EVALUATION OF FAO-56 PROCEDURES FOR ESTIMATING REFERENCE EVAPOTRANSPIRATION USING MISSING CLIMATIC DATA FOR A BRAZILIAN TROPICAL SAVANNA

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Abstract

Since the Brazilian Cerrado has been heavily impacted by agricultural activities over the last four to five decades, reference evapotranspiration (ET_o) plays a big role in water resources management for irrigation agriculture. The Penman-Monteith (PM) is one of the most accepted models for ET_o estimation, but it requires many inputs that are not commonly available. Therefore, assessing the FAO guidelines to compute ET_o when

meteorological data are missing could lead to a better understanding of how climatic variables are related to water requirements and atmospheric demands for a grass-mixed savanna region and which variable impacts the estimates the most. ET_o was computed from April 2010 to August 2019. We tested twelve different scenarios considering radiation, relative humidity, and/or wind speed as missing climatic data using guidelines given by FAO. When wind speed and/or relative humidity data were the only missing data, the PM method showed the lowest errors in the ET_o estimates and correlation coefficient (r) and Willmott's index of agreement (d) values close to 1.0. When radiation data were missing, computed ET_o was overestimated compared to the benchmark. FAO procedures to estimate net radiation presented good results during the wet season; however, during the dry season, their results were overestimated, especially because the method could not estimate negative R_n. Therefore, we can infer that radiation data have the largest impact on ET_o for our study area and regions with similar conditions and FAO guidelines are not suitable when radiation data are missing.

1 Introduction

Over the last few decades, the Brazilian savanna (locally known as Cerrado) hydrological cycle and climate have been heavily affected by human activities, especially the replacement of native vegetation by agricultural crops (Giambelluca et al. 2009; Rodrigues et al. 2014; Oliveira et al. 2014; Nóbrega et al. 2018; Silva et al. 2019; Valle Júnior et al. 2020). Due to this irrigated agricultural expansion, it is important to have good management of available water resources.

To handle issues involving water requirements and atmospheric demand, the United Nations Food and Agriculture Organization (FAO) recommended calculating crop evapotranspiration (ET_c) from reference evapotranspiration (ET_o) (Doorenbos and Pruitt 1977). Water demands and ET_c are important considerations to improve water use efficiency in agriculture (Hargreaves 1994; Allen 1996; Tyagi et al. 2000; Droogers and Allen 2002; She et al. 2017; Dong et al. 2020).

ET_o is the evapotranspiration of a defined hypothetical reference well-watered crop with a crop height of 0.12 m, a canopy resistance of 70 $s.m^{-1}$, and an albedo of 0.23 (Allen et al. 1994). A "real" ET_o value can only be obtained using lysimeters or other

precision measuring devices, which require time and are expensive (Droogers and Allen 2002; Sharifi and Dinpashoh 2014; Martins et al. 2017), however, ET_o can be computed from weather data, and climatic parameters are the only factors that affect ET_o estimates (Allen et al. 1998; Xu et al. 2006).

Several authors (Blaney and Criddle 1950; Jensen and Haise 1963; Priestley and Taylor 1972; Hargreaves and Samani 1985) have reported different methods to compute ET_o. Those different methods have been tested in distinct regions and climates (Tabari et al. 2013; Bourletsikas et al. 2017; Zhang et al. 2018; Shiri 2019; Valle Júnior et al. 2020); however, the Penman-Monteith (PM) method is suggested by FAO to calculate ET_o anywhere the requisite meteorological data are available (Allen et al. 1998). The FAO-PM method can be used globally without any regional correction and is well documented and tested, but it has a relatively high data demand (Droogers and Allen 2002; Gong et al. 2006; Dinpashoh et al. 2011).

For daily calculation, FAO-PM method meteorological inputs are maximum and minimum temperatures, relative air humidity, solar radiation, and wind speed. Allen *et al*. (1998) suggested using the Hargreaves-Samani (HS) method (Hargreaves and Samani 1985) as an alternative equation when only air temperature data are available. However, the HS method should be verified and compared with the FAO-PM method, since it has a tendency to overestimate ET_o under high relative humidity conditions, and underestimate under conditions of high wind speed (Allen et al. 1998). FAO also recommends the Pan evaporation (E_{pan}) method, which is related to ET_o using an empirically derived pan coefficient (K_p).

For many locations around the globe, there is a lack of meteorological data. In Brazil, it is possible to collect climatic data from automatic stations of the National Institute of Meteorology (INMET). Although these data are public and the stations cover a significant part of the Cerrado region, there are neither measures of net radiation or estimates of regional solar radiation. Several studies have been carried out to evaluate the use of FAO-PM method procedures to estimate ET_o when solar radiation, wind speed, and relative humidity data are missing (Popova et al. 2006; Jabloun and Sahli 2008; Todorovic et al. 2013; Raziei and Pereira 2013a, b; Djaman et al. 2016; Čadro et al. 2017), however, results varied according to the climatic condition. Recent studies have used

machine learning models to estimate ET_o (Mehdizadeh et al. 2017; Karimi et al. 2017; Mattar 2018; Ferreira et al. 2019; Valle Júnior et al. 2020) and E_{pan} (Kisi 2015; Wang et al. 2017a, b) with limited weather data. Still, few studies reported the effects of meteorological data variability on reference evapotranspiration in the Cerrado region.

Therefore, it is important to evaluate the performance of the procedures and recommendations when ET_o is obtained with missing climatic data. Knowing which meteorological data have the largest impact on ET_o estimates could guide better investments in measurement instruments and provide a better understanding of the seasonal behavior of weather variables for the Cerrado region. Thus, the objective of this study was to assess the guidelines provided by FAO to estimate ET_o when meteorological data is limited for a grass-mixed Cerrado region and discuss the impact of each climatic variables on the estimates.

2 Materials and methods

2.1 Study Area

This study was conducted at the Fazenda Miranda (15°17'S, 56°06'W), located in the Cuiaba municipality (Fig. 1), Brazil. The vegetation is grass-dominated with sparse trees and shrubs, known as *campo sujo* or "dirty field" Cerrado (Rodrigues et al. 2016b). According to the Köppen climate classification, the climate in this area is characterized as Aw, tropical semi-humid, with dry winters and wet summers (Alvares et al. 2013). The average rainfall is 1420 mm and the mean annual air temperature is 26.5°C, with a dry season that extends from May to October (Vourlitis and da Rocha 2011; Rodrigues et al. 2014). The study area is on flat terrain at an altitude of 157 m above sea level.

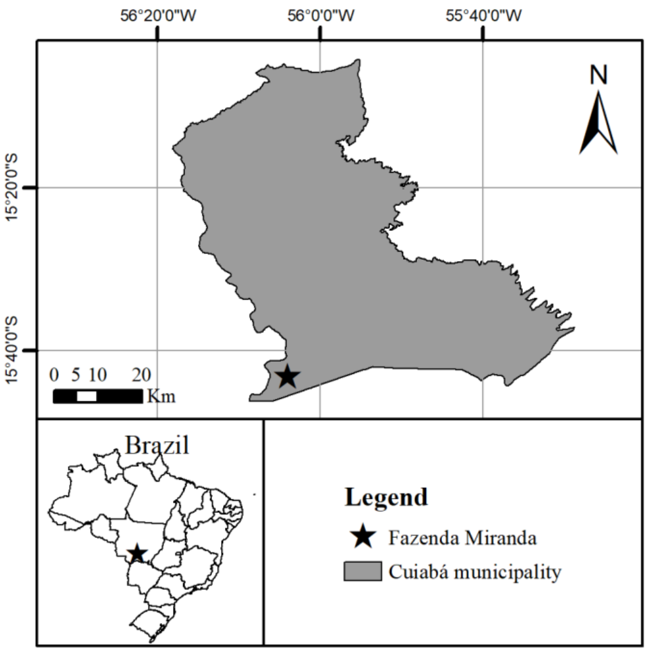

Fig. 1 Location of the study site (star) near Cuiabá, Mato Grosso, Brazil

2.2 Micrometeorological measurements

The measurements were conducted from April 2009 to August 2019. The measurement instruments were installed on a 20 m tall micrometeorological tower. The data collected were net radiation (R_n), solar radiation (R_s), soil heat flux (G), air temperature (T_a), relative humidity (RH), wind speed (*u*), soil temperature (T_{soil}), soil moisture (SM), and precipitation (P). R_n and R_s were measured 5 m above the ground level using a net radiometer (NR-LITE-L25,Kipp & Zonen, Delft, Netherlands) and a pyranometer (LI200X, LI-COR Biosciences, Inc., Lincoln, NE, USA), respectively. G was measured using a heat flux plate (HFP01-L20, Hukseflux Thermal Sensors BV, Delft, Netherlands) installed 1.0 cm below the soil surface. SM was measured by a time domain reflectometry probe (CS616-L50, Campbell Scientific, Inc., Logan, UT, USA) installed 20 cm below the soil surface. T_{soil} was measured by a temperature probe (108 Temperature Probe, Campbell Scientific, Inc., Logan, UT, USA) installed 1 cm below the ground level. T_a and RH were measured by a thermohygrometer (HMP45AC, Vaisala Inc., Woburn, MA, USA) installed 2 m above the ground level. *u* was measured 10 m above the ground level using an anemometer (03101 R.M. Young Company).

Precipitation was measured using a tipping bucket rainfall gauge (TR-525M, Texas Electronics, Inc., Dallas, TX, USA) installed 5 m above the ground level. We considered only data from days without gaps and measurement errors to avoid inconsistent information.

2.3 Penman-Monteith method and FAO procedures when climatic data are misssing

The Penman-Monteith (FAO-PM) method (Equation 1) is recommended by the Food and Agriculture Organization (FAO) as the standard method for determining reference evapotranspiration (ET_o) (Allen et al. 1998). We considered ET_o computed with full data set as reference data for comparisons.

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{(T_a+273)}u_2(e_s - e_a)}{\Delta + \gamma(1+0.34u_2)} \qquad (1)$$

where ET_o is the reference evapotranspiration (mm.day^{-1}), R_n is net radiation (MJ.m^{-2}.day^{-1}), G is the soil heat flux (MJ.m^{-2}.day^{-1}), T_a is the mean daily air temperature (°C), u_2 is the wind speed at 2 m height (m.s^{-1}), e_s is the saturation water vapor pressure (kPa), e_a is the actual water vapor pressure (kPa), γ is the psychrometric constant (kPA.°C^{-1}), and Δ is the slope of water vapor pressure curve (kPa.°C^{-1}). We used Equation 2 (Allen et al. 1998) to convert u to u_2.

$$u_2 = u_z \frac{4.87}{\ln(67.8z - 5.42)} \qquad (2)$$

where u_z is the measured wind speed at z m above ground surface (m.s^{-1}), and z is the height of measurement above ground surface (m), which is 10 m in our study.

To test the impact of radiation, relative humidity, and wind speed data, ET_o was also calculated by the FAO-PM using estimated meteorological variables, R_s, u_2, and e_a, obtained by procedures given by Allen *et al.* (1998) with data collected measurements.

FAO recommends two different approaches to estimate R_s when climatic data are missing: using temperature data or linear regression. In this study, we computed solar radiation by linear regression. R_s was estimated using Equation 3.

$$R_s = \left(a_s + b_s\frac{n}{N}\right)R_a \qquad (3)$$

where R_s is the solar radiation (MJ.m^{-2}.day^{-1}), n is the actual duration of sunshine (h), N is the maximum possible duration of daylight hours (h), R_a is the extraterrestrial radiation (MJ.m^{-2}.day^{-1}), and a_s and b_s are local regression constants. To estimate R_a we used Equation 4.

$$R_a = \frac{24(60)}{\pi} G_{sc} d_r [\omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s)] \qquad (4)$$

where R_a is the extraterrestrial radiation (MJ.m^{-2}.day^{-1}), G_{sc} is the solar constant of 0.0820 MJ.m^{-2}.min^{-1}, d_r is the inverse relative distance Earth-Sun, ω_s is the sunset hour angle (rad), φ is the latitude of the meteorological station (rad), and δ is the solar decimation (rad). The values of d_r and δ were computed using Equations 5 and 6.

$$d_r = 1 + 0.033 \cos\left(\frac{2\pi}{365} J\right) \qquad (5)$$

$$\delta = 0.409 \sin\left(\frac{2\pi}{365} J - 1.39\right) \qquad (6)$$

where J is the number of the day in the year between 1 (1 January) and 365 or 366 (31 December). ω_s was estimated using Equation 7.

$$\omega_s = \cos^{-1}[-\tan(\varphi) \tan(\delta)] \qquad (7)$$

N was estimated using Equation 8.

$$N = \frac{24}{\pi} \omega_s \qquad (8)$$

where N is the maximum possible duration of daylight hours (h), and ω_s is the sunset hour angle (rad) computed by Equation 7.

An estimate clear-sky solar radiation (R_{so}) (Equation 9), net shortwave radiation (R_{ns}) (Equation 10), and net longwave radiation (R_{nl}) is needed to estimate Rn from Rs (Equation 11).

$$R_{so} = (a_s + b_s) R_a \qquad (9)$$

where R_{so} is the clear-sky radiation (MJ.m^{-2}.day^{-1}), a_s and b_s are the parameters from Equation 3, and R_a is the extraterrestrial radiation (MJ.m^{-2}.day^{-1}).

$$R_{ns} = (1 - \alpha) R_s \qquad (10)$$

where R_{ns} is the net shortwave radiation ($MJ.m^{-2}.day^{-1}$), α is the albedo, which is 0.23 for the hypothetical grass reference crop, and R_s is the solar radiation ($MJ.m^{-2}.day^{-1}$)

$$R_{nl} = \sigma\left(\frac{T_{max,K}{}^4 + T_{min,K}{}^4}{2}\right)\left(0.34 - 0.14\sqrt{e_a}\right)\left(1.35\frac{R_s}{R_{so}} - 0.35\right) \qquad (11)$$

where R_{nl} is the net longwave radiation ($MJ.m^{-2}.day^{-1}$), σ is the Stefan-Boltzmann constant of 4.903 x 10^{-9} $MJ.K^{-4}.m^{-2}.day^{-1}$, $T_{max,K}$ is the maximum absolute temperature during the 24-hour period (K), $T_{min,K}$ is the minimum absolute temperature during the 24-hour period (K), e_a is the actual vapor pressure (kPa), R_s is the solar radiation ($MJ.m^{-2}.day^{-1}$), and R_{so} is the clear-sky radiation ($MJ.m^{-2}.day^{-1}$).

R_n was estimated using Equation 12.

$$R_n = R_{ns} - R_{nl} \qquad (12)$$

where R_n is the net radiation ($MJ.m^{-2}.day^{-1}$), R_{ns} is the net shortwave radiation ($MJ.m^{-2}.day^{-1}$), and R_{nl} is the net longwave radiation ($MJ.m^{-2}.day^{-1}$).

For locations that there is no solar radiation data available, or no calibration for improved estimates of a_s and b_s, Allen *et al.* (1998) recommends a_s = 0.25 and b_s = 0.50. We calibrated a_s and b_s values using observed R_s values from April 2009 to March 2010. Using linear regression, the values of a_s an d b_s were, respectively, 0.192 and 0.506 (R^2 = 0.833; *n* = 358 observations). Estimations of R_s were calculated using both the calibrated and recommended regression constants. Allen et al. (1998) suggests considering daily G ≈ 0.

e_a was estimated using Equation 13, considering absence of relative air humidity data.

$$e_a = 0.6108e^{\left(\frac{17.27T_{min}}{T_{min}+237.3}\right)} \qquad (13)$$

where e_a is the actual water vapor pressure (kPa), and T_{min} is the minimum temperature (°C). Allen *et al.* (1998) recommends to use dewpoint temperature, however, when humidity data are lacking, it can be assumed that dewpoint temperature is near the daily minimum temperature.

For estimates of wind speed at 2 m-height, Allen *et al.* (1998) suggest to use the average of wind speed from a nearby weather station over a several-day period. Therefore, u_2 was considered a constant value estimated using the daily mean value of wind speed during the period of measurements (April 2009 to August 2019).

2.4 Hargreaves-Samani method

The Hargreaves-Samani method (Hargreaves and Samani 1985) is recommended by FAO to compute ET_o, in mm.day^{-1}, when only temperature data are available,

$$ET_o = 0.0023(T_{mean} + 17.8)\sqrt{T_{max} - T_{min}}0.408R_a \quad (14)$$

where T_{mean} is the mean daily temperature (°C), T_{max} is the maximum daily temperature (°C), T_{min} is the minimum daily temperature (°C), and R_a is the extraterrestrial radiation (MJ.m^{-2}.day^{-1}). The constant value of 0.408 is a conversion factor for MJ.m^{-2}.day^{-1} to mm.day^{-1}.

2.5 ET_o with missing climatic data

Table 1 summarizes the calculation of ET_o from April 2010 to August 2019 using limited climatic data. We computed ET_o with the following scenarios of estimated data: a) solar radiation with calibrated parameters (R_s-a); b) solar radiation with recommended parameters (R_s-b); c) relative air humidity (RH); d) wind speed (WS); e) R_s-a and RH; f) R_s-b and RH; g) R_s-a and WS; h) R_s-b and WS; i) RH and WS; j) R_s-a, RH, and WS; k) R_s-b, RH, and WS, and l) using the Hargreaves-Samani method (HS).

Table 1 Summary of ET_o calculations with missing climatic data

Method	Symbol	Calculation of ET_o
FAO-PM, no radiation data (using calibrated parameters to estimate R_s)	R_s-a	ET_o (Eq. 1); R_n (Eq. 12); a_s and b_s calibrated
FAO-PM, no radiation data (using recommended parameters to estimate R_s)	R_s-b	ET_o (Eq. 1); R_n (Eq. 12), a_s and b_s recommended
FAO-PM, no relative air humidity data	RH	ET_o (Eq. 1); e_a (Eq. 13)

FAO-PM. no wind speed data	WS	ET_o (Eq. 1); u_2 calculated by daily mean wind speed
Hargreaves-Samani	HS	ET_o (Eq. 14)

2.6 Performance evaluation

We compared each result obtained from the calculations with the ET_o estimates with full data, considered as the benchmark. The comparisons were made by simple linear regression. The performance of each scenario was assessed using Willmott's index of agreement (d) (Willmott 1982) (Equation 15), correlation coefficient (r) (Equation 16), root mean square error (RMSE) in mm.day^{-1} (Equation 17), and mean bias error (MBE) in mm.day^{-1} (Equation 18).

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{O}| + |O_i - \bar{O}|)^2}\right] \qquad (15)$$

$$r = \frac{\sum_{i=1}^{n}[(P_i - \bar{P})(O_i - \bar{O})]}{\sqrt{[\sum_{i=1}^{n}(P_i - \bar{P})^2][\sum_{i=1}^{n}(O_i - \bar{O})^2]}} \qquad (16)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \qquad (17)$$

$$MBE = \frac{\sum_{i=1}^{n}(P_i - O_i)}{n} \qquad (18)$$

where P_i is the estimate value of the ith day (mm.day^{-1}), O_i is the observed value of the ith day (mm.day^{-1}), $\bar{P}$ is the mean of estimated values (mm.day^{-1}), $\bar{O}$ is the mean of observed values (mm.day^{-1}), and n is the number of observed values. Willmott's index of agreement (d) was used to quantify the degree of correspondence between P_i and O_i, where d = 1 indicates complete correspondence and d = 0 indicates no correspondence between measured and modeled values (Willmott 1982). The root mean square error (RMSE) used to quantify the amount of error between the observed and estimated values (Willmott 1982).

3 Results and discussion

3.1 Seasonal variation in micrometeorological condition

The climate in the study area showed a seasonal rainfall variation (Fig. 2). We considered the dry season as the period with a rainfall depth lower than 100 mm/month (Hutyra et al. 2005; Rodrigues et al. 2014, 2016a). The dry season was defined from April to October, with approximately 25% of the recorded rainfall during the study period (Fig. 2f). Mean yearly accumulated rainfall (±sd) was 941 ± 297 mm during the study period, which is 34% lower than the expected rainfall for this region.

Variations in air and soil temperatures (Fig. 2a) were higher during the dry season compared to the wet season, due to frequent cold fronts that come from the south (Grace et al. 1996). The mean (±sd) temperature during the study period was 26.4 ± 2.9°C. The month with the highest average air temperature was September (28.3 ± 3.4°C), while the month with lowest air temperature was July (23.5 ± 3.7°C). The maximum air temperature recorded was 42.0 °C, and the minimum was 6.3 °C. Relative humidity (Fig. 2c) also varied seasonally, with the highest average values observed during the wet season and the lowest observed during the dry season. Average monthly gravimetric soil moisture (mass water/mass dry soil) (Fig. 2c) ranged between 4 to 5.5% during the wet season, while soil water content reached 2.4% during the dry season when rainfall was scarce.

Wind speed at 2-m height (Fig. 2b) showed a small seasonal variation during the study period, with an average value (±sd) of 1.2 ± 0.5 $m.s^{-1}$. We found relatively large daily variation, due to the sporadic nature of the wind in the study area (Rodrigues et al. 2016b). Allen *et al.* (1998) classified mean wind speed below 1 $m.s^{-1}$ as light wind, and wind speed between 1 and 3 $m.s^{-1}$ as light to moderate wind.

Net radiation (Fig. 2d) was higher during the wet season than the dry season; however, we found a larger standard deviation of R_n for that period, since there is a frequent cloud cover during those months (Machado et al. 2004). The dry-season decline in net radiation may be due to changes in vegetation and decline of greenness during this season when soil moisture values were lower (Machado et al. 2004; Rodrigues et al. 2013). On the other hand, R_s did not show a notable seasonal pattern like R_n values (Fig. 2d).

Soil heat flux (Fig. 2e) presents a similar behavior to soil temperature, with its peak value in September. Mean monthly values (±sd) varied from -0.11 ± 0.54, in January, to 0.97 ± 1.37 $MJ.m^{-2}.day^{-1}$, in September. From July to November, G mean

monthly and standard deviation values were higher than 0.5 and 0.9 $MJ.m^{-2}.day^{-1}$, respectively. During the dry season, vegetation leaf area declined due to the low soil water availability (Rodrigues et al. 2013), causing an increase in uncovered area and, consequently, higher values of soil heat flux. According to Rodrigues et al. (2014), during September, G accounts for about 30% of the energy balance of *campo sujo* Cerrado. The contribution of G in other tropical ecosystems, such as transition and tropical forests, accounts for about 1 – 2% of the available energy (Giambelluca et al. 2009).

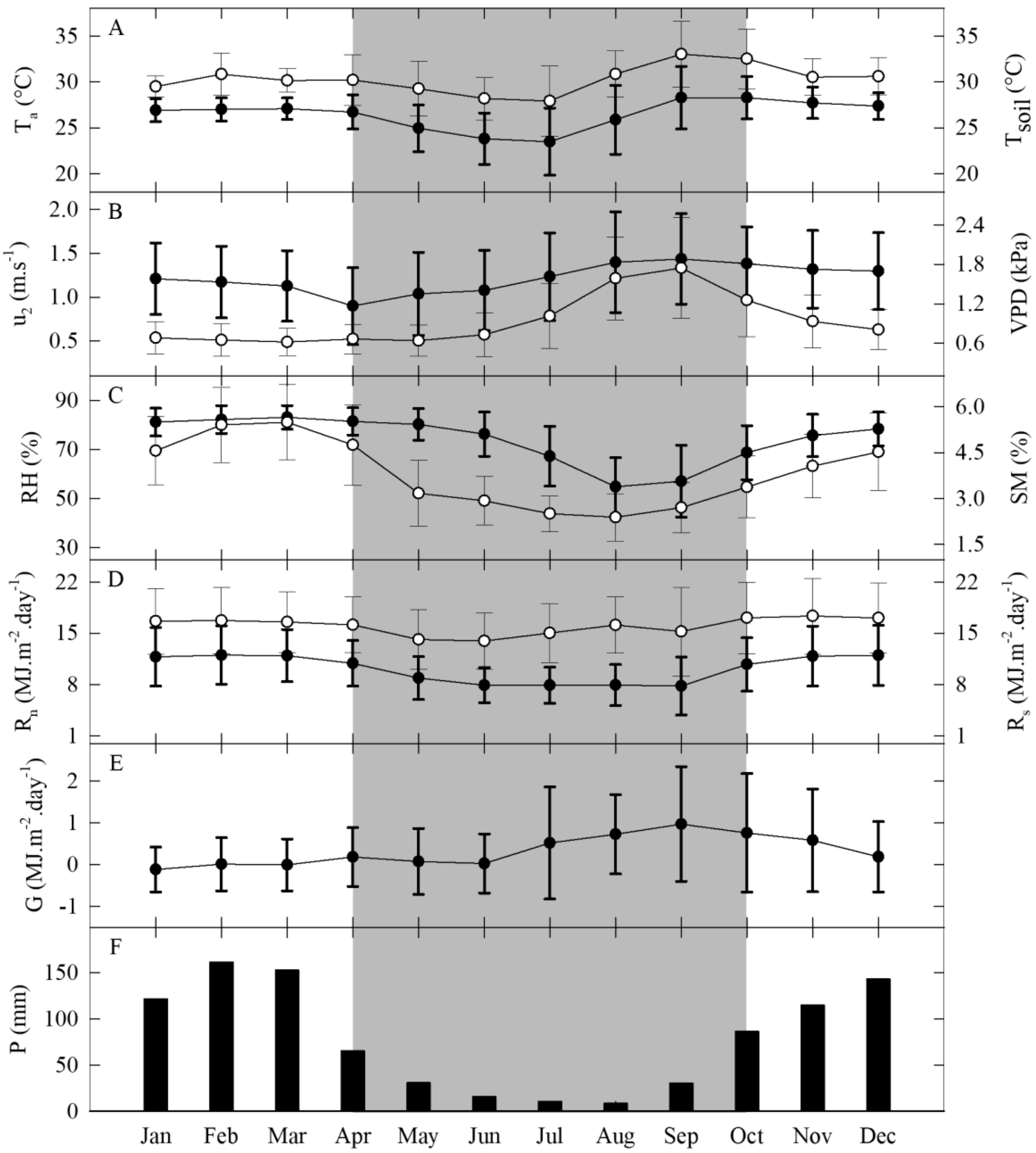

Fig. 2 Mean monthly micrometeorological measurements of: a) air temperature (black circles, left-hand axis) and surface soil temperature (white circles, right-hand axis); b) wind speed at 2 m-height (black circles, left-hand axis) and vapor-pressure deficit (white circles, right-hand axis); c) relative air humidity (black circles, left-hand axis) and surface soil moisture (white circles, right-hand axis); and d) net radiation (black circles, left-hand axis) and solar radiation (white circles, right-hand axis); e) soil heat flux; and f) total monthly precipitation. The whiskers indicate the range within the standard deviation. The shadowed area indicates the dry season

Fig. 3 shows monthly mean ET_o calculated using the Penman-Monteith method with observed meteorological data. The average ET_o computed ($\underline{+}$sd) was 3.49 ± 1.13 mm.day^{-1}. Higher ET_o values were observed during the wet season (November to March). When compared to the meteorological variables in Fig. 2, ET_o estimates behaved similarly to R_n values. Valle Júnior et al. (2020) pointed out that ET_o models based on R_n perform better than different methods based on other variables for the *campo sujo* Cerrado conditions.

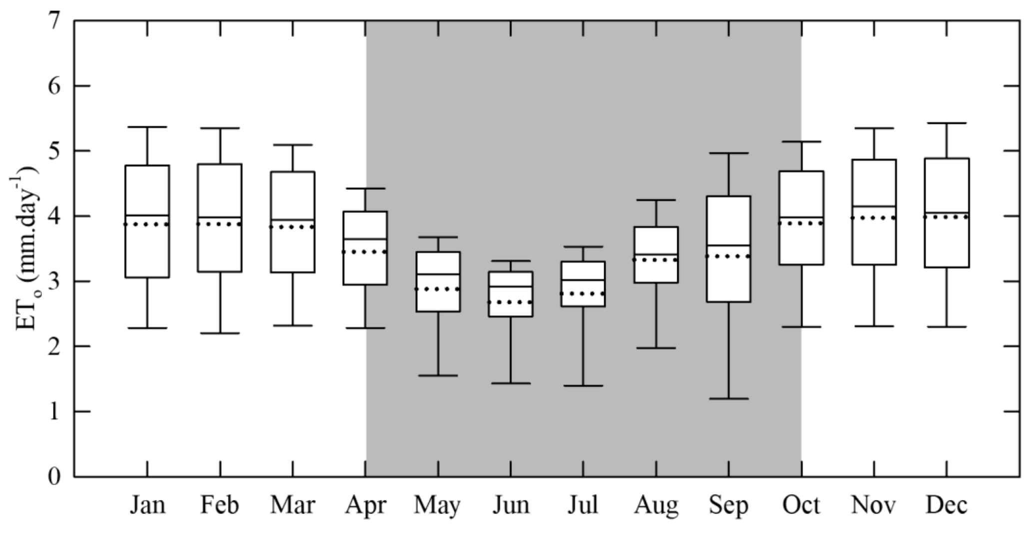

Fig. 3 Boxplots showing daily ET_o calculations for Fazenda Miranda site. Each box lies between the second and third quartile, the central line is the median, and the dotted line is the monthly mean. The whiskers indicate the range of data within the minimum and maximum values. The shadowed area indicates the dry season

3.2 ET_o estimates with limited climatic data

For ET_o values computed using limited meteorological data (Fig. 4), the d, r, RMSE, and absolute MBE values ranged from 0.64 to 0.99, 0.68 to 0.98, 0.21 to 1.56, and 0.01 to 1.29 mm.day^{-1}, respectively. Table 2 summarizes the statistical analyses and Fig. 5 shows the difference between the RMSE and MBE values found.

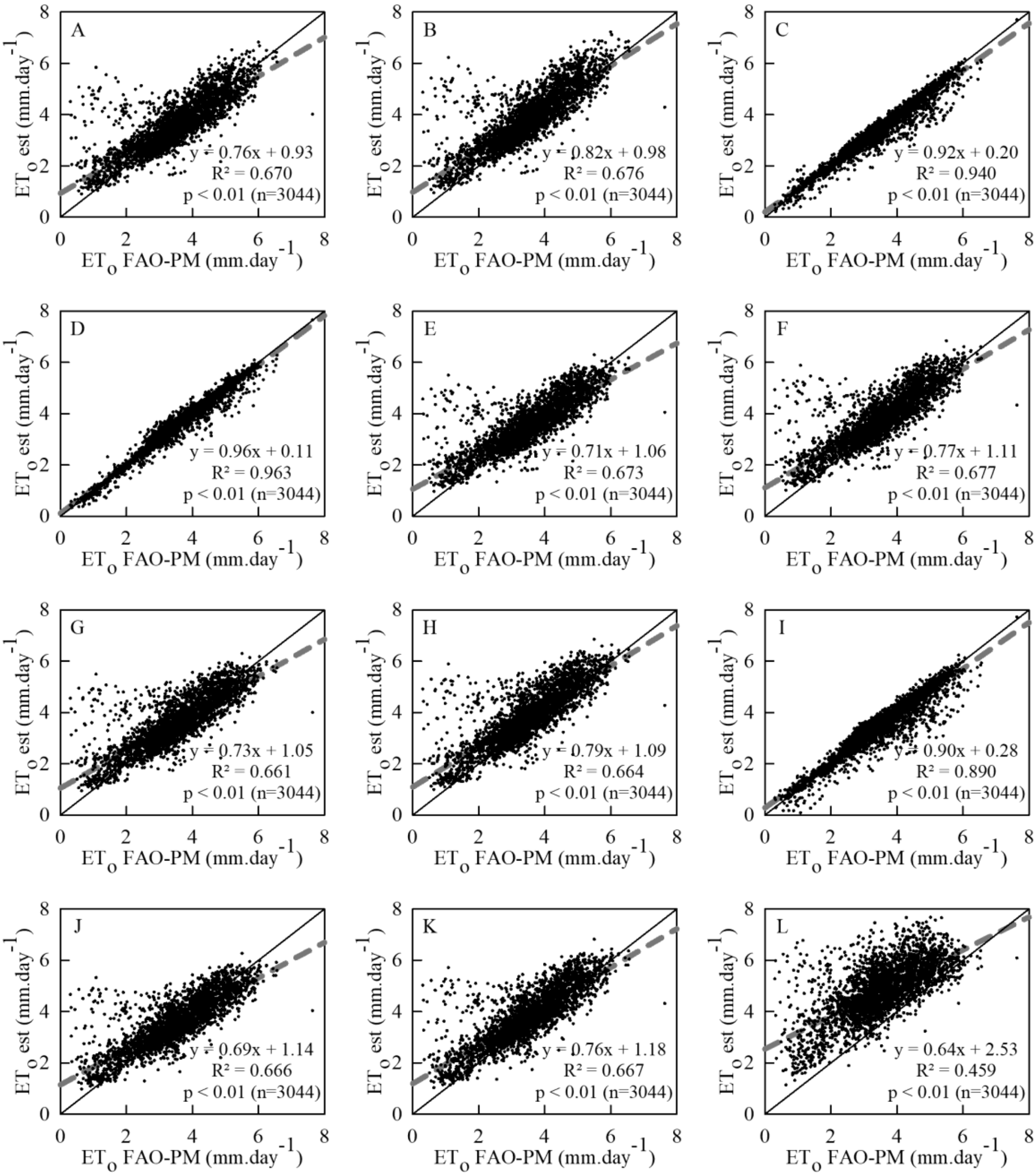

Fig. 4 ET_o values estimated using estimates of: a) Rs-a; b) Rs-b; c) RH; d) WS; e) Rs-a and RH; f) Rs-b and RH; g) Rs-a and WS; h) Rs-b and WS; i) RH and WS; j) Rs-a, RH, and WS; k) Rs-b, RH, and WS; and l) HS, in comparison with ET_o estimated with full data set (ET_o FAO-PM). The central line represents a 1:1 correlation and the dashed line represents the linear regression through the origin

Table 2 Comparison between ET_o computed from full data set and estimates of ET_o with missing climatic data

Method	d	r	RMSE (mm.day-1)	MBE (mm.day-1)
Rs-a	0.90	0.82	0.66	0.10
Rs-b	0.88	0.82	0.75	0.35
RH	0.98	0.97	0.28	-0.07
WS	0.99	0.98	0.21	-0.01
RS-a and RH	0.90	0.82	0.64	0.05
RS-b and RH	0.89	0.82	0.72	0.31
RS-a and WS	0.90	0.81	0.66	0.09
RS-b and WS	0.88	0.82	0.75	0.34
RH and WS	0.97	0.94	0.37	-0.06
RS-a, RH, and WS	0.90	0.82	0.65	0.07
RS-b, RH, and WS	0.88	0.82	0.73	0.33
HS	0.64	0.68	1.56	1.29

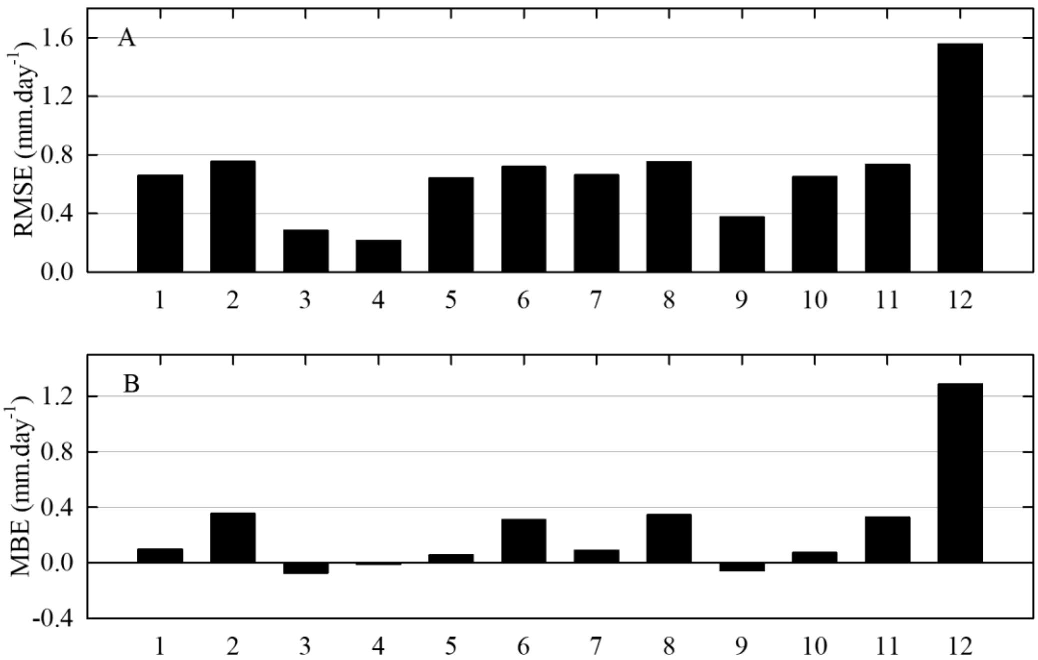

Fig. 5 a) Root Mean Square Error (RMSE) and b)Mean Bias Error (MBE) of computed ET_o using estimates of 1) Rs-a; 2) Rs-b; 3) RH; 4) WS; 5) Rs-a and RH; 6) Rs-b and RH;

7) Rs-a and WS; 8) Rs-b and WS; 9) RH and WS; 10) Rs-a, RH, and WS; 11) Rs-b, RH, and WS; and 12) HS

The methods with relative humidity and/or wind speed as missing data (Fig. 4c, d, and i) showed better performance than the other methods, with high r and d values that were close to 1.0, which indicate a perfect positive linear correlation and a perfect model performance for correlation coefficient and Willmott's index of agreement, respectively. When using only average annual wind speed as estimated data, we obtained the lowest RMSE and the closest to zero MBE, with values of 0.21 $mm.day^{-1}$ and -0.01 $mm.day^{-1}$, respectively. When relative humidity is the only missing climatic data, we obtained RMSE and MBE values of 0.28 $mm.day^{-1}$ and -0.07 $mm.day^{-1}$, respectively. For ET_o estimates calculated when both relative humidity and wind speed data are missing, we find relative low RMSE and MBE values of 0.37 $mm.day^{-1}$ and -0.06 $mm.day^{-1}$, which indicate that the estimations of ET_o using observed R_s, e_a computed from T_{min}, and u_2 from average values performed very well.

These findings were expected for missing humidity data since under humid conditions there is a high probability to $T_{dew} = T_{min}$ (Allen et al. 1998). Allen *et al.* (1998) also suggest using a wind speed value of 2 $m.s^{-1}$ when wind speed data are not available, however, 93% of data from measurements showed wind speed values below 2 $m.s^{-1}$. Since wind speed for Cerrado conditions does not vary greatly throughout the year, it is possible to use a constant value of wind speed for estimating ET_o.

Our results indicate that wind speed and relative humidity and their variations throughout the year have a small effect on ET_o estimates. Investments in accurate air temperature sensors instead of investments in relative humidity probes would be a good option to estimate RH when the budget is limited. Also, use a constant value of u_2 is also viable to estimate ET_o.

The methods without observed radiation data (Fig. 5a, b, e, f, g, h, j, and k) showed the lowest values of r, i.e., the model results do not indicate a good linear correlation with reference data, when comparing ET_o using FAO-PM method. However, when the benchmark values are close to the average ET_o value, those results with estimated

radiation were similar to ET_o with full data. In addition, ET_o computed with estimates of R_s showed higher RMSE and MBE values than ET_o computed when only wind speed and/or relative humidity are the missing variables. ET_o calculated using radiation data computed with calibrated parameters presented better results than ET_o results with R_s estimates using regression constants recommended by Allen et al. (1998).

When radiation values were considered as missing climatic data, it is possible to observe overestimated ET_o when the benchmark values are low. Since the Penman-Monteith model (Equation 1) uses $R_n - G$ as the radiation data input and Allen et al. (1998) suggests $G \approx 0$ on a daily basis when there are no G measurements, we compared R_n estimates from Equation 12 with observed $R_n - G$ values. Fig. 6 presents different linear regressions about R_n and e_a estimates from Equation 13 when relative humidity data are missing. Fig. 7 shows RMSE and MBE values for the linear regressions of Fig. 6, classified by seasons. R_n estimates did not present negative values and overestimated net radiation values during the dry season when negative observed R_n and $R_n - G$ were found.

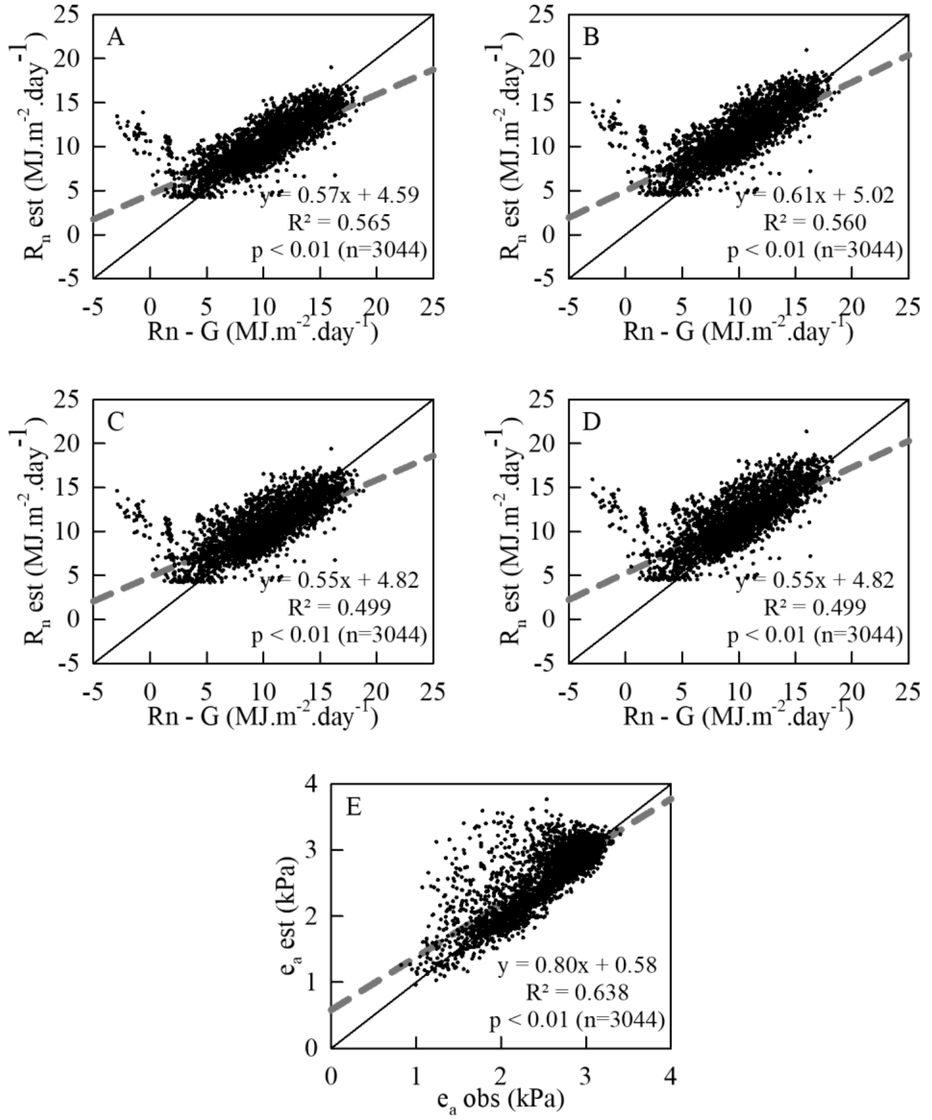

Fig. 6 Linear regressions of a) R_n estimates using calibrated parameters and real e_a; b) R_n estimates using recommended parameters and real e_a; c) R_n estimates using calibrated parameters and estimated e_a; and d) R_n estimates using recommended parameters and estimated e_a, in comparison with real values of R_n – G; and e) a.linear regression of estimated e_a versus observed values. The central line represents a 1:1 correlation and the dashed line represents the linear regression through the origin

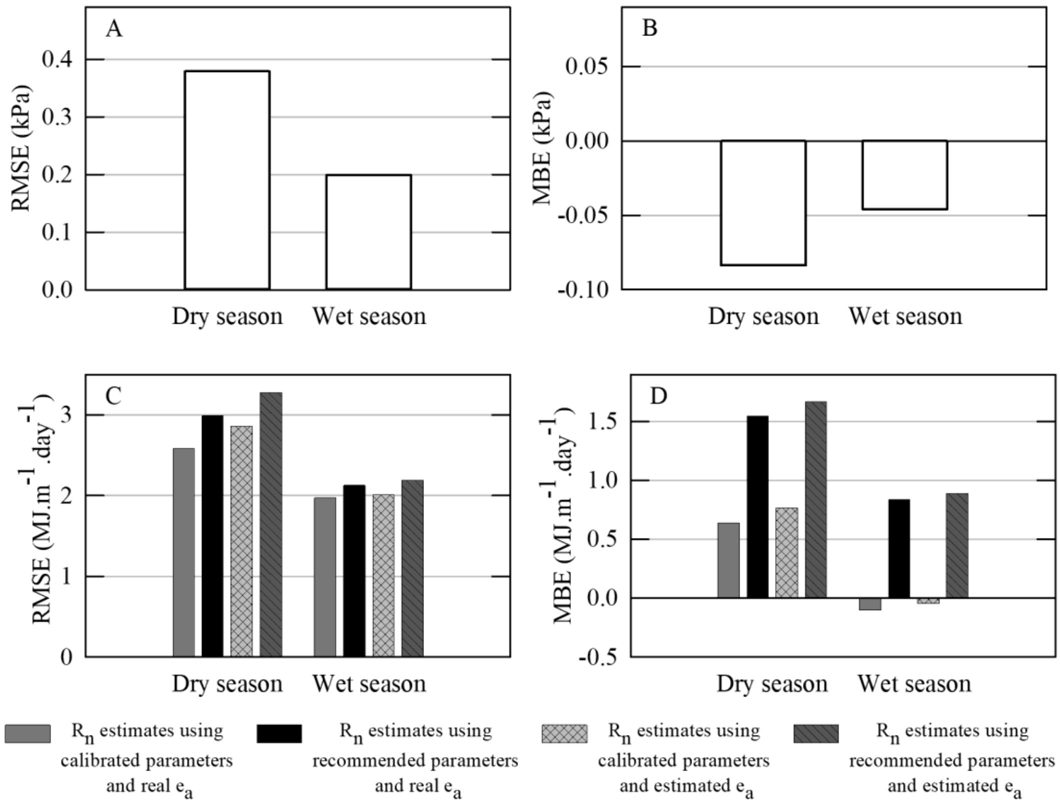

Fig. 7 a) Root Mean Square Error (RMSE) and b) Mean Bias Error (MBE) of estimated e_a versus real e_a; and c) Root Mean Square Error (RMSE) and d) Mean Bias Error (MBE) of estimated R_n.in comparison with measured R_n – G. The legend of colors and patterns are the same for both graphs c and d.

R_n estimates (Fig. 6a, b, c, and d) presented similar results; however, the errors regarding net radiation (Fig. 7c and d) had different behaviors between values computed from R_s with calibrated and recommended parameters. R_n using calibrated parameters presented lower absolute MBE values, especially during the wet season when both real relative humidity have smaller daily variations (Fig. 2c) and e_a estimates presented lower errors (Fig. 7a and b) than the dry season. ET_o computed when radiation data is missing also does not consider G; therefore, the suggestion given by Allen et al. (1998) to consider daily G ≈ 0 may not be suitable for our study area conditions.

Our findings for ET_o when R_s is missing presented unsuitable results when compared to those found with estimated wind speed and/or relative humidity, especially during the dry season when R_n values are above the average. Different studies (Trnka et al. 2005; Aladenola and Madramootoo 2014; Jahani et al. 2017) observed good results for R_s estimates using Equation 3. However, there is a lack of studies about solar radiation estimates in Brazilian Cerrado, therefore, more research is needed to find a better model to estimate solar and net radiation. Different results using estimated R_s were found by several authors (Popova et al. 2006; Cai et al. 2007; Jabloun and Sahli 2008; Córdova et al. 2015; Djaman et al. 2016; Paredes et al. 2018). Those studies were made in different regions of the world, however, ET_o estimates when R_s is the limited data performed better than our results.

The daily ET_o values computed from the Hargreaves-Samani model (Fig. 5l) showed the worst correlation between estimated and reference values. The RMSE and MBE values were 1.56 $mm.day^{-1}$ and 1.29 $mm.day^{-1}$. Thus, the Hargreaves-Samani equation is not adequate to estimate ET_o in Cerrado conditions. Despite our results, for different climatic conditions, especially arid regions, the Hargreaves-Samani and other temperature-based ET_o methods may present suitable results (Todorovic et al. 2013; Raziei and Pereira 2013a, b; Almorox et al. 2018). There are many different models to estimate ET_o, however, FAO does not recommend any other equation besides Penman-Monteith and Hargreaves-Samani models.

4 Conclusion

The FAO Penman-Monteith equation is the most adequate for calculating average daily ET_o. The use of this method is restricted to the availability of meteorological data. Several procedures to estimate ET_o were outlined by Allen et al. (1998), and we investigated the Penman-Monteith method performance in a grass-dominated Cerrado when climatic data are limited. We used ET_o computed with full data set of micrometeorological measurements as reference data and tested the Penman-Monteith method when climatic data are missing, considering radiation, wind speed, and relative air humidity as missing climatic data.

We noted better results for ET_o calculated with estimated relative humidity and wind speed. Using average annual wind speed showed excellent results, with an almost perfect linear correlation and the lowest errors. The use of $T_{dew} = T_{min}$ proved to be a great alternative to estimate ET_o when RH data are missing, especially during the wet season.

ET_o computed with solar radiation estimates performed worse than estimates when the other variables are missing. R_n estimates could not compute negative values and $G \approx 0$ may not be appropriate for the *campo sujo* Cerrado conditions. ET_o estimates are not suitable when solar radiation data are missing. Hargreaves-Samani method does not show good results when compared to the other methods and overestimates ET_o.

The results presented here can help us better understand which meteorological data have the largest impact on ET_o estimates of regions with similar characteristics to the study area. Thus, improvements and investments in solar radiation measurements would provide more adequate ET_o estimates and a better understanding of crop water demands. We also recommend such a study every five years in the same area, due to climate change and human activities in the study area.

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Declarations

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Conflicts of interest/Competing interests

The authors declare they have no conflicts of interest.

Availability of data and material

Available if required.

Code availability

Not applicable.

Authors' contribution

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Luiz Claudio Galvão do Valle Júnior and Thiago Rangel Rodrigues. The first draft of the manuscript was written by Luiz Claudio

Galvão do Valle Júnior and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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