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MODELAGEM *NEURO-FUZZY* DA EVAPOTRANSPIRAÇÃO DE REFERÊNCIA BASEADA NO MÉTODO DE CAMARGO

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1 RESUMO

O conhecimento sobre a evapotranspiração é fundamental para determinar o balanço hídrico de uma determinada região, pois pode afetar a política de gestão hídrica da bacia. Nesse contexto, o uso de modelagem matemática com abordagem difusa, como a modelagem *fuzzy*, cuja origem se deu justamente devido ao desafio de se trabalhar com incertezas, pode auxiliar na determinação da evapotranspiração, auxiliando no processo de tomada de decisão. Desta forma, no presente artigo, desenvolveu-se um modelo neuro-fuzzy (baseado em lógica *fuzzy* e redes neurais) para determinar a evapotranspiração de referência pelo método de Camargo. Definiu-se como variáveis de entrada a temperatura e radiação solar, ambas coletadas pelo Instituto Nacional de Meteorologia (INMET) na estação de Tupã, os dados foram considerados pelo período de um ano. Tal sistema, possibilita ao produtor a obtenção instantânea do valor da evapotranspiração de referência, além da classificação qualitativa em classes. A partir dos processos realizados neste trabalho, o método computacional estabelecido, mostrou-se capaz de calcular instantaneamente a evapotranspiração de referência pela equação de Camargo, a partir das variáveis radiação solar e temperatura, relatando que quanto menor os valores de temperatura e radiação solar, menor será o valor da evapotranspiração de referência.

Palavras-chave: lógica fuzzy, redes neurais, irrigação, balanço hídrico.

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NEURO-FUZZY MODELING OF REFERENCE EVAPOTRANSPIRATION BASED ON THE CAMARGO METHOD

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2 ABSTRACT

Knowledge about evapotranspiration is essential to determine the water balance of a given region, since it can affect the basin's water management policy. In this context, the use of mathematical modeling with diffuse approach as fuzzy modeling, in which its origin was rightly due to the challenge of working with uncertainties, it can assist in the determination of evapotranspiration, helping in the decision-making process. Thus, in this article, he developed a neuro-fuzzy model (based on fuzzy logic and neural networks) to determine the reference evapotranspiration by the Camargo method. The input variables were temperature and solar radiation, both collected at the National Meteorology Institute (INMET) at the Tupã station, the data were considered for a period of one year. Such a system allows the producer to instantly obtain the reference evapotranspiration value, in addition to the qualitative classification in classes. Based on the processes conducted in this work, the established computational method could instantly calculate the reference evapotranspiration from the Camargo equation, based on solar radiation and temperature variables, reporting that the lower the values of temperature and solar radiation, the lower will be the reference evapotranspiration value.

Keywords: diffuse logic, neural networks, irrigation, water balance.

3 INTRODUCTION

Evapotranspiration (ET) is a parameter that considers the simultaneous processes of water transfer to the atmosphere through plant transpiration and surface evaporation (ALLEN *et al*., 1998). This parameter is typically measured in millimeters per day (mm/day), with one millimeter of evapotranspiration corresponding to the displacement of one liter of water into the atmosphere for each square meter of surface. ET rates differ for each type of environment because they are influenced by several factors, such as leaf type, percentage of soil vegetation cover, plant growth stage, temperature, humidity, wind speed, and solar radiation (ALLEN *et al*., 1998).

To obtain the water balance of a given region, it is essential to know the water lost through evapotranspiration, and for this purpose, the calculation of reference evapotranspiration (ETo) is used (GURSKI; JERSZURKI; SOUZA, 2018). According to Allen *et al.* (1998), ETooccurs on a reference surface without the imposition of water deficit. Owing to the high cost of equipment and the sensitivity for determining ETo, many farmers do not have access to them and/or end up managing their systems incorrectly. Therefore, there are numerous methods for determining ETo, in which easier-to-use sensors and methods that require a smaller number of variables are used, such as the camera method (CAMARGO; CAMARGO, 2000).

The model presented by Camargo is a simplified version of Thornthwaite's method that uses only average temperature and solar radiation data. It was developed via an analytical equation to calculate evapotranspiration and is effectively applicable to any climate condition (CAMARGO, 1971). Thus, the method began to be refined in the 1960s, when it replaced Thornthwaite's. Its distinguishing feature was the replacement of the "I" index with the "T," which corresponds to the region's average annual temperature. Furthermore, Camargo developed an easy-to-understand table for obtaining the daily *ETo value*, eliminating the need for latitude correction on the basis of the "T" index, as in Thornthwaite's method, which facilitated the estimation (CAMARGO; CAMARGO, 2000). On the basis of the results obtained via Thornthwaite's method, Camargo proposed a new method in the 1970s based on average air temperature and extraterrestrial solar radiation data, which was similarly effective. This methodology, according to the Brazilian Agricultural Research Corporation (Embrapa) (2010), is based on *ETo results* estimated for more than one hundred locations (CAMARGO; CAMARGO, 2000).

There are currently numerous methods for determining evapotranspiration, and recent work has sought to indicate the model that best fits certain regions, such as the work of Cunha *et al*. (2021), in which the authors recommend the De Jong and Stewart model for the state of Minas Gerais. Additionally, several works can be highlighted in quantitative studies of meteorological variables and/or renewable energies in agricultural engineering, more specifically with solar energy (GABRIEL FILHO *et al*., 2012), solar radiation (2021b), wind speed (NAZARÉ *et al*., 2020; GABRIEL FILHO *et al*., 2011b) and hybrid solar and wind systems (GABRIEL FILHO *et al*., 2016; SERAPHIM *et al*., 2014).

Models based on artificial intelligence have shown great applicability in determining evapotranspiration (SANIKHANI *et al*., 2019; TIKHAMARINE *et al.*, 2020; GRANATA *et al*., 2020). The use of models in which the concepts of neural networks (MALIK, KUMAR and KISI., 2018; ASHRAFZADEH *et al*., 2020) and *neuro-fuzzy methods* (SHIRI, 2019; ADNAN *et al*., 2019) are applied has also been highlighted.

Fuzzy set theory was pioneered by Lotfi Asker Zadeh in 1965 and originated from the challenge of working with uncertainty. Fuzzy concepts bring mathematical modeling closer to human reasoning through *fuzzy sets*, which use numerical and linguistic variables to describe the phenomena under study. Thus, it is possible to describe subjective terms such as "approximately" and "approximately" mathematically (ZADEH, 1965).

Several studies have shown applications of fuzzy systems in irrigation areas in the mathematical modeling of orange and wheat productivity with reused water (PUTTI *et al.*). 2017b, 2021; BOSO *et al*. 2021a, 2021b), in the biometric variables of lettuce, tomato and radish crops from different irrigation depths (MATULOVIC *et al*. 2021; VIAIS NETO *et al*. 2019a, 2019b), and the vitality of orchids (PUTTI *et al*. 2014, 2017a). In agricultural engineering, work stands out in poultry production and companies (PEREIRA *et al*., 2008; CREMASCO *et al*., 2010), in cattle production (GABRIEL FILHO *et al*., 2011a, 2016), in the optimization of agricultural implements (GÓES *et al*., 2021), and in the agricultural products market (GABRIEL FILHO *et al*., 2015; MARTÍNEZ *et al*., 2020).

Models based on neural networks apply meteorological data, such as the one developed by Nazaré *et al*. (2020), seek to employ machine learning to obtain smaller errors, reducing model uncertainties.

The objective of this work was to develop a mathematical model for estimating evapotranspiration via the Camargo method via an adaptive neuro-*fuzzy inference system* (ANFIS), which employs *fuzzy logic* and neural networks in its design. Thus, when a farmer inputs the temperature and solar radiation of the period into the model, the model instantly obtains the reference evapotranspiration, enabling more efficient planning of irrigation projects.

4 MATERIALS AND METHODS

According to Back (2008), the reference evapotranspiration (*ETo*) calculated via the Camargo method is performed via Equation (1):

$$ETo = Ra.T.K.Nd \quad (1)$$

In addition, m, where Ra represents the solar radiation on the outer surface of the atmosphere (mm), T represents the average temperature obtained by averaging the maximum and minimum temperatures (°C), Nd represents the number of days in the period, and K represents the adjustment factor that varies according to the local average temperature, as shown in Table 1.

Table 1 Values of Kin relation to the local average temperature (T).

T	***K***
< 23°C	0.01°C $^{-1}$
= 24°C	0.0105°C $^{-1}$
= 25°C	0.011°C $^{-1}$
= 26°C	0.0115°C $^{-1}$
> 26°C	0.012°C $^{-1}$

The solar radiation () and temperature () Tdata Rarequired for the calculation were collected from the automatic meteorological station of the National Institute of Meteorology (INMET) - Tupã-A768 Station, located in the municipality of Tupã, São Paulo, at the geographic coordinates 21° 56' South Latitude and 50° 30' West Longitude with an average altitude of 524 meters.

The data were collected from March 20, 2018 (beginning of autumn), to March 20, 2019 (end of summer). The station records these data hourly, resulting in 24 hours × 366 days = 8,784 data points. Given that the weather station sensors failed to record some hourly data points, missing values were estimated by calculating the average of the previous and subsequent recorded values. If more than three consecutive missing data points were found, the data were removed from the analysis. The period in which data were not recorded is shown in

Table **2**; 102 missing data points were recorded, representing a loss of 1.20%.

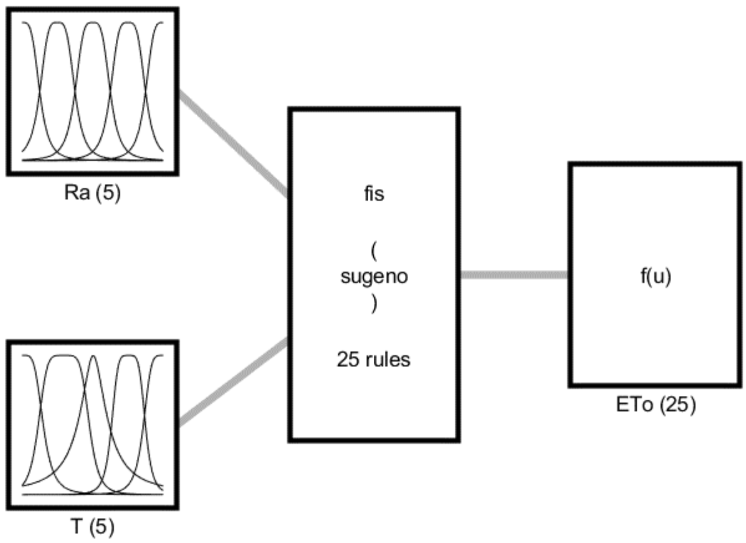
Table 2 Period exceeding three consecutive items of information not made available by INMET**.**

Day	Period
MAY 21, 2018	3am to 12pm
JUNE 21, 2018	3pm to midnight
11/23/2018	12am to 4am
12/08/2018	6am to 9am
12/09/2018	4am to 10am
11/12/2018	3am to 6am
JANUARY 19, 2019	5am to 10am
07/02/2019	7am to 10am
FEBRUARY 14, 2019	1am to 7am
FEBRUARY 21, 2019	3pm to 8pm
FEBRUARY 22, 2019	12am to 7am
FEBRUARY 23, 2019	6am to 10am
02/03/2019	5pm to 9pm
03/04/2019	12am to 3am
03/04/2019	5am to 11am
MARCH 13, 2019	4pm to 9pm
MARCH 15, 2019	3pm to 6pm

From the collected data, multiple linear regression analysis was performed with the aim of verifying the correlation and significance of the input variables in relation to the output variable, and it was also possible to obtain contour and three-dimensional surface maps of the behavior of the variables.

The development of the *neuro-fuzzy system* for the automatic calculation of reference evapotranspiration via the Camargo equation is represented in Figure 1.

Figure 1*Neurofuzzy* system for obtaining reference evapotranspiration from solar radiation and temperature**.**



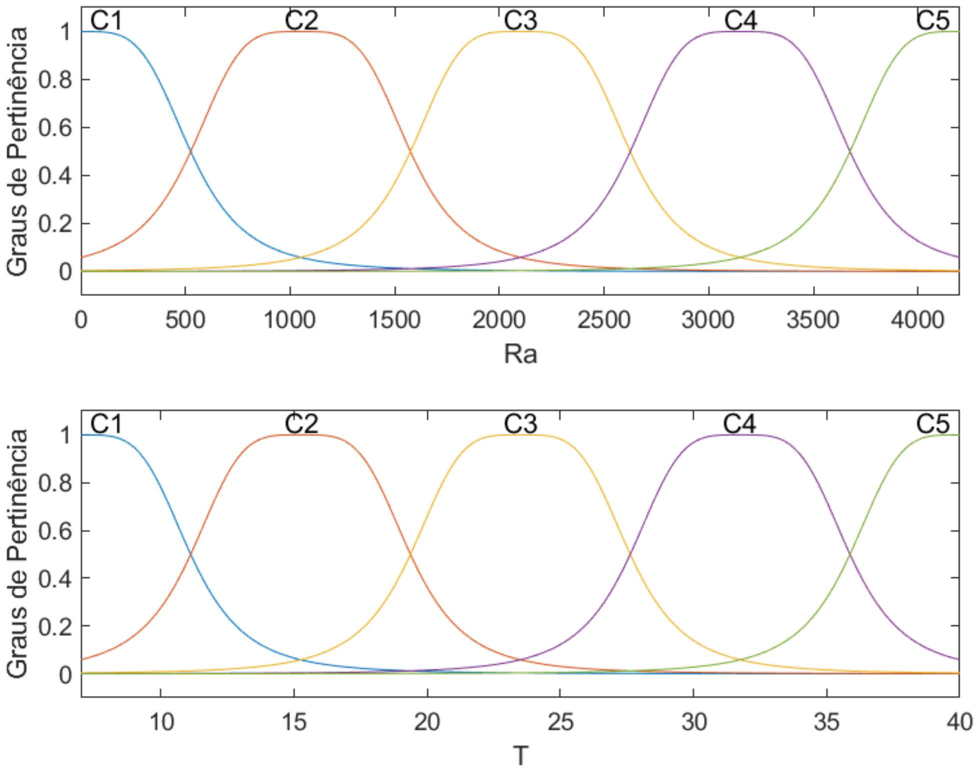
The system input variables were solar radiation (Ra) and temperature (T). For each of them, five fuzzy sets with generalized bell-type membership functions were defined, named "C1", "C2", "C3", "C4", and "C5". The limits initially defined for each set are shown in 1)). Since five *fuzzy*

Figure 2initially defined for the input variables solar radiation (Ra) and temperature (T).

The output variable refers to the evapotranspiration value calculated by the *sets were defined* for each of the two input variables, 25 (5 × 5) rules were adopted to establish the system.

Camargo method (defined by Equation (1)). Since five *fuzzy sets were defined* for each of the two input variables, 25 (5 × 5) rules were adopted to establish the system.

Figure 2initially defined for the input variables solar radiation (Ra) and temperature (T).



The rule base of the *fuzzy* system was obtained by considering all possible combinations between the *fuzzy sets* of input variables, with 5 × 5 = 25 rules.

Fuzzy sets allow an element to have partial membership in several sets due to the gradual transition of variables. Therefore, the use of the *adaptive network-based fuzzy inference system* (ANFIS) is relevant to this work, as it refers to a multilayer adaptive supervised learning network. The system's response is calculated for the provided parameters, obtaining a close relationship between outputs and inputs, as the training algorithm adjusts the parameters at the nodes of the model structures (SPACCA, 2019).

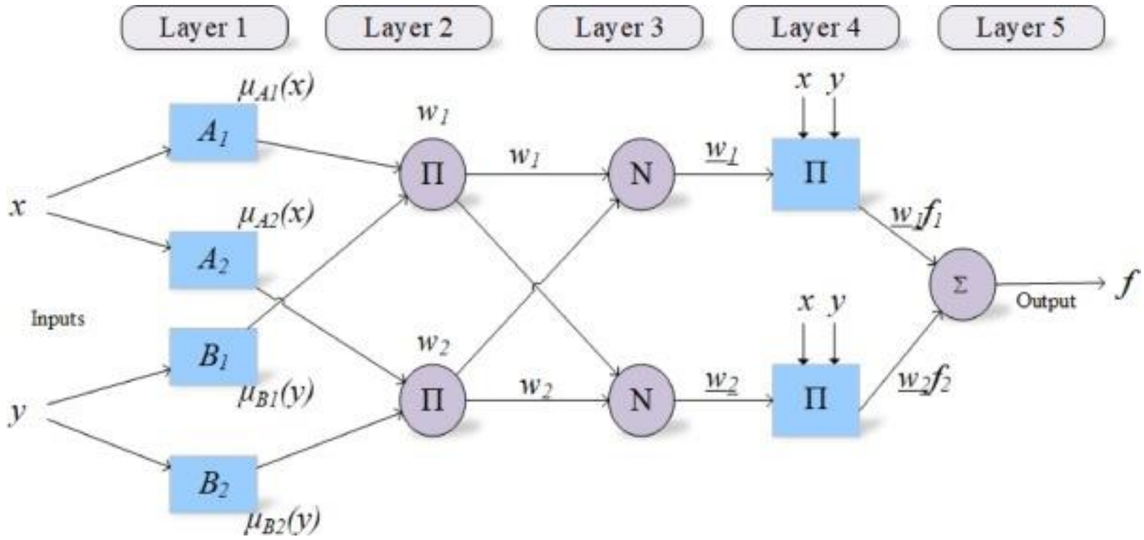
According to Haznedar and Kalinli (2018), an ANFIS model composed of two inputs with two membership functions each, one output and the Takagi–Sugeno inference model, which was used in this work, has its structure defined as shown in

Figure **3**, since the established rules are defined by the following sentence (Equation 2):

$$\text{“}Se\ x\ \acute{e}\ A_i\ e\ y\ \acute{e}\ B_i, ent\tilde{a}o\ f_i = p_i x + q_i y + r_i\text{”} \qquad (2)$$

where x are the y*fuzzy* variables; A_i and B_i refer to the *fuzzy sets*; f_i is the linear combination of the input variables and the constant; and p_i, q_i and r_i are the consequent parameters of the rule.

Figure 3of an ANFIS model according to Haznedar and Kalinli (2018).



Source: Haznedar and Kalinli (2018).

The structure of an ANFIS system is composed of five layers, described below.

Layer 1: This layer has adaptive nodes and antecedent parameters, which can be adjusted during the learning process (HAZNEDAR; KALINLI, 2018). In this layer, the *fuzzification* process occurs, in which the membership functions are associated with a *fuzzy set* with a certain degree of membership, with its output defined by Equation 3:

$$\text{“}Se\ x\ \acute{e}\ A_i\ e\ y\ \acute{e}\ B_i, ent\tilde{a}o\ f_i = p_i x + q_i y + r_i\text{”} \qquad (3)$$

where i represents the number of input variables, j é represents the number of combination rules, and µ represents the degree of membership associated with the *fuzzy set*.

Layer 2: the cells in this layer are nonadaptive, and their count is equal to the rule count, so Haznedar and Kalinli (2018) define it as the rule layer, since the rules are triggered with a certain degree of relevance, with the triggering strength defined by Equation (4):

$$w_i = \mu A_i(x).\mu B_i(y) \qquad (4)$$

where w_i is the trigger strength of the rule, A_i and B_i refer to the *fuzzy sets*, and μ is the degree of membership and x are the y *fuzzy* variables.

Layer 3: According to Mathur, Glesk and Buis (2016), this layer also does not have adaptive nodes since it is responsible for performing normalization, in which a weighted average of the triggering strengths of the rules is applied, which is calculated via Equation 5:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \quad (5)$$

where $\bar{w}$ refers to normalization, where i represents the number of input variables.

Layer 4: This is the *defuzzyification layer*, whose nodes are adaptive, and its output is the product of the normalized firing force and a first-order polynomial, represented by Equation 6:

$$\bar{w}_i . f_i = \bar{w}_i . (p_i x + q_i y + r_i); \quad i = 1,2 (6)$$

where $\bar{w}_i$ represents normalization and where p_i, q_i and r_i represent the set of parameters of each rule (MATHUR; GLESK; BUIS, 2016).

Layer 5, called the summation layer by Haznedar and Kalinli (2018), has a single nonadaptive node with the function of summing all the outputs from the previous layer to produce the global output of the ANFIS system, given by Equation 7:

$$f = \sum \bar{w}_i . f_i = \frac{\sum w_i . f_i}{\sum w_i}, \; i = 1,2 \quad (7)$$

where $\bar{w}_i$ represent the normalization and $f_i$linear combination of the input variables and the constant, respectively.

When traversing this structure, the model undergoes adjustments in the adaptive nodes, using the obtained output values so that the error between the model output and the real output is minimal (HAZNEDAR; KALINLI, 2018). The learning algorithm is responsible for making these adjustments. In this work, the hybrid algorithm was used, which corresponds to the combination of the *backpropagation technique* for adjusting the antecedent nodes and least squares estimation for the consequent parameters of the output functions (AL-DUNAINAWI; ABBOD; JIZANY, 2017).

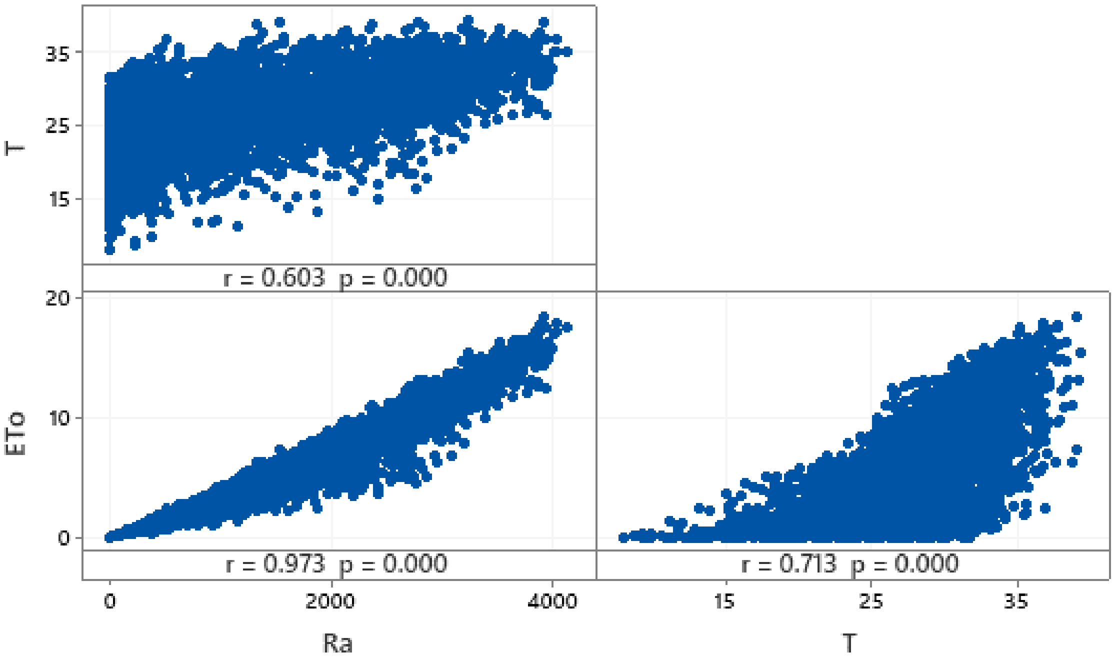
® software, which was used to implement the proposed models, through the *Fuzzy Logic Toolbox package.*

5 RESULTS AND DISCUSSION

Once valid data for modeling were obtained, regression analysis was performed. Regression analysis consists of statistical techniques that mathematically model the data, generating a function that represents them and relates the variables. In multiple regression, as used in this work, more than one input variable is modeled.

The input and output values showed a positive correlation when related, and the relationship between the two input variables (T and Ra) was significant, with an average explanation of the data (60%). In regard to the response variable (*ETo*), its relationship with the input variables was significant, with *a p* value equal to 0, presenting an explanatory power of 97% when related to the variable solar radiation (Ra) and 71% when related to temperature (T), as shown in Figure 4.

Figure 4the variables solar radiation (Ra), temperature (T) and *reference evapotranspiration (ETo*).



The multiple linear regression model presented 97.24% fit of the equation to the model data and is represented in Equation 8.

ETo = -4.3192 + 0.003363 Ra + 0.16550 T (8)

where *ETo* is the reference evapotranspiration (mm), Ra is the solar radiation (MJ m^{-2} day^{-1}), and T is the temperature (°C).

The analysis of variance revealed that the variables T and Ra are significant to the model (both with p values < *0.05*), in addition to highlighting the great variability of the data around the mean.

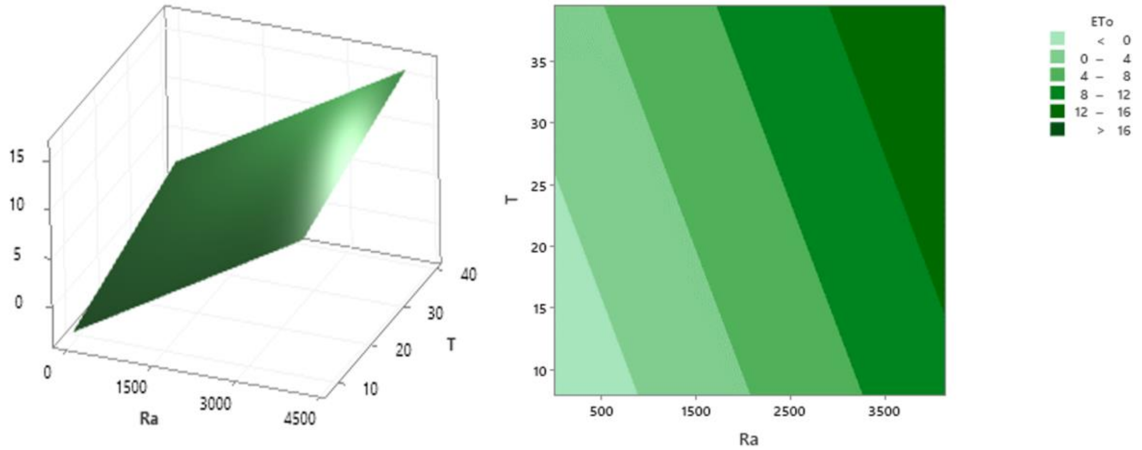
Table 3 variance of the multiple linear regression analysis of the dataset.

Source	Degree of Freedom	Sum of Squares	Mean Square	F value	P value
Regression	2	87981	43990.6	83242.21	0.000
Frog	1	41993	41993.1	79462.46	0.000
T	1	2255	22555	4268.00	0.000
Waste	4728	2499	0.5		
Total	4730	90480			

Ra represents the solar radiation (MJ m^{-2} day^{-1}), and T represents the temperature (°C).

Considering the importance of the input variables tested for the description of the evapotranspiration model, a surface and contour map was obtained, which can be seen in Figure 5These maps show numerous combinations of the model's input variables (solar radiation and temperature), making it possible to verify in a more didactic way the behavior of the dependent variable (*ETo*) as a function of the input variables (Ra and T), showing that the lower the values of T and Ra are, the lower the evapotranspiration value.

Figure 5 Surface and contour maps for the variables temperature (T) and solar radiation (Ra) and their influence on *evapotranspiration (ETo)*.



Considering the valid data for developing the *neuro-fuzzy model*, all the input variable values were combined to train the learning algorithm. Thus, for solar radiation (Ra), the values varied every 10 units between the minimum value of zero and the maximum value of 4200, whereas for the temperature variable (T), the interval was one unit, with the minimum value being seven and the maximum being 40. Thus, the model was trained using 14,315

Figure 2initially defined for the input variables solar radiation (Ra) and temperature (T).

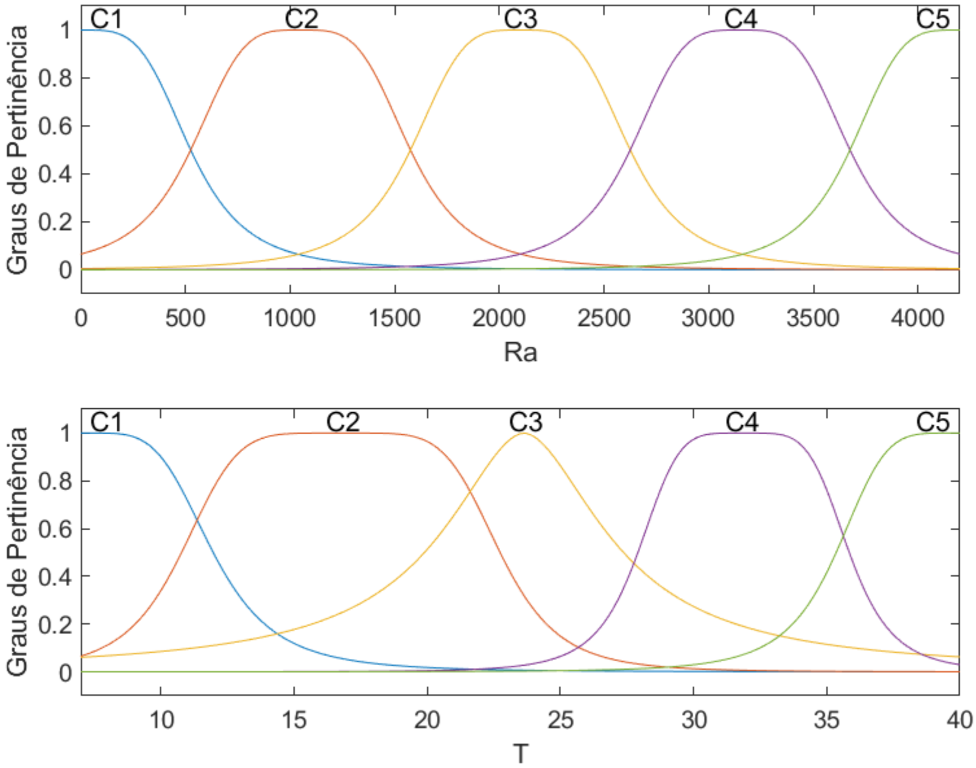
were adjusted by the learning algorithm itself, and their limits began to be defined by the Gaussian functions represented in

combinations of solar radiation and temperature.

Thus, when training the model, the membership functions of the input variables are adjusted with the aim of minimizing the prediction error (MATHUR; GLESK; BUIS, 2016). Thus, the membership functions of the input variables previously defined by 1)). Since five *fuzzy sets were defined* for each of the two input variables, 25 (5 × 5) rules were adopted to establish the system.

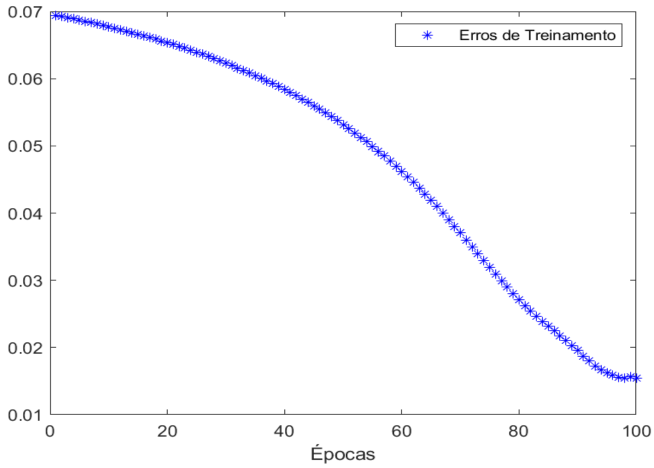
Figure **6**There were significant changes in the temperature variable (T).

Figure 6 Input variables: solar radiation (Ra) and temperature (T).



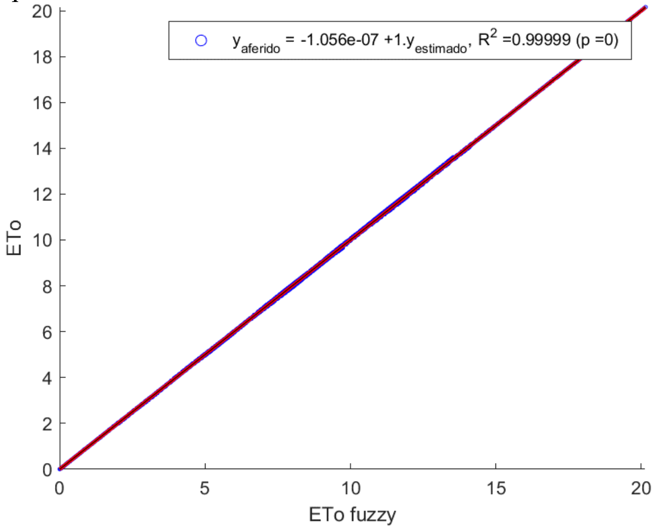
Additionally, according to Mathur, Glesk and Buis (2016), during training, several interactions occur between the input data to minimize the error, and these interactions are known as epochs. As shown in Figure 7, in this work, 100 epochs were established for training the model, and the predictive error decreased from 0.07 in the first iteration to approximately 0.015 from the 98th iteration onward, indicating that the model achieved the lowest possible training error.

Figure 7 Variations in training errors according to the epochs of the neuro-*fuzzy model*.



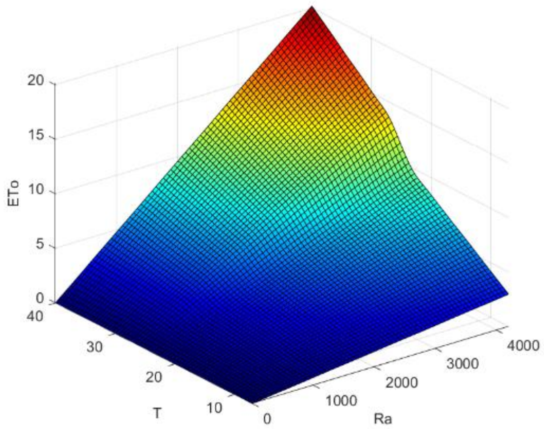
When the model's prediction equation (Figure 8) was obtained, the data fit to the model (R^2) was 99%, indicating superior performance to the prediction made through multiple linear regression, which presented an R^2 of 97.24%. Therefore, it is preferable to use the ANFIS model to determine the reference evapotranspiration (ETo) via the Camargo equation because of the greater precision in the calculation and the possibility of obtaining results instantly.

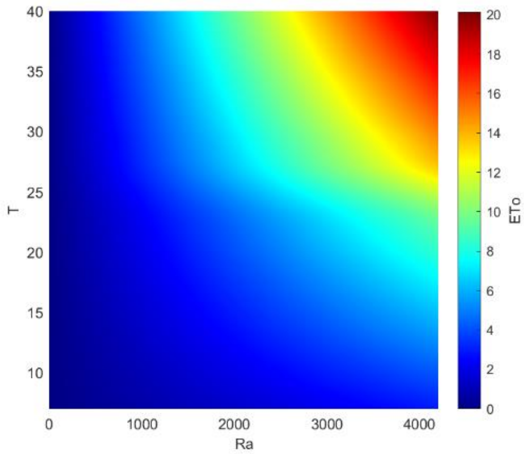
Figure 8 Prediction equation of the ANFIS model**.**



From the results obtained with the development of the model for calculating reference evapotranspiration via the Camargo equation, surface and contour maps were created (Figure 9), making it possible to visualize the behavior of the response variable (reference evapotranspiration) as a function of modifications to the input variables (Ra and T) in a more understandable way.

Figure 9and contour map obtained from the development of the *neuro-fuzzy model* for calculating the reference evapotranspiration.





The previous figures indicate that the lower the temperature and solar radiation values are, the lower the reference evapotranspiration value will be, with zero being the lowest value obtained and 20 mm being the highest value for the highest temperature and solar radiation values. Notably, this behavior of the model's response was expected since solar radiation is the main source of energy for the Earth, being one of the determining factors of the climate and, consequently, a parameter that influences temperature (GOMEZ *et al*., 2018).

6 CONCLUSIONS

Through this study, it is verified that the input variables (Ra, T), for calculating evapotranspiration via the Camargo method, are fundamental for adjusting the multiple regression model and for modeling via the *neuro-fuzzy inference method* (ANFIS).

Thus, the computational method established in this work was able to instantly calculate reference evapotranspiration via the Camargo equation on the basis of the input of solar radiation and temperature variables relative to the location of the crop to be monitored. This method, which is based on a *neuro-fuzzy* system, allows the producer to determine the reference evapotranspiration value, which, when multiplied by the required crop's crop coefficient, enables the determination of the plant's actual water needs for the adoption of more appropriate management practices to optimize resources.

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