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Prediction of rainfall reduction rate in the Kébir Rhumel catchment (Algeria) using statistical tests and the Artificial Neural Networks (ANN) methods

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The analysis of the spatio-temporal variability of precipitation in the context of climate change has become common practice, using a wide range of statistical methods, but its use for prediction in terms of values is relatively rare. The aim of this work is to highlight the climatic variability, at the scale of a catchment area, through the application of statistical tests and the Artificial Neural Network (ANN) method, in order to predict a rate of reduction of precipitation, after a break in the time series, in the Kébir Rhumel catchment (North-East Algeria). This analysis uses climate data from 1901 to 2021 (120 years). The reduction rates results obtained by the two methods ranged from 14% to 37% for the statistical method and 14% to 17% for the ANN. They were compared and mapped, leading to the conclusion that ANN is the better performing method.

KEY WORDS: artificial neural network (ANN), climate variability, Kébir Rhumel, reduction rate, statistical methods

Introduction

Statistical methods for precipitation forecasting have been widely studied in the field of meteorology. These methods have been used to extract and integrate information from historical atmospheric data to predict precipitation with high accuracy (Kalaivani et al., 2023). In addition, geostatistical tools such as Regression Kriging (RK) and machine learning methods such as Regression Enhanced Random Forest (RERF) have been compared to interpolate the spatial distribution of precipitation (Pareek et al., 2023). Statistical analysis techniques for deep extreme value data have also been used to predict precipitation data on a spatio-temporal scale. These methods have improved the accuracy and reliability of precipitation estimates, especially when considering different ranges of precipitation observations (Ahmed and Mohamed, 2021; Nasiri and Sarajzadeh, 2021).

Artificial neural networks (ANNs) are a new method for approximating complex systems, particularly useful when these systems are difficult to model using statistical methods. The different architectures of ANNs and their learning rules are adapted to facilitate the choice of approach. The connectionist approach can also be compared to classical stochastic methods in the context of hydrological forecasting (Coulibaly et al., 1999). Artificial neural networks have also been used in several studies to predict precipitation. A neural network model is developed for monthly precipitation forecasting in Brazil using meteorological variables as inputs, introduced into a multimodal framework of spatio-temporal characteristics, combining satellite imagery and radar echo maps to improve short-term precipitation forecasting (Zhang et al., 2023). Some authors have used artificial neural networks to reduce and evaluate satellite precipitation estimates, achieving better accuracy through optimisation algorithms (Salimi et al., 2019). Others have tested the feasibility of using artificial neural networks to predict the standardised precipitation index in different regions of Mexico, obtaining good performance (Anochi et al., 2021a; Anochi et al., 2021b). Others have developed a data-based precipitation forecasting model called DeepRain to predict precipitation from meteorological radar data (Kim et al., 2017). Hydrological forecasting is defined as the estimation of future conditions of hydrological phenomena for a given period, based on past and current observations. Its general objective is to provide the best estimates of what may happen at a given point at a specific future date, as opposed to prediction, which aims to estimate future conditions without reference to a specific time (Coulibaly et al., 1999). Artificial neural networks (ANNs) offer several advantages for precipitation forecasting. They can accurately predict precipitation by modelling the non-linearity and complexity of weather patterns (Mandal et al., 2022; Singh et al., 2021). ANNs, particularly the backpropagation algorithm, are reliable and accurate for monsoon forecasting (Barron and Darling-Hammond,

2010). They can be used to detect the temporal and spatial variability of urban rainfall, helping to prevent flooding (Lee et al., 1998; Nayak et al., 2013). ANNs outperform other techniques such as numerical weather prediction and statistical methods due to their ability to handle non-linear and complex physical conditions affecting precipitation (Mary Jasmine and Milton, 2022; Thakur et al., 2021). ANNs such as feed forward neural network, cascade forward neural network, recurrent neural network and Elman neural network have been successfully used for precipitation forecasting, with Elman neural network showing the best performance (Dada et al., 2021; Desai, 2021)

The approach adopted in this study is to determine the rate of precipitation reduction after a breakpoint. This rate is estimated using statistical methods and ANN (Artificial Neural Network). This approach is applied to rainfall data collected over a period of 120 years in the Kébir Rhumel catchment.

Materials and methods

Site presentation

The Kébir-Rhumel watershed (WS) is located in northeastern Algeria (Fig.1) and covers an area of 8831 km^2 and a perimeter of 1151 km, geographically spread over six wilayas: Oum El Bouaghi, Skikda, Constantine, Mila, Sétif and Jijel (Aidat, 2017; Kabour and Chebbah, 2023; Oulhaci, 2016; Zeghmar, 2023). The Kébir-Rhumel is composed of seven sub-basins (sub watershed: sws): Oued Kébir (sws1), O. Endja (sws2), O. Rhumel amont (sws3), O. Rhumel aval (sws4), O. Boumezroug (sws5), O. Smendou (sws6) and finally O. Kebir Rhumel (sws7) (Fig. 1); they form a highly branched and dense hydrographic network with a total length of about 8,000 km. It is a northern basin with an exoreic flow. Two dams are in operation in this basin: Beni Haroun and Hammam Grouz (Abdeddaim, 2018; Kabour and Chebbah, 2023; Zeghmar, 2023).

The Kébir Rhumel is equipped with a climatic observation network of 42 stations (Fig. 1) (Kabour and Chebbah, 2023; Oulhaci, 2016). In order to carry out this work, we selected seven of the 42 climate stations (Fig. 1), which are geographically representative of the seven subcatchments (Fig. 1) and are presented in Table 1 with their characteristics, namely: Chebabta, Tiberguent, Tadjnanet, Ain Smara, Guerrah, Grarem Gouga and El Milia.

Data description

The data used in this study were collected at seven selected climate stations (Table 1) in the Kébir Rhumel catchment area. The data consist of daily rainfall and temperature values for each station, with a series spanning 120 years (1901–2021). The sum of these values for a month constitutes the monthly values, and the sum of these monthly values makes it possible to obtain the annual sums, this for the precipitation, for the temperature, we have calculated the monthly averages, then an annual average.

For each station, on the same series of precipitation and temperature, we carried out a basic statistical analysis, that is, the determination of the minimum, maximum and average values of the annual values (Table 1), which will be used later in ANN, where we note that:

→ For the selected stations, the annual rainfall values vary between 288.10 mm in Chebabta and 918.70 mm in El Milia (Table 1).

→ The mean temperature in the Kebir Rhumel varies from 13.93°C at the Guerrah station to 16.18 ºC at the Grarem Gouga station (Table 1).

→ The annual variation of rainfall at the selected stations shows that the Chebabta station recorded the lowest values, with a minimum of 288.10 mm

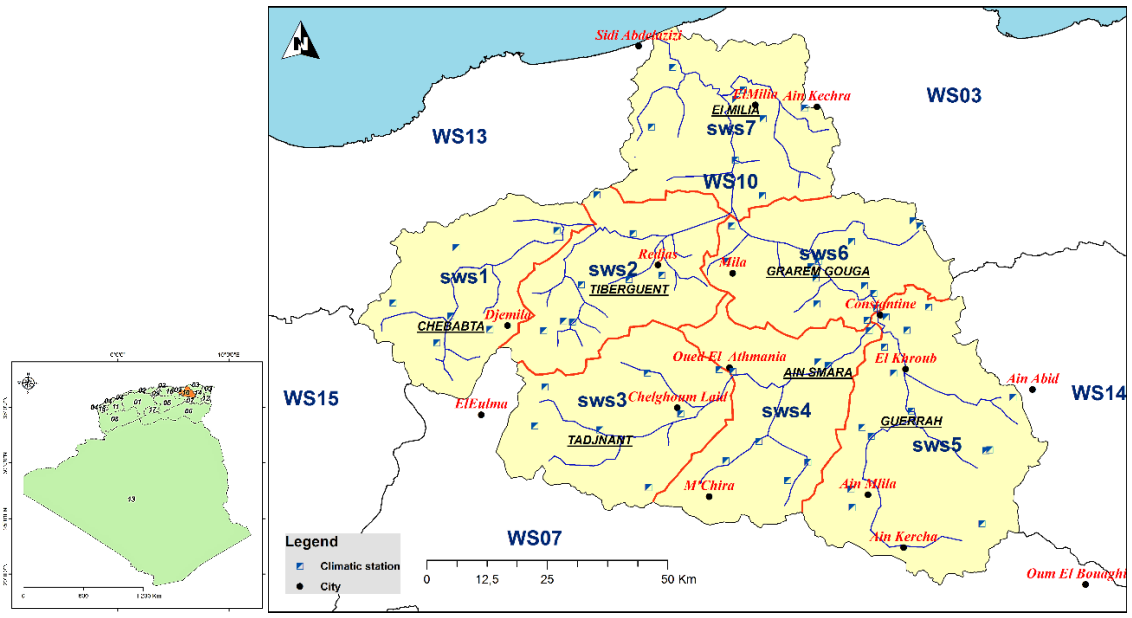


Fig. 1. Geographical location of the Kébir Rhumel (WS10) and location of the sub-catchment areas (sws) and climatic stations.

→ and a maximum of 689.40 mm, while the El Milia station recorded the highest values, with a minimum of 378.40 mm and a maximum of 918.70 mm.

These 120 years of data have been used to draw a map of the spatial variation of mean interannual precipitation (Fig. 2), which shows a decreasing distribution of values from 650 mm to 450 mm, with this slope oriented from northeast to south-west.

Methodology

In this paper, statistical tests and ANN methods are applied to rainfall time series in order to predict temporal variability in rainfall time series, i.e. the presence of a break point, and a reduction in mean values after this point by estimating a reduction rate (Fig. 3).
XLstat and SPSS IBM software were used to apply these methods to the rainfall time series for the Kébir Rhumel catchment. This catchment area is covered by about forty climate stations distributed in seven sub-catchments (Fig. 2), of which we selected seven geographically representative stations (Table 1), namely: Chebabta, Tiberguent, Tadjnanet, Ain Smara, Guerrah, Grarem Gouga and El Milia. The rainfall series used consists of 120 years (1901–2021) of annual data calculated from daily values.
The approach consists firstly in selecting the Kébir Rhumel catchment, then in applying the statistical test of segmentation by homogeneity (Table 2) to determine the year (2013 and 2020) of the break in the series studied, which allows us to calculate the average of the rainfall values before and after the break. We then determined the rate of reduction in precipitation compared to the average before the break point.
For the ANN application, we selected the input variables (Table 1) and chose the MLP (Multi-Layer Perceptron)

Table 1. Presentation of the selected climate stations (*P*mean: mean of annual sums, *T*mean: mean of annual means, SD: standard deviation)

1901–2021	Code	Stations selected	*Pmean* [mm]	*Pmin* [mm]	*Pmax* [mm]	SD (P)	*Tmean* [°C]
sws1	100110	Chebabta	495.75	288.10	689.40	91.02	14.69
sws2	100211	Tiberguent	508.88	303.70	695.50	92.52	15.02
sws3	100303	Tadjnanet	496.44	289.00	690.40	90.71	15.38
sws4	100403	Ain Smara	572.39	344.10	855.30	107.65	14.62
sws5	100508	Guerrah	573.09	344.60	856.10	107.67	13.93
sws6	100620	Grarem Gouga	651.29	377.90	917.90	114.26	16.18
sws7	100706	El Milia	651.99	378.40	918.70	114.28	15.49

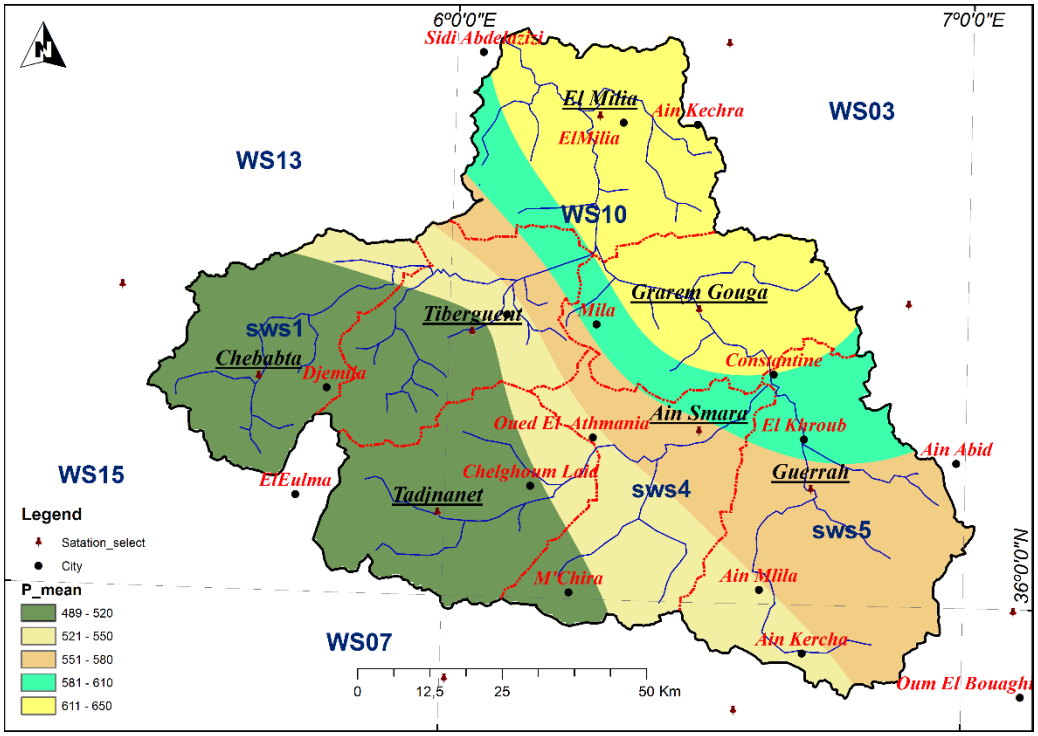


Fig. 2. Map of the spatial distribution of the mean interannual precipitation of the annual sums, for the series 1901–2021 (120 years), of the Kébir Rhumel (WS 10).

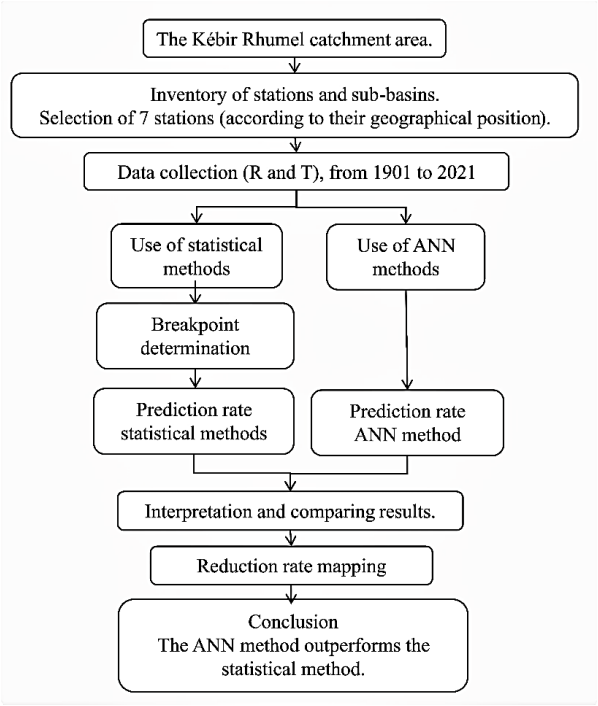


Fig. 3. A flowchart describing the methodology and approach.

method, which allowed us to calculate the precipitation reduction rate for each station. We then compared the values calculated by the two methods and used these results to create two maps of the spatial distribution of the reduction rate over the Kébir Rhumel BV, in order to observe the difference between the results of the two methods.

Results and discussion

The use of statistical methods and ANNs for the prediction of hydrological parameters has become common practice, but the prediction of the variability, positive or negative, of these parameters in a spatiotemporal dimension is rare. It is in this context that we have applied this approach (see methodology), the results of which are presented in the following paragraphs.

Statistical methods

Statistical analysis of time series of hydrometeorological data is one of the tools used to identify climatic variations. This analysis most often involves implementing and interpreting statistical tests of series homogeneity (Beaulieu, 2009; Lubes-Niel et al., 1998). The test used for the Kébir Rhumel precipitation series is segmentation by homogeneity, which consists of a statistical analysis aimed at determining a breakpoint in the time series. Applied to the precipitation series, it was used to identify a breakpoint year for each station (Table 2). The year 2020 for the Ain Smara and Guerrah stations, and 2013 for Chebabta, Tberguent, Tadjenant, Grarem Gouga and El Milia. By calculating the average before and after the breakpoint, it is possible to estimate the rate of rainfall reduction (Table 2).
The spatial distribution of the reduction rate calculated using the statistical method for the Kébir Rhumel catchment (Fig. 4) shows that values vary from 20% in the north to 40% in the south, following a decreasing slope from North-West to South-East.

Artificial neural network (ANN) method

Multi-layer perceptron (MLP) artificial neural networks have been used for precipitation forecasting in various studies. These studies have shown that MLP models can provide accurate precipitation forecasts based on input variables such as meteorological parameters (Lee et al., 1998) . For example, a study in Morocco used an MLP model with eight meteorological parameters to forecast monthly rainfall and found that the MLP model outperformed other models in terms of efficiency and accuracy (Esteves et al., 2019). Another study compared MLP-NN models with SARIMA models for modelling precipitation time series and found that MLP-NN models performed well in terms of statistical parameters such as RMSE, MAE, CC and BIAS (Hashim et al., 2017). Furthermore, MLP models trained with different learning

Table 2. Summary table of the different methods applied to the seven selected stations

Series: 1901–2021	Stations	Segmentation by Homogeneity			Reduction rate			
					Stat method		ANN method	
		Year of break point	Mean before	Mean after	[%]	[mm]	[%]	[mm]
sws1	Chebabta	2013	501.52	414.25	17.4	72.08	16.97	70.3
sws2	Tiberguent	2013	514.36	431.46	16.12	69.55	17.01	73.39
sws3	Tadjenant	2013	502.21	414.92	17.38	72.11	17.09	70.91
sws4	Ain Smara	2020	574.15	361.4	37.05	133.9	17.11	61.84
sws5	Guerrah	2020	574.48	361.9	37	133.9	16.99	61.49
sws6	Grarem Gouga	2013	657.7	560.76	14.74	82.66	14.7	82.43
sws7	El Milia	2013	658.4	561.44	14.73	82.7	14.7	82.53

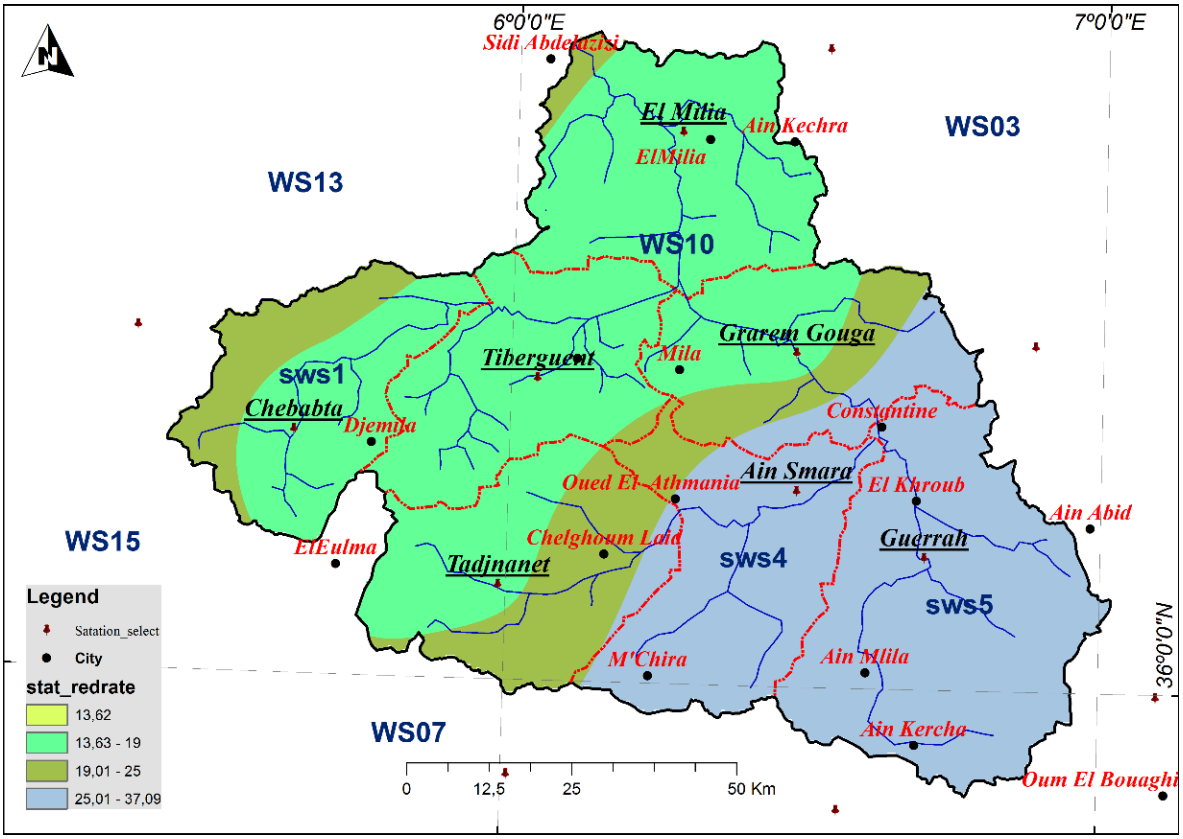


Fig. 4. Distribution map of the reduction [%] in rainfall calculated by the statistical method, in the Kébir Rhumel WS.

algorithms have been shown to produce accurate results for rainfall forecasting (Altunkaynak and Ozger, 2016).
In our case we used the multilayer perceptron (MLP) artificial neural network model, where the sample of 7 variables was divided into two slices, the first with 57.1% for training the model, and the second with 42.9% for testing. The percentage is introduced at the input layer with the following variables, for each station (Table 3):

1. *R*mean [mm]: the average value of the annual sums of precipitation.
2. *R*min [mm]: the minimum value of the annual sums of precipitation.
3. *R*max [mm]: the maximum value of the annual sums of precipitation.
4. SD (*R*): standard deviation of the mean value of annual precipitation sums.
5. *T*mean [°C]: the interannual mean temperature
6. Mean before the average value of precipitation before the breakpoint.
7. Mean after the average value of precipitation after the breakpoint.

After running the analysis according to the architecture in Fig. 5, or Hidden layer activation function is hyperbolic tangent, with a very low relative error of 0.005 and a very short training time (Table 4).
The Fig. 7 shows the importance of the independent variable, i.e. the most influential variable in determining the rate of reduction in precipitation, and as a result we have the Mean after parameter (the mean of the precipitation values after the breakpoint), with a score of 100% and in last place the mean temperature of the annual means of the whole series (*T*mean) with a score of 6.7%.
A comparison of the values calculated by the statistical method and those calculated by the ANN MLP method (Fig. 7) shows that the latter performs better, for the following reasons:

→ The statistical method gives values of 37.05% and 37% for the two stations of Ain Smara and Guerrah, which have a single value after the breakpoint (2020), while the ANN gives values of 17.11% and 16.99% for these same stations. The reduction rate values obtained by the two methods for the other stations (Chebabta, Tiberguent, Tadjnanet, Grarem Gouga and El Milia) vary between 14.7% and 17.38%, and are relatively close (Table 2).

→ The reduction rates obtained by ANN were used to draw up a map of their spatial distribution over the Kébir Rhumel catchment (Fig. 8), where it can be seen that these values vary between 14.5% in the northeast and 17.5% in the south, and their distribution follows a decreasing slope from south to north.

If we compare this map with the one based on the reduction rates obtained using statistical methods (Fig. 4), we can see that the values obtained using statistical methods are higher, ranging from 20% in the north to 40% in the south.

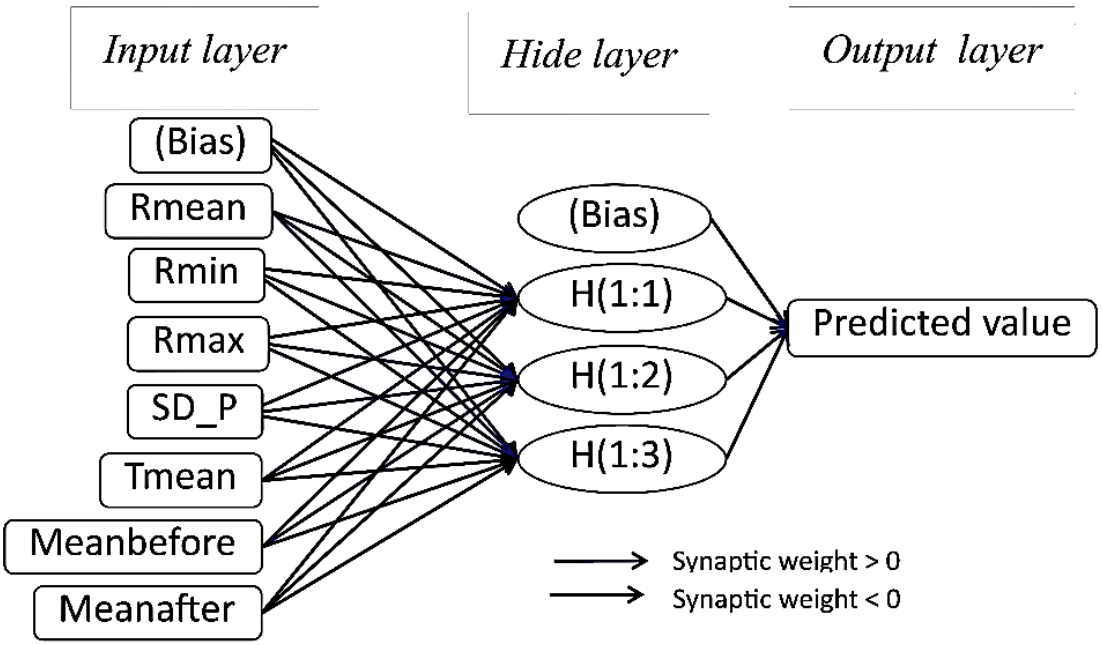


Fig. 5. Neural network architecture.

Table 3. Network Information

Input Layer	Covariates	1	*Rmean* [mm]
		2	*Rmin* [mm]
		3	*Rmax* [mm]
		4	SD (R)
		5	*Tmean* [°C]
		6	Mean before
		7	Mean after
	Number of Units[a]		7
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Predicted value
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

[a] *Excluding the bias unit*

Table 4. Model Summary

Training	Sum of Squares Error	2.720E-5
	Relative Error	1.813E-5
	Stopping Rule Used	Training error ratio criterion (0.001) achieved
	Training Time	0:00:00.53
Testing	Sum of Squares Error	0.007
	Relative Error	0.005

Dependent Variable: Predicted value

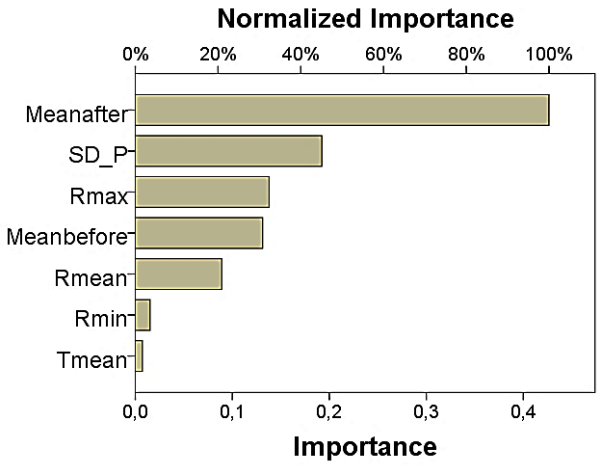


Fig. 6. Independent variable importance chart.

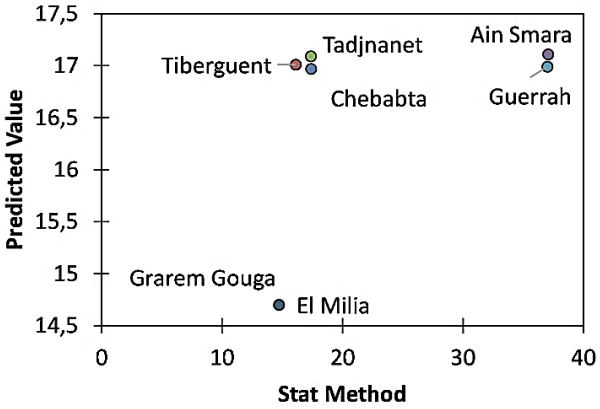


Fig. 7. Predicted value-by-stat method chart.

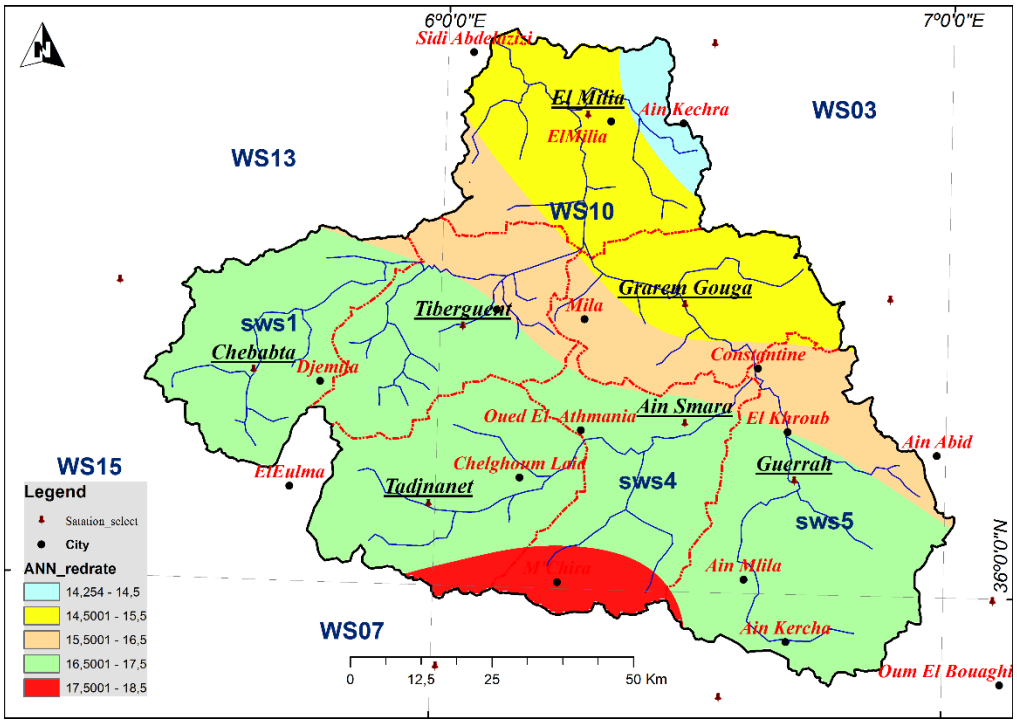


Fig. 8. Distribution map of the reduction [%] in precipitation calculated by the ANN method, in the Kébir Rhumel WS.

Conclusion

This paper presents the detection of the impact of climate change on a precipitation time series at the watershed scale through an approach using statistical methods and Artificial Neural Networks (ANNs), specifically Multilayer Perceptrons (MLPs), to predict the rate of reduction in interannual mean precipitation values estimated after a break in the time series. This break is identified by a homogeneity test. This application was carried out on a 120-year rainfall series in the Kébir Rhumel catchment, where seven stations were selected based on their spatial distribution (El Milia, Grarem Gouga, Tiberguent, Chebabta, Tadjnanet, Ain Smara, and Guerrah). The statistical method yielded reduction rates ranging from 14.73% at the El Milia station to 37.05% at the Ain Smara station, whereas the ANN method produced values varying from 14.70% at the El Milia station to 17.09% at the Tadjenant station.

The results obtained by the ANN model are significant and also allow us to conclude that this tool is more effective for forecasting variations in rainfall time series at the catchment level.

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