BAYESIAN REGULARIZED NEURAL NETWORKS APPROACH FOR REFERENCE EVAPOTRANSPIRATION MODELING ON SEMIARID AGROECOSYSTEMS

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ABSTRACT: The Penman–Monteith equation (PM) is widely recommended by The Food and Agriculture Organization (FAO) as the method to calculate reference evapotranspiration (ET_0). However, the detailed climatological data required by the PM are not often available. The present study aimed to develop bayesian regularized neural networks (BRNN)-based ET_0 models and compare its results with the PM approach. Forteen weather stations wre selected for this study,located in Juazeiro (BA) and Petrolina (PE) counties, Brazil. BRNN were trained with different parameters choices and obtained R^2 between 0.96 and 0.99 during training and between 0.95 and 0.98 with validation? dataset. Root mean squared error (RMSE) less than 0.10 mm.day^{-1} for BRNN when compared to PM denoted the good performance of the network.

KEYWORDS: modelling, R, Bayes, artificial intelligence in agriculture

UTILIZAÇÃO DE REDES NEURAIS COM REGULARIZAÇÃO BAYESIANA NA MODELAGEM DE EVAPOTRANSPIRAÇÃO DE REFERÊNCIA EM AGROECOSSISTEMAS SEMIÁRIDOS

RESUMO: A equação de Penman-Monteith (PM) é amplamente recomendada pela Food and Agriculture Organization (FAO) como método para calcular a evapotranspiração de referência (ET_0), no entanto, os dados climatológicos detalhados exigidos pelo PM frequentemente não estão disponíveis. O presente estudo objetivou desenvolver modelos de ET_0 baseados em redes neurais de regularização bayesiana (RNRB) e comparar seus resultados com a

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abordagem PM. As 14 estações meteorológicas selecionadas para este estudo estão localizadas nos municípios de Juazeiro (BA) e Petrolina (PE). RNRBs foram treinadas com diferentes opções de parâmetros e obtiveram R^2 entre 0,96 e 0,99 durante o treinamento e entre 0,95 e 0,98 com o conjunto de dados do teste, erro médio quadrático (EMQ) menor que 0,10 $mm.dia^{-1}$ em comparação ao PM.

PALAVRAS-CHAVE: modelagem, R, Bayes, inteligência artificial na agricultura

INTRODUCTION

According to Kumar et al. (2002), evapotranspiration is a complex and nonlinear phenomenon, because it depends on the interaction of several climatic elements as solar radiation, wind speed, air humidity, and temperature, as well as on the type and growth stage of the crop. According to Pereira et al. (2002), the selection of a method for estimating the evapotranspiration depends on several factors.

One of these factors is the availability of meteorological data, as the complex methods requiring a high number of variables have applicability only when all necessary data are available. When there is availability of data, Allen et al. (1998) recommend the application of the Penman-Monteith (PM) as the sole standard method for the definition and computation of the reference evapotranspiration (ET_o). Although the meteorological variables necessary for the application of the PM method are not always universally available, in particular those related to the solution of the aerodynamic term, wind speed and the deficit of water vapor pressure in the air. So, the methods for estimating ET_o as a function of the climatic elements that might be obtained on a more practical way, such as the air temperature and the extraterrestrial radiation, are very important. A tool that can be used to estimate ET_o is the artificial neural network (ANN).

According Haykin (1999) an Artificial Neural Network (ANN) is a popular statistical method which can explore the relationships between variables with high accuracy. Essentially, the structure of an ANN is computer-based and consists of several simple processing elements operating in parallel. An ANN consists of three layers: input, hidden, and output layers, hence it is referred to as a three-layer network. The input layer contains independent variables that are connected to the hidden layer for processing. The hidden layer contains activation functions and it calculates the weights of the variables in order to explore the effects of predictors upon the target (dependent) variables. In the output layer, the prediction or classification process is ended and the results are presented with a small estimation error.

In ANNs, some regularization techniques are used with the backpropagation training algorithm to obtain a small error. This causes the network response to be smoother and less likely to overfit to training patterns (HAYKIN, 1999). However, the backpropagation algorithm is slow to converge and may cause an overfitting problem. Backpropagation algorithms that can converge faster have been developed to overcome the convergence issue. Similarly, some regularization methods have been developed to solve the overfitting problem in ANNs. Among regularization techniques, Levenberg–Marquardt (LM) and Bayesian Regularization (BR) are able to obtain lower mean squared errors than any other algorithms for functioning approximation problems (HAGAN, MENHA, 1994). LM was especially developed for faster convergence in backpropagation algorithms. Essentially, BR has an objective function that includes a residual sum of squares and the sum of squared weights to minimize estimation errors and to achieve a good generalized model.

In order to estimate reference evapotranspiration in the state of Rio de Janeiro, Zanetti et al. (2008) used a neural network considering geographic coordinates and air temperature. Alves Sobrinho et al. (2011) developed an ANN capable of estimating ET_o through data of daily air temperature for the region of Mato Grosso do Sul and the neural network obtained the best adjustment, compared with the conventional methods. For example, Abedi-Koupai et al. (2009) used two hidden layers with five neurons, each one with four input values, one output layer and log-sigmoid function, and obtained coefficient of determination of 0.95 for reference evapotranspiration in protected environment.

In this paper we applied bayesian regularized neural networks (BRNN) to simulate PM-based reference evapotranspiration with less variables than the original PM formulation in a semiarid area from Brazil.

MATERIAL AND METHODS

Figure 1 shows the location of the reference semiarid area (dashed red square on the right side) inside the Petrolina County, Pernambuco state, Northeast of Brazil, together with the net of forty agrometeorological stations (blue arrows) used for the weather data interpolation processes in a geographic information system (GIS) environment.

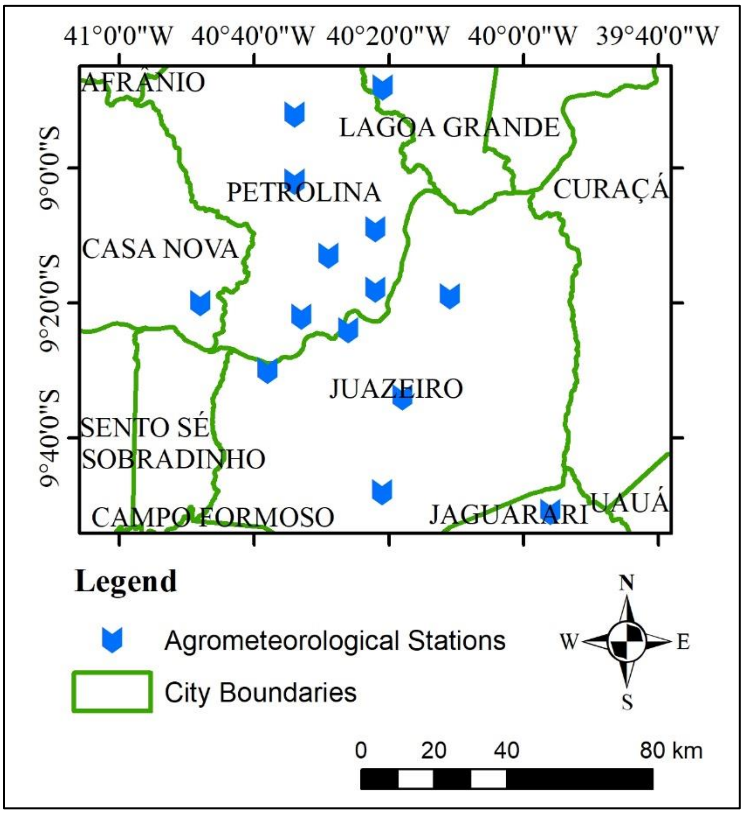

Figure 1. Location of agrometeorological stations in Petrolina/PE and Juazeiro/BA.

The reference evapotranspiration is the evapotranspiration referring to a hypothetical crop that completely covers the soil, is in active growth, does not present water and nutritional restriction, and presents specific characteristics such as albedo equal to 0.23 and height between 8 and 15 cm. Among the various methods of ETo estimation, the Penman-Monteith, presented by the FAO, is recommended as the standard, according to Equation 1.

$$ET_{0\_day} = \frac{0{,}408(R_n - G) + \left[\gamma\left(\frac{900}{T + 273}\right) u_2(e_s - e_a)\right]}{\Delta + \gamma(1 + 0{,}34\, u_2)} \tag{1}$$

where Δ (kPa °C^{-1}) is the slope of the saturated vapor pressure curve, γ is the psychrometric constant (kPa °C^{-1}), T is the daily average air temperature, e_a is the actual water vapor pressure of the air (kPa), e_s is the saturated water vapor pressure (kPa), $(e_s - e_a)$ (kPa) is the vapor pressure deficit in the air near the vegetated surfaces, R_n is the net radiation and G is the soil heat flux.

A neural network is formed by simple elements operating in parallel. Inspired by a biological neural network, the neural network receives its independent neurons in its input. The variables are passed to subsequent layers of neurons, where, passing through a transfer function, the weighted sum of input values is calculated, providing an output for the neuron in analysis (WANG et al., 2017). The bayesian regularized neural networks (BRNN) are more robust than the networks that use the back propagation of the errors, besides avoiding the over-fitting of the model (TICKNOR, 2013). Regularization refers to limiting the scale of weights and thresholds to improve the generalization ability of the neural network. In other words, on the basis of the neural network error function MSE, a penalty term, which can approximate the complex function, is added, thus improving the neural network function as the following Equation 2.

$$F = \beta E_D + \alpha E_W \tag{2}$$

where the square of the network weights is described as Equation 3.

$$E_W = \ln \sum_{0}^{n} W_i \tag{3}$$

W_i is the weight of the neural network connection; n is the total number of samples; E_D is the sum of the residuals of the expected value and target value of the neural network; and α and β represent the regularization parameters that determine the training target of the neural network and control the degree of fit achieved.

Bayesian regularization takes the objective function of the traditional neural network model as a likelihood function. The regularizer corresponds to the prior probability distribution on the network weights, and the network weights are regarded as a random variable. A Bayesian regularization neural network refers to a forward neural network based on Bayesian regularization training. Using a hypothesized parameter probability distribution, this network learns in the whole weight space and evaluates relevant parameters.

It then adjusts the regularization parameter and performs adaptive adjustment of the regularization parameters using Bayesian inference based on the posterior distribution. According to the probability density of weights to determine the optimal weighting function, and under the premise of ensuring the smallest squared network error, the weights are minimized to provide effective control of network complexity and to improve network generalization ability. Bayesian regularization optimizes the fit of the neural network of the training samples and minimizes model complexity by improving the training performance function of the neural network.

RESULTS AND DISCUSSION

The air temperature varied from 21.8 to 26.5°C, whereas ET_o ranged from 1.6 to 7.8 mm. BRNN were trained with different parameters choices and obtained R^2 between 0.96 and 0.99 during training and between 0.95 and 0.98 with test dataset, and root mean squared error (RMSE) less than 0.10 mm.day^{-1} compared to PM.

Table 1 show results for four parameters combination scenarios. Similar results were reported by Kumar et al. (2008) comparing an ANN model with the methods of Hargreaves and Penman-Monteith (PM-56) for the estimation of reference evapotranspiration, with coefficient of determination of 0.90.

Table 1. Weights found in the training of bayesian regularized neural networks (RBNN) to predict the reference evapotranspiration with only three variables (air temperature, solar radiation and wind speed at average daily scale)

Neurons	MC Samples	α	β	E_W	E_D	RMSE (mm.day^{-1})	R^2
2	20	0,34	150,97	31.05	17.19	0,10	0.97
5	40	0.56	223.06	45.46	11.57	0,08	0.98
10	40	0.17	253.71	290.01	10.07	0,06	0.98
15	40	0.73	122.23	43.94	21.06	0,07	0.97

Figure 2 shows the relationship between simulated values by BRNN and PM-sample values that were not applied in BRNN training.

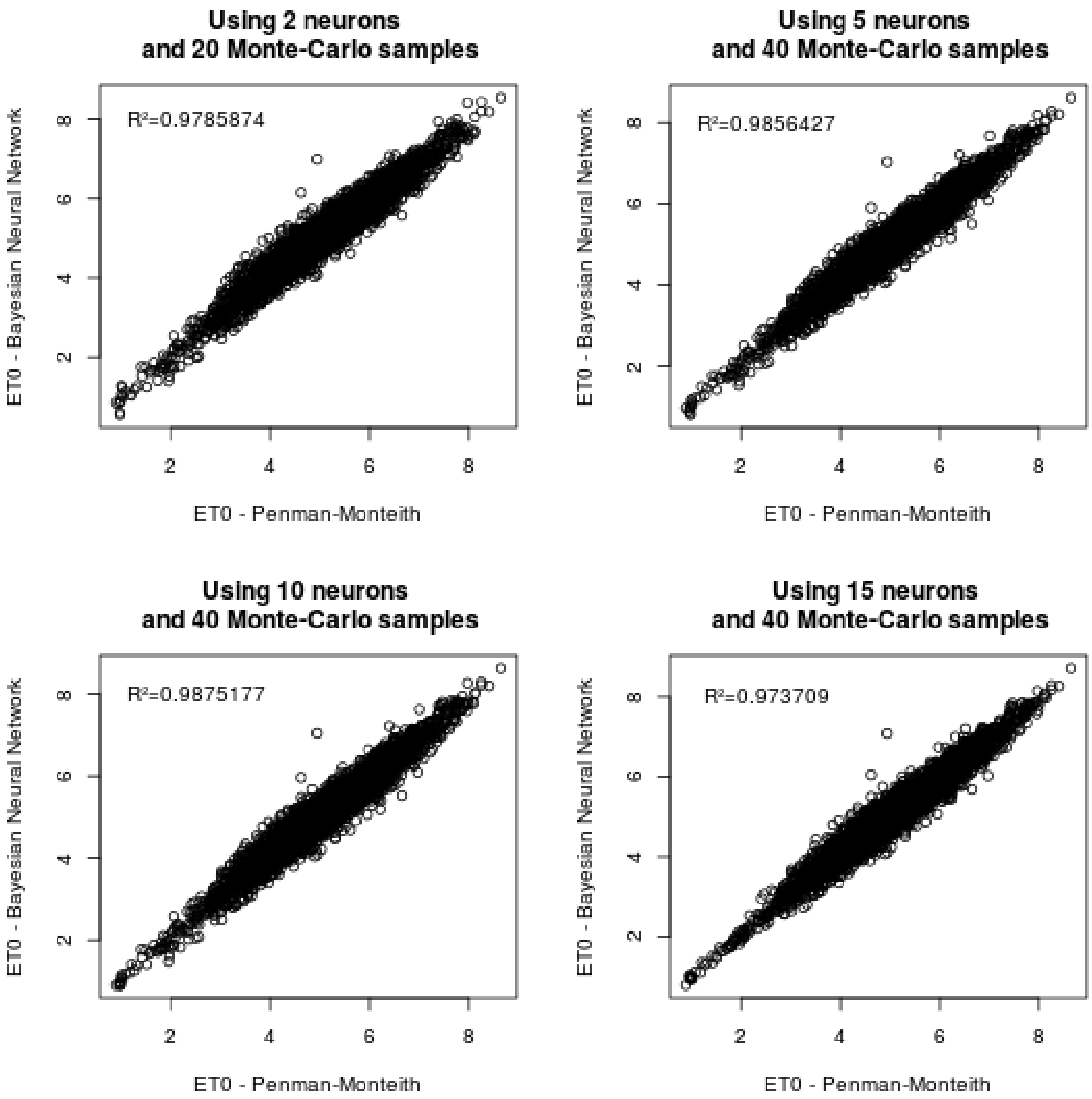

Figure 2. Performance of bayesian regularized neural networks (RBNN) trained to predict the reference evapotranspiration for different combinations of parameters

The success of neural networks is directly related to their great versatility and it makes them a very promising tool for decision taking. The selection of the parameters defined by the user also contributed to the optimal performance of the ANN in the estimation of reference evapotranspiration. It is important to point out that other network architectures or other parameters can also be applied for similar situations and that the proposed solution was selected to present the potential of application of the tool and its good performance.

CONCLUSIONS

Daily reference evapotranspiration calculated by Penman-Monteith can be simulated with less variables by a bayesian regularized neural networks with a great precision, showing high accuracy and using only air temperature, solar radiation and wind speed at average daily scale as input variable.

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