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ISSN: XXXX-XXXX

ICALRBH

Springer
SPRINGER NATURE

3RD International Conference On African Large River Basin Hydrology (ICALRBH)

Forecasting drought by three different autoregressive artificial neural network algorithms: Case of Beni Bahdel river basin

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Highlights:The ability of three different autoregressive artificial neural network (NAR) algorithms to forecast hydrological drought over Beni Bahdel river basin in the North-West of Algeria were compared. The Streamflow Drought Index (SDI) was computed at 12-months time window and used to train our models. Results showed that all of the three models are able to forcast the hydrological drought in such basin. Whereas, the autoregressive artificial neural network with Bayesian Regularization algorithm was chosen as the best model for forecasting hydrological drought that better reduces the root mean square error (RMSE). furthermore, this model can forecast reasonably well the drought events ahead 120 months.

Keywords: Drought; autoregressive artificial neural network; North-West Algeria; SDI.

1. Introduction

Over arid and semi-arid regions,the mobilization of water resources is mostly guaranteed by dams that are suggested toprecipitation variability. Algeria, where climate conditions varie relatively from wet to very dry, is confronted with the management and the sustainable development of its water resource problems, particularly the North-West part of the country. Where, the high level ofprecipitations deficit and water shortage is already observed after prolonged droughts events. Where also they seem to be worst in the future (Zeroual *et al.*, 2013). The observed temperature increaseswhile precipitations decreaseover the whole North of Algeria during 1951-2005 period that experienced significant shrinking of relatively wet zone area by approximately 30%, at a rate of ≃1000km^2/yr. The northwestern part of the countryhas been considered to be the region where there is the best agreement among models regarding the future (2045-2098) expansion of arid zone at the expense of warm temperate zones (Zeroual *et al.*, 2018). This water deficit, which had enormous consequences on water resources affecting spectacularly agricultural yields in Algeria. As consequence, the predictions of hydrological drought events and accurate reservoir-inflow still the most important tool for water resources management and reservoirs operation. In the literature, the detection and monitoring of drought conditions refer mainly to two basic approaches: (1) the prediction of hydrological conditions and second (2) is the prediction of drought indices (Mckee *et al.*, 1993). The latter one allow the determination and the classification of drought events at different time-scales using threshold determined according to the severity and duration of these drought events. The drought index times series has been used in several studies(e.g Mishra and Desai 2005)for building statistical models namely: Markov chain, the regression method, autoregressive integrated moving average (ARIMA) and Auto Regressive Moving Average (ARMA) in order to forecast future drought indices and also to estimate drought return periods.During the last two decades, many scientists have suggested to use the artificial neural networks as accurate method for drought forecasting. This approach has already been successfully usedover Algeria and other semi-arid region (e.g Salhi *et al.*, 2013, Zeroual *et al.*, 2016).

In this study, the ability of the autoregressive artificial neural network models with three different algorithms were comparedon their ability to forecast hydrological drought in the Beni Bahdel basin. These algorithms, including Scaled Conjugate Gradient, Levenberg-Marquardt and Bayesian Regularization were applied to the time series of the StreamflowDrought Index (SDI) at 12-months time scales. The algorithms were trained and tested with different monthly lag times (1:120 months) using 70-years (1941–2010) data record of SDI-12 selected randomly. Furthermore, four models inputs were constructed using SDI (t) and antecedents SDI (t-n) with different monthly times lag. Other artificial neural network methods than the ones used in the present study do exist in the literature. Valipour *et al.*, (2013)have compared the statistical model (ARMA ARIMA) with the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir in Iran. Theyfound the superiority of autoregressive ANN models with sigmoid activity function to the other statistical models.

2. Material and Methods

The observed inflow data, of the Beni Bahdel basin, used in this study are collected from the National Agency of the hydraulic resources (ANRH). This data covers the period 1941-2010 at monthly time step. Beni Bahdel basin (Figure.1) is characterized by a semi-arid climate with large spatial and temporal variation of rainfalls. On the other hand, thibasin has suffered from a persistence drought since the second half of the 1970s decade produced by a decrease of 27% in precipitations and rises in temperatures that led to 67% reduction of surface outflows(Meddi & Meddi, 2009). This generats major problems for agricultur development and water resource management.

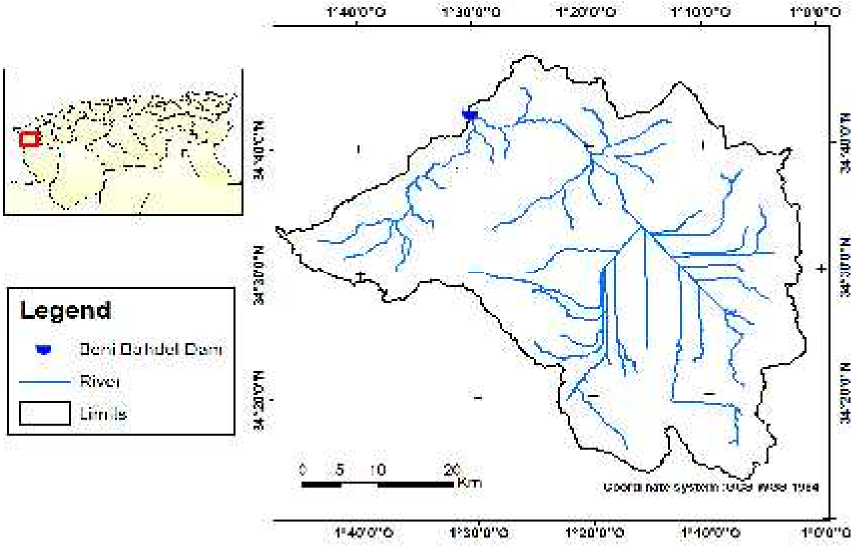

Figure.1 Geographical location of the Beni Bahdel Basin in Northwestern Algeria.

Drought forecasting can play very important role in the mitigation of its effects. To answer this objective, we usedautoregressive neuronal modelsof drought forcasting in advance of one to 120 months. The SDI series at 12-months time scale are used both for the model training and validation. We used the computation procedure defined in Nalbantis (2008)for SDI calculation.

In order to forcast drought conditions in advance of ‘t’ given time, several combinations of SDI values observed in the previous months (t-n) can be used as model inputs. To reach the optimum inputs combinations that should be included in the model, several combinations were constructed and the best one isestimated by the use of simple trial and errors procedure during the model learning. The four NAR models are constructed as shown in the Table.1.

Table.1. Conception of inputs used in the model learning NAR for drought forecasting of one month in advance.

Conception	Inputs vector	Prevised variable
01	SDI(t-1)	SDI (t)
02	SDI(t−1), SDI (t−2)	SDI (t)
03	SDI (t−1), SDI (t−2), SDI (t−3)	SDI (t)
04	SDI (t−1), SDI (t−2), SDI (t−3), SDI (t−4)	SDI (t)

For the model architecture based on NAR we opted for a simple architecture of three layers.After building the four models using the different combinations of variables SDI (t-n), the three algorithms: Levenberg–Marquardt (NAR_LM), Scaled conjugate gradient algorithm (NAR_SCG) and Bayesian Regularization (NAR_BR) algorithm will be used for NAR model training. The performances of all the four models were evaluated using the mean square error (MSE) and the coefficient of determination R^2.

After the selection of the input and output variables, the four models NAR were examined in order to find the best model that can capture the non-linearity in SDI series. To do this, two activation functions are used: a sigmoidal function in the hidden layer and a linear function in the output layer. The data base representing 12-months SDI series were subdivided into two sets, the first is 70% for model training, while the remaining data 30% is used for model validation. Finally, the trial and error methods were used to determine the optimum number of neurons (N) in the hidden layer.

After fixing the inputs variables, the number of neurons in the hidden layer and the activation function, the model is testedwith the data sets intended for model validation.

1. Discussion and Conclusion

The best NAR model for drought forecasting with training the three algorithms and the four conceptions was achieved as follow: the NAR model with conception n°1 in the case of the Conjugate Gradient algorithm, the conception n°2 in the case of Levenberg–Marquardt training and the conception n°4 in the case of the Bayesian Regularization algorithm.

The optimal number of hidden neurons (N) was found different from an algorithm to another. In the case of Bayesian Regularization algorithm, the number of neurons in the hidden layer is in accordance with the 2n+1 low.

The Scaled Conjugate Gradient and the Levenberg-Marquardt algorithms have the best performance during the model training compared to the Bayesian Regularization algorithm while the Bayesian Regularization algorithm was better in the validation period compared to the two others algorithms.

The MSE values for the validation phase of the NAR model with the best conception shows that the best optimization is obtained by the Bayesian Regularization algorithm where they vary from 0,22 to 0,003. The R^2 values obtained during the validation step vary from 0,61 à 0,98.

The MSE values were better minimized for the forecasting period from 3 to 5 years.For the Bayesian Regularization algorithm, the minimal MSE values of the last 5 years were much better estimated than the 5 first ones.

The NAR model with the Bayesian Regularization algorithm shows that the MSE fluctuations has a contra-version relation with the lag time, where the MSE values increase when we increase the lag time up to 10 years, particularly in pics. Thus, we can conclude that this model could forcast better the next 10 years.

This model can be used for planning and management of water resources. It can also be recommended for the neighboring regions characterized by very limited availability of monthly inflow data. Besides, this model does not require conceptual understanding of basin behaviors where the precision is only related on inputs data used for the learning of the model.

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