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RAIN PREDICTION MODEL USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Precipitation is important in maintaining the environment and life of living beings. Through their studies and increasingly accurate forecasts, we can reduce the impacts related to floods, environmental disasters, and losses in the agricultural and tourism sectors. However, climate change has made the analysis of this variable difficult. In this article we will present an hourly rain forecast model using Artificial Neural Networks, using the information on instantaneous, maximum and minimum temperature, relative humidity, wind, and precipitation through the automatic weather stations of the Instituto Nacional de Meteorologia, located in the city from Manaus/AM. First, a study was carried out to determine the network architecture best suited to the data set. Numerous combinations between the training and transfer functions were performed until finding the functions that presented the best error values. The predictions made with the model showed satisfactory results, showing that the model was able to reproduce the same behavior of the precipitation observed for the predicted day, presenting practically the same totals, especially on the rainiest days. On the other hand, in cases where the observed showed a characteristic of convective precipitation, the model was not able to capture the intensity, which shows that it must be tested with other atmospheric variables.

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INTRODUCTION

Precipitation is one of the meteorological variables that plays an important role in conserving the natural environment, maintaining the hydrological cycle and water supply sources in urban areas (SCHMIDT & MATTOS, 2013; SILVA *et al*., 2021; NETO *et al*. ., 2022; MAUD 2022). However, the precipitation regime has been modified by several factors, but mainly by climate change (HUANG *et al*., 2021; GEORGESCU *et al*., 2021; BACK *et al*., 2022). Studies on global warming and changes in the state of the world climate indicate that precipitation is the most significant variable in the process, however, knowing the behavior of precipitation in a given region and its variation over the period can be a useful tool for managers. public for actions during periods of extreme events, in addition to the actions necessary for possible solutions to climate change (CHOWDHUR *et al*., 2016; GOLDBERG *et al*., 2020; GOMES *et al*., 2021). However, climate variability is the main justification for continuing our efforts toward more accurate climate prediction, in the health, energy production, and agriculture sectors (HELLDÉN, *et al*., 2021; EBI *et al*., 2022; KUGO *et al*. 2022).

For these reasons, in recent decades efforts have been made to create models and tools that can estimate and predict precipitation in oceanic and continental areas (LIU *et al*., 2017; SUN *et al*., 2018). In Soko *et al*., (2021), a review is carried out on the importance of weather radars. The authors point to radars as an effective tool for estimating and predicting precipitation due to their temporal and spatial resolution, and their ability to provide practically real-time rainfall data, being able to assist in hydrological and meteorological applications (ZANG *et al*., 2018). Satellite precipitation estimation models are powerful tools. The TRMM mission (Tropical Rainfall Measuring Mission) (KUMMEROW *et al*., 1998; KUMMEROW *et al*., 2000; KIDD *et al*., 2017) has provided precipitation products for many years with high temporal and spatial resolution, being replaced by GPM precipitation products(Global Precipitation Measurement). KIRSCHBAUM *et al*., 2017; HUFFMAN *et al*., 2019). In addition to mathematical prediction models, COSMO-CLM (Consortium for Small-scale Modeling) (ROCKEL *et al*., 2008; MUGUME *et al*., 2018; PAUL & SURAHAMANYAM, 2021; BAUR *et al*., 2022), WRF (POLITI *et al*., 2021; ZHU, *et al*., 2021; PIERSANTE, *et al*., 2021; DEVI *et al*., 2021), and precipitation estimation, some computer models such as Artificial Neural Networks (ANNs) can reproduce meteorological variables (BENALI *et al*., 2019;

CARVALHO & DELGADO, 2022) and hydrological (OYEBODE & STRECTH, 2019; ALTHOFF *et al*., 2021; KARUNANAYAKE *et al*., 2021; LOPES *et al*., 2022).Because it is a self-adaptive model, ANNs, unlike traditional models, through examples and functional relationships between data and networks can improve, being suitable for problems that have substantial data even if the solutions are of great complexity such as the forecasts. (ZHANG *et al*., 1998). In Sonderby *et al*., (2021) the authors created an ANN-based model called MetNet, which predicted precipitation for 8 hours and a temporal resolution of 1 km^2, producing probabilistic maps of the variable through satellite and radar images. Chen *et al*., (2019) develop two ANN models, where the first trains the network with precipitation points, and surface radar reflectivity, while the second model adds precipitation from the TRMM satellite, showing the hybrid ANN model a Promising proposal for predicting precipitation. However, in Li *et al*., (2021) the authors used five years of data to train a nonlinear autoregressive RA, to predict precipitation for 48 hours, showing that the model is effective to predict the variable in urban areas. . While, in Pan *et al*., (2021) RNs were used as an alternative to downscaling models. The use of different precipitation estimation techniques, such as multiple linear regression, ANN and Spline interpolation, and satellite data (GPM-IMERG), in addition to the identification of the cloud and its morphology, shows that hybrid models allow greater geographic coverage (SHARIFH *et al*., 2019). Inspired by the families of deep learning models for binary segmentation, U-Net (RONNEBERGER *et al*., 2015) and SegNet (BADRINARAYANAN, *et al*., 2017; SHI *ET AL*., 2017), Ayzel *et al*., (2020) presented the colovional RNA model to estimate precipitation every 60 min, using radar data, called RainNet v. 1.0, despite the limitation for intense precipitation, the model showed great promise in the studies of RNA hybrid models. Also, Misra *et al*., (2018) uses a statistical downscaling model based on a long-term and short-memory recurrent ANN to capture the Spatio-temporal dependencies on local precipitation, the results showed that the coupled long-term memory recurrent ANN the autoencoder has the best performance compared to other existing methods, in addition to capturing precipitation extremes (MANDAL, SRIVASTAV AND SIMONOVIC, 2016; KLINSDONK, *et al*., 2022). Thus, in this article, I will show the development of an ANN model using meteorological variables collected through automatic surface stations to predict the precipitation punctually in a region.

MATERIALS AND METHODS

The ANN model proposed in this article used a set of atmospheric variables measured on the surface collected through the automatic surface meteorological station of the Instituto Nacional de Meteorologia (INMET- Brazil), located in the city of Manaus/AM. INMET's Web platform provides daily data which has undergone strict quality control, with outliers, absence of information, and others being removed. The meteorological variables chosen to compose the RNA training base total 20 years of hourly information on instantaneous temperature (^oC), maximum temperature (^oC), minimum temperature (^oC), relative humidity (%), wind (m /s), and precipitation (mm). For the development of this Intelligent System, the Neural Network Toolbox Toolbox (NNTool) from MATLABR2016a® (Matrix Laboratory) was used. Through the software, it was possible to test the various types of RNAs in this Toolbox. The procedures and directions applied in the conception of the ANN, for this, the method will be presented in three stages, called assembly, training, and forecast. The assembly phase is the most important, as it defines the type of network, architecture (layers and hidden neurons), activation functions, propagation type, learning algorithm, and other parameters. Subsequently, the network training phase was initiated, it is in this phase that the ANN training/learning takes place, where it captures all the relevant characteristics of the selected data set, such as the peaks, randomness, and seasonality of the information. It is at this stage that the data is divided so that 70% of the information available for the model to perform the network learning, 15% is saved to carry out the validation, and 15% in the network test. In this process, the main neurons are defined, called active neurons, the weight of these neurons remains constant and the others will adapt to them. The statistical parameters obtained during the training were analyzed and thus it was possible to choose the parameters that best adapt to the data set. After the construction, training of the network, and analysis of the parameters, the best architecture of the ANN was chosen. Thus, with the chosen model, precipitation predictions and corrections of the values found by the network were performed. Still at this stage, the model was validated by comparing the precipitation values observed in the period from January to May 2022, and the rain predicted by the RNA model tested.

RESULTS

The network used in this article was a "Feedforward" where all neurons from the upstream layer communicate with the downstream layer without feedback (Figure 1). The ANN architecture consists of five input variables that transmit stimuli to the neurons of the main layer, where the sum and activation function has the purpose of performing the processing of all inputs, while the transfer function verifies if the neuron is part of a neuron stimulus or inhibition process. And finally, all layers have the same direction, the output in Figure 1 is shown by the presence of only one neuron, which has the role of providing the answer to the system, which in this case, are the daily precipitation totals.

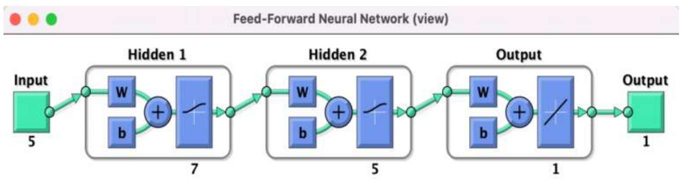


Figure 1. Graphic representation of the chosen architecture

Network training is one of the most important phases in the model creation process, as it is in it that, according to the error presented, the weights are corrected to minimize this error. Basically, the objective of the training is the reduction of global error, and the minimization of the error is one of the decisive factors for the correct modeling. For ANN training, combinations for twelve types of training functions Levenberg-Marquardt (trainlm), Bayesian Regularization (trainbr), BFGS Quasi -Newton (trainbfg), Backpropagation Resilient (t rainrp), Scaled Conjugate Gradient (trainscg), Powell/ Beale Reset Conjugate Gradient (traincgb), Fletcher -Powell Conjugate Gradient (traincgf), Polak-Ribire (traincgp), One Step Conjugate Gradient Secant (trainoss), Variable learning rate descending gradient (traingdx), Gradient descent with Momentum (traingdm), Gradient descending (traingd'). The training functions were combined with the three transfer functions, "purelin", "tansig" and "logsig", totaling 36 combinations. Determined the structural parameters of the ANN used during the simulation. In addition to testing the functions, tests were also performed to define the network architecture by varying the number of neurons in the main and hidden layer, which was determined by trial and error. Although the training shows good results, there is a very significant difference in the error presented for each transfer function for the same type of network, this is due to the absence of observations in some hours of the day, but this does not disqualify the results presented by the ANN, as can be verified through the values of Root Mean Square Error (ERRORMSE) and Mean square Error (MSE), presented in Tables 2 and 3, statistical variables which are indicators of ANN performance.

One of the objectives of the supervised training process of an ANN is to adjust the weights and *thresholds.*of atmospheric data and thus, find the most ANN model and the transfer function that best fits the data set used, being the basis for choosing the lowest possible value for errors (MSE). Usually, the MSE value starts high during the first iterations and as the ANN starts to converge the value stabilizes, and the closer to zero this stabilization happens, the better the ANN performance.

Table 1. Calculated MSE values of each combination of the Training functions (FTrain) with the Transfer functions (FTrans) after the simulations

MSE				ERROR			
Transfer Function	Transfer Function _			Transfer Function _	Transfer Function _		
	purelin	tansig	logsig		purelin	tansig	logsig
trainl	2.91	0.50	0.75	trainl	1.71	0.71	0.87
trainbr	2.91	105.00	0.92	trainbr	1.70	10.25	0.96
trainbfg	2.91	1.72	2.78	trainbfg	1.71	1.31	1.67
trainrp	2.95	12.64	3.41	trainrp	1.72	3.56	1.85
trainscg	74076.92	3.41	3.41	trainscg	272.17	1.85	1.85
traingb	162.33	3.41	3.42	traingb	12.74	1.85	1.85
traincgf	539869.27	3.41	3.42	traincgf	734.76	1.85	1.85
traincgp	119065.17	3.41	3.42	traincgp	345.06	1.88	1.85
trainoss	2.97	3.41	3.41	trainoss	1.72	1.85	1.85
trainingdx	26325722.85	78.75	3.41	trainingdx	5130.86	8.87	1.85
training	5759799655.07	3170.15	3.41	training	75893.34	56.30	1.85
training	5759799655.08	3170.15	3.41	training	75893.34	56.30	1.85

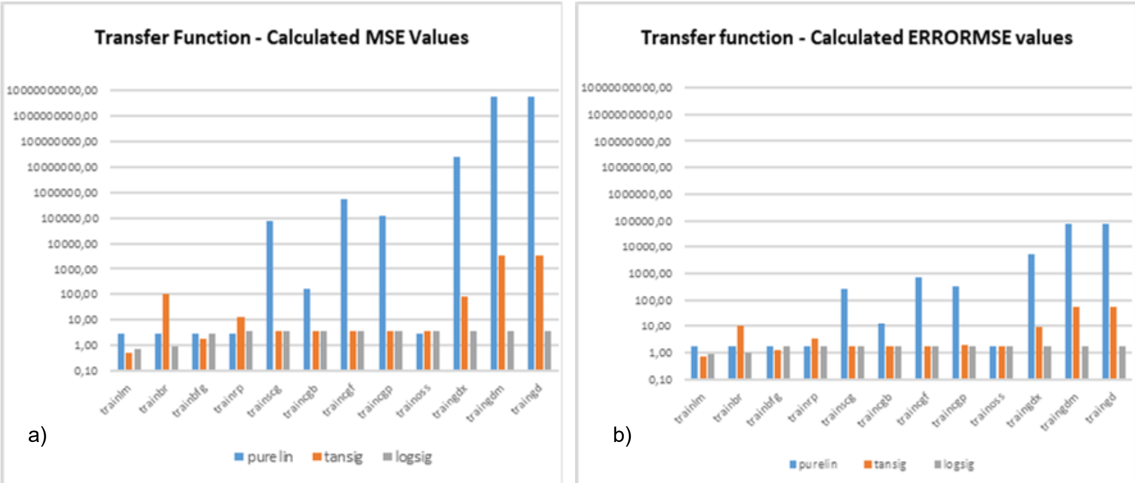


Figure 2. Statistical parameters between the transfer functions: a) MSE; b) ERROR

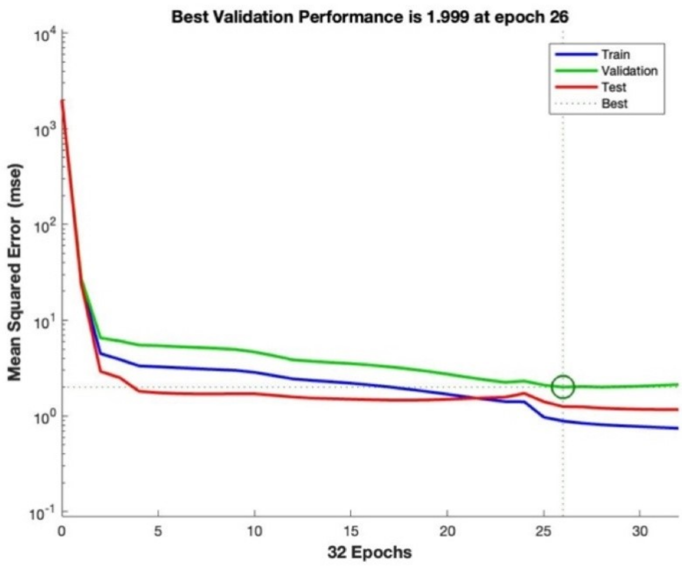


Figure 2 graphically presents the MSE values, where on the horizontal axis we relate the model type and the blue, orange, and gray color, the *Purelin*, *Transing,*and *Logsig transfer equations*, respectively. Note that for all combinations performed, the Transing transfer equation presents the lowest MSE value during training, and at the same time, Transing and the tranlm equation were the best evaluation, around 0.50. Despite this, other tests must be carried out so that this choice can be made official. ERRORMSE, like the other statistical analyzes presented, is also used to show the performance of the types of ANNs tested and the transfer functions available (see Table 1).

It is noted that the good performance and choice of parameters of the forecast ANN is also obtained through the lower values of the ERRORMSE generated by the combinations. Thus, it appears that among the combinations performed during the ANN training process, the one that presented the lowest error values was the Trainlm equation and the transfer equation - tansig, reaching 0.71. On Figure 3, it is shown *ANN performance*, where the blue curve shows the adjustment of the network training, while the validation is represented by the green curve, and the test the red curve, it is noted that the best performance of the curves and the test was possible through 26 evolutions (*Epochs*).

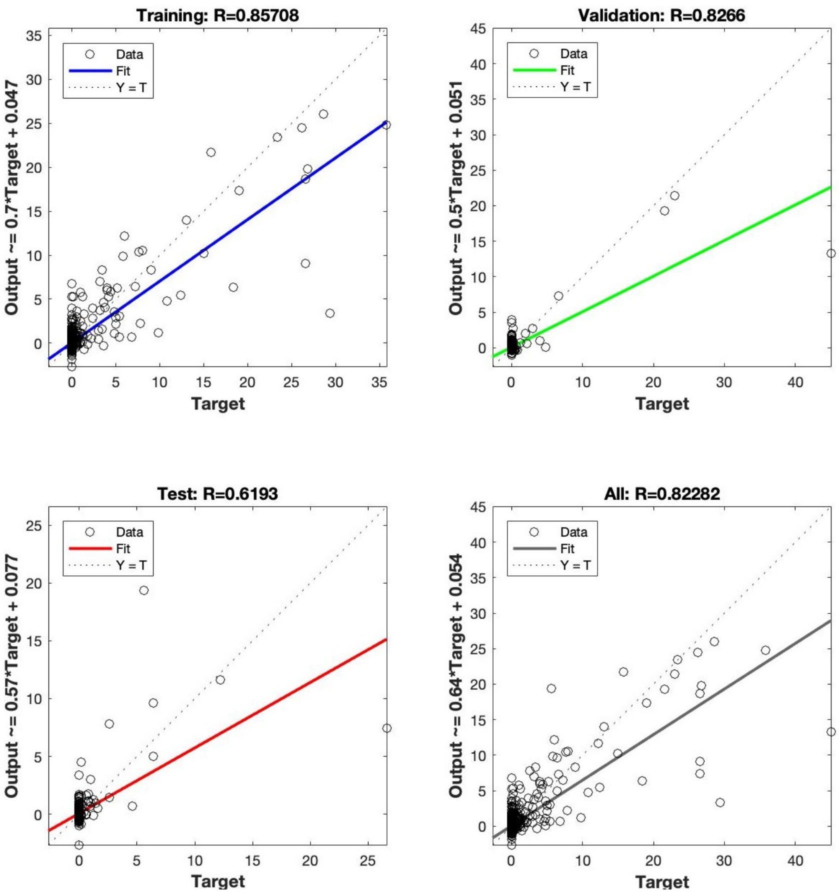


Figure 4: a) Regression test between the results obtained *versus* expected from the ANN: training; b) validation; c) test of the best network; d) joint aspects of the network

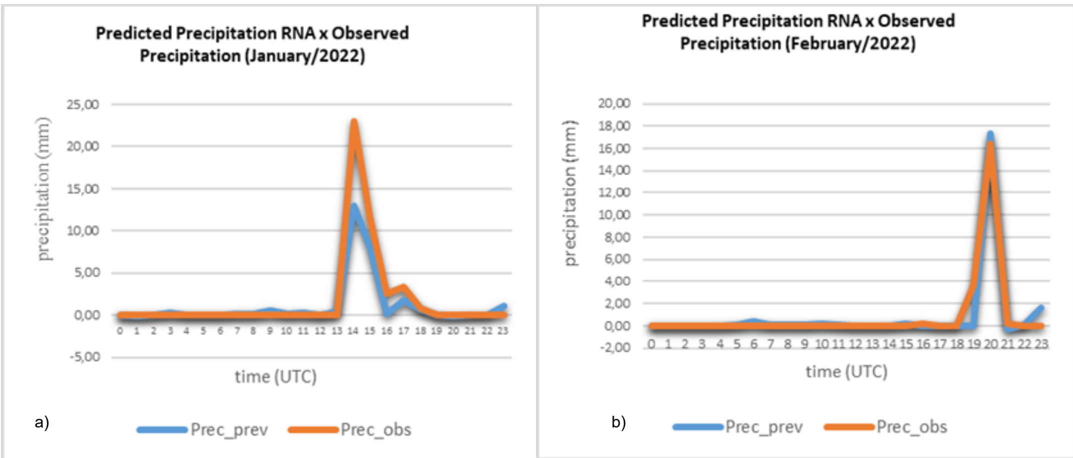
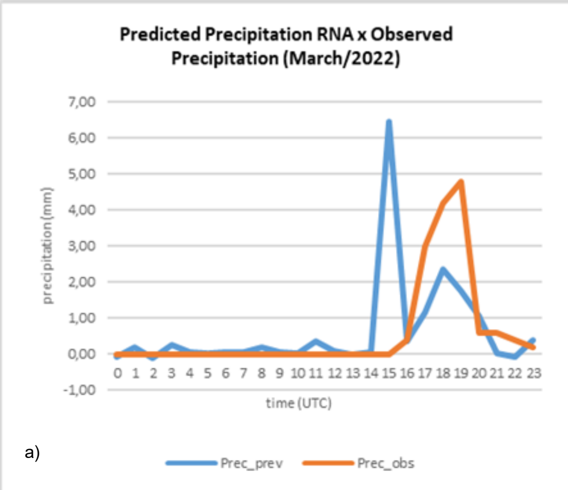


Figure 5. Predicted precipitation through the Neural Network compared to observed precipitation in mm/hour for 01/01 and 02/08/2022

The *epochs* represented by the circumference mean the stopping criteria of the ANN training when the best results are found (*best*). After the training phase, the ANN is prepared, it will be tested, and thus it will be possible to evaluate the network's ability to infer a coherent class to the training performed. At the same time, there is a major limitation in models based on neuron learning, which according to Haykin (1999) models have a single performance measure. But it is possible to measure this performance through statistical regression. Despite the excellent results obtained during the training, presented above, it is observed that after some attempts to train the network, the validation presented values above 1, (1.999) an expected result due to the size of the set of input values for the training. and network testing. The simulations and statistical analyzes of the network, present a significant degree of reliability in the specification of the Artificial Neural Network model for the prediction of precipitation in the very short term, obsessing the descent or adjustment of the slip curve, at each epoch performed we realize that the convergence time increases, according to the graph the algorithm took 26 epochs to find the best convergence state, demonstrating that this is the optimal state of convergence of the algorithm to reach a constant in the learning line. It can be used as a tool to aid decision-making. Figure 3 shows the Mean Square Error (MSE) curves between the input and output data set of the neural network. The curve in red color illustrates the test dataset, the curve in blue one, the training data, and the curve in green one, the validation dataset. The dashed line is the best value found. Data converge quickly (in 26 epochs). After training and choosing the ANN parameters, predictions and validations were performed, thus showing its performance to predict precipitation from surface data. Figure 4 presents the analysis between the results obtained and those expected during the training phase, which showed around 86% of accuracy (Figure 4a). Through the information entered in the ANN input, the 15% used to validate the tested network showed that it presented a high correlation index, which shows that of the data predicted by the ANN, around 82% are strongly correlated (Figure 4b). To demonstrate the best network test, (Figure 4c) is observed with a result closer to 1 when it is considered the best test, corroborating the network efficiency by (Figure 4c), when we analyze all aspects of the network together already presented in (figures 4a, 4b, and 4c) with a correlation value close to 1 with a correlation index of 82.2%. In a second moment, the performance of the model was tested to predict the daily precipitation in the city of Manaus using real-time data during the months of January to May 2022. In Figure 5a the forecast is represented by the blue line, while the orange line shows the observed precipitation on an automatic weather station. Applying the model, during the month of January it was found that the model showed excellent performance in predicting the behavior of rain, despite having a small record during the morning (09:00), while the observed rain was zero, but on the other hand, side overestimated the afternoon rain (14:00-15:00). It is worth noting that although the Amazon region is characterized by high rainfall, it is called the Amazon summer.

and 19:00 (UTC) that the network stabilized and had PREV, respectively. 2.35 mm and NOTE. 4.2 mm - PREV. 1.75 mm and NOTE. 4.8 mm, confirming the reliability of the RN. When observing Figure 6b, the neural network can be seen following the observed precipitations with overestimated values of the values in mm. We will highlight in Figure 09 the precipitation forecast for 12:00 (UTC) with PREV values. 9.4 mm and NOTE. 1.2 mm, as well as in the precipitation forecast for 14:00 (UTC) with PREV values. 8.5 mm and NOTE. 36.4 mm, however, the network was assertive with the precipitation forecast, requiring a new analysis of the values that may have passed through this distortion as the precipitation forecast involves numerous variables. We observe in Figure 6b, a greater margin of error with the forecast x observed where the neural network presented a small instability in the forecast of 15:00 (UTC) with value PREV. 6.45 mm, and it was OBS. 0.0 mm of precipitation, however,



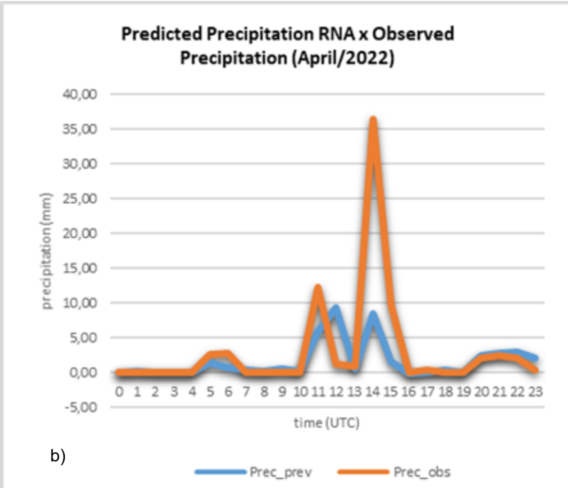


Figure 6. Prediction of precipitation generated by ANN (blue) and observed precipitation (orange) in mm/hour: a) March 07, 2022; b) April 2, 2022

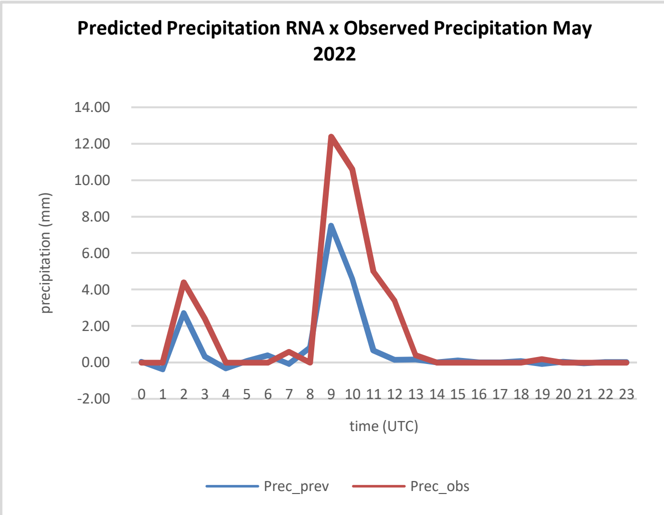


Figure 7. Prediction of precipitation generated by RNA (blue) and observed precipitation (orange) in mm/hour on March 7, 2022

Figure 5b shows that the rain forecast model using ANN was able to reproduce the behavior of the observed precipitation curve (orange line) in the month of February. It is noted that this similarity also occurs with the rainfall totals each hour, especially at 20:00, when a peak of precipitation occurred. On the other hand, it is noted that in the two months tested the model showed a small peak at the end of the night, a fact that does not appear in the observed data. When analyzing the transition months from the rainy to the dry season, the model overestimated at almost all times, in addition to the diurnal cycle curve showing practically no similarity with the observation curve. Figure 6a, a larger margin of error with the forecast (PREV) x observed (OBS) where the neural network showed a small instability in the forecast of 15:00 (UTC) with PREV value. 6.45 mm, and it was OBS. 0.0 mm of precipitation, however, we observed at 18:00 (UTC) and 19:00 the network stabilized and had PREV, respectively. 2.35 mm and NOTE. 4.2 mm - PREV. 1.75 mm and NOTE. 4.8 mm, confirming the reliability of the RN. When looking at Figure 7, we can see the neural network following the observed rainfall with overestimated values of the values in mm. We will highlight in Figure 7 the precipitation forecast for 12:00 (UTC) with PREV values. 9.4 mm and NOTE. 1.2 mm, as well as in the precipitation forecast for 14:00 (UTC) with PREV values. 8.5 mm and NOTE. 36.4 mm, however, the network was assertive with the precipitation forecast, requiring a new analysis of the values that may have passed through this distortion as the precipitation forecast involves numerous variables. For Figure 7, the linear pattern was maintained and the network proved to be efficient in predicting precipitation with a time of increase between 9:00 (UTC) and 10:00

(UTC) underestimating the values, PREV. 7.5 mm and NOTE. 12.4 mm and respectively PREV. 4.6 mm and NOTE. 10.6 mm.

FINAL CONSIDERATIONS

This article shows the construction of a model of Artificial Neural Networks of the feedforward type to predict the hourly precipitation punctually in the city of Manaus/AM. First, tests were performed to determine the architecture and training of the network, which was defined with seven neurons in the first layer, five neurons in the hidden layer, and one neuron in the output layer. It was determined that the ideal network uses the training and transfer functions, " transing " and " tranlm ", respectively. The training and validation of the network showed that it shows a strong correlation between training (85%) and prediction (82%). The tests carried out with the model during the period from January to May 2022, showed that it can represent the diurnal cycle of observed precipitation and was able to reproduce the total precipitation every hour during the rainy months (January and February), but during the transition from dry to wet season, the model overestimated.

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