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REFERENCE EVAPOTRANSPIRATION IN THE MUNICIPALITY OF INHAMBANE, MOZAMBIQUE: EMPIRICAL METHODS AND SUPPORT VECTOR MACHINE

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ABSTRACT: Reference evapotranspiration (ETo) is useful for calculating crops water demand and irrigation scheduling. Thus, eleven empirical methods for ETo estimation (four based on temperature, three on mass transfer and fouron solar radiation) and sixteen onSupport Vector Machine models: SVM (eight with the Radial Basic Kernel function: RBFK and eight with the Kernel polynomial: PK) were evaluated against the Penman Montheith FAO 56 method (PM FAO 56) based on the following statistical indicators: MBE (Mean Bias Error), RMSE (Root Mean Square Error), R^2 and t test. The RMSE was used as the main selection criterea of methods/models. Monthly meteorological data of Inhambane Municipality (maximum, minimum and average temperature: T, relative humidity: RH, wind speed and sunshine hour: n), from 1985 to 2009 were used. The results showed the following classification: RBFK7 = PK7> PK7> PK6> PK6> RBFK8 = PK8> Makm> PK3> Turc = RBFK3> RBFK1 = RBFK5 = PK5> BenL = RBFK4 = 24> Ham> Lin> Pen> Mah> Wmo. The RBFK7 (MBE = 0.26 mm d^{-1}, RMSE = 0.36 mm d^{-1} and R^2 = 0.96) and PK7 (MBE = 0.26 mm d^{-1}, RMSE = 0.36 mm d^{-1} and R^2 = 0.96) models require the measurement of T, RH and n. In the absence of n, which is common, the PK3 (MBE = -0.02 mm d^{-1}, RMSE = 0.42 mm d^{-1} and R^2 = 0.83) and RBFK1 (MBE = -0.01 mm d^{-1}, RMSE = 0.52 mm d^{-1} and R^2 = 0.74) models can be used as alternatives, which require T and RH data; and T, respectively. Contrary to SVM, the empirical methods were statistically different from the PM FAO 56 methodat 5% significance level.

Kewords: *Evapotranspiration, Empirical methods, SVM.*

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INTRODUTION

The current challenges that the Inhambane province faces regarding on the food prices rising and food demand lead to the need of increasing agricultural areas. In Inhambane province, arid to semi-arid climates are predominate, with erratic rainfall and weak distributed throughout the year, however, agricultural activity should be done using irrigation. According to Braz-Tangerino et al. (2014), irrigation consumes the largest amount of fresh water on planet earth. Thus, irrigation needs to be done rationally and sustainably, which can be achieved by improving irrigation efficiency.

According to Chatzithomas and Alexandris (2015), irrigation efficiency can be improved through accurate knowledge of reference evapotranspiration (ETo), which is used for irrigation depth calculation, agricultural activity planning and irrigation system design. According to Allen et al. (998), ETo expresses the amount of water demanded as vapor into the atmosphere under standard conditions: with 23% of refection rate; surface resistance 70 m s^{-1}; hypothetical 0.12 m crop, total soil surface coverageunder full growth and active conditions; and with adequate water supply. ETo can be obtained using several methods, among which those that use climate data are most used. Among these methods, Penman Monteith FAO 56 (PM FAO 56) is considered standard by Allen et al. (1998) for being more accurate in even though, its use is limited, as it involves complex calculations and requires a number of weather variables, some not available at various weather stations, especially solar radiation.

Thus, other simpler climatic methods called empirical were developed. Empirical methods can be divided into methods based on solar radiation, air temperature, mass transfer, water balance and combined methods. According to Valipour et al. (2017), mass transfer methods have produced poor performance compared to others. These authors conducted their research under different climatic conditions in Iran (arid, semi-arid, Mediterranean and super humid climates). Solar radiation methods have outperformed temperature methods, however, contradictory results have been reported in the literature. For example, Ologhadien and Nwaogazie (2017) found in Nigeria's equatorial climate that Hansen's modified Makkink radiation method (1984) outperformed the Hargreaves-Samani (HS) temperature method. In addition, in China's semi-arid climate, the Penman (1963) radiation method outperformed the performance of the HS, Hamon, Blaney-Criddle, and McCloud temperature methods (LIU et al., 2017). In the same study, the HS method outperformed Makkink's original method. In another study by Shiri et al. (2014), the HS method outperformed the Makkink, Turc and Priestley-Taylor radiation methods. These results show that although empirical methods are an alternative to PM FAO 56, their performance varies with the conditions at each location, so a careful choice must be made.

The reported performance variability has led researchers to find other alternatives. Lately, the literature has been highlighting the Artificial Neural Networks (RNAs) and Support Vector Machine (SVM). SVM has been reported as a great tool for modeling nonlinear processes such as ETo. According to Vapnik (1995), SVM is quite robust, conferring its potentiality in modeling complex processes. Moreover, the use of kernel functions confers SVM success, once transform complex processes into linear ones, besides adjusting the parameters of each function to the conditions of the study site. The most reported kernel functions in the literature are: Radial Basic, polynomial, sigmoidal, and linear. Studies on ETo conducted by several authors have shown that SVM outperformed RNAs and empirical methods (WEN et al., 2015; TANGUNE & ESCOBEDO, 2018).

This work aims to evaluate the performance of eleven empirical methods (four temperature, three mass transfer and four solar radiation) and sixteen SVM models (eight with the Kernel Radial Basic function and eight with the Kernel polynomial) . All methods were evaluated against the PM FAO 56 method using weather data from Inhambane Municipality, Mozambique. It is noteworthy that this research is relevant to the study site, once no such works are found, consequently contributing to the water economy, increased production and agricultural productivity.

MATERIALSAND METHODS

Characterization of Inhambane Municipality

The Municipality of Inhambane is located in the long narrow coastal of Inhambane Province, Southern Mozambique, with the following geographical coordinates: latitude 23.87º S and longitude 35.38º E with the elevation 14 m above sea level. The climate tpye of Inhambane province is tropical humid to the coastal strip and tropical dry inland. According to the data used, from 1985 to 2009, the total annualprecipitation is 921.30 mm, total annual evapotranspiration is 1396.52 mm, monthly average temperature and relative humidity of 24ºC and 76%, respectively.

Data collection and process

The monthly meteorological data used (maximum temperature -Tmax; minimum temperature -Tmin; average temperature - T; relative humidity - RH; wind speed - U_2; solar brightness - n), from 1985 to 2009,of Inhambane Municipality recorded by the National Institute of Meteorology of Mozambique. The meteorological data forward 2009 was discarded, due to numerous failures, especially for solar brightness. Additionaly, whenever the data from 1985 to 2009 had some flaws in U_2 and *n*, it was completed. For U_2, an average wind speed of 2 m s^{-1} was assumed to fill the missing values (ALLEN et al., 1998), while for n, the missing value in month was assumed equal to the arithmetic month mean. The monthly averages of meteorological data from 1985 to 2009 are presented in Table 1.

Further, ETo was estimated based on 11 empirical methods (Table 2) and 16 SVM models. The empirical methods were composed by 4 temperature methods, 3 mass transfer methods and 4 solar radiation methods, while SVM was composed by 8 models with the Kernel Radial Basic (RBFK) and 8 Kernel Polynomial (PK) functions.Additionaly, all methods were evaluated in relation to the standard PM FAO 56 method, also presented in Table 2. As this method demands global solar radiation (Rs), it was obtained from Equation 1 recommended by Allen et al. (1988). According to Allen et al. (1998), in places where the values of parameters *a* and *b* of Equation 1 are unknown, they can be assumed equal to 0.25 and 0.50, respectively. Thus, as this issue was observed in Inhambane Municipality,was adopted the methodology and the Rs values computedare presented in Table 1.

$$Rs = (a + b\ n / N)\ Ra \qquad \text{Equation (1)}$$

Where:

Rs - global solar radiation (MJ m^{-2} d^{-1});

Ra - extraterrestrial radiation (MJ m^{-2} d^{-1});

n - solar brightness (h);

N –photoperiod (h);

a - minimum atmospheric transmissivity and;

b - angular coefficient of Ångström.

Table 2 below shows the empirical methods of estimation the ETo used and the standard method of PM FAO 56.

Support Vector Machine (SVM)

The SVM bases on the to use Kernel functions (LIN and YEN, 2009). Thus, this reseach outlined on two SMV kernel functions: Radial Basic function (RBFK) and polynomial function (PK) and Regression Sequential Minimal Optimization algorithm. According to Tabari et al. (2012), the regression in SVM consists on estimating a function from a given set of data: $\{(X_i; Y_i)\}_{i=1}^{\eta}$, where: $X_i \in \Re^{\eta}$:vector that represents Input variables: $X_i \in \{-1; +1\}$: vector representing the output of the data, η: total number of data. It is noteworthy that each kernel function was composed of 8 architectures, as shown in Table 3.

After building of the architectures of each model, the ETo was estimated in the computer program called WEKA (Weikato Envioronment of Knowledge Analyis), which is open access and available at: <http: //www.cs. waikato.ac.nz/~ml/weka/>. In this program, 70% of the data were used for SVM training and 30% for validation. In WEKA it is recommended to adjust the cost (C) and gamma (γ) parameters, having been made using the iterative method, and the combination that generating the best results. Thus was selected the best combination (C = 65 and γ = 0.05). According to Raghavendra and Deka (2014), the parameters C, and γ are dependent and high values of C produce complex learning and low inadequate learning.

Evaluation of Results

The performance of the 27 methods in relation to the PM FAO 56 method was evaluated based on the following statistical indices: Mean Bias Error (MBE), Root Mean Square Error (RMSE), R^2 (coefficient of determination) and t-test. MBE> 0 indicates overestimation and the oppositeunderestimation. The RMSE index was used to skim the methods and shows the accuracy, while R^2 indicates the degree of mathematical fit. The t-test evaluates the significance level of each method. The best methods are those with the following results: MBE≅0; RMSE≅0 and R^2≅1. These indices were obtained from Equations 2; 3 and 4, respectively.

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(ETo_{Est} - ETo_{PMF56}) \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(ETo_{Est} - ETo_{PMF56})^2}{N}} \quad (3)$$

$$R^2 = \frac{\sum_{i=1}^{N}(ETo_{PMF56} - \overline{ETO}_{PMF56})(ETo_{Est} - \overline{ETo_{Est}})}{\sqrt{\sum_{i=1}^{N}(ETo_{PMF56} - \overline{ETO}_{PMF56})^2(ETo_{Est} - \overline{ETo_{Est}})^2}} \qquad 0 \leq R^2 \leq 1 \qquad (4)$$

Where:

ETo_{Est} - values estimated by methods / models (mmd^{-1});

$ETo_{PM\ FAO\ 56}$ - value obtained by the method of PM FAO 56 (mm d^{-1});

N - number of observations;

$\overline{ETo}_{PMFAO56}$-average ETo estimated by the method of PM FAO 56 (mm d^{-1}); and

ETo_{Est}: - average ETo estimated by the evaluated methods (mm d^{-1}).

RESULTS

Empirical methods of ETo estimation

Table 4 shows the performance of empirical ETo estimation methods in Inhambane Municipality. The methods presented in Table 4 showed a significant correlation with the PM FAO 56 method ($p < 0.05$), with R^2 ranging from 0.56 (Wmo method) to 0.98 (Turc, FAO 24 and PT methods). The letters *a* and *b* represent the linear and angular coefficients of the regression line, respectively.

According to Table 4, among the methods based on air temperature, only the BenL method over estimated the ETo obtained by the PM FAO 56 method (MBE = 0.30 mm d^{-1}). This method presented the lowest MBE value, showing the tendency to be the best method, and the worst result was found in the Lin method (MBE = -0.92 mm d^{-1}). All mass transfer methods underestimated the ETo, with the worst result found by the Wmo method (MBE = -1.78 mm d^{-1}). The methods based on solar radiation over estimated the ETo, with worse results found by the FAO 24 method (MBE = 0.75 mm d^{-1}) and the better results found by the Makm method (MBE = 0.26 mm d^{-1}). In general, the radiation methods presented the best results because their MBE values were closer to zero. However, MBE values are not decisive in method selection. Therefore, several methods were penalized based on the RMSE index (LIU et al., 2017; TANGUNE, 2018).

The RMSE values showed that among the temperature-based methods, the BenL method presented the highest accuracy (RMSE = 0.58 mm d^{-1}), and the Lin method presented the highest precision (RMSE = 1.16 mm d^{-1}). In mass transfer methods, the highest precision was observed by the Pen method (RMSE = 1.22 mm d^{-1}) and the lowest by the Wmo method (RMSE = 1.91 mm d^{-1}).

Aditionaly, regarding to Table 4, the solar radiation-based methods, the highest precision was observed by the Makm method (RMSE = 0.36 mm d^{-1}), while the lowest was observed by the FAO 24 method (RMSE = 0.77 mm d^{-1}).More over, in Table 4, is noted that the results of the t-test showed that all methods showed statistically significant differences in the estimation of ETo compared to the PM FAO method 56 at 5% level of significance.

Support Vector Machine (SVM)

Table 5 shows the statistical performance of the two types of SVM (RBFK and PK) in the climatic conditions of Inhambane Municipality. Both RBFK and PK showed a significant correlation with the PM FAO 56 method ($p < 0.05$), with R^2 values ranging from 0.61 to 0.98.

From the MBE index values of Table 5, is observed that both the RBFK and the PK tended not to sub and overestimate the ETo values obtained by the PM FAO 56 method, with MBE≅0. Among the two SVM, the worst results were observed in the RBFK3 model (MBE = 0.11 mm d^{-1}) and in the PK1 model (MBE = -0.18 mm d^{-1}). The models studied used the architectures: T and RH; and T, respectively.

The *t-test* results showed no statistically significant differences between the ETo values estimated by the PM FAO 56 method and by the SVM at 5% significance level (Table 5). Thus, any of the SVM can be used instead of PM FAO 56 method.

The RMSE values, which are decisive for model sellection, showed that in general, for the same input variables, the RBFK presented the same values, with better results (higher accuracy), except for the PK3 model composed of T and RH where the accuracy (RMSE = 0.42 mm d^{-1}) was relatively higher than that of RBFK3 (RMSE = 0.43 mm d^{-1}) and in models RBFK5 and PK5 (composed by T and n), RBFK7 and PK7 (composed by T, RH, n and Ra) and RBFK8 and PK8 (composed by T and Ra) where the precision was equal.

Both, RBFK and PK, the highest accuracy was observed in the RBFK7 and PK7 models (RMSE = 0.12 mm d^{-1}) and the lowest accuracy in the RBFK2 model (RMSE = 0.66 mm d^{-1}) and the PK4 model (RMSE = 0.75 mm d^{-1}). Therefore, the RBFK7 and PK7 models; RBFK6 (RMSE = 0.14 mm d^{-1}) and PK6 (RMSE = 0.15 mm d^{-1}); and RBFK8 and PK8 (RMSE = 0.22 mm d^{-1}) were the 3 best in sequence compared to the other models. Figure 1 shows pearson correlation of input variables used in SVM with the ETo values of the PM FAO method 56.

Comparison of all methods.

For the penalty of all methods the RMSE index was used. The classification of all methods according to the RMSE index is presented in Table 6.

The classification presented in Table 6 shows that the RBFK7 and PK7 models presented the best accuracy among the 27 methods evaluated (RMSE = 0.12 mm d^{-1}), while the Wmo empirical method presented the worst precision (RMSE = 1.91 mm d^{-1}). Additionaly, the Table 6, shows that the Makm empirical method surpassed the accuracy of the SVM composed by the models RBFK1 and PK1; RBFK2 and PK2; RBFK3 and PK3; RBFK4 and PK4; RBFK5 and PK5.

DISCUSSION

Although the results from Table 4 showed that all empirical methods are statistically different from the PM FAO 56 method, the RMSE index, which is decisive for methods sellection, showed that in general radiation-based methods presented good results, when compared to the other methods, especially the Makm method, which is recommended to estimate the ETo in Inhambane Municipality. In addition, the R^2 values in Table 4 showed better mathematical adjustments in solar radiation methods, ranging from 0.96 to 0.98. The success of radiation methods due to the fact that solar radiation is one of the most influential meteorological elements in ETo. Other authors also had the same finding (TABARI et al., 2012; VYAS; SUBBAIAH, 2016; TANGUNE, 2017), corroborating to the results found in this study.

The Makm method was best rated by Ologhadien and Nwaogazie (2017), with the following performance: MBE = -0.35 mm d^{-1}; RSME = 0.75 mm d^{-1} and R^2 = 0.40; while in Senegal (in the Senegal River basin), Djaman et al. (2015) reported that the Makm method presented RMSE values of 2.48 and 5.79 mm d^{-1} in Ndiaye and Fanaye, respectively. All performance presented is inferior to that found in the present study (MBE = 0.26 mm d^{-1}, RMSE = 0.36 mm d^{-1} and R^2 = 0.96), meaning that the parameter adjustment made by Hansen (1984) in Makkink's original method, it is adapted to the climatic conditions of Inhambane Municipality.

Although the Makm method was the best in this study, in practice its use in Mozambique is quite limited because many weather stations do not measure insolation or Rs which is one of the input variables required. Thus, the BenL temperature method, also presented in the Table 4, can be used as an alternative (MBE = 0.30 mm d^{-1}, RMSE = 0.58 mm d^{-1} and R^2 = 0.79), as it requires meteorological elements available in various weather stations (T and RH) and does not involve such high acquisition costs compared to the previous situation.

The performance reported by the BenL method is higher than the average performance obtained by Tangune and Escobedo (2018) in different cities of the state of São Paulo, Brazil, (MBE = -0.74 mm d^{-1}, RMSE = 0.88 mm d^{-1} and R^2 = 0.85), with greater mathematical adjustment. Another underperformance was reported by Gollo et al. (2018): RMSE = 1.10 mm d^{-1} and R^2 = 0.64. These results show a clear tendency of this method to adapt to the conditions of this study site, thus this method, can be used as an alternative to the Makm method. The variability of the performance of the Makm and BenL methods depending on the conditions of each place demand a careful use of these empirical methods, otherwise, there is a risk of supplying irrigation depths below or above the current crops water demand, thereby, lowering agricultural production and productivity and raising the water pumping costs.

The methods based on mass transfer (Pen, Wmo and Mah methods), the RMSE values scorred them as the worst methods, corroborating to the results obtained by Valipour et al. (2017). For these authors, the worst performance of the Pen, Wmo and Mah methods dues to the fact that they present a different concept from the PM FAO 56 method. The Wmo and Mah methods represent the evaporation of an open water surface, while the Pen's method represents the evaporation of an open water surface and on a bare soil.

Similary, the observed tendency of SVM on presentingMBE≅0 values was observed by (TABARI et al., 2012; TANGUNE and ESCOBEDO, 2018), corroborating to the results from Table 5. Regarding to the SVM, RMSE values are corroborating to the ones observed in researchesfrom Tabari et al. (2012) and Wen et al. (2015) reporting the following best precision values: 0.017; 0.15 and 0.26 mm d^{-1}, respectively. Some of these accuracies are lower than those reported in the 3 best models of this research: RBFK7 and PK7; RBFK6 and PK6; and RBFK8 and PK8. This possibly dues to the fact that the input variables used in the first two researches (T, RH, U_2 and Rs) and in the last one (Tmax, Tmin, U_2 and Rs) are different from those used in the above models. The models above scored the first three positions as reported, as they used *Ra* as one of the input variables, which most influences the atmospheric demand, especially in places with little interference of sky coverage (clouds), similarly to Inhambane Municipality. Moreover, Figure 1 shows that *Ra* presented the highest correlation with ETo among the presented variables (r = 0.95).

In Inhambane Municipality, the ETo should be estimated from the RBFK7 (MBE = 0.03 mm d^{-1}, RMSE = 0.12 mm d^{-1} and R^2 = 0.98) and PK7 (MBE = 0.02 mm d^{-1}, RMSE = 0.12 mm d^{-1} and R^2 = 0.98) models. However, in practice it is sometimes not measured at *n* and RH. Thus, under these cases, RBFK8 (MBE = -0.04 mm d^{-1}, RMSE = 0.22 mm d^{-1} and R^2 = 0.96) and PK8 (MBE = -0.05 mm d^{-1}, RMSE = 0.22 mm d^{-1} and R^2 = 0.96) can be used as an alternative as it only requires the measurement of T which is easily measured from various weather stations. The lower performance of the models RBFK8 and PK8 when compared to models RBFK6 and PK6 and RBFK7 and PK7 dues to the fact that they use more input variables. This performance was also observed by Yassin et al. (2016), corroborating to the present research.

Furthermore, when classifying all methods (empirical methods and SVM models), it is observed that the Makm model was better than some models, as shown in Table 6. This illustrates that although the literature has been reporting that SVM produces optimal results in nonlinear process modeling than empirical methods, care must be taken. Thus, the success of the Makm method over some SVM models shows that in addition to *Rs*, parameter setting plays a key role in the performance of the methods, as already mentioned. It is noteworthy that the models RBFK7 and PK7 were the best of the present research. In the absence of *n* or *Rs* data for its use, the PK3 model (RMSE = 0.42 mm d^{-1}) is an alternative among the evaluated models, followed by the RBFK1 model (RMSE = 0.52 mmd^{-1}), which require easily measured meteorological elements: T and RH; and T, respectively.

CONCLUSIONS

Among the 27 reference evapotranspiration estimation methods/evaluated models (11 empirical methods, 16 Support Vector Machine-SVM models), the RBFK7 (RBFK = Radial Basic Kernel Function) and PK7 (PK = Kernel Polynomial) models perfomed Best MBE = 0.26 mm d^{-1}, RMSE = 0.36 mm d^{-1} and R^2 = 0.96; and MBE = 0.26 mm d^{-1},RMSE = 0.36 mm d^{-1} and R^2 = 0.96, respectively. These models require the use of average air temperature values (T), relative air humidity (RH), solar brightness (n), and radiation at the top of the atmosphere;

In the absence of n, PK3 models (MBE = -0.02 mm d^{-1}, RMSE = 0.42 mm d^{-1} and R^2 = 0.83) can be used as an alternative, followed by model RBFK1 (MBE = -0.01 mm d^{-1}, RMSE = 0.52 mm d^{-1} and R^2 = 0.74). These models require T and RH data; and T, respectively;

The Makkink (Makm) empirical solar radiation model, performed better than some SVM models, showing the need for careful SVM selection. Its performance was: MBE = 0.26 mm d^{-1}, RMSE = 0.36 mm d^{-1} and R^2 = 0.96. Unlike SVM, all empirical methods were statistically different from PM FAO 56 method by t-test at 5% significance level.

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Appendix

Table 1: Meterological data of Inhambane Municipality, time serie 1985 - 2009.

Months	Tmax. (ºC)	Tmin. (ºC)	T (ºC)	RH (%)	U_2 (m s^{-1})	n (h)	Rs (MJ m^{-2} d^{-1})
Jan.	31.20	22.56	26.88	75.32	1.77	8.88	23.15
Feb.	31.54	22.90	27.22	75.16	1.76	8.37	23.04
Mar.	30.97	22.40	26.69	76.84	1.61	8.62	21.47
Apr.	29.50	20.28	24.89	76.28	1.72	8.63	18.60
May	27.86	17.89	22.88	78.28	1.55	8.50	15.74
Jun.	26.21	16.11	21.16	78.92	1.55	8.01	13.91
Jul.	25.40	15.48	20.44	78.00	1.66	8.40	14.94
Ago	26.01	16.28	21.15	77.48	1.65	8.70	17.62
Sept.	26.94	18.44	22.69	75.04	1.86	8.24	19.89
Oct.	28.07	19.33	23.70	73.96	1.85	8.33	22.31
Nov	29.29	21.02	25.15	75.40	1.93	8.06	23.14
Dec	30.63	21.88	26.25	75.76	1.87	8.62	24.46
Average	**28.64**	**19.55**	**24.09**	**76.37**	**1.73**	**8.45**	**19.85**

Table 2: empirical estimations methods for ETo.

Method	Reference	Equation	Input variabels
Penman Monteith FAO 56 (PM FAO 56)	Allen *et al*. (1998)	$ETo = \frac{0.408\Delta(Rn - G) + \gamma\frac{900U_2(es - ea)}{T+273}}{\Delta + \gamma(1 + 0.34U_2)}$	T, RH, U_2 and n
Hargreaves-Samani modificado (HST)	Trajkovic (2007)	$ETo = 0.0009384\mathrm{Ra}(Tmax - Tmin)^{0.424}(T + 17.8)$	T, Tmax, Tmin, Ra
Hamon (Ham)	Hamon (1961)	$ETo = 0.55\left(\frac{N}{12}\right)^2\left(\frac{4.95 * exp^{0.062T}}{100}\right) * 2.54$	T
Método de Benevides-Lopez (BenL)	Benevides and Lopez (1970)	$ETo = 1.21 * 10^{\left(\frac{7.5T}{237.5+T}\right)}(1 - 0.01RH) + 0.21T - 0.23$	T andRH
Linacre (Lin)	Linacre (1977)	$ETo = \frac{700\frac{T_m}{(100-\varphi)} + 15(T - T_d)}{(80 - T)}$ $Tm = T + 0.006Z;\ T_d = \frac{116.91 + 237.3Ln(ea)}{16.78 - Ln(ea)}$	T andRH
Penman (Pe)	Penman (1948)	$ETo = (2.625 + 0.713U_2)(es - ea)$	T, U_2 andRH
Wmo	Wmo (1996)	$ETo = (1.298 + 0.934U_2)(es - ea)$	T, U_2 andRH
Mahringer (Mah)	Mahringer (1970)	$ETo = 2.86{U_2}^{0.5}(es - ea)$	T, U_2 andRH
Makkink modeificado (Makm)	Hansen (1984)	$ETo = 0.70\frac{\Delta}{\Delta + \gamma}\frac{R_s}{\lambda}$	T and Rs
Turc (Turc)	Turc (1961)	$\lambda * ETo = \alpha_T 0.013\frac{T}{T + 15}(23.885R_s + 50)$ $T > -10℃;\ \alpha_T \begin{cases} 1 & RH \geq 50\% \\ 1 + \frac{(50 - RH)}{70} & RH < 50\% \end{cases}$	T, RH and Rs
FAO 24 Radiation (FAO 24)	Doorembos and Pruitt (1977)	$ETo = b\frac{\Delta}{\Delta + \gamma}\frac{R_s}{\lambda} - 0,30$ $b = 1.066 - 0.0013HR + 0.045U_2 - 0.0002RH.U_2 - 0.315 * 10^{-4}RH^2 - 0,0011{U_2}^2$	T, RH, $U_2$and Rs

Priestley-Taylor (PT)	Priestley and Taylor (1972)	$ETo = 1.26 \frac{\Delta}{\Delta + \gamma} \frac{R_n - G}{\lambda}$	T and Rn

Where; ETo: reference evapotranspration (mm d^{-1}), Rn : Radiotion balance (MJ m^{-2} d^{-1}), global radiotion (MJ m^{-2} d^{-1}), G: ground heat flux density (MJ m^{-2} d^{-1}), γ: *psychometric constant* (kPa $^{o}C^{-1}$), T: mean air temperature (˚C), Tmax: maximum temperature (˚C), Tmin: minimum temperature (˚C), T_d: dew point temperature, U_2: wind speed at 2 meters height (m s^{-1}), e_s: dry bulb temperature saturation pressure (kPa),e_a: current water vapor pressure (kPa), Δ : slope of the vapor saturation pressure curve (kPa $^{o}C^{-1}$), RH:relative humidit (%), N: photoperiod (h), λ:latent heat of vaporization (MJ m^{-2} d^{-1})

Table 3: input variables considered for SVM.

Items	input variables	Models
01	T	RBFK1 and PK1
02	Tmax and Tmin	RBFK2 and PK2
03	T and RH	RBFK3 and PK3
04	T, RH, Tmax and Tmin	RBFK4 and PK4
05	T and n	RBFK5 and PK5
06	T, n andRa	RBFK6 and PK6
07	T , RH, n and Ra	RBFK7 and PK7
08	T and Ra	RBFK8 and PK8

Table 4: Empirical methods performance for ETo estimatiom, time serie 1985 - 2009.

Tipo	Models	MBE (mm d^{-1})	RMSE (mm d^{-1})	a	b	R^2	Teste t
Models based on temperature	HST	-0.56	0.70	0.51	0.72	0.86	-7.29^{**}
	Ham	-0.71	0.78	-0.01	0.82	0.90	-8.90^{**}
	BenL	0.30	0.58	1.53	0.68	0.79	3.98^{**}
	Lin	-0.92	1.16	1.57	0.36	0.74	-14.13^{**}
Models basel on mass trnsference	Pen	-1.06	1.22	0.54	0.59	0.66	-14.16^{**}
	Wmo	-1.78	1.91	0.23	0.48	0.56	-24.71^{**}
	Mah	-1.21	1.38	0.32	0.61	0.59	-15.73^{**}
Models based on solar radition	Makm	0.26	0.36	0.98	0.81	0.96	3.36^{**}
	Turc	0.33	0.43	1.20	0.78	0.98	4.31^{**}
	FAO 24	0.75	0.77	0.57	1.05	0.98	8.52^{**}
	PT	0.52	0.61	-0.37	1.23	0.98	5.36^{**}
Nota: *** = Significative at 5% of signifcance level and NS = Non significative.**							

Table 5: Statistical performance of SVM, time serie 1985 - 2009.

Tyoe of SVM	Models	MBE (mm d^{-1})	RMSE (mm d^{-1})	a	b	R^2	Teste t
RBFK	RBFK1	-0.01	0.52	1.01	0.75	0.74	-0.01^{NS}
	RBFK2	-0.02	0.66	0.82	0.79	0.62	-0.02^{NS}
	RBFK3	0.11	0.43	0.79	0.83	0.85	0.78^{NS}
	RBFK4	-0.08	0.58	0.44	0.87	0.72	-0.53^{NS}
	RBFK5	0.03	0.52	1.25	0.69	0.76	0.19^{NS}
	RBFK6	-0.01	0.14	-0.15	1.04	0.98	-0.05^{NS}
	RBFK7	0.03	0.12	-0.04	1.02	0.98	0.18^{NS}
	RBFK8	-0.04	0.22	0.09	0.97	0.96	-0.24^{NS}
PK	PK1	-0.18	0.58	0.42	0.85	0.74	-1.15^{NS}
	PK2	0.01	0.69	0.87	0.78	0.61	0.03^{NS}
	PK3	-0.02	0.42	0.79	0.80	0.83	-0.13^{NS}
	PK4	0.04	0.75	0.32	0.93	0.62	0.25^{NS}
	PK5	-0.07	0.52	0.66	0.82	0.76	-0.46^{NS}
	PK6	-0.02	0.15	-0.12	1.03	0.98	-0.11^{NS}
	PK7	0.02	0.12	0.02	1.00	0.98	0.15^{NS}
	PK8	-0.05	0.22	0.17	0.95	0.96	-0.31^{NS}
Note: *** = Significativeat 5% of signifcance leveland NS = Non significative.**							

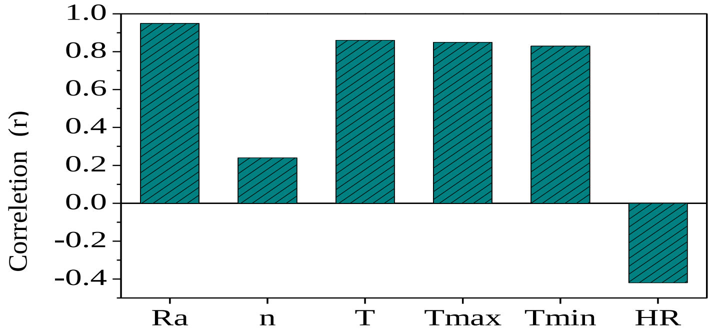

Figure 1:Pearson correlation of the inputs variables with ETo.

Table 6: Methods sellection based on RMSE index.

Position ([a])	Methods/Models	RMSE (mm d^{-1})	Position ([a])	Methods/Models	RMSE (mm d^{-1})
1	RBFK7 and PK7	0.12	11	RBFK2	0.66
2	RBFK6	0.14	12	PK2	0.69
3	PK6	0.15	13	HST	0.70
4	RBFK8 and PK8	0.22	14	PK4	0.75
5	Makm	0.36	15	FAO 24	0.77
6	PK3	0.42	16	Ham	0.78
7	Turc and RBFK3	0.43	17	Lin	1.16
8	RBFK1, RBFK5 and PK5	0.52	18	Pen	1.22
9	BenL, RBFK4 and PK1	0.58	19	Mah	1.38
10	PT	0.61	20	Wmo	1.91

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