Modelling and forecasting the rainy season by the mean of an Artificial Intelligent model: case of the Southern part of Madagascar.

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Introduction

- Fuzzy Logic has empowered/enhanced the AI system since it mimics human-reasoning. Examples: in consumer electronics, automotive industry, robotics, medical diagnosis,...
- The climate change challenges has spured scientists to investigate in including AI tools within their researches. Some researchers used Fuzzy Logic in increasing crop yield by controlling the efficiency of greenhouses [1]. Other used the rule-base of Fuzzy inference system for predicting rainfall [2] or determining the onset of the rainy season [3].
- Forecasting the rainy season might be an overarching topic/of interest to tackle some of these climate change issues.
- Let us use the rule-based fuzzy inference system to set accurate rainy season calendar.

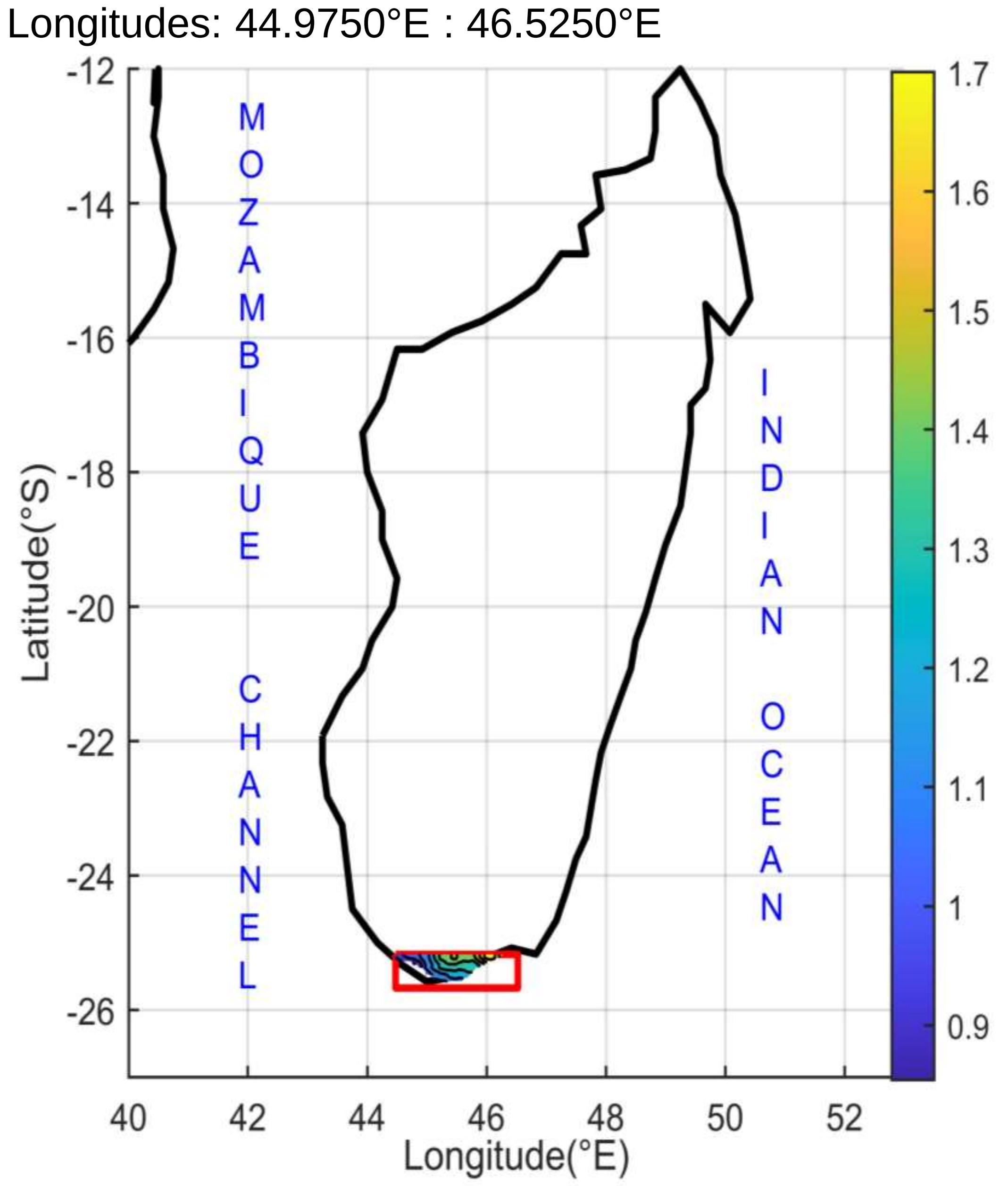
Data

Daily precipitation of 0.05° x 0.05° from 1 january 1981 to 31 December 2023 from the Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) [4].

West Dipole Mode Indexes (WDMI) from 1980 to 2023 from NOAA [5].

Zone of study

Southern part of Madagascar:
Latitudes: 25.6750°S : 25.1750°S
Longitudes: 44.9750°E : 46.5250°E



Over the zone of study (framed in red) , the daily climatological mean varies from 0.85mm to 1.79mm easterly.

Method and results

Daily precipitation (1981: 2023)

$$A(day) = \sum_{n=1}^{day}\left(R(n) - \overline{R}\right) \quad [6]$$

: precipitation at day 'n'
: daily climatological average

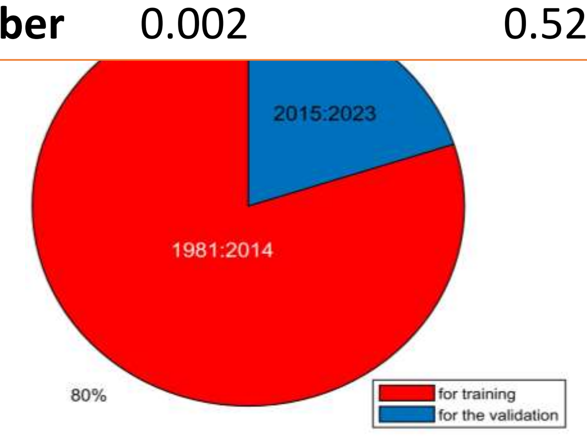
Onset dates and demise dates (1981: 2023)

Partial correlation (onset,WDMI)
Partial correlation (offset,WDMI)

Detection of the predictors

Pearson's parameters : p-value and the correlation coefficient (r) related to WDMI one year earlier the year of the rainy season

	p	r
Month	Onset	
February	0.006	0.479
March	0.003	0.503
June	0.012	0.438
	withdrawal	
June	0.008	0.459
July	0.008	0.461
August	0.003	0.502
November	0.002	0.526

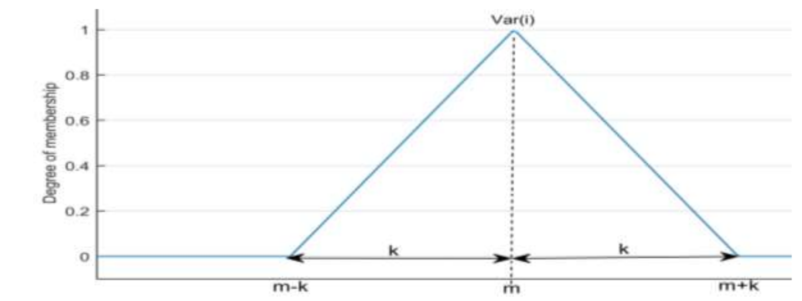


The piechart subdivides the data into:
80%, from 1981 to 2014, for training
20%, from 2015 to 2023, for the validation of the model

Modelling and forecasting with Fuzzy Logic

Definition of the parameters [7]

: the observed data in year 'a'
m : the value of the observation
μ(): the membership degree



The parameters 'k' of the triangular membership function related to the inputs(β) and outputs (α)

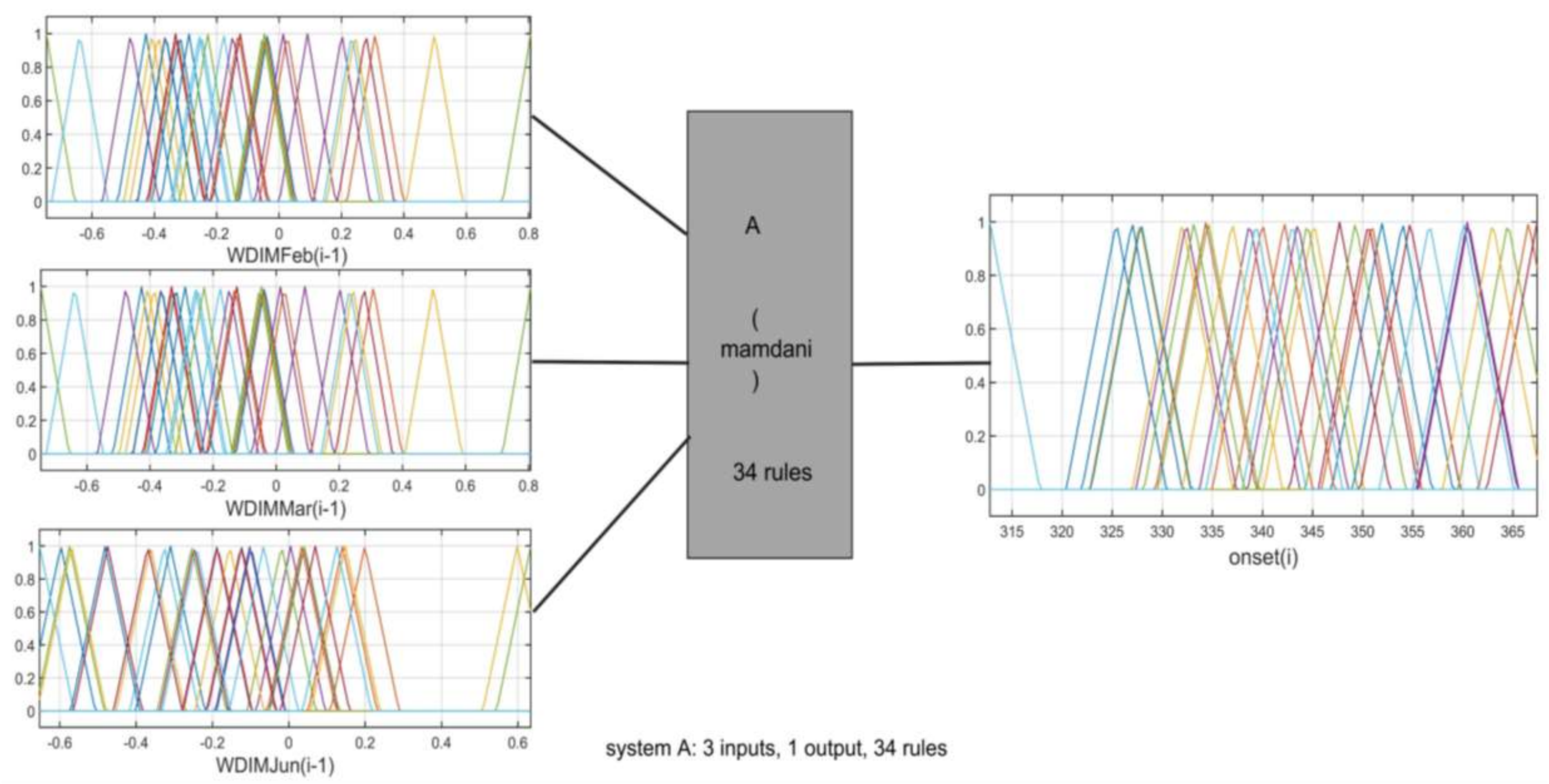
α	1: 1 :7

IF… THEN rules [7]

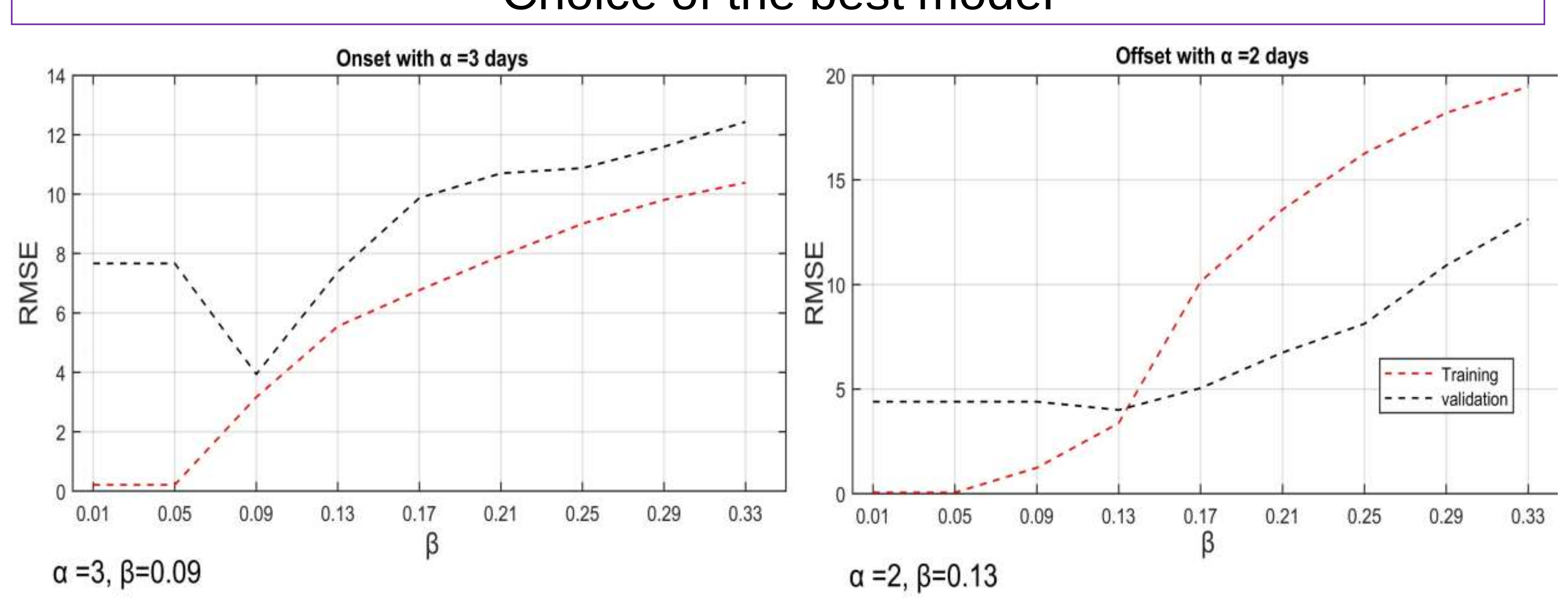
If (var1()) **and** (var2()) **and** … (varN()) **then** (Var_output())

year at rank i which ranges from 1 to 34(1981:2014) for training.

varN: the predictors and N: the number of predictors.

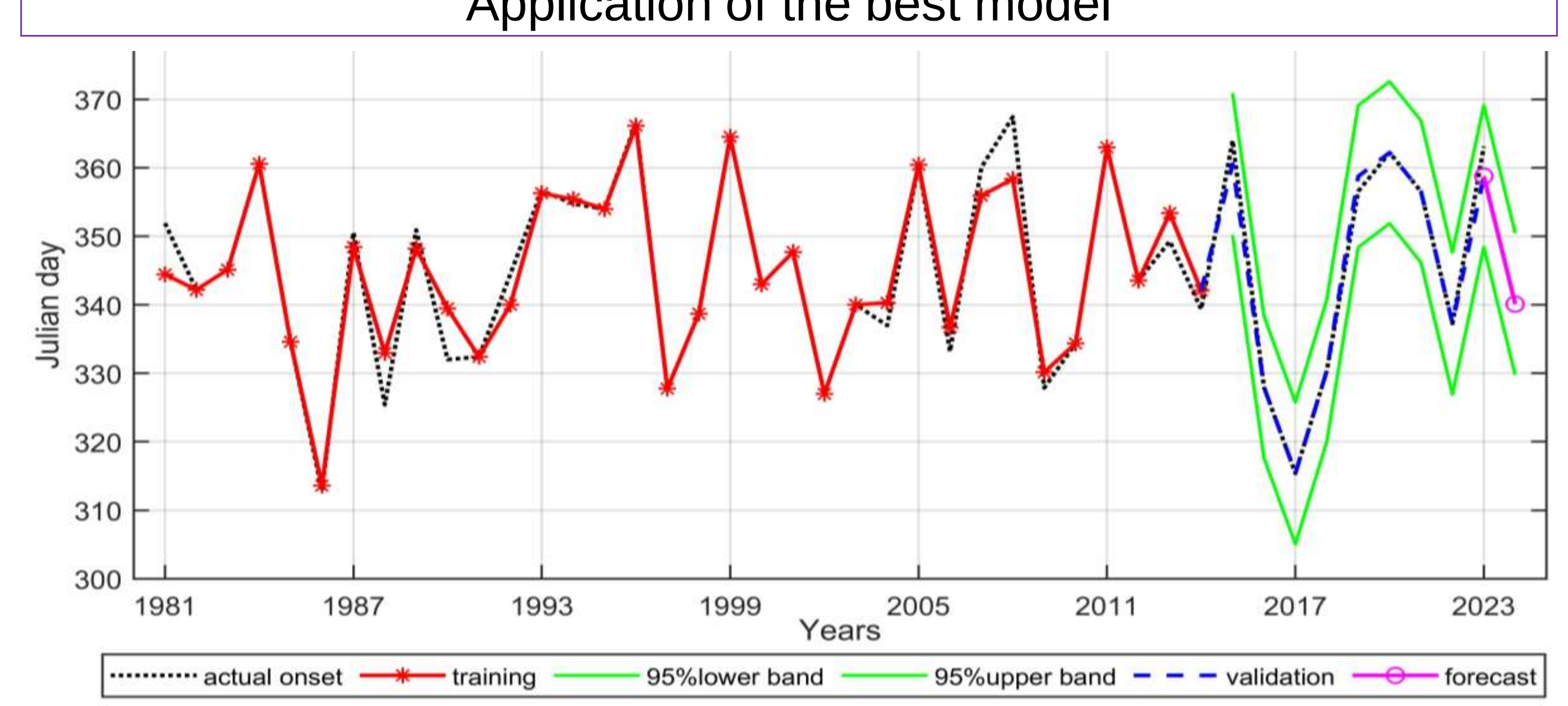


Choice of the best model

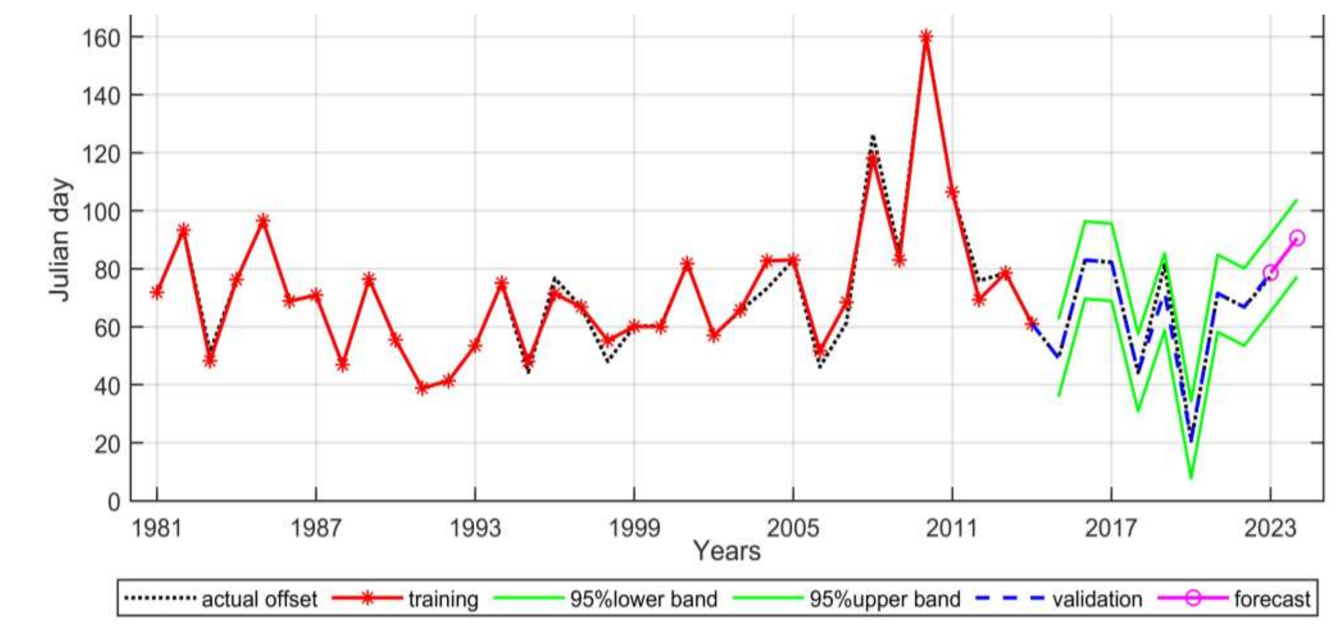


Different values of RMSE related to different values of β corresponding to the training (---red) and the validation (---black) of the onset and cessation dates of the rainy seasons over the southern part of Madagascar with a fixed value of α. The minima values of the RMSE related to the validation of the model correspond to the values of β being 0.09 and 0.13 for the onset and cessation respectively.

Application of the best model



This figure shows the actual onset(black), the predicted onset (red), the test(blue) and the forecast (magenta) with a 95% confidence band (green). The predicted output curves are from a Fuzzy Logic model with the parameters α=3 and β=0.09.



This figure shows the actual withdrawal(black), the predicted withdrawal(red), the test(blue) and the forecast (magenta) with a 95% confidence band (green). The predicted output curves are from a Fuzzy Logic model with the parameters α=2 and β=0.13.

Accuracy measure of the model

	onset	offset
RMSE	3.0073	3.3351
MAE	[illegible]	[illegible]

Forecast of the rainy season of 2024

onset	10 December (± 10 days)
offset	23 March (± 13 days)

Conclusion

- Correlation coefficient ≤ 0.50
- The less the parameter for training the better the model.
  min(RMSE) of the validation best model
- Accurate forecasting model: RMSE < 3.5 and MAE < 2
- Future works for improving the model:
  1. varying the parameter for each predictor
  2. add other predictors (neighbour SST, T,…)
  3. use of other membership functions.

References

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