مجلة جامعة طرطوس للبحوث والدراسات العلمية _ سلسلة العلوم الهندسية المجلد (10) العدد (9) 2026
Tartous University Journal for Research and Scientific Studies - engineering Sciences Series Vol. (10) No. (9) 2026

Simulation of the rainfall-runoff relationshıp in the AL-Kabir AL-Shamali river basin (Latakia Governorate) usıng artifıcial neural networks

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(Received 16/2/2026. Accepted 6/5/2026)

□ ABSTRACT □

This study aimed to simulate the dynamic and non-linear rainfall-runoff relationship in the Al-Kabir Al-Shamali River Basin (Latakia Governorate) for the period (2001-2011) using Multilayer Perceptron (MLP) artificial neural networks. The methodology relied on monthly hydroclimatic data (precipitation, potential evapotranspiration, runoff) to develop five predictive models. These models were trained using the Levenberg-Marquardt backpropagation algorithm as an optimization tool, and their performance was evaluated using the correlation coefficient (r) and the mean squared error (MSE). The results demonstrated the superiority of the ANN-4 model with a (5-15-1) architectural structure over the other models, achieving the highest predictive accuracy. The model recorded correlation coefficients of 0.94, 0.97, and 0.91 during the training, validation, and testing phases, respectively, while attaining the lowest mean squared error (MSE = 0.10) in both the validation and testi000000 ng phases. However, the results highlighted the model's limitation in accurately simulating peak flows. Despite its constraint in modeling peak events, the developed ANN-4 model proves to be an efficient, robust, and applicable predictive tool to support sustainable water resources planning and management processes in the studied basin.

Keywords: Rainfall-Runoff Modeling, Artificial Neural Networks (ANN), Multilayer Perceptron (MLP), Al-Kabir Al-Shamali River Basin.

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محاكاة العلاقة بين الهطول والجريان السطحي في حوض نهر الكبير الشمالي (محافظة اللاذقية) باستخدام الشبكات العصبية الاصطناعية

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(تاريخ الإيداع 2026/2/16 . قُبِل للنشر في 2026/5/6)

ملخّص

هدفت هذه الدراسة إلى محاكاة العلاقة الديناميكية وغير الخطية بين الهطول والجريان السطحي في حوض نهر الكبير الشمالي (محافظة اللاذقية) للفترة 2001–2011، باستخدام الشبكات العصبية الاصطناعية متعددة الطبقات (MLP). اعتمد المنهج على بيانات هيدرومناخية شهرية (هطول، تبخر–نتح كامن، جريان سطحي) لتطوير خمسة نماذج تنبؤية. تمّ تدريب هذه النماذج باستخدام خوارزمية ليفينبرغ–ماركاردت للانتشار العكسي كأداة تحسين، وتقييم أدائها باستخدام معامل الارتباط (r) ومتوسط مربع الخطأ (MSE). أظهرت النتائج تفوق النموذج ANN-4 ذي البنية المعمارية (1–15–5) على النماذج الأخرى، حيث حقق أعلى دقة تنبؤية. سجل هذا النموذج معاملات ارتباط بلغت 0.94 و0.97 و0.91 في مراحل التدريب والتحقق والاختبار على التوالي، مع تحقيق أدنى قيمة لمتوسط مربع الخطأ (0.10 = MSE) في مرحلتي التحقق والاختبار. ومع ذلك، أبرزت النتائج محدودية النموذج في محاكاة ذروات التدفق بدقة. وعلى الرغم من هذه المحدودية في نمذجة الحالات القصوى، يثبت النموذج المُطور (ANN-4) كفاءته كأداة تنبؤية قوية وعملية لدعم عمليات التخطيط والإدارة المستدامة للموارد المائية في الحوض قيد الدراسة.

الكلمات المفتاحية: نمذجة الهطول–الجريان السطحي، الشبكات العصبية الاصطناعية (ANN)، البيرسيبترون متعدد الطبقات (MLP)، حوض نهر الكبير الشمالي..

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1- Introduction

Accurately modeling the rainfall-runoff (R-R) relationship is a fundamental challenge in hydrology due to the inherent complexity of the process. This complexity arises from the pronounced spatial and temporal variability in watershed characteristics and precipitation patterns, along with the multitude of interacting physical variables involved (Senthil Kumar *et al*., 2005). Nevertheless, reliable runoff simulation and prediction are essential for effective urban planning, land-use management, flood control, and sustainable water resource management, as well as for mitigating drought impacts (Nourani *et al*., 2009; Liu *et al*., 2015; Shi *et al*., 2021). In response to the stochastic, non-linear nature of hydrological systems, a diverse range of modeling approaches has been developed (Zeng *et al*., 2016; Xue *et al*., 2018; Nonki *et al*., 2021), attracting significant research interest globally (Döll and Schmied, 2012; Gao *et al*., 2014). This interest is further intensified by climate change, which amplifies risks associated with both floods and water scarcity (Hanasaki *et al*., 2013; Schewe *et al*., 2014; Arnell and Lloyd-Hughes, 2014; Gosling and Arnell 2016).

R-R models are generally classified into three categories: physically based, conceptual, and data-driven (ASCE, 2000; Kratzert *et al*., 2018; Roy *et al*., 2021). While physically based and conceptual models rely on equations derived from an understanding of hydrological processes, data-driven techniques have gained substantial prominence (Zhang and Savenije, 2005; Lü *et al*., 2013; Kan *et al*., 2016; Özdoğan-Sarıkoç and Dadaser-Celik, 2024). Their appeal lies in their ability to discern complex, non-linear patterns directly from observational data without requiring an explicit mathematical description of the underlying physical mechanisms (Sahoo *et al*., 2020; Achite *et al*., 2022; Parisouj *et al*., 2022; Gichamo *et al*., 2024). Among data-driven methods, Artificial Neural Networks (ANNs)—a machine learning tool inspired by biological neural networks—have emerged as particularly powerful. ANNs are recognized for their self-adaptive learning and exceptional capability in modeling non-linear dynamics, consistently demonstrating superior performance to traditional methods in various hydrological applications (Dawson and Wilby, 1998; Daliakopoulos and Tsanis, 2016; Lees *et al*., 2021).

Since the 1990s, ANNs have been widely adopted in hydrology for R-R modeling, river flow and precipitation forecasting, water quality assessment, and other water resource challenges (ASCE, 2000; Govindaraju and Rao, 2000; Tanty and Desmukh, 2015). Regionally, research in Syria over the past decade has also shown successful ANN applications across multiple hydrological domains, including R-R modeling (Ammar and Olayan, 2014; Hamdan *et al*., 2017; Ammar and Hossein, 2019), streamflow forecasting (Ammar and Haider, 2017), rainfall prediction (Ammar and Aldarwesh, 2019), evapotranspiration estimation (Haider and Ammar, 2015; Ammar and Jouny, 2019), and the infilling of missing precipitation records (Ammar and Aldarwesh, 2019, Ammar and Aldarwesh, 2019). Despite these advances, there remains a need to apply and validate such advanced modeling frameworks for specific critical basins under increasing pressure.

This study focuses on the Al-Kabir Al-Shamali River, the principal watercourse on the Syrian coast and a vital source for irrigation and potable water. This crucial resource faces mounting stress from population growth and intensive socio-economic activities. To address the pressing need for advanced predictive tools, this research employs an ANN methodology to model the monthly R-R relationship in this basin for the period 2001–2011. The primary objective is to develop a robust and accurate model that can contribute to sustainable water management and serve as a reliable tool for flood prediction and impact mitigation in the region.

2- Materials and Methods

2-1- Study Area and Data

This study focuses on the upper watershed of the Al-Kabir Al-Shamali River, located within the Syrian coastal basin and covering an area of approximately 632 km². The study area is bounded by longitudes 35°45'40"E to 36°15'05"E and latitudes 35°28'30"N to 35°59'00"N (Figure 1). The region exhibits a Mediterranean climate characterized by cold, wet winters and moderate summers, with spatially variable precipitation patterns. Mean annual precipitation and temperature are 1064.1 mm and 16.1 °C, respectively. Geologically, the catchment comprises varied sedimentary formations. Impermeable green rock formations dominate the northwestern sector, while limestone lithologies prevail throughout much of the remaining area (*Ministry of State for Environment Affairs* and General Organization of Remote Sensing Damascus, 2017). The basin supports dense vegetation and diverse agricultural land use, including field crops, vegetables, and extensive orchards (e.g., olives, almonds, and apple trees), alongside natural forest cover (Al-Masri *et al*., 2010).

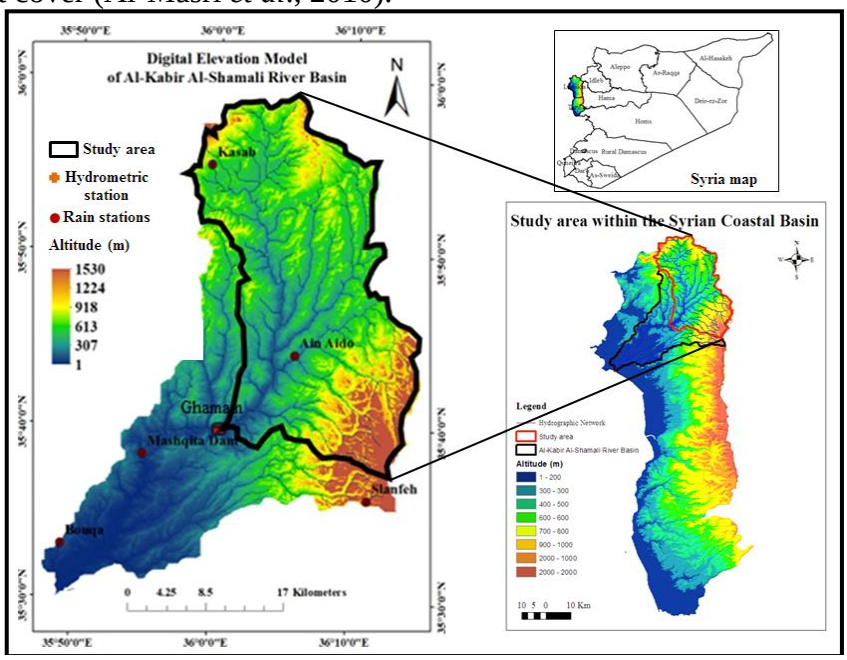


Fig. 1: Study area with gauge stations in the Al-Kabir Al-Shamali River basin.

This study utilized monthly hydrological and climatic data—specifically precipitation, air temperature, and river discharge—from the period 2001–2011 to develop a rainfall-runoff (R-R) model. Precipitation and temperature data were obtained from three meteorological stations: Kassab, Ain Aido, and Salnfa. The corresponding river discharge data were collected from the Ghamam gauging station, located in the middle reaches of the Al-Kabir Al-Shamali River. All datasets were provided by the Directorates of Water Resources and Agriculture in the Latakia Governorate. The spatial locations of these stations are presented in Figure 1.

Monthly Potential Evapotranspiration (PET) was calculated using the Blaney-Criddle equation (Eq. 1) (Doorenbos, and Pruitt, 1977).

$$PET = p\,(0.46\,T_{mean} + 8.13) \quad (1)$$

Where PET is the monthly Potential Evapotranspiration (mm/day), p is the monthly mean daily percentage of annual daytime hours, and T_mean is the mean daily air temperature (°C).

To obtain areal estimates for the entire catchment, point measurements of precipitation and PET were spatially interpolated using the Thiessen polygon method within a Geographic Information System (ArcGIS 10.3). The key descriptive statistics for the resulting catchment-wide meteorological and streamflow dataset (2001–2011) are summarized in Table 1.

Table 1: Descriptive statistics of the meteorological and streamflow data.

Statistical Parameter	Areal Rainfall (mm)	Potential Evapotranspiration (mm)	Discharge (m^3/s)
Mean	1041.2	1567.1	80.2
Minimum	796.8	1460.6	12.7
Maximum	1535.8	1616.5	240.9
Standard Deviation	224.7	41.7	73.1

2-2- Artificial Neural Networks (ANNs)

An Artificial Neural Network (ANN) is a computational model designed to process information through a network of interconnected units, drawing inspiration from the structure and function of biological neural networks (Haykin, 1999). At its core, an ANN comprises a collection of simple processing elements—artificial neurons—linked by connections with adjustable strengths, known as synaptic weights (Hajian, & Styles, 2018). This architecture enables a form of self-learning, wherein knowledge derived from data is encoded within the pattern of these weights, analogous to adaptive learning in biological systems (Doorenbos and Pruitt, 1977; Gichamo *et al*., 2024).

Since their foundational conception by McCulloch and Pitts in 1943, ANNs have evolved into versatile tools capable of modeling complex, non-linear relationships. They are characterized by diverse architectural designs, each suited to different applications. For this study, the Multilayer Perceptron (MLP) model was selected, as it is one of the most widely used and validated architectures in hydrological modeling (Haykin, 1999; Parisouj *et al*., 2022). The MLP is a class of feedforward neural network, meaning information flows in a single direction from the input layer, through one or more intermediate "hidden" layers, to the output layer, without cyclical feedback. The network is trained using the backpropagation algorithm to iteratively adjust its internal weights (Parisouj *et al*., 2022). A schematic of a typical MLP with one hidden layer is shown in Figure 2. This sequential structure—input layer, hidden layer(s), output layer—allows the MLP to approximate intricate, non-linear mappings between input and output variables. The mathematical expression representing the final output of a three-layer MLP network is given in Equation 2 (Hajian & Styles, 2018; Leahy, and Corcoran, 2008).

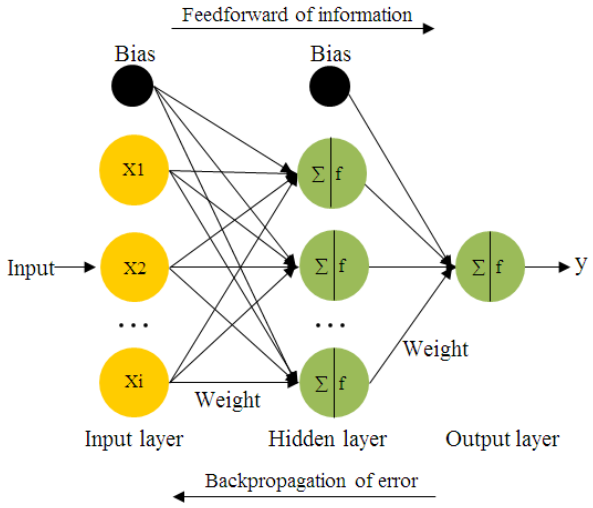


Fig. 2: Architecture of a MLP neural network with a single hidden layer.

$$\hat{y}_k = f_2\left(\sum_{j=1}^{n} w_{kj} f_1\left(\sum_{i=1}^{m} w_{ji} x_i + b_j\right) + b_k\right) \quad (2)$$

Where $\hat{y}_k$ is the *k*-th predicted output value, f_2 is the activation function for the output layer neuron, *n* is the number of neurons in the output layer, w_{kj} is the weight connecting the *j*-th neuron in the hidden layer to the *k*-th neuron in the output layer, f_1 is the activation function for the hidden layer neuron, *m* is the number of neurons in the hidden layer, w_{ji} is the weight connecting the *i*-th neuron in the input layer to the *j*-th neuron in the hidden layer, x_i is the *i*-th input variable, b_j is the bias for the *j*-th hidden neuron, b_k is the bias for the *k*-th output neuron.

2-3- Development of the ANN Model

ANN modeling was conducted in MATLAB R2015a (v8.5) using the Neural Fitting tool (Nftool). All input variables were standardized as a key preprocessing step by centering (subtracting the mean) and scaling (dividing by the standard deviation), as detailed in Equation 3.

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (3)$$

where μ is the arithmetic mean and σ is the standard deviation of the dataset.

Prior to model training, the complete dataset of 130 monthly records was randomly partitioned within the software environment into three subsets: 70% for training (91 samples), 15% for validation (20 samples), and the remaining 15% for testing (20 samples).

The predictive accuracy of ANN models is contingent upon three principal design criteria: the selection of pertinent input variables, the choice of an optimal training algorithm, and the determination of network architecture (Lee *et al*., 2018). Guided by this framework, six distinct network models, each featuring a single hidden layer, were developed. These models varied exclusively in the number and composition of independent hydroclimatic variables constituting their input layer. The candidate input variables encompassed monthly precipitation (P), potential evapotranspiration (ETP)—including their antecedent values—as well as streamflow (Q) with appropriate time lags,

as specified in Table 2. All models were configured with a single output neuron representing concurrent streamflow.

The architecture of each model was optimized by empirically determining the number of neurons in the single hidden layer. This was achieved through an iterative optimization process, testing configurations within a range of 5 to 15 neurons. Network training was conducted using the Levenberg–Marquardt backpropagation algorithm, selected for its computational efficiency and rapid convergence properties. Training was constrained to a maximum of 1000 epochs. Model performance and training efficacy were assessed by iteratively comparing predicted outputs against observed values. The backpropagation procedure continued until the validation error met pre-defined convergence criteria, thereby finalizing the network weights. For the activation functions, the hyperbolic tangent sigmoid (tansig) was applied to all neurons in the hidden layer (Eq. 4), while a linear (purelin) function was employed for the output neuron (Eq. 5).

$$f(x) = x \tag{4}$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{5}$$

In these equations, x represents the weighted sum of inputs to the neuron, also referred to as the net input signal, calculated as:

$$x = \sum_{i=1}^{m} w_{ji} x_i + b_j \tag{6}$$

where w_{ji} is the weight connecting the i-th input to the j-th hidden neuron, x_i is the i-th input, and b_j is the bias for the j-th hidden neuron.

Table (2): Input configurations for the proposed ANN models.

Model	Inputs	Outputs
ANN-1	P(t), ETP(t)	Q(t)
ANN-2	P(t), ETP(t), Q(t-1)	Q(t)
ANN-3	P(t), P(t-1), ETP(t), ETP (t-1)	Q(t)
ANN-4	P(t), P(t-1), ETP(t), ETP (t-1), Q(t-1)	Q(t)
ANN-5	P(t), P(t-1), P(t-2), ETP(t), ETP (t-1), ETP (t-2)	Q(t)
ANN-6	P(t), P(t-1), P(t-2), ETP(t), ETP (t-1), ETP (t-2), Q(t-1), Q(t-2)	Q(t)

2-4- Performance Evaluation: Statistical and Visual Assessment

The predictive efficacy of the developed ANN models was rigorously assessed using established quantitative statistical metrics, in line with standard hydrological modeling practices (Chekho, 2003; Boskidis *et al*., 2012; Aïzansi *et al*., 2018; Wahidna *et al*., 2024). The evaluation was based on two primary goodness-of-fit indicators.

1. Mean Squared Error (MSE): This metric measures the average squared deviation between observed (Q_i) and model-predicted ($\hat{Q}_i$) streamflow values. A lower MSE indicates higher model accuracy by heavily penalizing larger errors. It is calculated as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Q_i - \hat{Q}_i\right)^2 \tag{7}$$

2. Coefficient of correlation (r): This statistic quantifies the strength of the linear relationship between observed and predicted values. It ranges from -1 to 1, where values closer to 1 or -1 indicate a stronger linear association, and a value of 1 represents perfect positive correlation. It is defined as:

$$r = \frac{\sum_{i=1}^{n}(Q_i - \bar{Q})\left(\hat{Q}_i - \bar{\hat{Q}}\right)}{\sqrt{\sum_{i=1}^{n}(Q_i - \bar{Q})^2 \sum_{i=1}^{n}\left(\hat{Q}_i - \bar{\hat{Q}}\right)^2}} \quad (8)$$

Where Q_i is the observed streamflow, $\hat{Q}_i$ is the predicted streamflow, $\bar{Q}$ and $\bar{\hat{Q}}$ are their respective arithmetic means, and *n* is the total sample size.

In addition to quantitative metrics, visual diagnostic provide an essential complementary assessment of model performance. Scatter plots of observed versus predicted values were employed for this purpose. In an optimal model, data points align closely with the 1:1 line of perfect agreement (y = x). The clustering of points around this line offers an intuitive visual confirmation of the model's predictive reliability and accuracy.

3- Results and Discussion

Determining the optimal architecture for an ANN—encompassing the number of layers and neurons, activation functions, and learning algorithms—remains a major challenge in supervised learning, as no universal design heuristic exists. This study investigates the impact of incorporating temporal lags on the predictive accuracy of ANN models for simulating surface runoff (Q). The performance evaluation, summarized in Table 3, reveals a clear progression. The baseline model (ANN-1), which used only concurrent-month precipitation (P) and potential evapotranspiration (ETP), demonstrated limited capability. It yielded correlation coefficients (r) of 0.69, 0.62, and 0.63 during the training, validation, and testing phases, respectively. This underscores the insufficiency of instantaneous climatic data alone for accurate monthly runoff estimation. In contrast, the integration of temporally lagged variables substantially enhanced model performance. The superior configuration, ANN-4, employs a 5-15-1 architecture (Figure 3). Its input layer incorporates five variables: current and preceding month values for both precipitation (P(t), P(t-1)) and potential evapotranspiration (ETP(t), ETP(t-1)), along with the antecedent runoff (Q(t-1)). The network features a single hidden layer with 15 neurons and a single-neuron output layer predicting (Q(t)). The ANN-4 model achieved markedly superior results, with correlation coefficients of 0.974 and 0.919 during the validation and testing phases, respectively, and a significantly lower Mean Squared Error (MSE) of 0.10.

Table 3: Performance of ANN models in training, validation, and testing sets.

Model	Network Architecture	Training		Validation		Testing	
		r	MSE	r	MSE	r	MSE
ANN-1	2-20-1	0.696	0.610	0.626	0.669	0.631	0.149
ANN-2	4-10-1	0.921	0.039	0.811	0.181	0.833	0.936
ANN-3	3-5-1	0.943	0.106	0.936	0.171	0.906	0.196
ANN-4	**5-15-1**	**0.949**	**0.088**	**0.974**	**0.101**	**0.919**	**0.103**
ANN-5	6-10-1	0.979	0.038	0.821	0.181	0.756	0.918

ANN-6	8-15-1	0.988	0.016	0.952	0.243	0.908	0.207

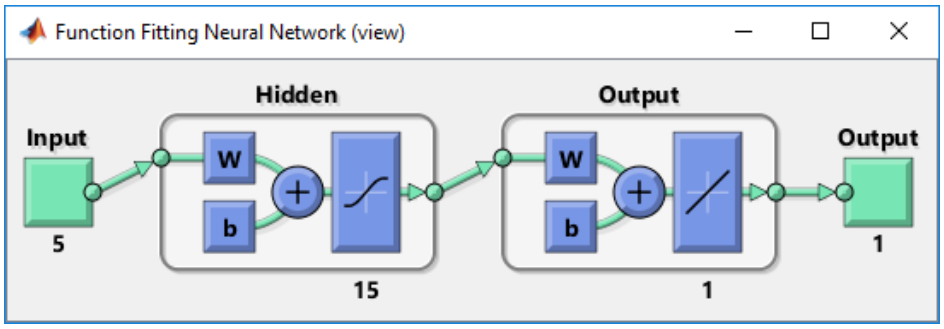


Fig. 3: Schematic architecture of the optimal ANN-4 model (5-15-1 configuration).

The predictive performance of the selected ANN-4 model is evaluated in Figure 4, which presents a scatter plot of predicted versus observed runoff values across all datasets. The model demonstrates strong agreement with measurements, as evidenced by correlation coefficients exceeding 0.91 for each subset (training, validation, and testing), confirming its high accuracy in simulating the hydrological data. The training dynamics are analyzed in Figure 5, which illustrates the progression of the Mean Squared Error (MSE) over successive epochs. While the training error showed a consistent decline, the validation error reached its minimum (0.10117) at epoch 5 before increasing thereafter. This pattern is characteristic of early-stage overfitting, where the model begins to lose generalizability. To preserve the model's generalizability, the training procedure was halted at this point, and the network parameters (weights and biases) corresponding to this optimal validation checkpoint were retained as the final model for all subsequent predictions. The distribution of the model's prediction residuals is shown in Figure 6. The residuals are predominantly clustered around zero within a narrow range of ±0.5, affirming the model's overall predictive efficiency. However, the presence of two notable outliers (1.74 and -1.05) warrants further investigation. A detailed examination of the specific conditions or potential data errors associated with these instances is recommended to strengthen the robustness of the conclusions and enhance the model's reliability for future applications.

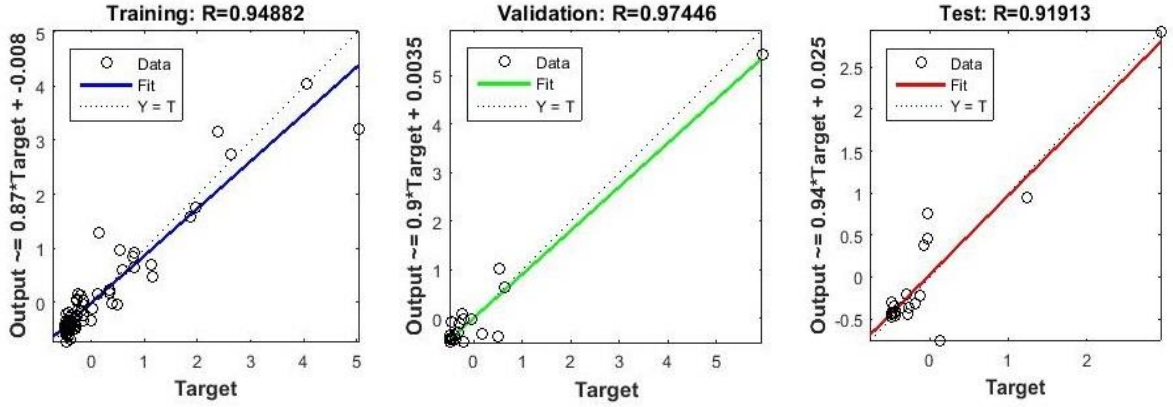


Fig. 4: Observed versus predicted monthly runoff from the optimal ANN-4 model for training, validation, and testing datasets.

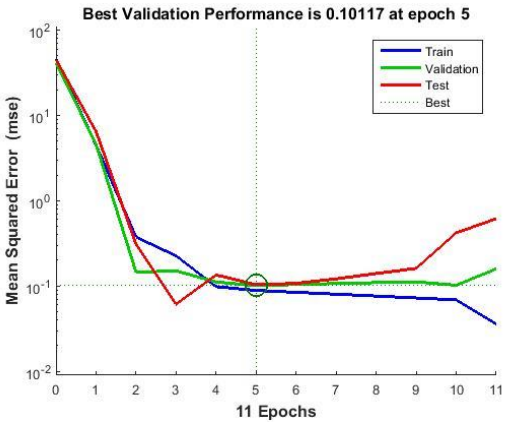


Fig. 5: Mean Squared Error (MSE) learning curves for the ANN-4 model.

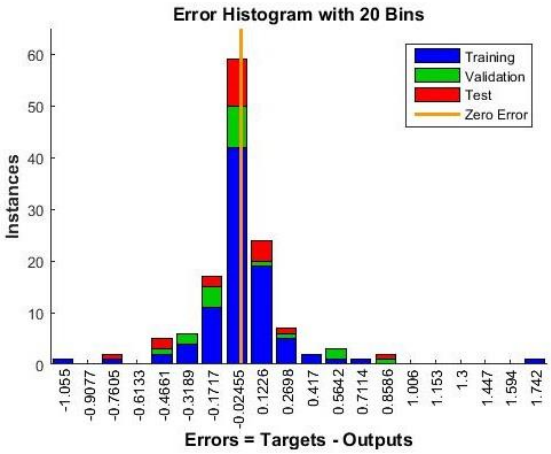


Fig. 6: Error plot of the ANN-4 model.

Figure 7 compares the ANN-4 model's simulated runoff with observed values during the testing phase. The results confirm the model's high overall accuracy while revealing a consistent systematic pattern: a tendency to alternately underpredict and overpredict monthly runoff, particularly for flows exceeding 10 m^3/s. This performance is further quantified in Figure 8, which presents a scatter plot of observed versus predicted values. The analysis validates a strong linear relationship, with a correlation coefficient (r) of 0.953 for the test set. The plot illustrates that prediction accuracy remains high for lower discharge rates, while errors become more pronounced during peak flow events.

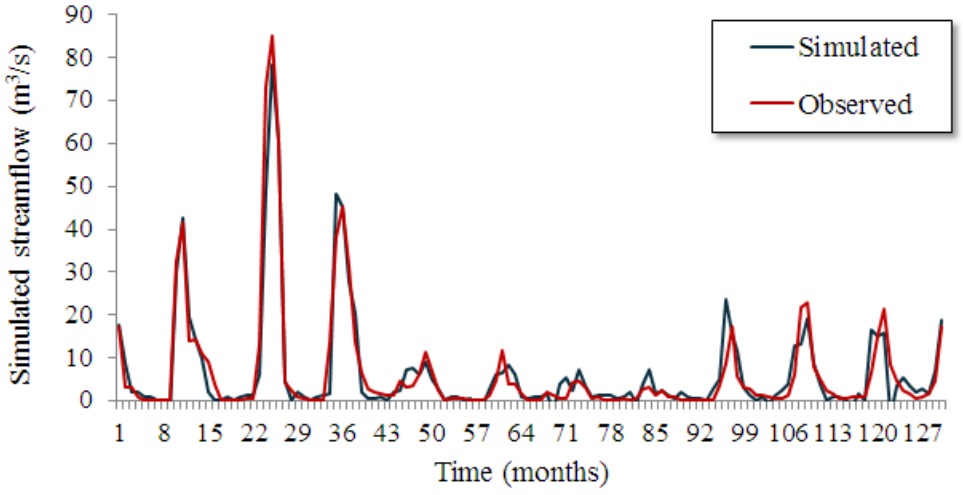


Fig. 7: Comparison of observed and simulated monthly streamflow (m^3/s) during the testing period.

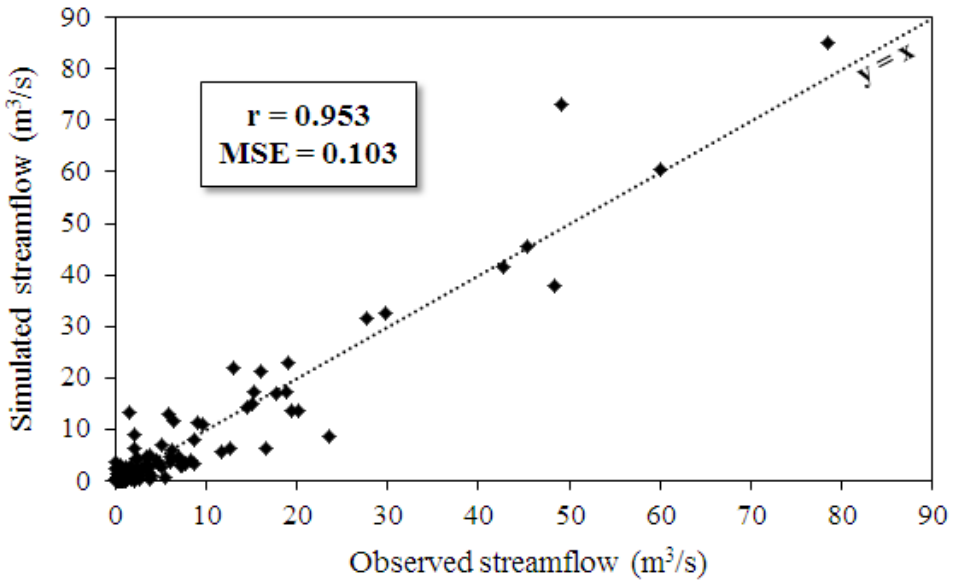


Fig. 8: Scatter plot of observed versus simulated monthly streamflow (m^3/s) during the testing phase.

4- Conclusions and Recommendations

This study demonstrates the high efficacy of MLP artificial neural networks, trained with the backpropagation algorithm, in modeling the complex rainfall-runoff relationship within the Al-Kabir Al-Shamali River Basin. The optimized ANN-4 model, with a 5-15-1 architecture, proved particularly capable. By incorporating current and antecedent values of precipitation and potential evapotranspiration, along with antecedent runoff, the model accurately simulated the monthly runoff hydrograph. This performance confirms its utility in representing the basin's key hydrological processes and memory effects. The achieved accuracy positions the ANN-4 model as a reliable, practical tool for estimating surface water resources and forecasting runoff in the basin. Its application can directly support strategic water management planning, including allocation and flood mitigation efforts.

Based on these findings, the following recommendations are proposed to advance hydrological modeling and water management in the region:

1. Broaden the application of ANN and other machine learning techniques to assess complex hydrological phenomena—such as floods, droughts, and water quality—in other Syrian river basins.
2. Conduct comparative studies between data-driven ANN models and traditional or physically-based hydrological models to delineate the optimal conditions, limitations, and specific objectives for each modeling paradigm.
3. Integrate validated predictive models, like the one developed here, into operational decision-support systems for water resource management. This integration is crucial for enhancing the efficiency of real-time operations and improving the robustness of long-term water security planning.

5- References

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