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 (ET₀) plays a big role in water resources management for irrigation agriculture. The Penman-Monteith (PM) is one of the most accepted models for ET₀ estimation, but it requires many inputs that are not commonly available. Therefore, assessing the FAO guidelines to compute ET₀ 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. ET₀ 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 ET₀ estimates and correlation coefficient (r) and Willmott’s index of agreement (d) values close to 1.0. When radiation data were missing, computed ET₀ 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 Rn. Therefore, we can infer that radiation data have the largest impact on ET₀ 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 (ETc) from reference evapotranspiration (ET₀) (Doorenbos and Pruitt 1977). Water demands and ETc 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).

ET₀ 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” ET₀ 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, ET₀ can be computed from weather data, and climatic parameters are the only factors that affect ET₀ 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 ET₀. Those different methods have been tested in distinct regions and climates (Tabari et al. 2013; Bourletskis 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 ET₀ 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 ET₀ under high relative humidity conditions, and underestimate under conditions of high wind speed (Allen et al. 1998). FAO also recommends the Pan evaporation (E_p) method, which is related to ET₀ 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 ET₀ 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\textsubscript{o} (Mehdizadeh et al. 2017; Karimi et al. 2017; Mattar 2018; Ferreira et al. 2019; Valle Júnior et al. 2020) and E\textsubscript{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\textsubscript{o} is obtained with missing climatic data. Knowing which meteorological data have the largest impact on ET\textsubscript{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\textsubscript{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 missing

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.

$$ET_o = \frac{0.408 \Delta (R_n - G) + \frac{900}{(T_a + 273)^2} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34 u_2)}$$  \hspace{1cm} (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 ($^\circ$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), $\gamma$ is the psychrometric constant (kPa.$^\circ$C$^{-1}$), and $\Delta$ is the slope of water vapor pressure curve (kPa.$^\circ$C$^{-1}$). We used Equation 2 (Allen et al. 1998) to convert $u$ to $u_2$.

$$u_2 = u_z \frac{4.87}{\ln(67.8z - 5.42)}$$  \hspace{1cm} (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.

$$R_s = (a_s + b \frac{n}{N}) R_a$$  \hspace{1cm} (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.

\[
R_a = \frac{24(60)}{\pi} G_{sc} d_r [\omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s)]
\]  (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, \( \omega_s \) is the sunset hour angle (rad), \( \varphi \) is the latitude of the meteorological station (rad), and \( \delta \) is the solar decimation (rad). The values of \( d_r \) and \( \delta \) were computed using Equations 5 and 6.

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

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

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

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

\( N \) was estimated using Equation 8.

\[
N = \frac{24}{\pi} \omega_s
\]  (8)

where \( N \) is the maximum possible duration of daylight hours (h), and \( \omega_s \) 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 \( R_n \) from \( R_s \) (Equation 11).

\[
R_{so} = (a_s + b_s)R_a
\]  (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\(^{-1}\)).

\[
R_{ns} = (1 - \alpha)R_s
\]  (10)
where $R_{ns}$ is the net shortwave radiation (MJ·m$^{-2}$·day$^{-1}$), $\alpha$ is the albedo, which is 0.23 for the hypothetical grass reference crop, and $R_s$ is the solar radiation (MJ·m$^{-2}$·day$^{-1}$)

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

where $R_{nl}$ is the net longwave radiation (MJ·m$^{-2}$·day$^{-1}$), $\sigma$ is the Stefan-Boltzmann constant of $4.903 \times 10^{-9}$ MJ·K$^{-4}$·m$^{-2}$·day$^{-1}$, $T_{\text{max},K}$ is the maximum absolute temperature during the 24-hour period (K), $T_{\text{min},K}$ 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.

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

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 $a_s$ and $b_s$ 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 $G \approx 0$.

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

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

where $e_a$ is the actual water vapor pressure (kPa), and $T_{\text{min}}$ is the minimum temperature ($^\circ$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,

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

| 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); $c_s$ (Eq. 13) |
2.6 Performance evaluation

We compared each result obtained from the calculations with the ET₀ 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).

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

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

\[
 RMSE = \sqrt{\frac{\sum_{i=1}^{n} (O_i - P_i)^2}{n}} \quad (17)
\]

\[
 MBE = \frac{\sum_{i=1}^{n} (P_i - O_i)}{n} \quad (18)
\]

where \(P_i\) is the estimate value of the \(i\)th day (mm.day⁻¹), \(O_i\) is the observed value of the \(i\)th 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$^{-2}.\text{day}^{-1}$, 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); 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$_{\text{o}}$ calculated using the Penman-Monteith method with observed meteorological data. The average ET$_{\text{o}}$ computed ($\pm$sd) was 3.49 ± 1.13 mm.day$^{-1}$. Higher ET$_{\text{o}}$ values were observed during the wet season (November to March). When compared to the meteorological variables in Fig. 2, ET$_{\text{o}}$ estimates behaved similarly to $R_n$ values. Valle Júnior et al. (2020) pointed out that ET$_{\text{o}}$ models based on $R_n$ perform better than different methods based on other variables for the *campo sujo* Cerrado conditions.
Boxplots showing daily ET\textsubscript{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\textsubscript{o} estimates with limited climatic data

For ET\textsubscript{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\textsuperscript{-1}, respectively. Table 2 summarizes the statistical analyses and Fig. 5 shows the difference between the RMSE and MBE values found.
Fig. 4 ET₀ 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 ET₀ estimated with full data set (ET₀ 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\textsubscript{o} computed from full data set and estimates of ET\textsubscript{o} with missing climatic data

| Method               | \(d\) | \(r\) | RMSE (mm.day\textsuperscript{-1}) | MBE (mm.day\textsuperscript{-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\textsubscript{o} using estimates of 1) Rs-a; 2) Rs-b; 3) RH; 4) WS; 5) Rs-a and RH; 6) Rs-b and RH;
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 \(\text{ET}_o\) 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 \(\text{ET}_o\) using observed \(R_s\), \(e_a\) computed from \(T_{\text{min}}\), 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 \(T_{\text{dew}} = T_{\text{min}}\) (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 \(\text{ET}_o\).

Our results indicate that wind speed and relative humidity and their variations throughout the year have a small effect on \(\text{ET}_o\) 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 \(\text{ET}_o\).

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 \(\text{ET}_o\) using FAO-PM method. However, when the benchmark values are close to the average \(\text{ET}_o\) value, those results with estimated
radiation were similar to ET₀ with full data. In addition, ET₀ computed with estimates of
Rs showed higher RMSE and MBE values than ET₀ computed when only wind speed
and/or relative humidity are the missing variables. ET₀ calculated using radiation data
computed with calibrated parameters presented better results than ET₀ results with Rs
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 ET₀ when the benchmark values are low. Since the Penman-
Monteith model (Equation 1) uses Rn – G as the radiation data input and Allen et al.
(1998) suggests G ≈ 0 on a daily basis when there are no G measurements, we compared
Rn estimates from Equation 12 with observed Rn – G values. Fig. 6 presents different
linear regressions about Rn and ea 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. Rn estimates did not present negative values and overestimated
net radiation values during the dry season when negative observed Rn and Rn – 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 $\approx 0$ may not be suitable for our study area conditions.
Our findings for ET$_o$ when Rs is missing presented unsuitable results when compared to those found with estimated wind speed and/or relative humidity, especially during the dry season when Rs values are above the average. Different studies (Trnka et al. 2005; Aladenola and Madramootoo 2014; Jahani et al. 2017) observed good results for Rs 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 Rs 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 Rs 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\textsubscript{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\textsubscript{dew} = T\textsubscript{min} proved to be a great alternative to estimate ET\textsubscript{o} when RH data are missing, especially during the wet season.

ET\textsubscript{o} computed with solar radiation estimates performed worse than estimates when the other variables are missing. R\textsubscript{n} estimates could not compute negative values and G \approx 0 may not be appropriate for the campo sujo Cerrado conditions. ET\textsubscript{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\textsubscript{o}.

The results presented here can help us better understand which meteorological data have the largest impact on ET\textsubscript{o} estimates of regions with similar characteristics to the study area. Thus, improvements and investments in solar radiation measurements would provide more adequate ET\textsubscript{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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