American Journal of Sciences and Engineering Research

E-ISSN -2348 – 703X, Volume 6, Issue 3, 2023

Modelling of Maximum Temperature Prediction by Neuro-Fuzzy Method of Marerano-Mahajanga II Madagascar

F. Rajesitera[1]*, R. Randrianantenaina[2], E. Rasoanandrasana[3], C. Lehimena[4]

[1,2,3] *Faculty of Technology and Environmental Sciences, Mahajanga University, Madagascar*

[4] *Faculty of Technology and Environmental Sciences, Antsiranana University, Madagascar*

Abstract:

The study area for Marerano-Mahajanga II, delimited in latitude between 15.5° South and 16° South and in longitude between 46.5° East and 47° East.

We modeled the maximum temperature from the year 1979 to 2018 by the Neuro-fuzzy method. According to this method, on average the values of the annual maximum temperature are between 29.64°C and 31°C. The year 1984 is the less hot year, the temperature is 29.64°C. The hottest year is 2017 with a value of 31°C.

Keywords: *Maximum Temperature, forecast, Neuro-fuzzy, Marerano-Mahajanga II.*

I. Introduction

Global warming is defined as the statistically significant change in mean climate state or variability that has persisted for several decades or more [1].

Among the serious consequences due to global warming is infectious disease. According to the IPCC, global warming will have repercussions on the health of populations living in tropical regions [2].

In Madagascar, the impact of climate change, especially temperatures, remains a major concern for the Great Island. It could hit the entire country hard in the coming years.

And that is why this study leads us to model the annual average value of the maximum temperature using the Neuro-fuzzy method. This article presents the regional maximum temperature results for Marerano-Mahajanga II. This analysis will make it possible to make an assessment of the development of maximum temperatures in this region.

II. Material and methods

2.1 Presentation of the study area

The study area (see Figure 1) is located between latitude 15.5°South and 16°South and longitude 46.5° East and 47° East

 Received-15-05-2023, Accepted- 26-05-2023

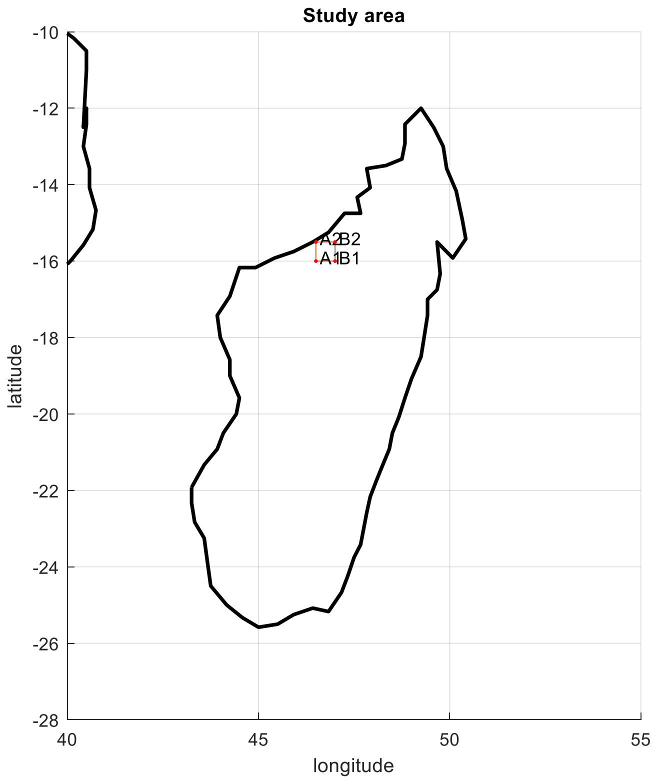

Figure 1: Study area 46.5°≤ longitude ≤ 47° and -16°≤ latitude ≤ -15.5°

2.2 Databases

The meteorological data we used are from the European Centre for Medium range Weather Forecasts (ECMWF) daily reanalysis experiment (ERA5) data at synoptic scale with a 0.5° x 0.5° grid of maximum temperature over a time depth covering the period 1979-2018.

2.3 Neuro-fuzzy modelling

Definition: Neuro-fuzzy systems combine the advantages of two complementary techniques. Fuzzy systems provide a good knowledge representation.

The integration of neural networks within these systems improves their performance thanks to the learning capacity of neural networks. Conversely, the injection of fuzzy rules into neural networks, which are often criticized for their lack of readability, clarifies the meaning of the network parameters and facilitates their initialization, which represents a considerable saving in computation time for their identification.

The Neuro-Fuzzy system refers to the way of applying various learning techniques developed in the neural network literature to the fuzzy inference system.

In order to clarify the definitions, we propose in this chapter a brief presentation of some types of Neuro-fuzzy systems and a more detailed presentation of ANFIS.

2.3.1 Some types of neuro-fuzzy combination

There are several types for combining neural networks and fuzzy systems. These types can be classified into functional and structural, depending on their architecture and the research configuration between the fuzzy inference system and the neural networks.

2.3.2 Cooperative and concurrent neuro-fuzzy systems [3] [4] [5]

A cooperative neuro-fuzzy system can be considered as a preprocessor where the learning mechanism of artificial neural networks (ANNs) determines the fuzzy inference system (FIS) membership functions or fuzzy rules from the training data. Once the FIS parameters are determined, ANN goes to the bottom. The based rule is usually determined by a fuzzy clustering algorithm. The membership functions are usually approximated from RNA by the training data.

In a concurrent neuro-fuzzy system, RNA helps the RIS continuously to determine the required parameters especially if the input variables of the controller cannot be measured directly. In some cases the outputs of RIS may not be directly applicable to the process. Figures 2 and 3 represent the cooperative and concurrent Neuro-Fuzzy models.

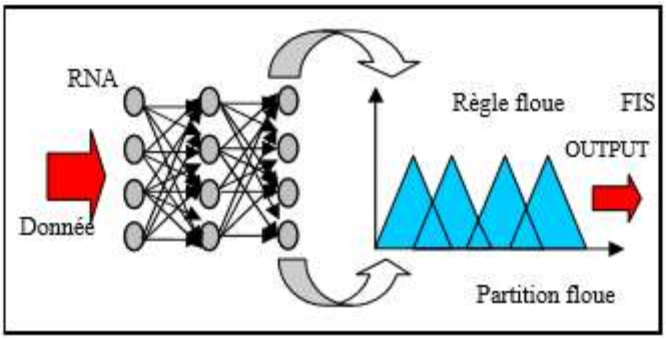

Figure 2: Cooperative neuro-fuzzy system

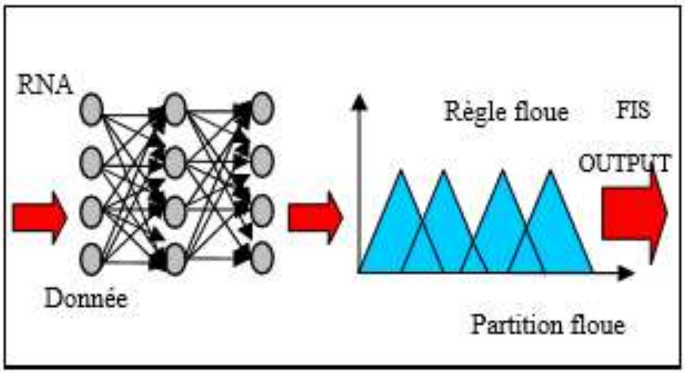

Figure 3: Competing neuro-fuzzy system

2.3.3 Fused neuro-fuzzy systems

In a fused neuro-fuzzy architecture, RNAs are used to determine the parameters of RIS. Fused Neuro-fuzzy systems share data structures and knowledge representation. A usual way to apply a learning algorithm to a fuzzy system is to represent it in a special architecture.

2.3.4 Falcon (Fuzzy Adaptive Learning Control Network) [6]

Falcon has a five-layer architecture, as shown in Figure 4.

There are two neurons for each output variable. One for the training data (desired output) and the other is for the output of FALCON. The first hidden layer is used to fuzzify the input variables. Each neuron in this layer represents a fuzzy set membership function. The second hidden layer defines the antecedent parts of the fuzzy rules followed by the consequence parts of the rules in the third hidden layer. FALCON uses a hybrid learning algorithm involving unsupervised learning to locate membership functions and initial rule bases and supervised learning to optimize the adjustment of the FM parameters to generate the desired outputs.

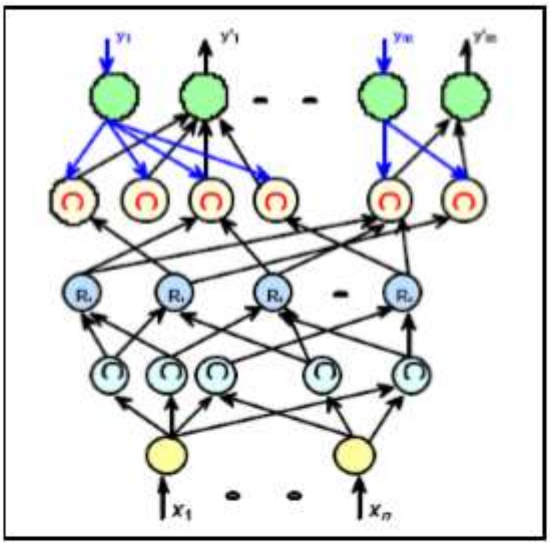

Figure 4: Architecture of FALCON

2.3.5 NEFCON (NEuro-Fuzzy CONtrol) [7]

NEFCON is designed to implement the Mamdani type fuzzy inference system. It consists of two layers whose weights are the fuzzy sets and the fuzzy rules. With the same assumed prior use shared weights, which are represented by ellipses drawn around the connections. They ensure the integrity of the rule base. The input layer provides the task of the fuzzification interface, the inference logic is represented by the propagation functions, and the output layer is the defuzzification interface. The learning of the NEFCON model is based on a mixture of unsupervised and supervised learning (back-propagation). NEFCON can be used to learn initial rules, if no system knowledge is available or even to optimize a manually defined rule base.

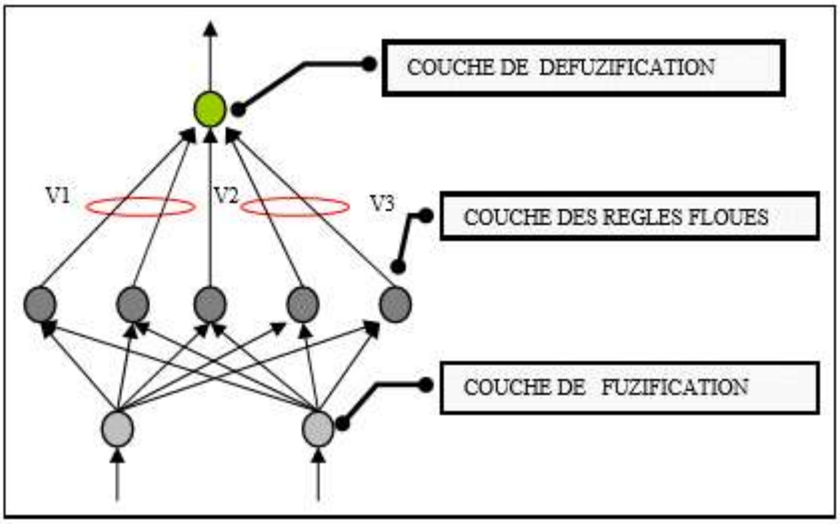

Figure 5: Architecture of NEFCON

2.3.6 ANFIS model

2.3.6.1 Architecture of ANFIS [8] [9] [10]

ANFIS (Adaptive Network Based Fuzzy Inference System) is a neuro-fuzzy adaptive inference system that consists of using a 5-layer MLP neural network for which each layer corresponds to the realization of a step of a Takagi-Sugeno type fuzzy inference system. For simplicity, we assume that the fuzzy inference system has two inputs x and y, and one output f. Assume that the rule base contains two Takagi-Sugeno fuzzy rules.

Rule1: $if\,(x\ is\ A_1)\ and\ (y\ is\ B_1)\ then(f_1 = p_1x + q_1y + r_1)$ (1)

Rule2: $if\,(\,x\ is\ A_2)\ and\ (y\ is\ B_2)\ then(f_2 = p_2x + q_2y + r_2)$ (2)

ANFIS has a five-layer architecture as shown in Figure 6.

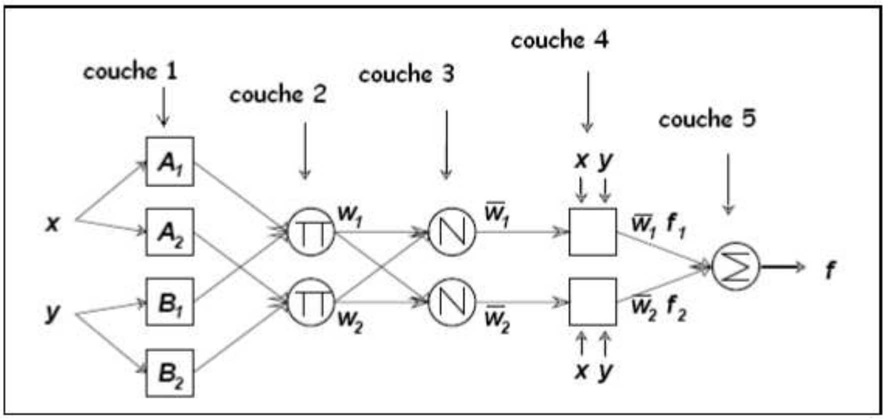

Figure 6: Architecture of ANFIS

A typical architecture can be described as follows:

1. The first layer of an ANFIS architecture has as many neurons as there are fuzzy subsets in the represented inference system. Each neuron calculates the truth degree of a particular fuzzy subset by its transfer function. The only restriction on the choice of this function concerns its derivability. In the literature, Gaussian functions are used and the modifiable parameters are the center and the slope of the Gaussian (variance).

The activation function of the neurons i of the first layer:

$$f_i^1 = \mu_{Ai}(X) \quad (3)$$

Where x is the input to neuron i, and Ai is a fuzzy subset corresponding to variable x. In other words, f_i^1 is the membership function of Ai and it indicates the degree to which given x satisfies the quantifier Ai. We choose $\mu_{Ai}(X)$ to be (Gaussian, triangle, trapezoidal) shaped with maximum equal to 1 and minimum equal to 0, such that the generalized functions of these shapes is:

Triangle: $\mu(x) = \max(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0)$ (4)

trapezoidal: $\mu(x) = \max(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0)$ (5)

Gaussian: $\mu(x) = \exp\left(-\frac{(x-c)^2}{\sigma^2}\right)$ (6)

Where {a, b, c, σ} is the set of parameters. As the values of these parameters change, the functions in the previous form change accordingly, thus presenting various forms of membership function on the linguistic variable Ai. The parameters in this layer are referred to as membership function parameters.

2. The second hidden layer is used to calculate the degree of activation of the premises. The neurons in this layer each represent the premise of a rule. They receive as input the degree of truth of the different fuzzy subsets composing this premise and are in charge of computing its own degree of truth. The activation functions used for these neurons depend on the operators present in the rules (AND or OR).

The activation function of the neurons i of the first layer:

$$W_k = \mu_{Ai}(X) * \mu_{Bj}(Y) \quad (7)$$

Where k: represents the number of rules, i: represents the number of partitions of x, and j: the number of partitions of y.

3. The third hidden layer normalizes the degree of rule activation. Each neuron in this layer is a circle neuron denoted N. The i^{th} neuron calculates the ratio between i^{th} rule weight and the sum of all rule weights. This operation is called weight normalization.

$$\overline{W_k} = \frac{w_k}{\sum w_i} \tag{8}$$

The set of outputs from this layer will be called the normalized weights.

4. The fourth hidden layer is used to determine the parameters of the consequence part of the rules (p, q, r). The function of each neuron in this layer is as follows

$$f_k^4 = \overline{W_k} * f_k = \overline{W_k}(p_k x + p_k y + r_k \tag{9}$$

Where W_k is the output of the third layer, and $\{r_i, q_i, p_i\}$ is the set of parameters. These parameters are referred to as the consequential parameters.

5. The output layer contains a single neuron in this layer, is a circle neuron denoted S which calculates the overall output as the sum of all incoming signals, that's to say:

$$f^5 == \sum_k \overline{W_k} * f_k^4 \tag{10}$$

Figure 7 shows an ANFIS system, with 2 inputs each divided into three fuzzy subsets and 9 rules.

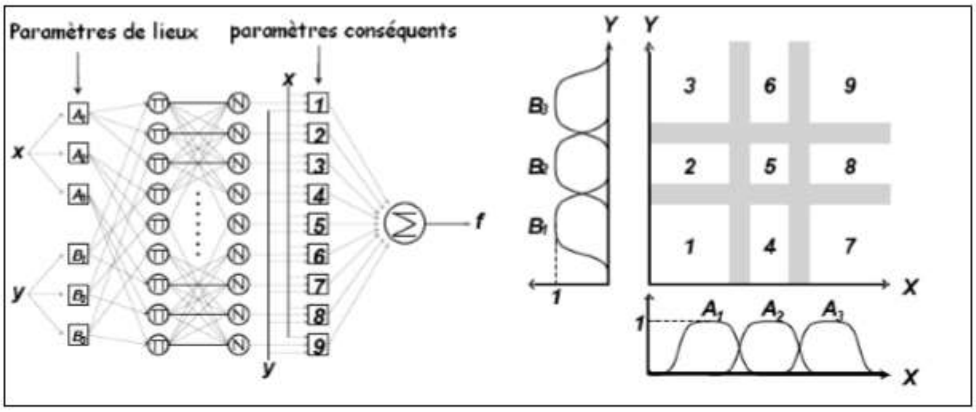

Figure 7: Example ANFIS with 2 inputs and 9 rules

Table 1: Different layers of an ANFIS system

Different layers	Type of the layers	Number of neurons in the layer
Layer 0	Inputs	n
Layer 1	Values	(p. n)
Layer 2	Rules	p^n
Layer 3	Normalization	p^n
Layer 4	Linearization of the functions	p^n
Layer 5	Sum	1

Such that:

n: the number of inputs.

p: the number of fuzzy input subsets (fuzzy partition).

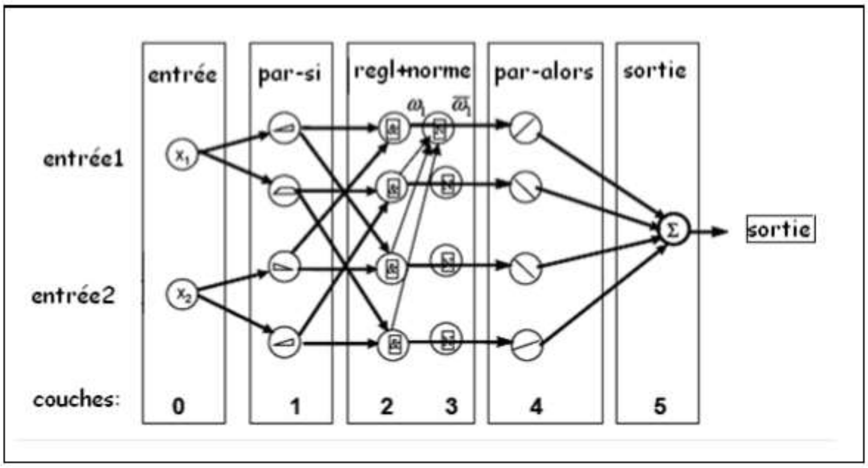

Figure 8: ANFIS network

Note that neurons in ANFIS have different structures:

- Values [membership function defined by different forms];
- Rules [usually product];
- Normalization [sum and arithmetic division];
- Functions [linear regressions and multiplication with $\overline{w}$, such that $\overline{w}$ is the normalisation of the weight w];
- Output [Algebraic Sum].

3.3.7 ANFIS learning algorithm

ANFIS applies the learning mechanism of neural networks to fuzzy inference techniques. In other words, ANFIS is a fuzzy inference system (FIS) whose membership function parameters are adjusted using the back-propagation learning algorithm, or in combination with another type of algorithm such as least square.

In the ANFIS architecture proposed in Figure 6, the overall output can be expressed as linear combinations of the resulting parameters. More precisely, the conclusion (the output) in Figure 6 can be rewritten as:

$$f = \frac{W_1}{W_1+W_2} f_1 + \frac{W_2}{W_1+W_2} f_2$$
$$= (\overline{W_1}x)p_1 + (\overline{W_1}y)q_1 + (\overline{W_1})r_1 + (\overline{W_2}x)p_2 + (\overline{W_2}y)q_2 + (\overline{W_2})r_2 \quad (11)$$

The output is a linear function of the consequence parameters (p, q, r). ANFIS is a parametric representation of two sets of parameters: S1 and S2 such that:

- S1 represents the parameters of the fuzzy sets used for fuzzification in the first ANFIS layer

$$S1 = \left\{\{a_{11}, b_{11}, c_{11}\}, \{a_{12}, b_{12}, c_{12}\}, \dots, \{a_{1p}, b_{1p}, c_{1p}\}, \dots, \{a_{np}, b_{np}, c_{np}\}\right\} \quad (12)$$

Where p is the number of fuzzy partitions of each of the input variables and n is the number of input variables.

- S2 represents the coefficients of the linear functions (the consequent parameters)

$$S2 = \{p_1, p_2, p_3 \dots, q_1, q_2, q_3 \dots, r_1, r_2, r_3 \dots\} \quad (13)$$

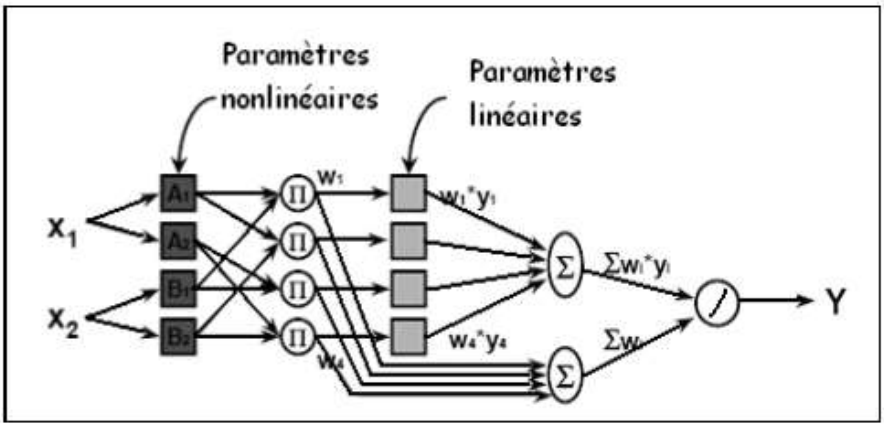

Figure 9 : Hybrid learning method

Table 2 : Parameters to be adjusted of an ANFIS system

	Passage Forward	Passage Backward
Membership function parameter (non linear a_i, b_i, c_i)	fixed	Retro propagation
Coefficient parameter (Linear p, q, r)	least squares	fixed

ANFIS uses a two-pass learning cycle:

- the forward run: S1 is fixed and S2 is calculated using the least square error (LSE) algorithm; (The LSE is applied only once when starting to obtain the initial values of the resulting parameters)
- backtracking: S2 is fixed and S1 is calculated using the Backpropagation algorithm.

III. and discussion

3.2.5 Graphical representation of the model

Figures 10 and 11 show the forecasts of the annual average maximum temperature observed during the study period. The curve of the observation data in blue, the curve in black is the model and the curve in purple is the forecast. The forecast values of the annual average maximum temperature for the years 2019 to 2028 are shown in Table 3.

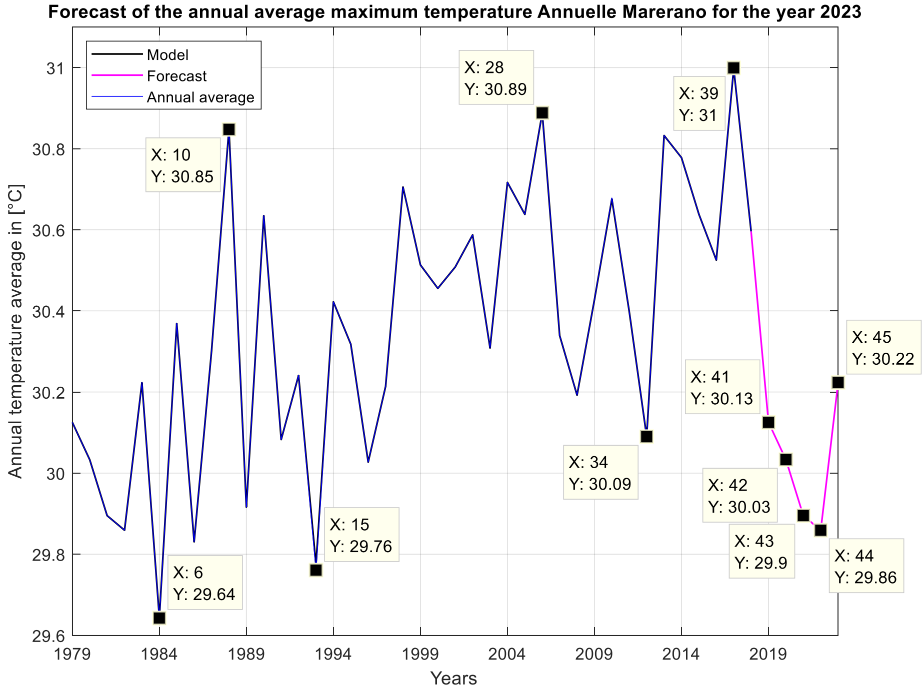

Figure 10: Forecast curve for the maximum temperature in 2023

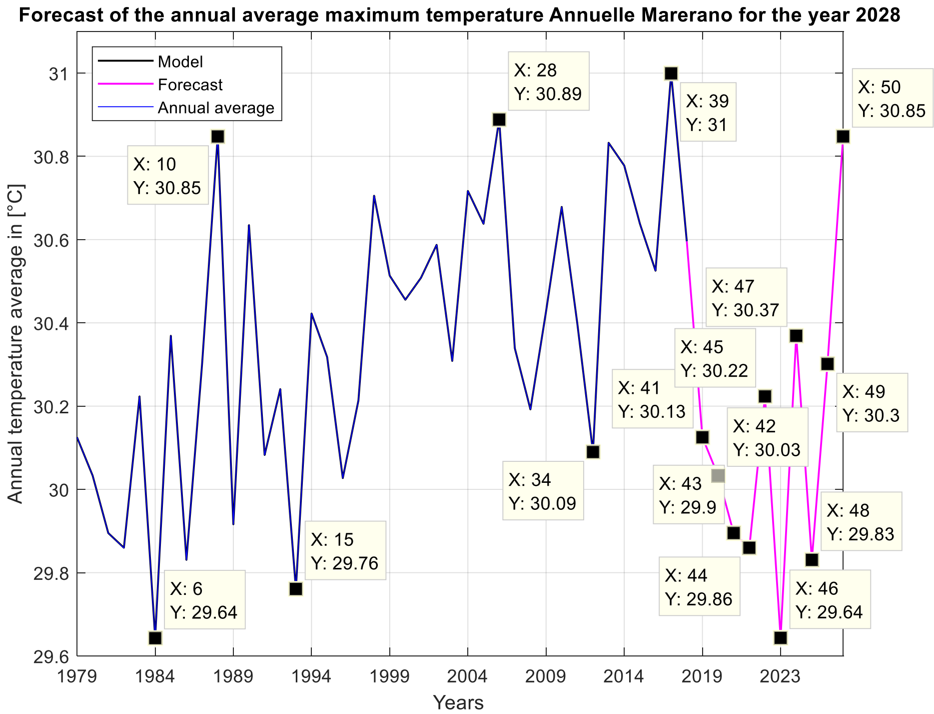

Figure 11: Forecast curve for the maximum temperature in 2028

Table 3: Forecast of the annual mean of the maximum temperature by the Neuro-fuzzy method

Forecast years	Values of the annual average temperature in [°C]
2019	30,13
2020	30,03
2021	29,90
2022	29,86
2023	30,22
2024	29,64
2025	30,37
2026	29,83
2027	30,30
2028	30,85

When analyzing the curves, the average maximum temperature values are between 29.64°C and 31°C. The minimum value is 29.64°C (in 1984) and the maximum value is 31°C (in 2017).

IV. Conclusion

In this article, we interested at the quantitative analysis of the maximum daily temperature from 1979 to 2018 for Marerano-Mahajanga II Madagascar. This part is between longitude 46.5°East and 47°East, latitude 16°South and 15.5°South. To study the predictability of these parameters, it is necessary to make a quantitative study of some climatological parameters. In our case, we used the statistical method, the Neuro-fuzzy method.

According to the Neuro-fuzzy method, the models chosen for the mean values of the maximum temperature are between 29.64°C and 31°C. The year 1984 is the less temperate year, the temperature value is 29.64°C. The warmer year is 2017 with a temperature value of 31°C.

This method gives us the forecast values from 2019 to 2028, i.e. ten years.

V. References

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