

## REFERENCE EVAPOTRANSPIRATION ESTIMATION WITH ARTIFICIAL NEURAL NETWORKS

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**SUMMARY:** Irrigation, when rationally used, can contribute to the efficient performance of the agribusiness. Planning irrigation, monitoring the soil moisture, the rainfall and the reference evapotranspiration ( $ET_0$ ) is necessary for a rational water management. The FAO Penman-Monteith (FAO PM) method is the standard method for estimating  $ET_0$ , but in some cases, the use of this method is restricted due to missing some climatic variables. For this reason, methods with a lower number of meteorological variables, as temperature values, are quite often used. This study aims to propose an artificial neural network (ANN) to estimate the  $ET_0$  as a function of maximum and minimum air temperatures for the city of Salinas, Minas Gerais State, Brazil. After training and validating the ANN, it was observed the existence of a good correlation between the values estimated by the standard method and those estimated by ANN, with the performance index classified as optimal. The use of ANN proved to be an excellent alternative for  $ET_0$  estimation, reducing the costs of acquiring climatic data.

**KEYWORDS:** artificial neural network, reference evapotranspiration, Salinas.

## ESTIMATIVA DA EVAPOTRANSPIRAÇÃO DE REFERÊNCIA COM REDES NEURAIAS ARTIFICIAIS

**RESUMO:** A irrigação, sempre que utilizada de forma racional, contribui de forma importante para o desempenho do agronegócio nacional. Para um manejo racional da água de irrigação é preciso um bom planejamento das irrigações, de monitoramento da umidade do solo, das precipitações e da evapotranspiração de referência ( $ET_0$ ). O método Penman-Monteith FAO é o método padrão para a estimativa da evapotranspiração de referência, porém, em alguns casos, o uso do método é restrito pela ausência de algumas variáveis climáticas. Por essa razão, muitas vezes há necessidade de se calcular a  $ET_0$  empregando-se métodos que utilizem somente valores

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de temperatura. O objetivo deste trabalho foi propor uma rede neural artificial (RNA) para estimar a evapotranspiração de referência em função das temperaturas máxima e mínima do ar para a cidade de Salinas, Minas Gerais State, Brazil. Após o treinamento e validação, pode-se observar a existência de boa correlação entre os valores estimados pelo método padrão e pela RNA, além do índice de desempenho classificado como ótimo. O uso da RNA mostrou-se uma excelente alternativa para a determinação da  $ET_0$ , proporcionando a diminuição dos custos de aquisição de dados climáticos.

**PALAVRAS-CHAVE:** redes neurais artificiais, evapotranspiração de referência, Salinas.

## INTRODUCTION

The irrigation technique, when used in a rational way, can contribute significantly to the efficient performance of the national agribusiness, increasing the productivity of the crops, enabling short cycle crops, improving the quality of the products, allowing harvests in the off-season, improving socioeconomic development, among other benefits (Testezlaf et al., 2002).

The irrigation scheduling, the soil moisture monitoring, the precipitation, and the reference evapotranspiration ( $ET_0$ ) are required for a rational water management in agriculture (Pires et al., 2008).

The reference evapotranspiration is a term that expresses the simultaneous occurrence of the soil water evaporation and the crop transpiration processes on a vegetated surface (Pereira, 1997). In this way, it is possible to estimate the water consumption by the plants and calculate the replacement through irrigation.

There are several methods for estimating  $ET_0$ . The FAO Penman-Monteith method is considered, internationally, the most appropriate for the estimation of reference evapotranspiration and uses values of air temperature, solar radiation, wind speed and relative air humidity (Allen, 2006).

In some cases, the use of the FAO Penman-Monteith method is restricted by the lack of some input variables. According to Conceição & Mandelli (2005), most meteorological services in Brazil only provide data on rainfall and air temperature. For this reason, it is often necessary to calculate  $ET_0$  using methods that use only temperature values.

In this context, the use of intelligent systems, such as artificial neural networks, in the estimation of  $ET_0$  has shown to be a reliable method, as shown in Sobrinho et al. (2011); Silva (2002); Zanetti et al. (2008) and Khoob (2008).

An artificial neural network (ANN) is a system designed to model the way the brain performs a particular task, usually implemented using electronic components or simulated by propagation on a digital computer. To achieve good performance, neural networks employ a massive interconnection of simple computational cells, called 'neurons' or processing units (Haykin, 2001). These neurons make up a distributed parallel system, arranged in one or more interconnected layers (Braga, 2012).

Considering the importance of evapotranspiration in irrigation management, this work aimed to propose an ANN to estimate  $ET_o$  as a function of maximum and minimum air temperatures for the city of Salinas, in Minas Gerais State, Brazil.

## MATERIAL AND METHODS

For the development of this work we used climatic data available in the Meteorological Database for Teaching and Research (BDMEP) of the conventional meteorological station of Salinas - MG (N ° 83441), of the National Institute of Meteorology, located at latitude 16.15 ° South, Longitude 42.28 ° West and altitude of 471.32 m (INMET, 2016).

The variables used in the study were: maximum and minimum air temperatures, relative air humidity, wind speed and the sunshine from January 1980 to December 2015. It should be emphasized that the days that did not have values for at least one of the variables were excluded.

From the meteorological data, the reference evapotranspiration ( $ET_o$ ) was determined by the FAO Penman-Monteith method (Equation 1), using electronic spreadsheets from the MS Excel software.

$$ET_o = \frac{0,408\Delta (R_n - G) + \gamma \frac{900}{T+2} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0,34 u_2)} \quad (1)$$

where:

$ET_o$  = reference evapotranspiration, mm d<sup>-1</sup>;

$R_n$  = net radiation at the crop surface, MJ m<sup>-2</sup> d<sup>-1</sup>;

$G$  = soil heat flux density, MJ m<sup>-2</sup> d<sup>-1</sup>;

$T$  = air temperature at 2 m height, °C;

$u_2$  = wind speed at 2 m height, ms<sup>-1</sup>;

$e_s$  = saturation vapour pressure, kPa;

$e_a$  = actual vapour pressure, kPa;

$\Delta$  = slope vapour pressure curve, kPa °C<sup>-1</sup>;

$\gamma$  = psychrometric constant, kPa °C<sup>-1</sup>;

With the ET<sub>o</sub> data calculated by FAO Penman-Monteith method, the data were divided into two sets, one for training (7,560 daily values between January 1980 and November 2005) and one for ANN validation (3,595 daily values between February 2006 and December 2015).

The implementation of ANN was done in Matlab software. ANN input variables were the maximum air temperature, the minimum air temperature and the day of the year, represented by numbers from 1 to 366, normalized between -1 and 1. As the output variable, it was used the ET<sub>o</sub> value calculated by the FAO Penman-Monteith method.

Aiming to train the network with all the data to generate more reliable results, cross-validation was used with the division of the data set for training in 10 subgroups. We tested some neural networks with different intermediate layer numbers and different numbers of neurons for these layers.

In order to evaluate the performance of the ANNs, it was calculated the mean square error (MSE) of the 10 iterations using Equation 2, with the ANN being chosen with a lower number of intermediate layers, a smaller number of neurons and a lower MSE.

$$MSE = \frac{\sum_{i=1}^n (Y_p - Y_{RNA})^2}{n} \quad (2)$$

where:

MSE = mean square error, mm d<sup>-1</sup>;

$Y_{RNA}$  = ET<sub>o</sub> estimated by the standard method, mm d<sup>-1</sup>;

$Y_p$  = ET<sub>o</sub> estimated by the ANN, mm d<sup>-1</sup>;

N = number of samples.

The ANN chosen was a Feedforward Multilayer Perceptron type, consisting of 3 neurons in the input layer, 10 neurons in the intermediate layer and 1 in the output layer, as shown in Figure 1. The sigmoid hyperbolic tangent function was defined for activation of the intermediate layer and the linear function for output layer activation.

The ANN was trained with the Levenberg-Marquardt algorithm. The criteria used to finish the training was the maximum number of 100 epochs or mean square error of less than 0.0000001.

To validate the ANN, daily mean climate data from February 2006 to December 2015 were used. The ANN estimated values were compared using the mean square error (MSE), the standard error of estimate (SEE), the Pearson correlation coefficient (r), the agreement index (d) and the performance index (c) in relation to the FAO Penman-Monteith standard method.

The SEE was determined through Equation 3.

$$SEE = \left[ \frac{\sum_{i=1}^n (Yp_i - YRNA_i)^2}{n-1} \right]^{0,5} \quad (3)$$

The Pearson correlation coefficient (r) was determined by the Equation 4.

$$r = \frac{\sum_{i=1}^n Yp_i YRNA_i - \frac{\left( \sum_{i=1}^n Yp_i \right) \left( \sum_{i=1}^n YRNA_i \right)}{n}}{\sqrt{\left[ \sum_{i=1}^n Yp_i^2 - \frac{\left( \sum_{i=1}^n Yp_i \right)^2}{n} \right] \left[ \sum_{i=1}^n YRNA_i^2 - \frac{\left( \sum_{i=1}^n YRNA_i \right)^2}{n} \right]}} \quad (4)$$

According to Willmott (1982), the agreement index (d) was obtained as follows.

$$d = 1 - \frac{\sum_{i=1}^n (YRNA_i - Yp_i)^2}{\sum_{i=1}^n \left( |YRNA_i - \bar{Yp}| + |Yp_i - \bar{Yp}| \right)^2} \quad (5)$$

The performance index (c), presented by Camargo & Sentelhas (1997), evaluates the performance of the different ET<sub>o</sub> estimation methods. This index gathers the precision indexes, given by the Pearson correlation coefficient (r) which indicates the degree of dispersion of the data obtained in relation to the mean, that is, the random error and the agreement index (d). The performance index is calculated by multiplying the r and the d and the Table 1 defines its interpretation criteria.

## RESULTS AND DISCUSSION

The values of maximum, average and minimum air temperature for the period studied are shown in Figure 2. The mean temperature was 24.4°C and the mean maximum and minimum temperatures were 30.6 and 18.1°C, respectively.

The daily mean values of the reference evapotranspiration ( $ET_0$ ) estimated by the FAO Penman-Monteith and artificial neural network (ANN) methods were 4.77 and 4.78 mm d<sup>-1</sup>, respectively.

Table 2 shows the statistical indicators of the adjustment between the  $ET_0$  values calculated by the FAO Penman-Monteith method and those estimated by the ANN. A performance index of 0.95 shows that the ANN performance was "excellent" according to the interpretation criteria, and the ANN also has a standard error of estimate (SEE) of 0.24 mm d<sup>-1</sup>.

The results were higher than those found by Vicente et al. (2014) in Salinas-MG. The authors found values of the performance index (c) equal to 0.33 and SEE at 1.52 mm d<sup>-1</sup> for the Blaney-Criddle method and values of c equal to 0.63 and SEE of 0.695 mm d<sup>-1</sup> for the Hargreaves one. Both methods, Blaney-Criddle and Hargreaves, are based only on air temperature data.

The results were also superior to that found by Alencar et al. (2015) for the same region. The study estimated the  $ET_0$  with the standard method in the absence of wind speed, radiation, and air humidity, and found a c value of 0.25, presenting "poor" performance with a SEE of 0.24 mm d<sup>-1</sup>.

It can be observed in Figure 3 that the maximum and the minimum  $ET_0$  daily values estimated by the ANN were observed in October and June, respectively, coinciding with periods of higher and lower average monthly temperatures, as shown in Figure 2. The values estimated by the ANN follow the trend of the data estimated by the FAO Penman-Monteith method.

In Figure 4, the regression analysis of the  $ET_0$  estimated by RNA is observed in relation to the values estimated by the standard method. The existence of a good correlation between the values by the standard and RNA methods can be proved by the Pearson correlation coefficient of 0.97.

## CONCLUSIONS

According to the results obtained, it was concluded that the artificial neural network proved to be a reliable alternative to estimate the reference evapotranspiration from maximum and minimum air temperatures for Salinas.

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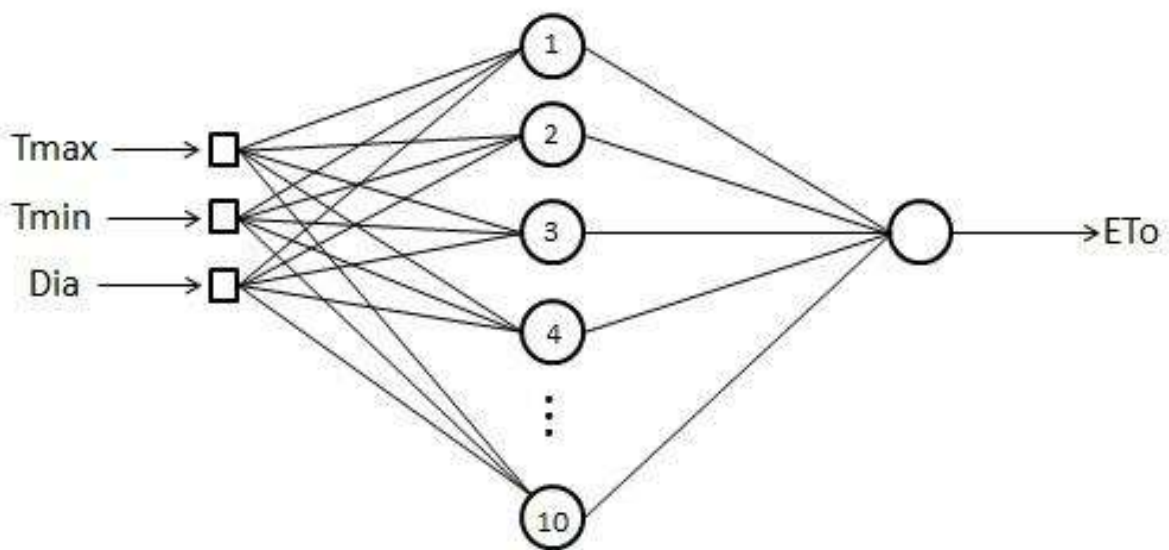
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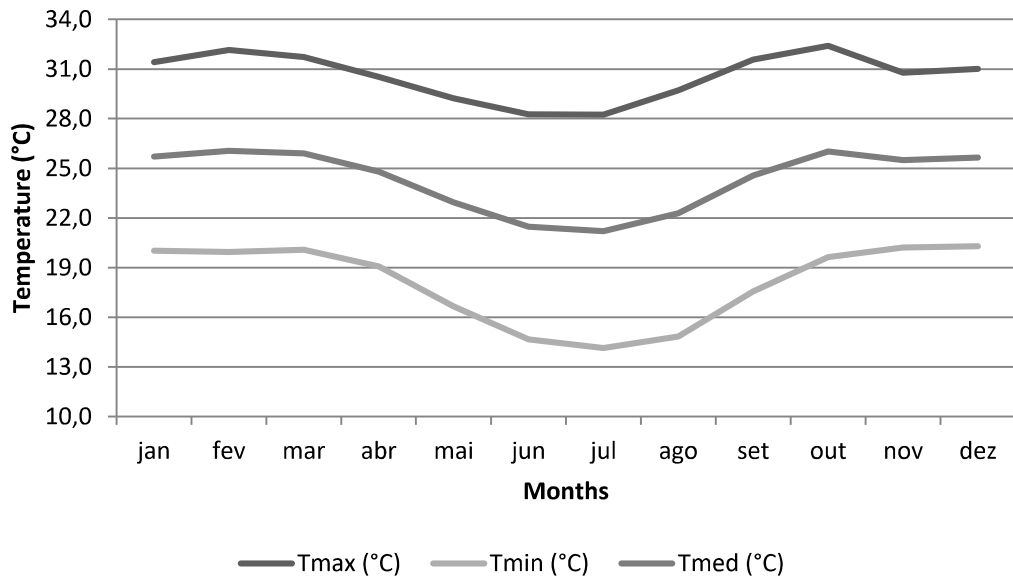


**Figure 1.** The ANN model used for reference evapotranspiration ( $ET_o$ ) estimation.

**Table 1.** The Performance Index classification of the estimation models, proposed by Camargo & Sentelhas (1997).

Performance index (c)	Classification
> 0.85	Excellent
0.76 a 0.85	Very good
0.66 a 0.75	Good
0.61 a 0.65	Reasonable
0.51 a 0.60	Bad
0.41 a 0.50	Very bad
$\leq 0.40$	Unacceptable

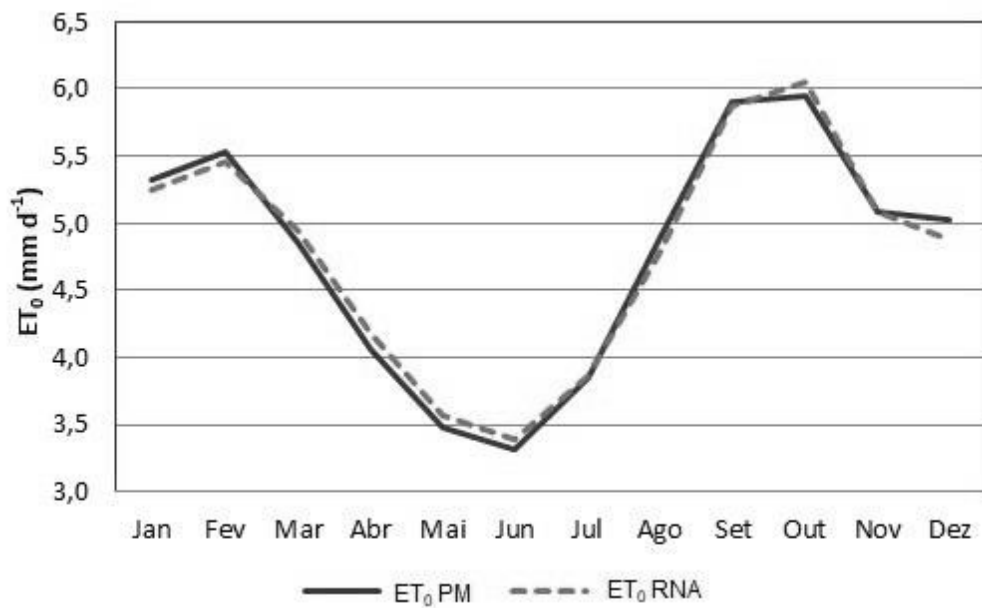




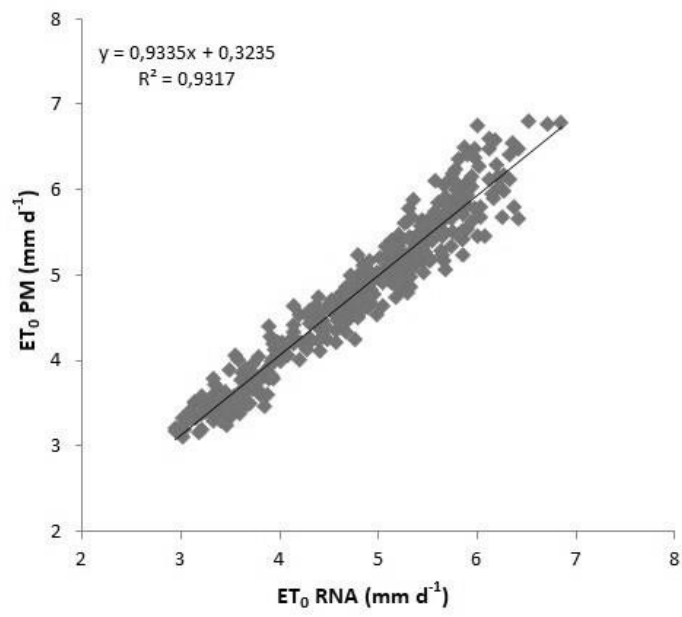
**Figure 2.** Maximum, minimum and mean air temperature of Salinas, Minas Gerais State, Brazil, from 1980 to 2015.

**Table 2.** Pearson correlation coefficient (r); agreement index (d); performance index (c), and the standard error of estimate (SEE), mm d<sup>-1</sup>.

r	d	c	SEE (mm d <sup>-1</sup> )
0,97	0,98	0,95	0,24



**Figure 3.** Monthly mean reference evapotranspiration (ET<sub>0</sub>) values estimated by the artificial neural network (ANN) in relation to the values of the FAO Penman-Monteith method, from 2006 to 2015.



**Figure 4.** Regression analysis of the reference evapotranspiration ( $ET_0$ ) estimated by the artificial neural network (ANN) in relation to the values of the FAO Penman-Monteith method.