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 pivotal 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. In this study, 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 the 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 highest impact on ET_o for our study area and also regions with similar conditions and FAO guidelines are not suitable when radiation data are missing.

Keywords: reference evapotranspiration, FAO Penman-Monteith, limited data, Cerrado.

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 crops (Giambelluca et al., 2009; Nóbrega et al., 2018; P. T. S. Oliveira et al., 2014; Rodrigues et al., 2014; 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 & Pruitt, 1977). Water demands and ET_c are important considerations to improve water use efficiency in agriculture (Allen, 1996; Dong et al., 2020; Droogers & Allen, 2002; Hargreaves, 1994; She et al., 2017; Tyagi et al., 2000).

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 & Allen, 2002; Martins et al., 2017; Sharifi & Dinpashoh, 2014), 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 & Criddle, 1950; Hargreaves & Samani, 1985; Jensen & Haise, 1963; Priestley & Taylor, 1972) have reported different methods to compute ET_o. Those different methods have been tested in distinct regions and climates (Bourletsikas et al., 2017; Shafieiyoun et al., 2020; Shiri, 2019; Tabari et al., 2013; Valle Júnior et al., 2020; Zhang et al., 2018); 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 (Dinpashoh et al., 2011; Droogers & Allen, 2002; Gong et al., 2006).

For daily calculation, FAO-PM method meteorological inputs are the maximum and minimum temperatures, relative air humidity, solar radiation, and wind speed. Allen et al., (1998) suggested using the Hargreaves-Samani (HS) method (Hargreaves & 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 tends 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 is neither measure of net radiation or estimates of regional solar radiation. Several studies have evaluated the use of FAO-PM method procedures to estimate ET_o when solar radiation, wind speed, and relative humidity data are missing (Čadro et al., 2017; Djaman, Irmak, Asce, et al., 2016; Jabloun & Sahli, 2008; Popova et al., 2006; Raziei & Pereira, 2013a, 2013b; Todorovic et al., 2013), however, results vary according to the climatic conditions. Recent studies have used machine learning models to estimate ET_o (Ferreira et al., 2019; Karimi et al., 2017; Mattar, 2018; Mehdizadeh et al., 2017; Salam & Islam, 2020; Valle Júnior et al., 2020) and E_{pan} (Kisi, 2015; Wang, Kisi, Hu, et al., 2017; Wang, Kisi, Zounemat-Kermani, et al., 2017) with limited weather data. Though, few studies have reported the effects of meteorological data variability on reference evapotranspiration in the Cerrado region. However, no studies are addressing missing climatic data for estimating ETo in a Brazilian tropical savanna.

Therefore, this research intends to close this gap in the literature. It is important to evaluate the performance of the procedures and recommendations when ET_o is obtained using missing climatic data. Knowing which meteorological data have the highest 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 prime objective of this study was to assess the guidelines provided by FAO to estimate ET_o when meteorological data are limited for a grass-mixed Cerrado region and discuss the impact of each climatic variable on the estimates. The outcomes of this work will provide a scientific and practical database and information to the water resource managers, irrigation engineers, and other professionals in this vital region.

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, Vourlitis, et al., 2016). 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 (Rodrigues et al., 2014; Vourlitis & da Rocha, 2011). The study area is on flat terrain at an altitude of 157 m above sea level.

[Insert Figure 1]

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.

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

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.

$$u_2=u_z\frac{4.87}{\ln\left(67.8\,z-5.42\right)} \quad (2)$$

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.

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

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.

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

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.

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

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

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.

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

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 4.903×10^{-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 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.

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

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

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

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).

[Insert Table 1]

2.5 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).

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

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

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

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

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 ($mm.day^{-1}$), $\overline{P}$ is the mean of estimated values ($mm.day^{-1}$), $\overline{O}$ 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

3.1 Micrometeorological conditions

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; Rodrigues, Curado, et al., 2016). 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.

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 the 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 $m.s^{-1}$. Net radiation (Fig. 2d) was higher during the wet season than the dry season. 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.

[Insert Figure 2]

Fig. 3 shows monthly mean ET_o calculated using the Penman-Monteith method with observed meteorological data. The average ET_o computed ($\pm$sd) was 3.49 ± 1.13 $mm.day^{-1}$. Higher ET_o values were observed during the wet season (November to March).

[Insert Figure 3]

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.

[Insert Figure 4]

[Insert Table 2]

[Insert Figure 5]

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.

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.

[Insert Figure 6]

[Insert Figure 7]

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.

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.

4. DISCUSSION

4.1 Seasonal variation in micrometeorological condition

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). We found relatively large daily wind speed variation, due to the sporadic nature of the wind in the study area (Rodrigues, Vourlitis, et al., 2016). 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.

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).

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). 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.

4.2 Evaluation of FAO guidelines to estimate ET_o

Our 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). Several locations presented similar results with e_a estimated from minimum temperature (Djaman, Irmak, Kabenge, et al., 2016; Jabloun & Sahli, 2008; Popova et al., 2006). Sentelhas et al. (2010) reported R^2 from 0.76 to 0.96 when compared ET_o computed with actual vapor pressure computed from T_{min}. This method may not be suitable to estimate ET_o in humid climates since there are overestimation in VPD values (Allen et al., 1998; Córdova et al., 2015).

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. Sun et al. (2020) found similar results regarding the impact of wind speed on ET_o in a mountainous region in China. Similar results were found by Popova et al. (2006) and Córdova et al. (2015), with the RMSE and MBE values near to 0 when $u_2 = 2$ $m.s^{-1}$. Djaman, Irmak, Kabenge, et al. (2016) presented unsuitable FAO-PM performances in dry conditions when wind speed was considered as 2 $m.s^{-1}$; however, using daily average wind speed in the same conditions, the results presented MBE values between -0.05 to 0.04.

Our outcomes 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.

Our results 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 (Aladenola & Madramootoo, 2014; Jahani et al., 2017; Trnka et al., 2005) 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 (Cai et al., 2007; Córdova et al., 2015; Djaman, Irmak, Asce, et al., 2016; Jabloun & Sahli, 2008; Paredes et al., 2018; Popova et al., 2006; Salam et al., 2020). 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. ET_o presented a strong correlation with solar radiation in several different locations (Bourletsikas et al., 2017; R. G. de Oliveira et al., 2021; Jhajharia et al., 2012; Shiri, 2019). Despite our results for the HG method, for different climatic conditions, especially arid regions, the Hargreaves-Samani and other temperature-based ET_o methods may present suitable results (Almorox et al., 2018; Raziei & Pereira, 2013a, 2013b; Todorovic et al., 2013). There are many different models to estimate ET_o, however, FAO does not recommend any other equation besides Penman-Monteith and Hargreaves-Samani models. However, the quality control of dataset utilized for ETo computation with the FAO-PM, or the HS equation is vital for the precision of estimates. Therefore, quality control of site and weather dataset is certainly needed; as it is essential the appraisal of the quality of satellite-based and reanalysis datasets when applied to compute FAO-PM. Future studies along this line are needed. The data-driven model in this vital agricultural region can also be used for estimating ETo in future studies. The outcome obtained from our study can be seasonal climate-sensitive. This deserves also further examination. The main implication of this study is that the availability of precise models and datasets for quantifying ET_o is significant for agricultural managers and irrigation engineers in a region with the similar climatic condition.

5. CONCLUSIONS

Overarching goal of our study is to 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. Since the Cerrado is the main agricultural region in Brazil, our results could lead to new studies regarding algorithms and alternatives to estimate solar and net radiation in similar weather conditions. 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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DATA AVAILABILITY

Data will be available upon request from the corresponding author.

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Table 1 Summary of ET_o calculations with missing climatic data

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

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

Figure 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

Figure 3 Boxplots showing daily ETo 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

Figure 4 ETo 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 ETo estimated with full data set (ETo FAO-PM). The central line represents a 1:1 correlation and the dashed line represents the linear regression through the origin

Figure 5 a) Root Mean Square Error (RMSE) and b)Mean Bias Error (MBE) of computed ETo 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

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

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