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Verification of MIKE 11-NAM Model for runoff modeling using ANN, FIS, and ARIMA methods in poorly studied basin

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Abstract. Hydrological information is the basis for conducting water balance studies in any region, and surface runoff is one of the most important hydrological parameters and one of the most difficult in the process of estimation and prediction. This study aims to verification of the MIKE 11-NAM Model for runoff modeling using artificial neural network (ANN), fuzzy inference system (FIS), and autoregressive integrated moving average (ARIMA) methods at Al-Jawadiyah hydrometric station on the Orontes River in Syria. MATLAB was used to build neural and fuzzy models, where many models were built with the change in all parameters, functions, and algorithms that can be used, and the Minitab was used to build ARIMA models. Many models were prepared with the addition of seasonal effect, and the comparison results showed an advantage for artificial neural network models in terms of evaluation parameters. After that, the artificial neural network models were adopted in the process of filling the gaps in the time series of surface runoff in the study area to be used in the Mike program for modeling the runoff and through the method of trial and error with a high number of iterative cycles, model parameters were calculated and runoff values estimated. Still, the results were not good, and there were significant differences between the measured values and the values simulated by the model, and this is due to the significant lack of available data. This study recommends the use of artificial intelligence and machine learning models in the field of estimation and prediction of hydrological parameters.

1 Introduction

Water resources play an important role in developing various agricultural, industrial, and economic activities. Hydrological information is the basis for conducting water balance studies in any region [1].

Many studies have been conducted in the field of estimating surface runoff, where some researchers are interested in using artificial intelligence models in this field. Among these models, they used artificial neural networks models, for example (Zhang B. and Govindaraju R. S, 2003) developed a geomorphology-based artificial neural network (GANN) to estimate runoff hydrographs from several storms [2]. Also, (Yazdani M. R, and

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Saghafian B, 2009) used an artificial neural networks model for runoff estimation in the Plaszjan River basin in Iran [3].

Artificial neural network models were also used to estimate the rainfall-runoff relationship in different regions and scenarios. These models showed high reliability with high evaluation coefficients, for example (Srinivasulu S. and Jain A., 2006) compare various training methods available for training multi-layer perceptron (MLP) type of artificial neural networks (ANNs) for modeling the rainfall-runoff process [4], (Solaimani K., 2009) also used Artificial Neural Network (ANN) to modeling the rainfall-runoff relationship in a catchment area located in a semiarid region of Iran [5]. In addition, (Chen S M, *et al.,* 2013) developed a model for estimating runoff by using rainfall data from a river basin and employed a neural network technique to recover missing data [6], and (Chakravarti A, et al., 2019) used ANN for the validation of observed runoff hydrograph data [7].

Also, researchers were interested in using fuzzy inference models, as many studies were conducted to estimate surface runoff using fuzzy inference models or to predict water supplies. Comparisons were also made with other traditional or statistical methods, and fuzzy models showed high capabilities in the modeling process. Other studies were also conducted using fuzzy neural models. Hybrid runoff estimation results were good. For example, (Mahabir C., et al., 2003) investigated the applicability of fuzzy logic modeling techniques for forecasting water supply, and fuzzy logic has been applied successfully in several fields where the relationship between cause and effect (variable and results) are vague [8], also (Tayfur G. and Singh V. P., 2006) used artificial neural network (ANN) and fuzzy logic (FL) models for predicting event-based rainfall runoff and tested these models against the kinematic wave approximation (KWA) [9], and (Şen Z. and Altunkaynak A., 2006) prepared a comparative study of the use of fuzzy inference models to runoff coefficient and runoff estimation [10]. (Lohani A. K. et al., 2011) compared artificial neural network (ANN), fuzzy logic (FL), and linear transfer function (LTF)-based approaches for daily rainfall-runoff modeling [11], and (Wang K. H. and Altunkaynak A., 2012) conducted a comparative case study between SWMM and a presently developed fuzzy logic model for the predictions of total runoff within the watershed of Cascina Scala, Pavia in Italy [12], also (Nath A. at al., 2020) resolved this problem of ANFIS by incorporating one of the evolutionary algorithms known as Particle Swarm Optimization (PSO) which was used in estimating the parameters pertaining to ANFIS [13].

On the other hand, ARIMA models were used in many studies related to forecasting and estimating hydrological parameters, especially surface runoff. Comparisons were also made with other methods, and the results differed according to the studied parameter and the study area. For example, (Montanari A. and Rosso R., 1997) used several types of ARIMA models to estimate and predict hydrological data series [14], and (Ghanbarpour M.R., 2010) used time-series analysis to model karstic flow in the Sangsoorakh karst drainage basin in the Karkheh subbasin of southwest Iran [15], also (Valipour M., 2015) investigated the ability of the seasonal autoregressive integrated moving average (SARIMA) and autoregressive integrated moving average (ARIMA) models for long-term runoff forecasting in the United States [16], and (Oliveira P. J. et al., 2017) used a double seasonal ARIMA model to generate water demands forecast (one-day) for a district metering area (DMA) [17].

While other researchers used the Mike model in the process of modeling surface runoff and managing water runoff, and the results differed according to the region and the availability of data, as some studies showed a good agreement between the measured data and the simulation results with good evaluation criteria values [18-20]. In contrast, the results showed a significant exaggeration in the estimated values of poorly studied river basin [21].

So, this study aims to verification of the MIKE 11-NAM Model for runoff modelling using artificial neural network (ANN), fuzzy inference system (FIS) and autoregressive integrated moving average (ARIMA) methods at Al-Jawadiyah hydrometric station on the Orontes River in Syria.

2 Methods

2.1 Study site & data availability

The study area is the Upper Orontes River Basin in Syria. The surface runoff data were mainly used at Al-Jawadiya station at the entrance to Qatina Lake. Assistive, the surface runoff data at Al-Amairi station, and rainfall and evaporation data from the Qatina meteostation were used.

2.2 Artificial neural networks (ANN)

Artificial neural networks are a kind of black box, as there is no particular structure or computational method. Neural networks consist of neurons that form a local memory used in the various steps of model building and data processing [22]. Feed-forward and backpropagation artificial neural networks are the most widely used types of artificial neural networks, and they mostly consist of an input layer, an output layer, and one or more hidden layers [5]. The data is divided into three datasets for training, validation, and testing so that the data of any period is not used in the subsequent period, and the division of blocks was used so that we use the same data in each training process, which increases the quality of comparison between the results

2.3 Fuzzy inference system (FIS)

Fuzzy inference models are used to model complex and uncertain systems, and they start from the concept of a fuzzy set that is an extension of the classical set so that its elements can partially belong to that set [23]. Building fuzzy models depends on three main steps (Fuzzification, Fuzzy Inference Operations, Defuzzification) [24]. The degree of membership of the inputs in the fuzzy group is determined using membership functions, and membership functions of Gaussian, Triangle, and Trapezoidal are among the most widely used types [24].

2.4 Autoregressive integrated moving average (ARIMA)

In this study, ARIMA models were used without the addition of the seasonal effect and with the addition of the seasonal effect as models were used, where: Autoregressive integrated moving average ARIMA (p,d,q) as p,d,q are the order of the non-seasonal autoregressive model, the number of non-seasonal differences and the order of non-seasonal moving average model respectively. Also, Seasonal autoregressive integrated moving average SARIMA (p,d,q) $(P,D,Q)_s$ where P,D,Q are the order of seasonal autoregressive model, the number of seasonal differences, and the order of seasonal moving average model, and s is the periodic term [16].

2.5 Mike 11 NAM

The model of MIKE 11 NAM simulates the rainfall-runoff relationship in the basin as part of modelling these components in the MIKE 11 river [19]. Figure 1 shows the Structure of the model MIKE NAM.

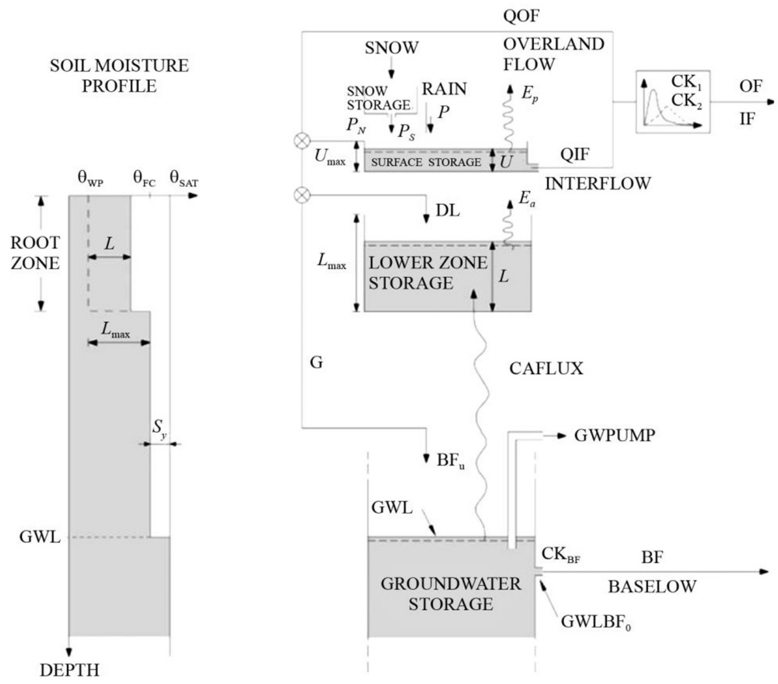

Fig. 1. Structure of model MIKE NAM [21]

The calibration of the Mike model uses nine parameters that depend on the type of soil, the depth, the characteristics of the root zone, etc. [19]. However, these parameters are not present in the case of the study as in this article, so the trial-and-error method can be adapted to optimize these parameters and obtain the best possible values for them. Table 1 shows the basic parameters of the MIKE 11 NAM model.

Table 1. Basic parameters of MIKE 11 NAM model [21]

Parameter	Description
U_{max}	The upper limit of the amount of water in the surface water storage reservoir. It is the water content in interception storage, depression storage, and surface storage reservoirs. It is continuously lost to evaporation, interflow, and infiltration. The typical values of U_{max} are in the range of 10-20 mm
L_{max}	Maximum water content in the lower zone storage. It represents soil moisture below the surface from which plants take water for transpiration. As a rule, U = 0.1 L where L is in the range of 100-300 mm
CQOF	Overland flow runoff coefficient. CQOF values are in the range of 0 and I and determine the distribution of excess rainfall between the overland flow and infiltration

Continuation of table № 1

Parameter	Description
CK_{IF}	Time constant for the interflow from the surface storage reservoir. CK, is the dominant routing parameter of the interflow because CK_{IF}>CK_{12}. CKIF values are in the range of 500-1,000 hours
CK_{12}	Time constant for overland flow and interflow routing. The overland flow and the interflow are routed through two successive linear reservoirs with time constants CK_{12} Typical values are in the range of 3 48hours
TOF, TIF, TG	Threshold values for overland flow, interflow and groundwater recharge, respectively. The flow is only generated if the relative moisture content in the lower storage zone is above the threshold value. Their values are in the range of 0-1
CK_{BF}	Time constant for baseflow routing. The baseflow from the groundwater storage reservoir is generated using a linear reservoir model with time constant CK_{BF}. CK_{BF} values being in the range of 500 5.000 hours

Building a Mike model depends on three types of required data which consist of setup parameters, model parameters, meteorological data, and streamflow data for calibration of the model [25].

3 Results and Discussion

3.1 Artificial neural networks

Initially, the necessary data were collected for the inputs of the artificial neural networks, which are the surface runoff at Al-Amiri station at the time (t). The surface runoff at Al-Jawadiya station at the time (t-1), corresponding to the outputs of the target values, which are the runoff at Al-Jawadiya station at the time (t), then these data were measured and divided into three datasets, with 70 percent for the train dataset, 15 percent for the validation dataset, and 15 percent for the test dataset. The MATLAB program prepared the code for building and training neural networks. Many artificial neural networks have been built using various training algorithms, activation functions, and the number of neurons in the hidden layer. These networks were trained with 1000 iterative cycles, and correlation coefficients and root mean square errors were used to compare different models and choose the best and most accurate results. Table 2 shows the results of the best-obtained artificial neural networks

Table 2. Table presents correlation coefficient (R) values and root mean square error (RMSE) obtained by best ANNs models.

№	Network architecture	Train		Validation		Test	
		R %	RMSE m^3/sec	R %	RMSE m^3/sec	R %	RMSE m^3/sec
(A)	2-12-1	88.941	1.4833	93.986	0.8383	94.795	0.7331
B	2-18-1	89.022	1.4277	92.494	0.9683	92.311	0.8738
C	2-6-1	88.099	1.5455	93.595	0.9670	94.4158	0.9867
D	2-10-1	87.048	1.5783	91.756	0.9631	93.312	0.8619

As shown in the table, the network 2:12:1 is the best and gives values of root mean square errors equal to 1.4833 m^3/sec for the train dataset, 0.8383 m^3/sec for the verification dataset, and 0.7331 m^3/sec for the test dataset. Figure 2 compares the measured and estimated values of surface runoff using the network 2:12:1 during the verification and testing periods.

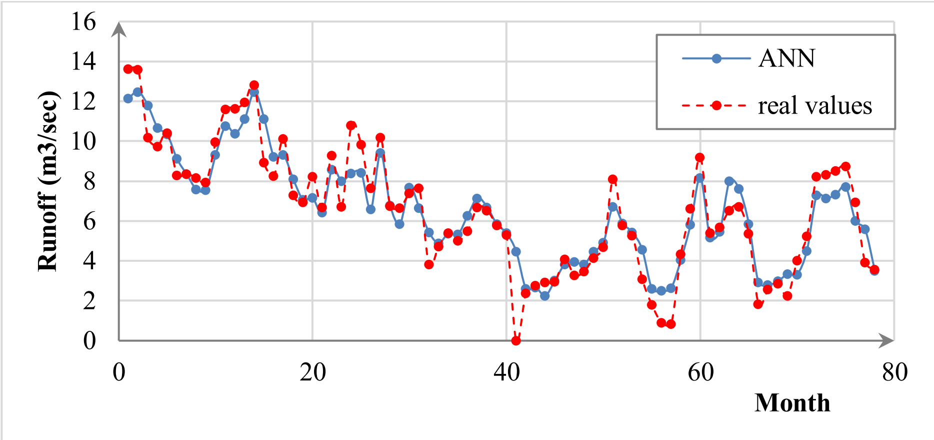

Fig. 2. Figure presents between measured values and estimated values of surface runoff using network 2:12:1 during verification and testing periods.

3.2 Fuzzy inference system

The data used in building and training fuzzy inference models are the same as the data used in building neural network models according to the same division ratios for the three datasets. Many fuzzy inference models have been built with varying the number and types of membership functions used. Artificial neural networks were relied upon in the training process of fuzzy inference models to speed up and improve the training process and obtain the best models. Table 3 shows the results of the best-obtained fuzzy models.

Table 3. Table presents results of best-obtained fuzzy models.

Number of membership functions	Type of membership functions	Train		Validation		Test	
		R %	RMSE m^3/sec	R %	RMSE m^3/sec	R %	RMSE m^3/sec
(4)	Gauss mf	91.49	1.2368	87.150	1.2770	94.789	0.7791
3	Gauss mf	91.13	1.2617	90.772	1.1222	95.230	0.8022
4	Tri mf	91.48	1.2372	88.336	1.2367	95.027	0.7928
3	Tri mf	90.99	1.2709	90.975	1.110	95.044	0.7813

As shown in the table, the model which contains four gauss membership functions is the best and gives values of root mean square errors equal to 1.2368 m^3/sec for the train dataset, 1.2770 m^3/sec for the verification dataset, and 0.7791 m^3/sec for the test dataset. Figure 3 compares the measured values and the estimated values of surface runoff using the FIS model during the verification and testing periods.

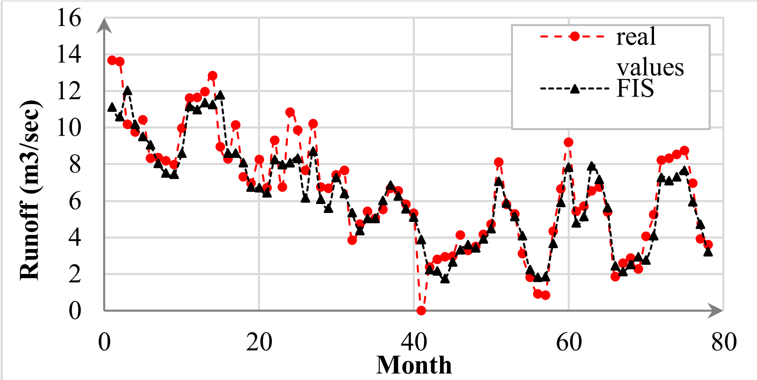

Fig. 3. Figure compares measured and estimated surface runoff values using the FIS model during verification and testing periods.

3.3 Autoregressive integrated moving average (ARIMA)

The data used to build ARIMA models differs slightly from the data of neural and fuzzy models because ARIMA modeling is based on a complete time series without any gaps. First, stability in variance, normal distribution, autocorrelation, and partial autocorrelation of the data were investigated. Then a large number of ARIMA models were built, with changing in all components, as well as with the effect of the seasonal components, and Table 4 shows the results of the best models obtained.

Table 4. Root mean square error (RMSE) obtained by the best ARIMA models.

Model	RMSE (m^3/sec)
$(2,1,1)\ (0,1,2)_{12}$	1.747
$(2,1,2)\ (1,1,1)_{12}$	1.758
$(3,1,2)\ (0,1,1)_{12}$	1.738
$(4,1,1)\ (0,1,1)_{12}$	**1.726**
$(4,1,1)\ (0,1,2)_{12}$	1.745

As shown in the table, the model $(4,1,1)\ (0,1,1)_{12}$ is the best with a value of root mean square errors equal to 1.726 m^3/sec, and it includes the effect of seasonality on the time series, and Figure 4 shows a comparison between the measured values and the value estimated by the model $(4,1,1)\ (0,1,1)_{12}$.

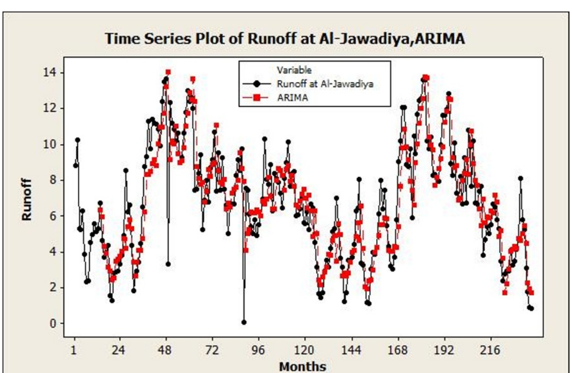

Fig. 4. Comparison between measured values and values estimated by ARIMA model

By comparing the results of the three models, we find a preference for the artificial neural network models in terms of evaluation parameters

3.4 Mike 11 NAM

After selecting the artificial neural networks as the best model for estimating the missing runoff values in the study area, they were used to fill the gaps in the runoff time series and then used in MIKE. Because of the limited data available in the study area, the trial-and-error method was used to calculate the model's basic parameters with 8000 iterations to reach the optimal values. Table 5 shows the obtained optimal values for the model's basic parameters.

Table 5. The obtained optimal values for the model's basic parameters

Parameter	Value	Parameter	Value	Parameter	Value
U_{max}	10	CK_{IF}	911.524	TIF	0
L_{max}	100	CK1	10	TG	0
CQOF	0.963	TOF	0.988	CK_{BF}	4000

Then the measured and estimated surface runoff values were represented for comparison. Figure 5 shows the comparison between the measured values and the estimated values, while Figure 6 shows the comparison between the accumulated values.

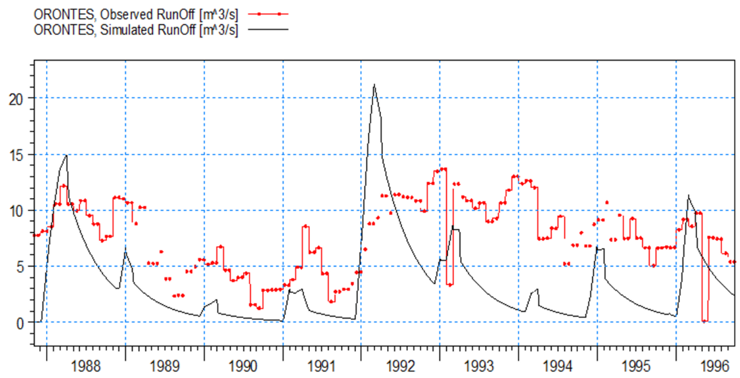

Fig. 5. Measured and estimated runoff data

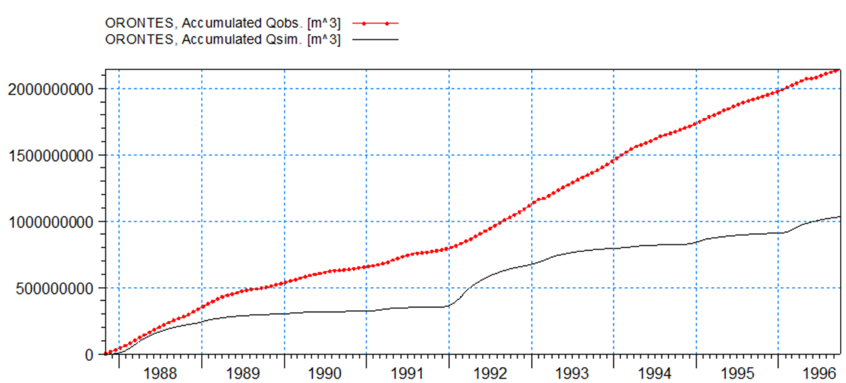

Fig. 6. Measured and estimated accumulated runoff data

By comparison, the results are not good, and the model could not estimate the surface runoff values in the study area, as the root mean square error value reached 5.482 m^3/sec. The error value given by the model is not acceptable, and this is due to the lack of available data, as we need to increase the quality of the available data in addition to the length and accuracy of the available time series.

4 Conclusions

In this study, the possibility of using the MIKE 11-NAM Model for runoff modeling using artificial neural network (ANN), fuzzy inference system (FIS), and autoregressive integrated moving average (ARIMA) methods at Al-Jawadiyah hydrometric station on the Orontes River in Syria was verified. MATLAB was used to build neural and fuzzy models, where many models were built with the change in all parameters, functions, and algorithms that can be used, and the Minitab was used to build ARIMA models. Many models were prepared with the addition of seasonal effect, and the comparison results showed an advantage for artificial neural network models in terms of evaluation parameters. After that, the artificial neural network models were adopted in the process of filling the gaps in the time series of surface runoff in the study area to be used in the Mike program for modeling the runoff and through the method of trial and error with a high number of iterative cycles, model parameters were calculated and runoff values estimated. Still, the results were not good and there were significant differences between the measured values and the values simulated by the model due to the significant lack of available data. This study recommends using machine learning models in the field of estimation and prediction of hydrological parameters and comparison with traditional and statistical methods to reach the most accurate possible models.

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