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Assessment of Climatological Variables for Daily Evapotranspiration Modelling Using Artificial Neural Networks: Case Study on Brazilian State of Santa Catarina

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ABSTRACT

The Penman-Monteith's equation is known as the most precise and used estimation of evapotranspiration method. The estimation of reference evapotranspiration (ETo) is essential for public administration of water resources in order to attend the necessary demands over water use. However, this equation needs several climatological variables data which are not always available, particularly to a developing country such as Brazil. For that reason, the study aimed to evaluate the performance of an Artificial Neural Network (ANN) method called Multi-Layer Perceptron (MLP) on the estimation of ETo using different inputs of climatological variables and assess the key variables to this estimation. This research used a four years' time series, with average (Tmean), maximum (Tmax) and minimum (Tmin) air temperature, maximum (RHmax) and minimum (RHmin) relative humidity, global solar radiation (GR) and wind speed (WS), combined in 13 treatments of input vectors. The performance of the models varied from R^2 0.523 and RMSE of 34% (RHmax and RHmin model) to R^2 0.924 and RMSE of 4.6% (Tmax, Tmin, RHmax, RHmin, GR and WS model). Hence, the MLP neural networks obtained satisfactory results on the ETo estimation. The key variables for ETo estimation using MLP neural networks were, in order of importance, the global radiation, temperature, relative humidity and wind speed.

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INTRODUCTION

The knowledge of evapotranspiration is of utmost importance in activities related to watershed management, hydrological and meteorological modeling, and mainly for irrigation of agricultural crops (Bezerra *et al*., 2008). The reference evapotranspiration (ETo) express the atmosphere evaporation power at one specific location and time of the year. It considers only the climatic parameters (FAO-56), thus not taking into account the crop characteristics and soil factors (Allen *et al*. 1998).

There are several methods to estimate ETo, such as direct measurements using lysimeters and indirect inferences using water balance and empirical equations, where the Penman-Monteith (PM) equation is the most recommended (Tucci, 2005).

However, the evapotranspiration estimative has been an obstacle in project management and planning due to the difficulty in obtaining meteorological data required for its determination, mainly because of the high financial cost of data acquisition. One alternative to estimate ETo is the application of Artificial Neural Networks (ANN), which are mathematical models whose architecture and operation are inspired by networks of biological neurons, being suitable for modeling nonlinear processes, such as the ETo (Haykin, 2001).

Several studies have been using ANNs and climatological data to estimate evapotranspiration, where the most applied architecture was the Multi-Layer Perceptron (MLP) (Zanetti *et al*., 2008; Wang *et al*. 2008; Rahimikhoob, 2010; Alves Sobrinho *et al*., 2011; Huo *et al*., 2012). Zanetti *et al*. (2008) applied MLP to estimate daily ETo using PM as a reference for training. The MLP model presented R^2 ranging from 0.61 to 0.84 in the modelling process, where the input vectors were constituted of variables

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from 17 meteorological stations, such as: latitude, longitude, altitude, average air temperature, temperature range and sequential day of the year. Wang *et al*. (2008) applied a MLP model to estimate ETo using series of maximum temperature of vectors and minimum air and extraterrestrial radiation, and obtained R^2 between 0.84 and 0.98. Rahimikhoob (2010) used MLP to estimate the daily ETo, where the training was conducted using the maximum temperature and minimum variables air and extraterrestrial radiation. The model presented R^2 between 0.90 and 0.93. Alves Sobrinho *et al*. (2011) applied MLP to estimate ETo using average temperature, maximum and minimum air as input vectors and the ETo obtained by the PM equation as reference. The performance was satisfactory with root mean square (RMS) between 0.166 to 0.496 $mm.d^{-1}$. Huo *et al*. (2012) used MLP to determine the monthly ETo using eight input vectors combinations with variables obtained from three meteorological stations, such as: average maximum temperature variables and monthly air minimal, relative humidity, wind speed and duration of sunshine hours. The model obtained R^2 from 0.43 to 0.99, and it was observed variations in the estimation between seasons.

Although these studies have achieved satisfactory results, there is still a lack of information about the performance of ETo modelling using ANN in Brazil and, in general, in relation to what are the key variables for the modelling process. The present study was motivated by the possibility of finding models using less input variables and produce better results. Thus, the study aimed to determine the key variables for modeling reference evapotranspiration using the Multi-Layer Perceptron method and climatological variables.

MATERIALS AND METHODS

Study area:

The study was performed over the area that comprehends the EPAGRI/INMET weather station from Lages city, Santa Catarina state, Brazil (27º08'S, 50°34' W, 937 m altitude) (Figure 1). The climate of the region is subtropical with average temperature around 16 °C and average annual rainfall around 1400 mm. The native vegetation is composed of Araucária forest and grasslands.

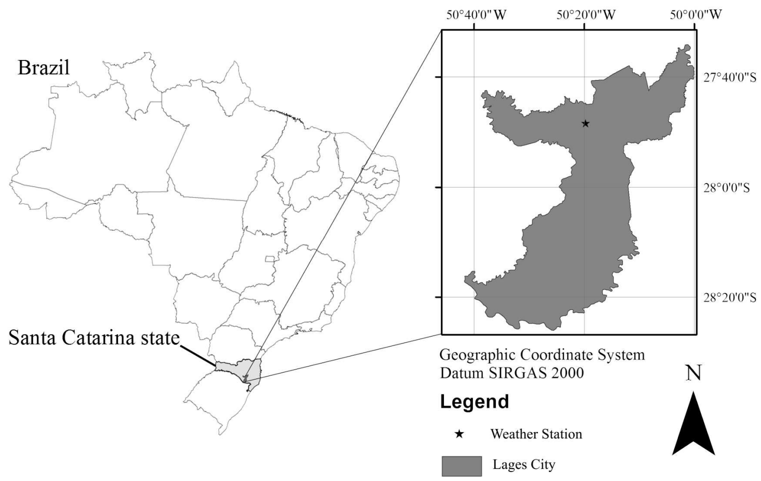

Fig. 1: Study area comprehending the EPAGRI/INMET weather station from Lages city, Santa Catarina state, Brazil.

Climatic Variables:

The data used on the study was obtained for the time span of 01 January 2002 to 31 December 2005 from the weather station. It were obtained climatic variables to calculate the daily ETo by the classic Penman Monteith (PM) equation (Allen *et al*., 1998), described in Eq. 1, and also to compose input vectors on the modelling process. The calculated ETo was used as a reference for assessment of MLP modelling performance.

$$ETo = \frac{0{,}408s(Rn-G) + \frac{y900WS(e_s - e_a)}{T+273}}{s + y(1+0{,}34WS)} \quad (1)$$

where, ETo = reference evapotranspiration ($mm.dia^{-1}$); S = slope of the vapor pressure curve in air temperature (kPa $ºC^{-1}$); Rn = net total daily radiation ($MJ\ M^{-2}\ d^{-1}$); G = heat flow in soil ($MJ\ M^{-2}\ d^{-1}$); Y = psychrometric constant (0.063 kPa $ºC^{-1}$); WS = wind speed at 2 m height ($m\ s^{-1}$); Es = saturation vapor pressure (kPa); Ea = vapor partial pressure (kPa); and T = average air temperature (°C).

The variables obtained for modelling purposes were minimum (Tmin) and maximum (Tmax) temperature, minimum (RHmin) and maximum (RHmax) relative humidity, global solar radiation (GR) and wind speed at 2 m height (WS). The GR variables was selected rather than the number of hours of sunshine due to be best represent the amount of energy that effectively reaches the earth's surface, which is necessary for the evaporation process to occur.

Exploratory Analysis:

In order to identify key variables in evapotranspiration estimative, it was conducted a correlation analysis on each variable (autocorrelation) and between variables and ETo (cross-correlation), using the autocorrelation function (ACF). It was calculated a 95% confidence interval for the mean on each analysis and applied a lag time of 10 days. These analyzes allowed us to evaluate the relationship between one or more variables in relation to a shift in time.

Modelling daily ETo using neural networks:

The climatological data were divided into three sample subsets, such as training (50%), validation (25%) and test (25%), which subset corresponded to a period of time. The input data were normalized following the standard normal distribution, in which the average and standard deviation are equal to 0 and 1, respectively. This normalization process contributes to the optimization of the modeling process (Fu, 1994).

It was applied the Multi-Layer Perceptron (MLP) ANN architecture, implemented in Neural Network Toolbox of Matlab 2014a, for modelling the ETo. It was used the learning algorithm Levenberg-Marquardt (Hagan and Menhaj, 1994), sigmoidal tangent activation function and the learning rate was set at 0.01. The architecture of the MLP consisted of three layers, as follows: (i) the input layer, where the number of neurons was equal to the number of input variables; (ii) hidden layer, in which processing occurs, where the number of neurons ranged around a satisfactory number specific to each treatment; (iii) the output layer, consisting of a single neuron related to ETo.

The calculation of the satisfactory number of neurons in the hidden layer was done following the relationship of 10 times more training equations than the number of weights (Heath, 2010). An iterative training process was conducted varying the number of neurons in the hidden layer around the calculated number of neurons, between -5 and +5 neurons. It was also tested ten random initializations of the starting synaptic weights during the training phase.

The number of neurons in the input layer of the MLP varied accordingly to the number of variables used on each of the 14 treatments. The treatments consisted of the variables: 1) Tmax, Tmin; 2) Tmax, Tmin, WS; 3) Tmax, Tmin, GR; 4) Tmax, Tmin, RHmax, RHmin; 5) Tmax, Tmin, RHmax, RHmin, GR; 6) Tmax, Tmin, RHmax, RHmin, WS; 7) RHmax, RHmin; 8) RHmax, RHmin, GR; 9) RHmax, RHmin, WS; 10) Tmax, Tmin, RHmax, RHmin, GR, WS; 11) Tmax, Tmin, GR, WS; 12) Tmean; 13) Tmax; 14) GR.

In order to prevent over adjustment of the MLP, a monitoring procedure was conducted during the training process in order to assess when to interrupt the training. Hence, the network performance was monitored by the comparison between simulated ETo and observed ETo of the validation subset. In the end of the training process, the performance of the modelling was assessed using the independent test subset.

The performance was evaluated using the coefficient of determination (R^2) and normalized root mean square (RMSE%) statistics. The R^2 varies between 0 and 1, wherein a value of 1 represents a perfect model adjustment, while the value 0 indicates the opposite. The RMSE% consist is a representation of the percent of variation on the measurements around the mean error and can be used to model comparison. The adjustment of the models was tested for statistical significance ($p <0.01$).

RESULTS AND DISCUSSION

Exploratory Analysis:

The maximum and minimum temperature and global radiation variables presented strong temporal autocorrelation (Figure 2 A-C). On the other hand, relative humidity and wind speed presented weak temporal autocorrelation (Figure 2 D-F). This indicates that the air temperature and global radiation are more associated to past values than the other variables. The observed behavior of air temperature variable is explained by the fact that it is controlled by seasonal factors such as the seasons and the length of day, and factors that do not vary on a time scale such as latitude, altitude and continental influence (Tucci, 2005).

The solar radiation varies according to the latitude and the time of day, which also suggest a seasonality effect. Thus, the radiation and temperature variables tend not to vary significantly between two consecutive days, except when there is a sudden arrival of a cold or warm air mass. The RH and WS variables are more influenced by the movement of air masses and the amount of rainfall. Therefore, these variables may inherit the high temporal variability of rainfall (Tucci, 2005).

ETo presented strong and statistically significant ACF for the whole analysed lag time (Figure 2G). Besides the high ACF values in the whole analysed period (ACF = 0.6), the maximum ACF was achived on one day lag (ACF = 0.78). As previously mentioned, the ETo is directly influenced by air temperature, relative humidity, wind speed and global radiation. This strong temporal autocorrelation of ETo indicates a strong influence of the seasonal variables as the global radiation and air temperature.

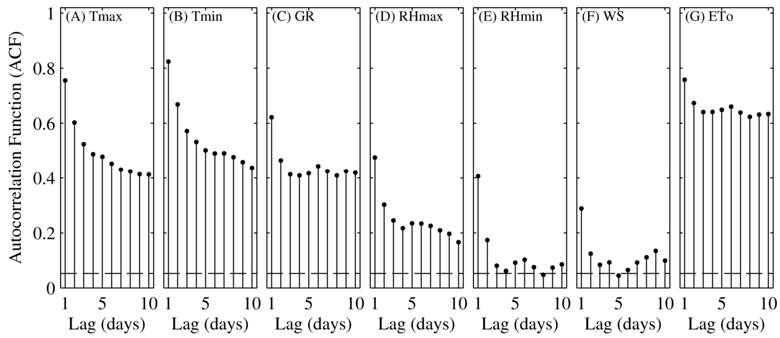

Fig. 2: Autocorrelation function (ACF) and 95% confidence intervals (dahsed line) of (A) maximum temperature; (B) minimum temperature; (C) global radiation; (D) maximum relative humidity; (E) minimum relative humidity; (F) wind speed; and (G) ETo.

It was observed that air temperature and global radiation variables presented stronger correlations with ETo than the other variables (Figure 3 A-C). Among the analyzed variables we found that the global radiation showed the strongest correlation with ETo (CC = 0.92). This is an evident relationship, since that this energy is crucial for the evapotranspiration process to occur. Therefore, the greater the total amount of radiation reaching the surface, the larger the kinetic energy of the water molecules, and the evaporation is facilitated. Moreover, the air temperature is directly influenced by the amount of radiation reaching the Earth's surface. Therefore, global radiation, air temperature and ETo are closely related. In general, the ETo is controlled by the availability of energy, the atmospheric demand and the supply of water to plants (Pereira *et al*., 1997).

The wind speed (Figure 3F) presented a statistically significant positive weak correlation with ETo (CC = 0.2). This might be related to the role of wind in the renewal of humidity (Varejão Silva, 2006), which allows an increase in atmospheric evaporative demand and consequently evapotranspiration. Nevertheless, due to the weak correlation between wind speed and ETo, it is possible that the wind speed could be disregarded in the evapotranspiration modeling.

The only type of variable that presented negative correlation was the relative humidity (Figure 3D-E), which is inversely proportional to ETo. Varejão Silva (2006) suggests that when the atmosphere is saturated the amount of molecules leaving the surface at a certain time interval becomes equal to the amount of molecules which return to the liquid state at a same interval, stopping the evaporation. Thus, when the relative humidity is high, the air is close to saturation and the saturation deficit is low. The higher the saturation deficit, the greater is the evaporative power of the atmosphere and evaporation rate.

Modelling daily ETo using neural networks:

The iterative training process tested variations from 9 to 22 neurons in the hidden layer over the 14 input vector combinations (Table 1).

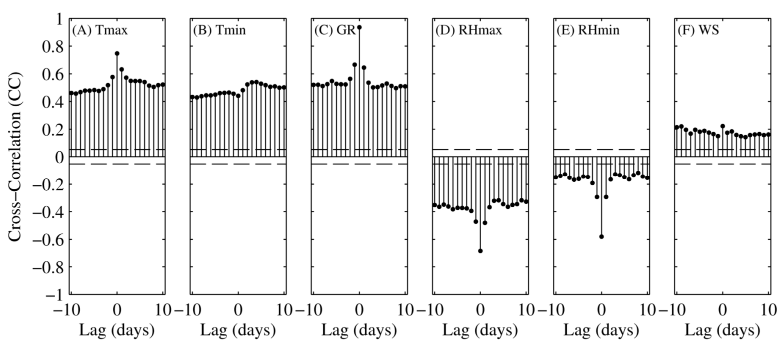

Fig. 3: Cross-correlation (CC) with a confidence interval of 95% (dashed line) between ETo and the (A) maximum temperature; (B) minimum temperature; (C) global radiation; (D) maximum relative humidity; (E) minimum relative humidity; and (F) wind speed.

Table 1: Performance of the models on the daily ETo simulation using MLP.

N	Treatments	Training subset		Test subset		Number of neurons Input/Hidden/Output
		R^2	RMSE%	R^2	RMSE%	
1	Tmax, Tmin	0.630	29.7	0.641*	30.3	2/19/1

2	Tmax, Tmin, WS	0.847	22.3	0.829*	22.3	3/11/1
3	Tmax, Tmin, GR	0.969	8.5	0.970	8.6	3/15/1
4	Tmax, Tmin, RHmax, RHmin	0.852	18.7	0.832*	20.6	4/17/1
5	Tmax, Tmin, RHmax, RHmin, GR	0.972	8.1	0.973*	8.3	5/5/1
6	Tmax, Tmin, RHmax, RHmin, WS	0.904	15.1	0.899*	16.1	5/14/1
7	RHmax, RHmin	0.539	33.6	0.523*	34.0	2/21/1
8	RHmax, RHmin, GR	0.910	14.6	0.925	7.6	3/12/1
9	RHmax, RHmin, WS	0.585	31.4	0.586*	32.5	3/9/1
10	Tmax, Tmin, RHmax, RHmin, GR, WS	0.991	4.6	0.991*	4.6	6/11/1
11	Tmax, Tmin, GR, WS	0.984	6.28	0.986	5.96	4/8/1
12	Tmean	0.558	34.9	0.607*	33.2	1/22/1
13	Tmax	0.567	32.8	0.609*	31.7	1/22/1
14	GR	0.874	17.6	0.910	15.57	1/19/1

* p-value < 0.01

Treatment 10 presented the best performance between the 14 models studied ($R^2 = 0.991$, RMSE = 4.6%). This model used all six climatic variables as input vector: maximum temperature, minimum temperature, maximum relative humidity, minimum relative humidity, wind speed and global radiation. Several other studies achieved similar performance when modelling the ETo using MLP and climatic variables. Ferraz (2013) obtained R^2 of 1.0 using the variables of maximum and minimum temperature, relative humidity, wind speed and global radiation. Huo *et al*. (2012) reached R^2 of 0.995 using the variables of average temperature, maximum and minimum air, relative humidity, wind speed and number of hours of sunshine. Trajkovic (2005) obtained R^2 of 0.940 using duration of sunshine, temperature, relative humidity and wind speed. Arca *et al*. (2001) obtained R^2 of 0.90 using wind speed, extraterrestrial radiation, air temperature and vapor pressure deficit variables. It seems that all the climatological variables used in this study, and that were also used on the other studies, are essential to a good estimation of ETo.

The variables of temperature and GR presented decent performance on the ETo modelling on the treatment 3 ($R^2 = 0.970$ RMS = 8.6%). Also, when using only the GR variable, the treatment 14 presented the best result on the usage of one type of variable ($R^2 = 0.910$, RMSE% = 15.57%). The results of GR alone were also better than the usage of combinations of other several variables on the other treatments.

Comparing treatments 6 and 10, it was observed that GR caused treatment 10 to improve the estimation of ETo and reach the best R^2 observed in the study. This could be explained due to the high influence of global radiation on the process of ETo, so that the higher global radiation, the more energy is available for the water molecules to pass from the liquid to a gaseous state. Amatya *et al*. (1992) observed that radiation is the most important climatic element in estimating the transpiration rate. This result indicates that the evaporation process on the study area is much more dependent on the amount of energy than the power of the evaporating air. Hence, future modelling of ETo on the study are region should be focused on the usage of variables related to the amount of energy, such as global radiation and temperature, rather than the ones related to the evaporative power of the atmosphere. Similar conclusions were found in Rahimikhoob (2010) and Zanetti *et al*. (2007), which used energy related variables to model ETo and obtained R^2 of 0.93 e 0.806, respectively.

The importance of air temperature can be observed when comparing the results of treatments 1 and 7, and 9 and 2, wherein the temperature variables contributed most to the simulation of the MLP than the humidity variables. While humidity is also a determining factor in the evaporation process, the observed data show that the influence of temperature was more decisive on the values of ETo than the humidity. This can also be observed comparing treatment 10 and 11, where the lack of relative humidity presented almost no difference at all on the results. The simulation of treatment 7 showed that using only the maximum and minimum humidity, the model proved to be less efficient for estimating ETo ($R^2 = 0.523$, RMSE = 34%). Hence, the usage of relative humidity might not be the best option on the ETo estimation and it is a candidate to be discarded in future modelling processes. This result corroborate with the previous results related to the evaporative power variables not being strong related to ETo on this study area.

It was observed that the wind speed data represented an increase of only 0.018 in the value of R^2, when comparing treatments 10 ($R^2 = 0.991$, RMSE = 4.6%), which used all climatic variables, and 5 ($R^2 = 0.973$, RMSE = 8.3%), which used all climatic variables except wind speed. This corroborates to result presented in the exploratory analysis that indicated a low influence of wind in the evaporative process due to the weak cross-correlation between wind speed and ETo. The study area usually does not show big variations in absolute wind speed in the course of the day due to the predominantly cold temperature of the region. Also, because it is a subtropical region, temperatures do not reach high levels and hence the wind generated by the saturation deficit is not too high, which reduces the contribution of this variable to ETo. Arid conditions show great variation in the evaporation rate due to small changes in wind speed (Medeiros, 2002). We believe that tropical regions might show similar behavior due to higher temperatures and humidity saturation of the air. However, at least for the study area regions and, possibly to subtropical regions, considering the low contribution of wind speed, the variable could not be used in future modelling exercises. This is a good result for the evapotranspiration estimation on Brazil, since the Brazilian climatological data array have a low availability of time series of wind speed.

Conclusions:

The usage of neural networks posed as an effective tool for determining daily ETo, even in situations of absence of some meteorological data considered in the Penman-Monteith equation. Nevertheless, the model that presented best performance used all variables and showed a R^2 of 0.991 and RMSE of 4.6%.

In respective order of importance, the global radiation, temperature, relative humidity and wind speed are key variables in determining the daily ETo using MLP neural networks. Among these variables, the energy related ones such as global radiation and temperature are more important on daily ETo estimation, while relative humidity and wind speed variable could be disregarded without major loss in model performance.

Future research should consider applying this methodology in other climatic regions of Brazil to verify whether these variables exhibit the same behavior on different climatic and environmental circumstances.

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