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The MLR model showed a modest performance prediction. The linear character of estimators MLR model makes it inadequate to provide good predictions for a highly nonlinear variable. On the other hand, the ANN model developed as a tool for non-linear relationship, which is potentially more suitable for predicting precipitation (nonlinear physical variable), has been successful prediction.

Somvanshi et al. (2006) [5] have applied two fundamentally different approaches, the statistical method based on the Autoregressive Integrated Moving Average (ARIMA) and new computational techniques based on RNA. The approaches ANN and ARIMA are applied to the average annual rainfall data to calculate respectively the weights and regression coefficients. The study shows that the performance of ANN model is more appropriate to predict precipitation compared to ARIMA model.

In this context, our main objective in this work is to build a hybrid model based on ANN Multilayer Perceptron type and SPI developed by McKee for the prediction of drought at different time scales on the basis of data selected stations located within the watershed Inaouen.

2. APPLIED METHODS

2.1 The Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) was developed by McKee et al. (1993) [1] as a way to define and monitor drought events. It is a simple index, based solely on rainfall data, and allows equally checking the wet periods / cycle's and the dry periods / cycles. The SPI compares precipitation over a certain period (normally 1-24 months) to the average long-term precipitation observed at the same site. [6]

The SPI was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of drought on the availability of different types of water resources. Ground moisture reacts relatively quickly to rainfall anomalies in the short term, while groundwater, stream flow and water volumes stored in reservoirs are sensitive to rainfall anomalies in the longer term.

The SPI is determined by a normalization of rainfall for a given station, after which there is a probability density adjusted. The distribution that best represents the evolution of sets of rain is the Gamma distribution ([7] and [8]). This Gamma distribution is defined by its probability density represented, for x> 0, by:

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-(\frac{x}{\beta})}$$

Where:

- α is the shape parameter
- β is the scale parameter
- x is the height of the monthly precipitation
- $\Gamma(\alpha)$ represents the Gamma mathematical function defined as:

$$\Gamma(\alpha) = \int_0^{+\infty} x^{\alpha-1} e^{-x} dx$$

The adjustment of the gamma distribution to data requires therefore to determine α and β. They can be estimated in this way [7]:

$$\alpha = \frac{1}{4A}\left[1 + \sqrt{\left(1 + \frac{4A}{3}\right)}\right], \beta = \frac{\bar{x}}{\alpha} \text{ with } A = \ln \bar{x} - \frac{\Sigma \ln x}{N}$$

Where N is the size of the sample and is the mean of observations.

The equation for the probability density function can be integrated to provide the cumulative function F(X) of probability for x> 0:

$$F(X) = \int_0^X f(x)dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^X x^{\alpha-1} e^{-(\frac{x}{\beta})} dx$$

But we note that, for this definition, x> 0, however there are periods where x = 0. To take into account of the probability of zero, the function of the cumulative probability distribution of gamma is modified as follows:

$$H(X) = q + (1-q)F(X)$$

With q, the probability of each station to have a zero precipitation over the entire period.

If m is the number of zeros in a series of precipitation of N variable, q can be estimated by [6]:

$$q = \frac{m}{N}$$

We therefore obtain for each x, a corresponding value H(x). This finally allows to calculate the SPI, as follows [9]:

$$SPI = -\left(W - \frac{c_0 + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}\right)$$

$$\text{with} W = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \text{ for } 0 < H(x) \leq 0.5$$

$$SPI = +\left(W - \frac{c_0 + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}\right)$$

$$\text{with} W = \sqrt{\ln\left(\frac{1}{(1-H(x))^2}\right)} \text{ for } 0.5 < H(x) \leq 1$$

The constants are: c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308.

Negative values correspond to a SPI deficit rainfall while, conversely positive values indicate higher than normal rains. Table 1 details a classification system that defines the intensity of droughts based on the value of the SPI for a timescale whatsoever [1].

Table 1: Classification of categories of drought according to the values of the SPI [1]

SPI Values	Category
2.0 and more	Extremely humid

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1.5 to1.99	Highly humid
1.00 to1.49	Moderately humid
-0.99to0.99	Close to normal
-1.0to-1.49	Moderately dry
-1.5to-1.99	Highly dry
-2.0and less	Extremely dry

2.2 Artificial Neural Networks (ANN): Multilayer Perceptron (MLP)

An artificial neural network is a computational model whose original inspiration was a biological model. The main strength of ANN is their ability to identify complex and nonlinear relationship between input and output data sets without the need to understand the nature of phenomena [10]. Multilayer Perceptron Type (MLP) is the simplest and most commonly neural network used. The mathematical representation of an artificial neuron called artificial neuron is shown schematically in Figure 1 [11].

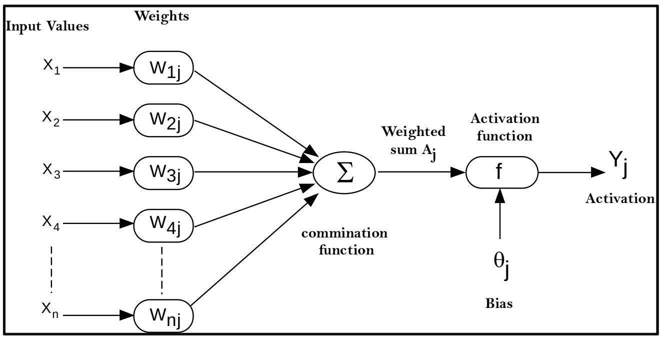

Figure 1: Structure of artificial neural network

We can then characterize a formal neuron by:

- A combination function or an added that performs the weighted sum. The weighted sum is equal to:

$$A_j = \sum_{i=1}^{n} W_{ij} X_i$$

Where W_{ij} is the synaptic weight and Xi is the input value relative to the variable i. This is the weighted sum of activation, which converges to the neuron j;

- An activation function (or transfer) f that animates the neuron by determining its activation;
- An activation, the equivalent of neuron output. It is equal to:

$$Y_j = f\left(\sum_{i=1}^{n} W_{ij} X_i + \theta_j\right)$$

Where θ_j is the bias of the neuron j.

There are several activation functions (hyperbolic tangent, Gaussian, sigmoid ...), but the most used is the sigmoid function ([12], [13], [14]). It is written as follows:

$$f(x) = \frac{1}{1 + \exp(-x)}$$

The configuration of the best MLP model and its implementation amounts to choosing the transfer functions, to identify the relevant inputs, the number of neurons in the hidden layer, to choose the learning algorithm and then optimize and test the network.

3. APPLICATION

3.1 Study region and data used

This study focuses on the basin of Inaouen (Figure 2). Located between latitudes 34°35’24’’N and 33°50’24’’N, and longitudes 4°49’48’’W and 3°48’36’’W, it covers an area of 3648 km2 with an average altitude of 694 m. Located in the western part of the basin of Sebou, the Inaouenregion profits from a Mediterranean climate with oceanic influence [15]. This climate is characterized by strong seasonal contrasts and very irregular rainfall [16]. Geological domain of Inaouenbasin is divided into two main areas: the northern part of the basin belongs to the Pre-Rif area and the southern part of the basin is related to the Atlas area.

The data used to present the results in this article are the monthly rainfall in the Bab Marzouka station located upstream of the basin and Idrissfirst station located at the downstream (Figure 2). These values were used to calculate the SPI. Also the values of the NAO index were used to estimate the influence of global climate index North Atlantic.

The following Table 2 shows some characteristics of the two stations used:

Table 2: Description of the stations

stations		BabMarzouka	Idriss 1st
Latitude / longitude		34° 12' 2'' N / 4° 8' 27'' W	34° 9' 47'' N / 4° 45' 2'' W
Altitude (m)		368	200
Period of data used		1971-2011	1975-2012
Nb. Of observations (months)		480	444
Statistical description of Monthly Precipitation	Average (mm)	46.86	32.69
	Max (mm)	311.1	192.3
	Standard deviation	54.21	37.54

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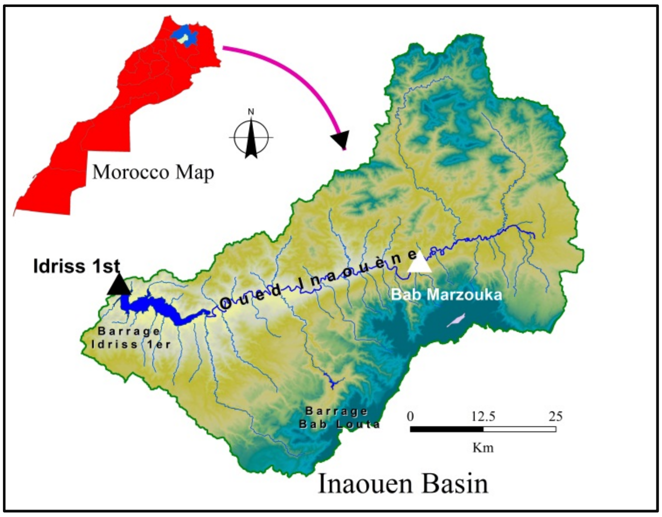

Figure 2: Location of rainfall stations used within the basin Inaouen

3.2 Elaboration and processing of the database

3.2.1 Data Collection

The purpose of this step is to collect data, both to develop different prediction models and to test them.

In the case of applications on real data, the goal is to gather a sufficient number of data to provide a representative basis of data that may occur during use of different prediction models.

The data used in this study are related to the measurement collected during the period 1971-2011 for the Bab Marzouka station and the period 1975-2012 for the first Idriss station.

The independent variables are standardized precipitation index, rainfall and the North Atlantic Oscillation index. (Figure 3)

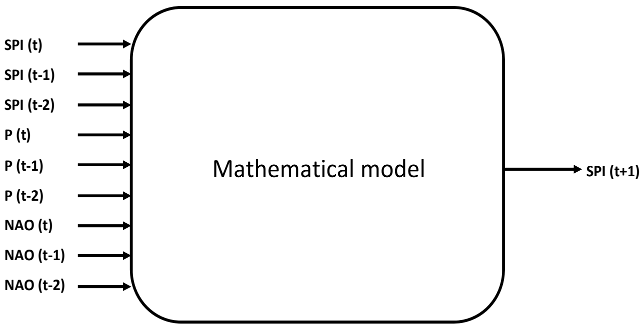

Figure 3: Inputs/Outputs of prediction model

3.2.2 Data analysis

After data collection, an analysis is required to determine the discriminating features to differentiate or detect these data. These characteristics are the input of the neural network.

The determination of the characteristics has consequences on both the size of the network (and thus the simulation time), on system performance (separation power, prediction rate), and development time (learning time).

Data filtering can help remove those that are absurd and redundant.

3.2.3. Data normalization

In general, databases require a pretreatment in order to be adapted to the inputs and outputs of the stochastic mathematical models. A common preprocessing is to conduct a proper normalization that takes into account the magnitude of the valuesaccepted by the models.

Normalization of each input xi is given by the formula:

$$x_{i\,new}^{k} = 2 * \frac{x_{i\,old}^{k} - \min(x_i)}{\max(x_i) - \min(x_i)} - 1$$

However, the output variable is normalized between 0 and 1 by the formula:

$$x_{i\,new}^{k} = \frac{x_{i\,old}^{k} - \min(x_i)}{\max(x_i) - \min(x_i)}$$

This provides a standardized database between -1 and 1 for the different variations of the independent variables (model inputs) and between 0 and 1 for the different variations of the dependent variables (model output).

3.3 Designing the architecture of artificial neural networks

When developing an ANN model, the main objective is to achieve the optimal ANN architecture that captures the relationship between the input and output variables. First, a three-layer perceptron MLP was chosen since it was found that a three-layer model is sufficient for forecasting and simulation in the field of water science [17]. Then the task is to identify the number of neurons in each layer. For these input and output, it is simple and it is normally dictated by the input variables and output considered, to model a physical process. For the number of neurons in the hidden layer, it should be optimized using the available data. To do so, we proceeded by trial and error based on the measurement of the mean absolute error (MAE) for the data used to test for each model. Figure 4 illustrates an exemplary model for established SPI 24 (SPI calculated for a window of 24 months) and shows that, 26 neurons in the hidden layer is the optimal number.

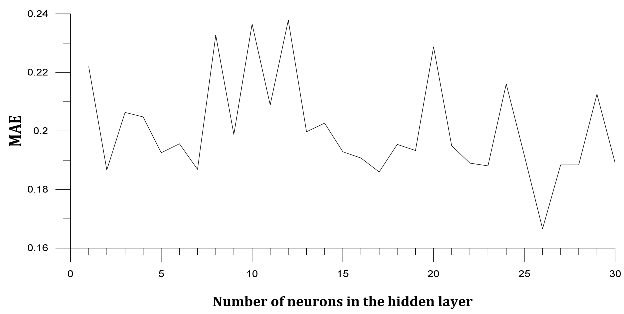

Figure 4: Determination of the optimum number of neurons in the hidden layer, depending on the mean absolute error for the SPI24Bab Marzouka station

3.4 Learning of Artificial neural network

Learning, supervised by the neural network consists of determining the weights that minimize the data set of training base, the differences between the values of the desired output, and the values of the estimated output. When comparing the calculated and actual, an error function called global squared error E is calculated:

$$E = \frac{1}{2}\sum_{k} e_k^2$$

With:

ek : the error between the desired value and the output

k : number of iterations

Optimize the network therefore, is to minimize this function. The minimization is achieved by adjusting the weight w, of the ANN using an optimization algorithm. Among the different algorithms for minimizing functions such as "the least squares", we opted for the Levenberg-Marquardt back-propagation of error algorithm that is fast, accurate and reliable [10].

Learning the model stops when the mean squared error (MSE) decreases by less than 0.01 or if the model has completed 20,000 iterations, depending on the situation occurs first. Thus, the optimal solution calculated by the network is used as an output target.

3.5 Test and Performance Analysis

This step is to evaluate the network formed by comparing the difference between the estimated value and the real value. The result of the evaluation is expressed in two ways: by statistical indicators and examination of the graphs. The indicators that have been taken in this study are: the correlation coefficient (r), coefficient of determination (R^2), the mean absolute error (MAE) and the mean squared error (MSE), which are defined as follows:

- The correlation coefficient (r)

$$r = \frac{\sum_{i=1}^{N}(x_{real,i} - \overline{x_{real}})\,(x_{estim,i} - \overline{x_{estim}})}{\sqrt{\sum_{i=1}^{N}(x_{real,i} - \overline{x_{real}})^2 \sum_{i=1}^{N}(x_{estim,i} - \overline{x_{estim}})^2}}$$

- The coefficient of determination (R^2)

$$R^2 = \frac{\sum_{i=1}^{N}(x_{estim,i} - \overline{x_{estim}})^2}{\sum_{i=1}^{N}(x_{real,i} - \overline{x_{real}})^2}$$

- Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|x_{real,i} - x_{estim,i}\right|$$

- Mean Square Error(MSE)

$$MSE = \frac{\sum_{i=1}^{N}(x_{real,i} - x_{estim,i})^2}{N}$$

Where $x_{real,i}$ the real value of SPI is, $x_{estim,i}$ is the estimated value of SPI by the model, at the moment i. $\bar{x}$is the average value and N is the number of samples.

The best prediction is when r and R2 on the one hand and MAE and MSE on the other hand tend to 1 and 0 respectively.

These steps listed to design a network model of artificial neuron are shown in the following chart methodology (Figure 5):

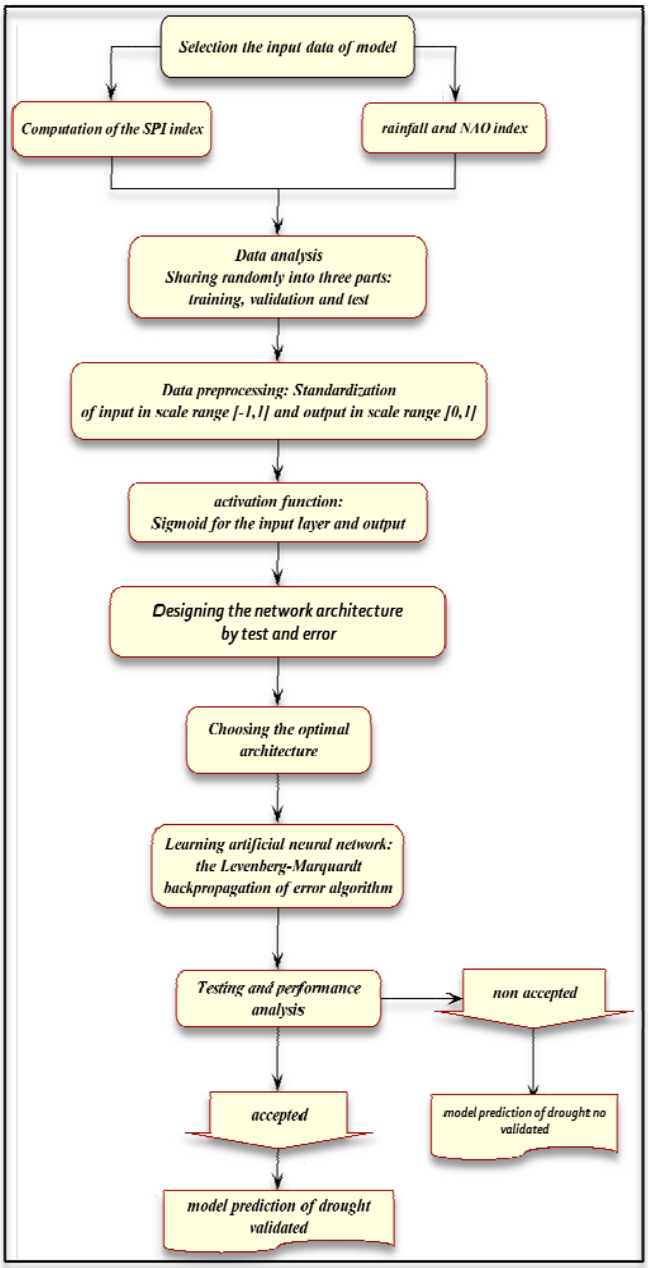

Figure 5: Methodological flowchart applied to the prediction of drought

4. RESULTS AND DISCUSSION

In this study, drought (SPI values) is predicted using ANN previously considered (Figure 5). In our case, we have developed three models MLP: MLP 1 based on the time series of precipitation, MLP 2 based on variable rainfall and SPI, and MLP 3 on variable rainfall, SPI index and the index north Atlantic Oscillation. These three models are shown in Table 3 below:

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Table 3: Different tested models

Input Variables	Predicted Variable	Model Name
$P(t)$, $P(t-1)$, $P(t-2)$	$SPI\ (t+1)$	MLP 1
$SPI\ (t)$, $SPI\ (t-1)$, $SPI\ (t-2)$, $P(t)$, $P(t-1)$, $P(t-2)$	$SPI\ (t+1)$	MLP 2
$SPI\ (t)$, $SPI\ (t-1)$, $SPI\ (t-2)$, $P(t)$, $P(t-1)$, $P(t-2)$, $NAO(t)$,$NAO(t-1)$, $NAO\ (t-2)$	$SPI\ (t+1)$	MLP 3

For these three models, the SPI values were calculated for a range of time windows varying from 3 months to 24 months. Assessing the accuracy of predictions for each model was performed using R^2, r, MAE and MSE coefficients.

The evaluation of the three models built showed that the prediction results related to MLP 3 (Figure 6) model had the lowest error (MAE and MSE values are lower and R^2 and r values are higher). It is interesting to express the addition of NAO as an input variable for the MLP improves the efficiency of prediction models. Thus, in this study, only the results of MLP 3 are presented and discussed.

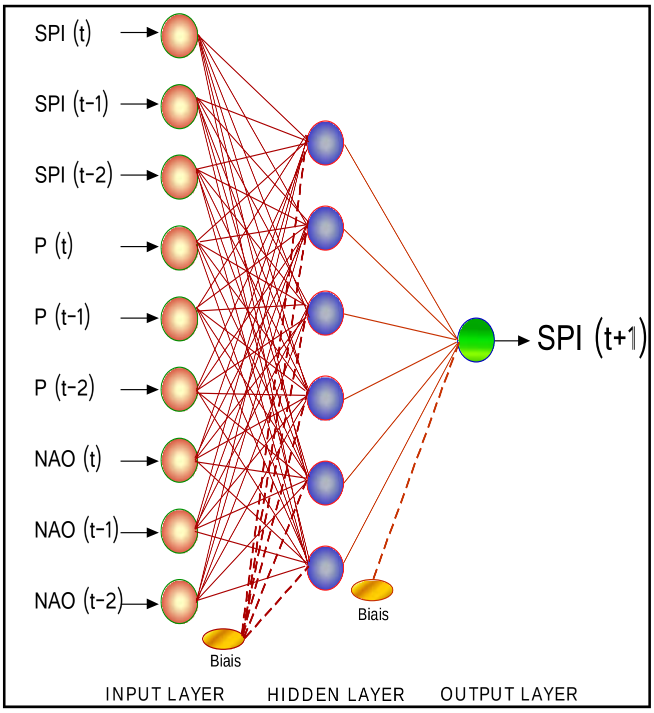

Figure 6: Model ANN (three-layer Perceptron) used to predict the risk of drought

All network settings on MLP3 model are summarized in Table 4.

Table 4: Information about the MLP3 model used

Input Layer	Covariables	9	$SPI\ (t)$, $SPI\ (t-1)$, $SPI\ (t-2)$, $P(t)$, $P(t-1)$, $P(t-2)$, $NAO(t)$,$NAO(t-1)$, $NAO\ (t-2)$
	Number of neurons		9
Hidden layer (s)	Number of hidden layers		1
	Number of neurons in the hidden layer		Variable depending on model
	Activation Function		Sigmoïde
Output Layer	Dependent variables	1	SPI (t+1)
	Number of neurons		1
	Activation function		Sigmoïde
	ErrorFunction		Sum of squares

The estimated precisions of the model MLP3 by comparison of the actual values and the predicted values for both stations Idriss 1st and Bab Marzouka for different time windows (SPI 3 to SPI 24) and the optimal architectures of the models are presented in Table 5.

Table 5: Prediction results of SPI values (at different time scales) for MLP3 model at the stations Idriss 1st and Bab Marzouka

	Idriss 1st				
	Architecture	R^2	r	MAE	MSE
SPI 3	[9-13-1]	0.47	0.686	0.547	0.486
SPI 6	[9-11-1]	0.671	0.819	0.433	0.315
SPI 9	[9-17-1]	0.758	0.871	0.357	0.238
SPI 12	[9-9-1]	0.828	0.91	0.286	0.153
SPI 24	[9-20-1]	0.914	0.956	0.214	0.08
	BabMarzouka				
	Architecture	R^2	r	MAE	MSE
SPI 3	[9-23-1]	0.51	0.714	0.536	0.498
SPI 6	[9-20-1]	0.62	0.788	0.489	0.399
SPI 9	[9-6-1]	0.786	0.887	0.362	0.219
SPI 12	[9-9-1]	0.871	0.933	0.275	0.132
SPI 24	[9-26-1]	0.923	0.961	0.214	0.079

To visualize the evolution of performance indicators based on the time window of SPI, the results in the table 5 have been transformed into the following two graphs (Figure 7):

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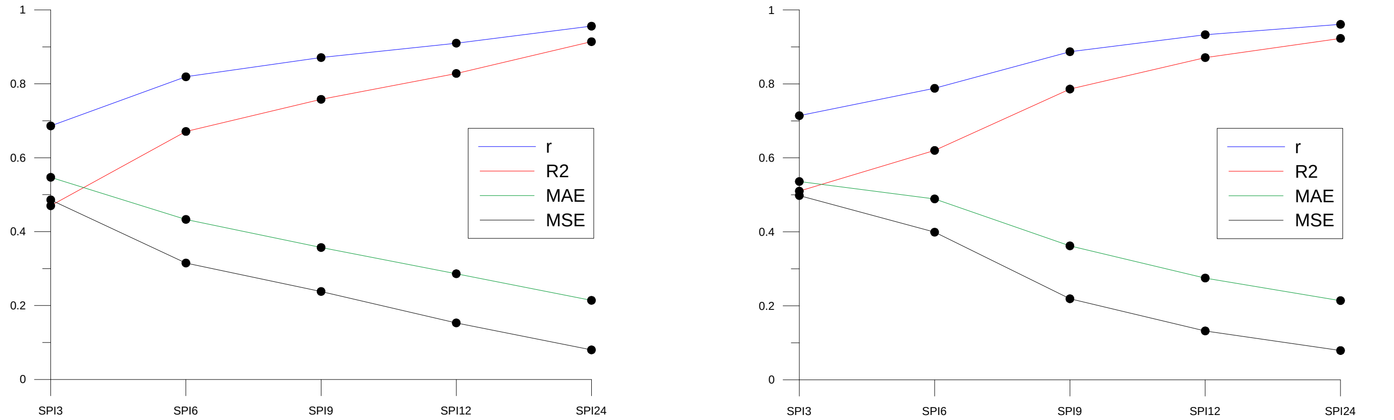
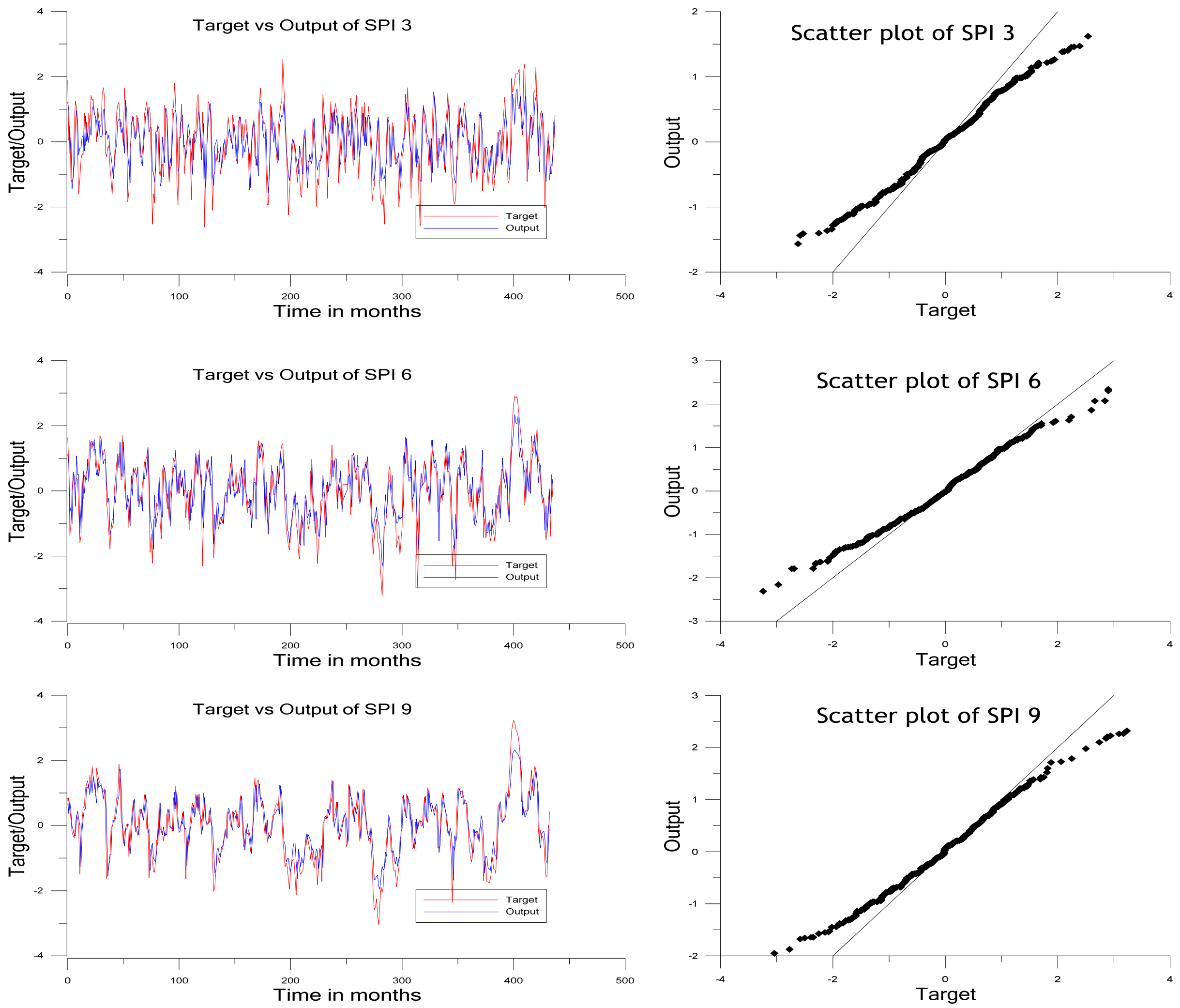


Figure 7: Evolution of performance indexes r, R2, MAE and MSE according to the time window of SPI for Idriss1ststations (left) and Bab Marzouka (right)

We can see that all the predictions SPI produce very good precision except for SPI 3 with differences between observed and predicted values, are not very acceptable. We also see that when the time window is increased, the correlation between the model prediction and the actual values increases significantly. This observation can be explained by the way the time series SPI is calculated. Unlike the series of precipitation, SPI follows a standard normal distribution. This conversion eliminates sudden peaks leaving a slowly varying smooth curve that is easier to predict using models of neural networks.

To better visualize the performance of the tested model, graphs that compare the observed SPI values and SPI values predicted one month ahead, and their scatter diagrams for the first Idriss station are shown in Figure 8.

It can be concluded that the neural network model of MLP, has successfully predicted the drought one month ahead for several time scales of SPI.



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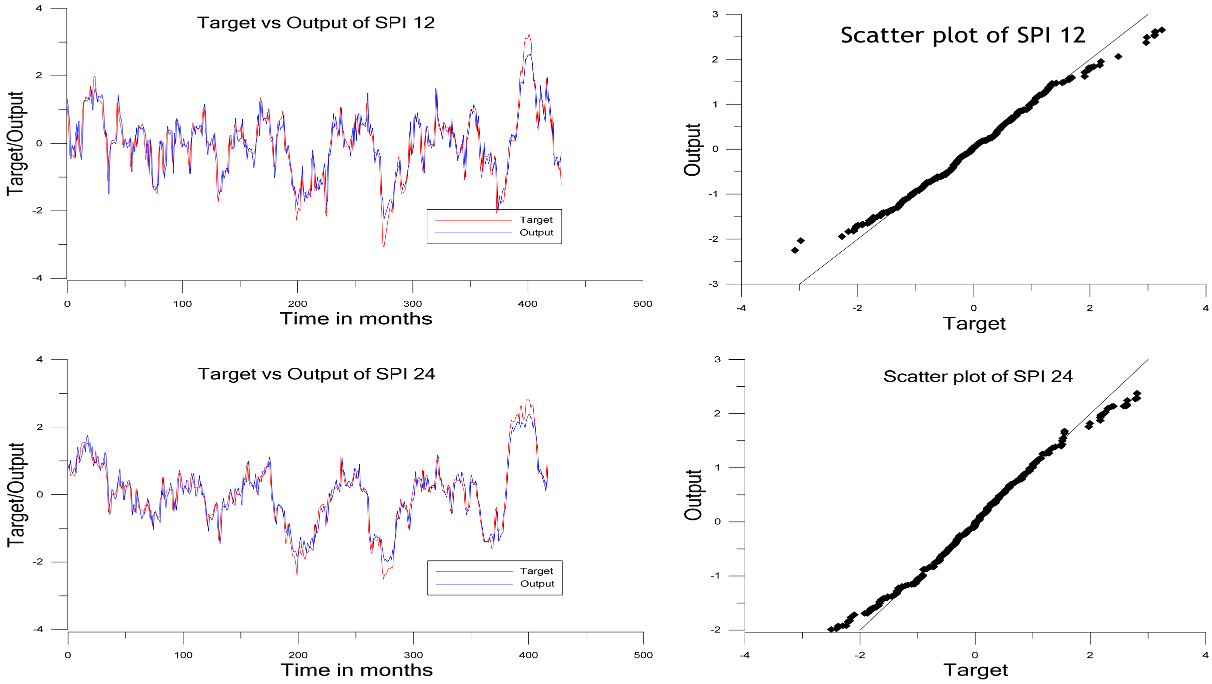

Figure 8: Comparison of predicted and observed SPI values for the first Idriss station

5. CONCLUSION

In this study, the drought prediction is made for the region of Inaouenbasin in northern Morocco using a system based on artificial neural network of MLP. Firstly, the time series of the Standardized Precipitation Index (SPI) built in for different periods of time ranging from 3 months, 6, 9, 12 and 24 months using the values of average monthly rainfall of the two stations selected within the watershed weather. Then an ANN-MLP model was developed and selected for his performance in predicting SPI categories for periods of 3, 6, 9, 12 and 24 months.

The model shows superior forecasts when going from SPI3 to SPI24. The neural network model developed can be therefore a very useful tool for planners of water resources to take the necessary measures in advance when there is shortage of water which can eventually develop into drought conditions.

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