of the American Meteorological Society, 85(3), 381–394. doi:10.1175/bams-85-3-381

Running, S., Mu, Q., Zhao, M. (2017). MOD16A2 MODIS/Terra Net Evapotranspiration 8-Day L4 Global 500m SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 23-Feb-2022 from doi:10.5067/MODIS/MOD16A2.006

Sahnoun, F., Abderrahmane, H., Kaddour, M., Abdelkader, K., Mohamed, B., & Castro, T. A. H. D. (2021). Application of SEBAL and T s/VI Trapezoid Models for Estimating Actual Evapotranspiration in the Algerian Semi-Arid Environment to Improve Agricultural Water Management. Revista Brasileira de Meteorologia, 36, 219-236. doi:10.1590/0102-77863610020

Salazar-Martínez, D., Holwerda, F., Holmes, T. R. H., Yépez, E. A., Hain, C. R., Alvarado-Barrientos, S., … Vivoni, E. R. (2022). Evaluation of remote sensing-based evapotranspiration products at low-latitude eddy covariance sites. Journal of Hydrology, 610, 127786. doi:10.1016/j.jhydrol.2022.127786

Santos, R. M., Oliveira-Filho, A. T., Eisenlohr, P. V., Queiroz, L. P., Cardoso, D. B. O. S., & Rodal, M. J. N. (2012). Identity and relationships of the Arboreal Caatinga among other floristic units of seasonally dry tropical forests (SDTFs) of north-eastern and Central Brazil. Ecology and Evolution, 2(2), 409–428. doi:10.1002/ece3.91

Santos, M. G., Oliveira, M. T., Figueiredo, K. V., Falcão, H. M., Arruda, E. C. P., Almeida-Cortez, J., … Antonino, A. C. D. (2014). Caatinga, the Brazilian dry tropical forest: can it tolerate climate changes? Theoretical and Experimental Plant Physiology, 26(1), 83–99. doi:10.1007/s40626-014-0008-0

Santos, C. A. C., Mariano, D. A., das Chagas A. do Nascimento, F., da C. Dantas, F. R., de Oliveira, G., Silva, M. T., … Neale, C. M. U. (2020). Spatio-temporal patterns of energy exchange and evapotranspiration during an intense drought for drylands in Brazil. International Journal of Applied Earth Observation and Geoinformation, 85, 101982. doi:10.1016/j.jag.2019.101982

Schaaf, C., & Wang, Z. (2015). MCD43A4 MODIS/Terra+Aqua BRDF/Albedo Nadir BRDF Adjusted Ref Daily L3 Global - 500m V006 [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 23-Feb-2022 from doi:10.5067/MODIS/MCD43A4.006

Senay, G. B., Bohms, S., Singh, R. K., Gowda, P. H., Velpuri, N. M., Alemu, H., & Verdin, J. P. (2013). Operational Evapotranspiration Mapping Using Remote Sensing and Weather Datasets: A New Parameterization for the SSEB Approach. JAWRA Journal of the American Water Resources Association, 49(3), 577–591. Portico. https://doi.org/10.1111/jawr.12057

Senay, G. B., Friedrichs, M., Morton, C., Parrish, G. E., Schauer, M., Khand, K., ... & Huntington, J. (2022). Mapping actual evapotranspiration using Landsat for the conterminous United States: Google Earth Engine implementation and assessment of the SSEBop model. Remote Sensing of Environment, 275, 113011. doi:10.1016/j.rse.2022.113011

Senkondo, W., Munishi, S. E., Tumbo, M., Nobert, J., & Lyon, S. W. (2019). Comparing Remotely-Sensed Surface Energy Balance Evapotranspiration Estimates in Heterogeneous and Data-Limited

Regions: A Case Study of Tanzania's Kilombero Valley. Remote Sensing, 11(11), 1289. doi:10.3390/rs11111289

Shuttleworth, W. J. (2012). Terrestrial hydrometeorology. John Wiley & Sons.

Silva, A. M., da Silva, R. M., & Santos, C. A. G. (2019). Automated surface energy balance algorithm for land (ASEBAL) based on automating endmember pixel selection for evapotranspiration calculation in MODIS orbital images. International Journal of Applied Earth Observation and Geoinformation, 79, 1–11. doi:10.1016/j.jag.2019.02.012

Silva, J. M. C.; LEAL, I.R.; TABARELLI, M. (Ed.). (2017a). Caatinga: the largest tropical dry forest region in South America. Springer.

Silva, P. F. da, Lima, J. R. de S., Antonino, A. C. D., Souza, R., Souza, E. S. de, Silva, J. R. I., & Alves, E. M. (2017b). Seasonal patterns of carbon dioxide, water and energy fluxes over the Caatinga and grassland in the semi-arid region of Brazil. Journal of Arid Environments, 147, 71–82. doi:10.1016/j.jaridenv.2017.09.003

Singh, R. K., & Irmak, A. (2011). Treatment of anchor pixels in the METRIC model for improved estimation of sensible and latent heat fluxes. Hydrological Sciences Journal, 56(5), 895–906. doi:10.1080/02626667.2011.587424

Singh, R. K., Liu, S., Tieszen, L. L., Suyker, A. E., & Verma, S. B. (2012). Estimating seasonal evapotranspiration from temporal satellite images. Irrigation Science, 30(4), 303-313. doi:10.1007/s00271-011-0287-z

Souza, L. S. B. de, Moura, M. S. B. de, Sediyama, G. C., & Silva, T. G. F. da. (2015). Balanço de energia e controle biofísico da evapotranspiração na Caatinga em condições de seca intensa. Pesquisa Agropecuária Brasileira, 50(8), 627–636. doi:10.1590/s0100-204x2015000800001

Stewart, J. B., Kustas, W. P., Humes, K. S., Nichols, W. D., Moran, M. S., & de Bruin, H. A. (1994). Sensible heat flux-radiometric surface temperature relationship for eight semiarid areas. Journal of

Applied Meteorology and Climatology, 33(9), 1110-1117. doi:10.1175/1520-0450(1994)033%3C1110:shfrst%3E2.0.co;2

Su, Z., Schmugge, T., Kustas, W. P., & Massman, W. J. (2001). An evaluation of two models for estimation of the roughness height for heat transfer between the land surface and the atmosphere. Journal of applied meteorology, 40(11), 1933-1951. doi:10.1175/1520-0450(2001)040%3C1933:aeotmf%3E2.0.co;2

Su, Z. (2002). The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes. Hydrology and Earth System Sciences, 6(1), 85–100. doi:10.5194/hess-6-85-2002

Teixeira, A. D. C., Bastiaanssen, W. G., Ahmad, M., & Bos, M. G. (2009). Reviewing SEBAL input parameters for assessing evapotranspiration and water productivity for the Low-Middle Sao Francisco River basin, Brazil: Part A: Calibration and validation. Agricultural and forest meteorology, 149(3-4), 462-476. doi:10.1016/j.agrformet.2008.09.016

Thom, A. S. (1972). Momentum, mass and heat exchange of vegetation. Quarterly Journal of the Royal Meteorological Society, 98(415), 124–134. doi:10.1002/qj.49709841510

Tomasella, J., Silva Pinto Vieira, R. M., Barbosa, A. A., Rodriguez, D. A., Oliveira Santana, M. de, & Sestini, M. F. (2018). Desertification trends in the Northeast of Brazil over the period 2000–2016. International Journal of Applied Earth Observation and Geoinformation, 73, 197–206. doi:10.1016/j.jag.2018.06.012

Trezza, R. (2006). Evapotranspiration from a remote sensing model for water mngement in an irrigtion system in Venezuela. Interciencia, 31(6), 417-423

Trezza, R., Allen, R., & Tasumi, M. (2013). Estimation of Actual Evapotranspiration along the Middle Rio Grande of New Mexico Using MODIS and Landsat Imagery with the METRIC Model. Remote Sensing, 5(10), 5397–5423. doi:10.3390/rs5105397

Troufleau, D., Lhomme, J. P., Monteny, B., & Vidal, A. (1997). Sensible heat flux and radiometric surface temperature over sparse Sahelian vegetation. I. An experimental analysis of the kB− 1 parameter. Journal of Hydrology, 188, 815-838. doi:10.1016/s0022-1694(96)03172-1

Verhoef, A., De Bruin, H. A. R., & Van Den Hurk, B. J. J. M. (1997a). Some practical notes on the parameter kB− 1 for sparse vegetation. Journal of Applied Meteorology, 36(5), 560-572. doi:10.1175/1520-0450(1997)036%3C0560:spnotp%3E2.0.co;2

Verhoef, A., McNaughton, K. G., & Jacobs, A. F. G. (1997b). A parameterization of momentum roughness length and displacement height for a wide range of canopy densities. Hydrology and Earth System Sciences, 1(1), 81–91. doi:10.5194/hess-1-81-1997

Wang, C., Yang, J., Myint, S. W., Wang, Z.-H., & Tong, B. (2016). Empirical modeling and spatio-temporal patterns of urban evapotranspiration for the Phoenix metropolitan area, Arizona. GIScience & Remote Sensing, 53(6), 778–792. doi:10.1080/15481603.2016.1243399

Wilson, K., Goldstein, A., Falge, E., Aubinet, M., Baldocchi, D., Berbigier, P., … Verma, S. (2002). Energy balance closure at FLUXNET sites. Agricultural and Forest Meteorology, 113(1-4), 223–243. doi:10.1016/s0168-1923(02)00109-0

WRB, I.W.G., 2006. World reference base for soil resources 2006, 2nd ed. In: FAO (ed.), World Soil Resources Reports No. 103, Rome. ISBN 92-5-105511-4.

Wu, Q. (2020). geemap: A Python package for interactive mapping with Google Earth Engine. Journal of Open Source Software, 5(51), 2305. doi:10.21105/joss.02305

Yin, L., Wang, X., Feng, X., Fu, B., & Chen, Y. (2020). A comparison of SSEBop-Model-Based evapotranspiration with eight evapotranspiration products in the Yellow River Basin, China. Remote Sensing, 12(16), 2528. doi:10.3390/rs12162528

Zhang, Y., Kong, D., Gan, R., Chiew, F. H. S., McVicar, T. R., Zhang, Q., & Yang, Y. (2019). Coupled estimation of 500 m and 8-day resolution global evapotranspiration and gross primary production in 2002–2017. Remote Sensing of Environment, 222, 165–182. doi:10.1016/j.rse.2018.12.031

Zhao, M., Heinsch, F. A., Nemani, R. R., & Running, S. W. (2005). Improvements of the MODIS terrestrial gross and net primary production global data set. Remote sensing of Environment, 95(2), 164-176. doi:10.1016/j.rse.2004.12.011

Supplementary material

Table S1. Performance statistics of the values observed with the STEEP model at each proposed refinement (*z0m*, *rah* and remaining *λET* in the endmembers pixels) and their two by two combinations. The comparison is made using the general basis of SEB models by RS as a reference, that in our study was SEBAL.

Site	Round	Performance statistics				
		RMSE	R^2	*NSE*	ρ_c	*PBIAS*
PTN (N = 252; 2011)	SEBAL	1.52	0.19	-0.45	0.34	47.30
	z0m	1.58	0.24	-0.37	0.39	36.54
	rah	1.41	0.21	-0.09	0.40	30.18
	rλET	0.95	0.55	0.51	0.67	-13.54
	z0m & *rah*	1.53	0.28	-0.28	0.42	31.25
	z0m & *rλET*	0.89	0.58	0.52	0.73	-15.79
	rah & *rλET*	1.01	0.41	0.39	0.61	-4.69
	STEEP	0.80	0.66	0.58	0.79	-17.27
SNN (N = 304; 2014)	SEBAL	1.08	0.55	0.39	0.67	40.62
	z0m	1.10	0.60	0.44	0.72	25.69
	rah	1.05	0.53	0.49	0.69	19.81
	rλET	0.99	0.64	0.55	0.65	-11.11

	z0m & *rah*	1.11	0.64	0.43	0.71	23.24
	z0m & *rλET*	0.79	0.64	0.63	0.75	5.32
	rah & *rλET*	0.92	0.55	0.51	0.64	14.23
	STEEP	0.76	0.69	0.65	0.80	20.80
SET (N = 283; 2015)	SEBAL	1.51	0.14	-3.69	0.18	143.58
	z0m	1.63	0.16	-4.48	0.19	112.36
	rah	1.37	0.12	-2.85	0.20	118.21
	rλET	0.72	0.20	0.01	0.37	33.07
	z0m & *rah*	1.69	0.22	-4.5	0.25	89.55
	z0m & *rλET*	0.78	0.09	-0.33	0.28	30.03
	rah & *rλET*	0.89	0.14	-0.57	0.29	59.55
	STEEP	0.85	0.24	-0.42	0.41	53.92
CGR (N = 201; 2014)	SEBAL	1.64	0	-4.34	-0.03	84.79
	z0m	1.71	0.01	-4.32	-0.02	72.95
	rah	1.37	0	-2.40	-0.01	46.48
	rλET	0.77	0.22	-0.19	0.45	16.21
	z0m & *rah*	1.66	0	-4	-0.01	62.45
	z0m & *rλET*	1.05	0.39	-0.85	0.48	43.26
	rah & *rλET*	0.94	0.28	-0.51	0.45	31.89

	STEEP	0.77	0.43	-0.17	0.61	11.89
CGR (N = 48; 2020)	SEBAL	1.75	0.04	-1.48	-0.10	79.77
	z0m	1.97	0.06	-2.16	0.35	48.62
	rah	1.50	0.01	-0.83	0.05	57.22
	rλET	0.99	0.25	0.20	0.37	19.19
	z0m & *rah*	1.89	0	-1.91	0.04	59.64
	z0m & *rλET*	1.13	0.19	-0.17	0.36	46.37
	rah & *rλET*	0.93	0.42	0.30	0.55	29.24
	STEEP	0.93	0.47	0.31	0.62	30.95

z0m = roughness length for momentum transfer; *rah* = aerodynamic resistance for heat transfer; r*λET* = remaining *λET* in the endmembers pixels.

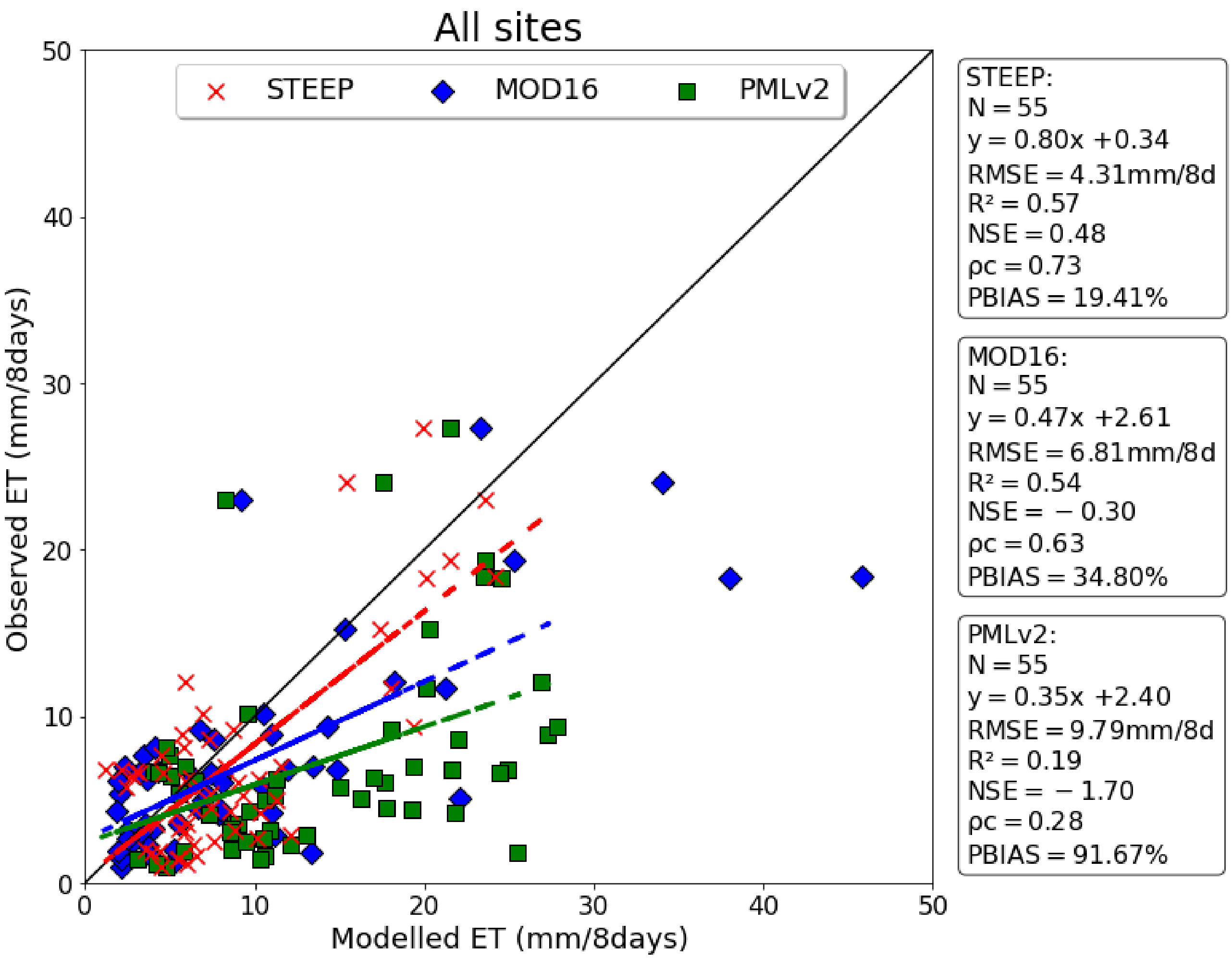

Figure S1. Evaluation of evapotranspiration (ET, mm/8days) observed and modelled with STEEP (red crosses), MOD16 (blue diamonds) and PMLv2 (green squares) for all experimental sites considering only where the field-observed data had eight consecutive days. The black line is the 1:1 line; dashed lines are the fitted linear regressions of observed on modelled values by the STEEP model (red), MOD16 (blue) and PMLv2 (green) products.

Appendix A – Equations adopted to formulate the STEEP model

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

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

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

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

$$Rn = R_{S\downarrow} \times (1-\alpha) + \varepsilon_S \times R_{L\downarrow} - R_{L\uparrow} \tag{A.2}$$

where $R_{S\downarrow}$ is incident shortwave radiation (W/m^2), α is surface albedo (dimensionless), estimated following Trezza et al. (2013), ε_S is surface emissivity (dimensionless), estimated following Long et al. (2010), $R_{L\downarrow}$ is longwave radiation from the atmosphere (W/m^2); $R_{L\uparrow}$ is emitted longwave radiation (W/m^2).

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

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

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

Sensible heat flux was modeled using:

$$H = \frac{\rho \times c_p \times dT}{rah} \tag{A.4}$$

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

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

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

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

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

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

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

Roughness length for momentum transport was estimated, based on the studies by Verhoef et al. (1997b) and Paul et al. (2013):

$$z0m = (HGHT - d0) \times exp^{(-k \times GAM + PSICORR)} \quad \text{(A.7)}$$

where $HGHT$ is the height of the vegetation (m) and $PSICORR$ is taken as 0.2.

Zero plane displacement height was obtained from:

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

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

GAM was obtained using:

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

if *GAM* < 3.33, *GAM* is set to 3.33

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

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

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

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

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

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

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

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

$$SM_{rel} = \frac{SM - SM_{min}}{SM_{max} - SM_{min}} \tag{A.13}$$

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

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

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

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

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

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

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

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

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

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

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

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

$$Re = \frac{u^* * 0.009}{v}, \qquad v = 1.461 * 10^{-5} \tag{A.18}$$

where v is the kinematic viscosity (m^2/s).

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

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

where $NDVI_{max}$ and $NDVI_{min}$ are maximum and minimum NDVI values, respectively.

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

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

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

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

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

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

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

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

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

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

where αpt is the empirical Priestley-Taylor coefficient, nominally set to 1.26, but here adjusted according to local conditions, i.e. set to 0.55 and 1.75 for the hot and cold pixel in the endmembers, respectively. Δ is the slope of the saturation vapor pressure-air temperature curve (kPa/ºC) and γ is the psychrometric constant (kPa/ºC).

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

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

where T_a is the air temperature (°C), λET is derived from Eq. A1, and Rn_{24h} corresponds to the daily net radiation (W/m^2); in this study both driving variables were obtained with data from the ERA5-Land product.