PREDICTABILITY OF CYCLOGENESIS IN THE MOZAMBIQUE CHANNEL USING EIGENVALUES OF METEOROLOGICAL VARIABLES

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ABSTRACT

Using eigenvalue analysis, this study examines cyclogenesis in the cyclone-prone Mozambique Channel. When it comes to meteorological variables like humidity, vorticity, and mean sea level pressure (MSLP), this technique aids in identifying the prominent fluctuation modes. Eigenvalues facilitate the understanding of pre-cyclonic dynamics by indicating the proportion of variance explained by each mode. According to the analysis, there is a dominant tendency in the variability, with the first eigenvalue explaining most of the variance and consistently being bigger than 1. But the second eigenvalue, which can occasionally be greater than 1, emphasizes the significance of a bidimensional component in particular circumstances. This implies that cyclone formation may be influenced by an additional major component in addition to the basic structure. As a result, the study highlights how crucial it is to take into account the second eigenvalue in addition to the first in order to fully comprehend the intricate interactions that lead to cyclogenesis.

Keyword: - *Mozambique Channel; cyclogenesis; variables; eigenvalue.*

1. INTRODUCTION

The Mozambique Channel, located between Madagascar and the south-east coast of Africa, is a region prone to the formation of tropical cyclones, particularly during the rainy season, generally from November to April. Forecasting cyclogenesis in regions such as the Mozambique Channel is a major challenge for the safety of populations and economic activities. Tropical cyclones can cause considerable damage, including flooding, strong winds and landslides. To improve the accuracy of forecasts, researchers are taking a close look at the physical mechanisms that govern the formation and evolution of these systems. One approach to improving predictability is to analyse key meteorological variables, using advanced techniques such as eigenvalue analysis (or principal component analysis, PCA). PCA reduces the dimensionality of the data by identifying the main modes of variability, making it easier to understand the physical processes underlying cyclone formation. These eigenvalues are essential for capturing the dominant structures in meteorological fields and can be used as precursors or indicators of cyclogenesis.

2. MATERIELS ET METHODOLOGIES

2.1 DATABASE

- The meteorological data used in this work are daily data from 01 January 1979 to 31 December 2018. The variables Mean Sea Level Pressure (MSLP), Sea Surface Temperature (SST), wind components (u and v) at different altitudes, vorticity, specific humidity, divergence are taken from ERA5 (European Centre for Medium-Range Weather Forecasts - ECMWF Reanalysis 5) with a spatial resolution of $0,5° \times 0,5°$ [1]. On the other hand, the NOAA (National Oceanic and Atmospheric Administration) provides OLR (Outgoing Longwave Radiation) measurements from satellites with a spatial resolution of $2,5° \times 2,5°$ [2].
- Cyclone data are obtained from IBTrACS (International Best Track Archive for Climate Stewardship) [3] and Centre Météorologique Régional de La Réunion (CMR La Réunion) [4].

2.2 STUDY AREA

We will focus our study on the area framed in blue in Figure 1, delimited by longitudes between 35°E and 45°E, and latitudes between 12°S and 24°S.

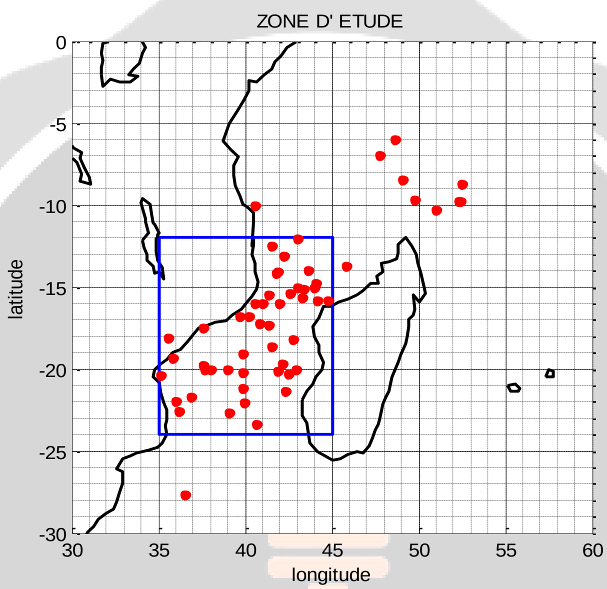

Fig- 1 : Representation of the study area

2.3 METHODOLOGY

2.3.1 Eigenvalue method

The eigenvalue method is a powerful tool for analysing meteorological phenomena such as cyclogenesis, in particular for identifying the dominant modes of variability in atmospheric data. Applied to the study of cyclogenesis, this method can be used to analyse the dynamics of fields of pressure, temperature, wind and other meteorological variables, in order to extract the most significant spatial and temporal structures associated with cyclone formation.

2.3.1.1 Eigenvalue method for cyclogenesis analysis

In the analysis of cyclogenesis, eigenvalues are often used as part of the analysis of orthogonal empirical modes (or Principal Component Analysis, PCA). This makes it possible to identify the main spatial structures of variability and the temporal modes associated with phenomena such as cyclone formation [5].

If X is a matrix of meteorological data, of dimension $n \times p$, where n represents the number of observations (for example, the number of days) and p the number of spatial points, the PCA is based on the following decomposition:

$$X = U \Lambda V^T \qquad (1)$$

where:

- U is a matrix $n \times n$ whose columns are the eigenvectors of the matrix XX^T,

- Λ is a diagonal matrix containing the eigenvalues,

- V is a matrix $p \times p$ containing the eigenvectors of the matrix $X^T X$.

This breakdown makes it possible to identify the dominant modes of variability. The first largest eigenvalues correspond to the spatial structures that explain most of the variability in the phenomenon studied (in this case, cyclogenesis).

2.3.1.2 Specific application to cyclogenesis

As part of the study of cyclogenesis, the eigenvalue method can be applied to extract the dominant modes associated with cyclone formation in a given region, such as the Mozambique Channel. For example, meteorological variables such as atmospheric pressure at sea level (MSLP), specific humidity or vorticity can be decomposed to identify the spatial structures that contribute to cyclogenesis [6].

2.3.1.3 Key formulas

The covariance matrices are decomposed into eigenvalues and eigenvectors, where the eigenvectors represent the main directions of variability, and the eigenvalues represent the contribution of each component to the total variability.

The eigenvalues and eigenvectors are obtained by solving the following equation for the covariance matrix C:

$$Cv_i = \lambda_i v_i \qquad (2)$$

The highest eigenvalues correspond to the spatial structures that explain most of the variability in meteorological data [7].

2.3.2 Fuzzy logic

Fuzzy logic is an extension of classical logic proposed by Lotfi A. Zadeh in 1965. Unlike classical logic, which is based on binary values (0 or 1, true or false), fuzzy logic allows degrees of membership between 0 and 1 to be represented and manipulated, providing a framework for modelling uncertainty and imprecision in complex systems. It is particularly useful in areas where human decisions are often based on approximate judgements rather than precise values [8].

2.3.2.1 Fundamental Concepts of Fuzzy Logic

❖ *Fuzzy Set [9]*

A fuzzy set is a generalisation of classical sets. In a fuzzy set, an element can have a membership degree between 0 and 1. If we consider a fuzzy set A in a universe U, then the membership function μ_A is defined by :

$$\mu_A(x): U \rightarrow [0,1] \qquad (3)$$

Here, $\mu_A(x)$ represents the degree to which element x belongs to set A.

❖ *Operations on Fuzzy Sets [10]*

The classical operations of set theory can be generalised to fuzzy sets. For two fuzzy sets A and B, the main operations are:

- **Union** : $\mu_{A\cup B}(x) = \max\left(\mu_A(x), \mu_B(x)\right)$ (4)
- **Intersection** : $\mu_{A\cap B}(x) = \min\left(\mu_A(x), \mu_B(x)\right)$ (5)
- **Complement** : $\mu_{\overline{A}}(x) = 1 - \mu_A(x)$ (6)

These operations enable fuzzy sets to be combined flexibly to represent complex situations.

2.3.2.2 Fuzzification and Defuzzification

❖ Fuzzification [11]

Fuzzification is the process of transforming a net value into a fuzzy value. For example, the temperature of a room measured at 22°C could be transformed into fuzzy values such as "moderate temperature" or "high temperature", with corresponding degrees of membership. Fuzzification is achieved using membership functions such as triangular, trapezoidal or Gaussian functions (Fig. 2).

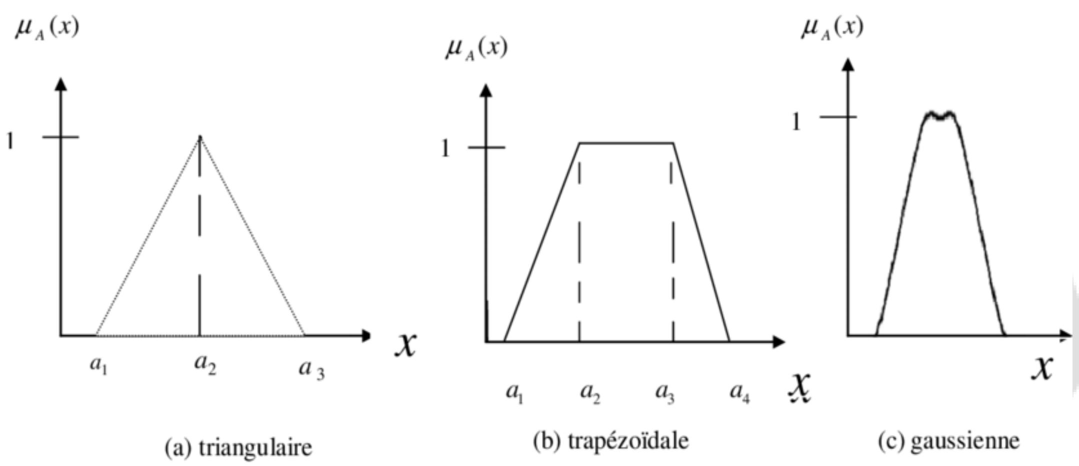

Fig. 1 : Examples of membership functions [12]

❖ Defuzzification [13]

Once the fuzzy rules have been applied, it is necessary to convert the fuzzy results into a crisp value. This process is called defuzzification. The most common methods of defuzzification include :

- **Centre of Gravity (COG):** This is the most commonly used method and calculates the weighted average of the blurred values:

$$z = \frac{\int z.\mu_A(z)dz}{\int \mu_A(z)dz} \quad (7)$$

- **Average of Maxima (MoM):** This method takes the average of the maximum values in the fuzzy domain.

2.3.2.3 Fuzzy Rules System [14]

Fuzzy rule systems are based on conditional rules of the form: if x_1 is A and x_2 is B ; then y is C .

The inputs x_1, x_2, etc., are associated with fuzzy sets (A, B, ...) and the output y is also fuzzy. Each rule is a linguistic interpretation based on human observations. For example, a rule in a temperature control system might be: if the temperature is "high" and the humidity is "low", then reduce the air temperature.

These systems make it possible to create very flexible and robust models, capable of handling complex situations with many input variables.

3. RESULTS AND INTERPRETATIONS

3.1 Study of eigenvalue spectra of raw data matrices

To study the preconditions for cyclone formation, we have tracked the evolution of key meteorological variables in regions, focusing on the points where these variables reach their extreme values. These areas are square and have a side length of 226 km ($2° \times 2°$), chosen to surround the cyclone's initial development zone. For each day preceding the formation of a cyclone, we extracted a 3×3 data matrix corresponding to the values of the variables in this zone. Analysis of the eigenvalues of these matrices enables us to identify the dominant modes of variability and to explore the relationships between different meteorological variables during the pre-cycle period.

3.1.1 Behaviour of the eigenvalue spectrum before cyclogenesis

Consider tropical cyclone FUNSO, which officially began its cyclogenesis on 18 January 2012 in the Mozambique Channel at around 15°S latitude and 40°E longitude. We located a zone centred around the MSLP minimum point on a daily basis over a period of 15 days prior to the day of the cyclone's christening. It is important to note that the MSLP minimum zone can change from one day to the next, which implies that cyclone FUNSO could be the result of a disturbance distinct from the one observed 15 days before.

We extracted the data matrices corresponding to these minimum MSLP zones for each day and calculated their eigenvalues. The eigenvalues obtained for each day are shown in Table I.

Table I: MSLP eigenvalue matrix before the formation of cyclone FUNSO

For day -15 : 3.0191 0 0 0 0.7273 0 0 0 0.2536	For day -14 : 3.2329 0 0 0 0.7646 0 0 0 0.0024	For day -13 : 3.2232 0 0 0 0.7621 0 0 0 0.0148	For day -12 : 3.5869 0 0 0 0.4054 0 0 0 0.0077
For day -11 : 3.1160 0 0 0 0.8436 0 0 0 0.0404	For day -10 : 2.9023 0 0 0 1.0605 0 0 0 0.0372	For day -9 : 2.8088 0 0 0 1.1897 0 0 0 0.0015	For day -8 : 2.7206 0 0 0 1.2778 0 0 0 0.0016
For day -7 : 2.5712 0 0 0 1.1965 0 0 0 0.2324	For day -6 : 2.4699 0 0 0 1.4667 0 0 0 0.0634	For day -5 : 2.8808 0 0 0 0.7762 0 0 0 0.3431	For day -4 : 2.3276 0 0 0 1.3879 0 0 0 0.2844
For day -3 : 3.5146 0 0 0 0.3120 0 0 0 0.1734	For day -2 : 3.0322 0 0 0 0.8186 0 0 0 0.1492	For day -1 : 3.1801 0 0 0 0.8054 0 0 0 0.0145	For day 0 : 3.0802 0 0 0 0.8324 0 0 0 0.0873

Interpretation of the eigenvalue matrices from the MSLP data (Table I) provides a better understanding of the dominant structures in the precyclogenesis phase, by analysing the distribution of variance associated with each component.

The eigenvalue matrices have three values, corresponding to the main directions of variability of the data in the 2° x 2° zone. Each eigenvalue indicates the amount of variance explained by the corresponding component (also known as the principal axis or mode). In general, a large eigenvalue indicates a direction of high data variability, which means that this component is significant in describing the structure of cyclogenesis, and a small eigenvalue (close to 0) indicates a direction of low variability, which means that this component contributes little to the variability of the system.

The three eigenvalues can be used to assess whether the dynamics of precyclogenesis are dominated by one or more dimensions. The sum of the eigenvalues is constant (around 4) for each day, which is normal as it represents the total variance of the data.

The third eigenvalue is always practically zero.

The first eigenvalue is dominant because its value is always greater than 1 and it is the largest eigenvalue. This shows that a major component explains most of the variance and suggests that a main mode of variability dominates the area analysed. When the difference between the first and third eigenvalues is large, the dynamics of the system is predominantly one-dimensional (concentrating on a single dominant direction).

We also note that the second eigenvalue is sometimes greater than 1. If the second eigenvalue is significant, there may be a significant two-dimensional component. The fact that the first eigenvalue always remains dominant throughout the days shows the importance of a main direction in the evolution of precyclogenesis, but the emergence of the second eigenvalue (e.g. 1.2778 for day -8) shows that a secondary component is becoming increasingly significant. The changes in the eigenvalues, especially the increase in the second eigenvalue, could indicate a reorganisation of the pressure field in the days preceding cyclogenesis.

3.1.2 Variation of the second eigenvalue

Chart 1 shows the variation in the second eigenvalue for different meteorological variables over a period of 15 days preceding the FUNSO cyclogenesis. High variability is observed for all the variables, indicating dynamic changes in the atmospheric structure.

Variations in the second eigenvalue indicate changes in the secondary structure of the meteorological fields. Differences in behaviour between levels (e.g. SHUM 200 vs SHUM 700) suggest distinct processes at different altitudes. We observe that 8 days before cyclogenesis, four variables (OLR, SHUM 700, MSLP and VENT 850) have eigenvalues greater than 1.

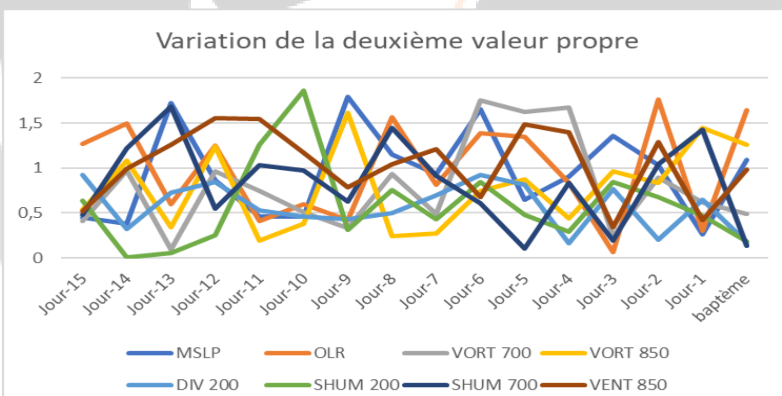

Chart -1 : Variation de la deuxième valeur propre

Table II: Dates of appearance of combination of eigenvalues simultaneously ≥1

CYCLONE	MSLP	OLR	VORT 700	VORT 850	DIV 200	SHUM 200	SHUM 700	VENT 850	Day before cyclogenesis
EDWIG	0,9439	1,5913	0,4121	0,5344	1,3615	0,6293	1,1431	1,6205	02
20S_1982	1,1052	1,8615	0,7851	1,4391	0,8687	0,4209	0,5841	1,2971	02
CABOTO	1,1435	0,1934	1,5037	0,291	1,2782	0,503	1,6216	0,9395	12
IMBOA	1,3405	0,9103	1,413	0,4968	0,6324	1,5996	0,4076	1,4563	11
FELIKSA	1,2564	1,4361	1,2835	1,1247	0,4635	0,222	1,5289	1,7308	10
ALIFREDY	1,4197	1,6039	0,4104	0,1506	0,7047	1,0475	0,1442	1,5033	13

BEROBIA	1,0642	0,6661	0,9141	0,191	1,2666	0,8495	1,0431	1,7129	12
GISTA	0,615	1,3036	1,283	0,139	1,3213	1,1315	1,0489	1,142	05
CALASANJY	0,8939	1,7541	0,615	1,1804	1,1856	1,1901	0,3411	1,5274	11
IANA	1,1543	1,564	0,9333	0,239	0,4975	0,7562	1,4456	1,0442	08
HANTA	1,5886	0,1338	0,5386	0,759	0,6815	1,2798	1,325	1,521	12
CYNTHIA	1,1075	0,7954	1,2366	1,3701	0,1309	0,9888	0,3595	1,3753	09
DEBRA	0,533	1,3889	0,5941	0,6898	1,4624	0,8259	1,5393	1,147	09
ELIZABETHA	1,2847	1,3512	1,6907	0,971	0,4333	0,5949	1,1998	1,0785	11
C3_1992	1,5055	1,0399	0,5659	0,872	0,9705	0,5338	1,4901	1,1379	07
DESSILIA	1,2564	1,6474	1,3795	1,48	0,234	1,367	0,3731	0,3102	11
GRACIA	0,5027	1,4851	0,6617	0,4745	1,0479	1,3738	0,7186	1,082	11
IONIA	1,3311	0,1728	1,2593	0,6579	1,0915	0,3787	1,2359	0,8891	12
FODAH	1,0889	0,8727	0,3411	1,26	0,3001	1,4008	0,28	1,2298	13
JOSTA	1,2716	1,3269	0,8921	1,4505	0,7346	0,4364	1,1532	1,3358	11
LISETTE	1,2329	0,8799	0,2029	1,2997	1,6073	0,3326	0,2388	1,1084	11
13S_1998	0,2693	1,3023	0,608	0,0471	1,2172	0,4482	1,5087	1,2649	01
BELTANE	1,1544	1,6582	0,8619	0,8267	0,8223	1,8575	0,8285	1,3624	14
ALDA	1,1919	1,3617	1,2496	0,5008	0,5538	0,4504	0,4776	1,0256	04
21S_1999	1,6681	1,3503	0,8842	0,6635	1,0101	1,2784	1,3194	1,0678	15
CYPRIEN	1,0171	1,7333	1,5947	1,89	1,7382	0,4076	0,6786	0,8749	14
DELFINA	1,2147	1,3572	1,0519	0,068	0,3146	0,2947	1,1169	0,5512	10
JAPHET	0,575	0,7994	0,7562	1,6023	0,3402	1,5068	1,78	1,3203	14
ELITA	1,6934	1,2503	1,4495	0,5309	1,3446	0,5398	0,9971	0,6608	06
FELAPI	0,1519	0,238	0,9271	1,2006	1,1284	1,082	0,7051	1,5213	11
ANITA	0,8753	0,8066	1,4198	0,2727	0,55	1,4075	1,3496	1,4637	11
15_2007	0,2989	1,713	0,1975	1,1667	1,2869	0,2821	1,4859	0,9073	13
ELNUS	1,0541	1,1298	1,0792	0,828	1,1045	1,2702	0,9636	1,3182	14
FANELE	1,1101	0,8024	0,7418	1,2259	1,0635	1,3009	0,9613	0,2227	15
IZILDA	0,0644	1,0787	1,3767	1,2373	1,126	1,2069	0,5796	1,4748	14
FAMI	1,0512	0,3234	1,0496	0,2685	1,1667	0,7843	0,4378	1,1123	13
CHANDA	1,3302	0,8525	1,0824	0,066	0,3804	1,5585	1,1476	0,9602	05
FUNSO	1,2778	0,1614	0,7282	0,4391	0,348	1,0192	1,3055	1,0058	08
HARUNA	0,4111	1,4311	0,1969	0,5117	0,6112	1,2599	1,2004	1,4188	13
DELIWE	1,6169	0,2869	1,2407	0,5522	0,5935	1,5557	1,5734	0,6035	14
GUITO	0,6304	0,0704	1,478	1,5705	1,5146	0,6143	1,2082	1,483	10
HELLEN	0,2444	1,1363	0,7912	1,0235	1,3624	1,2847	0,6065	0,6136	13
CHEDZA	0,9734	1,2668	1,457	0,6576	1,5557	0,641	1,9587	1,6821	09
FUNDI	1,3727	1,2007	0,7735	0,6197	1,2637	0,1459	1,6317	1,1959	13
15S_2015	1,3826	1,5542	1,1617	1,0265	1,0921	0,356	0,6935	1,1494	12
DINEO	1,3507	1,4345	0,7666	0,2631	1,0579	0,8043	0,4479	1,3358	09
04_2018	1,2229	1,0341	0,5066	1,2001	1,005	0,7069	0,8284	1,5469	08

Table II shows that the most frequently significant variables (eigenvalue > 1) are the wind at 850 hPa (74.5%), the RLO (61.7%), the MSLP (59.6%) and the specific humidity at 700 hPa (53.2%), suggesting their importance in cyclone formation. The majority of observations (59.6%) were made 11 to 15 days before the cyclone formed, suggesting that the favourable conditions were put in place well in advance. Low-level variables (850 hPa) appear to be more significant than high-level variables (200 hPa), with the exception of RLO, which is an integrated measurement over the entire atmospheric column. The specific humidity at 700 hPa appears to be greater than that at 200 hPa, underlining the role of humidity in the middle layers of the atmosphere. The divergence at 200 hPa is less frequently significant, but could play an important role in certain cases.

3.2 Modelling with fuzzy logic

Modelling meteorological events such as cyclogenesis is essential for understanding and predicting the atmospheric dynamics that lead to the formation of cyclones. However, the complex and uncertain nature of these processes makes it difficult to use strictly deterministic models. To overcome this difficulty, fuzzy logic offers a flexible approach that makes it possible to model dynamic systems with inherent imprecision, based on simple rules and fuzzy concepts. The Mamdani-type fuzzy inference system (FIS), commonly used in meteorology, is particularly well suited to capturing these uncertainties and providing reliable approximations. The aim of this study is to apply fuzzy logic to model and predict the days before cyclogenesis, based on events observed between 1979 and 2018. A Mamdani-type model with 15 rules will be used, and the performance of the model will be compared with real data via an analysis of the deviations and the quality of the approximation.

3.2.1 Data representation

Chart 2 represents the evolution of days before cyclogenesis where the eigenvalues are simultaneously ≥1 as a function of the rank of cyclogeneses observed between 1979 and 2018. Two curves are plotted namely the actual data (in blue) and the linear trend (in red).

The trend equation indicates that the number of days before cyclogenesis increases slightly over time. In fact, the coefficient 0.067 ahead shows a gradual increase in this delay. Although this increase is small, it may indicate a slight trend towards longer delays before the onset of cyclogenesis as the events progress in the historical series.

The actual data (blue curve) show considerable variability, with values fluctuating irregularly around the trend. There are periods when the time to cyclogenesis is very short (sometimes close to 0), and others when it is longer (up to around 15 days). This fluctuation shows the unpredictable nature of the meteorological conditions that lead to cyclogenesis.

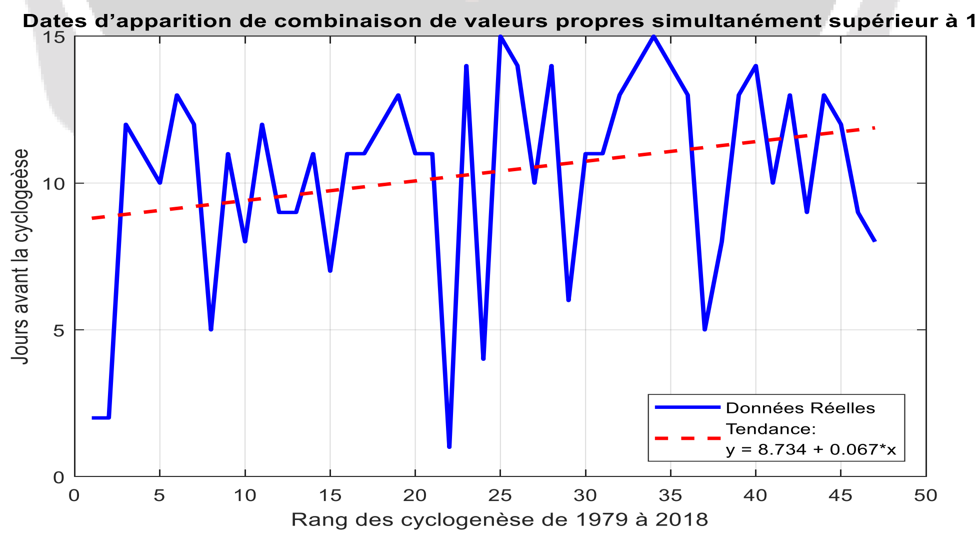

Chart -2 : Dates of appearance of combinations of at least four eigenvalues simultaneously

3.2.2 Fuzzy Inference System (FIS)

Chart 3 shows a Mamdani-type fuzzy logic model, which is a system with one input and one output, with 15 rules for establishing the correspondence between input and output.

The model uses a Mamdani approach, which is one of the most common types of fuzzy logic system. It is well suited to modelling complex systems where uncertainty and imprecision are present, as is often the case in meteorology or in dynamic systems such as cyclones. The rules of the model are based on fuzzy logic, where inputs are transformed into outputs through a set of conditional rules of the type "IF input is MFx THEN output is MFy". The Mamdani system will fuzzify the input, apply the rules, aggregate the results, then defuzzify to produce a precise output.

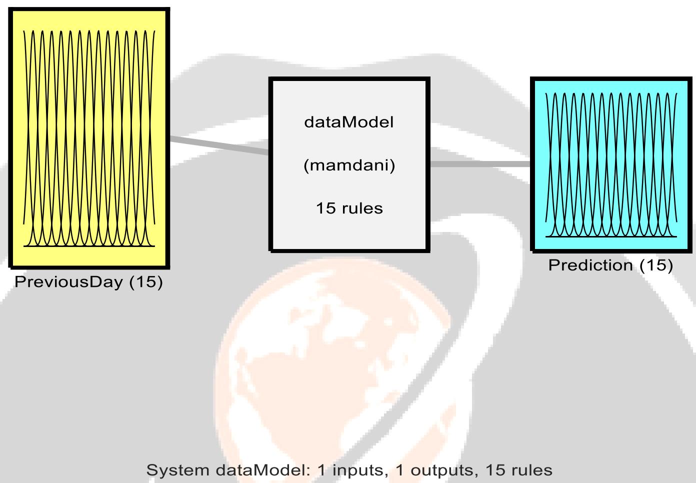

Chart -3: Fuzzy inference system

3.2.3 Model representation

Chart 4 shows the evolution of the number of days before cyclogenesis as a function of cyclogenesis rank between 1979 and 2018. The x-axis represents the "Rank of cyclogenesis from 1979 to 2018". Each point on this axis corresponds to a specific cyclogenesis event during this period. There are approximately 48 cyclogenesis events listed. The y-axis shows the number of "Days to cyclogenesis", i.e. how many days before cyclone formation the data is taken or modelled. The red curve represents the actual observed data for the days preceding each cyclogenesis, while the blue curve represents a fuzzy model used to predict the number of days before each cyclogenesis.

The majority of points indicate that the days before cyclogenesis vary between around 5 and 15 days. There are a few peaks where the number of days before cyclogenesis increases significantly, but there are also some abrupt drops. The actual data and the fuzzy model appear to be very similar, although there are times when the red curve breaks away slightly from the blue model (for example, around the 25th and 34th ranks), where there is a small mismatch between the actual values and the fuzzy model.

The fuzzy model used here seems to provide a good approximation of the days before cyclogenesis for the majority of events. However, some small differences appear in the moments when conditions can deviate more strongly from the model, suggesting the possibility of improvements or limitations in the modelling of extreme events.

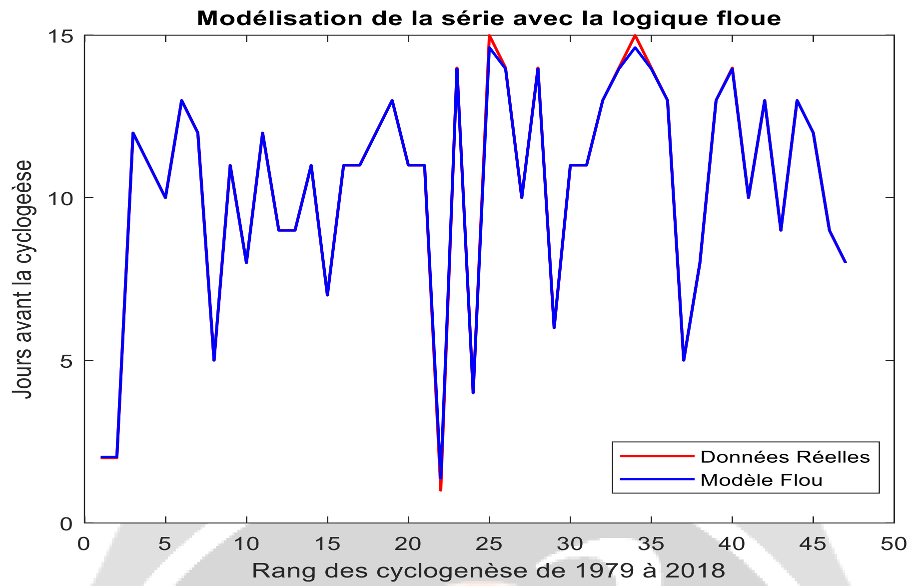

Chart -4: Fuzzy logic modelling

3.2.4 Comparison between the fuzzy model and its approximation

Chart 5 shows a comparison between a fuzzy model (in blue) and its approximation (in dotted red). The model appears to fit the data well, with only minor deviations, particularly in the lower range of input values (around 0 to 5).

The MSE (mean square error) is 0.0204, which indicates that the fuzzy model approximation is very accurate. A smaller MSE suggests that the values predicted by the model are close to the actual output values. In this case, an MSE of 0.0204 means that the approximation error is very small, confirming that the model is very effective in approximating the underlying data.

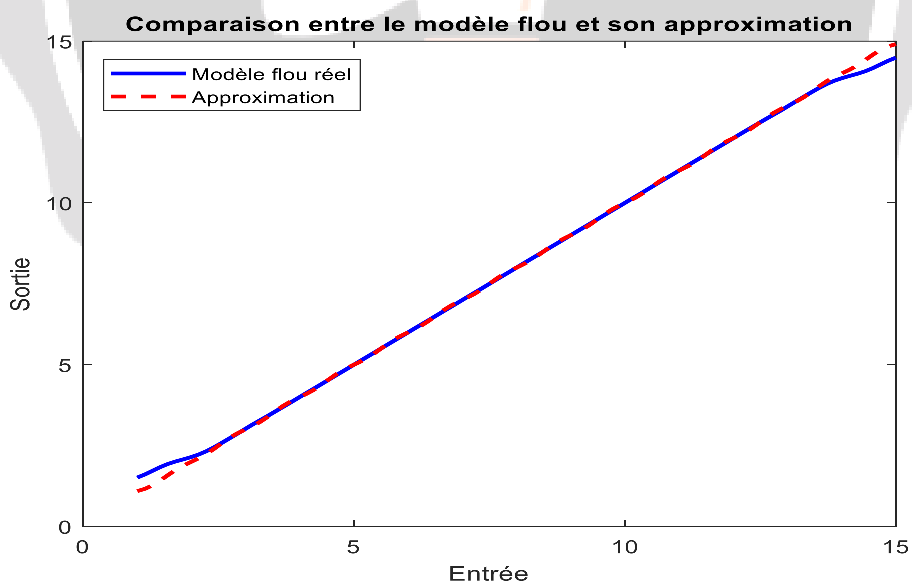

Chart -5: Comparison between the fuzzy model and its approximation

3.2.5 Fuzzy model equation

The given equation represents the fuzzy model using Gaussian membership functions. It can be interpreted as a weighted sum of the output centres y_i, where the weights are determined by Gaussian functions applied to the difference between the input x and entry centres x_i.

$$y=\frac{\sum\left(y_i.e^{\left(-\frac{(x-x_i)^2}{2\sigma^2}\right)}\right)}{\sum\left(e^{\left(-\frac{(x-x_i)^2}{2\sigma^2}\right)}\right)} \qquad (8)$$

$\sigma = 0,4667$: This represents the standard deviation of the Gaussian functions used in the fuzzy model. It controls the width of the Gaussian curve. A smaller value of σ indicates sharper peaks, while a larger value indicates wider peaks.

4. CONCLUSION

The use of fuzzy logic in modelling the days before cyclogenesis proved to be an effective method, particularly for capturing uncertainties and fluctuations in the real data. The fuzzy model proposed in this study showed robust approximation capability, as evidenced by the low mean square error (MSE). However, although the fuzzy model closely follows observed trends, some deviations exist, particularly during certain extreme events where conditions may deviate from predictions. This suggests that there is room for improvement, in particular by refining the fuzzy rules or introducing additional factors to model exceptional cases. Despite this, the model remains a valuable tool for forecasting cyclogenesis, offering a complementary perspective to deterministic approaches.

5. REFERENCES

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