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Study of Anomalies and Modeling of the Maximum Temperature by the Fuzzy Logic Method in the Boeny Region of Madagascar

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Abstract: *The study area is the BOENY region, delimited in latitude between 15°South and 18°South and in longitude between 44°East and 48°East.*

The maximum temperature anomaly gives us temperate years represent 15% of cases, while less temperate years are 20% and normal years 65%.

The maximum temperature for the year 1979 to 2018 was modelled by the fuzzy inference system. According to this second-order and third-order fuzzy inference system the obtained models fit better with the observed maximum temperature data.

The MAPE validation criterion shows us that both models receive a percentage below 4%. The accuracy of the models is very high, i.e. there is a good correlation. For the forecast of the annual mean value of the maximum temperature for the year 2019, the temperature value is 28.8 °C

Keywords: *Temperature, anomaly, modeling, fuzzy logic, Boeny region.*

I. Introduction

Global warming is defined as a statistically significant change in the mean state of the climate or its variability, persisting for a period of several decades or more. The causes of this undisputed phenomenon are likely to be found in both natural processes and anthropogenic changes in the atmosphere and soil composition [1]. One important natural cause that can be mentioned is solar activity. It is clearly linked to climate, as can be seen from the climate study of the last millennium. High solar activity during the High Middle Ages is correlated with warmer temperatures in our regions during this period, while the Little Ice Age is linked to low solar activity (especially between 1645 and 1715) [2].

In Madagascar, the impact of climate change, in particular, temperatures, remains a major concern for the Big Island. It is likely to hit the entire country hard in the coming years.

It is for this reason that this study leads us to analyse the maximum temperature anomaly and to model the annual average value of the maximum temperature by the fuzzy logic method. From this point of view, the proposal of a temperature model and the forecasting in a study area are essential steps to conduct this study.

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II. Material and methods

2.1 Presentation of the study area

The study area (see Figure 1) lies between 15°South and 18°South latitude and between 44°East and 48°East longitude.

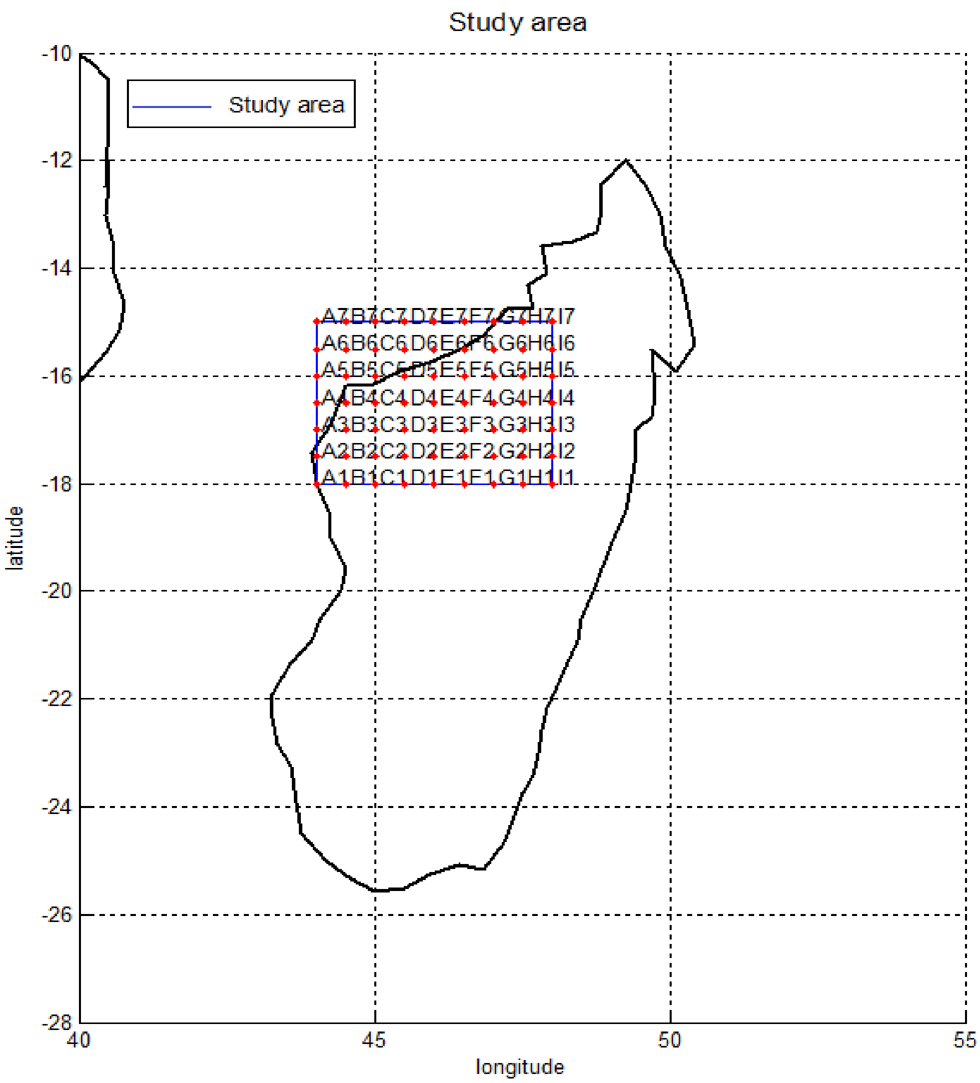

Figure 1: Study area 44° ≤ longitude ≤ 48° and -18° ≤ latitude ≤ -15°

2.2 Databases

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

2.3 Determination of the maximum temperature anomaly [3]

The interannual variability of the temperature anomaly regime can be analysed from the distribution of temperate and less temperate years. Indeed, a temperate and a less temperate year can be defined either in terms of quantiles, standard deviations or, in percentage terms, in terms of the median or the mean. In this study, a temperate or less temperate year is defined in terms of the Lamb index (the deviation from the mean normalised by the standard deviation) which is expressed as:

$$A(i) = \frac{[H(i) - m]}{\sigma}$$

Where H(i): annual average accumulation for year I,
m: the average of the series,
σ: standard deviation of the series,
A(i): Temperature anomaly.

Thus, a year will be considered normal (moderate) if its A(i) anomaly is between -1 and +1. It will be temperate if its anomaly is above +1 and less temperate below -1. This interval remains open to criticism since it is relatively small, so that there are very few normal years. However, it allows a clear distinction between temperate and less temperate years.

2.4 Arithmetic mean [4] [5]

According to common parlance the average generally refers to the arithmetic mean. It is expressed by the formula :

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

where n is the total number of observations in the sample to be studied.

Its empirical standard deviation is :

$$\sigma = \sqrt{\frac{(x_i-\bar{x})^2}{n}}$$

2.5 Sliding or moving average [6] [7]

The rolling average is a type of statistical average used to analyse ordered series of data. It removes transient fluctuations in order to highlight longer-term trends. This average is called a moving average because it is recalculated in a continuous manner, using a subset for each calculation.
The simple moving average is calculated by the formula:

$$\bar{x} = \frac{1}{N}\sum_{k=0}^{N-1} x_{n-k} \text{ ou}$$

$$\bar{x}_n = \bar{x}_{n-1} + \frac{\bar{x}_n - \bar{x}_{n-N}}{N}$$

Where N≤n and N is the number of values in the consecutive subgroup.
The advantage of a moving average is to smooth out any accidental deviations.

2.6 Methodology of fuzzy systems

2.6.1 Fuzzy subsets

Fuzzy subsets were introduced to model the human representation of knowledge, and thus improve the performance of decision systems using modelling [8]. A fuzzy subset A defined over a universe of discourse U, is characterised by a membership function μA. An element x belongs to a subset A, with a membership degree μA(x) between 0 and 1.

2.6.2 Linguistic variable

Reasoning from imperfectly defined knowledge uses fuzzy logic to overcome the shortcomings of classical logic [9]. A linguistic (fuzzy) variable is therefore a variable whose fuzzy values belong to fuzzy sets that can represent words in natural language. Thus, a fuzzy variable can simultaneously take on several linguistic values [10].
The linguistic variable X can be characterised by a triplet (X, T(X), U), where X is the name of the linguistic variable, T(X) the set of linguistic values of X and U the universe of discourse [11]. In general, fuzzy logic uses the following rule: If X is A, then Y is B.

2.6.3 Fuzzy inference system

A fuzzy inference system (FIS) proposes a modelling approach very close to human reasoning to deal with imprecision and uncertainty. It can be considered as a logic system that also uses linguistic rules to establish relationships between input and output variables [12]. The inputs are derived from the fuzzification process and the set of rules are normally defined by the expert's know-how [13].

A fuzzy inference system consists of three steps as shown in Figure 2. The first, fuzzification, transforms numerical values into degrees of membership of the different fuzzy sets of the partition. The second step is the inference engine, consisting of the set of rules. Finally, defuzzification is a decision step, which transforms a fuzzy value of a variable into a real (net) value from the result of the aggregation of rules (Madami or Sugeno).

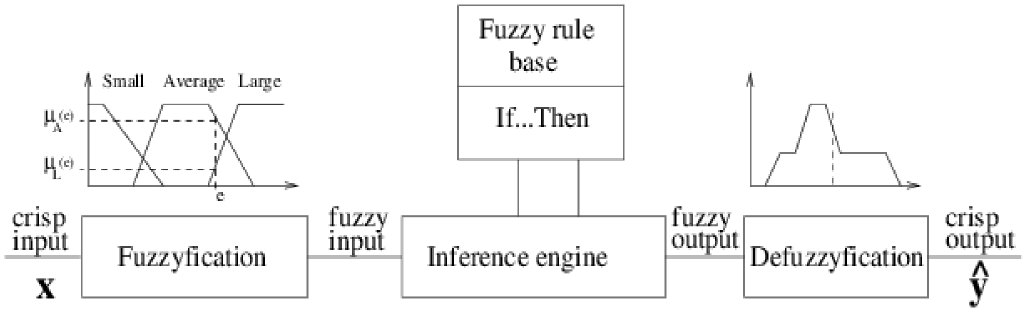

Figure 2: Architecture of the fuzzy interference system [14]

III. Results and discussion

3.1 Annual maximum temperature anomaly

Figure 3 shows :

- the maximum temperature anomaly in red histogram ;
- the global average in green
- the moving average in black;
- the blue lines delimiting moderate maximum temperatures.

Negative anomalies dominate during the period 1979/1997 while positive anomalies from 1998/2018. The same applies to the moving average. It can be concluded that the temperature increases from 1998 onwards.

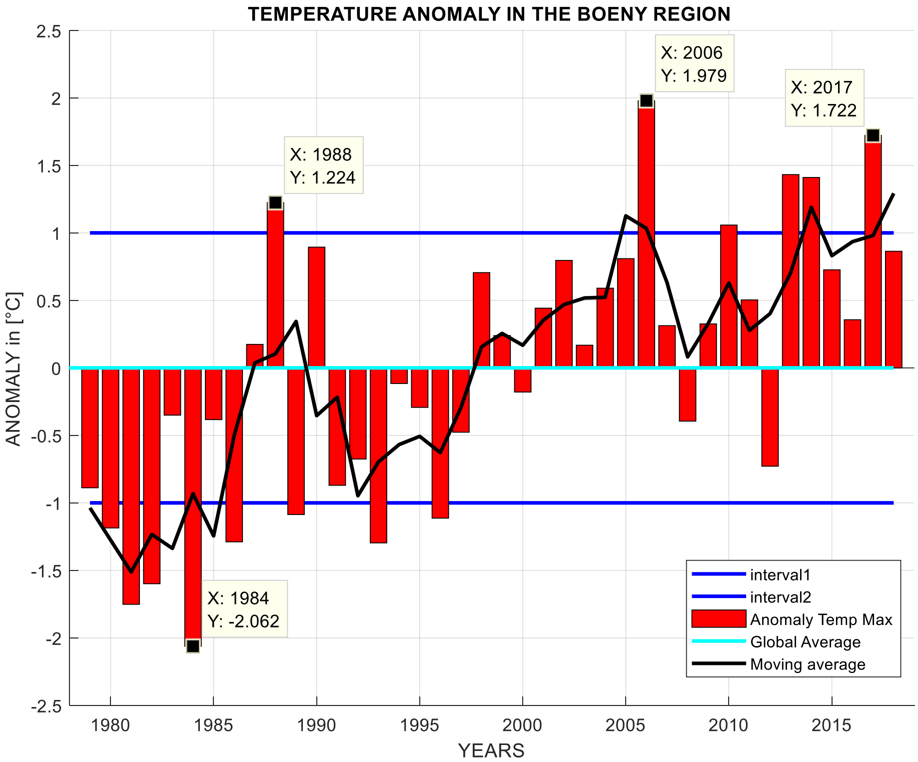

Figure 3: Maximum temperature anomalies in the Boeny region during the period 1979-2018

Figure 3 shows that :

- the least warm years are 1980, 1981, 1982, 1984, 1986, 1989, 1993 and 1996;
- the hottest years are 1988, 2006, 2010, 2013, 2014 and 2017;
- the warmest year is 1984;
- the warmest year is 2006.

3.2 Learning parameters

3.2.1 Discourse universe

The climate variables to be modelled are time series of annual means of maximum temperature from 1979 to 2018 during the 40 years of study. These dates are used as the input and output of the RIS model. In this study, the universe of discourse, the number of partitions and the number of inputs for the rainfall data are given in Table 1:

Table 1: Universe of discourse, number of partitions and number of inputs for rainfall

Annual averages	Universe of discourse	Number of partitions	Input Number
Temperature	U_2= [24,77 31.77]	63 partitions (A0, A2, … A62)	Two entries
Temperature	U_3= [24,77 31.77]	63 partitions (a0, a2, … a62)	Three entries

3.2.2 Membership function

The membership function can be represented as a triangular, trapezoidal, parabolic, Gaussian, sigmoid, etc. function. For the sake of clarity and ease of calculation, we have used the triangular membership function. The following figure shows the membership function for the maximum temperature.

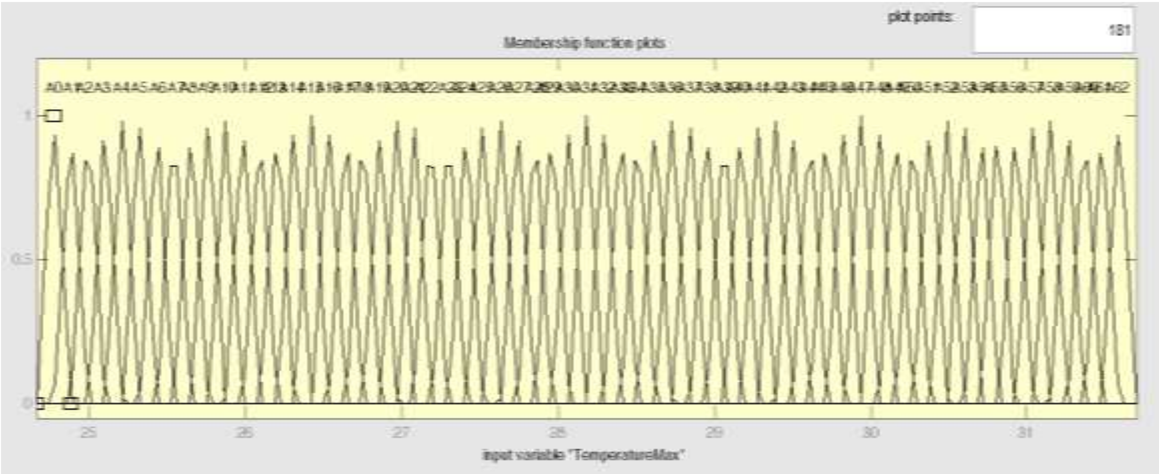

Figure 4: Membership functions for annual average maximum temperature

3.3 Implementing a FIS for annual average maximum temperature values

The implementation of a fuzzy inference system involves several steps: fuzzification and defuzzification of input and output variables, and the implementation of an inference engine. The structure of a FIS for modelling the average maximum temperature is illustrated in figures 5 and 6.

There are several approaches to the fuzzy inference system. In general, all approaches can be applied in fuzzy systems. In our case, we have exploited the Mamdani (1974) type of FIS model.

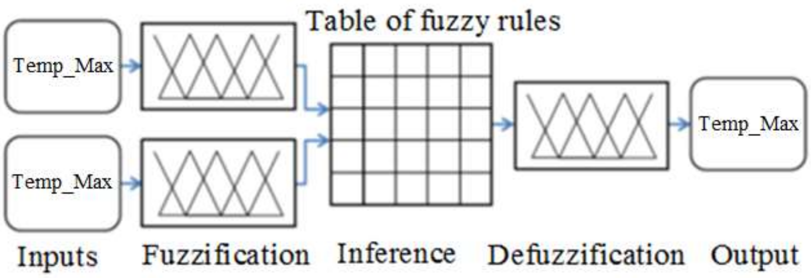

Figure 5: Structure of a RIS for annual average maximum temperature with two inputs

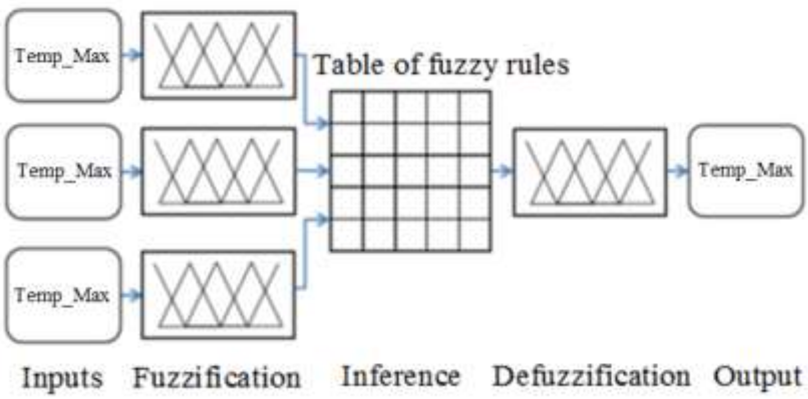

Figure 6: Structure of a RIS for annual average maximum temperature with three inputs

3.3.1 Fuzzification

This step allows the transformation of physical quantities of climate parameters into linguistic variables. Table 2 summarises the numerical values as well as the values transformed into linguistic terms of the annual average maximum temperature during the study period (1979-2018).

Table 2: Fuzzification of annual average value of maximum temperature

YEAR	REAL [°C]	FUZZY WITH TWO INPUTS [°C]			FUZZY WITH THREE INPUTS [°C]		
1979	27.91	A29			A29		
1980	27.81	A28			A28		
1981	27.62	A26	A29, A28	27.62	A26		
1982	27.67	A26	A28, A26	27.67	A26	A29, A28, A26	27.67
1983	28.09	A30	A26, A26	28.10	A30	A28, A26, A26	28.10
1984	27.52	A25	A26, A30	27.50	A25	A26, A26, A30	27.52
1985	28.06	A30	A30, A25	28.10	A30	A26, A30, A25	28.06
1986	27.77	A27	A25, A30	27.80	A27	A30, A25, A30	27.77
1987	28.26	A32	A30, A27	28.30	A32	A25, A30, A27	28.26
1988	28.61	A35	A27, A32	28.60	A35	A30, A27, A32	28.61
1989	27.84	A28	A32, A35	27.80	A28	A27, A32, A35	27.84
1990	28.51	A34	A35, A28	28.50	A34	A32, A35, A28	28.51
1991	27.91	A28	A28, A34	27.90	A28	A35, A28, A34	27.91
1992	27.97	A29	A34, A28	27.97	A29	A28, A34, A28	27.97
1993	27.76	A27	A28, A29	27.76	A27	A34, A28, A29	27.76
1994	28.16	A31	A29, A27	28.16	A31	A28, A29, A27	28.16
1995	28.10	A30	A27, A31	28.10	A30	A29, A27, A31	28.10
1996	27.85	A28	A31, A30	27.85	A28	A27, A31, A30	27.85
1997	28.03	A30	A30, A28	28.04	A30	A31, A30, A28	28.03
1998	28.44	A33	A28, A30	28.44	A33	A30, A28, A30	28.44
1999	28.29	A32	A30, A33	28.30	A32	A28, A30, A33	28.29
2000	28.14	A31	A33, A32	28.14	A31	A30, A33, A32	28.14
2001	28.36	A33	A32, A31	28.36	A33	A33, A32, A31	28.36
2002	28.47	A34	A31, A33	28.47	A34	A32, A31, A33	28.47
2003	28.26	A32	A33, A34	28.27	A32	A31, A33, A34	28.26
2004	28.40	A33	A34, A32	28.40	A33	A33, A34, A32	28.40
2005	28.49	A34	A32, A33	28.50	A34	A34, A32, A33	28.49
2006	28.87	A37	A33, A34	28.90	A37	A32, A33, A34	28.87
2007	28.31	A32	A34, A37	28.30	A32	A33, A34, A37	28.31
2008	28.07	A30	A37, A32	28.10	A30	A34, A37, A32	28.07
2009	28.32	A32	A32, A30	28.30	A32	A37, A32, A30	28.32
2010	28.58	A35	A30, A32	28.57	A35	A32, A30, A32	28.58
2011	28.38	A33	A32, A35	28.34	A33	A30, A32, A35	28.38
2012	27.96	A29	A35, A33	27.97	A29	A32, A35, A33	27.96
2013	28.67	A35	A33, A29	28.67	A35	A35, A33, A29	28.67
2014	28.67	A35	A29, A35	28.67	A35	A33, A29, A35	28.67
2015	28.44	A33	A35, A35	28.44	A33	A29, A35, A35	28.44
2016	28.32	A32	A35, A33	28.30	A32	A35, A35, A33	28.32
2017	28.78	A36	A33, A32	28.80	A36	A35, A33, A32	28.78
2018	28.49	A34	A32, A36	28.50	A34	A33, A32, A36	28.50

3.3.2 Creating fuzzy rules

For the modelling of the maximum temperatures, after several scenarios and several trials, we set a second and third order FIS model. These are models for a two-input output and for a three-input output.

Table 3 shows the adopted fuzzy rules. The numbered letters are linguistic variables used for the maximum temperature model during the study period.

Table 3: Example of the fuzzy rules for the second and third order maximum temperature model

Maximum temperature model (order 2) :	**Maximum temperature model (order 3)**
Previous ---> consequent	Previous ---> consequent
A29, A28 ---> A26	A29, A28, A26 ---> A26
A28, A26 ---> A26	A28, A26, A26 ---> A30
A26, A26 ---> A30	A26, A26, A30 ---> A25
……………………	……………………
……………………	……………………
A32, A36 ---> A34	A33, A32, A36 ---> A34

3.3.3 Defuzzification

The input for the defuzzification process is the combinatorial result of the fuzzified set. The objective is to transform this fuzzy set into non-fuzzy values [15]. Table 4 shows the defuzzified values of the maximum temperature model output.

Table 4: Defuzzification of the average maximum temperature

YEAR	**REAL** [°C]	**OUTPUT VALUES** [°C]		**YEAR**	**REAL** [°C]	**OUTPUT VALUES** [°C]	
		ORDER 2	**ORDER 3**			**ORDER 2**	**ORDER 3**
1979	27.91			1999	28.29	28.30	28.29
1980	27.81			2000	28.14	28.14	28.14
1981	27.62	27.62		2001	28.36	28.36	28.36
1982	27.67	27.67	27.67	2002	28.47	28.47	28.47
1983	28.09	28.10	28.10	2003	28.26	28.27	28.26
1984	27.52	27.50	27.52	2004	28.40	28.40	28.40
1985	28.06	28.10	28.06	2005	28.49	28.50	28.49
1986	27.77	27.80	27.77	2006	28.87	28.90	28.87
1987	28.26	28.30	28.26	2007	28.31	28.30	28.31
1988	28.61	28.60	28.61	2008	28.07	28.10	28.07
1989	27.84	27.80	27.84	2009	28.32	28.30	28.32
1990	28.51	28.50	28.51	2010	28.58	28.57	28.58
1991	27.91	27.90	27.91	2011	28.38	28.34	28.38
1992	27.97	27.97	27.97	2012	27.96	27.97	27.96
1993	27.76	27.76	27.76	2013	28.67	28.67	28.67
1994	28.16	28.16	28.16	2014	28.67	28.67	28.67
1995	28.10	28.10	28.10	2015	28.44	28.44	28.44
1996	27.85	27.85	27.85	2016	28.32	28.30	28.32
1997	28.03	28.04	28.03	2017	28.78	28.80	28.78
1998	28.44	28.44	28.44	2018	28.49	28.50	28.50

3.3.4 Mamdani RIS model by Matlab software

The structure of the SIF Mamdani model obtained by Matlab software is presented in Figure 7. One of this model is formed by 2 inputs, one output with 63 fuzzy rules and the other is formed by 3 inputs, one output always with 63 fuzzy rules.

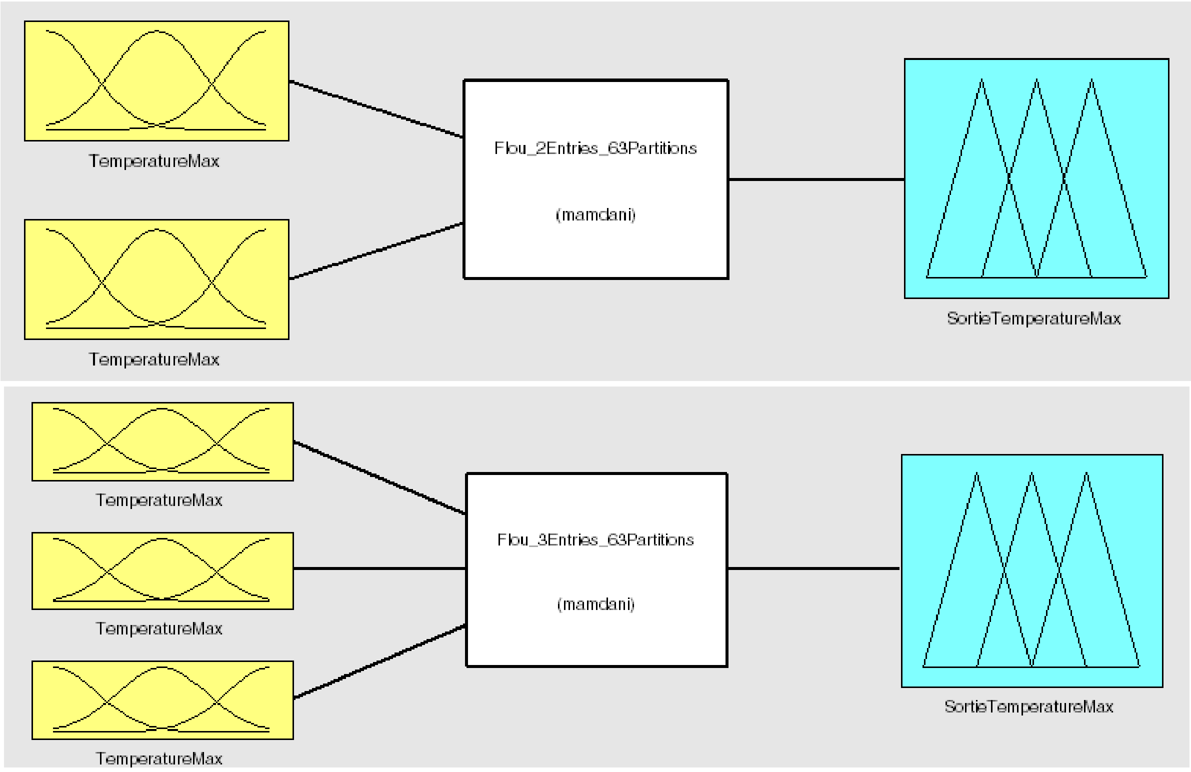

Figure 7: Fuzzy logic models in Matlab

3.3.5 Graphical representation of the model

Figures 8 and 9 show the time series of maximum temperature forecasts observed during the study period and for the RIS models respectively. We can see that the curves of the observed data (black) are merged with the curves of the obtained models (blue). This suggests that we have good models. For the short-term forecast, the temperature value for the year 2019 is 28.8 °C for the second-order model and the third-order model respectively.

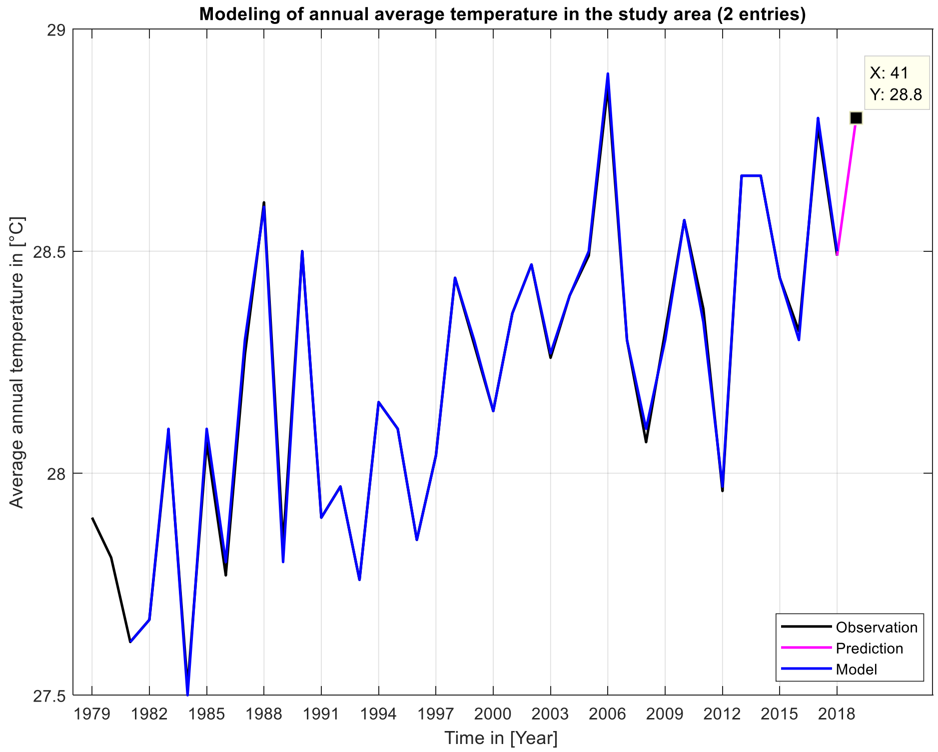

Figure 8: Maximum temperature forecast model curve with two inputs

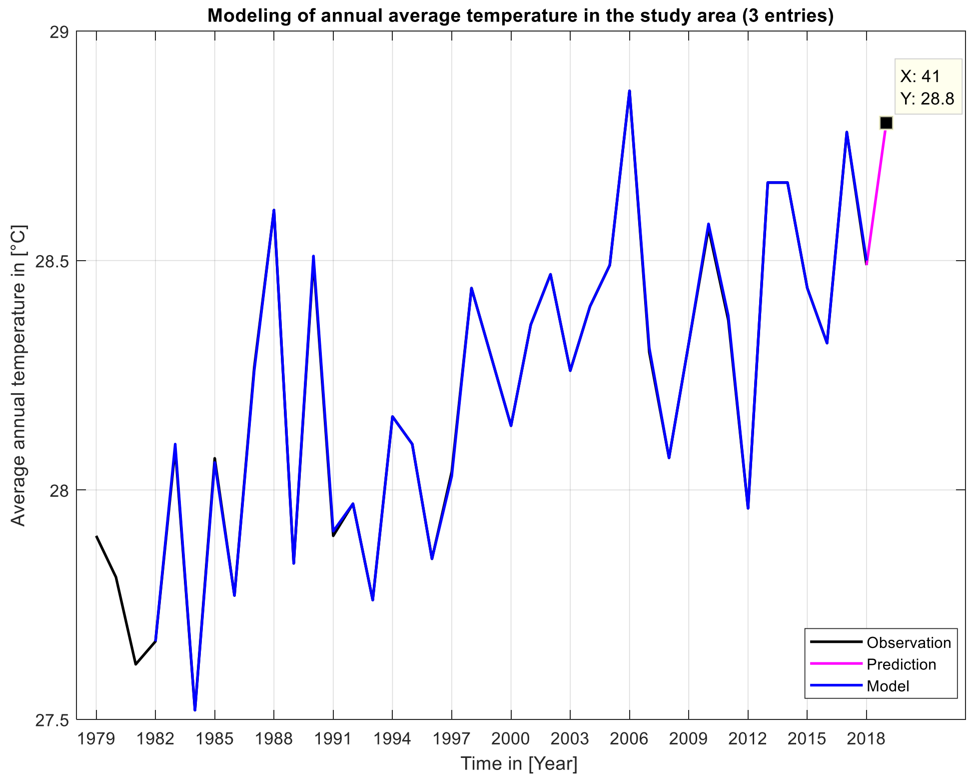

Figure 9: Maximum temperature forecast model curve with three inputs

3.3.6 Model validation criteria

The performance measures of the FIS models are the mean absolute percentage error (MAPE) and the percentage accuracy (P). The calculated MAPE values and accuracy percentages are summarised in Table 5. The mean absolute percentage error is successively 3.49% for the second order model and 0.92% for the third order model. Since the MAPEs are very low, the FIS model gives satisfactory results. The percentage accuracy is 99.98% (second order) and 99.99% (third order) respectively. However, the accuracy of the results is very high. Indeed, the simulation results show that our models used for rainfall forecasting are excellent.

Table 5: MAPE values and percentage accuracy of the model

Validation criteria	FUZZY WITH TWO INPUTS	FUZZY WITH THREE INPUTS
MAPE	3,49%	0,92%
P	99,98%	99,99%

IV. Conclusion

In this study area, we are interested in the quantitative analysis of the daily maximum temperature from 1979 to 2018 in the Boeny region of Madagascar. This area lies between longitude 44°East and 48°East, latitude 18°South and 15°South. To study the predictability of these parameters, it is necessary to make a quantitative study of some climatological parameters. In our case we proceeded by using statistical methods and the fuzzy logic method.

The maximum temperature anomaly, temperate years represent 15% of cases, while less temperate years are 20% and normal years 65%.

According to the fuzzy logic method, the models selected for the average values of the maximum temperature are of order 2 and order 3 with 63 fuzzy rules (partitions). The fuzzy inference system models used fit the maximum temperature observation data better.

According to the MAPE validation criterion, both models receive less than 4%. The accuracy of the models is very high. The annual average value of the maximum temperature for the year 2019 is 28.8°C.

Finally, it would be interesting to use hybrid models such as neuro-fuzzy or another method to determine the medium-term of the maximum temperature forecast.

V. References

[1] VijayaVenkataRaman S., Iniyan S., Goic R., 2012. A review of climate change, mitigation and adaptation. Renewable and Sustainable Energy Reviews 16:878–897.

[2] Keller C.F., 2004. 1000 Years of climate change. Advances in Space Research 34, 315–322.

[3] Éric Zeltz, “Analysis and climatological interpretation of the evolution of global average temperatures since 1880”, Physio-Géo, Volume 16 | -1, 49-70.

[4] D. Veneziano, P. Furcolo, V. Iacobellis. Imperfect scaling of time and space-time rainfall. Journal of Hydrology, Volume 322 (2006), p. 105-119. 2005.

[5] https://fr.wikipedia.org/wiki/Average_arithm%C3%A9tique, 01 February 2016.

[6] http: // Wikipedia, org/wiki/ Moving Average, March 25, 2016.

[7] LUBES, JM. DASSON, E.SREVAT, JE. PATUREL, B .KOUAME, JF. BOYER 1994. Characterization of fluctuation in a time series by application of statistical test.

[8] P.A. Bisgambiglia (2008). Approximate modeling approach for discrete event systems: Application to the study of forest fire propagation (Doctoral dissertation, Université Pascal Paoli).

[9] L. Zadeh, (1965). Fuzzy sets. Information and Control, 8(3):338-353.

[10] C. C. Lee, “Fuzzy logic in control systems: fuzzy logic controller. Part1”, IEEE Transactions on systems Man and Cybernetics, Vol. 20, 1990, p. 404-418.

[11] Ralescu, A., & Hartani, R. (1995, March). Some issues in fuzzy and linguistic modeling. In Proceedings of 1995 IEEE International Conference on Fuzzy Systems. (Vol. 4, pp. 1903-1910). IEEE.

[12] Talbi, N. (2019). Design of fuzzy controller rule base using bat algorithm. Energy Procedia, 162, 241-250.

[13] E. Bonilla-Huerta, B. Duval and J. K. Hao. Fuzzy logic for elimination of redundancy information of microarray data. Genomics Proteomics and Bioinformatics, Elsevier, October 2008, Vol.6, No. 2.

[14] N. Tremblay, M.Y. Bouroubi, B. Panneton, S. Guillaume, P. Vigneault, et al.. Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features. Precision Agriculture, Springer Verlag, 2010, 11 (6), pp.621-635.

[15] S. Zribi Boujelbene, D. Ben Ayed MezghaniN. Ellouze. Fuzzy Inference Systems for Phonemic Classification. SETIT 07 4th International Conference: Sciences of Electronic, Technologies of Information and Telecommunications, TUNISIA, March 25-29, 2007.