Urmia University

Water and Environmental Challenges

2025;1(2):1-11

Journal homepage: https://jwec.urmia.ac.ir

Water & Environmental Challenges

A Novel Approach for Streamflow Modeling Using Hybrid Machine Learning Techniques

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A B S T R A C T

This study aimed to predict the daily flow of Zarrineh Rud River using time-lagged inputs and the Artificial Neural Network (ANN) models with a combination of the metaheuristic Firefly Algorithm (FFA) and Reptile Search Algorithm (RSA). The results showed that combining ANN with metaheuristic algorithms consistently improved the prediction accuracy, so that in ANN–RSA_1 model at the Sari-Qamish station, the statistics indices were obtained as $R^2 = 0.95$ and RMSE = 15.77 m^3/s and for ANN–RSA_2 model at the Nezam-Abad station, the same indices were calculated as $R^2 = 0.98$ and RMSE = 13.21 m^3/s both in the test stage. Overall, ANN–RSA delivered the best predictive performance. Increasing time lags improved forecasts at the Nezam-Abad station; however, at the Sari-Qamish station, the input structure to the model was optimized with one time lag, suggesting site-specific lag requirements and potential redundancy when excessive lags are used. The proposed ANN–RSA framework demonstrates high predictive accuracy in arid and semi-arid regions. The findings recommend the application of ANN–RSA for streamflow forecasting and water resources planning, while emphasizing the careful selection of time-lagged inputs to balance complexity and generalization. Future research should evaluate the inclusion of meteorological variables and explore the transferability of the ANN–RSA framework across neighboring basins to strengthen generalizability and support operational decision-making under climate variability, as well as to provide stakeholder-oriented forecasting products for water managers.

Keywords:
Artificial neural network
Modelling
Reptile search algorithm
Time series
Urmia lake

1. Introduction

Iran, with an average annual precipitation of about 250 mm, is classified between the arid and semi-arid regions of the world (Taheri et al., 2019). Freshwater scarcity and its availability are among the major challenges to the country's agricultural sector. Therefore, finding effective solutions to address water shortages has consistently remained a priority for research and planning sections (Amirashayeri et al., 2023). River streamflow forecasting has become one of the key challenges in water resources management in recent decades, so that researchers have tried to explore a wide range of techniques. Accurate streamflow prediction on both monthly and daily timescales is a vital importance for operation, planning, and distribution of hydropower facilities and water management systems. The inherent complexities of hydrological processes, coupled with uncertainties and nonlinear relationships among influencing factors, cause the hardness of accurate and reliable modeling. Traditional methods based on physical or statistical equations, despite their advantages, often fail to provide precise and stable predictions. Therefore, the use of linear models doesn’t have the necessary accuracy, and considering the importance of river flow forecasting from various perspectives, finding an appropriate method in this regard is of great importance.

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https://doi.org/ 10.30466/jwec.2025.56476.1007
Received: 19 August 2025
Accepted: 14 October 2025

In recent years, data-driven and machine learning models have been effective alternatives for simulating hydrological processes. In these models, it is not necessary to know the explicit relations of the system; however, hidden patterns in historical data are explored and reasonable predictions of hydrological variables without explicit knowledge of the physical system relationships are provided (Mosavi et al., 2018; Ayzel et al., 2019).

Among these, Artificial Neural Networks (ANNs) have gained widespread use in river flow modeling due to their ability to simulate nonlinear behaviors, high flexibility, and data-driven learning structure (Kişi et al., 2007). However, if the ANN is properly configured and tuned, it may suffer from overfitting or become trapped in local minima (Solomatine and Ostfeld, 2008).

Recently, to overcome these challenges, the hybrid intelligent models that integrate neural networks with metaheuristic algorithms have been widely used. These nature-inspired algorithms can optimize weights, learning rates, and network structures, leading to substantial improvements in model performance.

In recent years, a variety of optimization techniques, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Firefly Algorithm (FA), have been introduced to enhance the performance of Artificial Neural Networks (Kayhomayoon et al., 2023).

In this regard, various studies have demonstrated the positive impact of metaheuristic algorithms. For example, Yaseen et al (2017) applied the FA optimization method to refine the outputs of the Adaptive Neuro-Fuzzy Inference System (ANFIS) for river flow prediction. The results of their study indicated that the integrated ANFIS–FA model achieved higher accuracy compared to the standalone ANFIS.

Similarly, Kilinc and Yurtsever (2022) applied the GWO to optimize a hybrid deep learning model for short-term streamflow forecasting. The results demonstrated that the optimized hybrid model achieved higher accuracy compared to standalone models.

Moreover, Bahmani et al. (2025) developed a novel hybrid model combining an Artificial Neural Network (ANN) with the Reptile Search Algorithm (RSA) for streamflow forecasting. The model was designed to address data scarcity and incorporated three key hydrological variables: temperature, precipitation, and streamflow. The results indicated that the ANN-RSA hybrid model demonstrated satisfactory predictive performance but was outperformed by an optimized ANN model using the Particle Swarm Optimization algorithm.

Furthermore, the inclusion of lagged monthly streamflow as an input significantly enhanced the forecasting accuracy. The study highlighted that integrating metaheuristic optimization algorithms can improve the accuracy of streamflow modeling; however, model performance is influenced by spatial and temporal variability as well as input data characteristics.

Despite these advances, flow modeling in semi-arid climates, such as the Zarrineh River in West Azerbaijan, Iran, still faces unique challenges. This river exhibits significant seasonal and interannual discharge fluctuations, making it necessary to develop more accurate and stable prediction tools.

Considering the unique challenges associated with streamflow forecasting in semi-arid regions such as the Zarrineh River basin in West Azerbaijan, Iran, characterized by significant seasonal and interannual discharge variability, the development of accurate and robust daily flow prediction models is of paramount importance.

The primary objective of this study is to propose a novel modeling framework that integrates Artificial Neural Network (ANN) with two powerful metaheuristic algorithms to enhance the predictive performance of streamflow forecasting. This hybrid model is not only designed for effectively capturing the complex nonlinear relationships inherent in hydrological processes but also for optimizing network parameters, thereby improving prediction accuracy and stability under varying climatic conditions and limited data scenarios.

Achieving this goal will provide critical support for water resource management, flood control, agricultural planning, and sustainable development in the region. Ultimately, this research was undertaken to significantly enhance the accuracy of river streamflow forecasting in arid and semi-arid regions of Iran.

2. Materials and Methods

2.1. Study Area

Urmia Lake basin is one of the water basins in Iran. This basin consists of different sub-basins. Urmia Lake basin is located in the northwest of Iran with a temperate and humid climate. The direction of water flow starts from the heights and finally discharges into Lake Urmia. The major rivers within the basin include Nazlu Chay, Barandoz Chay, Aji Chay, Zarrineh Rud, Simineh Rud, Mahabad Chay, Zola Chay, and several other rivers, which collectively drain to

Lake Urmia (Kakahaji et al., 2019). Zarrineh Rud River is located in the northwest of Iran, flowing through the southern plain of Lake Urmia. This river, with a length of 302 km and a catchment area of 11,850 km², places among the most abundant rivers in the northwest of Iran. In this study, two hydrometric stations, including Sari-Qamish and Nezam-Abad, were utilized for the estimation and modeling of the daily flow of Zarrineh Rud. Fig. 1 illustrates the locations of these two stations.

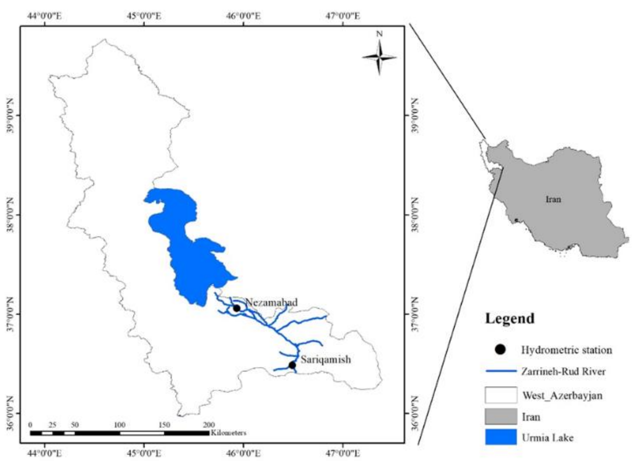

Figure 1.Geographical location of the studied hydrometric stations

2.2. Used Data

Daily streamflow records of Zarrineh Rud River over 26 years (1990–2016) were analyzed at two hydrometric stations: Sari-Qamish and Nezam-Abad. The temporal variations in streamflow for both stations are illustrated in Fig. 2. As shown, the streamflow ranges for the two stations are relatively similar, reflecting the comparable geographical and hydrological conditions at these locations.

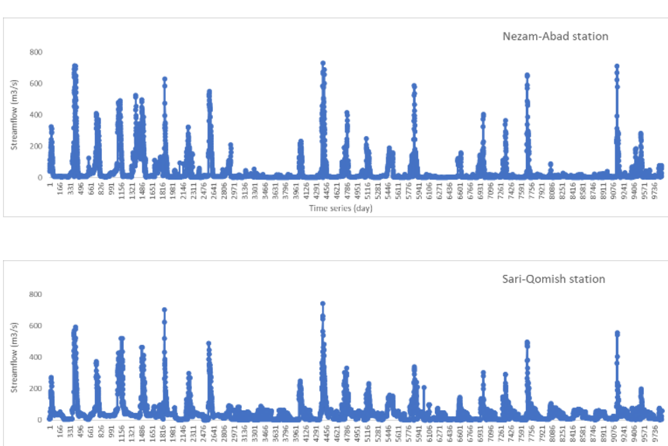

Figure 2. Daily flow time series plot in Sari-Qamish and Nezam-Abad hydrometric stations

Table 1 presents the descriptive statistics of daily streamflow for the Zarrineh River at the Sari-Qamish and Nezam-Abad stations over the 1990–2016 period. The observed maximum streamflow reached 742.2 m³/s at Sari-Qamish and 731 m³/s at Nezam-Abad. The minimum flow values were close to zero, indicating dry periods or baseflow conditions, with absolute minimums of 0 m³/s and 0.001 m³/s, respectively. The mean daily streamflow was higher at Sari-Qamish 45.19 m³/s than at Nezam-Abad 35.74 m³/s, likely reflecting upstream contributions and local hydrological variations. Interestingly, the standard deviation was greater at Nezam-Abad 83.65 m³/s compared to Sari-Qamish 67.19 m³/s, suggesting more pronounced temporal variability and fluctuations in streamflow at the downstream station. Missing values within the streamflow time series were addressed using correlation-based imputation methods, including mean substitution and regression techniques.

Figure 3. Statistical characteristics of Zarrineh River daily flow series in Sari-Qamish and Nezam-Abad stations

River	Hydrometric Station	Statistical course (Year)	Max flow (m³/s)	Min flow (m³/s)	Average flow (m³/s)	Standard deviation (m³/s)
Zarineh River	Sari-Qamish	1990-2016	742.2	0	45.19	67.19
Zarineh River	Nezam-Abad	1990 - 2016	731	0.001	35.74	83.65

2.3. Artificial neural networks

In this research, streamflow modeling was conducted using an artificial neural network (ANN) with two hidden layers and 8 neurons. The ANN training employed the Levenberg-Marquardt algorithm (LV et al., 2017), which demonstrates superior convergence speed and requires fewer training cycles compared to the traditional backpropagation method. A maximum of 1000 iterations was set for the training process. Ultimately, the trained model was utilized to simulate streamflow. Alongside the ANN model, two metaheuristic algorithms, the Reptile Search Algorithm (RSA) and the Firefly Algorithm (FFA), were incorporated to enhance the ANN's accuracy. Each of these algorithms possesses unique characteristics that can significantly improve the conventional ANN model. The following sections describe the employed algorithms to enhance the training process of the artificial neural network (ANN).

2.4. Metaheuristic optimizer

2.4.1. Firefly Algorithm

The firefly algorithm, proposed by Yang and Xin-She (2009), is a solution to solve optimization problems. Yang and Xin-She (2009) modeled this algorithm based on the hunting behavior of fireflies utilizing gravity and the produced scattered light. Fireflies emit light for mating and hunting purposes, so that Yang and Xin-She (2009) created an algorithm based on this behavior. The algorithm's key components are its brightness and intensity, along with the beta separation parameter. In simpler terms, the brightness parameter of a firefly at a specific location x can be defined as $I(x) \propto f(x)$. Conversely, the light intensity parameter (I) exhibits a variable range, governed by the inverse law, as elucidated in Eq. (1) (Yang XS, 2009).

$$I = \frac{I_s}{r^2} \tag{1}$$

The parameter signifies the light intensity emanating from the source. In the context of a medium (like air) with a constant light absorption coefficient (γ), the light intensity I will fluctuate with the distance r as Eq. (2) (Yang XS, 2009):

$$I = I_0 e^{-\gamma r} \tag{2}$$

where I0 represents the intensity of the original light. The β attraction parameter of a firefly is calculated using Eq. (3), which considers the luminosity of a firefly, which is directly proportional to the intensity of light it produces and is perceived by neighboring fireflies.

$$\beta\ (r) = \beta_0 e^{-\gamma r^2} \tag{3}$$

where β0 is the maximum attractiveness in the range of [0, 1], γ is the attractiveness coefficient in the range of [0, ∞], and r denotes the distance of firefly i from firefly j. The distance between two fireflies, i and j, is equal to the Cartesian distance between them (Eq. (4)) (Yang XS, 2009):

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{4}$$

Finally, the motion of a firefly drawn to a more attractive firefly is described by Eq. (5) (Yang XS, 2009).

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r_{ij}^2} \left(x_j - x_i\right) + \alpha(rand - \frac{1}{2}) \tag{5}$$

Where α is a random value, and rand is a random number generator that produces a number between 0 and 1. In this study, the population size and the number of iterations were set to 30 and 250, respectively.

2.5. Reptile Search Algorithm

Reptile search algorithms (RSA) are among the most recent meta-heuristic algorithms introduced by Abualigah et al. (2022). The fundamental concept of this algorithm is derived from the hunting strategies employed by crocodiles in capturing prey, such as deer. The algorithm meticulously details the crocodiles' movements towards their prey, encompassing two distinct modes: rapid walking and slow walking on their bellies. Notably, for successful hunting in both stages, the crocodiles adhere to the specified rules. The total number of repetitions was divided into four parts based on these methods. In the exploration strategy, two conditions for high walking ($t \leq \frac{T}{4}$) and belly walking ($t > \frac{T}{4}$ and $t \leq \frac{2T}{4}$) must be met (Fig. 3). The RSA algorithm is implemented by starting with solutions chosen at random and generating them as (Eqs 6 and 7) (Abualigah et al., 2022):

$$y_{(i,j)} = rand \times (UB - LB) + LB, \qquad j = 1,2,\dots,n \tag{6}$$

$$y_{(i,j)}(t+1) = \begin{cases} Best_{j1}(t) \times h_1(t) \times \beta_1 - R_{1(i,j)} \times rand, & \leq \frac{T}{4} \\ Best_{j1}(t) \times x_{(r,j)} \times ES_1(t) - R_{1(i,j)} \times rand, & t > \frac{T}{4} \text{ and } t \leq \frac{2T}{4} \end{cases} \tag{7}$$

$$ES(t) = 2 \times r_3 \times \left(1 - \frac{1}{T}\right) \tag{8}$$

$$h_{1(i,j)} = Best_{j1}(t) \times h_1(t) \times P_1 - R_{1(i,j)} \tag{9}$$

$$R_{1(i,j)} = \frac{Best_{j1}(t) - x_{(r_2,j)}}{Best_{j1}(t) + \epsilon} \tag{10}$$

The best previous solution (*Best$_{j1}$(t)*) is the optimal solution found so far. The *rand* is a random number generated between 0 and 1. Additionally, β_1 is a vital parameter that influences the performance of the heuristic algorithm. Also, t and T represent the current and total number of iterations, respectively. *ES(t)* is a random value generated between -2 and 2 in all iterations evaluated. $x_{(r1,j)}$ represents the arbitrary position of the solution *i*. $R_{1(i,j)}$ is a reduced search, where r_1 is a randomly selected integer within the range [1, *N*]. This parameter defines the hunting operator for the jth position of the *i*th solution. ϵ represents a small value, r_2 belongs to [1, *N*] and r_3 signifies the arbitrary value in [–1, 1]. In the RSA algorithm's exploitation phase, Eq. (11) was utilized to calculate the new solution (Abualigah et al., 2022) (Fig. 3).

$$y_{(i,j)}(t+1) = \{Best_{j1}(t) \times h_1(t) \times P_{1(i,j)} \times rand, \quad t > \frac{2T}{4} \; t \leq \frac{3T}{4} \; Best_{j1}(t) - h_{1(i,j)}(t) \times - R_{1(i,j)} \times rand, \quad t > \frac{3T}{4} \; and \; t \leq T \tag{11}$$

$P_{1(i,j)}(t)$ represents the percentage discrepancy between the jth place of the best and the jth place of the current performance, as calculated by Eq. (12) (Abualigah et al., 2022).

$$P_{1(i,j)}(t) = \alpha + \frac{x_{(i,j)} - M_1(x_i)}{Best_{j1}(t) \times (UB_j - LB_j) + \epsilon} \tag{12}$$

where α(another parameter with fixed value 0.1) is used to restrain the exploration precision and $M_1(x_i)$ is computed by Eq. (13) as (Abualigah et al., 2022):

$$M_1(x_i) = \frac{1}{n}\sum_{j=1}^{n} x_{(i,j)} \tag{13}$$

In this study, the population size and the number of iterations were set to 30 and 3000, respectively.

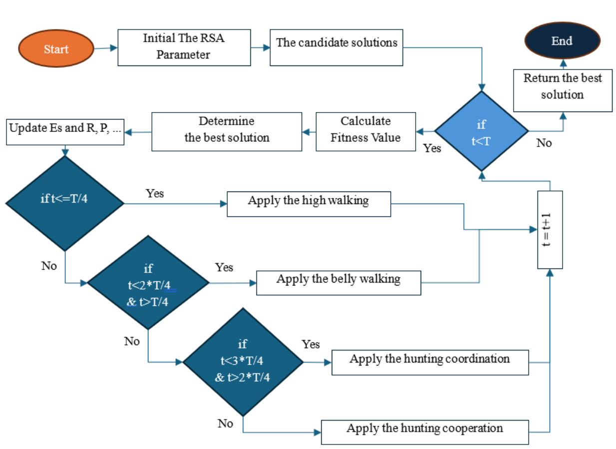

Figure 3. RSA flowchart

2.6. Performance Evaluation Metrics

To evaluate the performance of the machine learning models, several error evaluation criteria were used. The dataset was randomly divided into two groups, with 75% of the data for model training and 25% of the data for test stages. Coefficient of determination R^2 (Hejabi et al., 2025), Root mean square error (RMSE) (Sharafi et al., 2025) and Nash Sutcliffe Index (NSE) (Asgharinejad et al., 2025) were utilized as equations 14, 15, and 16:

$$R^2 = \frac{[\sum_{i=1}^{n}(\mathrm{Yr_{Simulated}} - \overline{\mathrm{Yr}}_{\mathrm{Actual}})(\mathrm{Yr_{Actual}} - \overline{\mathrm{Yr}}_{\mathrm{Actual}})]^2}{\sum_{i=1}^{n}(\mathrm{Yr_{Simulated}} - \overline{\mathrm{Yr}}_{\mathrm{Actual}})^2 \sum_{i=1}^{n}(\mathrm{Yr_{Actual}} - \overline{\mathrm{Yr}}_{\mathrm{Actual}})^2} \tag{14}$$

$$0 \leq R^2 \leq 1$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Yr_{Actual} - Yr_{Simulated})^2}{n}} \quad 0 \leq RMSE < \infty \tag{15}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Yr_{Actual} - Yr_{Simulated})^2}{\sum_{i=1}^{n}(Yr_{Actual} - \overline{Yr}_{Actual})^2} \tag{16}$$

$$-\infty \leq NSE \leq 1$$

In these equations, Yr_{Actual} and $Yr_{Simulated}$ represent the observed and simulated values of streamflows, respectively. The terms $\overline{Yr}_{Actual}$ and $\overline{Yr}_{Simulated}$ donate the mean values of the actual and simulated streamflows across the dataset. The variable n refers to the total number of data samples used in the evaluation.

3. Results and discussion

The selection of appropriate input variables plays a crucial role in the performance of artificial intelligence and data mining models. Based on empirical evidence and previous research, time-lagged streamflow values are among the most influential inputs in streamflow forecasting, as they effectively capture the autocorrelation and temporal dynamics of river discharge. In this study, three input scenarios were developed using daily streamflow values with different time lags. The first scenario used a one-day lag (Q−1), the second scenario included both one-day and two-day lags (Q−1, Q−2), and the third scenario incorporated one-day, two-day, and three-day lags (Q−1, Q−2, Q−3). These input structures, as summarized in Table 2, were designed to assess the effect of increasing time lags on the predictive performance of the models.

Pattern	Input variables	Target
S_1	Q(t-1)	Daily streamflow
S_2	Q(t-2) + Q(t-1)	
S_3	Q(t-3) + Q(t-2) + Q(t-1)	

In many cases, recorded streamflow data exhibit non-symmetric distributions and may be non-stationary due to the existence of trend, the effect of seasonality, and other inherent hydrological patterns. Therefore, data normalization and stationarity checks were applied to modeling to ensure the reliability and consistency of the input time.

Table 3. The performance evaluation criteria of forecasting models at the Sari-Qamish and Nezam-Abad stations

Station	Scenario	Model	Training			Test		
			R^2	RMSE (m^3/s)	NSE	R^2	RMSE (m^3/s)	NSE
Sari-Qamish	**S_1 (Q-1)**	ANN_1	0.90	21.59	0.90	0.92	19.22	0.92
		ANN-FFA_1	0.91	21.01	0.90	0.90	21.18	0.90
		ANN-RSA_1	**0.92**	**18.80**	**0.92**	**0.95**	**15.77**	**0.95**
	S_2 (Q-1) + (Q-2)	ANN_2	0.92	19.01	0.92	0.89	22.96	0.89
		ANN-FFA_2	0.91	20.14	0.91	0.92	19.67	0.91
		ANN-RSA_2	0.93	20.00	0.92	0.95	15.91	0.93
	S_3 (Q-1) + (Q-2) + (Q-3)	ANN_3	0.89	22.57	0.88	0.91	21.28	0.91
		ANN-FFA_3	0.91	20.10	0.91	0.91	20.18	0.91
		ANN-RSA_3	0.91	19.94	0.91	0.92	19.78	0.91
Nezam-Abad	S_1 (Q-1)	ANN_1	0.91	26.46	0.90	0.93	23.29	0.92
		ANN-FFA_1	0.95	17.83	0.95	0.95	18.23	0.95
		ANN-RSA_1	0.96	16.16	0.96	0.96	18.07	0.96
	S_2 (Q-1) + (Q-2)	ANN_2	0.93	22.29	0.93	0.95	19.07	0.95
		ANN-FFA_2	0.96	16.80	0.96	0.97	13.44	0.97
		ANN-RSA_2	**0.96**	**16.08**	**0.96**	**0.98**	**13.21**	**0.98**
	S_3 (Q-1) + (Q-2) + (Q-3)	ANN_3	0.94	21.23	0.94	0.94	19.14	0.94
		ANN-FFA_3	0.95	18.74	0.95	0.95	18.69	0.95
		ANN-RSA_3	0.96	17.27	0.96	0.97	14.88	0.97

To forecast the streamflow of Zarrineh Rud River at Sari-Qamish and Nezam-Abad gauging stations, the performance of three modeling approaches namely, the standalone Artificial Neural Network (ANN), the ANN optimized via the Firefly Algorithm (ANN–FFA), and the ANN optimized through the Reptile Search Algorithm (ANN–RSA) was rigorously evaluated under three distinct temporal input scenarios. These input scenarios consisted of one-day lag (S_1), combined one-day and two-day lags (S_2), and an integrated sequence of one-, two-, and three-day lagged inputs (S_3). Model accuracy was quantitatively assessed using key statistical metrics, including the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Nash-Sutcliffe Efficiency (NSE) during both training and testing phases. The comprehensive performance results are summarized in Table 3. At the Sari-Qamish station, the ANN–RSA_1 model under the first scenario (S_1) demonstrated superior predictive capability, yielding R^2 = 0.95, RMSE = 15.77 m^3/s, and NSE = 0.95 during the testing phase. This represents a significant enhancement compared to the baseline ANN model, which recorded RMSE = 19.22 m^3/s, R^2 = 0.92, and NSE = 0.92. Furthermore, ANN–RSA_1 outperformed other scenarios (S_2 and S_3) at this station; in scenarios S_2 and S_3, despite the increased input dimensionality through additional time lags, RMSE values obtained to 15.91 and 19.78 m^3/s, respectively, accompanied by a decline in model accuracy. These findings indicate that for Sari-Qamish, employing a single one-day lag input suffices for accurate streamflow forecasting, whereas increasing the number of lagged inputs may introduce noise and degrade model performance. Notably, the RSA optimization algorithm consistently enhanced ANN performance across all scenarios compared to the FFA algorithm. Conversely, at the Nezam-Abad station, the inclusion of additional time lags markedly improved model performance. The ANN–RSA_2 model in scenario S_2 (one- and two-day lags) produced the most accurate forecasts, with R^2 = 0.98, RMSE = 13.21 m^3/s, and NSE = 0.98 during testing. This underscores the value of integrating multiple lagged streamflow inputs to capture temporal dependencies more effectively at this site. The RSA algorithm again outperformed both the standalone ANN and the ANN–FFA models by optimizing network parameters more effectively. Specifically, in scenario S_2, the standalone ANN model exhibited RMSE = 19.07 m^3/s and R^2 = 0.95, reflecting approximately 31% greater error compared to ANN–RSA_2. While the FFA algorithm also delivered competitive results (RMSE = 13.44 m^3/s, R^2 = 0.97, NSE = 0.97), the RSA optimization approach demonstrated superior calibration efficiency and prediction accuracy at Nezam-Abad. Overall, the presented results in Table 3 confirm that ANN–RSA_1 under scenario S_1 is the optimal model for Sari-Qamish, whereas ANN–RSA_2 under scenario S_2 is the most accurate model for Nezam-Abad, as evidenced by the highest R^2 and NSE values and the lowest RMSE. To further substantiate model evaluation, four figures (Figures 4 to 7) were generated using the full observational and predicted datasets, enabling a comprehensive assessment of model behavior throughout the entire study period. Fig. 4 illustrates the scatter plot of the entire observed and predicted datasets at the Sari-Qamish station for all scenarios and models. It is evident that the hybrid ANN-RSA_1 model under Scenario 1 achieved the highest accuracy, R^2 = 0.93, outperforming the hybrid ANN-FFA model in the same scenario. The predicted values from ANN-RSA_1 cluster more closely around the 1:1 reference line, indicating a stronger agreement between observed and predicted data. Additionally, the ANN-RSA_2 model under Scenario 2 also demonstrated commendable performance, R^2 = 0.9294, signifying that the RSA algorithm provided superior optimization of the ANN model and better predictive capability compared to the FFA algorithm. These observations are in strong concordance with the numerical results reported in Table 3. Similarly, Fig. 5 presents the corresponding scatter plot for the Nezam-Abad station. Here, the hybrid ANN-RSA_2 model under Scenario 2 achieved the highest predictive accuracy, R^2 = 0.97, surpassing all other models. Furthermore, the ANN-RSA_1 model also exhibited notable predictive performance, achieving an R^2 of 0.9616, which confirms the RSA algorithm's enhanced effectiveness in optimizing the ANN model relative to the FFA algorithm. The findings depicted in this figure are fully consistent with the metrics summarized in Table 3.

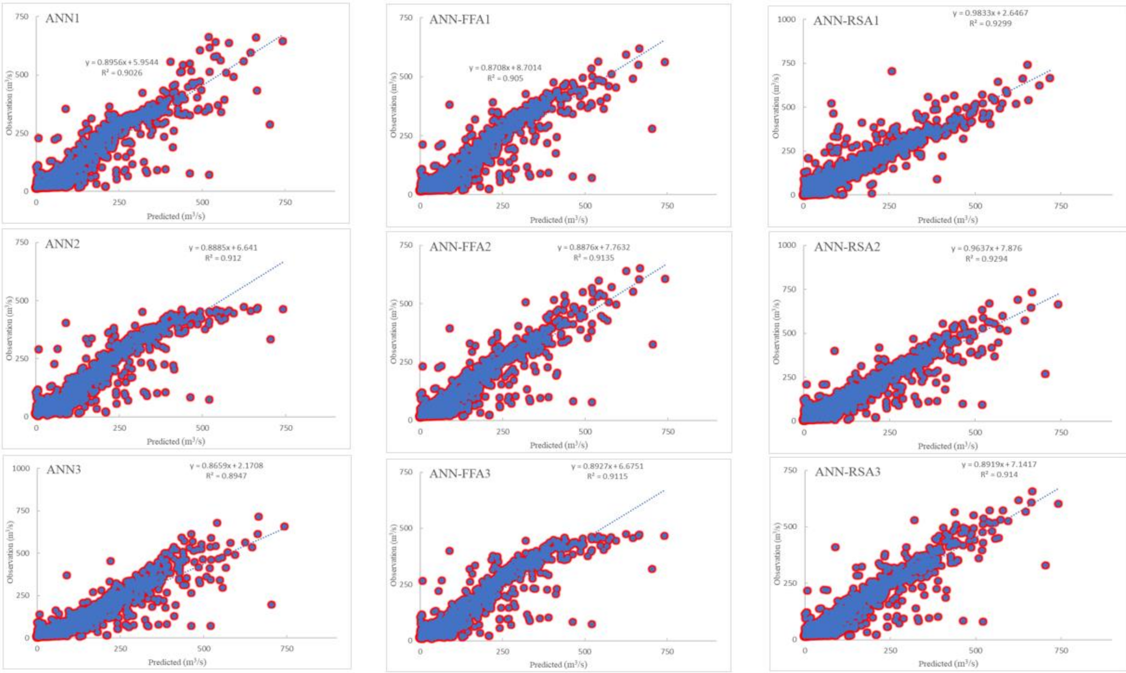

Figure 4: Scatter plot, Sari-Qamish station (all data) = 0.67

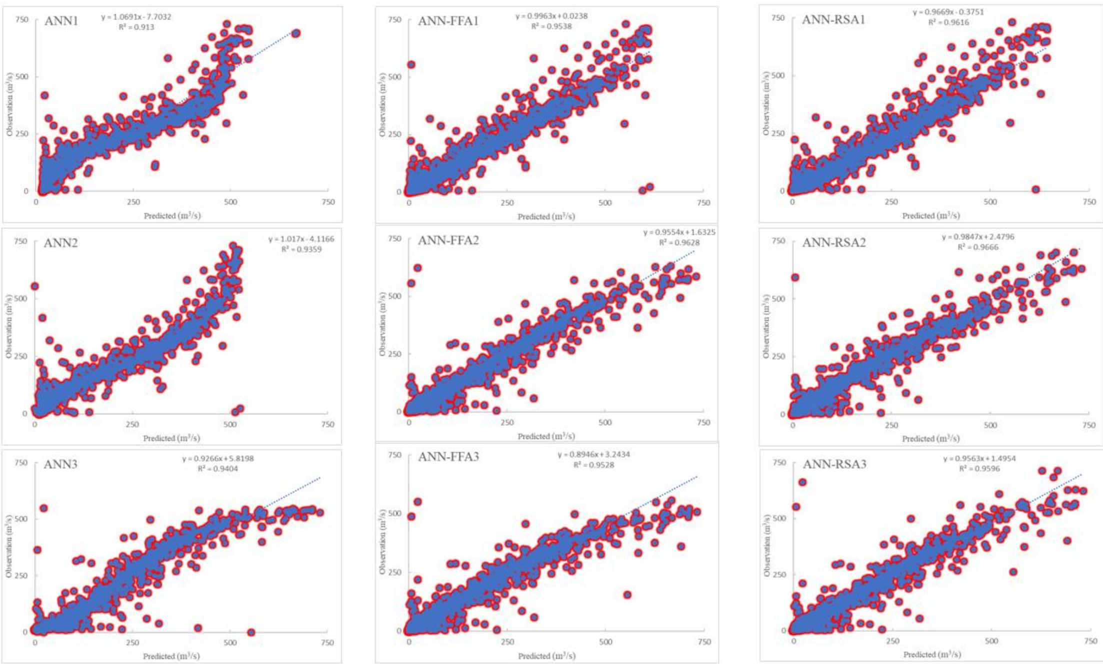

Fig 5. Scatter plot, Nezam-Abad station (all data)

Fig. 6 displays the complete time series of observed versus predicted daily streamflow using the superior ANN-RSA$_1$ model (Scenario 1) at the Sari-Qamish station. As shown, the model successfully captures the complex temporal dependencies and nonlinear dynamics inherent in the daily river discharge data with high precision. The close alignment between predicted and observed values over various temporal intervals, including both dry and wet periods, demonstrates the model's capability to replicate overarching trends as well as intermediate fluctuations. Moreover, the limited dispersion of predicted values relative to observations indicates reduced systematic errors and robust generalization capacity during the testing phase. Fig. 7 presents a similar time series comparison for the Nezam-Abad station, where the ANN-RSA$_2$ model under Scenario 2 was identified as optimal. The predicted streamflow closely tracks the observed daily variations, reflecting the model's ability to capture the site-specific hydrological dynamics and temporal variability effectively. This plot not only validates the model's accuracy in estimating mean flow values but also highlights its stability in handling pronounced fluctuations and high-magnitude hydrological events. Consequently, the results in Fig. 7 underscore that the hybrid ANN-RSA$_2$ model possesses a strong aptitude for simulating hydrological processes with multi-day temporal dependencies, positioning it as a reliable tool for operational daily streamflow forecasting under complex and variable climatic conditions.

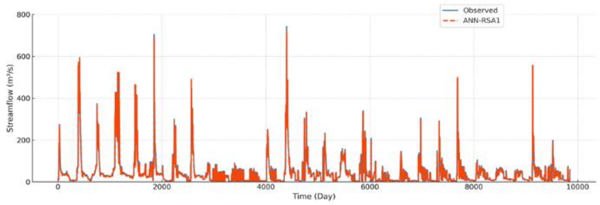

Fig 6. Daily streamflow time series, Sari-Qamish station (all data

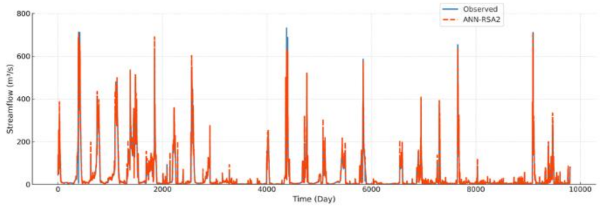

Fig 7. Daily streamflow time series, Nezam-Abad station (all data)

Nevertheless, across all scenarios, the ANN–RSA model consistently outperformed the standalone ANN and ANN–FFA models at both Sari-Qamish and Nezam-Abad stations, demonstrating superior accuracy, robustness, and adaptability. Consequently, the hybrid ANN–RSA model can be considered an optimal approach for operational streamflow forecasting and simulation within water resources management systems. The results of the studies by Bahmani et al. (2025) and Tikhamarine et al. (2020) are consistent with the results of this study. It can be inferred that metaheuristic algorithms can enhance the accuracy of streamflow prediction by ANN. Consequently, this finding confirms the significance and effectiveness of the proposed methodology. On the other hand, these comparisons emphasize that the optimal integration of advanced metaheuristic search algorithms such as RSA with ANN architectures, alongside well-designed time lag input scenarios, plays an important role in enhancing the precision of streamflow predictions. For operational forecasting in semi-arid basins like the Zarrineh Rud basin, the ANN–RSA model presents a promising and accurate framework. However, practitioners should calibrate the lag structure individually for each station and rigorously evaluate model performance relative to time lag configurations before deployment. Future research may investigate the incorporation of meteorological variables (e.g., precipitation and temperature) in conjunction with time lags, as well as explore transfer learning approaches utilizing hybrid intelligent models across neighboring basins to improve forecasting resilience under changing climatic conditions.

4. Conclusions

In this study, a novel modeling framework was developed for daily streamflow forecasting of Zarrineh Rud River, combining Artificial Neural Networks (ANN) with two powerful metaheuristic algorithms, the Firefly Algorithm (FFA) and the Reptile Search Algorithm (RSA).

In particular, the ANN–RSA hybrid models showed superior performance at both stations. Additionally, the evaluation of time-lagged inputs revealed that increasing the number of lags improved model accuracy at the Nezam-Abad station, whereas the optimal performance at the Sari-Qamish station was achieved with only one time lag, highlighting the importance of customizing input configurations according to site-specific characteristics. These models effectively captured the nonlinear complexities of Zarrineh Rud's flow under significant seasonal and interannual variability, maintaining reliable performance despite data limitations and climatic fluctuations. Given the critical role of this river in water supply, flood control, and agricultural development in the region, the application of such hybrid models can serve as a powerful tool to support water resources management and sustainable planning. Future research should focus on incorporating meteorological variables and assessing the transferability of the proposed framework to neighboring basins to broaden its applicability and robustness. Moreover, developing forecasting products tailored to stakeholders' needs can enhance adaptive and efficient water management under changing climate conditions. Overall, this study represents a significant step forward in improving streamflow prediction for Zarrineh Rud River at Sari-Qamish and Nezam-Abad stations and improving hydrological modeling systems in semi-arid regions of Iran.

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