MODELISATION OF SEA SURFACE SALINITY IN THE SOUTH-EAST PART OF MADAGASCAR

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ABSTRACT

This research is based on artificial neural network methods. The Self-Organizing Map network (KOHONEN'S network) allowing to organize our study area and the perceptron network is applied to modeling our data. The objective is to predict the variation of sea surface salinity in the southeastern part of Madagascar. The study area, is delimited by East longitudes 48°E to 54°E and South latitudes 22°S to 28°S. Monthly salinity data collected from the NOAA site covering 38 years period (1980 to 2017) were studied. In this case, we took the first 5 meters of ocean depth. Our study area is classified into three distinct sub-areas. The variation of monthly salinity in this region is around 33.90 PSU to 34.14 PSU and it also varies with latitude. Each model adopted by the prediction has confirmed that the salinity of the ocean in the next 10 years will become increasingly salty.

Keyword: *salinity, artificial neural networks, organizing, modelisation.*

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1. INTRODUCTION

Salinity has an indispensable place not only in ocean exchanges but also in climate regulation [1]. It is the key parameter for understanding changes in the water cycle; as well as a time-integrated tracer of changes in the freshwater balance on the ocean [2]. Considering current climate change, studying the evolution of this parameter is essential. In the case of Madagascar, fishing plays an important role in the economic activity of Malagasy but it endures a lot of strain with this climate change [3]. That reason why we predict this salinity variation in order to improve the contribution into economy of Madagascar.

2. METHODOLOGIES

2.1 Delimitation of study area

Our study area is located between 48°E to 54°E East longitude and 22°S to 28°S South latitude. Thus, we worked on 133 points (individuals A1, A2, A3 …) with a grid 1° x 0.33° as illustrated in the following figure (Fig-1).

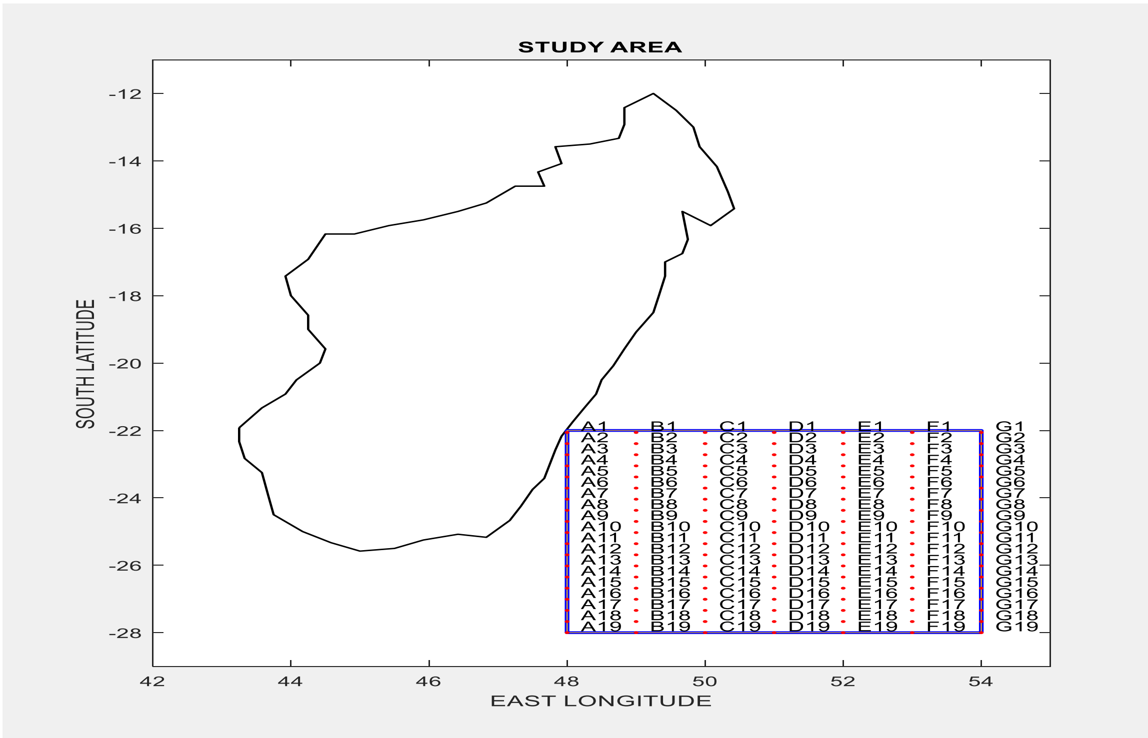

Fig -1: Study area

2.2 Data

Salinity data are taken from the National Oceanographic and Atmospheric Administration (NOAA) site in the monthly average data available on “http://www.esrl.noaa.gov/psd/data/gridded/data.godas.html”. These data have a netcdf or “.nc” extension and a spatial resolution of 1° x 0.33°. Our data have a 3-dimensional matrix whose third dimension is the month; 456 months from January 1980 to December 2017 with a unit expressed in PSU where Practical Salinity Unit is equivalent to g/kg.

2.3 Climatological average [4]

The climatological average characterizes or measures the quantity of monthly salinity data. It is calculated by the formula below:

$$\overline{\mathrm{x}} = \frac{1}{T}\sum_{t=1}^{T} X_t \qquad (1)$$

2.4 Self-Organizing Map (SOM) [5][6][7]

The Self-Organizing Map is a classification method type of neural network with unsupervised and competitive learning. The objective is to reduce the infra-class distances and increase the interclass distances, so that the elements of a class are more similar to each other.
The size of the map depends on the type of classification desired, but the optimal dimension is given by the following formula: $M = 5\sqrt{N}$ (2) where M is the number of neurons on a map and N is the number of observations. In our case, we retained a hexagonal topology map with 7x8 neurons.

2.5 Hierarchical Ascending Classification (HAC)

This method classifies the neurons where they are grouped by zones, according to their similarities.

2.6 Perceptron multilayer [8][9]

Perceptron multilayer is a type of artificial neural networks with supervised learning and followed by error correction. It is composed an input layer, one or more hidden layers and an output layer. The calculated error is the error between the target and the output (square sum of errors on each output neuron). In our case, this method is used to predict salinity data and only one hidden layer is satisfactory for modeling.

3. RESULTS

3.1 Classification by KOHONEN's network

The average salinity monthly climatological data for 38 years on the 133 individuals in our study area are used by the self-organizing map method. We chose a hexagonal topology map with 7x8 neurons. The following map (Fig-2) shows the distances between these neurons. The blue hexagons represent the neurons (56 neurons), the red lines connect neighboring neurons, the hexagons containing these red lines represent the distances between neurons, the darker colors characterize a larger distance and the lighter colors indicate a smaller distance.

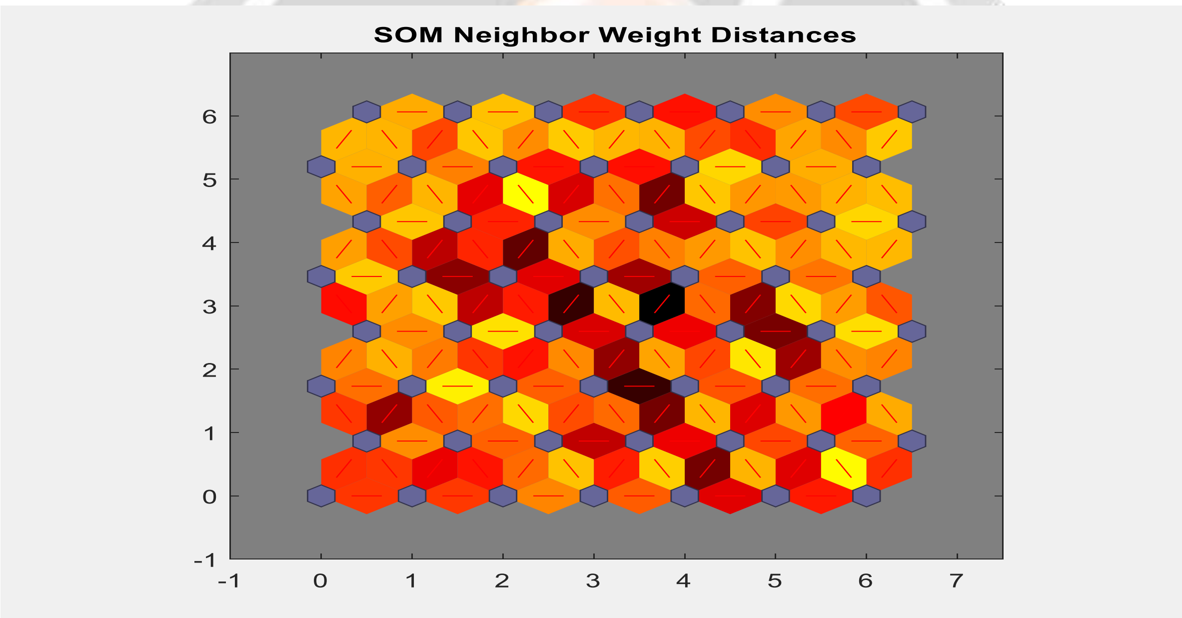

Fig-2: Neighbor distances

The individuals distributed to each winning neuron after learning are represented on the map in the following figure (Fig-3). Neurons are numbered from left to right – from bottom to up. The numbers shown on each hexagon represent the individual numbers classified to each neuron. For example, neuron n° 1 wins six individuals, neuron n° 2 wins two individuals and so on.

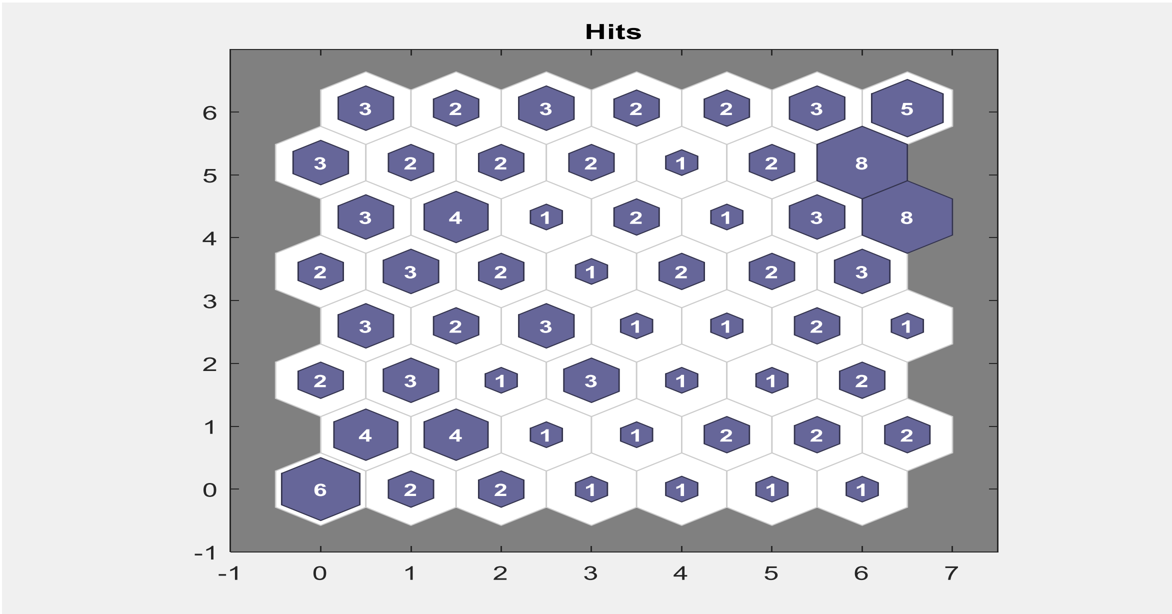

Fig-3: Counts plot

To clearly identify the individuals who group together in each of these neurons, the network outputs are visualized using the following table (Table-1). The bold letters represent the individual's names and the numbers indicate the neuron's numbers. So, individual n° 1 that we note by A1 is won by neuron n° 30, individual n° 2 or A2 is won by neuron n° 22, etc.…

Table -1: SOM output

A1	30	**B1**	29	**C1**	43	**D1**	50	**E1**	51	**F1**	52	**G1**	46
A2	22	**B2**	30	**C2**	29	**D2**	43	**E2**	50	**F2**	51	**G2**	52
A3	15	**B3**	22	**C3**	30	**D3**	36	**E3**	43	**F3**	50	**G3**	52
A4	8	**B4**	15	**C4**	22	**D4**	23	**E4**	36	**F4**	44	**G4**	45
A5	1	**B5**	8	**C5**	9	**D5**	16	**E5**	23	**F5**	36	**G5**	44
A6	1	**B6**	1	**C6**	8	**D6**	9	**E6**	16	**F6**	24	**G6**	37
A7	1	**B7**	1	**C7**	8	**D7**	9	**E7**	16	**F7**	24	**G7**	37
A8	1	**B8**	2	**C8**	9	**D8**	17	**E8**	24	**F8**	37	**G8**	45
A9	2	**B9**	3	**C9**	10	**D9**	18	**E9**	37	**F9**	38	**G9**	46
A10	3	**B10**	4	**C10**	18	**D10**	18	**E10**	25	**F10**	39	**G10**	53
A11	5	**B11**	11	**C11**	31	**D11**	31	**E11**	32	**F11**	39	**G11**	53
A12	6	**B12**	12	**C12**	12	**D12**	19	**E12**	26	**F12**	33	**G12**	47
A13	7	**B13**	13	**C13**	13	**D13**	20	**E13**	33	**F13**	40	**G13**	48
A14	14	**B14**	14	**C14**	21	**D14**	21	**E14**	34	**F14**	48	**G14**	49
A15	28	**B15**	27	**C15**	27	**D15**	34	**E15**	41	**F15**	49	**G15**	56
A16	35	**B16**	35	**C16**	41	**D16**	41	**E16**	49	**F16**	56	**G16**	56
A17	35	**B17**	42	**C17**	42	**D17**	49	**E17**	49	**F17**	56	**G17**	56
A18	42	**B18**	42	**C18**	42	**D18**	49	**E18**	49	**F18**	55	**G18**	55
A19	42	**B19**	42	**C19**	42	**D19**	49	**E19**	55	**F19**	54	**G19**	54

It is difficult to determine the characteristics of these neurons according to the individuals they have won. Therefore, we use the Hierarchical Ascending Classification (HAC) method to classify these neurons according to their climatic behavior. The following table (Table-2) shows the neuron groups obtained by CAH.

Table -2: Clusters of neuronal

CLUSTER 1	14	21	27	28	34	35	40	41	42	47	48
	49	53	54	55	56						
CLUSTER 2	1	2	3	4	5	8	9	10	11	15	16
	17	18	22	23	24	29	30	31			
CLUSTER 3	6	7	12	13	19	20	25	26	32	33	36
	37 38	39	43	44	45	46					

The classification is obtained as follows:

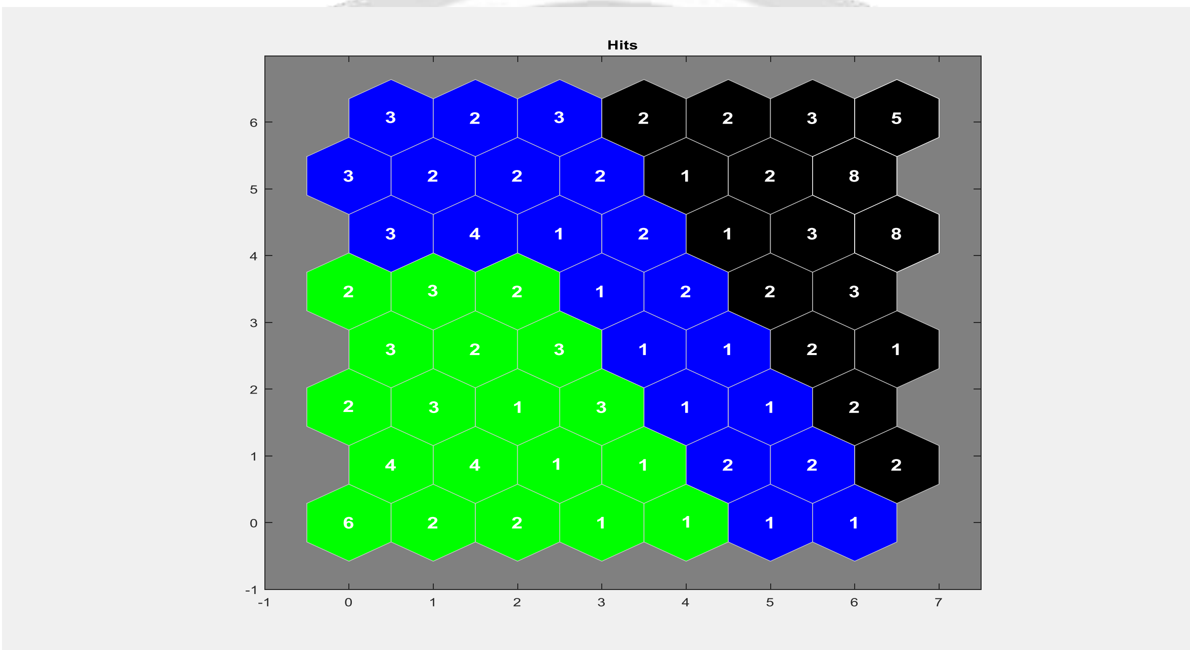

Fig-4: colormap for each neuronal cluster

After classifying the neurons, we were able to subdivide our study area into three distinct sub-zones. We find that salinity at 1m to 5m depth of the ocean in the southeast part of Madagascar varies according to the latitude (see Fig-5).

- Sub-zone 1: low salinity region (black),
- Sub-zone 2: medium salinity region (green),
- Sub-zone 3: High salinity region (blue).

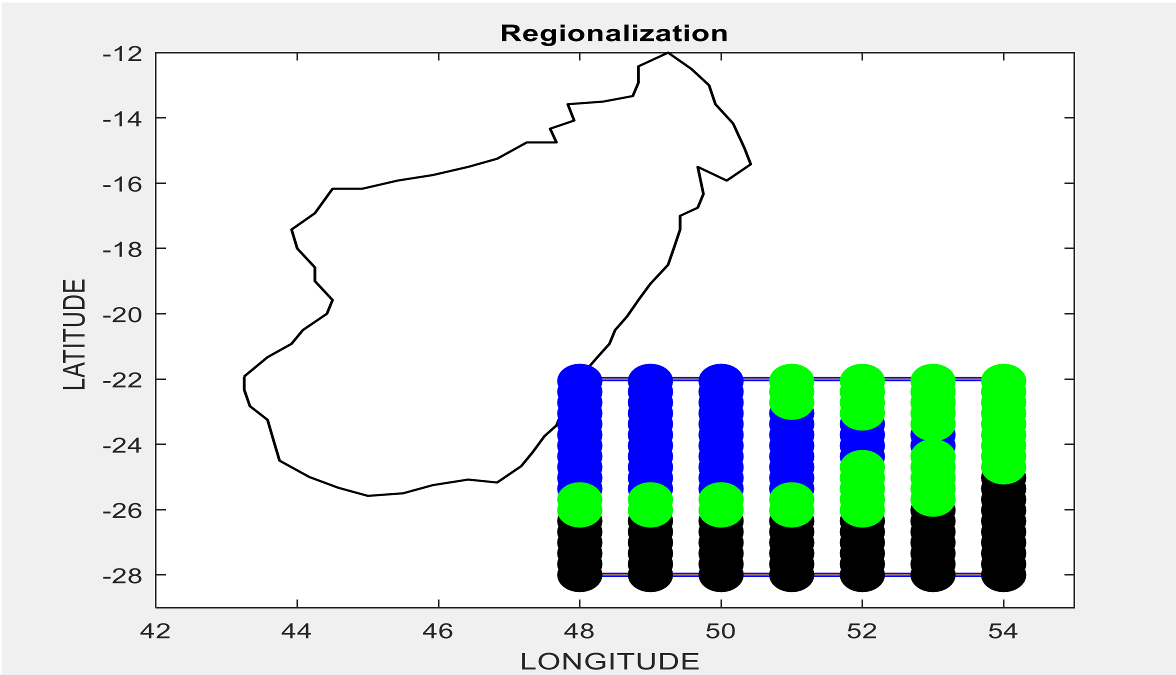

Fig-5: Regionalization on the geographical map

The monthly climatological averages calculation for each obtained sub-area determines their characteristics. Therefore, the graphs in the following figure (Fig-6) confirm that sub-zone 1 (black) includes low salinity (33.90 PSU to 34.06 PSU), sub-zone 2 (green) places medium salinity individuals (33.98 PSU to 34.09 PSU) and sub-zone 3 (blue) localizes groups of points with high salinity (34.02 PSU to 34.14 PSU). We note that maximum salinity in the three sub-areas is indicated in October and the minimum is marked in March. It is also important during the winter season, but it is low during the summer.

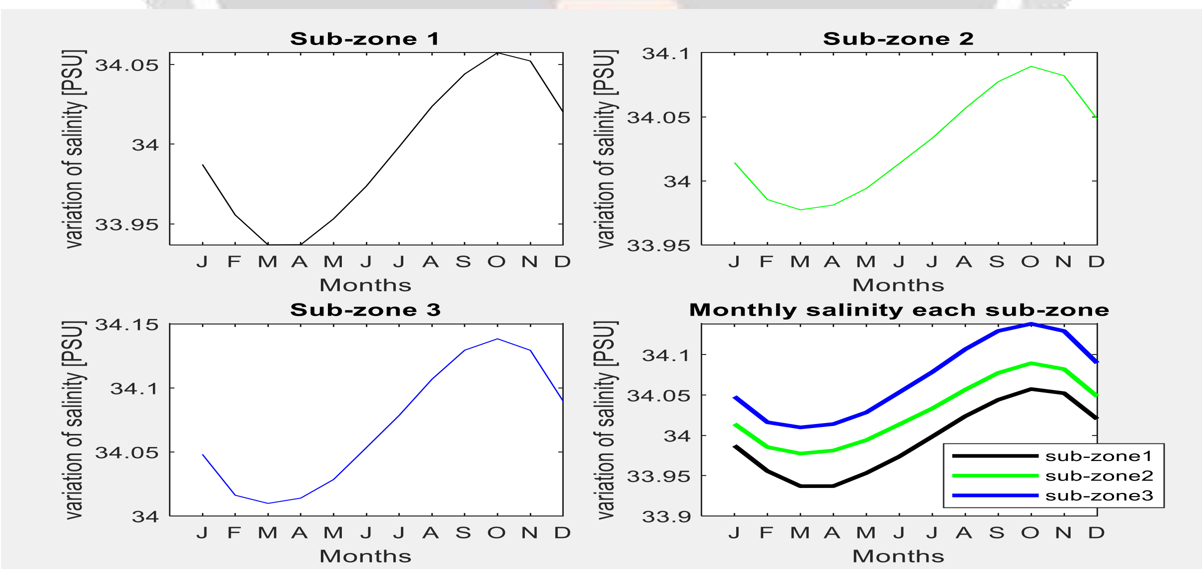

Fig-6: Monthly average climatological for each sub-zone

3.2 Modelisation of monthly salinity in sub-zone 1

After several learnings, we selected the model of artificial neural networks with 40 inputs, a hidden layer and an output for modeling in sub-area 1. Let us see the neural architecture of this model in the figure (Fig-7) below.

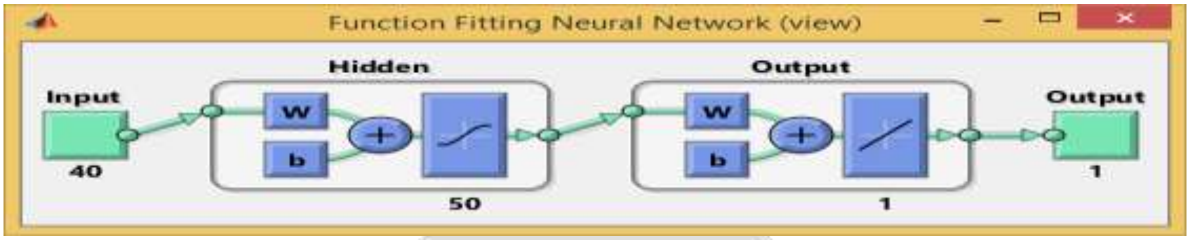

Fig-7: Neuronal architecture model for sub-zone 1

The calculation of correlation coefficient between Target and Output R=0.98666 confirms that this model is excellent (see Fig-8).

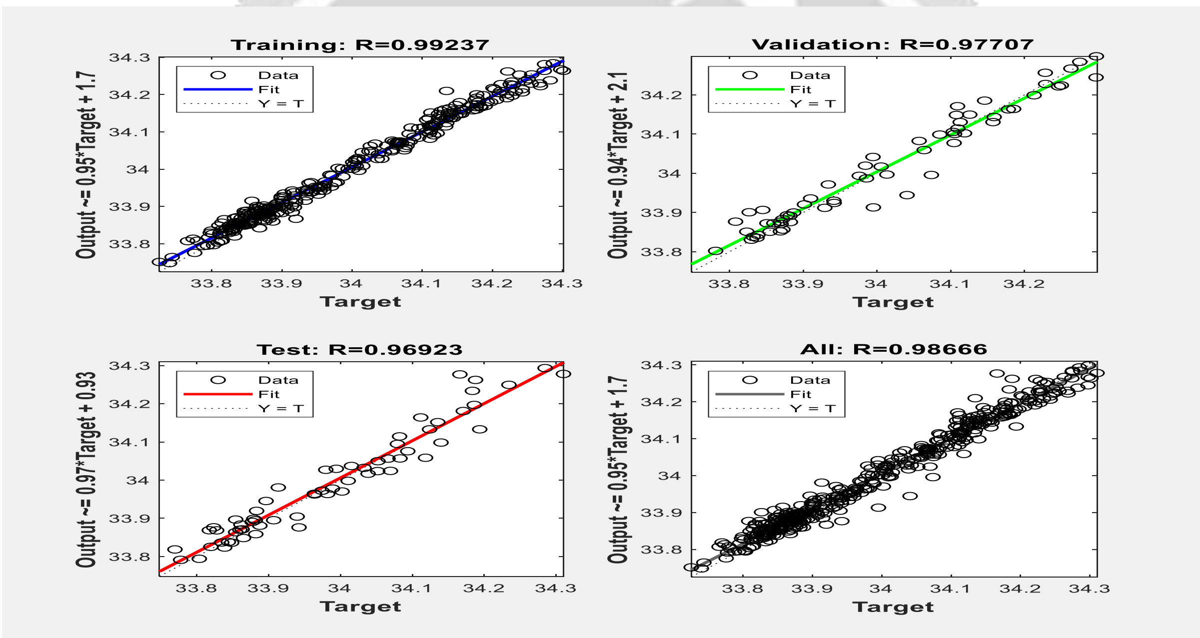

Fig-8: Correlation between output and target for sub-zone 1

From this model we can predict the salinity variation in this region from 2018 until 2027. The following figure (Fig-9) illustrates the salinity data (black), network learning (pink) and salinity prediction (red). The salinity prediction increases compared to our data in last 10 years of observations. However, there is a remarkable peak in 539-th month (November 2024) which means low salinity. It reaches a value around 33.5 PSU. There may be a strong precipitation in that area during that period of time.

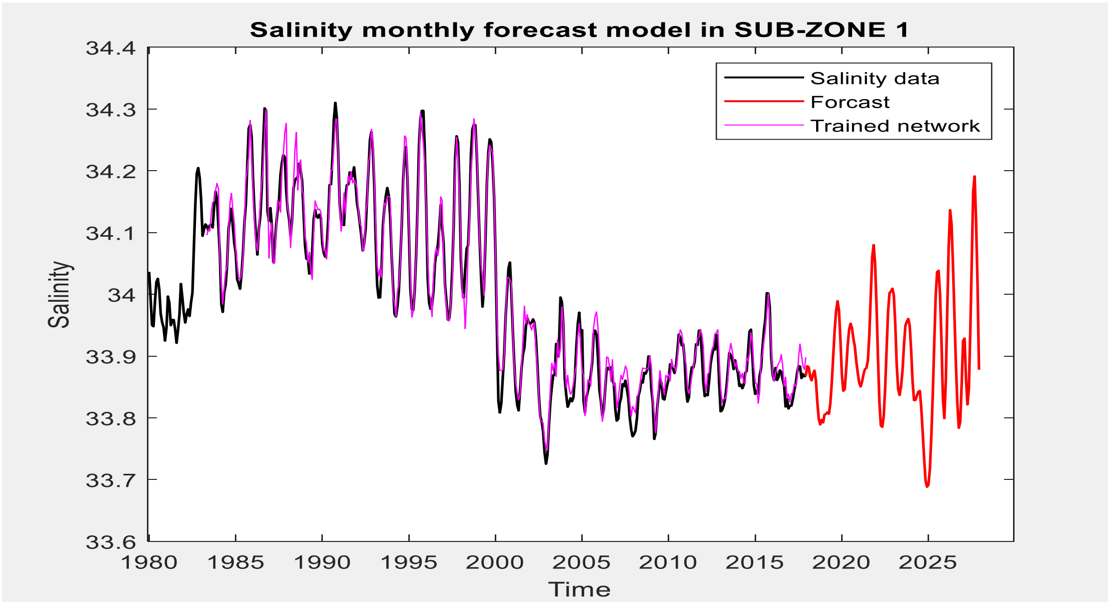

Fig-9: Output of salinity forecast model in sous-zone 1

3.3 Modelisation of monthly salinity in sub-zone 2:

For sub-zone 2, 23 inputs model, a hidden layer and an output were adopted for modeling. The following figure (Fig-10) shows its architecture.

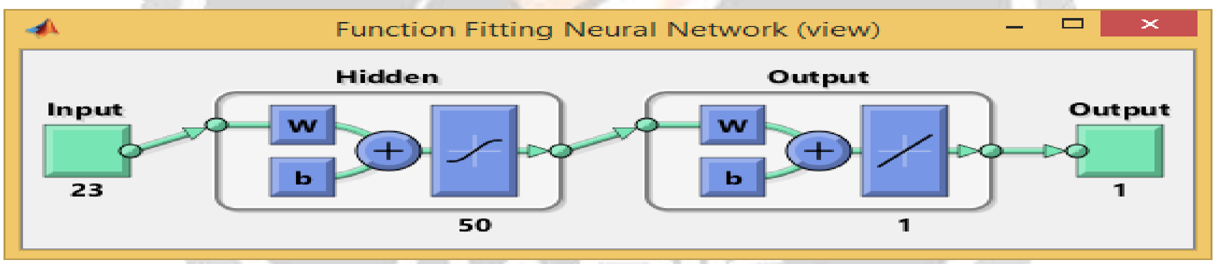

Fig-10: Neuronal architecture model for sub-zone 2

The correlation coefficient between output and target is 0.99114. Thus, the model we have chosen is excellent. The following figures (Fig-11) show this result.

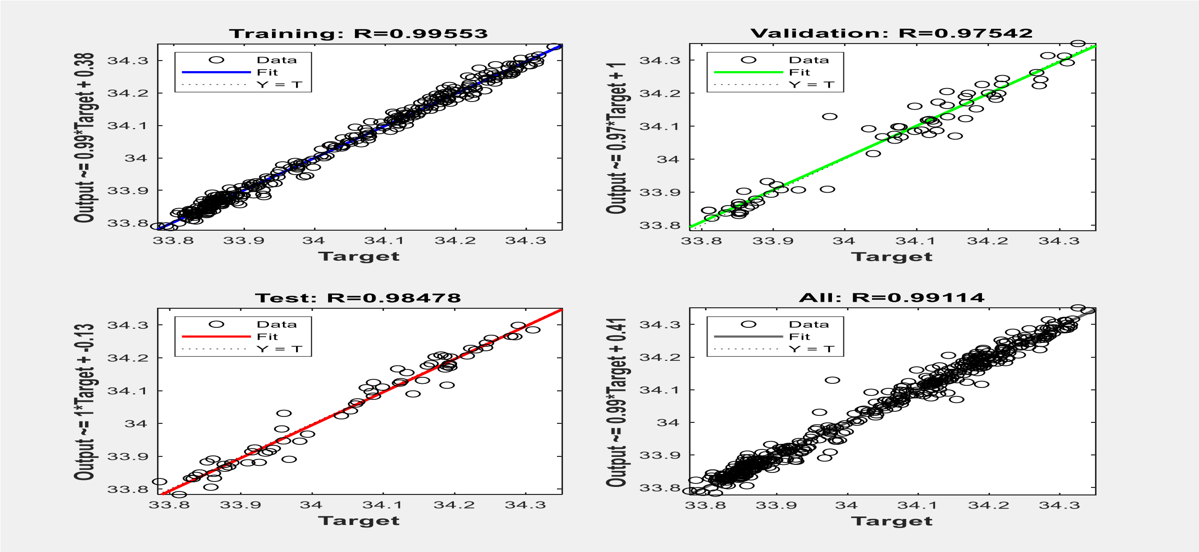

Fig-11: Correlation between output and target for sous-zone 2

The prediction for sub-zone 2 is fairly consistent for the following years. There is not much of a sharp increase compared to the last 10 years of observations however an upward trend appears. This prediction is shown on the figure (Fig-12) below.

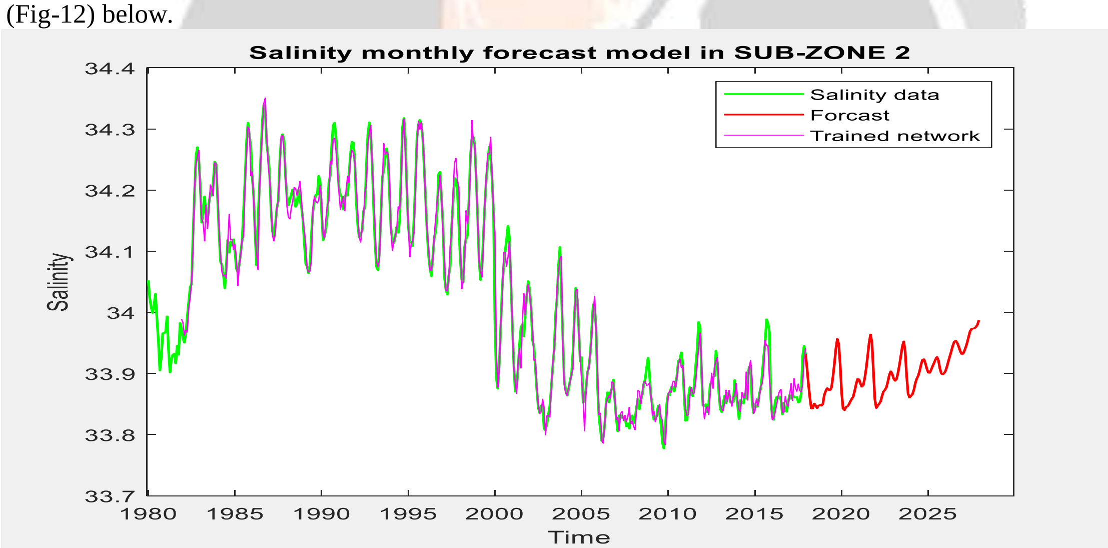

Fig-12: Output of salinity forecast model in sous-zone 2

3.3 Modelisation of monthly salinity in sub-zone 3:

As illustrate on the figure (Fig-13) below, the model with 27 inputs, a hidden layer and an output was chosen for sub-zone 3.

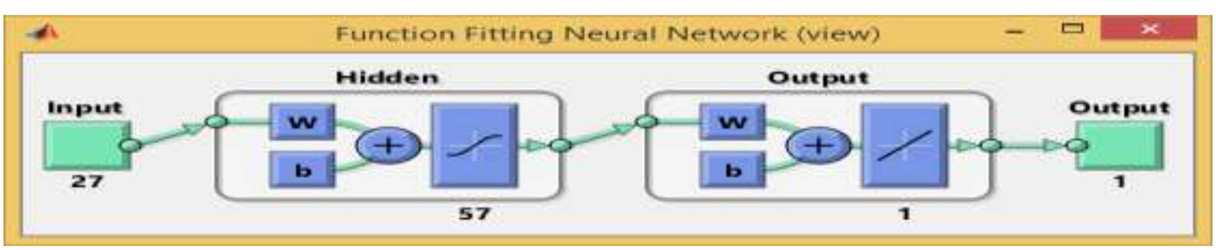

Fig-13: Neuronal architecture model for sub-zone 3

We can say that this model is excellent because the correlation coefficient between output and target is 0.98594 (see Fig-14).

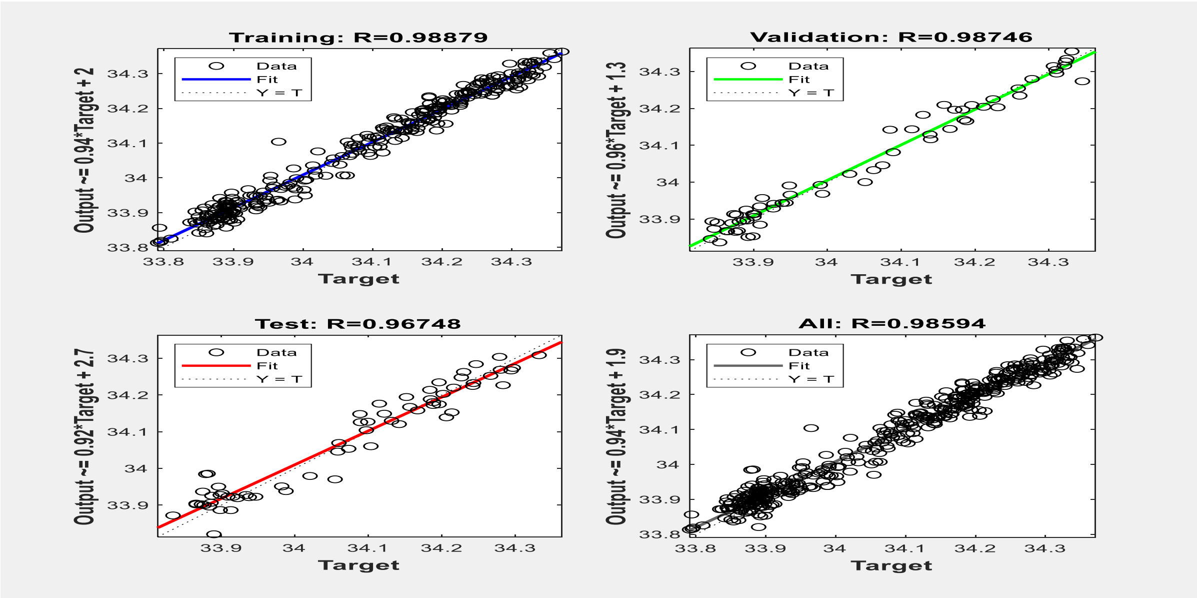

Fig-14: Correlation between output and target for sub-zone 3

The salinity in sub-zone 3 increase over the 10 next years compared to observation's data. The prediction has an upward trend as illustrated on the figure below (Fig-15).

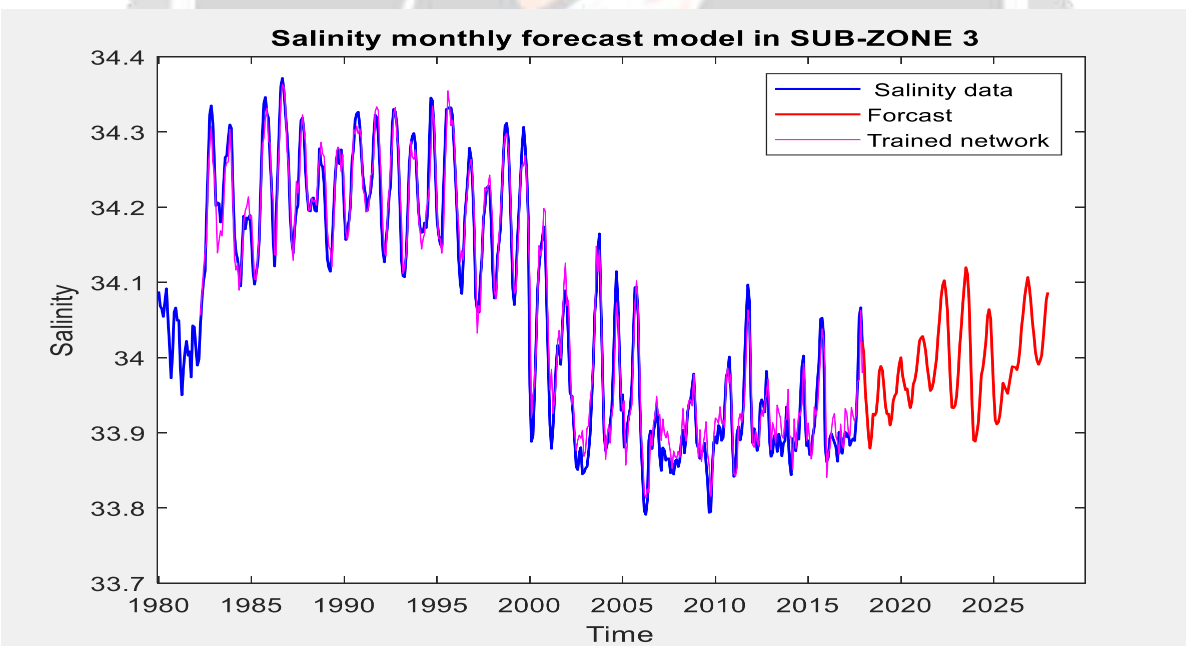

Fig-15: Output of salinity forecast model in sub-zone 3

4. CONCLUSIONS

This work has gotten us the information on Sea Surface Salinity from 1m to 5m ocean's depth. The KOHONEN's Network Map method led to subdivide our study area into three distinct sub-areas (high salinity sub-areas, medium salinity sub-areas and low salinity sub-areas). For this purpose, the monthly ocean's salinity in the South-East part of Madagascar is around 33.90 PSU to 34.14 PSU and it increases according to latitude (from South to North). Each sub-zone obtained has its own neural network model chosen for modeling and these models are considered excellent. In general, the salinity forecast from 1m to 5m ocean's depth in our study area has an increasing trend compared to the last 10 years of our observation's data. As a result, the ocean becomes more and more salty. Intuitively, this increase's salinity is due to current climate change, specifically the lack of rain.

5. REFERENCES

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