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Reference evapotranspiration in São Paulo State: Empirical methods and machine learning techniques

Bartolomeu Félix Tangune[1*] and João Francisco Escobedo[2]

[1]Rural Engineering Departament, Eduardo Mondlane University, Vilankulo, Mozambique.
[2]Rural Engineering Department, FCA/UNESP, Botucatu, São Paulo, Brazil.

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Reference evapotranspiration (ETo) is a key factor for water management and irrigation scheduling. In this paper, eight empirical methods, including four temperature-based (Benevides-Lopez, Hamon, Blaney-Criddle Original and Hargreaves-Samani: HS), four radiation-based (Abtew: AB, Jensen and Haise, Makkink and Irmak) and machine learning techniques (MLT) were tested against Penman Monteith FAO 56 method. The MLT comprised six architectures for artificial neural networks (ANN) as well as support vector machine (SVM). The results of the empirical methods showed that AB method performed best with Mean Bias Error (MBE) = -0.17 mm day^{-1}; Root Mean Square Error (RMSE) = 0.45 mm day^{-1} and R^2 = 0.89. However, in case of missing data of solar radiation (Rs), HS method can be a perfect alternative (MBE = 0.51 mm day^{-1}; RMSE = 0.82 mm day^{-1} and R^2 = 0.87). Afterwards, performance of AB and HS methods was compared to performance resulting from MLT. In MLT, 70% of data was used for training and the remaining 30% was used for validation. The used ANNs were of multilayer perceptron type, with backpropagation algorithm; in support vector machine, Kernel's radial basic function was used with regression sequential minimal optimization algorithm. The results obtained with MLT is as follows: MBE = 0.07 mm day^{-1}; RMSE = 0.20 mm day^{-1}; R^2 = 0.96 for A6 (ANN) and MBE = 0.00 mm day^{-1}; RMSE = 0.18 mm day^{-1}; R^2 = 0.95 for S6 (SVM). A6 and S6 architectures were composed of maximum temperature (T max.), minimum (Tmin.), average temperature (T), extraterrestrial radiation (Ra) and Rs. The HS method was the worst method in terms of performance, while AB method had the best results than A1 and S1, which only used T.

Key words: Evapotranspiration, support vector machine, empirical methods, artificial neural networks.

INTRODUCTION

Reference evapotranspiration (ETo) is the rate of water loss of an hypothetical crop which totally covers the soil, with a height of 0.12 m; it has a fully active and steady growth, with 23% refection rate, 70 m s^{-1} of surface strength and is properly irrigated (Allen et al., 1998). ETo is necessary for an adequate farming activities planning.

Accurate estimation of ETo in irrigated areas improves farming activities planning. Lysimeters are the most

*Corresponding author. E-mail: tanguneb@gmail.com.

commonly applied methods for estimating ETo; however, their use is very limited because a series of meteorological data that are not available in several stations is required (Valipour, 2015). In practice, instead of lysimeters, ETo estimation is based on available climatic data using indirect methods. Among these methods, Penman Monteith FAO 56 (PMF-56) is the recommended method for estimating ETo by Allen et al. (1998). Several authors noted that PMF-56 method performs better compared to any other indirect methods (Subedi et al., 2013; Cao et al., 2015). However, Vicente Serrano et al. (2014) reported that its application is rather limited due to large amount of data required, such as air temperature, relative humidity, wind speed, and solar radiation. These variables are mostly unavailable in various meteorological stations. So, several simpler indirect methods (empirical methods) were developed: Temperature- based methods, solar radiation based-methods and direct evaporation based- methods.

Tabari et al. (2012) observed that temperature-based methods (HS and Blaney- Criddle: BCO) have better performance than solar radiation-based methods (Turc, Makkink: Mak, Jensen- Haise: JensH, Abtew: AB, etc). Other authors reported a better performance of some temperature-based methods compared to solar radiation-based ones in different locations (Vicente Serrano et al., 2014; Ahooghalandari et al., 2016). In contrast, Landeras et al. (2008) observed a better performance of solar radiation-based method of Mak in relation to some temperature-based ones in Northern Spain. On the other hand, higher performance of solar radiation-based method of JensH than temperature- based methods (HS, Hamon, BCO) was reported by Liu et al. (2017) in Northern China. In addition, Xu et al. (2013) reported higher performance of radiation methods than temperature-based ones. Meanwhile, empirical methods performance vary from place to place, thus, their choice should be carefully made.

Performance variation of empirical methods has drawn much interest of continuous studies. Highlights of these are the machine learning techniques (MLT), namely artificial neural networks (ANN), Neuro Fuzzy Systems, Support Vector Machine (SVM), among others. The ANNs are algorithm models, whose principle is similar to biological neurons. They are adequate for non-linear modelling processes such as evapotranspiration (Landeras et al., 2008). Nourani and Fard (2012) applied ANN with different architectures for estimating ETo, whose results suggested higher performance in PMF-56 method than empirical methods. Moreover, Parasuraman et al (2004) confirmed that ANN estimation of ETo is better than the PMF-56. According to Kumar et al. (2011), there are several types of ANN, being the Multilayer Perceptron (MLP) with backpropagation algorithm, which was the most applied with more than 70% of published papers.

Compared to ANN, few SVM studies have been carried out so far. However, the existing ones have noted that SVM is the most efficient in estimating complex processes than ANN. According to Kumar and Kar (2009), SVM is a powerful methodology for solving non-linear problems. To Amari and Wu (1999), SVM performance is strongly dependent on Kernel function, requiring a careful choice of function type to apply. Kisi (2013), assessing the estimation of ETo methods, noted that least square SVM displayed better results than ANN and empirical methods. Studies carried out by Tabari et el. (2013) and Wen et al. (2015) emphasized that SVM performance was higher than ANN, and empirical methods for estimating ETo have also been indicated. Opposing results have also been observed by Tezel and Buyukyildiz (2016). Despite the performance success of ANN and SVM, few studies have been carried out with ETo in Sao Paulo State, particularly using SVM.

The main objective of this paper is to assess the performance of eigth empiral methods (four temperature and four solar radiation-based methods), and compare the efficiency between best empirical method with ANN and SVM, and different input variables (six each), in Sao Paulo State, Brazil. The study was carried out in São Paulo State because there is no similar stadies developed, and ETo studies are very important to find a best alternative for saving water.

MATERIALS AND METHODS

Study area and dataset

Four types of climate can be distinguished in all regions of Sao Paulo State that are part of this study, namely: Savanna tropical climate (Aw), high altitude tropical climate (Cwa), rainny forest tropical climate (Af) and mountain climate (Am) (Table 1). As shown in Table 1, Aw is one of the most prevalent. In Aw climate, the average temperature is over 18ºC in coldest month and the winter is dry with average rainfall of 60 mm in at least in one of the months (Souza et al., 2013).

The dataset used (maximum temperature-Tmax, minimum temperature-Tmin, average- T, UR, U_2 and Rs) were transformed from an hourly scale into a daily scale, using integration criterion for Rs and arithmetic average for other data. Then, estimation of ETo was based on eigth empirical methods: Four methods based on air temperature and the remaining four methods based on solar radiation (Table 2). After that, the best efficiency of temperature and radiation-based methods was compared with the efficiency produced by different architectures of MLT. Both empirical methods and MLT were tested against PMF-56 standard method, as shown in Table 2.

Estimating ETo using ANN and SVM

To employ ANN and SMV, various variables were combined to simulate many estimates of ETo possibilities (Table 3). For simulation, 70% variables were used for trainning while the remaining 30% were used for validation. The WEKA 3.6.13 (Weikato Environment of Knowledge Analysis) program was used to estimate ETo. WEKA is a computing program equipped with data pre-processing, classification, regression, rules of association and visualization tools (Witten at al., 2011).

Table 1. Automatic meteorological stations of São Paulo State.

Code	Station (region)	Latitude degrees)	Longitude (degrees)	Altitude (m)	Period (years)	Climate
A-736	Ariranha	21.01S	48.83E	525	2008 - 2015	Aw
A-725	Avaré	23.00S	48.88E	654	2007 - 2015	Cwa
A-705	Bauru	22.30S	49.70E	550	2005 - 2015	Aw
A-738	Casa Branca	21.77S	47.01E	730	2008 - 2015	Aw
A-708	Franca	20.57S	47.37E	1026	2005 - 2015	Aw
A-737	Ibitinga	21.85S	48.80E	492	2008 - 2015	Aw
A-712	Iguape	24.70S	47.55E	3	2007 - 2015	Af
A-714	Itapeva	23.97S	48.85E	707	2007 - 2015	Cwa
A-733	Jales	20.02S	50.58E	457	2008 - 2015	Aw
A-735	José Bonifácio	21.00S	49.68E	405	2008 - 2015	Aw
A-727	Lins	21.65S	49.73E	459	2007 - 2015	Aw
A-716	Ourinhos	22.95S	49.85E	448	2007 - 2015	Am
A-726	Piracicaba	22.70S	47.62E	574	2007 - 2015	Cwa
A-707	Presidente Prudente	22.01S	51.40E	436	2005 - 2015	Aw
A-718	Rancharia	22.37S	50.97E	350	2007 - 2015	Aw
A-711	São Carlos	21.95S	47.87E	863	2007 - 2015	Cwa
A-740	Luis do Paraitinga	23.22S	45.52E	874	2008 - 2015	Cwa
A-715	São Miguel de Arcanjo	23.85S	48.00E	678	2007 - 2015	Cwa
A-701	São Paulo	23.50S	46.62E	792	2007 - 2015	Cwa
A-728	Taubaté	23.00S	45.52E	571	2007 - 2015	Cwa
A-734	Valparaiso	21.32S	50.92E	374	2007 - 2015	Aw
A-729	Votuporanga	20.40S	49.95E	486	2007 - 2015	Aw

Artificial neural networks (ANN)

There are several numbers of ANN models, but in this study, the MLP with backpropagation algorithm (BP) was used. MLP is most commonly used and it is composed of three interconnected layers, where the first, second and third are called input, middle and output layers, respectively. The middle layer has at least a hidden layer in various neurons where input variables are multiplied by weight given and then lead to the output layer. The MLP basic structure can be expressed from the Equation 1.

$$Yi = \sum_{i=j}^{N} W_{i,j}\, X_{i,j} + \theta_i \quad (1)$$

Where: Y_i is ANN output; $W_{i,j}$ is direct connecting weight from j neuron to i neuron (in hidden layer); $X_{i,j}$ is entry signal from the j neuron (to the entry layer); θ_i is neuron i Bias.

For Huo et al. (2012), in BP algorithm, an activation function of neurons is used to generate the output data. In WEKA the sigmoidal function (Equation (2)) was used considering learning rate = 0.3; momentum = 0.2 and training time = 500. Various hidden layers were tested (1 to 10 layers): the WEKA standard parameter "a" was sellected for having the best results.

$$f(x) = {}^{1}\!/_{[1 + exp(-x)]} \quad (2)$$

Support vector machine (SVM)

In SVM there is the need to use Kernel Functions (Lin and Yeh, 2009). For this study, Kernel radial basic function (RBF) and regression sequential minimal optimization algorithm were used. This algorithm is faster, consumes much less memory and it is less complex. When RBF is used, an appropriate adjustment of parameters should be taken into account C (cost), γ (gamma value) and ε (insensitive loss function and default value of 0.001 was used). According to Raghavendra and Deka (2014), C and γ parameters are dependents and complex and low and inadequate learning are produced from high values of C. In this study, parameters $C = 50$ and $\gamma = 0.04$ were determined by attempt, and the combination that produced the best results was sellected. Meyer et al. (2003) pointed the following values:

$C = 2^{-5}\ to\ 2^{12}$ and $\gamma = 2^{-10}\ to\ 2^{5}$.

Data analysis

Empirical methods and MLT were evaluated against PMF-56 method using the following statistical indicators: MBE (Mean Bias Error), RMSE (Root Mean Square Error) and R^2 (coefficient of determination). MBE < 0 indicates the ETo is underestimated and the opposite indicates that it is overestimated by the method used. RMSE is a measure of the magnitude of error, with the value from 0 (perfect fit) to ∞ (the worst fit). The closer to 1 R^2 is, it indicates the best mathematical adjustment, and it varies from zero to one. MBE, RMSE, R^2 were calculated using the following equations.

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(ETo_{Est} - ETo_{PMF56})^2}{N}} \quad (4)$$

$$R^2 = \frac{\sum_{i=1}^{N}[(ETo_{Est} - \overline{ETo_{Est}})(ETo_{PMF56} - \overline{ETO}_{PMF56})]^2}{\sum_{i=1}^{N}(ETo_{Est} - \overline{ETo_{Est}})\sum_{i}^{N}(ETo_{PMF56} - \overline{ETO}_{PMF56})} \quad (5)$$

Table 2. Empirical methods of estimation of ETo.

Method	Reference	Equation	Parameter
Standard method			
Penman Monteith FAO 56 (PMF56)	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,UR, U_2, Rs
Temperature- based method			
Benevides e Lopez (BenL)	Benevides and Lopez (1970)	$ETo = 1.211x10^{\left(\frac{7.5T}{237.5+T}\right)}(1 - 0.01UR) + 0.21T - 2.3$	T, UR
Hamon (Ham)	Hamon (1961)	$ETo = 0.55\left(\frac{N}{12}\right)^2\left(\frac{4.95exp^{0.062T}}{100}\right)25.4$	T
Blaney Criddle Original (BCO)	Blaney and Criddle (1950)	$ETo = p(0.457T + 8.13)$	T
Hargreaves e Samani (HS)	Hargreaves and Samani (1985)	$ETo = 0.0023x0.408Ra(Tmax - Tmin)^{0.5}(T + 17.8)$	T, Tmax, Tmin, Ra
Solar radiation-based method			
Abtew	Abtew (1966)	$ETo = \frac{0.53}{\lambda}Rs$	T,Rs
Jensen-Haise (JensH)	Jensen and Haise (1963)	$ETo = 0.408Rs(0.0252T + 0.078)$	T,Rs
Makkink (MAK)	Makkink (1957)	$ETo = 0.408x0.61Rs\frac{\Delta}{(\Delta + \gamma)} - 0.12$	T,Rs
Irmak	Irmak et al. (2003)	$ETo = 0.419Rs + 0.079T - 0.611$	T,Rs

ETo, Reference evapotranspiration (mm d^{-1}); Rn, Net radiation balance (MJ m^{-2} d^{-1}); G, Soil heat flux (MJ m^{-2} d^{-1}); γ, Psychometric constant (kPa $^oC^{-1}$); T, Average air temperature (˚C); Tmax, Tmin-maximum and minimum air temperature; U_2, Wind speed at 2 meters high (m s^{-1}); e_s, saturation pressure in dry-bulb temperature (kPa); e_a, Actual pressure (kPa); Δ, Slope of the saturated vapor pressure curve (kPa $^oC^{-1}$); UR, Relative air humidity (%); N, Photoperiod (h); λ, latent heat evaporization (MJ m^{-2} d^{-1}); p, Percentage of annual daylight hours for any day of the year.

Table 3. Architecture of ANN and SVM using at annual and seasonal scale.

Input variable	Architecture
T	A1 and S1
T, Tmax, Tmin and Ra	A2 and S2
T, Tmax, Tmin, Ra and U_2	A3 and S3
T, Tmax, Tmin, Ra and UR	A4 and S4
T and Rs	A5 and S5
T, Tmax, Tmin, Ra and Rs	A6 and S6

A and S corresponding to ANN and SVM, respectively.

Where: ETo_{Est}-values estimated using empirical methods or MLT (mm day^{-1}); $\overline{ETo_{Est}}$- average estimated by empirical method or MLTETo;$_{PMF56}$-value estimated using standard method (mm day^{-1}); $\overline{ETo_{PMF56}}$-average estimated using standard method (mm day^{-1}) and N-estimates number per period.

RESULTS AND DISCUSSION

Temperature- based methods

Statistical performance of temperature- based methods (BenL, Ham, BCO and HS) in estimating ETo regarding standard method PMF 56 in different regions of state of São Paulo are given in Table 4.

As a result, in all regions of Sao Paulo state, BenL, Ham, and BCO methods underestimated ETo values. While HS method overestimated ETo, except in Franca, Jales and Lins (Table 4). It was also observed that BenL and Ham methods showed a maximum values of MBE of -1.10 and -1.46 mm day^{-1}, in Franca respectively. BCO and

Table 4. Estimate of ETo from temperature-based modelling.

Station	Benevides Lopez (BenL)			Hamon (Ham)			Blaney Criddle Original (BCO)			Hargreaves Samani (HS)		
	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2
Ariranha	-0.49	0.76	0.88	-0.78	0.89	0.85	-0.90	1.08	0.86	0.99	1.03	0.94
Avaré	-1.07	1.19	0.81	-1.15	1.25	0.72	-1.15	1.28	0.74	0.30	0.46	0.88
Bauru	-0.50	0.64	0.88	-0.71	0.82	0.76	-0.77	0.89	0.77	0.88	0.95	0.92
Casa Branca	-0.38	0.53	0.85	-0.69	0.84	0.67	-0.75	0.89	0.69	0.86	0.93	0.88
Franca	-1.10	1.17	0.86	-1.46	1.58	0.37	-1.46	1.57	0.42	-0.07	0.57	0.58
Ibitinga	-0.97	1.12	0.86	-1.20	1.30	0.76	-1.29	1.44	0.76	0.59	0.65	0.94
Iguape	-0.29	0.58	0.85	-0.12	0.34	0.90	-0.18	0.55	0.90	0.68	0.73	0.94
Itapeva	-0.99	1.09	0.83	-0.95	1.04	0.81	-0.94	1.07	0.81	0.41	0.52	0.92
Jales	-0.72	0.86	0.88	-1.24	1.45	0.40	-1.61	1.76	0.44	-0.79	1.08	0.42
José Bonifâcio	-0.92	1.08	0.86	-1.36	1.47	0.67	-1.51	1.65	0.69	0.36	0.48	0.90
Lins	-0.72	0.88	0.88	-1.11	1.24	0.71	-1.27	1.41	0.74	-1.27	1.41	0.88
Ourinhos	-0.51	0.65	0.88	-0.65	0.77	0.81	-0.74	0.89	0.83	0.96	1.02	0.92
Piracicaba	-0.87	0.98	0.86	-0.99	1.10	0.74	-1.05	1.18	0.76	0.68	0.73	0.92
Presidente Prudente	-0.33	0.60	0.79	-0.79	0.93	0.72	-0.94	1.09	0.74	0.49	0.59	0.90
Rancharia	-0.59	0.74	0.85	-0.65	0.79	0.79	-0.74	0.91	0.79	1.25	1.28	0.94
São Carlos	-1.01	1.08	0.85	-1.17	1.25	0.71	-1.15	1.25	0.74	1.22	1.31	0.86
São Luis de Piraitinga	-1.01	1.09	0.88	-0.87	0.94	0.85	-0.84	0.96	0.86	0.77	0.80	0.94
São Miguel de Arcanjo	-0.92	1.01	0.85	-0.75	0.83	0.85	-0.74	0.87	0.86	0.74	0.79	0.94
São Paulo	-0.67	0.77	0.85	-0.79	0.87	0.79	-0.80	0.90	0.81	0.41	0.55	0.90
Taubaté	-0.56	0.69	0.85	-0.63	0.76	0.79	-0.68	0.83	0.81	1.01	1.06	0.92
Valparaiso	-0.88	1.04	0.83	-1.27	1.44	0.56	-1.45	1.60	0.59	0.41	0.60	0.83
Votuporanga	-0.76	0.89	0.85	-1.25	1.41	0.50	-1.45	1.58	0.52	0.31	0.56	0.76
Average	-0.74	0.88	0.85	-0.94	1.06	0.72	-1.02	1.17	0.73	0.51	0.82	0.87

HS methods had maximum values of -1.61 and -1.27 mm day^{-1} in Jales and Lins regions, respectively. Regarding the value accuracy of RMSE, BenL method ranged from 0.53 to 1.19 mm day^{-1}, observed in Casa Branca and Avaré regions; and Ham method ranged from 0.34 to 1.58 mm day^{-1} in Iguape and Franca regions; BCO method ranged from 0.55 to 1.76 mm day^{-1} in the regions of Iguape and Jales, and HS method ranged from 0.46 to 1.41 mm day^{-1} in Avaré and Lins regions, respectively. More values of RMSE < 1.0 mm day^{-1} were observed in HS method, showing a greater precision trend.

Compared to BenL (MBE = -0.94 mm day^{-1}; RMSE = 1.06 mm day^{-1} and R^2 = 0.72), Ham (MBE = -0.94 mm day^{-1}; RMSE = 1.06 mm day^{-1} and R^2 = 0.72) and BCO (MBE = -1.02 mm day^{-1}; RMSE = 1.17 mm day^{-1} and R^2 = 0.73), on average, HS method had the best performance in estimating ETo, since it reported lower value of MBE (0.51 mm day^{-1}), lower value of RMSE (0.82 mm day^{-1}) and greater value of R^2 (0.87); it means low overestimate, high accuracy and high mathematical adjustment, respectively (Table 4). The extraterrestrial radiation (Ra) in HS method has justified its best performance, since, apart from temperature, Ra is one of the main energy sources for ETo, whose effect depends on dispersal degree resulting from atmospheric constituents. Lower results in this method have

Table 5. Estimate of ETo from solar radiation- based methods.

Station	Abtew			Jensen Haise			Makkink			Irmak		
	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2
Ariranha	-0.37	0.58	0.86	0.65	1.03	0.85	1.12	1.35	0.85	-0.36	0.54	0.83
Avaré	-0.06	0.23	0.94	0.60	0.78	0.94	1.38	1.45	0.94	-0.32	0.44	0.94
Bauru	-0.09	0.25	0.92	0.77	0.90	0.92	1.35	1.41	0.92	-0.16	0.32	0.92
Casa Branca	-0.23	0.38	0.90	0.58	0.69	0.90	1.17	1.21	0.90	-0.25	0.40	0.88
Franca	-0.25	0.43	0.81	0.56	0.69	0.81	1.38	1.43	0.83	-0.53	0.66	0.81
Ibitinga	-0.04	0.30	0.92	1.05	1.21	0.92	1.65	1.72	0.92	-0.30	0.48	0.92
Iguape	0.26	0.32	0.98	1.00	1.14	0.98	1.49	1.55	0.98	0.25	0.35	0.96
Itapeva	0.06	0.21	0.98	0.61	0.75	0.96	1.42	1.47	0.98	-0.19	0.32	0.96
Jales	-0.88	1.09	0.58	0.89	1.20	0.56	1.05	1.28	0.52	-0.83	1.03	0.50
José Bonifâcio	-0.57	0.77	0.76	0.69	1.10	0.76	1.13	1.35	0.76	-0.68	0.85	0.74
Lins	-0.30	0.50	0.88	0.95	1.10	0.86	1.41	1.48	0.86	-0.43	0.61	0.86
Ourinhos	0.05	0.29	0.96	0.97	1.06	0.96	1.53	1.56	0.96	-0.06	0.32	0.95
Piracicaba	0.00	0.29	0.94	0.87	0.99	0.92	1.54	1.58	0.94	-0.21	0.40	0.92
Presidente Prudente	-0.61	0.66	0.90	0.46	0.74	0.90	0.86	0.98	0.92	-0.51	0.60	0.92
Rancharia	0.03	0.32	0.96	0.9	1.01	0.96	1.46	1.49	0.96	-0.07	0.34	0.94
São Carlos	0.02	0.28	0.92	0.63	0.72	0.92	1.49	1.52	0.92	-0.28	0.42	0.9
São Luis de Piraitinga	0.42	0.47	0.98	0.9	0.98	0.98	1.83	1.86	0.98	0.06	0.26	0.96
São Miguel de Arcanjo	0.33	0.39	0.98	0.86	0.97	0.98	1.68	1.73	0.98	0.05	0.23	0.96
São Paulo	-0.17	0.27	0.98	0.43	0.56	0.96	1.14	1.18	0.96	-0.27	0.36	0.96
Taubaté	-0.13	0.3	0.96	0.57	0.71	0.96	1.19	1.24	0.96	-0.18	0.33	0.92
Valparaiso	-0.59	0.77	0.76	0.68	1.00	0.76	1.09	1.24	0.77	-0.67	0.85	0.77
Votuporanga	-0.55	0.72	0.76	0.82	1.01	0.74	1.22	1.32	0.76	-0.62	0.79	0.74
Average	-0.17	0.45	0.89	0.75	0.92	0.89	1.34	1.43	0.89	-0.30	0.50	0.88

been reported by Melo and Fernandes (2012): RMSE = 1.04 mm day^{-1} and R^2 = 0.77; Tabari et al. (2012): MBE = - 0.851 mm day^{-1} and RMSE = 0.901 mm day^{-1}.

The worst performance of BCO (Table 4) is because the method did not take into account the local coefficient adjustments, which are recommended in the FAO-24 report by Doornbos and Pruitt (1975). The behaviour observed in BCO confirms the results of Tabari et al. (2012).

Solar radiation- based methods

Performance of solar radiation methods (AB, JensH, Mak and Irmak) in estimating ETo, regarding PMF-56 are illustrated in Table 5. ETo was overestimated by both JenH and Mak methods in all regions with a threshold value of MBE of 1.05 mm day^{-1} in Ibitinga and 1.83 mm day^{-1} in São Luís de Piraitinga, respectively. Meanwhile AB and Irmak were verified, showing a differentiated underestimating trend reaching maximum values of -0.88 and -0.83 mm day^{-1} in Jales, respectively. Based on RMSE, AB, JensH, Mak and Irmak methods were observed showing the following values respectively 1.09; 1.21; 1.86 and 1.03 mm day^{-1}. AB and Irmak methods in Jales, JensH in Ibitinga and Mak methods in São Luís de Piraitinga. Maximum values of RMSE of AB and of Irmak are lower than the maximum values of other methods, indicating a trend of

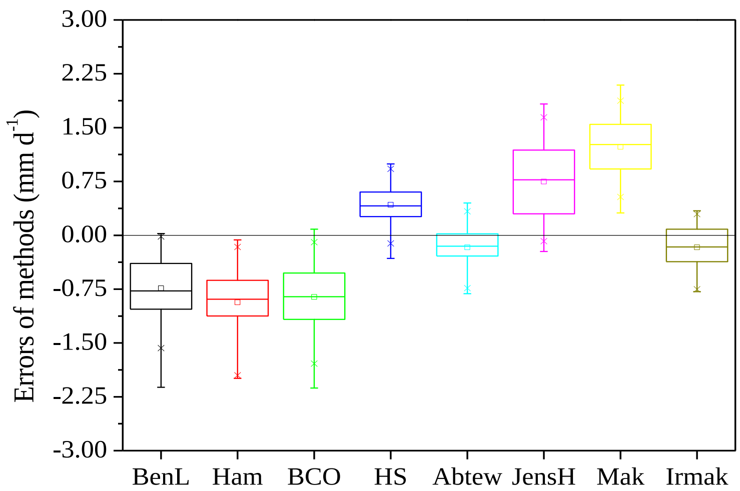

Figure 1. Box plot errors of eight empirical methods.

being more accuracy in estimating ETo.

Overall, AB method had average in lower values of MBE = -0.17 mm day^{-1} and RMSE = 0.45 mm day^{-1}, than those observed in Irmak (MBE = -0.30 mm day^{-1} and RMSE = 0.50 mm day^{-1}), JensH (MBE = 0.75 mm day^{-1} and RMSE = 0.92 mm day^{-1}) and Mak (MBE = 1.34 mm day^{-1} and RMSE = 1.43 mm day^{-1}) methods; this indicates a lower underestimate and high accuracy, respectively. AB method has shown a good mathematical adjustment (R^2 = 0.89) (Table 5). In a different study, there was a high efficiency of this method in various locations (Zhai et al., 2010). In semi-arid of Iran, Tabari (2010) observed that AB method (RMSE = 1.705 mm day^{-1} and R^2 = 0.823) outperformed Irmak efficiency (RMSE = 1.849 mm day^{-1} and R^2 = 0.674) and Mak (RMSE = 2.098 mm day^{-1} and R^2 = 0.715) and had a lower efficiency compared to JensH model (RMSE =1.274 mm day^{-1} and R^2 = 0.734). Moreover, Samaras et al. (2014) reported poorer efficiency of AB than some empirical methods

Selection of the best empirical methods

The box plot illustrates maximum, mean, average and error median produced by empirical methods in São Paulo state (Figure 1). While average value of error is represented by the mark inside the box, maximum and minumum values are indicated by the edges, and median at the central part.

It was noted in Figure 1 that among temperature-based models, HS had the lowest errors (0.43 mm day^{-1}) while BCO had the highest ones (-0.86 mm day^{-1}); for solar radiation- based models, AB had the lowest errors (-0.17 mm day^{-1}) while Mak showed the highest (1.23 mm day^{-1}). Of the models compared, AB is the most trusted method for estimating ETo; it does not only have the lowest error, but also illustrates a narrower box plot, meaning a high accuracy. On other hand, it was observed that all the models underestimated ETo, except HS, JensH and Mak which overestimated ETo, thus confirming the results already presented. Despite its best efficiency, AB practical use can be very limited, since Rs, one of the necessary variables for its application is only measured by few meteorological stations. Therefore, HS model can be a good alternative, as it takes third position (Figure 1), plus the advantage of requiring easily measurable input variables (Tmax,Tmin and T).

The use of Rs in AB model was pointed as one of the crucial reasons for better efficiency than HS. However, it was observed that HS had better performance than JensH and Mak methods, which, like AB method, used Rs as one of the input variables. HS, JensH and Mak methods are suitable for arid and semi-arid conditions, according to Todorovic et al. (2013), Jensen and Haise (1963) and Makkink (1957), respectively, and AB method for humid conditions (Zhai et al., 2010; Samaras et al., 2014). It is revealed, therefore, that besides input variables, climate plays a crucial role in making a very careful choice of empirical models.

Comparison of the performance of MLT against HS and AB methods

MLT is a perfect computing for ETo modelling. So, in Tables 6 and 7 MLT will be compared against the selected best empirical methods (HS e AB) (Tables 4 and 5), respectively

In Tables 6 and 7 it was observed that A1 and A5 displayed an overestimate of ETo trend. In addition, ANN and SVM showed both underestimate and overestimate, and in some regions, showed neither under nor overestimation of ETo (MBE = 0.00 mm day^{-1}). Absolute values were shown in all MLT, MBE < 0.5 mm day^{-1} with

Table 6. Estimate of ETo from MLT (architectures 1, 2 and 3).

Station	A1			S1			A2			S2			A3			S3		
	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2
Ariranha	0.02	0.39	0.88	-0.03	0.37	0.88	0.06	0.24	0.96	0.02	0.23	0.96	-0.07	0.22	0.96	-0.02	0.20	0.96
Avaré	0.48	0.70	0.71	-0.01	0.51	0.69	0.27	0.40	0.90	0.05	0.27	0.92	0.19	0.29	0.94	0.05	0.23	0.94
Bauru	0.41	0.57	0.77	-0.03	0.38	0.77	0.22	0.28	0.96	0.04	0.16	0.96	0.12	0.19	0.96	0.03	0.15	0.96
Casa Branca	0.11	0.44	0.71	-0.01	0.41	0.72	-0.09	0.24	0.92	0.00	0.22	0.92	-0.05	0.16	0.96	-0.02	0.16	0.96
Franca	0.22	0.59	0.52	-0.16	0.59	0.53	0.09	0.32	0.85	-0.68	0.85	0.61	0.11	0.26	0.92	-0.06	0.25	0.90
Ibitinga	0.08	0.54	0.74	0.00	0.52	0.74	-0.07	0.28	0.94	0.00	0.23	0.96	-0.14	0.28	0.94	0.00	0.22	0.96
Iguape	0.22	0.48	0.85	-0.02	0.44	0.83	0.02	0.25	0.94	0.02	0.25	0.94	-0.02	0.25	0.94	0.00	0.24	0.94
Itapeva	0.15	0.46	0.77	-0.01	0.48	0.77	0.00	0.25	0.94	-0.03	0.25	0.94	0.02	0.18	0.96	0.03	0.18	0.96
Jales	0.35	0.60	0.71	-0.12	0.50	0.71	-0.04	0.34	0.86	-0.11	0.37	0.85	-0.03	0.30	0.88	-0.11	0.33	0.88
José Bonifâcio	0.27	0.62	0.72	-0.04	0.54	0.72	-0.15	0.32	0.92	-0.03	0.27	0.94	-0.13	0.27	0.94	-0.04	0.23	0.96
Lins	0.21	0.53	0.77	-0.06	0.48	0.77	0.12	0.30	0.94	0.02	0.24	0.94	0.01	0.20	0.96	-0.01	0.18	0.96
Ourinhos	0.14	0.44	0.83	-0.13	0.44	0.83	0.04	0.24	0.94	0.00	0.24	0.94	0.03	0.21	0.96	0.00	0.22	0.94
Piracicaba	0.25	0.51	0.76	-0.04	0.46	0.76	0.17	0.28	0.94	0.02	0.22	0.94	0.10	0.20	0.96	-0.01	0.17	0.96
Presidente Prudente	0.36	0.60	0.72	0.01	0.48	0.72	0.21	0.29	0.96	0.01	0.20	0.96	0.17	0.23	0.96	-0.03	0.17	0.96
Rancharia	0.20	0.54	0.76	-0.03	0.51	0.76	0.02	0.30	0.92	0.01	0.27	0.92	0.06	0.25	0.94	0.00	0.25	0.94
São Carlos	0.12	0.39	0.81	-0.09	0.37	0.81	0.17	0.30	0.92	-0.02	0.24	0.92	0.12	0.24	0.94	0.00	0.21	0.94
São Luis de Piraitinga	0.09	0.38	0.83	-0.08	0.37	0.85	0.07	0.19	0.96	0.06	0.18	0.96	0.05	0.18	0.96	0.02	0.15	0.98
São Miguel de Arcanjo	0.03	0.39	0.81	-0.04	0.40	0.81	-0.12	0.24	0.96	0.01	0.19	0.96	-0.03	0.18	0.96	0.03	0.18	0.96
São Paulo	0.10	0.39	0.79	-0.01	0.37	0.79	0.00	0.20	0.94	-0.02	0.21	0.94	0.09	0.17	0.96	0.00	0.17	0.96
Taubaté	0.04	0.38	0.83	-0.02	0.40	0.81	0.05	0.24	0.94	0.01	0.22	0.96	0.09	0.23	0.94	-0.02	0.21	0.94
Valparaiso	0.39	0.74	0.62	-0.04	0.62	0.64	0.19	0.40	0.88	0.06	0.36	0.88	0.02	0.22	0.96	-0.02	0.22	0.96
Votuporanga	0.25	0.51	0.76	-0.04	0.46	0.76	0.35	0.48	0.86	-0.01	0.29	0.88	0.10	0.24	0.94	-0.04	0.21	0.94

Input variables: A1 and S1 (T); A2 and S2 (T, Tmax, Tmin, Ra); A3 and S3 (T, Tmax, Tmin, Ra, U_2).

an exception of A5 with MBE = 0.65 mm day^{-1}, in Votuporanga region. In Tables 4 and 5, ETo was overestimated and underestimated by HS and AB that showed that trend in all regions respectively, displaying more values of MBE > 0.5 mm day^{-1} than MLT.

Concerning RMSE and R^2, extreme values of poor efficiency were reported in both ANN and SVM models while using average air temperature as an input variable. The values for ANN ranging from RMSE = 0.38 to 0.74 mm day^{-1}; R^2 = 0.52 to 0.88 mm day^{-1} and for SVM ranging from RMSE = 0.37 to 0.62 mm day^{-1}; R^2 = 0.53 to 0.88 mm day^{-1} (Table 6 and Table 7). In HS and AB methods, values ranged from RMSE = 0.46 to 1.41 mm day^{-1}; R^2 = 0.42 to 0.94 mm day^{-1} and from RMSE = 0.21 to 1.09 mm day^{-1}; R^2 = 0.58 to 0.98 mm day^{-1}, respectively (Table 4 and Table 5).

In average, it was observed that ETo was underestimated by HS and ANN in state of São Paulo. HS method presented value of MBE = 0.51 mm day^{-1} and ANN with highest values in A1 (MBE = 0.20 mm day^{-1}) and in A5 (MBE = 0.22 mm day^{-1}), with poor estimates compared to HS. While AB (MBE= -0.17 mm day^{-1}) and SVM (MBE = -0.05 mm day^{-1} in S1 and S5) underestimated ETo. S1 and S5 represented highest values observed. Consequently, SVM had lowest underestimate of ETo (Figure 2).

Based on RMSE rate shown in Figure 2, AB

Table 7. Estimate of ETo from MLT (architectures 4; 5 and 6).

Station	A4			S4			A5			S5			A6			S6		
	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2	MBE	RMSE	R^2
Ariranha	0.07	0.23	0.96	0.01	0.19	0.96	0.22	0.42	0.88	-0.04	0.33	0.90	0.09	0.19	0.98	-0.01	0.18	0.98
Avaré	0.13	0.26	0.94	0.07	0.22	0.94	0.24	0.31	0.96	0.00	0.20	0.96	0.22	0.28	0.96	0.02	0.17	0.96
Bauru	0.10	0.19	0.96	0.02	0.14	0.96	0.42	0.47	0.92	-0.08	0.22	0.94	0.21	0.25	0.98	0.01	0.11	0.98
Casa Branca	0.10	0.19	0.96	0.00	0.31	0.85	0.15	0.28	0.90	-0.08	0.27	0.90	0.01	0.20	0.94	-0.05	0.21	0.94
Franca	-0.15	0.25	0.94	0.02	0.20	0.94	0.27	0.40	0.85	-0.10	0.33	0.85	0.21	0.29	0.94	-0.06	0.25	0.90
Ibitinga	-0.08	0.25	0.94	0.01	0.20	0.96	0.23	0.34	0.94	-0.03	0.25	0.94	-0.01	0.13	0.98	0.06	0.59	0.69
Iguape	-0.02	0.25	0.96	-0.03	0.24	0.96	0.05	0.13	0.98	0.01	0.12	0.98	0.03	0.08	1.00	0.00	0.05	1.00
Itapeva	0.00	0.18	0.96	0.02	0.17	0.96	0.17	0.23	0.98	0.00	0.14	0.98	0.09	0.14	0.98	-0.02	0.12	0.98
Jales	0.06	0.25	0.92	0.01	0.22	0.94	0.36	0.61	0.71	-0.24	0.57	0.67	0.03	0.32	0.88	-0.05	0.34	0.86
José Bonifâcio	-0.03	0.24	0.94	-0.04	0.22	0.96	0.29	0.56	0.79	-0.08	0.51	0.77	-0.09	0.28	0.94	0.00	0.24	0.94
Lins	-0.03	0.23	0.96	-0.02	0.20	0.96	0.31	0.45	0.90	-0.07	0.32	0.90	0.12	0.22	0.96	0.12	0.18	0.96
Ourinhos	0.00	0.21	0.96	0.00	0.21	0.96	0.14	0.21	0.98	0.03	0.17	0.98	0.08	0.12	1.00	0.01	0.08	1.00
Piracicaba	0.03	0.19	0.96	0.00	0.17	0.96	0.40	0.45	0.94	-0.03	0.20	0.96	0.10	0.21	0.96	0.01	0.19	0.96
Presidente Prudente	0.08	0.17	0.98	0.00	0.16	0.98	0.18	0.29	0.94	-0.08	0.23	0.94	0.09	0.17	0.98	-0.01	0.15	0.98
Rancharia	0.05	0.25	0.94	0.01	0.23	0.94	0.07	0.20	0.96	0.02	0.19	0.96	0.01	0.13	0.98	0.00	0.13	0.98
São Carlos	0.01	0.18	0.96	-0.01	0.17	0.96	0.27	0.35	0.94	-0.05	0.22	0.94	0.13	0.19	0.98	0.00	0.12	0.98
São Luis de Piraitinga	0.09	0.19	0.98	-0.01	0.15	0.98	0.11	0.16	0.98	0.00	0.12	0.98	-0.03	0.07	1.00	0.00	0.06	1.00
São Miguel de Arcanjo	-0.07	0.18	0.96	0.01	0.15	0.98	0.03	0.13	0.98	-0.02	0.13	0.98	-0.06	0.12	0.98	-0.01	0.10	0.98
São Paulo	0.03	0.16	0.96	0.01	0.15	0.96	0.06	0.16	0.96	-0.02	0.15	0.96	-0.02	0.13	0.98	0.01	0.11	0.98
Taubaté	0.11	0.26	0.94	-0.01	0.23	0.94	-0.01	0.19	0.96	-0.01	0.18	0.96	-0.09	0.13	0.98	0.00	0.10	0.98
Valparaiso	0.10	0.25	0.96	0.06	0.21	0.96	0.20	0.51	0.79	-0.08	0.46	0.81	0.16	0.36	0.90	0.00	0.32	0.90
Votuporanga	0.05	0.22	0.94	-0.01	0.19	0.96	0.65	0.77	0.77	-0.18	0.46	0.77	0.28	0.39	0.90	-0.01	0.26	0.90

Input variables: A4 and S4 (T, Tmax, Tmin, Ra, UR); A5 and S5 (T, Rs); A6 and S6 (T, Tmax, Tmin, Ra, Rs).

method had higher accuracy (RMSE = 0.45 mm day^{-1}) than HS (RMSE = 0.82 mm day^{-1}), A1 (RMSE = 0.51 mm day^{-1}) and S1 (RMSE = 0.46 mm day^{-1}). For A1 and S1, AB high accuracy can be explained for having used more input variables (T and Rs), since combining those variables in MLT, high accuracy was obtained (A5: RMSE = 0.35 mm day^{-1} and S5: RMSE = 0.26 mm day^{-1}). The increase of MLT performance by increasing the number of input variables has been reported in other papers (Huo et al., 2012; Wen et al., 2015; Traore et al., 2016), confirming the results here presented. Although AB method had been more accurate for A1 and S1, MBE value was the highest. However, it was considered good for being close to zero. It is noted that all MLT had good mathematical adjustment though A1 (R^2 = 0.76) and S1 (R^2 = 0.76) had shown low values compared to HS (R^2 = 0.87) and AB (R^2 = 0.89) methods.

Comparing MLT to the same number of input variables, in average SVM performance was the best (Figure 3, Table 6 and Table 7). SVM trend shows better results than ANN for the same architecture observed in various studies (Kisi, 2013; Wen at al., 2015). According to Tabari et al. (2013), SVM is more suitable for modelling complex phenomena than ANN, since more optimized solutions are sought.

Combined architectures A6 (MBE = 0.07 mm

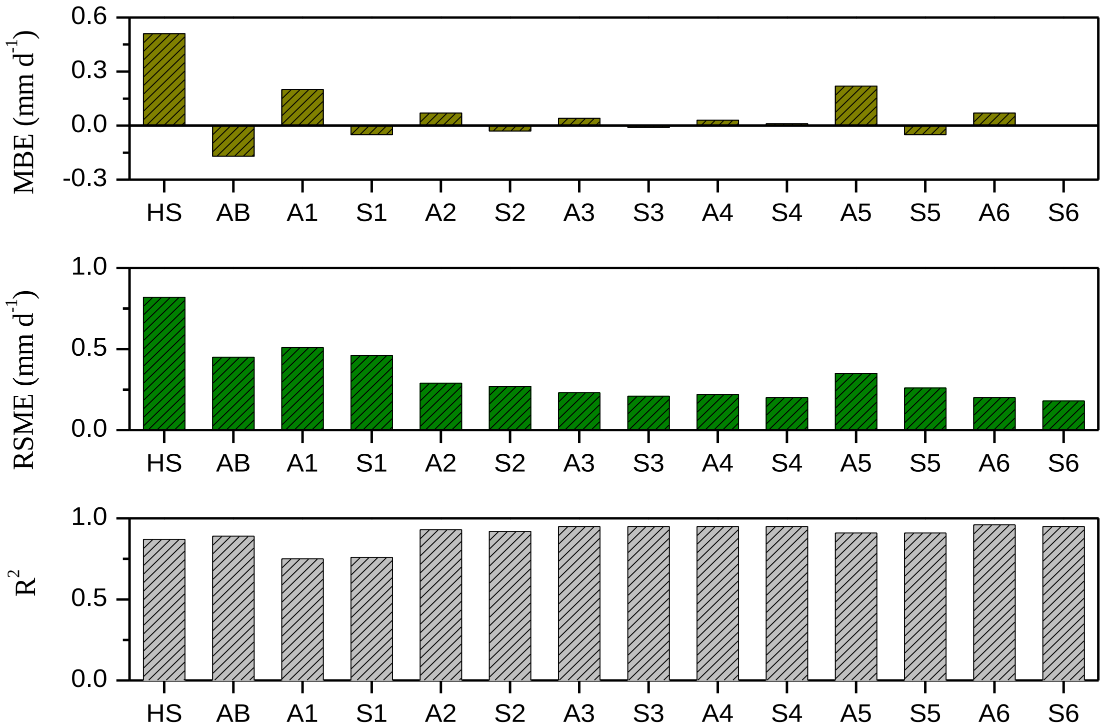

Figure 2. Average performance of ANN and SVM.

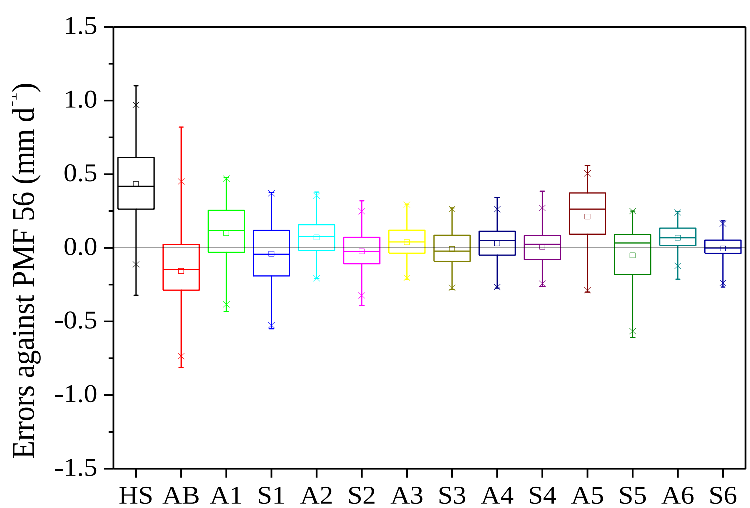

Figure 3. Error of the twelve methods Box plots.

day^{-1}; RMSE = 0.20 mm day^{-1} and R^2 = 0.96) and S6 (MBE = 0.00 mm day^{-1}; RMSE = 0.18 mm day^{-1} and R^2 = 0.95) had highest results (Figure 2). Higher performance of A6 and S6 over A1, S1, A2, S2, A5 and S5 was due to the use of more input variables. A3, S3, A4 and S4 had same number of input variables used in A6 and S6, whose difference in U_2 was in A3, S3 and UR used in A4, S4 in lieu of Rs used in A6 and S6. Hence, best performance is explained by Rs used in A6 and S6, since it is one of the ETo influential elements.

A6 and S6 had lower average error and narrow boxes (Figure 3). It is a confirmation of trend that ETo is neither underestimated nor overestimated (MBE$\cong 0.00\ mm\ d^{-1}$) and high accuracy reported through RMSE rate, being that S6 is more accurate than A6. The remaining methods displayed wider boxes, making them lesser reliable than

A6 and S6; narrower box is farther to zero value. HS method had worst results. While AB method has better accuracy than A1 and S1, validating reported results.

Conclusion

Comparison of empirical methods of temperature- based (Benevides– Lopez: BenL, Hamon: Ham, Blaney- Criddle Original: BCO and Hargreaves- Samani: HS) with those of solar radiation- based (Abtew: AB, Jensen- Haise: JensH, Makkink: Mak and Irmak) revealed that AB performed best (MBE = -0.17 mm day^{-1}; RMSE = 0.45 mm day^{-1} and R^2 = 0.89) and the worst was observed in Mak (MBE = 1.34 mm day^{-1}; RMSE = 1.43 mm day^{-1} and R^2 = 0.89) methods. Despite of AB reaviling best performance, its practical usage is limited because not all meteorological stations measure Rs, which is one of the input method variables. Hence it was found that, in absence of Rs, HS method can be an alternative (MBE = 0.51 mm day^{-1}; RMSE = 0.82 mm day^{-1} and R^2 = 0.87), which requires measuring Tmax, Tmin and T.

Comparing AB and HS with MLT comprising six architectures for artificial neural networks (ANN: A1, A2, A3, A4, A5, A6) and support vector machine (SVM: S1, S2, S3, S4, S5, S6), it was concluded that: HS remained the worst method while AB showed high performance in A1 (MBE = 0.20 mm day^{-1}; RMSE = 0.51 mm day^{-1} and R^2 = 0.76) and S1(MBE = -0.05 mm day^{-1}; RMSE = 0.46 mm day^{-1} and R^2 = 0.76) architectures, which only used T. Having same variables required in AB method, MLT of A5 (MBE = 0.22 mm day^{-1}; RMSE = 0.35 mm day^{-1} and R^2 = 0.91) and S5 (MBE = -0.05 mm day^{-1}; RMSE = 0.26 mm day^{-1} and R^2 = 0.91) is suitable. In the event of combining Tmax, Tmin, T, Ra and Rs, A6 (MBE = 0.07 mm day^{-1}; RMSE = 0.20 mm day^{-1} and R^2 = 0.96) and S6 (MBE = 0.00 mm day^{-1}; RMSE = 0.18 mm day^{-1} and R^2 = 0.95) are advisable. These architectures showed highest performance in this study.

Finally, an increase in number of input variables in MLT improved its efficiency with SVM trend showing better results than ANN in same architecture. The tendency of SVM presenting best results shows that it is better for sustainable use of water in São Paulo, among all evaluated methods. In different conditions of São Paulo, it is necessary to carry out further research, because perfomance of SVM models depends on the behavior of the data and size of the database used.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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