FORECAST OF THE RAINY SEASON BY ARTIFICIAL NEURON NETWORKS

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ABSTRACT

The Forecast of the start and end date of the rainy season precipitation is defined by milestones. The first step is to determine the architecture of neural networks for forecasting. And the second focuses on the modeling and forecasting of rainy seasons by the Multilayer Perceptron (MLP) neural network. All of these steps have given rise to an ANN model capable of providing efficient rainy season forecasts up to 2035. The use of the Perceptron Multilayer artificial neural network technique on rainy season data has made it possible to create a model to understand the hydrological complexity and produce the information needed to simulate the future season. From historical data rainy season date, we made the rainy season modeling and forecasting. And we can estimate that around 2035, in the northern part of Madagascar, the rainy season will start rather mid-November to mid-December and will mainly end at the end of March. The season usually lasts for 4 months. And we will find a downward trend in the duration of the rainy seasons in some area

Keyword: - *Forecast, rainy season, start, end, duration, precipitation, neural network, Multilayer Perceptron, from north, Madagascar*

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1. INTRODUCTION

The start and end dates of these seasons are not known exactly and climate change makes their forecast even more difficult. As a side note, no similar study has yet been performed. The forecasts of the rainy periods could advance research in the field of meteorology, especially the forecast of the rainy seasons as well as that of the dry seasons in Madagascar [1]

It is important to know the start and end dates of a rainy season for sowing and harvesting. A wise decision is to prepare in advance. This helps farmers avoid losses due to early start-up. It allows you to choose what to grow for such a length of the season. This is why our study has the main objective of predicting these dates for the years to come.

The use of artificial neural networks in the field of hydrology is becoming increasingly important. This technique has been successfully applied in hydrological modeling and has shown significant computational power in several works. The major advantages of ANN modeling are its nonparametric nature and its simple adaptation to data of different types. However, successful application of ANNs in hydrological modeling depends on determining the optimal ANN structure, learning phase, and decision-making procedures. [2]

This work is subdivided into two parts. We will see throughout the first part some methods and materials. Then, the next part, we will focus on the results and discussion, and will end with conclusion.

2. MATERIAL AND METHODS

In this part we will detail the mathematical tools as well as the approaches that we use to carry out our study.

2.1 Artificial neural networks

Artificial neural networks consist of models more or less inspired by the functioning of the brain of human beings based mainly on the concept of neuron.

2.1.1 Modeling a formal neuron

A "formal neuron" (or simply "neuron") is a nonlinear, bounded algebraic function, whose value depends on parameters called coefficients or weights. The variables of this function are usually called the "inputs" of the neuron, and the value of the function is called its "output".

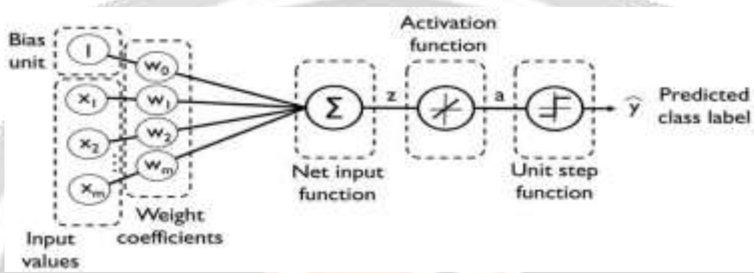


Fig- 1: Model of an artificial neuron.

A neuron is essentially made up of an integrator which performs the weighted sum of its inputs. The result s of this sum is then transformed by a transfer function f which produces the output y of the neuron. Following the notations presented in the previous section, the n inputs of the neuron correspond to the vector $x = \left[x_1, x_2, x_3, \ldots x_n\right]^T$, while $w = \left[w_{11}, w_{21}, w_{31} \ldots w_{n1}\right]^T$ represents the vector of the weights of the neuron. The output s of the integrator is given by the following equation:

$$s = \sum_{i=1}^{n} w_{i1} x_i \pm b \qquad (1)$$

$$= w_{11}x_1 + w_{21}x_2 + w_{31}x_3 + \ldots + w_{n1}x_n \pm b \qquad (2)$$

This output corresponds to a weighted sum of the weights and the inputs plus what is called the bias b of the neuron. The result s of the weighted sum is called the activation level of the neuron. Bias b is also called the neuron activation threshold. When the activation level reaches or exceeds the threshold b, then the argument of f becomes positive (or zero). Otherwise, it is negative.

Another limiting factor in the model that we have given ourselves concerns its discrete nature. Indeed, to be able to simulate a neural network, we will make time discrete in our equations. In other words, we will assume that all the neurons are synchronous, i.e., at each time t, they will simultaneously calculate their weighted sum and produce an output:

$$y(t) = f(s(t)) \qquad (3)$$

2.1.2 Activation functions

The most used activation functions are the "threshold" (in English "hard limit"), "linear" and "sigmoid" functions. The sigmoid is an interesting compromise between the two previous ones. The equation of the sigmoid transfer function is given by:

$$y = \frac{1}{1+\exp^{-s}} \tag{4}$$

Finally, note that the “hyperbolic tangent (tanh)” function is a symmetric version of the sigmoid.

2.1.3 The Multi layer Perceptron (MLP)

A single layer of neurons can only achieve linear separations, so the idea comes to add so-called hidden layers to achieve a multilayer neural network. In a layer, the neurons are not connected to each other [3].
A layered network is an extension of the famous perceptron with one or more intermediate layers called "hidden". The Multi Layered Perceptron (MLP) are the best-known neural networks. A perceptron is an artificial neural network of the “feed forward” type that is to say with direct propagation.
In fact, on each neuron, in addition to its inputs which link it with the previous neurons, we add a particular input which is called polarization of the neuron, it corresponds to a bias which plays a role of translation of the field of activity of the neuron. Its value is therefore linked to the activation function since it allows the displacement of this function [4].
In order to keep a generalized notation, we represent these biases as the product of an input x_0^m by the weights w_{0j}^m.
We set the input x_0^m to unity the weight then carries the information on the polarization of the neuron.

2.1.3.1 The error gradient back-propagation algorithm.

One of the most widespread algorithms is that of "backpropagation". This algorithm changes the weights of a network whose architecture is fixed by the operator, each time an example $y_1 = f(x_1)$ is presented [5]. This change is made in such a way as to minimize the error between the desired output and the network's response to an input x_i.
This is achieved through the gradient descent method. At each iteration the input signal propagates in the network in the input-output direction, an output is thus obtained, the error between this output and the desired output is calculated then by back-propagation "error back-propagation", errors intermediates, corresponding to the hidden layer are thus calculated and allow the adjustment of the weights of $w_{ij}(t)$ the hidden layer [6]..
To train a multilayer network, we use the generalized delta learning rule for each neuron i:

$$w_{ij}(t+1) = w_{ij}(t) + \alpha(t)\delta_j(t)x_i \tag{5}$$

Where $\delta_j(t)$ is the error made by neuron i.
The idea then consists in propagating the errors of the network towards the initial neurons, through the weights, hence the name of backpropagation of the error gradient of the algorithm proposed independently by Rumelhart, Le Cun and Hinton in 1984.
We have just taken a learning step. It is necessary to repeat these operations for all the learning vectors, then test the quality of the learning with the test vectors which were not used for learning: this makes it possible to test the capacities of the generalization of the network.
The gradient backpropagation algorithm consists of performing a gradient descent on the cost function already used for the single neuron:

$$\varepsilon(w,k) = \frac{1}{2}(d(k) - y(k))^2 \tag{6}$$

Where y is the output of the network (thus a weighted sum of sigmoid) and not the output of a single neuron. By differentiating this expression with respect to each weight W_{ij} until obtaining $\varepsilon \langle \varepsilon_{seuil}$, and this for each input output pair (x_i, y_i) .

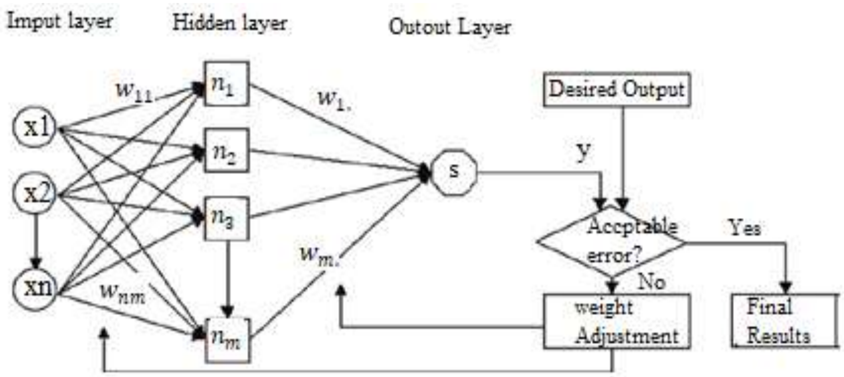


Fig- 2 : Presentation of back-propagation algorithm

2.1.4 Benchmark test for forecasting

The evaluation of the quality of the model must meet performance criteria. For this, the introduction of modeling and forecasting user requirements is mandatory to define the criteria used in this work. These tests that we have implemented in this work are the following:

2.1.4.1 Mean Squared Error MSE

Mean squared error is one of the most widely used evaluation criteria in forecasting research, which gives a quantitative indication of the overall error produced by the model [7], [8]. This criterion determines the deviation of the calculated value from the observed mean. This is the reason why we chose the root mean square error in this work. This criterion is written as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2 \tag{7}$$

Where n is the number of values tested; X_i is the ith date of the observed rainy season; Y_i is the ith date of the rainy season calculated by the forecast model.

2.1.4.2 The linear correlation coefficient (R)

The linear correlation coefficient aims to measure the intensity of the linear connection between the values predicted by the network and the desired values. It is given by the following relationship [9]:

$$R = \frac{Cov_{X,Y}}{\sigma_X \sigma_Y} \tag{8}$$

With σ_X and σ_Y are the standard deviations of the observed and predicted values, and $Cov_{X,Y}$ their covariance, respectively. The correlation coefficients range from -1 to 1, where

- Values close to 1 indicate that there is a positive linear relationship between the data columns.
- Values close to -1 indicate that one column of data has a negative linear relationship to another column of data (anti-correlation).
- Values close to or equal to 0 suggest there is no linear relationship between the data columns.

2.2 Presentation of study area:

As this is an area in Madagascar, our study area is located entirely in the tropical zone. It is delimited by latitude between 12 and 15 south, and longitude between 47 and 51. It groups together thirteen districts (Antsiranana I and Antsiranana II, Ambilobe, Ambanja, Nosy Be, Vohemar, Andapa, Sambava, Antalaha, Analalava, Antsohihy, North Befandrina, and Bealanana). It contains culminating massifs between 1475 and 2876 meters of altitude which runs from the four corners to the center where we find the massif of Tsaratanana. The eastern part of the zone has a humid climate due to the trade wind, while the western part suffers from the drought of a leeward climate. The Tsaratanana massif causes an extremely humid climate and is softened by the relief in the central part. The very varied climatic conditions encountered in this area are caused by this geographical location, the shape of the relief, the maritime influence and the wind regime.

Fig- 3: Presentation of individuals in our study area

2.3 Database and materials used

We used rainfall data. These are daily reanalyzed data, for a spatial resolution of 1° x 1° over the period from 1979 until 2018 download in ECMWF.
According to the Kohonen network classification method, we have 20 homogeneous groups for precipitation. To obtain data on the start and end dates of the rainy season, we used the Anomalous Accumulation (A. A) Method. They can be seen in our article [10]. From these data we will model and forecast the dates of the start and end of the rainy season for each of these areas. In this work, our database is divided into two distinct parts:

- the start (and end) dates of the year 1979 to 1999 are intended as the input to our ANN to recognize the dynamics of the system during the learning phase
- and the start (and end) dates of the year from 2000 to 2018 are as desired outputs of our ANN. And these allow us a confirmation of the performance of the ANN model

We used in our study software such as: MATLAB, for programming codes on statistical and mathematical studies and data preparation; Microsoft Office Excel, for certain operations.

3. RESULT AND DISCUSSION

This part shows the results of the different steps. The first step is to determine optimal forecast network architecture, the second is the calibration of the model, confirmation of the latter, and at the end forecast of the date of the rainy season.

3.1 Forecast model architecture

We're trying to determine the number of neurons in each layer. As for the output layer, it depends on the nature of the desired result. If we want to have n numbers at the output, we will need n neurons at the output layer. For the hidden layer, there are difficulties. There is no rule to determine the number the number of neurons to be placed in the hidden layer to have an optimal neural network. The method to get closer is to try "randomly" several numbers of neurons in a hidden layer until you have the most convincing results possible after learning.

Our prediction model consists of an input layer, a single hidden layer with sigmoid type activation functions at the level of the nineteen artificial neurons and an output layer with type activation functions linear. The architecture of our model which is illustrated in **Fig-3**.

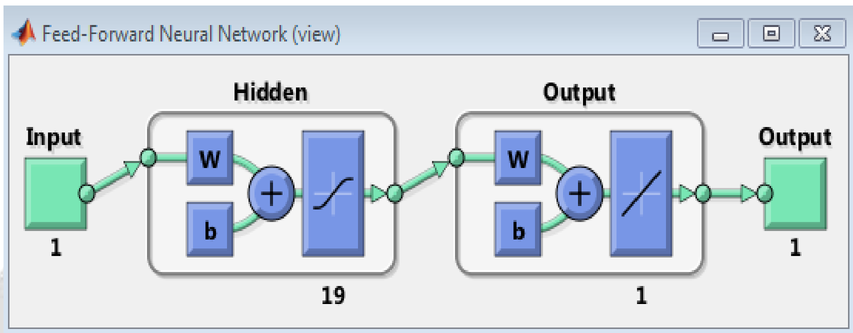


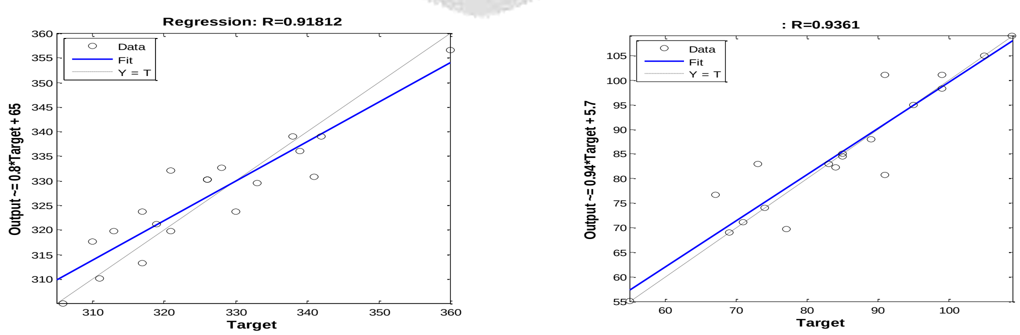
Fig- 4: Optimal forecasting model architecture

3.2 Modeling and forecasting of the rainy season from 2017 to 2035

We did many learnings until the model was perfect. We therefore want the correlation coefficient between the outputs calculated by the model and the desired output to be close to 1. **Chart-1** shows a comparison between the dates of the observed rainy season and the dates calculated for the forecast horizon. The blue line corresponds to the trend curve of the calculated data. The representation of the data calculated from the observed data constitutes a cloud of points on the line (Y = T). The scatter plots exhibit a linear trend that coincides with the Y=T curve. This linear configuration of the scatter plot means that there is a strong correlation between the observed data and the calculated data.

Chart-1 -(a)-(b)-(c)-(d) respectively represent the correlation coefficient between the observed rainy season and the season calculated by the forecast model in zone 1, zone 5, zone 9 and area 14. For the expected start (or end) date of the rainy season in zone 1, we notice a minimal deviation of the trend line of the point dispersion from the Y = T curve (**Chart-1 (a)** left and right). This discrepancy explains why the observed values are underestimated. However, it can be accepted with a correlation coefficient value between calculated output and observed data 0.918 and 0.936. These values lie close to 1. Thanks to these successful correlations, the graphs of the temporal variation of the observed rainy season almost coincide with those calculated by the model.

(a)



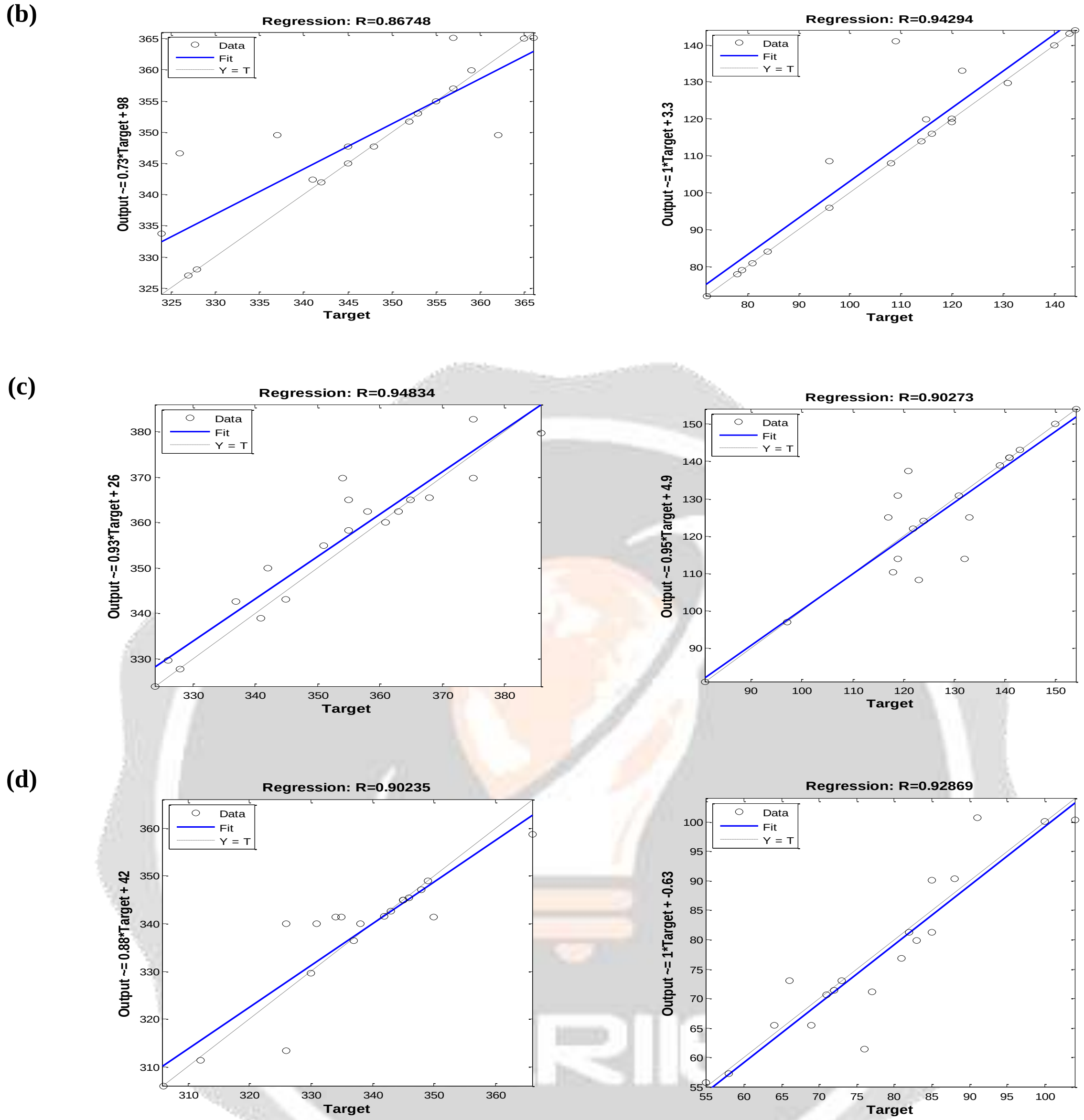


Chart- 1 : Correlation coefficient between the observed rainy season and those calculated by the forecast model

3.3 Predictions of the rainy season

In **Chart- 2**, the curve in blue color presents the observed data of the start (and end) of the rainy season calculated by the Anomalous Accumulation during 39 years from 1979 to 2017 in zone 1. The curve in green is the result of our ANN during the data test phase from 1998 to 2016 (i.e. 19 years). And the curve in red color is the forecast offered by the forecast model.

Chart- 2 show that the curve of the observed and calculated data almost coincided with each other. This confirms the coefficients of high-performance correlations that we mentioned above. In zone 1, the start of the rainy season from 2017 to 2035 is expected to fluctuate between October 15 and December 7. On average, it will be approximately at mid-November. As for the end of the rainy season, it is expected to end between February 8 (2030-2031 season) and April 17.

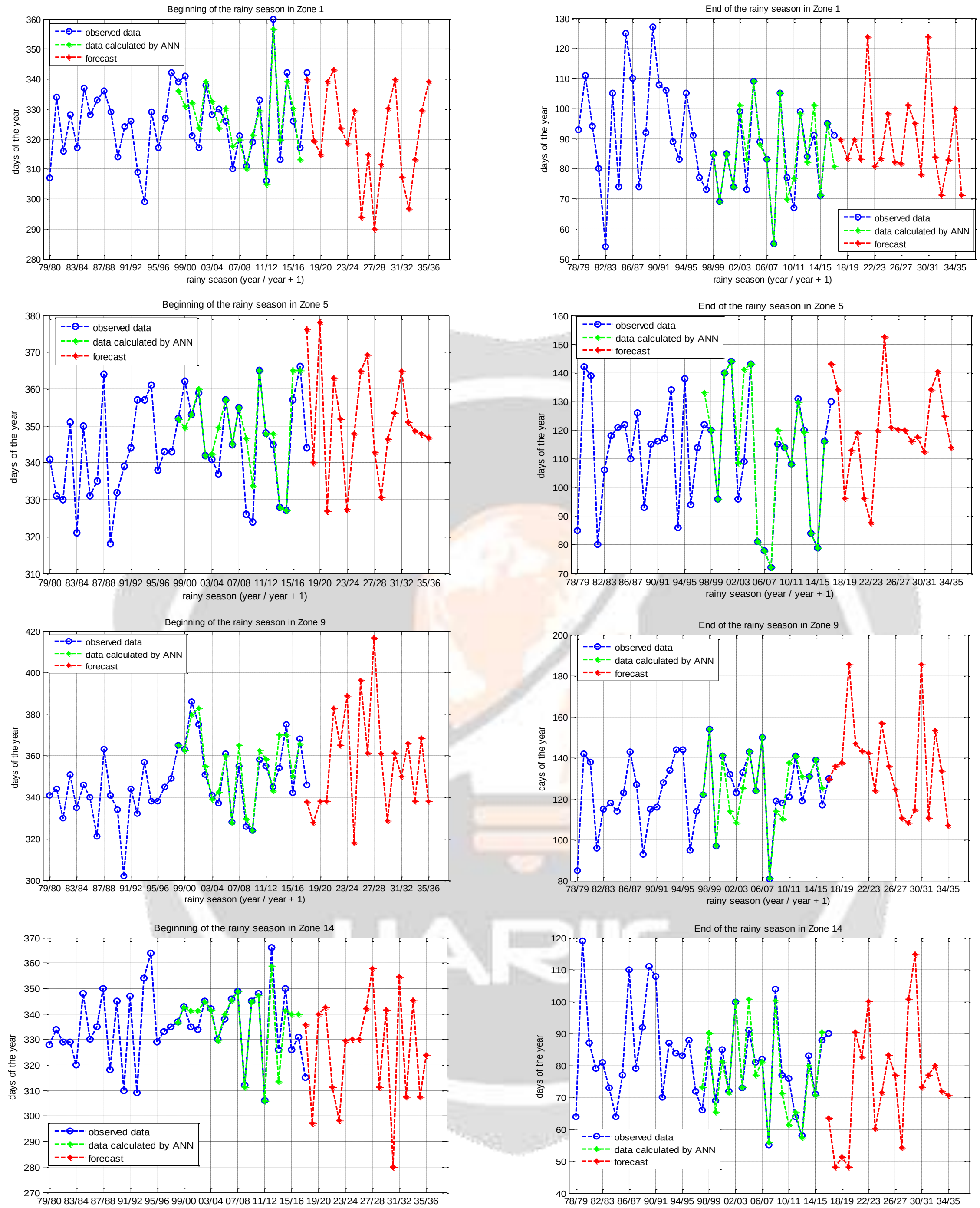


Chart- 2: forecasting of the rainy season until the season of the year 2035/2036

The durations of the rainy season in this work were not produced by the forecasting model. It was calculated as follows; the duration of the rainy season between two successive years is obtained by subtracting the value of the end of the season of year j with that of the start of the previous year. In **Chart-4**, the duration of the rainy season in zone 1 will fluctuate between 61 days (i.e. 2 months) and 174 days (i.e. 6 months at most). These durations will be determined during the 2021-2022 and 2027-2028 rainy seasons, respectively. Overall, the season in this region will last 128 days or approximately 4 months. We observe a downward trend in the duration of the rainy seasons. This shortcut is weak with discounts of 4 days in 18 years.

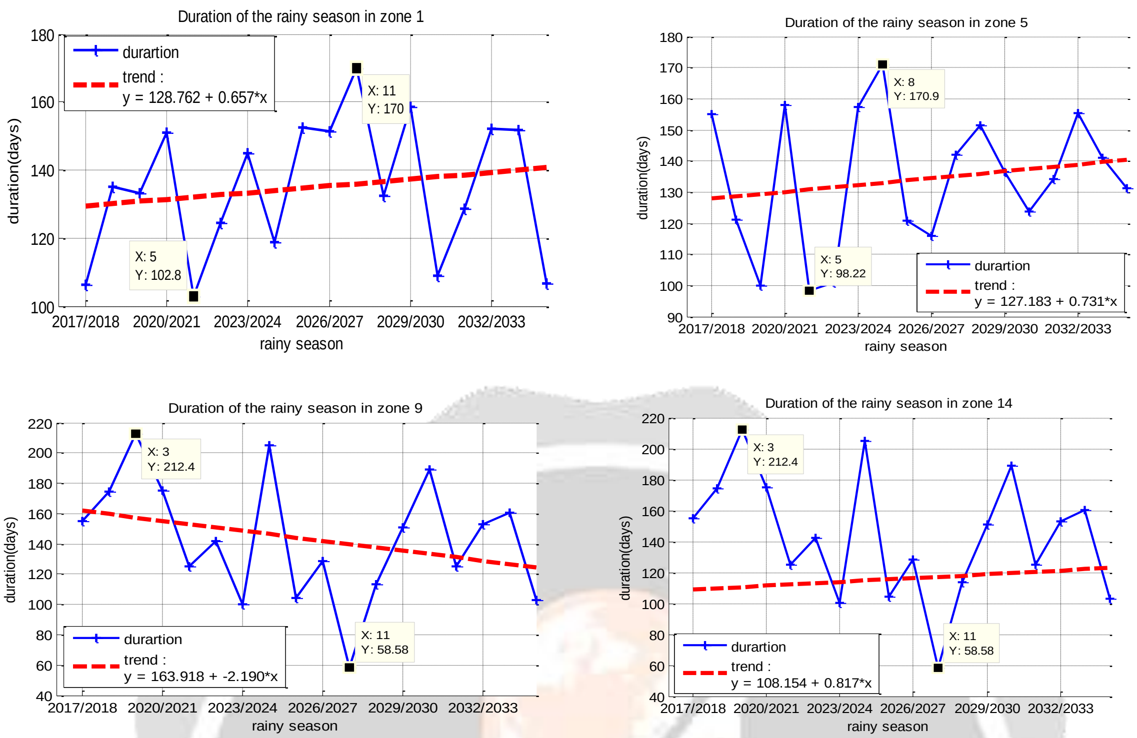


Chart- 3: duration of the rainy season in zone 1 until the season of the year 2035/2036

Similarly, interpretations of the rainy season forecast for all other areas are summarized in Table 4, Table5 and Table 6 respectively

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Table 1: forecast for the start of the rainy season from 2017 to 2036

Season	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10	Zone 11	Zone 12	Zone 13	Zone 14	Zone 15	Zone 16	Zone 17	Zone 18	Zone 19	Zone 20
2017-2018	4-Dec	3-Dec	21-Nov	12-Nov	10-Jan	11-Dec	2-Jan	8-Nov	2-Dec	15-Nov	21-Nov	14-Oct	18-Nov	30-Nov	13-Nov	1-Jan	27-Dec	1-Nov	30-Nov	8-Nov
2018-2019	14-Nov	2-Jan	15-Nov	1-Dec	4-Dec	13-Nov	25-Dec	20-Nov	22-Nov	20-Oct	4-Oct	4-Dec	27-Nov	23-Oct	8-Dec	28-Dec	10-Jan	28-Nov	26-Nov	19-Nov
2019-2020	9-Nov	28-Dec	2-Jan	28-Nov	11-Jan	21-Nov	14-Dec	16-Dec	2-Dec	14-Dec	22-Nov	8-Dec	28-Dec	4-Dec	9-Dec	11-Dec	2-Dec	22-Nov	27-Nov	1-Dec
2020-2021	4-Dec	11-Dec	29-Nov	18-Dec	21-Nov	23-Nov	1-Dec	14-Dec	2-Dec	28-Dec	21-Nov	9-Dec	21-Nov	7-Dec	24-Nov	25-Dec	27-Nov	10-Nov	27-Nov	13-Dec
2021-2022	7-Dec	2-Jan	11-Jan	16-Nov	27-Dec	17-Nov	25-Dec	1-Jan	16-Jan	6-Jan	4-Oct	20-Dec	20-Dec	6-Nov	15-Dec	9-Jan	22-Dec	15-Dec	1-Dec	23-Dec
2022-2023	18-Nov	21-Dec	13-Nov	13-Dec	16-Dec	15-Nov	19-Dec	1-Jan	30-Dec	14-Dec	16-Oct	27-Dec	29-Nov	24-Oct	10-Dec	2-Jan	24-Dec	22-Dec	28-Nov	10-Dec
2023-2024	13-Nov	4-Dec	3-Jan	10-Dec	22-Nov	19-Nov	24-Dec	8-Nov	22-Jan	21-Dec	20-Oct	15-Oct	21-Nov	24-Nov	8-Nov	10-Jan	3-Dec	28-Nov	1-Dec	12-Dec
2024-2025	24-Nov	30-Dec	28-Nov	1-Dec	12-Dec	15-Nov	17-Dec	9-Dec	12-Nov	9-Dec	10-Dec	9-Dec	8-Dec	25-Nov	15-Dec	9-Jan	23-Dec	5-Dec	9-Dec	12-Dec
2025-2026	19-Oct	24-Dec	30-Nov	14-Nov	29-Dec	17-Nov	19-Dec	25-Nov	30-Jan	7-Jan	23-Nov	20-Nov	7-Dec	25-Nov	15-Dec	9-Dec	14-Dec	22-Nov	1-Dec	4-Dec
2026-2027	9-Nov	7-Dec	30-Nov	6-Dec	3-Jan	22-Nov	1-Dec	27-Nov	26-Dec	12-Dec	8-Nov	18-Nov	23-Dec	7-Dec	26-Nov	8-Dec	20-Nov	4-Dec	26-Nov	26-Dec
2027-2028	15-Oct	18-Dec	3-Dec	22-Dec	7-Dec	23-Nov	14-Dec	9-Dec	19-Feb	7-Jan	18-Nov	8-Dec	9-Dec	22-Dec	27-Nov	14-Dec	9-Dec	31-Dec	11-Dec	1-Dec
2028-2029	6-Nov	3-Dec	7-Dec	6-Jan	25-Nov	27-Nov	10-Nov	9-Dec	25-Dec	10-Jan	8-Nov	6-Nov	19-Jan	6-Nov	12-Dec	15-Dec	9-Dec	31-Dec	5-Dec	4-Dec
2029-2030	25-Nov	21-Dec	6-Dec	18-Dec	11-Dec	14-Nov	4-Nov	15-Dec	23-Nov	25-Dec	19-Oct	5-Dec	19-Nov	6-Dec	28-Nov	19-Nov	7-Dec	6-Dec	10-Dec	27-Dec
2030-2031	4-Dec	2-Dec	17-Dec	14-Dec	18-Dec	1-Dec	2-Jan	22-Nov	26-Dec	16-Jan	6-Oct	27-Dec	1-Dec	5-Oct	26-Dec	10-Dec	21-Nov	2-Dec	1-Dec	12-Nov
2031-2032	2-Nov	3-Jan	11-Jan	21-Jan	29-Dec	15-Nov	17-Dec	27-Dec	15-Dec	25-Oct	17-Oct	5-Dec	21-Dec	19-Dec	10-Dec	9-Jan	11-Nov	15-Dec	1-Dec	25-Dec
2032-2033	22-Oct	25-Dec	17-Dec	7-Dec	16-Dec	10-Nov	17-Nov	5-Dec	30-Dec	10-Oct	7-Nov	3-Dec	15-Jan	2-Nov	5-Dec	30-Nov	9-Dec	22-Nov	30-Nov	27-Nov
2033-2034	8-Nov	25-Dec	28-Nov	18-Dec	13-Dec	24-Nov	29-Nov	6-Dec	2-Dec	19-Dec	20-Jan	30-Nov	30-Jan	10-Dec	4-Dec	19-Dec	23-Nov	13-Dec	30-Nov	21-Nov
2034-2035	24-Nov	3-Dec	18-Dec	30-Nov	12-Dec	10-Nov	11-Dec	9-Dec	2-Jan	14-Dec	10-Dec	22-Nov	24-Nov	2-Nov	24-Nov	10-Dec	17-Nov	31-Dec	21-Nov	20-Nov
2035-2036	4-Dec	6-Nov	6-Jan	12-Nov	11-Dec	15-Nov	2-Nov	29-Dec	2-Dec	14-Jan	17-Oct	8-Nov	1-Nov	18-Nov	10-Dec	19-Nov	27-Nov	29-Oct	26-Nov	23-Nov

Table 2: forecast for the end of the rainy season from 2017 to 2036

Saison	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	Zone 10	Zone 11	Zone 12	Zone 13	Zone 14	Zone 15	Zone 16	Zone 17	Zone 18	Zone 19	Zone 20
2016-2017	29-Mar	6-May	12-Apr	9-May	9-May	29-Mar	30-Mar	5-May	9-May	9-May	30-Mar	7-May	5-May	30-Mar	30-Mar	30-Mar	30-Mar	1-Apr	12-Apr	13-Apr
2017-2018	23-Mar	9-Mar	28-Mar	7-Apr	13-May	20-Mar	13-Apr	18-Apr	14-May	30-Apr	2-Mar	21-Apr	9-Mar	17-Feb	26-Mar	17-Mar	1-May	4-Apr	30-Mar	15-Mar
2018-2019	29-Mar	19-Mar	17-Apr	30-May	5-Apr	7-Mar	29-Mar	23-Mar	16-May	24-Apr	24-Feb	16-Mar	10-Mar	20-Feb	5-Apr	14-Mar	31-Mar	31-May	29-Mar	21-Mar

2019-2020	23-Mar	15-Feb	19-Apr	6-May	21-Apr	20-Mar	17-Mar	21-Mar	3-Jul	13-Apr	4-Mar	28-Mar	20-Mar	17-Feb	26-Mar	15-Mar	20-Apr	27-Mar	30-Mar	29-Feb
2020-2021	2-May	9-Mar	8-Mar	27-Jun	28-Apr	22-Mar	4-Apr	3-Apr	25-May	25-Mar	31-Mar	2-May	22-Apr	30-Mar	22-Apr	4-Apr	26-Mar	21-Apr	23-Mar	12-Mar
2021-2022	20-Mar	8-Apr	25-Mar	22-May	5-Apr	17-Mar	17-May	17-Apr	22-May	6-May	16-Mar	18-Apr	9-Mar	22-Mar	13-Mar	15-Mar	1-May	25-Apr	27-Mar	9-Apr
2022-2023	23-Mar	13-Mar	29-Apr	10-Jun	27-Mar	22-Mar	26-Mar	16-Mar	21-May	22-Apr	4-Mar	27-Apr	20-Apr	9-Apr	19-Apr	6-Apr	12-Mar	19-Apr	21-Apr	9-Apr
2023-2024	7-Apr	4-Mar	12-May	12-May	28-Apr	17-Mar	28-Feb	2-Apr	2-May	11-Apr	16-Mar	28-Mar	20-Apr	29-Feb	10-Mar	7-Mar	29-Mar	28-May	11-Apr	21-Mar
2024-2025	22-Mar	6-Mar	18-Apr	30-Apr	31-May	24-Mar	11-Mar	27-Mar	4-Jun	8-May	4-Apr	26-Apr	26-Mar	11-Mar	25-Mar	15-Mar	13-Mar	17-Mar	2-May	9-Apr
2025-2026	21-Mar	20-Apr	1-Apr	5-May	29-Apr	11-Mar	8-May	3-Apr	14-May	27-Apr	22-Feb	16-Mar	11-Mar	23-Mar	5-Apr	4-Apr	8-Apr	19-Mar	29-Mar	9-Apr
2026-2027	10-Apr	13-Mar	15-Apr	2-Jun	29-Apr	5-Mar	26-Mar	3-Apr	3-May	8-May	4-Apr	23-Mar	31-Mar	16-Mar	2-Mar	28-Mar	30-Mar	23-Mar	30-Mar	18-Mar
2027-2028	4-Apr	7-Apr	23-May	19-May	28-Apr	6-Mar	30-Mar	18-Mar	19-Apr	21-Apr	16-Mar	19-May	24-Apr	23-Feb	29-Mar	17-Apr	25-Mar	11-Mar	29-Mar	18-Mar
2028-2029	17-Mar	31-Mar	24-Apr	2-May	24-Apr	5-Apr	2-May	8-Apr	17-Apr	22-Mar	31-Mar	21-Apr	9-Mar	9-Apr	27-Mar	2-Apr	3-Apr	21-Mar	18-Apr	9-Apr
2029-2030	2-May	15-Apr	5-May	2-May	26-Apr	12-Apr	18-Apr	22-Feb	23-Apr	6-May	4-Apr	27-Apr	3-May	23-Apr	30-Mar	13-Apr	21-Apr	2-Apr	24-Mar	3-Mar
2030-2031	23-Mar	29-Mar	4-May	21-Apr	21-Apr	5-Apr	11-Apr	9-Mar	3-Jul	14-Apr	22-Feb	29-May	14-May	13-Mar	30-Mar	18-Apr	26-Mar	27-Mar	11-Apr	17-Apr
2031-2032	11-Mar	16-Feb	24-Mar	17-May	13-May	5-Mar	26-Mar	11-Apr	19-Apr	22-Mar	22-Feb	13-May	9-Mar	16-Mar	26-Mar	28-Mar	14-Feb	21-Mar	17-Apr	14-Apr
2032-2033	22-Mar	5-Mar	4-Apr	27-Jun	19-May	17-Mar	3-Mar	31-Mar	1-Jun	19-Apr	22-Feb	20-Mar	8-Feb	19-Mar	21-Mar	10-Mar	21-Mar	17-Mar	18-Apr	21-Mar
2033-2034	8-Apr	6-Apr	19-Apr	16-May	3-May	10-Apr	9-Apr	3-Apr	12-May	26-Apr	24-Feb	20-Mar	31-Mar	11-Mar	5-Apr	6-Apr	12-Mar	17-Apr	21-Apr	14-Apr
2034-2035	11-Mar	22-Mar	1-Apr	4-May	22-Apr	3-Apr	1-Apr	16-Mar	15-Apr	12-May	19-Feb	18-Apr	20-Apr	10-Mar	11-Mar	2-Apr	26-Mar	27-Mar	26-Apr	18-Mar

Table 3: Forecast duration (days) of the rainy season between the year 2017 to 2035

	Zone 1	**Zone 2**	**Zone 3**	**Zone 4**	**Zone 5**	**Zone 6**	**Zone 7**	**Zone 8**	**Zone 9**	**Zone 10**	**Zone 11**	**Zone 12**	**Zone 13**	**Zone 14**	**Zone 15**	**Zone 16**	**Zone 17**	**Zone 18**	**Zone 19**	**Zone 20**
2017-2018	106	90	109	117	155	132	126	131	155	140	114	132	89	98	98	126	168	117	110	121
2018-2019	135	77	154	180	121	114	94	123	175	186	142	103	103	119	118	76	80	184	122	123
2019-2020	133	48	107	159	100	119	92	95	212	121	103	111	82	73	107	94	139	125	123	90
2020-2021	151	89	100	192	158	120	125	111	175	87	132	144	154	114	149	100	120	163	116	90
2021-2022	103	96	74	187	98	120	143	106	125	120	163	118	80	136	89	66	131	130	116	107
2022-2023	125	83	167	179	101	128	97	74	142	129	140	121	142	167	130	94	79	118	143	119
2023-2024	145	90	129	153	157	119	65	144	100	111	147	165	150	96	123	56	116	181	130	99
2024-2025	119	67	143	151	171	129	85	109	205	151	116	139	109	107	101	67	81	102	145	119
2025-2026	153	117	122	171	121	114	140	129	104	110	90	117	93	118	111	117	115	117	118	126
2026-2027	151	96	137	178	116	103	115	128	128	147	147	125	98	100	95	109	130	109	124	82
2027-2028	170	109	171	148	142	103	106	100	59	104	118	162	136	61	122	124	106	71	109	107

2028-2029	132	119	140	117	151	130	175	121	113	72	145	168	50	155	106	109	116	81	134	126
2029-2030	159	115	151	135	136	149	166	68	151	133	167	143	165	138	122	146	135	117	104	66
2030-2031	109	117	138	128	124	125	99	106	189	88	138	154	164	158	93	130	124	114	131	156
2031-2032	129	43	71	116	134	110	99	105	125	148	127	160	79	87	106	78	93	95	137	111
2032-2033	152	71	108	203	156	128	106	117	153	192	108	108	24	138	107	102	103	115	140	115
2033-2034	152	102	143	149	141	137	131	118	161	128	34	110	60	91	121	108	110	125	141	144
2034-2035	107	109	105	155	131	144	112	97	103	150	70	146	146	128	107	113	129	86	156	118

Table 4: Trend of the forecast duration of the rainy season over the period from 1917 to 2035

	Slope of linear regression line (y=ax+b)	Variation during 18 years (in days)
Zone 1	-0,269	-4,842
Zone 2	1,198	21,564
Zone 3	0,079	1,422
Zone 4	-1,142	-20,556
Zone 5	0,731	13,158
Zone 6	0,744	13,392
Zone 7	0,924	16,632
Zone 8	-0,631	-11,358
Zone 9	-2,19	-39,42
Zone 10	0,33	5,94
Zone 11	-2,388	-42,984
Zone 12	1,088	19,584
Zone 13	-0,725	-13,05
Zone 14	0,817	14,706
Zone 15	-0,319	-5,742
Zone 16	1,525	27,45
Zone 17	-0,574	-10,332
Zone 18	-3,124	-56,232
Zone 19	1,34	24,12
Zone 20	0,987	17,766

4. CONCLUSION

The study we conducted in this research allowed us to review the main techniques used to predict the rainy season, more specifically the start and end dates of the raining season in our study area. Because of our interest in the neuron network forecasting method, especially the Perceptron Multi-layer prediction method. This work was structured into two crucial stages. The first step in creating neural networks for prediction is figuring out their architecture. In the second, neural networks are used to simulate and forecast rainy seasons. All of these methods have produced an RNA model that can accurately predict the rainy season.

We had a hard time deciding on the network design during our investigation. Determining the bare minimum required number of layers is crucial for obvious reasons related to processing speed and generalization capability. A model to understand hydrological complexity and produce the information needed to simulate the upcoming season has been created using the technique of artificial neural networks on rainy season data.

To summarize, here are the results of our study. We predict that until 2035:

- The rain will start mainly in November in the sea and coastal regions to the west of the Sofia and Ambanja region, as well as in the districts of Vohemar and Bealanana. And the others will start in December. In the northern region of Madagascar, the rainy season usually lasts for 4 months, with the exception of the zone 2 which lies between Bealanana and Andapa and north of the municipality of Antsakabary, where the rain lasts only about 3 months
- The duration of the rainy seasons will decrease on the maritime coast of the district of Analalava and antsohihy, on the eastern shore of our study area (from the town cote of Antalaha to Cape Ambre), all the cities that make up the SAVA region (Sambava, Andapa, Vohemare and Antalaha) and in the area that surrounds the Ambilobe district.

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