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# Neo-fuzzy neuron model for seasonal rainfall forecast: A case study of Ceara's eight homogenous regions

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**Abstract**. The knowledge about the seasonal rainfall in some Brazilian regions is essential for agriculture and the adequate management of water resources. For this purpose, linear and nonlinear models are commonly used for seasonal rainfall prediction, while some of them are based on Artificial Neural Networks, demonstrating great potential as shown in literature. According to this tendency, this work presents a rainfall seasonal forecast model based on a neuro-fuzzy technique called Neo-Fuzzy Neuron Model. Improved performance by using this approach has been obtained in terms of reduced root mean square error (RMSE) and increased correlation between predicted and real output when compared with dynamic downscaling model using the Regional Spectral Model. Experimental results show the effectiveness of the proposed method in predictions regarding the first four trimesters from year 2002 up to the current one.

Keywords: Seasonal rainfall prediction, ANN, neo-fuzzy neuron, dynamic model

## 1. Introduction

Forecasting of rainfall is a must for rain-fed agriculture of arid and semi-arid regions around the world, where agriculture consumes nearly 80% of the total water demand [4]. Moreover, the socio-economic impact is directly affected in regions where harvest is dependent on irregular climatic conditions [2], bringing the attention to the necessity of predicting future climatic conditions, mainly those regarding rainfall for the accurate management of water resources. There is about 190 water resources, that represents 90% of the total, being monitored in the state of Ceará in order to prevent the drought and flood [5].

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Over 90% of the Ceará area, a state located in northeastern Brazil, has semi-arid and irregular climatic conditions, thus demanding the application of adequate tools in the prediction of the rainfall inter-annual variability. The rainy season in Ceará lasts four months, where over 60% of the total rainfall at an average of 650 per year is distributed from February to May, period for which the models must be valid.

The dynamic model used for rainfall forecasting in Ceará is the Regional Spectral Model (RSM) developed by the Center of Environmental Modeling of the National Centers for Atmospheric Prediction (NCEP) nested in the atmospheric general circulation model ECHAM4.5 [1]. Typically, such dynamic model requires very high computational effort. Over the last 20 years, significant improvement on techniques to forecast rainfall has occurred. Analogously to classical techniques, empirical ones have also been improved, also demonstrating high potential [1]. The most common empirical methods for forecasting are based on

Artificial Neural Networks (ANN). Recent works have shown their potential in the field of meteorology forecast [8–11], since the use of ANNs seems prominent.

The work proposed in [11] used a Multilayer Perceptron Network (MLP) in combination with Fuzzy C-Means (FCM) clustering. For each formed cluster, a MLP is trained, so that the final forecast model is able to identify the input pattern and apply it to the respective trained MLP. In the aforementioned case study, it has been demonstrated that this technique overcomes other approaches such as the k-nearest neighbors and stepwise linear regression. A Neuro-Fuzzy technique was used in [9] to model an event-based rainfall-runoff, showing the effectiveness of the proposed architecture in the case study. Ocean-atmospheric indices were used in [8] as an input vector in an ANN rainfall forecast model. A MLP network in combination with a feature selection algorithm based on Fuzzy-Ranking Algorithm (FRA) was used in [8] to predict rainfall.

Following the empirical approaches, this work proposes a rainfall forecast model based on Neo-Fuzzy Neuron (NFN) model [12], using the learning technique proposed in [3]. The NFN model combines the advantages of fuzzy logic and neural networks in a simple manner by fusing complementary triangular fuzzy memberships and rules into a neuron in order to model complex and highly nonlinear relationships. This network can be trained very fast and is found to converge to global minimum of the weight error space [4]. One of the main contributions of this work consists in providing complementary information related to rainfall forecasting by verifying the performance of NFN model.

The proposed case study includes eight homogenous regions in Ceará, Brazil. Fig. 1[1] shows the region map. The proposed NFN model aims to generate the seasonal rainfall forecast for the aforementioned sites.

The results obtained by the ANN are compared to a dynamic downscaling model using RSM model [1], which is currently used by the Foundation for Meteorology and Hydric Resourses of Ceara (FUNCEME). The RSM model was nested into the global model ECHAM4.5, whose atmospheric variables are chosen to feed the model at each six hours in the forecasting process. Additional detail on the nested-downscaling can be found in [1].

The paper is organized as follows. Section 2 provides the description of rainfall forecasting issues and introduces the input data used for prediction. The Neo-Fuzzy Neuron model is described in Section 3. Section 4 presents experimental results for the case study. Finally, concluding remarks are discussed in Section 5.

[1] http://www.funceme.br/.

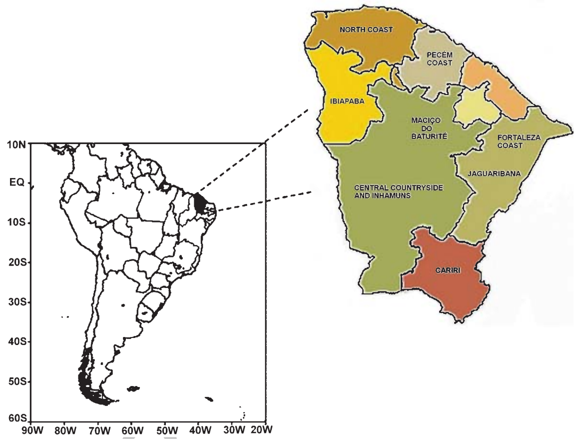



Fig. 1. Eight homogeneous regions in the state of Ceará.

## 2. Problem description

The problem of future rainfall prediction can be stated as follows: "Given a set of meteorological variables in a certain region, determine the future rainfall precipitation in such region using a pre-trained model". Thus, the problem of future rainfall prediction consists in determining an adequate model as well as the respective input variables for an accurate prediction.

In this work, the region where rainfall is supposed to be predicted is the state of Ceará, while the chosen model is the Neo-Fuzzy Neuron, as described in Section 3. The input variables, except for the Nino and the sea surface temperature (SST) dipole from Atlantic Ocean anomalies, were acquired from Reanalysis Project [7]. For the reanalysis data, the average between the pressure levels corresponding to 925 $hPa$ and 850 $hPa$ were adopted for a coordinate grid comprehending $3^\circ S$–$8^\circ S$ and $41^\circ W$–$38^\circ W$, thus containing the whole state of Ceará. Besides, the following variables are considered: divergence, vertical motion, air temperature, specific humidity, vorticity, and the zonal and meridional wind. Table 1 gives a brief description of each variable. The input of the NFN model is a data set composed by 9 variables and 27 samples, corresponding to three consecutive months.

The observed rainfall data regarding each month were obtained in [6]. Four periods corresponding to three consecutive months were considered i.e. from January to March, from February to April, from March to May, and from April to June. For the rainfall data

Table 1
Input Variables Description

| Variable | unit | Description |
|---|---|---|
| Vertical motion | $hPas^{-1}$ | It indicates the degree of ascending mass areas in atmosphere |
| Divergence | $s^{-1}$ | It indicates whether there are regions of convergence or divergence of atmospheric mass, being directly related to the probability of raining |
| Vorticity | $s^{-1}$ | It indicates the extent of rotation of a fluid. Cyclonic vorticity (negative values) or anticyclonic(positive) in the southern hemisphere are associated with areas of higher(positive) or lower(negative) atmospheric instability and cloud formation, respectively |
| Air temperature | $K$ | It corresponds to areas with higher or lower warming temperature temperature along the surface |
| Specific humidity | $gkg^{-1}$ | It indicates the amount of water present in the air. High and low values correspond to regions with wet and dry air, respectively |
| Zonal and meridional wind | $ms^{-1}$ | It indicates the east-west and north-south wind components |
| Niño 3+4 | $^{\circ}C$ | Anomaly index of sea surface temperature(SST) in the area between $5^{\circ}N$-$5^{\circ}S$ and 170–120$^{\circ}W$ representing the warming (El Niño) or cooling (La Niña) phenomenon in the Eastern Central Pacific Ocean |
| Dipole SST | $^{\circ}C$ | Representative index for the dipole of SST in the Tropical Atlantic given by the difference in SST anomalies between the area from the north (50–20$^{\circ}N$ , 60–30$^{\circ}W$) to the south (00–20$^{\circ}S$, 30$^{\circ}W$-10$^{\circ}E$) of the basin |

provided by the RSM model, the average of its ten members is considered, having as boundary condition the predicted SST [1]. Grid interpolation of the rainfall provided by RSM model was performed from 60*km* to 10*km* within the area for each homogeneous sub-region using the Thiessen polygon technique, and then the sum of the three-monthly data was calculated according to the observed data.

## 3. Neo-Fuzzy neuron model

The use of Neuro-Fuzzy techniques has grown significantly in the forecasting field. Within this context, this work presents the use of Neo-Fuzzy Neuron (NFN) model [3] to forecast the rainfall in the Ceará region. The NFN architecture is similar to a single layer multilayer perceptron, nonlinear synapses, and Fig. 2 shows the NFN network. This network is composed by $n$ fuzzy-neurons, where $n$ is the input space dimensionality. These fuzzy-neurons are composed by membership functions and a respective synaptic weight. There is a respective fuzzy-neuro for each input $x_i$, which is propagated into fuzzyfication and a defuzzyfication process according to:

$$f(x_i) = \sum_{j=1}^{h_i} \left[\mu_{ji}(x_i) w_{ji}\right], \tag{1}$$

where $\mu_{ji}$ and $w_{ji}$ are the membership functions and synaptic weights, respectively, for a given partition $j$ and input $i$, $h_i$ and $f(x_i)$ denote the number of partitions and the neuron output for the input $i$, respectively. Then, the output $y$ for the final model can be written as:

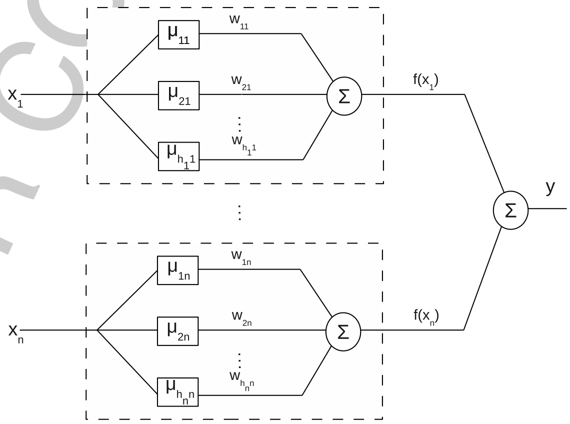



Fig. 2. Neo-Fuzzy neuron network structure.

$$y = \sum_{i=1}^{n} f(x_i) = \sum_{i=1}^{n} \sum_{j=1}^{h_i} \left[\mu_{ji}(x_i) w_{ji}\right], \tag{2}$$

The membership functions $\mu_{ji}$ were chosen to be a triangular function, as Fig. 3 shows the employed membership function. The used learning algorithm used is described in detail in [3], and it is shown that it is an optimal learning algorithm. A brief overview on the learning algorithm is provided in next section.

### *3.1. Learning algorithm*

The weight update algorithm is described in [3] as an optimal learning algorithm. It chooses the best learning rate for each sample, aiming to minimize the sum of square error (SSE). Given the error at sample $k$, $e(k) = y_d(k) - y(k)$, SSE is defined as:

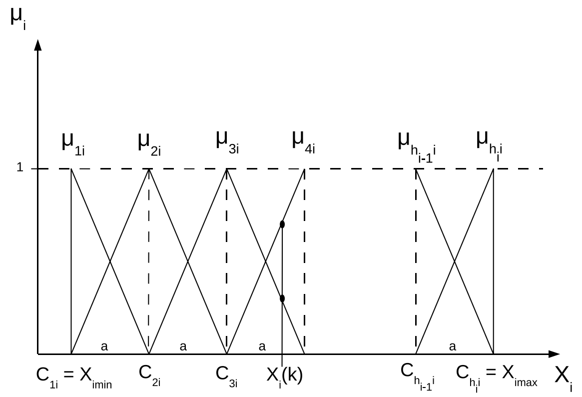



Fig. 3. Triangular membership functions.

$$E_{sse}(y, y_d) = \frac{1}{2L}\sum_{k=1}^{L} e(k)^2, \tag{3}$$

where $y(k)$ and $y_d(k)$ are the predicted and desired output of $k$th input data sample, respectively, and $L$, is the number of exemplars. It is minimized via gradient descendant procedure as:

$$w_{ji}(k+1) = w_{ji} + \eta e(k)\mu_{ji}[x_i(k)] \tag{4}$$

where $\mu_{ji}$ and $w_{ji}$ are the membership function and synaptic weight, respectively, of partition $j$ and input $i$, $h_i$ and $f(x_i)$ denotes the number of partitions and the neuron output for the input $i$. The learning algorithm is described as follows.

For each neuron $i$ and the respective partition $h_i$, the following vectors are defined: $\boldsymbol{\mu}^{(i)} = [\mu_{1i}, \ldots, \mu_{h_i i}]^T$ and $\mathbf{w}^{(i)} = [w_{1i}, \ldots, w_{h_i i}]^T$. Thus, the output $y$ at sample $k$ can be defined as:

$$y(k) = \sum_{i=1}^{n}\left[\left(\mathbf{w}^{(i)}(k)\right)^T \cdot \boldsymbol{\mu}^{(i)}(k)\right], \tag{5}$$

Without loss of generality, the vector $\boldsymbol{\mu}^{(i)}$ is defined in a normalized version $\tilde{\boldsymbol{\mu}}^{(i)}$ as:

$$\tilde{\boldsymbol{\mu}}^{(i)}(k) = \frac{\boldsymbol{\mu}^{(i)}(k)}{\sum_{j=1}^{h_i}\mu_{ij}(k)}. \tag{6}$$

Thus, the output $y$ is re-written as:

$$y(k) = \sum_{i=1}^{n}\left[\left(\mathbf{w}^{(i)}(k)\right)^T \cdot \tilde{\boldsymbol{\mu}}^{(i)}(k)\right] \tag{7}$$

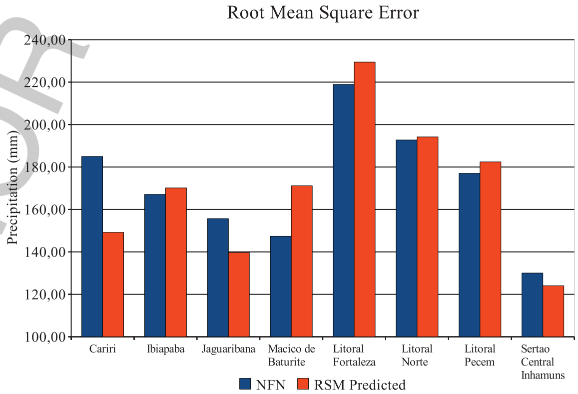
Defining the following vectors: $\tilde{\boldsymbol{\mu}}^T = [(\tilde{\boldsymbol{\mu}}^{(1)})^T, \ldots, (\tilde{\boldsymbol{\mu}}^{(n)})^T]$ and $\mathbf{w}^T = [(\mathbf{w}^{(1)})^T, \ldots, (\mathbf{w}^{(n)})^T]$, the learning algorithm is expressed as:

$$\begin{cases} \mathbf{w}(k+1) = \mathbf{w}(k) + e(k)\tilde{\boldsymbol{\mu}}(k)(\alpha^w)^{-1}(k), & (8)\\ \alpha^w(k+1) = \alpha\alpha^w(k) + \| \tilde{\boldsymbol{\mu}}(k+1) \|^2, & (9) \end{cases}$$

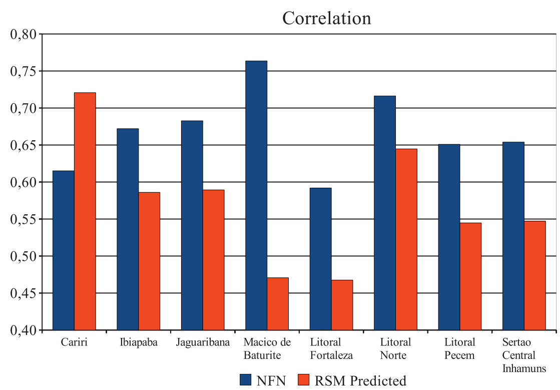
where $\alpha$ is the forgetting factor and $0 \leq \alpha \leq 1$. Additional detail on NFN learning can be found in [3].

## 4. Experimental results

The NFN model has considered the months of October, November, and December from 1961 to 2010 in order to compose the training data set and forecast the rainfall in four trimesters (January to March, February to April, March to May, and April to June) among 1962 and 2011. The training and test data set are composed by 9 input variables and 27 samples, and the objective for each year is to predict rainfall during the next four trimesters using the data acquired in October, November, and December. The training data set was divided in two groups. The first group is composed by the data from




(a) RMSE between predicted and real outputs




(b) Correlation value between predicted and real outputs

Fig. 4. Performance rates at different regions for NFN and RSM models.

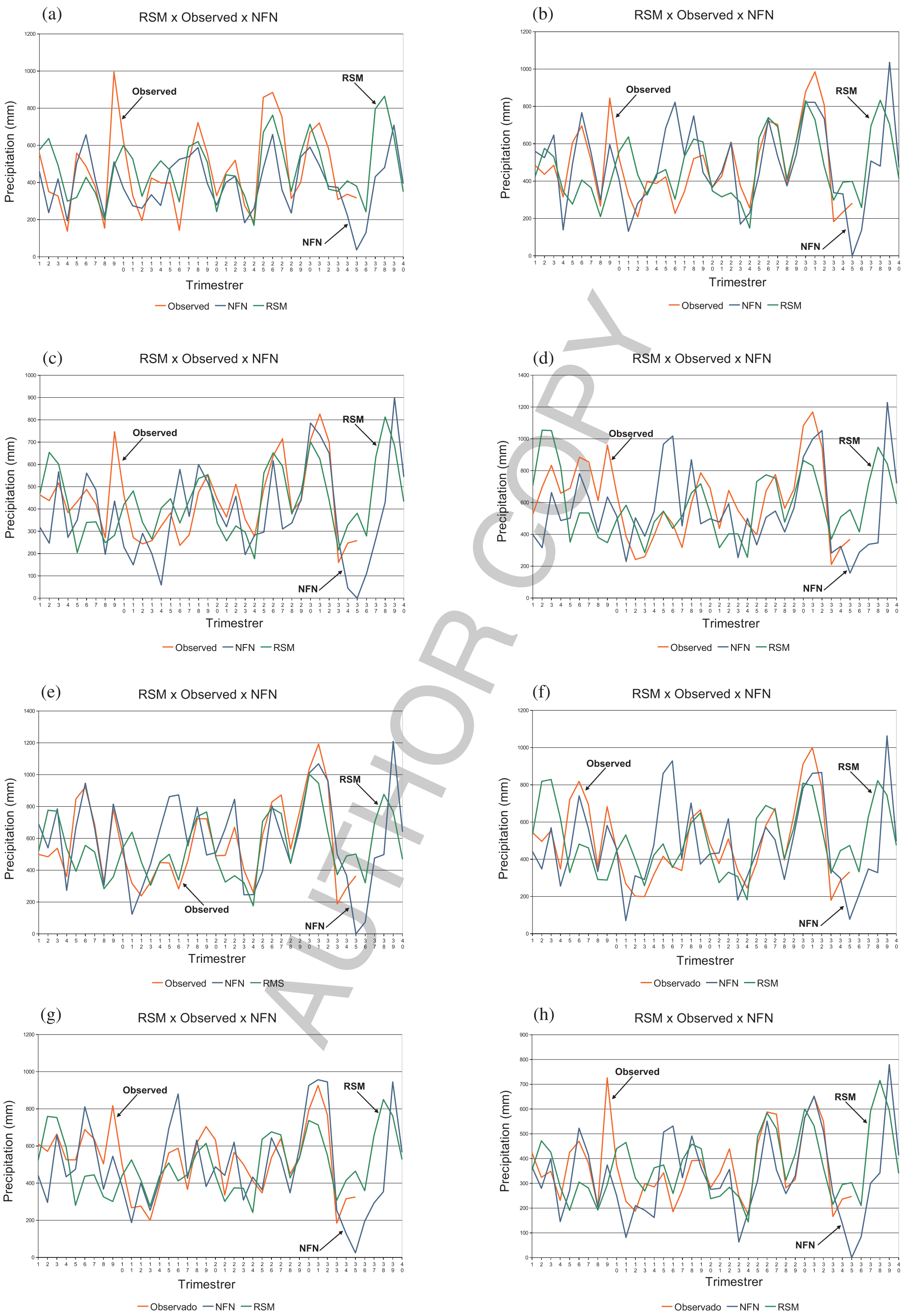



Fig. 5. Observed and forecasted rainfall for the Ceará regions using NFN, RSM models, and the observed data.

the years 1961 to 2000 and was used to train the network. The results for the remaining years i.e. from 2001 to 2010 were used for validation purposes and compared to the results from RSM considering the same period.

The results were obtained using the RSM and NFN models for each one of the eight regions. For the NFN model, the forgetting factor is adopted as 0.5. The performance is evaluated using the root mean square error (RMSE) and correlation coefficient between predicted and desired output data.

### *4.1. Results for rainfall forecasting in Ceará region*

Figures 4(a) and (b) show the evaluation performance for each region using the NFN and RSM models. The NFN model overcomes the RSM model, except in Cariri region, in terms of the correlation coefficient value. Considering RMSE, RSM has presented improved performance in Cariri, Juaguaribana, and Sertão Central Inhamuns. However, from a general point of view, it is possible to say that NFN presents improved performance than RSM model.

Figure 5 shows the predicted response in test set. The nomenclature on the x-axis used represented the first four trimesters (January to March, February to April, March to May, and April to June) for each year from 2002 to 2011.

## 5. Conclusion

This work has demonstrated that the ANN model has great potential for the seasonal forecast of accumulated rainfall considering the first four trimesters of the year. The evaluation parameters, RMSE and correlation, for the NFN model have shown less satisfactory results for a single region i.e. Cariri, if compared with those provided by the dynamic model.

Although some regions e.g. Jaguaribana and Sertão Central Inhamuns have presented higher RMSE for the NFN model, the respective correlation is higher than that of the RSM model. This can be explained by the spike in rainfall for both regions during the period from April to June, 2003, as seen in Figs. 5(c) and (h).

The training of the ANN is relatively fast, corresponding to less than one minute by using a PC with Intel® Core™2 Duo processor at 2.00 GHz, converging in few epochs. On the other hand, the RSM model takes one day to provide forecast, running in a cluster composed by ten computers, each one of them equipped with Intel® Core™2 Quad at 2.40GHz.

The proposed model has presented significant improvement compared to the dynamic one using RMSE and correlation as evaluation parameters. By presenting low computation effort, it can certainly contribute with information for the reports on the rainy season in the state of Ceará.

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