Evaluating performance of MIKE 11 NAM model for runoff modeling on upper basin of Orontes River in Syria

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Abstract. This study aims to evaluate the performance of MIKE 11 NAM model for runoff modeling in case of lack of data as a case study on the upper basin of the Orontes River in Syria. In this study, MIKE 11 NAM was relied on as one of the most important hydrological analysis and modeling models. At first, the data used was processed, and the gaps in the time series were filled; then, the data was entered into the model, and the trial-and-error method was used to adopt the model parameters that give the best results. By comparing the results with the measured real values of the flow, it was found that there are large errors and unreliability of the model, which is due to the lack and unreliability of the available data, and this is consistent with the results of other studies conducted in similar cases using the same model. Therefore, this study recommends expanding the possibility of using Mike's model and other models for hydrological analysis and modeling, especially in case of lack of data, because of this great importance in the preparation of hydrological studies, water balance studies, and sustainable development of water resources in the studied area.

1 Introduction

The hydrological analysis of the water basins is an important step in all studies of runoff, as it is one of the most important water resources and the process of analysis and modeling of this resource helps in planning the water resources in the study area and its sustainable development.

This topic has attracted the attention of many researchers, as several researchers have resorted to using artificial intelligence models such as artificial neural networks and fuzzy inference models to estimate and predict runoff values, and they have obtained good results [1-8]. While others used the HMS model, and the results showed high correlation values [9-13]. In other studies, the ARC SWAT program was used to model surface runoff, and they obtained good evaluation coefficients for the results during the verification and testing stages [14, 15].

Also, many researchers have used the MIKE model to model runoff, where (Kok *et al.,* 2019) used MIKE URBAN to evaluate the performance of Active, Beautiful and Clean (ABC) on stormwater runoff management in a case study in a residential estate in

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Singapore and Calibration results showed an overall good fit between the measured data and the simulated results based on three goodness-of-fit stats. [16]. On the other hand, (Ghebrehiwot and Kozlov 2020) assess the applicability of climate reanalysis data to rainfall-runoff modeling in the poorly studied river basin in Eritrea using MIKE 11 NAM, and the results suggest that a considerable overestimation of precipitation in the reanalysis data set [17]. In the study of (Aredo *et al.,* 2021), the rainfall-runoff modeling was carried out using MIKE 11 NAM model at the Shaya catchment in Ethiopia, and the results revealed that there is a very good agreement between the observed and computed runoff [18]. Also, (Ghosh *et al.,* 2022) use the MIKE NAM model in the MIKE HYDRO RIVER environment to integrate rainfall-runoff analysis with the hydrodynamic condition through the food region encompassing the Bhagirathi–Hooghly River, and the calibrated result creates a fairly good relationship with the simulated data [19]. And (Shamsudin and Hashim 2022) used MIKE11 NAM model for the estimation of rainfall runoff in Layang river; the reliability of MIKE11 NAM was evaluated based on the Efficiency Index (EI) and Root Mean Square Error (RMSE). The EI and RMSE obtained during this study are 0.75 and 0.08, respectively [20].

In the study area, many studies were conducted to model the surface runoff and rainfall runoff relationship modeling [21,22], but no research was conducted using the MIKE 11 NAM model. So, this study aims to verify the possibility of using the MIKE 11 NAM model to surface runoff modeling in case of lack of data as a case study on the upper basin of the Orontes River in Syria.

The methods and materials used will be discussed, including the study area and the available data in it, in addition to an explanation of the model used, and then a presentation of the results of using the model and comparing these results with the results of other studies, discussing of these results and presenting the possibility for developing of this research and recommendations in this field.

2 Methods

2.1 Study site & data availability

This study focuses on the upper Asi River basin, between the Lebanese border and Lake Qattinah. The runoff data were used from al-Amiri station on the Syrian-Lebanese border and Al-Jawadiyah station on the entrance to Lake Qattinah, and the rainfall and evaporation data from the Qatina meteorological station; figure 1 shows the location of the study area.

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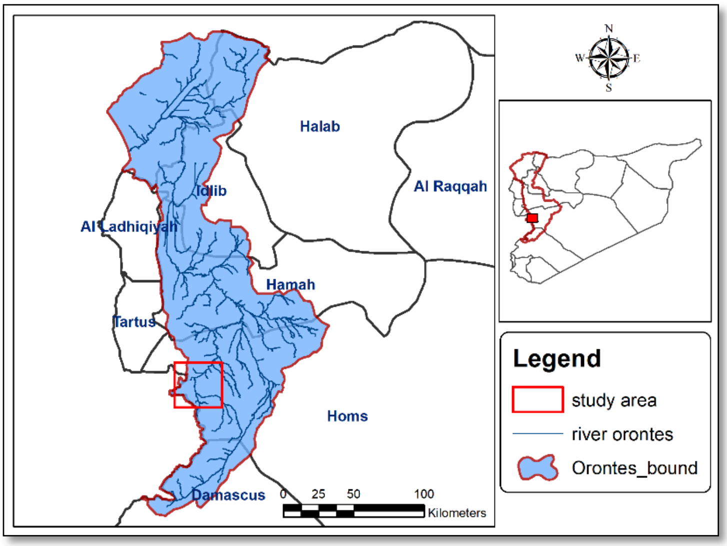

Fig. 1. Upper ASI-ORONTES river basin.

2.2 Mike 11 NAM

The model of MIKE 11 NAM simulates the rainfall-runoff processes within a catchment, and this model forms a part of the rainfall-runoff component in the MIKE 11 river [18]. Figure 2 shows a schematic representation of the NAM model structure.

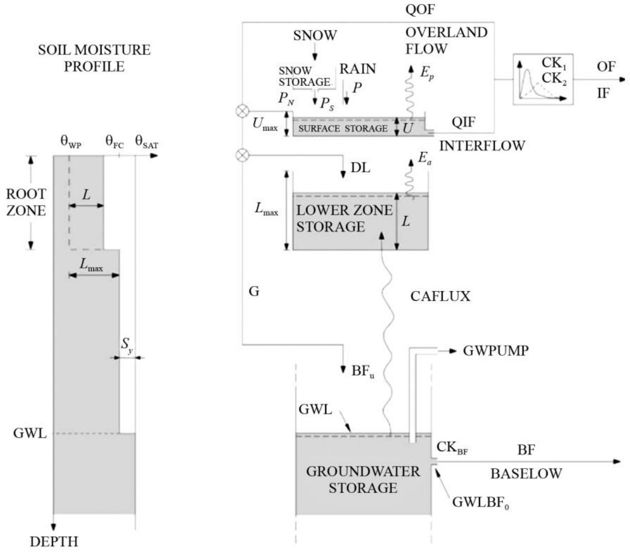

Fig. 2. Structure of model MIKE NAM [17].

MIKE 11 NAM model was calibrated using nine parameters, which relate to soil, root area of plants, and other factors [18], and table 1 shows MIKE 11 NAM model's basic parameters.

Table 1. MIKE 11 NAM model's basic parameters [17].

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, $U_{max} = 0.1\ L_{max}$ where L_{max} is in the range of 100–300 mm
$CQOF$	Overland flow runoff coefficient. $CQOF$ values are in the range of 0 and 1 and determine the distribution of excess rainfall between the overland flow and infiltration
CK_{IF}	Time constant for the interflow from the surface storage reservoir. CK_{IF} is the dominant routing parameter of the interflow because $CK_{IF} > CK_{12}$. CK_{IF} 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 3–48 hours
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

To build a MIKE11 NAM model, there is a set of data required, which consists of Setup parameters (like catchment area, topography, and soil properties), Model parameters (like time constants and threshold values for routing of overland flow, interflow, and baseflow), meteorological data (like as precipitation and potential evaporation) and streamflow data for the model calibration [20].

The comparison between the results was made by using root mean square error (RMSE), which is defined as Eq. (1) [19]:

$$RMSE = \left[\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}\right]^{0.5} \quad (1)$$

where n is the number of observations, y_i is the estimated using the artificial neural networks, $\hat{y}_i$ is the observed runoff, $\bar{y}$ and $\bar{\hat{y}}$ are the average value for y_i and $\hat{y}_i$.

3 Results

At first, statistical processing of the available data was performed, then the gaps in the data series were filled using artificial intelligence models such as artificial neural networks models and fuzzy inference models. And figure 3 shows the runoff data at Al-Jawadiyah station within the working environment of the MIKE model.

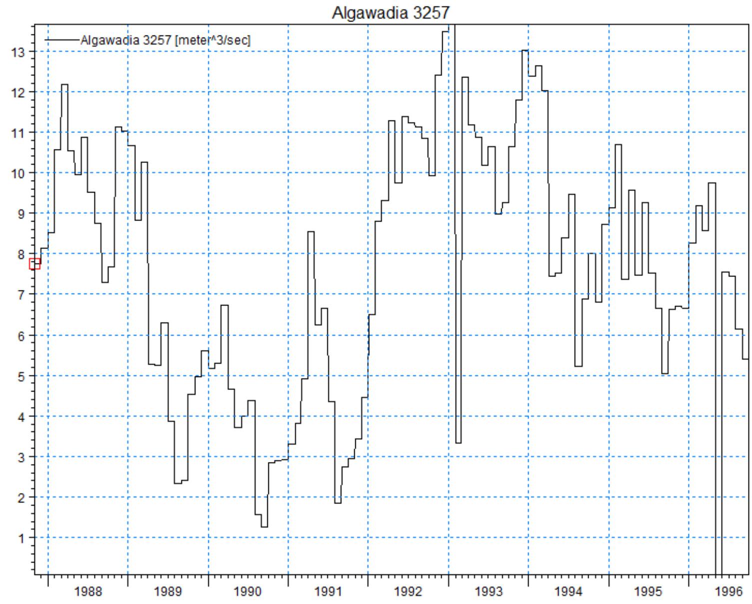

Fig. 3. Runoff data at Al-Jawadiyah station.

It relied on the principle of trying and reducing errors and repetition in the calculation to obtain the optimal model and examples of model evaluating coefficients. Eight thousand iterative cycles were performed to obtain the best model parameters, and table 2 shows the Model's basic parameters for the ASI-ORONTES river basin.

Table 2. Model's basic parameters for the ASI-ORONTES river basin.

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 time series of observed runoff data and the model's simulated values were represented to compare the results and verify the degree of agreement between them. Figure 4 shows a comparison between observed and simulated runoff data, and figure 5 shows a comparison between observed and simulated accumulated runoff data.

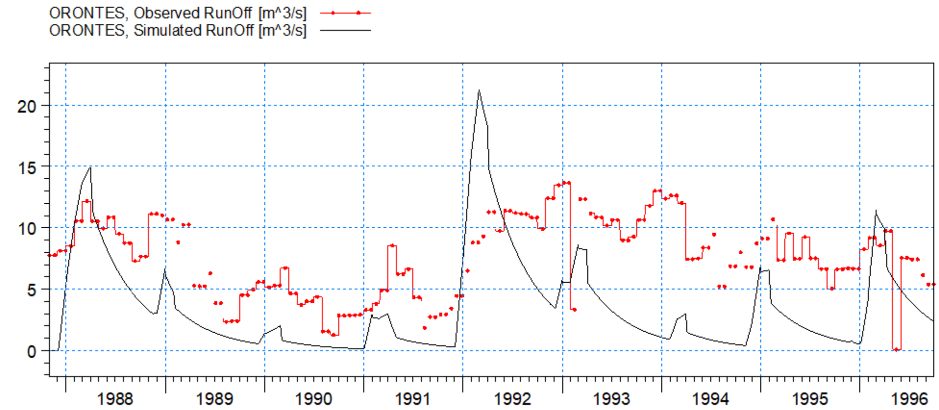

Fig. 4. Observed and simulated runoff data.

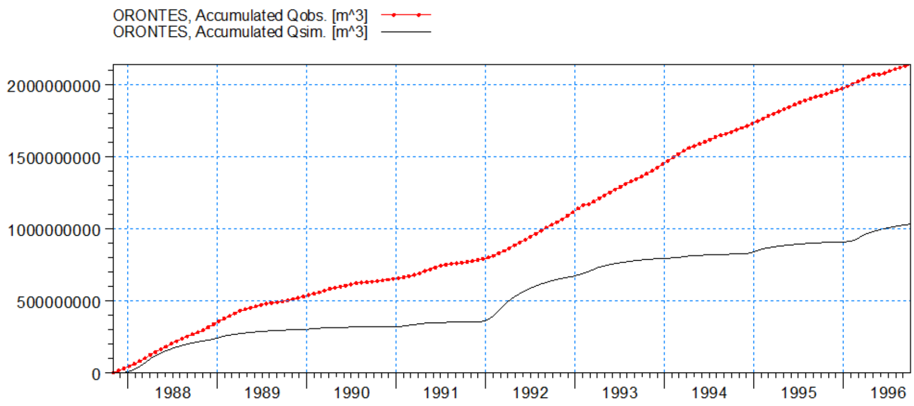

Fig. 5. Observed and simulated accumulated runoff data.

4 Discussion

By comparing observed and simulated runoff data, we find a great disparity between the results, as the value of the root mean squares of errors reached 5.482 m^3/sec, which is a high and not good value. The reason for this is due to the lack of available data, as it turns out that according to this model, we will need better data in terms of quantity or accuracy, which means that the available database includes data on a larger area and includes a larger period with the least number of missing data in addition to data of soil and vegetation cover with acceptable accuracy.

Returning to the results of previous studies and comparing with them, we find that this model has also given unacceptable results, as is the case in the study conducted by (Ghebrehiwot and Kozlov 2020) in the case of poorly studied river basins [17], which requires the use of a larger amount of data to take advantage of the capabilities of the model.

5 Conclusions

This study verified the possibility of using the Mike 11 NAM model to surface runoff modeling in case of lack of data as a case study on the upper basin of the Orontes River in Syria. The results showed the lack of reliability of this model according to the used data in the event of a lack of data in the study area. Therefore, this study recommends continuing researching the possibility of conducting hydrological analyzes and modeling in light of the lack of data, as is the case resulting from crises and wars, and trying to use remote sensing and satellite data in this field, in addition to verifying the possibility of using other models for hydrological modeling and comparing the results, because of its great importance in the possibility of conducting water budget studies and managing water resources.

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