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Meteorology

Application of RBF artificial neural networks to precipitation and temperature forecasting in Paraná, Brazil

Aplicação de Redes Neurais Artificiais RBF para previsão de precipitação e temperatura no Paraná, Brasil

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ABSTRACT

Precipitation and temperature have an impact on various sectors of society, such as agriculture, power generation, water availability, so it is essential to develop accurate monthly forecasts. The objective of this study is to develop an artificial neural network (ANN) model for monthly temperature and precipitation forecasts for the state of Paraná, Brazil. An important step in the ANN model is the selection of input variables, for which the forward stepwise regression method was used. After identifying the predictor variables for the forecasting model, the Radial Basis Function (RBF) ANN was developed with 50 neurons in the hidden layer and one neuron in the output layer. For the precipitation forecasting models, better performances were obtained for forecasting the data smoothed by the three-month moving average, since noisy data, such as monthly precipitation, are more difficult to be simulated by the neural network. For the temperature forecasts, the ANN model performed well both in the monthly temperature forecast and in the 3-month moving average forecast. This study showed the suitability of forecasting precipitation and temperature with the use of RBF ANNs, especially in the forecast of the monthly temperature.

Keywords: Precipitation and temperature forecasting; Artificial neural network; Selection of input variables

RESUMO

Precipitação e temperatura têm impacto em vários setores da sociedade, como agricultura, geração de energia, disponibilidade hídrica, por isso é essencial o desenvolvimento de previsões mensais acuradas. O objetivo deste estudo é desenvolver um modelo de Rede Neural Artificial (RNA) para previsões mensais de precipitação e temperatura para o estado do Paraná, Brasil. Uma etapa importante no desenvolvimento de um modelo de RNA é a seleção das variáveis de entrada, no qual foi utilizado o

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método de regressão stepwise forward. Após identificar as variáveis preditoras para o modelo de previsão, foi desenvolvida a RNA Radial Basis Function (RBF) com 50 neurônios na camada oculta e um neurônio na camada de saída. Para os modelos de precipitação, obtiveram-se melhores desempenhos na previsão de dados suavizados pela média móvel de três meses, uma vez que dados ruidosos, como precipitação mensal, são mais difíceis de serem simulados pela rede neural. Para as previsões de temperatura, o modelo de RNA teve bom desempenho tanto na previsão de temperatura mensal quanto na previsão de média móvel de três meses. Este estudo mostrou a adequação da previsão de precipitação e temperatura com o uso de RNAs RBF, especialmente na previsão da temperatura mensal.

Palavras-chave: Previsão de precipitação e temperatura; Redes neurais artificiais; Redes neurais de Funções de Base Radial; Seleção de preditores

1 INTRODUCTION

Unlike weather forecasts, in which one intend to anticipate how the weather will be over the next few days, the climate forecast focus on whether a given season will be, for example, drier or wetter than the climate average, warmer or colder etc. as well as the intensity of the anomalies in relation to the average (Reboita et al., 2018).

Climate forecasts are of great importance to many sectors of society, especially those sensitive to atmospheric variations, such as agriculture, power generation, water availability, etc. In addition, the ability to predict extreme events (e.g. droughts, storms and landslides) allows decisions to be made in time to minimize their impacts.

Precipitation and temperature are controlled by very complex nonlinear phenomena that vary in space and time. Therefore, several methods have been developed for climate forecasting, such as numerical prediction models, statistical methods, and machine learning techniques. Among these methods, machine learning techniques, such as artificial neural network (ANN), k-nearest neighbor, support vector machine, and random forest model, are more suitable for climate forecasting because physical processes are highly complex and non-linear. The ANN is a form of machine learning technique that has been widely used in climate prediction given its ability to identify highly complex non-linear relationships between input and output variables without the need to understand the nature of the physical processes (Lee et al., 2018).

Several studies have used the ANNs methods on precipitation and temperature prediction. Nezhad et al. (2019) developed an ANN model for predicting Tehran maximum winter temperature. Also in Tehran, Gholizadeh et al. (2009) used an ANN model for predicting the next-month-precipitation in the next year for a meteorological station using actual monthly precipitation data for a time period of 53 years. Bodri and Čermák (2000) used an ANN model for forecasting next-month-precipitation and summer precipitation in the next year using actual monthly precipitation data from two Czech meteorological stations. Abbot and Marohasy (2015) predicted monthly precipitation with lead times of 3, 6, 9, 12 and 18 months, respectively, in Australia. In Brazil, Anochi and de Campos Velho (2016) used a self-configured neural network for monthly and seasonal precipitation predictions in southern Brazil. Those studies revealed that ANNs are a useful tool and the interest of the scientific community in using ANNs to forecast precipitation is increasing.

One of the most important steps in developing a satisfactory ANN prediction model is the selection of suitable input variables. For this reason, the different atmospheric systems that control the climate variability in the Paraná region and which were used as an input for ANN in climate forecasting in the work will be detailed in section 2.

The purpose of this work is to develop ANN models in order to provide accurate precipitation and temperature climate forecasts in Paraná. Several experiments are presented here to demonstrate the performance and feasibility of ANN models in climate forecast applications.

2 CLIMATE CHARACTERISTICS OF PARANÁ

Paraná is in a transition region between the tropical climate, predominant in the northern part of Brazil, and the subtropical climate, characteristic of the southern region of the country. According to the Köppen classification, the climate of Paraná is divided into: Af (tropical) always humid, without dry season and free of frost, located in the coastal plain; Cfa (subtropical) with hot summers, infrequent frost and summer rains in the northern, western, and southwestern parts of the state; Cfb (temperate) with fresh summers, without defined dry season, located between the first, second and part of the third plateaus.

In addition to the spatial and seasonal variability of the average climate in Paraná, there are also climate variabilities around this average state at various time scales. Studying climate variations requires a close look at the different systems that operate in this region. Thus, describing the circulations that influence the study area requires the exam of other key regions in explaining climatic extremes, over years or decades and even the seasonal, intraseasonal and interannual variability of Paraná.

The South American continent is located between two quasi-stationary high-pressure systems of the South Atlantic and South Pacific, with associated anticyclonic and subsidiary circulations. The South Atlantic Subtropical Anticyclone (ASAS) is the main influence on surface winds in southern Brazil. This pattern is present in all seasons, but it is stronger in winter, when it is further north and west, penetrating over the continent. In summer, the high-pressure center shifts further east and south over the ocean, bringing moisture to the continent (Grimm, 2009).

Another center of anticyclonic pressure is the polar high, known as the Mobile Polar High (MPH) of South America. This high, upon invading the southern region, brings in unstable weather, with an important disturbed current acting on the southern region of Brazil, which is the polar front (Nimer, 1989).

During summer, at low levels, a north-northwest jet that begins near the eastern slope of the Andes and can penetrate near the western boundary of the southern region, called the Low Level Jets (LLJ) occurs. Those wind systems are very important to transport moisture from the Amazon region to south - southeast regions. At high levels there are also an anticyclonic circulation, called the Bolivian High, and a trough over northeastern Brazil. Another feature of the circulation in the lower troposphere and dominant in summer is the formation of the South Atlantic Convergence Zone (SACZ). The SACZ causes a north-east-west cloud band that generally persists for periods of more than three days and is often associated with serious social and economic problems in the southeastern region of Brazil due to the large rainfall volumes.

From October to April, which corresponds to the warm semester, frequent Mesoscale Convective Complexes (MCC) are responsible for much of the total precipitation. An MCC is a system with thick cloud cover, approximately circular in shape (diameter in the order of a few hundred kilometers) and a minimum lifetime of six hours, but longer than isolated convective systems. The intensification of these complexes is related to the seasonal change of the high-level subtropical jet (which is in this region in the fall and spring) and its interaction with the LLJ (Grimm, 2009).

During winter, surface temperature contrasts are large at medium latitudes, producing strong westerly winds. Above large temperature contrasts, such as those occurring along fronts, there are very strong currents, called jet streams. In the middle latitudes, where Paraná is located, near the tropopause, there is a jet associated with the polar front, which is between the easterly polar winds and the warmer middle latitude westerly winds, called the Polar Jet (PJ). The PJ has an average speed of 125 km/h in winter and approximately half that value in summer and plays a very important role in the middle latitude weather because in addition to providing energy to the surface storm circulations, it also controls their trajectories.

3 METHODOLOGY

3.1 Climatological Database

The monthly atmospheric, oceanic and surface parameters used in this study were extracted from European Centre for Medium-Range Weather Forecasts (ECMWF) dataset. ECMWF periodically uses its prediction models and observed data to produce a reanalysis dataset. The reanalysis data contain past estimates of atmospheric parameters such as air temperature, pressure and wind at different heights and surface parameters such as precipitation, soil moisture and sea surface temperature. Estimates are produced spanning the whole globe and long periods of time. ECMWF reanalysis data are freely available from https://www.ecmwf.int/en/forecasts/datasets/browse-reanalysis-datasets.

The latest ECMWF reanalysis project is ERA5, whose data cover the period from 1979 to present. However, it is intended to extend the period from January 1950 to present. ERA5 reanalysis data are distributed on a regular grid with horizontal spatial resolution (latitude and longitude) of 0.25°×0.25°. Vertically, data is available at pressure levels or at a single level (for surface data). For pressure levels, there are 16 atmospheric variables at 37 levels from the surface to 1 hPa (around the top of the stratosphere) (Copernicus, 2019).

The data used in this study for temperature and precipitation prediction experiments are spatial and monthly averages. The data period ranges from January 1979 to December 2018 (480 months). Based on the climatology study presented in section 2, we selected the main phenomena that may control variations in the average climatic conditions of Paraná and were employed as input to the ANN models. The regions and possible predictor variables to the model obtained from the ERA5 reanalysis project are presented in Table 1.

Table 1 – Possible predictor variables for rainfall and temperature forecast in Paraná

Regions	Variables	Abbreviation
South Atlantic Subtropical Anticyclone	SST	sst_sasa
	Surface pressure	pres_sasa
South Pacific Subtropical Anticyclone	SST	sst_spsa
	Surface pressure	pres_spsa
Mobile Polar High	SST	sst_mph
	Surface pressure	pres_mph
El Niño 3.4	SST	sst_en
Low Level Jet	V-component of wind at Pressure level 850 hPa	v850_llj
Polar Jet	U-component of wind at Pressure level 250 hPa	u250_pj
Subtropical Jet	U-component of wind at Pressure level 250 hPa	u250_sj
Darwin	Surface pressure	pres_darw
Tahiti	Surface pressure	pres_tahi
South Atlantic Convergence Zone	Vertical velocity at Pressure level 500 hPa	w500_sacz
	Specific humidity at Pressure level 700 hPa	h700_sacz
Inter tropical Convergence Zone	Vertical velocity at Pressure level 500 hPa	w500_itcz
	Specific humidity at Pressure level 700 hPa	h700_itcz

Source: From the authors (2020)

In addition to the variables presented in Table 1, the vertical velocity at 500 hPa, air temperature at 2 m from the surface, specific humidity at 700 hPa and geopotential height at 850, 500 and 200 hPa, respectively, for the Paraná region were also selected.

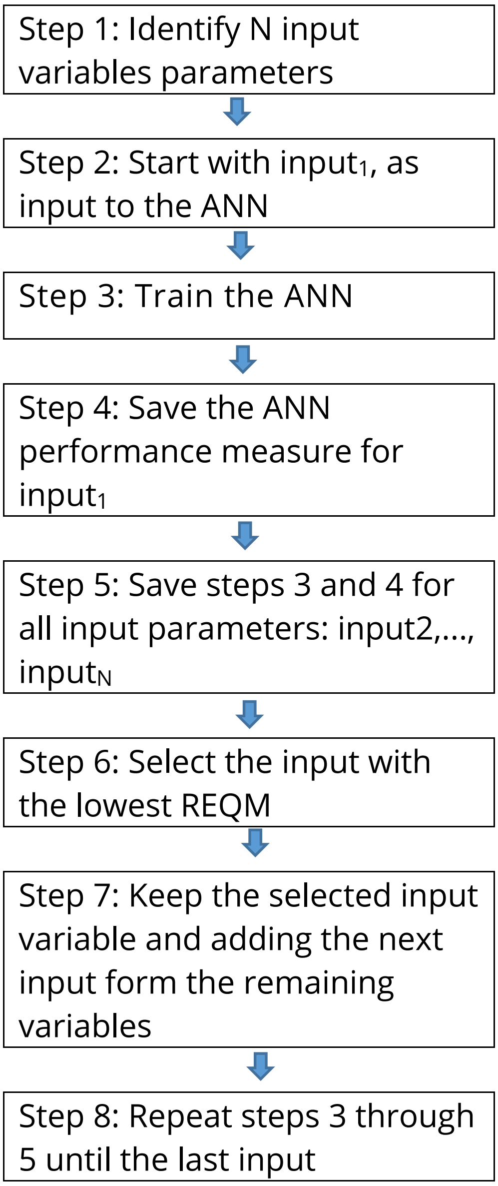
3.2 Selection of Input Variables

ANNs, like other empirical models, require an input predictor data set. There is a large number of input variables potentially relevant to monthly and seasonal precipitation and temperature prediction. However, one should select as few entries as possible that retain as much information as possible from the patterns to be predict, avoiding the use of redundant information.

Dimension reduction methods are important tools for selecting the best predictor data set. These methods avoid multicollinearity, which is caused by the presence of many variables in the model expressing the same information. Another advantage of applying these methods is that computational time can be reduced by increasing model speed because redundant predictors are discarded (Maheshwari, 2019).

In this study the method used to select model inputs was stepwise regression, which selects those predictors that most influence the output set. This method is implemented by either adding (forward step) or removing (backward step) variables from a selection criterion. In this work we used the forward step method, with the criterion of the lowest Mean Square Error Root (REQM) value between simulated and observed rainfall values. The input parameters were determined by the investigation of cross correlations between the previous variables presented in Table 1, and the variable of interest for different time lags. The forward stepwise regression flowchart is shown in Figure 1.

Figure 1 – Forward stepwise regression flowchart

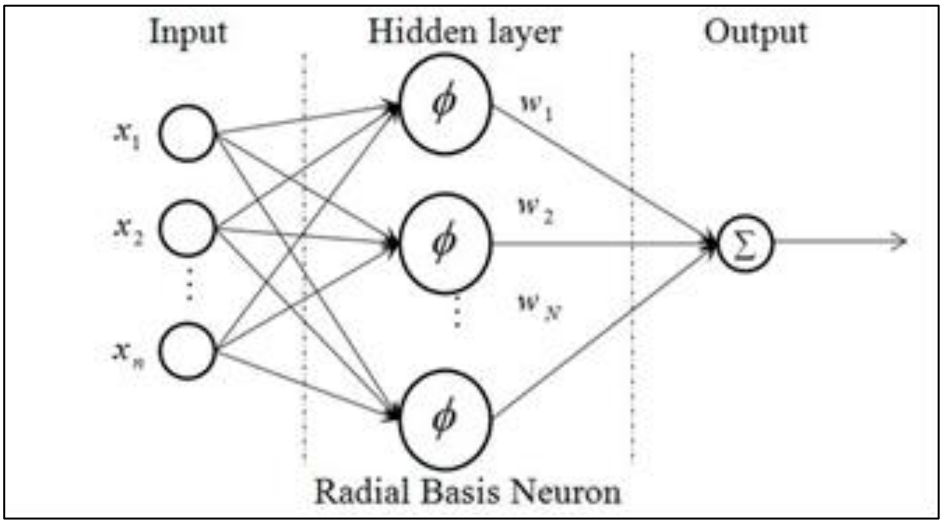


Source: From the authors (2020)

3.3 ANN structure and training algorithm

An ANN is a data-driven mathematical model that was developed to imitate the structure of a human brain neural network and has been widely applied to solve problems such as prediction and discrimination (Lee et al., 2018). The ANN of this work is based on the Radial Basis Function (RBF). RBF is a feedforward neural network, which is nonlinear and hierarchic. The architecture of the RBF ANN contains three layers: an input layer, a hidden layer with nonlinear processing neurons and an output layer (Liu et al., 2019). It is shown schematically in Figure 2.

Figure 2 – Architecture of the RBF neural network. Fonte: He et al. (2019)



Source: From the authors (2020)

The RBF network training process consists of two steps. In the first step the hidden layer neuron weights are adjusted by using an unsupervised learning method, which is dependent only on the characteristics of the input data. The second step, which adjusts the output layer neuron weights, uses the generalized delta rule learning method (Silva et al., 2010).

3.4 ANN Model Development

After identifying the significant input variables by the stepwise method, those variables served as input to the ANN model. Of the total input-output pairs, approximately 10% were used for network validation and the remaining ones for training. The preparation of the data consisted of its normalization within the range [-1, +1], so that the different order of magnitude parameters did not affect the learning of the network, because higher order of magnitude values tend to mask the importance of the smaller magnitude ones.

The number of input nodes is equivalent to the number of input variables and the number of nodes in the hidden layer was experimentally determined by trial and error. Only one neuron was used in the output layer, because only one variable (precipitation or temperature) was predicted by each ANN model.

The neural networks were evaluated for prediction of monthly precipitation and temperature forecasts, respectively with the original data and also for the 3-month moving averages of those variables. The objective of applying the moving average of the data was to filter out high frequency ("noise") variations of the time series and to assess the impact of "noise" on ANN model performance.

Since the ANN randomly sets the initial weight value at the beginning of the training, a different neural network model is created for each training process, yielding different performance. Therefore, the optimal prediction model was selected based on the average accuracy obtained by running the ANN model training process five times, with a different input dataset for each iteration, which is called cross validation.

In order to evaluate the performance of the RBF ANN in the forecasting of temperature and precipitation in the state of Paraná, some statistical metrics were used to quantify the similarities between the observed data (yi) and the estimated data (yi*). These statistical metrics are presented as follows: the root mean square error (RMSE), an index that measures the average magnitude of errors. It always has a positive value and the closer to zero, the higher the quality of the estimated values. The RMSE has value in the same dimension as the analyzed variable and is defined by

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^* - y_i)^2}$$

the correlation coefficient (R), which indicates the degree of linear correlation between two variables. It varies between values -1 and 1, where R = 0 represents no correlation between the variables analyzed and R = 1 there is a strong positive correlation. The value of R is obtained by

$$R = \frac{\sum_{i=1}^{n}(y_i^* - \overline{y^*})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(y_i^* - \overline{y^*})^2}\ \sqrt{\sum_{i=n}^{n}(y_i - \bar{y})^2}}$$

the Nash-Sutcliffe efficiency (NSE), an index that determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information"). The NSE varies on the range [−∞,1]. It is commonly understood that NSE values less than zero are undesirable since NSE = 0 implies that the model simulation gives performance no better than the mean of the observed system output. The NSE is defined as

$$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i^*)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

and, the mean absolute error (MAE), which represents the mean absolute deviation between observed and predicted values. Like RMSE, the MAE has the same dimension as the analyzed variable and is defined as

$$MAE = \frac{1}{2}\sum_{i=1}^{n}|y_i^* - y_i|$$

4 RESULTS AND DISCUSSION

In this section, we present the results of the stepwise method and the performance of the RBF network in the monthly temperature and precipitation forecasts of the state of Paraná.

4.1 Identification of Significant Input Variables

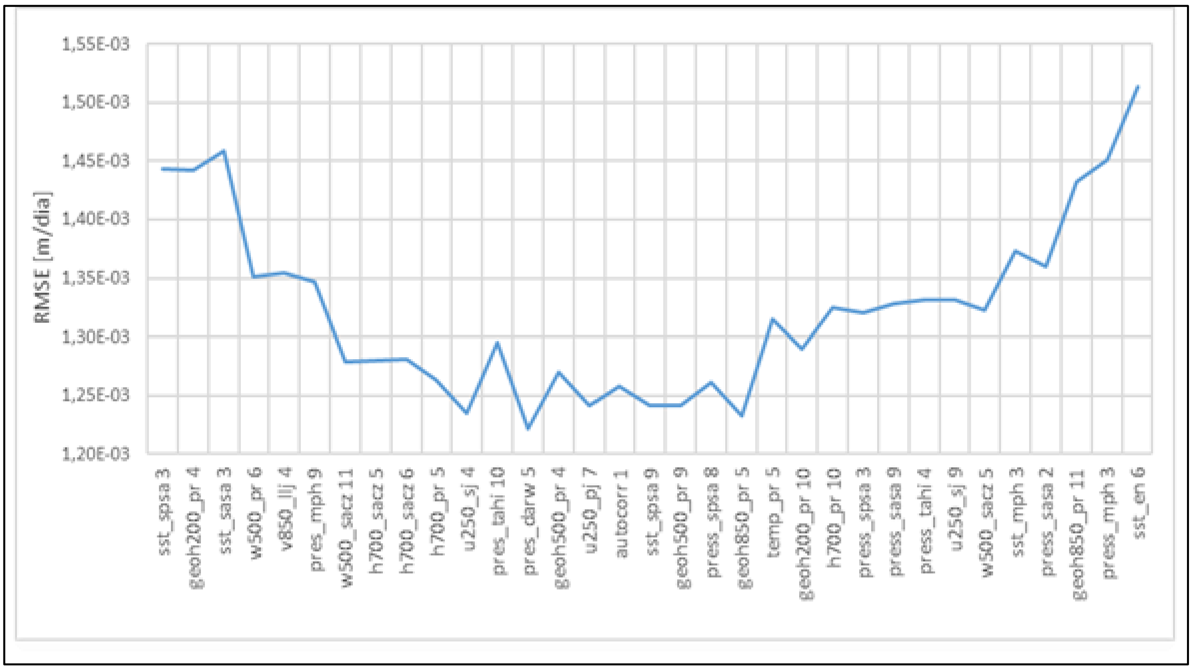
The identification of significant input variables and the optimization of the network structure are important steps in building an effective ANN model. As described in section 3.2, the input variables were determined by stepwise regression. Before using the stepwise regression to select the most important variables of the prediction model, we investigated relationships that the variables presented in Table 1 have with the variables of interest through the use of cross-correlation coefficients. From this analysis 34 variables were selected as potential predictors.

Stepwise regression was performed for 34 variables with the RBF neural network and its performance was evaluated based on the RMSE in the monthly precipitation and 3-month moving average precipitation analyses. The results of stepwise regression for monthly and 3-month moving average precipitation are shown in Figures 3 and 4, respectively.

As shown in Figures 3 and 4, the performance of the RBF network improves initially, but if too many variables are added, the network will perform worse in the forecast of precipitation. For monthly precipitation forecast, the network improves its performance with approximately 10 input variables, which include sst_spsa 3, geoh200_pr 4, sst_sasa 3, w500_pr 6, v850_llj 4, pres_mph 9, w500_sacz 11, h700_sacz 5 and 6, h700_pr 5. The number after acronym indicates the months of the lagged variable with respect to the predicted precipitation. Between the eleventh and the twentieth variable the network performance did not improve and after the twentieth variable the performance started to decay with a higher RMSE.

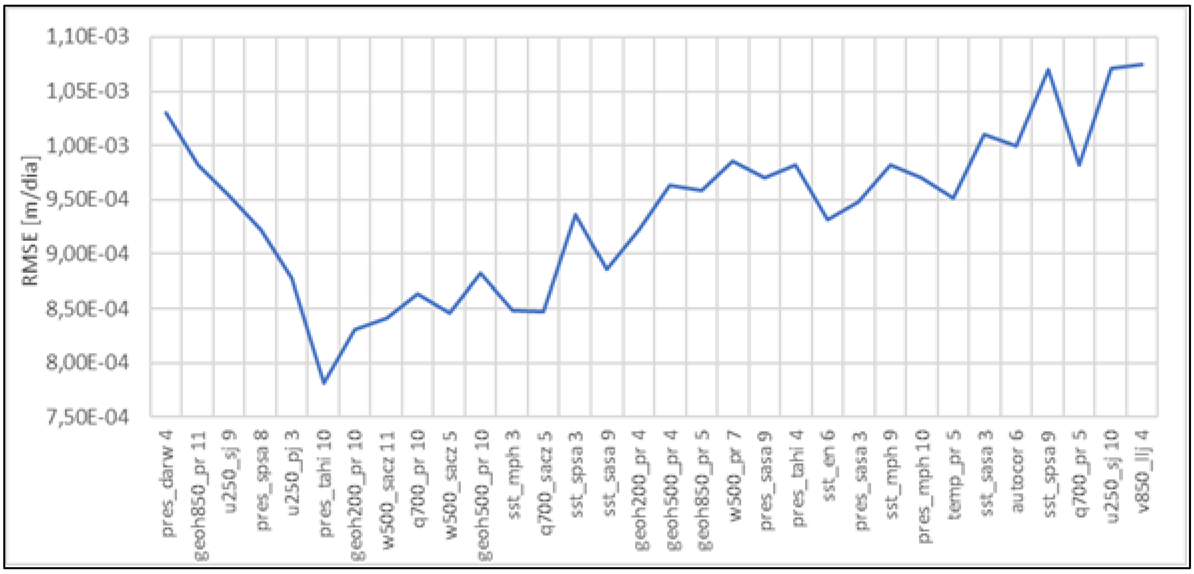
As shown in Figure 4, the neural network performance in forecasting 3-month moving average of precipitation improved until the sixth variable, with the following variables: pres_darw 6, geoh850_pr 11, u250_sj 9, pres_spsa 8, u250_pj 3, pres_tahi 10. After the sixth variable, the effect of multicollinearity is observed, causing the RMSE values between the observed and estimated data to increase, consequently reducing the network performance.

Figure 3 – Stepwise Regression for monthly precipitation



Source: From the authors (2020)

Figure 4 – Stepwise Regression for 3-month moving average precipitation

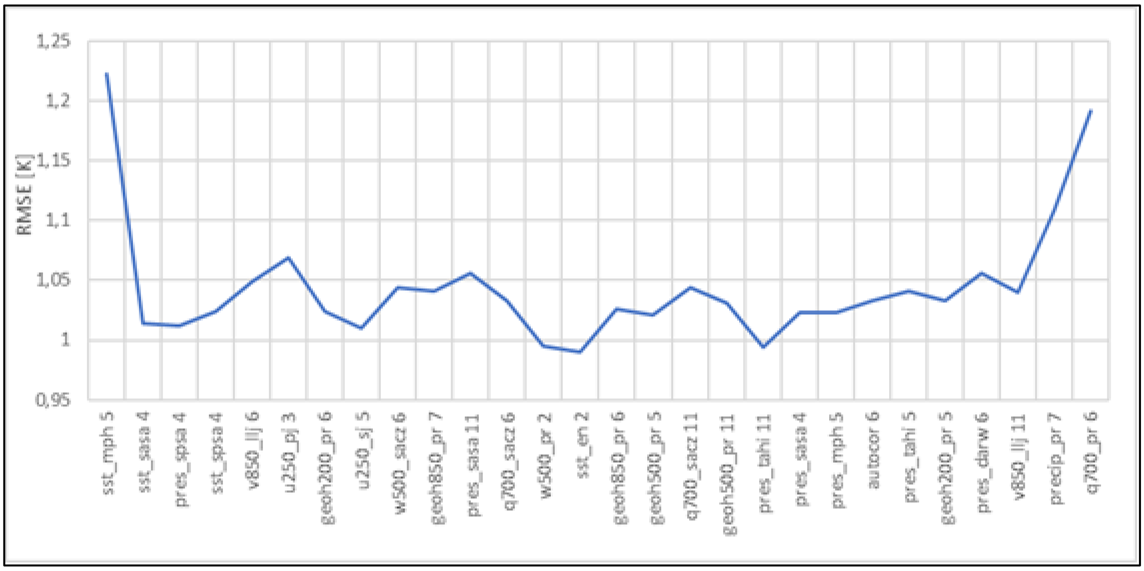


Source: From the authors (2020)

Figures 5 and 6 show the results of the stepwise regression for monthly temperature and the 3-month moving average temperature. Figure 5 shows that few input variables were necessary for the ANN model to improve its performance. The sst_mph 5, sst_sasa 4 and pres_spsa4 variables are candidate predictors to the

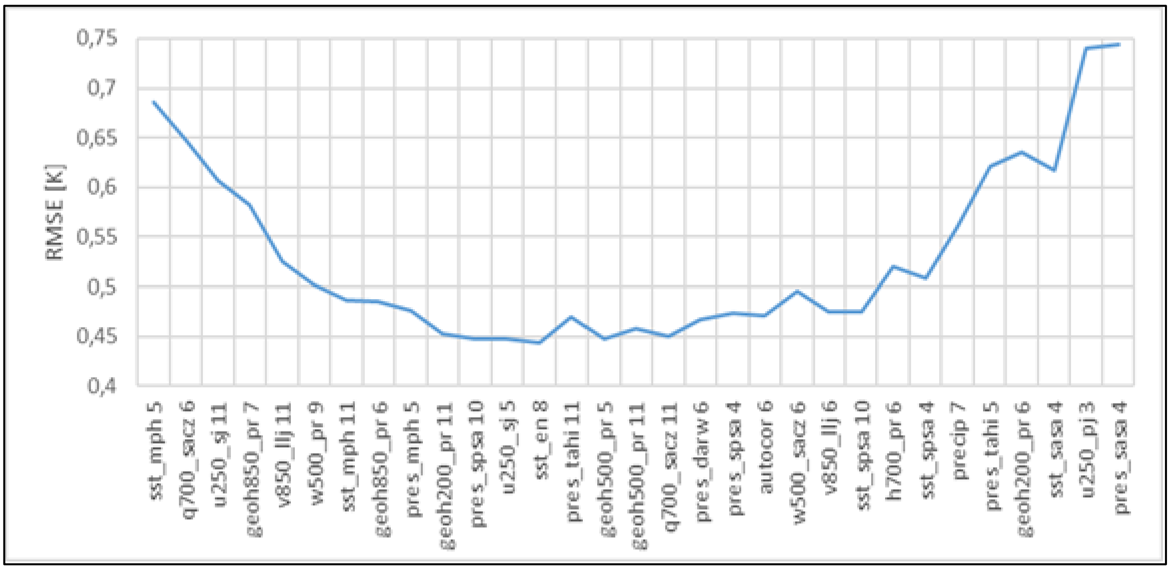
ANN monthly temperature forecasting model. For predicting the 3-month moving average temperature, more variables are needed, because the neural network performed better with 11 variables, as can be seen in Figure 6. The 11 variables selected as possible predictors to the model were: sst_mph 5 and 11, q700_sacz 6, u250_sj 11, geoh850_pr 6 and 7, v850_llj 11, w500_pr 9, pres_mph 5, geoh200_pr 11 and pres_spsa 10.

Figure 5 – Stepwise Regression for monthly temperature



Source: From the authors (2020)

Figure 6 – Stepwise Regression for 3-month moving average temperature



Source: From the authors (2020)

4.2 ANN model for rainfall and temperature forecasting

After the stepwise regression analysis, 11 input variables were selected for the monthly precipitation forecast, 6 for the 3-month moving average forecast, 3 for the monthly temperature forecast and 11 for the average 3-month temperature forecast, as described in section 4.1. As in stepwise regression, 50 neurons were used in the hidden layer, which was a value obtained after running a few tests and which presented the best performance of the ANN.

The statistical metrics of the artificial neural network model for the precipitation forecast are presented in Table 2. The scatter plots between the simulated data and the monthly and 3-month moving average precipitation are shown in Figures 7 and 8, respectively.

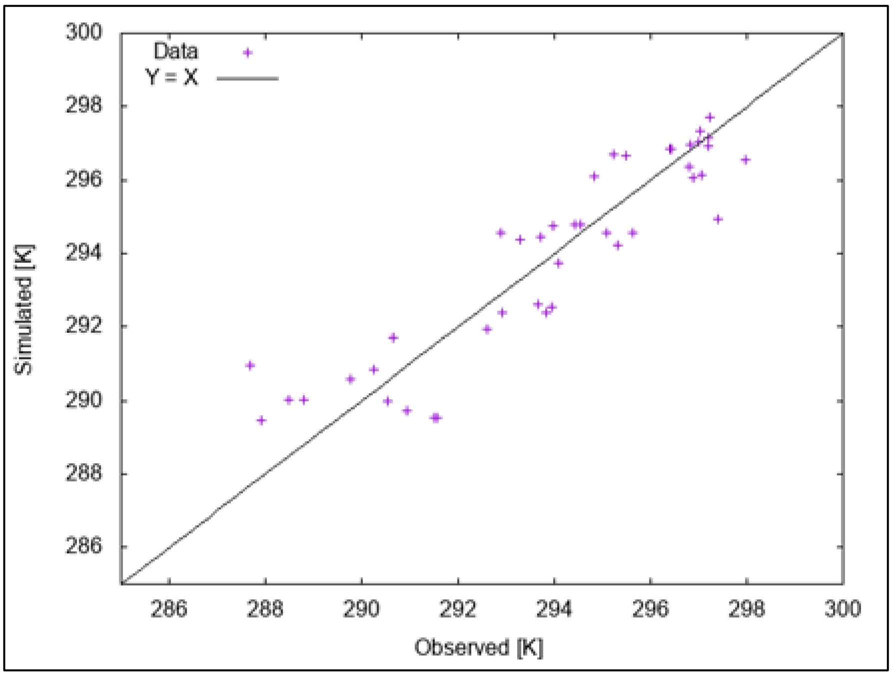
The results show that the performance of the ANN model for the prediction of precipitation is better when the data are smoothed over the average of 3 months, since noisy data, such as monthly precipitation, are more difficult to be simulated by the neural network.

Table 2 – Artificial Neural Network (ANN) model performance for precipitation forecasting

Forecast	RMSE [m/dia]	R	NSE	MAE [m/dia]
Monthly precipitation	0.15E-02	0.62	0.39	0.13E-02
3-month moving average precipitation	0.11E-02	0.83	0.68	0.10E-02

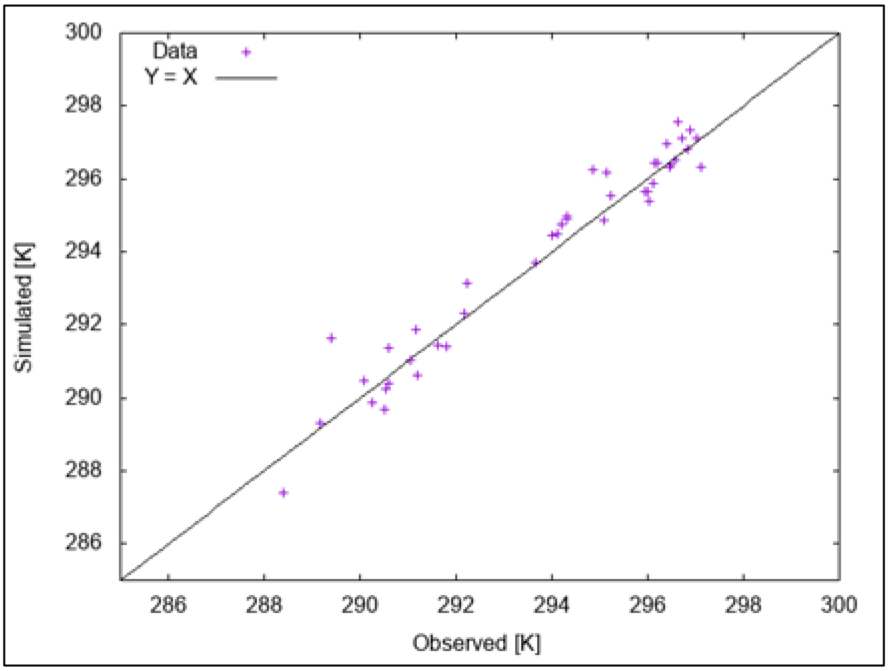
Source: From the authors (2020)

Figure 9 – Scatter plot of observed and predicted monthly temperature using ANN



Source: From the authors (2020)

Figure 10 – Scatter plot of observed and predicted 3-month moving average temperature using ANN



Source: From the authors (2020)

5 CONCLUSIONS

Estimating monthly climatic variables is of great importance for various sectors of society. In this research, artificial neural networks were used as a tool in modeling nonlinear processes in order to forecast monthly temperature and precipitation in Paraná.

The influence of climatic variables on the ANN model was assessed using the stepwise regression method. The stepwise regression identified the potential predictor variables for the ANN models of temperature and precipitation, respectively. Among the relevant predictors, the most important were sea surface temperature in the south Pacific subtropical anticyclone region and the south Atlantic subtropical anticyclone region for the monthly precipitation forecast, pressure in Darwin for the three-month moving average precipitation forecast, sea surface temperature in mobile Polar high for monthly temperature forecast and 3-month moving average temperature forecast.

The experiments showed that the neural network model for the temperature forecast had a better performance than the precipitation forecast model. The performance of the neural network for the forecast of the 3-month moving averages of the temperature was slightly better in relation to the monthly forecast.

In conclusion, this study showed the suitability of forecasting precipitation and temperature with the use of RBF ANNs. The results show that the network performs better when the data are smoothed out in time. Very noisy data, such as monthly precipitation, are more difficult to forecast. On the other hand, since the temperature series are less noisy than precipitation, the ANN temperature forecast model, in general, performed better than the precipitation forecast models. Also, this work demonstrated that the stepwise predictor selection methodology, which is usually based on the use of linear regression models, can be successfully adapted to a nonlinear prediction system such as the RBF ANN employed in this study. Therefore, we conclude that ANN models can be a useful and effective methodology to be incorporated into routine climate forecast activities.

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