Pure Appl. Geophys.
© 2026 The Author(s)
https://doi.org/10.1007/s00024-026-03973-6

Pure and Applied Geophysics

An Optimization-Focused Comparative Framework for Machine Learning-Based Suspended Sediment Load Modeling

Muhammed Ernur Akiner[1] and Mehdi Ghasri[2]

Abstract—Urbanization in the Göksu River Basin increases sediment movement toward the Göksu Delta. The research used hydrometeorological data to assess machine learning techniques, including hybrid and deep learning systems, for Suspended Sediment Load (SSL) forecasting. The development of conventional models, including Backpropagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), and Support Vector Machine (SVM), received optimization algorithm improvements through the implementation of Adaptive Moment Estimation (ADAM), Sequential Minimal Optimization (SMO), and the Water Cycle Algorithm (WCA), which boosted model accuracy and development speed. The BPNN_ADAM hybrid model performed better than all other methods because it achieved superior R^2, adjusted R^2, Nash–Sutcliffe Efficiency (NSE), RMSE-observations standard deviation ratio (RSR), and Normalized Root Mean Square Error (NRMSE) results, resulting in a low Mean Absolute Error (MAE) of 0.09. The BPNN_WCA hybrid system showed consistent performance across all tested metrics, which measured both error and operational efficiency. The deep learning models Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM) achieved exceptional predictive performance, with R^2 values close to 0.99 in both univariate and multivariate testing modes. Deep learning models (LSTM/Bi-LSTM) have NRMSE values of 8–12%, followed by optimized hybrid models such as BPNN_ADAM and BPNN_WCA, with NRMSE values of 35–50%. In contrast, standalone machine learning models, such as SVM, show significantly higher errors with NRMSE values exceeding 60–90%. The research indicated that time-lagged hydrological and sediment variables play a crucial role in improving SSL prediction accuracy while also capturing the memory of catchment systems.

Keywords: Stochastic gradient descent, deep learning, backpropagation neural network, optimization algorithms, radial basis function neural network.

1. Introduction

1.1. Problem Definition

The Göksu River originates from the Taşeli Plateau. It flows through the Taurus Mountains before discharging into the Mediterranean Sea, forming the Göksu Delta—one of Turkey's most critical Ramsar-designated wetlands (Akiner, 2019). This delta supports exceptional biodiversity, which includes endangered species such as the Nile soft-shelled turtle and sea turtles (Dervisoglu, 2022). The river-delta system derives its ecological integrity from suspended sediment load (SSL), which results from extensive agricultural activity and natural geomorphic processes. Accurate prediction of SSL is therefore essential for evaluating sedimentation, erosion risks, contaminant transport, and flood hazards.

1.2. Traditional Methods

Traditional methods for estimating SSL include empirical linear equations and physical models, such as SWAT and KINEROS (Gupta et al., 2018; Pan & Huang, 2010). Empirical methods used to test the system fail to identify all the relationships among the main system variables (Ciğizoğlu, 2002; Zhang et al., 2012). Physically based models require a complete dataset to operate, yet they become vulnerable to errors when model parameters are changed (dos Santos et al., 2023; Heddam et al., 2024; Nhu et al., 2020). The methods face challenges because they must operate in environments with limited data availability and complex operational conditions.

[1] Department of Environmental Protection Technologies, Vocational School of Technical Sciences, Akdeniz University, Antalya, Turkey. E-mail: ernurakiner@gmail.com

[2] Department of Civil Engineering, University of Sistan and Baluchestan, Zahedan, Iran. E-mail: mehdighasri@pgs.usb.ac.ir

Published online: 17 April 2026

1.3. Machine Learning Approaches

Machine learning (ML) and artificial intelligence (AI) techniques have developed into practical methods for modeling complex relationships across diverse datasets (Badrulhisham et al., 2024; Khajure & Mohod, 2016). Multiple studies have established that SSL prediction achieves better results through ANN, SVM, and ensemble-based methods (Nourani et al., 2021; Rajaee & Jafari, 2020; Rezaei et al., 2021). The most recent deep learning models achieve their greatest effectiveness through long short-term memory networks, which track temporal patterns in sediment transport phenomena (Allawi et al., 2023a, 2023b; Latif et al., 2023). However, current studies mostly report the predictive performance of a specific model architecture but do not systematically examine the role of optimization algorithms, which directly affect model performance. Yet, recent research shows that the choice of optimization algorithm has a decisive effect on the generalization capacity, convergence speed, and ultimate prediction accuracy of machine learning models (Chen et al., 2025; Karri & Muntala, 2025; Liu et al., 2025). For example, Barrett et al. (2023) emphasize the critical role of optimization policy in learning processes, while Roy et al. (2024) highlight the importance of selecting the appropriate model and optimization strategy in complex hydrological systems. These findings clearly reveal the lack of a comprehensive framework for comparing optimization algorithms, specifically in SSL prediction.

1.4. Aims and Scope

This study aims to fill a gap in the literature by presenting a unique, integrated comparative framework that centers the optimization algorithm in the modeling process. Within the scope of the research, three fundamental models representing different learning paradigms (Backpropagation Neural Network—BPNN, Radial Basis Function Neural Network—RBFNN, and Support Vector Machine—SVM) are combined with algorithms reflecting three different optimization philosophies (Adaptive Moment Estimation—ADAM, Sequential Minimal Optimization—SMO, and Water Cycle Algorithm—WCA) to systematically examine the decisive effect of optimization choice on model performance. Furthermore, deep learning models such as long short-term memory (LSTM) and bidirectional LSTM (Bi-LSTM) are used as reference performance metrics; thus, the potential of the proposed hybrid models to provide alternatives to deep learning approaches in terms of both interpretability and computational efficiency is evaluated. Another unique aspect of the study is its systematic analysis of the role of time-lagged hydrological and sediment variables (SSC^{-1}, Q_t^{-1}) in capturing basin memory using eleven different input scenarios. All model-optimizer combinations were trained and tested on 13,149 days of data spanning 1987–2022. The selection of the data period was based on the fundamental criteria of representing long-term hydrological variability and providing sufficient statistical power for model training. This integrated approach, tested in the complex hydrological dynamics of the Göksu Basin, aims to provide transferable methodological insights for sustainable water resource management in sensitive river ecosystems.

The main contributions of this study to the literature are as follows:

- Optimization-centered comparative analysis: Presenting a framework that systematically examines the impact of optimization algorithms with different theoretical foundations (ADAM, SMO, WCA) on various machine learning models and demonstrates the critical role of optimizer selection in model success.
- Modeling of watershed memory: Quantitatively demonstrating the indispensable role of time-delayed hydrological and sediment variables in SSL estimation with comprehensive input scenarios.
- Balance between accuracy and interpretability: Using the superior accuracy of deep learning models (LSTM, Bi-LSTM) as a reference, revealing the potential of hybrid models (BPNN_ADAM, BPNN_WCA) that offer similar success with lower computational load and higher interpretability, and establishing an effective balance point for practical applications.

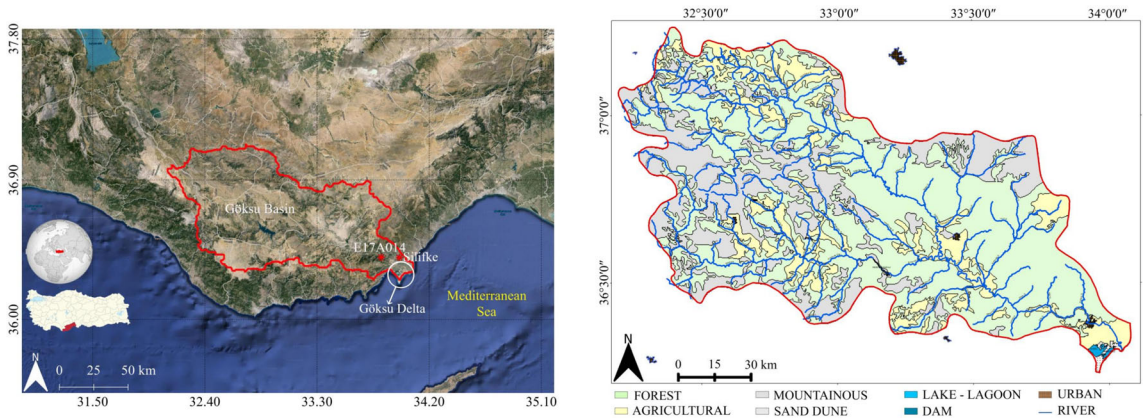


Fig. 1
The Göksu River Basin research area shows critical features, including the hydrological sampling point (E17A014), the meteorological station (Silifke), and the distribution of land cover and land use

Table 1

Geographic information of the hydrological station

Station ID	Station Name	Latitude (N°)	Longitude (E°)	Drainage Area (km^2)	Period
E17A014	Karahacılı	36° 24′ 12.4“	33° 48′ 50.8”	10,065.2	1987–2022

Table 2

Geographic information of the weather station

Station	Latitude (N°)	Longitude (E°)	Altitude (m)	Climate Type
Silifke	36° 22′ 54.43“	33° 56′ 10.55”	10	Mediterranean

2. Study Area

2.1. Study Area Description

The Göksu River Basin (illustrated in Fig. 1) is located in southern Turkey. It drains an area of approximately 10,065 km^2 before discharging into the Mediterranean Sea at the Göksu Delta (Demirel et al., 2011). The Turkish General Directorate of Electrical Power Resources Survey and Development Administration operates Station E17A014 (Karahacılı) to provide hydrological data on the basin's outlet and its complete flow pattern. The Silifke station, operated by the Turkish State Meteorological Service (MGM), served as the site for collecting all meteorological information, including rainfall measurements. The geographic characteristics of both stations are shown in Tables 1 and 2.

The Göksu River Basin water system features steep valley walls and flowing river sections that intensify erosion and sediment movement, as the area contains alluvial silt, sand, and clay that cover limestone bedrock. The Central Taurides supply sediment to the Göksu Delta, which develops through sedimentation processes operating over extended time scales (Akiner, 2020; Demir, 2021; Demirel, 2010). The delta has been designated as a Ramsar Wetland of International Importance and a Special Environmental Protection Zone because its ecosystem exhibits high ecological value, but agricultural

runoff and sediment inflow into lagoon systems like Akgöl and Paradeniz increase nitrogen and phosphorus pollution, which causes harmful eutrophication effects (Kılıç & Yücel, 2021; Kingsford et al., 2021; Pittock, 2021). Environmental pressures require, above all, the accurate estimation of suspended sediment load (SSL) for management purposes. The Göksu River Basin was selected as a research location because it includes protected regions, intricate physical features, a Mediterranean climate, extensive delta agricultural activities, and karst geological formations that produce unpredictable sediment patterns, creating difficulties for testing various optimizer-model combinations.

2.2. Data Collection and Preparation

The Göksu River basin monitoring program collected hydrological, sedimentological, and meteorological data from 1987 to 2022, resulting in a complete dataset containing 13,149 individual records. The selection of these 35 years was guided by two primary considerations: (i) data continuity and availability, which ensured an unbroken time series that enabled complete time-series analysis and model training; and (ii) long-term hydrological variability, which included different climatic conditions and flow patterns that improved model development. The monitoring station, located at a specific site, monitored how the entire basin responded to multiple hydrological and sediment-transport conditions by recording measurements at different times of day. The research team studied key variables, which included temperature (mean, minimum, and maximum, °C), precipitation (mm), suspended sediment concentration (SSC, g/L), flow rate (Q_t, m^3/s), and total suspended sediment load (SSL, tons/day). The different variables provide distinct information, showing how sediment travels through water bodies and revealing water movement patterns and the sediment they carry. The researchers conducted a comprehensive numerical stability assessment and machine learning evaluation before building their model, as they required reliable numerical conditions that required preprocessing. The researchers applied min–max scaling (Patel, 1995) to all variables, transforming them to a 0–1 scale, thereby improving model performance and reducing convergence time. The researchers used interpolation methods to fill in missing data points, thereby creating a complete dataset. The preprocessing steps created a high-quality dataset that maintained consistency throughout the process and was suitable for advanced machine learning and deep learning SSL prediction in the Göksu River system.

3. Data and Methodology

3.1. Core Methodological Framework and Study Objective

The primary methodological contribution of this study is the formulation of an optimization-focused comparative framework for suspended sediment load (SSL) modeling. Rather than proposing a new predictive algorithm, the study aims to systematically isolate and evaluate the influence of optimization strategies on model performance, independent of model architecture. Within this framework, multiple learning models, namely Support Vector Machine (SVM), Radial Basis Function Neural Network (RBFNN), and Backpropagation Neural Network (BPNN), are employed as benchmark learners. A global metaheuristic optimizer (Water Cycle Algorithm, WCA) is applied uniformly across all models to ensure comparability. In contrast, model-specific optimizers (SMO for SVM and ADAM for neural networks) are retained to preserve algorithmic integrity. This design enables a controlled investigation of optimizer–model compatibility, allowing performance differences to be attributed to structural interactions rather than optimizer bias. The governing objective of the framework is therefore not to rank models based solely on accuracy, but to establish a methodologically coherent basis for comparative evaluation in SSL modeling.

3.2. Input Procedures for Forecasting SSL

The study aimed to identify the most suitable factors for predicting suspended sediment load (SSL) and to test how different input configurations would impact model performance. The study developed 10

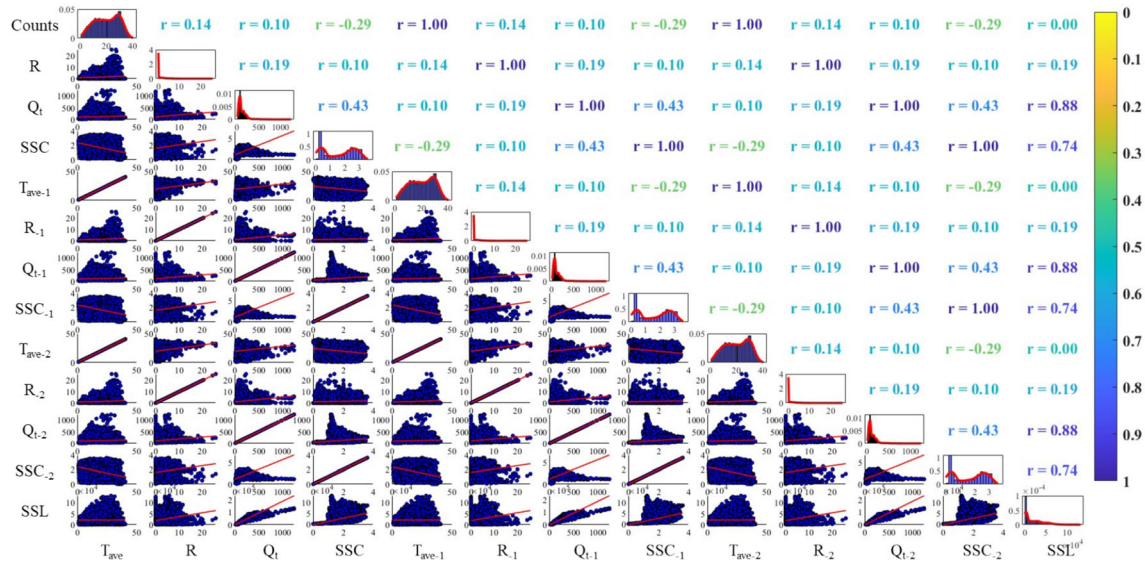


Fig. 2
The correlations between the observed and lagged input parameters

Table 3

Input procedures for forecasting SSL based on the training dataset

No.	Input parameter	Output	Type
1	Q_t	SSL	Based on the highest r
2	SSC	SSL	Based on the highest r
3	Q_t, SSC, R	SSL	No months-long lag-time
4	Q_t, SSC, R, SSC^{-1}	SSL	With months lag-time
5	Q_t, SSC, R, SSC^{-1}, SSC^{-2}, $Q_w{}^{-1}$	SSL	With months lag-time
6	Q_t, SSC, R, SSC^{-1}, SSC^{-2}, $Q_t{}^{-1}$, $Q_t{}^{-2}$	SSL	With months lag-time
7	Q_t, $Q_t{}^{-1}$, $Q_t{}^{-2}$	SSL	River discharge
8	SSC, SSC^{-1}, SSC^{-2}	SSL	Suspended sediment concentration
9	Q_t, SSC	SSL	River discharge and suspended sediment concentration
10	Q_t, R	SSL	River discharge and rainfall
11	Q_t, SSC, SSC^{-1}, SSC^{-2}, $Q_t{}^{-1}$, $Q_t{}^{-2}$	SSL	WFS

*The superscripts -1 and -2 indicate variables with one and two months of lag time

scenarios that used Pearson correlation coefficients (R-values) to assess the association between potential predictors of SSL and SSL in the training dataset (Fig. 2). The study used the Wrapper Feature Selection (WFS) method. This supervised technique identifies the best feature sets for the model by measuring their impact on model performance during training and testing (Seyyedabbasi, 2023). The study required systematic testing of multiple input combinations because different hydrological and meteorological variables are more or less useful across different watersheds. The study found that configurations that included one-month lagged variables produced the strongest effects on SSL prediction results, according to Table 3 and previous research results (Aytek & Kişi, 2008; Choubin et al., 2018; Khosravi et al., 2022; Kişi et al., 2012; Melesse et al., 2011; Nhu et al., 2020).

The analysis of correlation showed that river discharge had the strongest relationship with suspended sediment load (SSL; R = 0.88) while rainfall showed the lowest relationship (R = 0.19), which

matched previous studies that showed major performance drops resulted when discharge data was removed from SSL modeling (Khosravi et al., 2022; Kişi et al., 2012; Nhu et al., 2020; Ranjan & Roshni, 2024). Although some investigations have identified rainfall alongside discharge as a dominant sediment driver (Baniya et al., 2024; Chiang & Tsai, 2011; Kanga et al., 2020; Kişi et al., 2012), the reduced rainfall influence observed here is likely attributable to watershed-scale hydrological buffering and temporal aggregation effects. Input procedures 1–6 were incrementally constructed by adding predictors in descending order of correlation to assess the sufficiency of high-R variables. In contrast, procedures 7 and 8 isolated lagged discharge and lagged SSC, and Procedures 9 and 10 evaluated the combined effects of discharge with SSC and rainfall without lag terms, with all scenarios assessed using RMSE on the testing dataset. A key feature of the framework is the systematic inclusion of time-lagged variables (Scenarios 4–8 and 11), which capture delayed sediment transport responses arising from storage and remobilization processes; comparative analysis (Sect. 4.4) shows that lag-inclusive configurations, particularly Scenario 6, achieve the highest predictive accuracy, highlighting the critical importance of temporal representation in SSL forecasting for the Göksu River basin.

3.3. ML Models Review

The researchers used three machine learning models that already exist to model how suspended sediment load SSL behaves through its nonlinear multiscale patterns. The SVM model, grounded in statistical learning theory, constructs an optimal separating hyperplane using kernel functions, with a sigmoid kernel adopted to address nonlinear separability (Wang et al., 2023; Zhang et al., 2023). BPNN, a multilayer feedforward architecture trained through error backpropagation, employs sigmoid activation functions to approximate complex nonlinear input–output relationships (Li et al., 2024). RBFNN, composed of Gaussian radial basis neurons and a linear output layer, provides efficient localized nonlinear approximation with rapid convergence and strong interpolation capability (Alitasb & Salau, 2024). The three models demonstrate different learning methods by using margin-based learning, global gradient-driven approximation, and localized nonlinear mapping, and they show their results under the same data conditions.

The research used three distinct optimization methods, each with its own theoretical foundations, to achieve unbiased training results. The SVM training process used Sequential Minimal Optimization (SMO) as its sole method because SMO solves the SVM's convex quadratic programming problem analytically, maintaining numerical accuracy and achieving fast convergence (Yu et al., 2023). The Adaptive Moment Estimation (ADAM) optimizer enabled BPNN and RBFNN to achieve faster, more stable convergence through its combination of momentum and adaptive learning rates (Li et al., 2023; Hoang & Tran, 2023). The Water Cycle Algorithm (WCA), which uses population-based global optimization methods that mimic hydrological systems, was used to optimize neural network parameters, thereby improving their ability to avoid local minima and achieving better generalization (Eskandar et al., 2012; Ghasemi et al., 2024; Ghasri et al., 2024). The system lets users compare different optimization methods, including convex gradient-based techniques and global search methods, across diverse models.

The process used correct hyperparameter initialization, along with tuning methods, to achieve both numerical stability and convergence efficiency. The ADAM optimizer used a learning rate of 0.01, which fell within the typical range of recommended values according to Hoang & Tran (2023) while all other hyperparameters used values of $\beta_1 = 0.99$ and $\beta_2 = 0.9999$ and $\varepsilon = 1 \times 10^{-5}$ to achieve an optimal balance between fast and stable convergence according to Yu et al., 2023. The selection of the regularization parameter C for SVM training via SMO followed standard practice to achieve a balance between maximizing the margin and minimizing training error, according to Platt's (1998) guidelines. The WCA required initialization of population-based parameters via 8 streams, 100 population members, a 1×10^{-3} maximum distance threshold, and 500 iterations, which ensured a proper exploration–exploitation balance, as per Eskandar et al. (2012). The

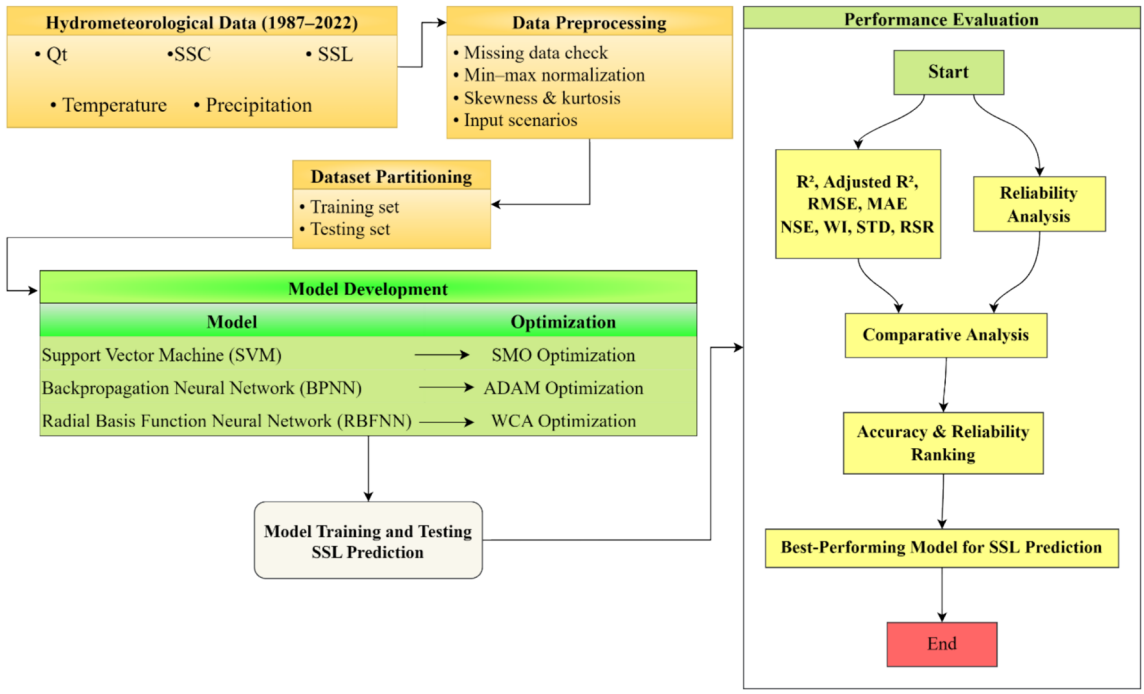


Fig. 3
The flowchart of the study

framework uses optimizer-aware techniques and precise tuning methods to assess SSL forecasting results and demonstrate how optimization affects model performance, as described in the workflow in Fig. 3.

3.4. Optimum Procedure and Input Variable

This study uses a trial-and-error approach combined with a single-hidden-layer multilayer perceptron (MLP) to determine the most effective input configuration for suspended sediment load (SSL) prediction. As MLPs are well-established for modeling nonlinear input–output relationships in

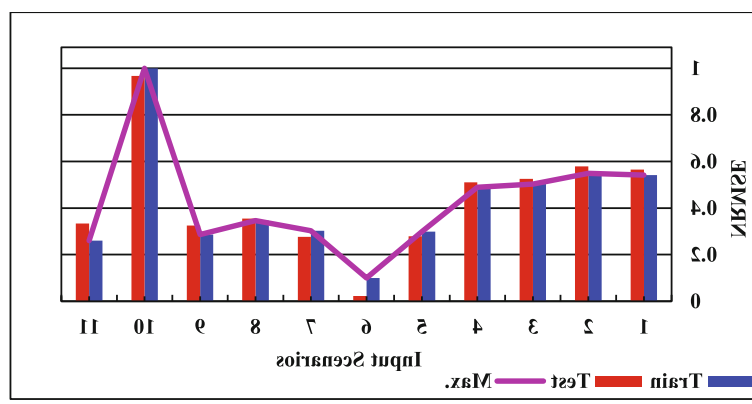


Fig. 4
Selecting the best procedure based on performance

Table 4

Statistical metrics used to compare models

Methods	Abbreviation	Lower; upper bound	Optimal value
Coefficient of determination	R^2	0; 1	1
Adjusted coefficient of determination	R^2_{adj}	0; 1	1
Normalized Root Mean Square Error	NRMSE	0;+∞	0
Mean Absolute Error	MAE	0;+∞	0
Nash–Sutcliffe Efficiency	NSE	−∞; 1	1
Wilmot Index	WI	0; 1	1
Standard Deviation	STD	0;+∞	0
Ratio of RMSE to STD	RSR	0;+∞	0
Reliability Analysis	RA	0; 100	100

$$R^2 = \frac{\left[\sum_{i=1}^{N}\left(SSL_{Pre,i}-SSL_{Pre,avg}\right)\left(SSL_{Obs,i}-SSL_{Obs,avg}\right)\right]^2}{\sum_{i=1}^{N}\left(SSL_{Pre,i}-SSL_{Pre,avg}\right)^2\sum_{i=1}^{N}\left(SSL_{Obs,i}-SSL_{Obs,avg}\right)^2} \quad (21)$$

$$R^2_{adj} = 1 - \frac{\left(1-R^2\right)-(N-1)}{N-J-1} \quad (22)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(SSL_{Pre,i} - SSL_{Obs,i}\right)^2} \quad (23)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|SSL_{Pre,i} - SSL_{Obs,i}\right| \quad (24)$$

$$\sigma_{obs} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(SSL_{Pre,i} - \overline{SSL_{Obs,i}}\right)^2} \quad (25)$$

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(SSL_{Pre,i}-SSL_{Obs,i}\right)^2}}{\sigma_{obs}} \quad (26)$$

$$NSE = 1 - \left[\frac{\sum_{i=1}^{N}\left(SSL_{Obs,i}-SSL_{Pre,i}\right)^2}{\sum_{i=1}^{N}\left(SSL_{Obs,i}-SSL_{Obs,avg}\right)^2}\right] \quad (27)$$

$$WI = 1 - \left[\frac{\sum_{i=1}^{N}\left(SSL_{Pre,i}-SSL_{Obs,i}\right)^2}{\sum_{i=1}^{N}\left(\left|SSL_{Pre,i}-SSL_{Pre,avg}\right|+\left|SSL_{Obs,i}-SSL_{Obs,avg}\right|\right)^2}\right] \quad (28)$$

$$STD = \sqrt{\frac{\sum_{1}^{N}\left(\frac{SSL_{Pre,i}}{SSL_{Obs,i}}-\frac{SSL_{Pre,avg}}{SSL_{Obs,avg}}\right)}{N-1}} \quad (29)$$

$$RSR = \left[\frac{\sum_{i=1}^{N}\left(SSL_{Obs,i}\right)-\left(SSL_{Pre,i}\right)^2}{\sum_{i=1}^{N}\left(SSL_{Obs,i}\right)-\left(SSL_{Obs,avg}\right)^2}\right] \quad (30)$$

$$RA = 100 \times \left[\frac{1}{n} \times \sum_{i=1}^{n} P_i\right] \quad (31)$$

Where N represents the number of data points, *Pre* signifies the predicted values, *Obs* denotes the experimental (observed) values, *avg* represents the average of the data, d stands for the difference between the two ranks of each observation, and J illustrates the number of predictor parameters. The variable P_i is calculated based on the relative average error (RAE). If RAE is less than or equal to 0.2, then P_i equals 1; otherwise, P_i equals 0 (Khosravi et al., 2022)

regression and classification tasks, selecting an optimal model among diverse architectures is crucial to balance accuracy, complexity, and computational efficiency (Akiner & Ghasri, 2024). A simplified MLP was adopted to address practical constraints, including limited computational resources and time. Performance analysis across various configurations (Fig. 4) revealed that using all available input variables (Input No. 6) achieved the highest predictive accuracy, surpassing Input No. 1 by 41% and Input No. 10 by 52%. These results demonstrate the inherent complexity of the hydrological processes governing SSL and the importance of variable synergy, particularly when the Wrapper Feature Selection (WFS) method partially matched Input No. 5 but failed to identify the optimal configuration due to the omission of rainfall (R) and the inclusion of lagged discharge (Q_t^{-2}).

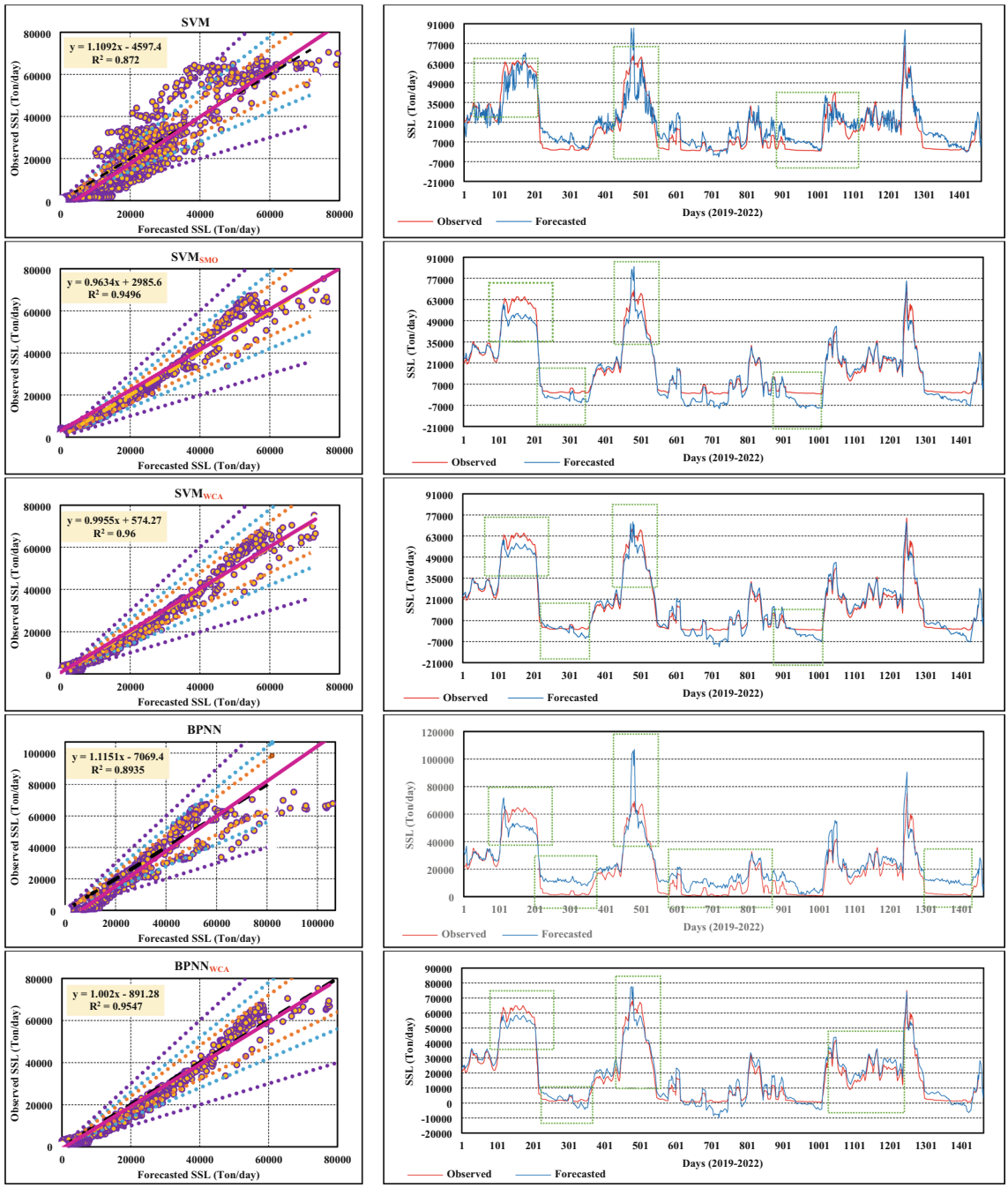


Fig. 5
Scatter plots and time series of the models created throughout the assessment period

4. Results

4.1. Performance Evaluation Indicators

SSL forecasting was performed using three classical standalone models, six hybrid models, and two deep learning models. The predictive models' accuracy was extensively assessed using metrics such as R^2, R^2_{adj}, NRMSE, MAE, NSE, WI, and STD (Bazoobandi et al., 2024). The statistical indicators for model comparison, as per the equation, are shown

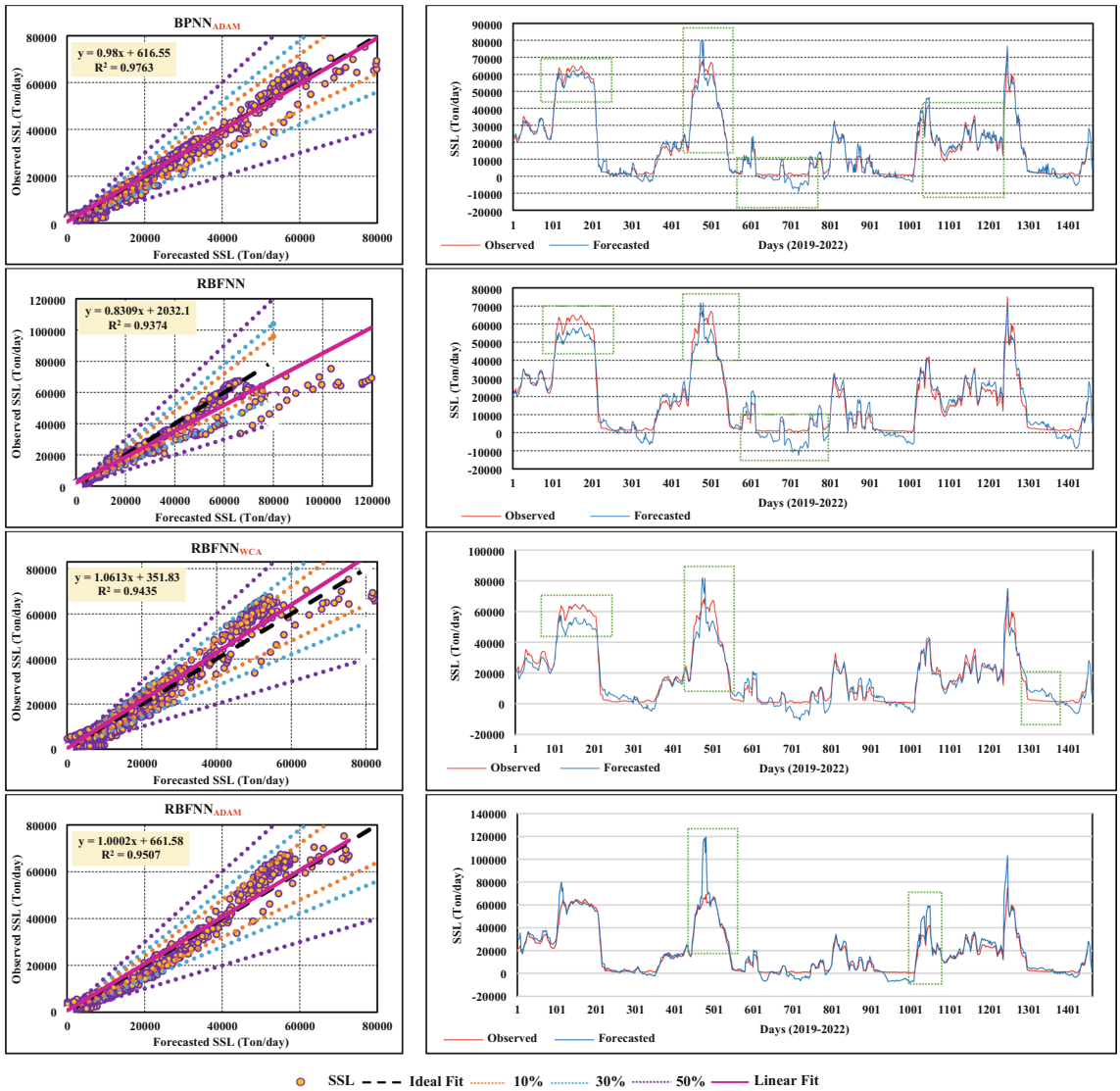


Fig. 5
continued

in Table 4. In addition to the aforementioned indices, the Combined Accuracy (CA) index (Adnan et al., 2024) was used to evaluate the models' performance.

4.2. *Models' Performance and Evaluation*

The temporal dataset was partitioned into three periods: 1987–2012 for model development, 2013–2018 for calibration, and 2019–2022 for testing. The researchers developed 11 machine learning models and tested them using optimal input configurations and model parameters, and evaluated them using visual representations and statistical metrics. The results presented in Fig. 5 show that scatter plots and time-series comparisons reveal a significant difference between actual suspended sediment load (SSL) measurements and predicted values. The combined use of deep learning and hybrid models produced better results than single models, achieving higher accuracy in predicting peak SSL events.

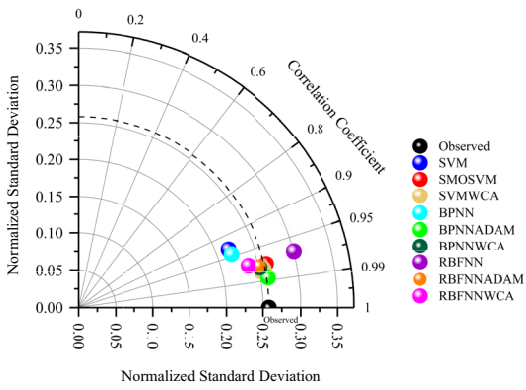


Fig. 6
Taylor diagram showing the performance of the models relative to the observed SSL using the correlation coefficient and normalized standard deviation

Accurate prediction of such extremes is crucial for river management and engineering applications, including reservoir sedimentation assessment, hydraulic structure design, and flood risk mitigation (Heddam et al., 2024). The hybrid models showed the best performance, but all models failed to predict when extreme events would occur because they incorrectly determined when peak events began, as shown in the green rectangles of Fig. 5. The current model scenarios fail to explain non-stationary and threshold-driven processes that control high sediment transport, because monthly input resolution filters out short-term signals generated by heavy precipitation and watershed dynamics. Model integration improved overall fit, but none of the models successfully predicted the occurrence of extreme events. This limitation may stem from data constraints, such as unrecorded climatic events or insufficient instances of extreme conditions in the training dataset. The research requires future work to use extended time-series and event-based data to develop its solution. Operational forecasting requires precise magnitude estimation together with efficient prediction of extreme events. The research should focus on creating a model that is sensitive to extreme-event precursors, using high-resolution inputs, peak-focused loss functions, and specialized sequential data-anomaly-detection architectures.

The scatterplot shown in Fig. 5 displays model performance results as regression slope measurements at 10%, 30%, and 50% angles, which it compares to the 1:1 (45°) standard. The results show that the standalone models fail to capture all inherent variations in the observed dataset. Time-series plots highlight this limitation by showing ongoing temporal discrepancies that warrant further investigation. The Taylor diagram in Fig. 6 supports this analysis by showing that the BPNN_ADAM model delivers the best results, with an R2 value of 0.98 and a normalized standard deviation of 0.26, which closely matches the observed data value of 0.25. The standalone SVM achieves the lowest accuracy. Single models produce R^2 values between 0.91 and 0.96, while integrated-optimizer models achieve a 5.5% performance boost, resulting in BPNN_ADAM delivering the highest output.

The statistical performance indices NRMSE, MAE, R^2, R^2adj, WI, NSE, and CA provide a comprehensive assessment, showing that the models differ in their ability to achieve accurate results, maintain consistent performance, and simulate the changing patterns of suspended sediment load (Fig. 7). The baseline SVM shows its lowest performance, with an NRMSE of 0.944, an actual MAE of 0.390, and R^2 and NSE values of 0.87 and 0.85, indicating weak forecasting capacity. The standalone BPNN minimizes absolute error, achieving the lowest MAE (0.09) and the highest CA (0.897), though its variance explained remains moderate (R^2 = 0.89). The model performance improves through the ADAM and SMO optimization processes, resulting in BPNN_ADAM producing the best fit (R^2 = 0.976, R^2adj = 0.98, WI = 0.781, NSE = 0.860) and the lowest NRMSE (0.353). However, it has a lower CA (0.73) than other methods. The WCA-based hybrid models deliver stable, strong results, while BPNN_WCA achieves the highest NSE (0.890) and WI (0.815), very low MAE (0.026), and high R^2 (0.955), and maintains steady CA performance at approximately 0.79–0.81. BPNN_ADAM has the highest reliability score of 90.12% as the best model, while multi-criteria evaluation shows its advantages and overall performance levels (Fig. 8).

The results show that both optimization methods reduced prediction errors and improved model performance, as evidenced by better time-series curve results. The SVM_WCA model achieved better

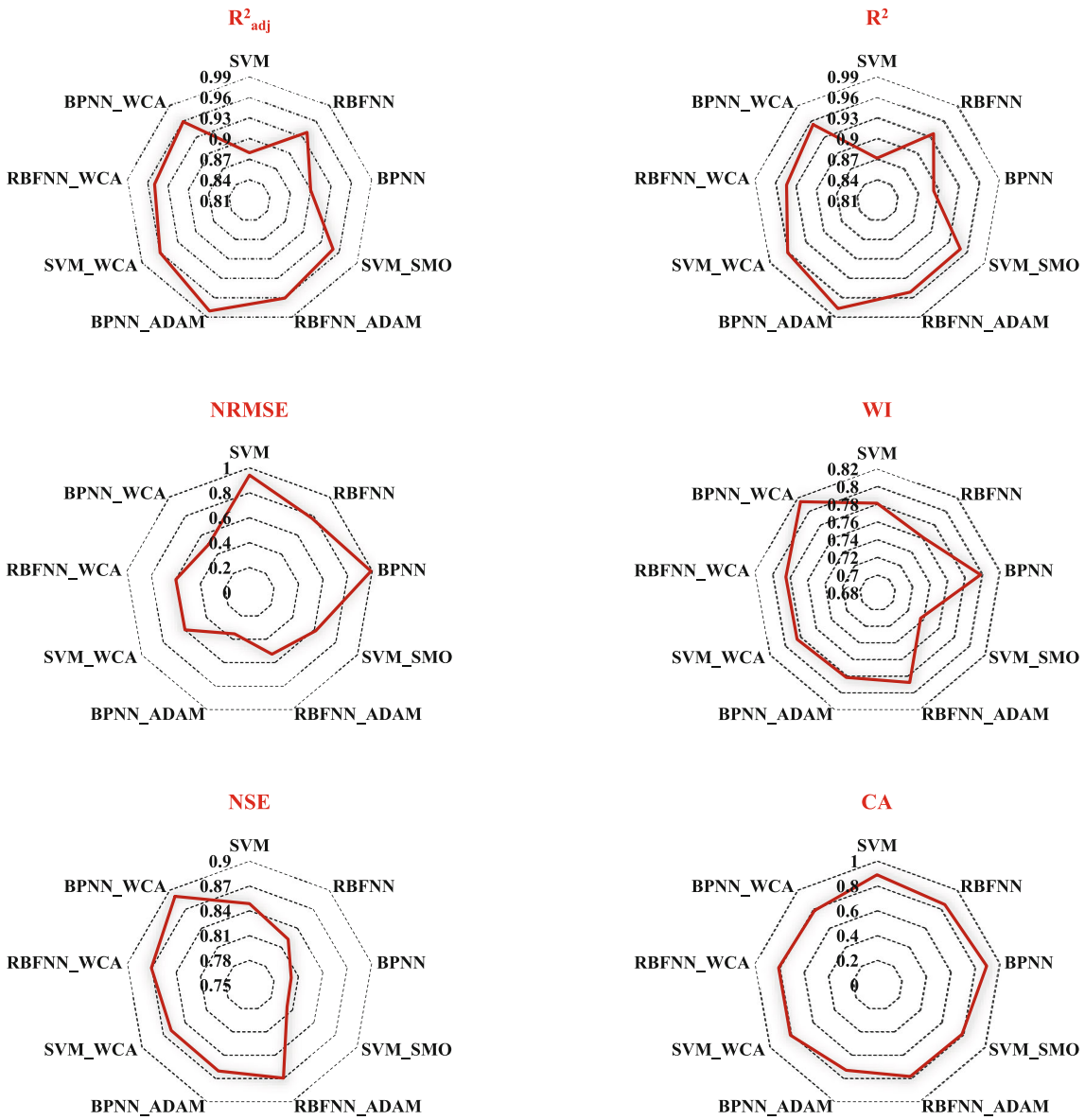


Fig. 7
A radar chart to facilitate a comprehensive comparison among the models

results than SVM_SMO because it demonstrated a stronger ability to reduce data noise while maintaining stable predictions. The WCA optimizer performed the worst among both RBFNN and BPNN systems, as its efficiency fell short of that of ADAM-optimized models. The superior performance of ADAM relative to WCA arises from its adaptive learning rate and momentum mechanisms, which determine parameter-wise step sizes based on previous gradients, leading to faster convergence and better weight optimization. The combination of ADAM's resilience against sparse gradients and WCA's need for extensive hyperparameter tuning creates two separate optimization challenges for WCA, which also suffers from increased sensitivity to data quality issues. The persistent, strong results achieved by ADAM-optimized models stem from these factors, underscoring the need to choose

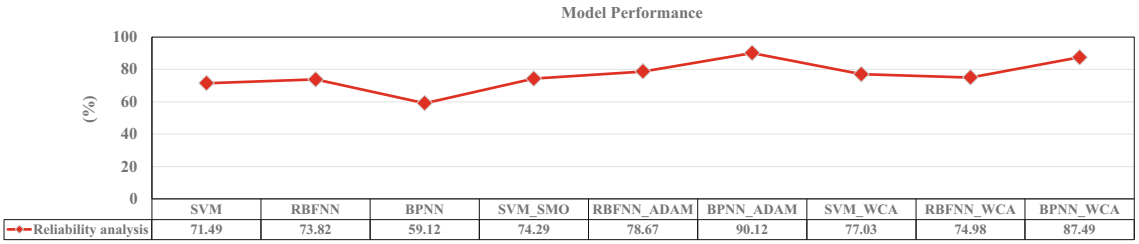


Fig. 8
Reliability analysis applied to model performance evaluation

optimization methods that align with both dataset properties and neural network architectural choices.

To further clarify the rationale behind optimizer selection, the Water Cycle Algorithm (WCA) was chosen as a model-agnostic global metaheuristic optimizer to serve as a common optimization baseline across all learning models. Unlike gradient-based optimizers such as ADAM, which rely on differentiability and smooth error surfaces, WCA performs population-based global search. It can therefore handle non-convex, discontinuous, or multimodal objective functions. This characteristic is significant because specific models, most notably kernel-based SVMs, do not naturally align with adaptive gradient-based optimizers such as ADAM.

The comparative results conceptually illustrate that using a non-specialized optimizer for a given model can negatively affect performance, even when the optimizer itself is powerful. For example, although WCA effectively avoids local minima and improves generalization stability, it does not consistently surpass SMO for SVM or ADAM for neural networks, both of which are mathematically tailored to their respective learning dynamics. This outcome highlights a critical methodological insight: optimizer strength alone does not guarantee optimal performance unless it is structurally compatible with the underlying model (see Table 5). Consequently, improper optimizer selection may lead to misleading conclusions regarding model superiority. By jointly presenting model-specific optimizers alongside a unified metaheuristic, this study provides a transparent, conceptually sound framework for understanding how optimization strategy influences comparative model evaluation.

4.3. SHAP Analysis of Input Contributions

SHAP provides a robust, game-theory-based framework for interpreting machine learning predictions by quantifying the contribution of each input feature to deviations from the mean model output (Fig. 9a). SHAP improves transparency in complex models by assigning importance values that describe the significance of individual elements in each instance (Ergen & Katlav, 2024). The SHAP analysis for the BPNN_ADAM model, illustrated in a heatmap, reveals the distribution and magnitudes of feature contributions across different instances (Fig. 9b). The results show that discharge (Q_t) and one-month-lagged suspended sediment concentration (SSC^{-1}) are the main predictors of suspended sediment load, as their SHAP values differ across samples, demonstrating their essential role in accurate predictions. The heatmap displays a color gradient indicating how positive (red) and negative (blue) influences affect the model output. The observed instance-dependent variability highlights the model's sensitivity to specific input configurations, providing valuable insights for identifying influential parameters, improving interpretability, and supporting informed decision-making to enhance model performance and reliability.

4.4. Deep Learning Implementation

Deep learning models, especially Long Short-Term Memory (LSTM) networks, function effectively for sequential data analysis because their gated memory systems enable them to maintain long-term temporal relationships (Zhou et al., 2023). LSTMs achieve better performance than standard RNNs on

Table 5

Conceptual comparison of WCA and model-specific optimizers

Model	Model-specific optimizer	Optimization nature	WCA as common optimizer	Conceptual interpretation
SVM	SMO	Convex, analytical QP solver	Global, population-based	SMO is structurally aligned with SVM's convex formulation; WCA provides stable global search but cannot outperform an exact solver
BPNN	ADAM	Gradient-based, adaptive learning	Gradient-free global search	ADAM efficiently exploits smooth loss surfaces; WCA improves robustness but converges more slowly
RBFNN	ADAM	Continuous parameter optimization	Global exploration mechanism	ADAM is better suited for fine-tuning centers and weights, while WCA primarily improves global generalization
All models	–	Model-dependent	WCA (shared)	Using WCA across all models isolates architectural effects and prevents optimizer-driven bias in comparison

difficult sequence-learning tasks because they address the vanishing gradient problem (Khennour et al., 2023). Their effectiveness has been demonstrated across a wide range of applications, including speech processing, handwriting recognition, and structural prediction (Khanam et al., 2022). Bidirectional LSTMs (Bi-LSTMs) provide extended functionality by analyzing sequences in both forward and backward directions, resulting in better contextual understanding and more accurate predictions (Yadav et al., 2019, 2022).

The research developed a Bi-LSTM model with a single-layer structure using 100 units and a teacherless learning system with the ADAM algorithm for RMSE-based optimization. The model was trained for 100 periods using precisely adjusted hyperparameters. The suspended sediment load (SSL) prediction system implemented both univariate and multivariate configurations, achieving high accuracy with R^2 values of 0.99 (Fig. 10). The deep learning model outperforms traditional and hybrid models, as shown in Fig. 11, which compares the models using RMSE, R^2, and NSE metrics.

4.5. Methods Comparison Through Literature

The comparison was conducted to assess the efficacy of the methods outlined in this paper by reviewing the pertinent literature. Quite a few studies were included in this comparison, and the results are illustrated in Fig. 12, where the NSE coefficient and R^2 served as performance metrics. Khosravi et al. (2022) conducted a study to predict SSL amounts in the Talar watershed. They analyzed the EN, AM Tree, and REP Tree techniques separately and teamed up with the RF method. The authors also compared the outcomes of the aforementioned methods with those obtained from the ANFIS technique in conjunction with the ICA and BAT optimization algorithms. The report said that the hybrid models built on the Tree and EN model surpassed the optimized ANFIS algorithms. Among the main factors why this is so is that ANFIS models are highly dependent on data quality; hence, they are less robust and flexible than the new models (Allawi et al., 2021a, 2021b, 2021c).

Furthermore, the optimized ANFIS models failed to detect extreme values, leading to a gross overestimation or underestimation of the maximum SSL value. The maximum values of NSE and R^2 reported in the study were 0.84 and 0.85, respectively, for the RF-EN method. Fadaee et al. (2022) reported a similar study in which they applied seven techniques to forecast sediment concentration in the Eagle Creek watershed in the USA. The techniques used were ANFIS-FCM, ANFIS-BOA, ANFIS-GA, ANN, ANN-GA, ANN-BOA, and MLR. The major finding of this study was that the ANFIS-BOA model was more accurate for suspended sediment modeling, yielding NSE and R^2 of 0.92 and 0.93, respectively.

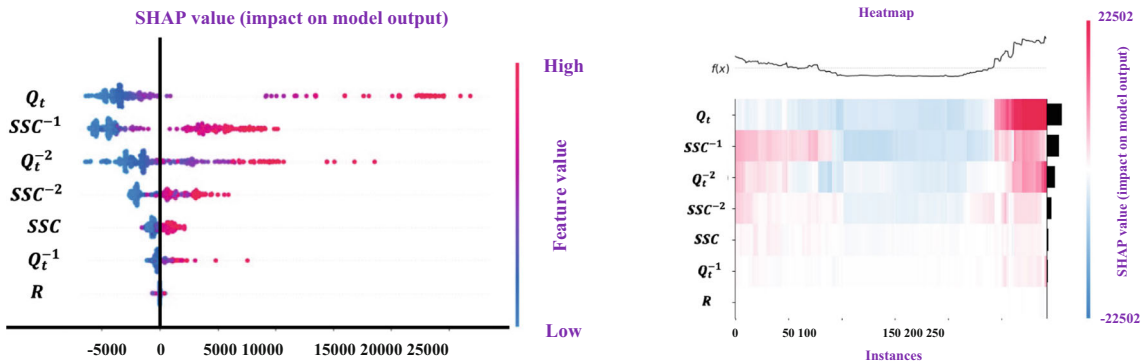


Fig. 9
SHAP analysis of input contributions: **a** SHAP summary plot for input features and **b** SHAP heat maps for input features

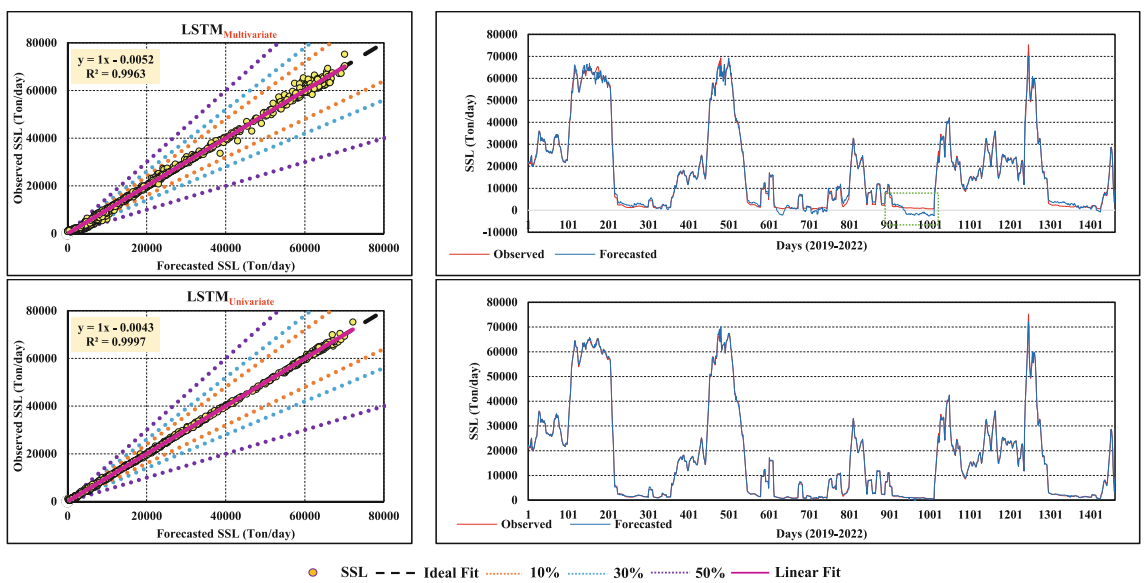


Fig. 10
Time series and scatter plots for the LSTM models during the evaluation period

The methods presented in Fig. 12, developed by Khosravi et al. (2022) and Fadaee et al. (2022) for suspended sediment load (SSL) prediction, represent established approaches in hydrological modeling. However, recent advancements in machine learning have introduced novel deep learning and hybrid techniques, such as those listed in Table 6 (RVM, RVM IMRFO, ANN, ANN-ERUN, RVFL, RVFL-EROA, LSTM-INFO, LSTM-ALO, BiRNN, CNN, BiRNN-CNN), which have been increasingly applied to hydrological forecasting (Hochreiter & Schmidhuber, 1997; Hu et al., 2018; Koutsovili et al., 2023). As illustrated in Table 6, these hybrid and standalone models demonstrate competitive performance, often surpassing traditional methods in predictive accuracy.

The evaluation process for these models requires an essential observation: assessing how model complexity affects interpretability. Implementing deep learning architectures requires developers to build more complex models that better detect nonlinear

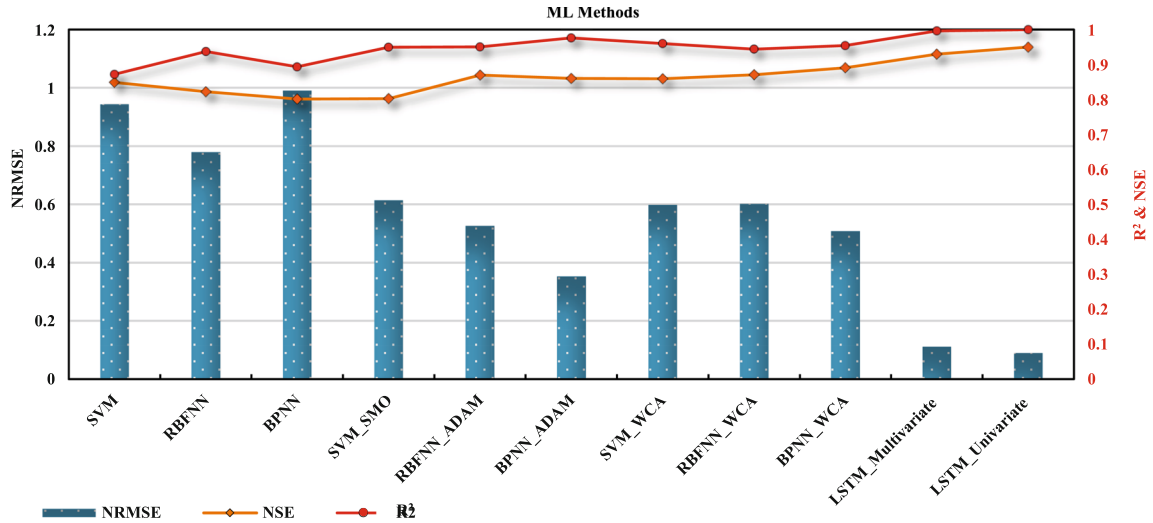


Fig. 11
Comparison of deep learning models with hybrid and standalone ML models

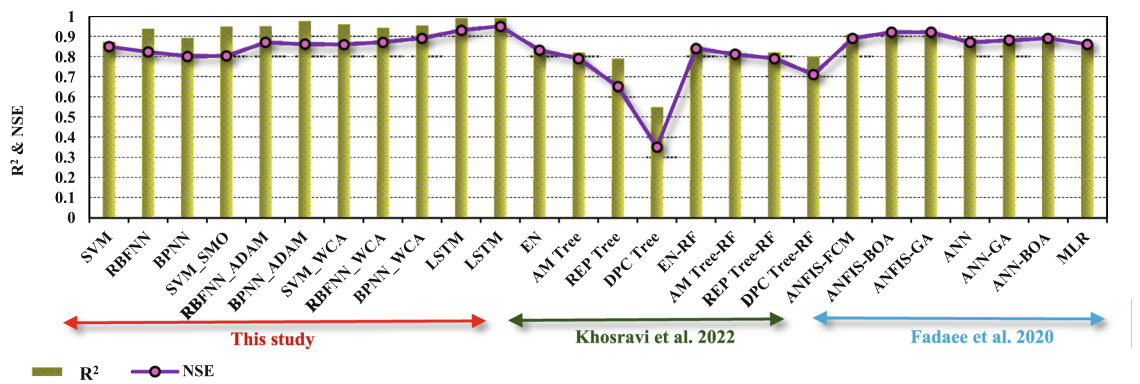


Fig. 12
Performance analysis between this study and previous studies regarding R^2 and NSE (Fadaee et al., 2022; Khosravi et al., 2022)

Table 6

Comparative performance of DL models for SSL prediction

	RVM	RVM-IMRFO	ANN	ANN-ERUN	RVFL	RVFL-EROA	LSTM-INFO	LSTM-ALO	BiRNN	CNN	BiRNN-CNN
R^2	0.75	0.85	0.80	0.87	0.82	0.88	0.95	0.91	0.90	0.99	0.95
NSE	0.75	0.82	0.77	0.84	0.79	0.85	0.90	0.89	0.88	0.99	0.91

relationships across various input–output patterns. Yet, this development approach creates obstacles to understanding and analyzing model behavior. The system operates as a "black box," preventing users from comprehending its core mechanisms, making it difficult to interpret results and verify them against established hydrological principles. The Backpropagation Neural Network (BPNN) with ADAM optimization shows decent predictive accuracy across all nonlinear relationships when tested with deep

learning methods. The BPNN system provides better predictive performance and operational implementation advantages. The system establishes clear input–output pathways that enable users to test model validity and use that information within engineering and management environments. Deep learning models achieve excellent predictive performance, yet their complex design makes them difficult to use in real-world settings. BPNN databases enable operational hydrological forecasting through their simple design, which delivers equal performance and interpretability while maintaining essential system transparency and physical consistency.

5. Discussion

The research used advanced machine learning techniques to improve suspended sediment load (SSL) predictions for the ecologically valuable Göksu Delta using the ADAM optimizer and Long Short-Term Memory (LSTM) networks. The hybrid BPNN_ADAM model demonstrated high accuracy, with an R value of 0.98, indicating a normalized standard deviation that closely matched the observed value. The single Support Vector Machine (SVM) model performed at its lowest level, producing R values between 0.91 and 0.96. The deep learning Bi-LSTM architecture proved exceptionally effective at capturing temporal dependencies, achieving an R^2 of 0.99. The models demonstrated that time-lagged variables are necessary for accurate modeling of catchment memory effects and sediment transport delays in the Göksu Basin, according to their findings from Q_t^{-1} and SSC^{-1} (Table 3, Scenarios 4–6, 11). The models have achieved success because of their empirical design, which relies on historical data patterns. Still, this design limits their ability to interpret physical systems and predict outcomes beyond their training data (Baniya et al., 2024).

The main methodological issue arises from the diagnostic circularity problem that occurs when researchers use suspended sediment concentration (SSC) and prior SSC measurements as study inputs, as is common in comparative research (e.g., Joshi et al., 2024; Stull & Ahmari, 2024; Yue et al., 2025). This method enables researchers to evaluate algorithm performance under optimal data conditions. Still, it prevents the model from being used for real-time predictions when suspended sediment concentration is unknown. The high-performance metrics of models like BPNN_ADAM and LSTM should be understood as the best possible performance the models can achieve when operating under conditions of complete data access. The study examined only one basin, limiting its results to the specific hydrological conditions of the Göksu River. The research must develop effective operational models that leverage common discharge and precipitation data, while creating hybrid systems that combine physical sediment transport equations with machine learning methods to enhance prediction accuracy and physical model validation.

The results indicate that flow discharge (R = 0.88) is the most influential predictor of SSL, while the linear relationship with simultaneous rainfall depth is weak (R = 0.19). This research identifies discharge as the primary factor, aligning with previous studies by Kişi et al. and Nhu et al. Still, it diverges from others that establish rainfall as an essential element (e.g., Baniya et al., 2024). The discrepancy arises because the limestone geology of the Göksu Basin, together with its Mediterranean climate, creates optimal conditions for infiltration, leading to monthly separation of sediment yield from rainfall. The modeling framework lacks R_{-1} and R_{-2} as lagged rainfall variables, limiting its ability to identify delayed erosive responses that depend on prior moisture conditions and subsurface water movement. The weak rainfall correlation requires analysis from a combined perspective that considers both basin-specific hydrology and the limitations of the research methods used. Future research should use lagged rainfall data alongside seasonally aggregated rainfall information to examine how rainfall produces complex effects on sediment movement over different time scales.

The primary contribution of this study lies in establishing and validating a strict optimization-focused comparative framework that is conceptually distinct from conventional model comparison approaches. Unlike most previous studies, which typically compare machine-learning models using a single optimizer or implicitly assume optimizer

neutrality, this framework explicitly disentangles model architecture effects from optimizer-induced performance gains. This is achieved through a two-level strategy: (i) applying a standard metaheuristic optimizer (Water Cycle Algorithm) uniformly across all models to ensure methodological consistency, and (ii) benchmarking these results against model-specific optimizers that are theoretically aligned with each learning mechanism. By doing so, the framework demonstrates that superior performance cannot be attributed solely to either model structure or optimizer strength, but rather to their structural compatibility. This optimization-centric perspective provides a more rigorous and transferable basis for comparative evaluation, enabling researchers to avoid misleading conclusions caused by inappropriate optimizer selection. Consequently, the framework advances current practice by shifting comparative analysis from outcome-based ranking toward mechanism-aware performance interpretation, thereby offering a robust foundation for future studies across diverse environmental and data-driven modeling applications.

Future work should expand the input feature set to include crucial geomorphological (topography, soil type) and hydrological parameters (streamflow, precipitation patterns), acknowledging that factors like steep slopes and human activities (deforestation, urbanization) are major drivers of sediment mobilization (Jing et al., 2024; Zena et al., 2024). The scientific process requires researchers to understand the complex interactions that have developed among sediment, land, and biota systems over millions of years, as this knowledge is necessary for advancing scientific research and developing effective management strategies for Göksu Delta ecological restoration and settlement monitoring systems.

6. Conclusion

Rapid urbanization and land-use changes in the Göksu River Basin have intensified soil erosion, making suspended sediment load (SSL) a critical indicator of watershed response and deltaic sustainability. Addressing this challenge requires modeling strategies that are not only accurate but also methodologically robust and interpretable.

The key contribution of this study is the development and validation of a strict optimization-focused comparative framework for SSL modeling. Unlike conventional approaches that emphasize the numerical superiority of individual models, this framework explicitly examines the interaction between the learning architecture and the optimization strategy. By systematically integrating a shared metaheuristic optimizer with model-specific optimization methods, the study demonstrates that model performance is strongly governed by optimizer–model compatibility, rather than by model complexity alone.

The findings reveal that hybrid machine learning models offer a favorable balance among predictive capability, computational efficiency, and interpretability. While deep learning models provide strong benchmark performance, the results show that carefully optimized conventional neural networks can achieve comparable reliability with substantially lower computational demand. This insight is particularly relevant for data-limited or operational hydrological applications.

Beyond predictive accuracy, the study highlights the importance of methodological transparency in model comparison. Inappropriate or inconsistent optimizer selection can lead to misleading conclusions regarding model superiority. The proposed framework mitigates this risk by providing a transferable and reproducible basis for comparative evaluation, thereby advancing best practices in environmental machine-learning research.

Future research should extend this framework by incorporating additional geomorphological and anthropogenic drivers and by testing its generalizability across different hydro-climatic regions. Such efforts will further enhance the reliability of sediment forecasting systems and support informed decision-making for river basin and delta management.

7. Key Contributions of this Study

- Establishment of an optimization-focused comparative framework:

This study introduces a rigorous framework that explicitly disentangles model-architecture effects from optimizer influence by jointly evaluating model-specific optimizers and a shared global metaheuristic, thereby moving beyond conventional performance-based comparisons.

- Demonstration of optimizer–model compatibility as a governing factor:
  The results reveal that predictive superiority is primarily driven by structural compatibility between learning algorithms and optimization strategies, rather than by model complexity or optimizer strength alone.
- Provision of a transferable and reproducible evaluation strategy for environmental ML:
  The proposed framework offers a generalizable methodology for a fair and transparent comparison of machine learning models in sediment load modeling and other hydro-environmental applications, reducing the risk of optimizer-induced bias.

Acknowledgements

The authors express their gratitude to the General Directorate of Meteorology (MGM) and the General Directorate of Electrical Power Resources Survey and Development Administration (EIE) for the database, which was made available to them and served as the primary data source for the present study. The authors express their thanks to Grammarly Premium for the assistance in correcting grammar and spelling mistakes. The authors also appreciate the free version of DeepL, the translator that was used to translate the article into English.

Author contributions Conceptualization, methodology, supervision, writing-review and editing, M.E.A. and M.G.; Software, writing-original draft preparation, investigation, M.E.A. and M.G. Data collection and analysis were carried out by M.E.A. and M.G. All authors were involved in the study's conception and design.

Funding

Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK). There was no specific grant from any funding agency for this research.

Data availability

Authors can provide the data upon request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethical approval All authors have read and comprehended the statement on "Ethical Responsibilities of Authors" as found in the Instructions for Authors and have conformed to it where applicable.

Consent to participate The authors grant permission to participate in this research.

Consent to publication The authors grant permission for the publication of this research work.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

Adnan, R. M., Mirboluki, A., Mehraein, M., Malik, A., Heddam, S., & Kisi, O. (2024). Improved prediction of monthly streamflow in a mountainous region by Metaheuristic-Enhanced deep learning and machine learning models using hydroclimatic data. *Theoretical and Applied Climatology, 155*(1), 205–228. https://doi.org/10.1007/s00704-023-04624-9

Akiner, M. E. (2019). Investigating the effects of agricultural best management practices on water quality of a surface water. *Zastita Materijala, 60*(4), 369–378. https://doi.org/10.5937/zasmat1904369e

Akiner, M. E. (2020). The problem of environmental pollution in the Mediterranean Sea along the coast of Turkey. *Journal of Engineering Studies and Research, 26*(2), 7–14. https://doi.org/10.29081/jesr.v26i2.161

Akiner, M. E., & Ghasri, M. (2024). Comparative assessment of deep belief network and hybrid adaptive neuro-fuzzy inference system model based on a meta-heuristic optimization algorithm for precise predictions of the potential evapotranspiration. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-024-33987-3

Alitasb, G. K., & Salau, A. O. (2024). Multiple-input multiple-output Radial Basis Function Neural Network modeling and model predictive control of a biomass boiler. *Energy Reports, 11*, 442–451. https://doi.org/10.1016/j.egyr.2023.11.063

Allawi, M. F., Abdulhameed, U. H., Adham, A., Sayl, K. N., Sulaiman, S. O., Ramal, M. M., & El-Shafie, A. (2023a). Monthly rainfall forecasting modelling based on advanced machine learning methods: Tropical region as case study. *Engineering Applications of Computational Fluid Mechanics, 17*(1), 2243090. https://doi.org/10.1080/19942060.2023.2243090

Allawi, M. F., Ahmed, M. L., Aidan, I. A., Ravinesh, C. D., & El-Shafie, A. (2021a). Developing reservoir evaporation predictive model for successful dam management. *Stochastic Environmental Research and Risk Assessment, 35*, 499–514. https://doi.org/10.1007/s00477-020-01918-6

Allawi, M. F., Aidan, I. A., & El-Shafie, A. (2021b). Enhancing the performance of data-driven models for monthly reservoir evaporation prediction. *Environmental Science and Pollution Research, 28*, 8281–8295. https://doi.org/10.1007/s11356-020-11062-x

Allawi, M. F., Hussain, I. R., Salman, M. I., & El-Shafie, A. (2021c). Monthly inflow forecasting utilizing advanced artificial intelligence methods: A case study of Haditha Dam in Iraq. *Stochastic Environmental Research and Risk Assessment, 35*, 2391–2410. https://doi.org/10.1007/s00477-021-02052-7

Allawi, M. F., Sulaiman, S. O., Sayl, K. N., Sherif, M., & El-Shafie, A. (2023b). Suspended sediment load prediction modelling based on artificial intelligence methods: The tropical region as a case study. *Heliyon, 9*(8), Article e18506. https://doi.org/10.1016/j.heliyon.2023.e18506

Aytek, A., & Kişi, Ö. (2008). A genetic programming approach to suspended sediment modelling. *Journal of Hydrology, 351*(3–4), 288–298. https://doi.org/10.1016/j.jhydrol.2007.12.005

Badrulhisham, F., Pogatzki-Zahn, E., Segelcke, D., Spisak, T., & Vollert, J. (2024). Machine learning and artificial intelligence in neuroscience: A primer for researchers. *Brain, Behavior, and Immunity, 115*, 470–479. https://doi.org/10.1016/j.bbi.2023.11.005

Baniya, M. B., Asaeda, T., Fujino, T., Talchabhadel, R., Baniya, A., Shivaram, K. C., & Jayasanka, S. M. (2024). Effects of rainfall on fluvial discharge and suspended sediment transport in the Central Himalayan region, Nepal. *Theoretical and Applied Climatology, 155*(3), 1553–1572. https://doi.org/10.1007/s00704-023-04706-8

Barrett, N., Sadeghi, Z., & Matwin, S. (2023). Evolutionary augmentation policy optimization for self-supervised learning. *Advances in Artificial Intelligence and Machine Learning, 03*(02), 1135–1164. https://doi.org/10.54364/aaiml.2023.1167

Bazoobandi, P., Mousavi, S. R., Karimi, F., Karimi, H. R., Ghasri, M., & Aliha, M. R. M. (2024). Cracking resistance of crumb rubber modified green asphalt mixtures, using calcium carbonate nanoparticles and two by-product wax-based warm mix additives. *Construction and Building Materials, 424*, 135848. https://doi.org/10.1016/j.conbuildmat.2024.135848

Chen, S. R., Chen, S. J., & Hsieh, W. B. (2025). Enhancing machine learning-based DDoS detection through hyperparameter optimization. *Electronics, 14*(16), 3319. https://doi.org/10.3390/electronics14163319

Chiang, J. L., & Tsai, Y. S. (2011). Suspended sediment load estimate using support vector machines in Kaoping River Basin. In 2011 International Conference on Consumer Electronics, Communications and Networks (CECNet) (pp. 1750–1753). IEEE. https://doi.org/10.1109/CECNET.2011.5769267.

Choubin, B., Darabi, H., Rahmati, O., Sajedi-Hosseini, F., & Kløve, B. (2018). River suspended sediment modelling using the CART model: A comparative study of machine learning techniques. *Science of the Total Environment, 615*, 272–281. https://doi.org/10.1016/j.scitotenv.2017.09.293

Ciğizoğlu, H. K. (2002). Suspended sediment estimation for rivers using artificial neural networks and sediment rating curves. *Turkish Journal of Engineering and Environmental Sciences, 26*(1), 27–36.

Demir, A. (2021). Speciation, risk assessment and bioavailability of metals in the agricultural soils of the Göksu Delta, Turkey. *Soil and Sediment Contamination: An International Journal, 30*(3), 292–313. https://doi.org/10.1080/15320383.2020.1839740

Demirel, Z. (2010). The influence of seawater on a coastal aquifer in an international protected area, Göksu Delta Turkey. *Journal of Water Resource and Protection, 02*(07), 651–659. https://doi.org/10.4236/jwarp.2010.27075

Demirel, Z., Özer, Z., & Özer, O. (2011). Investigation and modeling of water quality of Göksu River (cleadnos) in an international protected area by using GIS. *Journal of Geographical Sciences, 21*(3), 429–440. https://doi.org/10.1007/s11442-011-0855-4

Dervisoglu, A. (2022). Investigation of long and short-term water surface area changes in coastal Ramsar sites in Turkey with Google Earth Engine. *Isprs International Journal of Geo-Information, 11*(1), 46. https://doi.org/10.3390/ijgi11010046

dos Santos, F. M., de Souza Pelinson, N., de Oliveira, R. P., & Di Lollo, J. A. (2023). Using the SWAT model to identify erosion prone areas and to estimate soil loss and sediment transport in Mogi Guaçu River basin in São Paulo State, Brazil. *CATENA, 222*, Article 106872. https://doi.org/10.1016/j.catena.2022.106872

Ergen, F., & Katlav, M. (2024). Machine and deep learning-based prediction of flexural moment capacity of ultra-high performance concrete beams with/out steel fiber. *Asian J Civ Eng, 25*, 4541–4562. https://doi.org/10.1007/s42107-024-01064-2

Eskandar, H., Sadollah, A., Bahreininejad, A., & Hamdi, M. (2012). Water cycle algorithm–A novel metaheuristic optimization method for solving constrained engineering optimization problems. *Computers & Structures, 110–111*, 151–166. https://doi.org/10.1016/j.compstruc.2012.07.010

Fadaee, M., Mahdavi-Meymand, A., & Zounemat-Kermani, M. (2022). Suspended sediment prediction using integrative soft computing models: On the analogy between the butterfly optimization and genetic algorithms. *Geocarto International, 37*(4), 961–977. https://doi.org/10.1080/10106049.2020.1753821

Ghasemi, M. R., Salarnia, A., & Ghasri, M. (2024). Optimal design of steel structures using innovative black widow algorithm hybridized with greedy sensitivity-based Particle Swarm

Optimization Technique. *Journal of Soft Computing in Civil Engineering, 8*(1), 55–84. https://doi.org/10.22115/scce.2023.370472.1568

Ghasri, M., Ghasemi, M., & Salarnia, A. (2024). Leveraging the power of hybrid and standalone machine learning for enhanced FRP-confined concrete columns strength prediction. *Journal of Soft Computing in Civil Engineering*. https://doi.org/10.22115/scce.2024.425414.1748

Guo, Z., Chen, M., Ouyang, W., Lin, C., & He, M. (2024). Fine particle contents in sediment drive silica transport and deposition to the estuary in the turbid river basin. *Water Research, 255*, Article 121464. https://doi.org/10.1016/j.watres.2024.121464

Gupta, A. K., Rudra, R. P., Gharabaghi, B., Daggupati, P., Goel, P. K., & Shukla, R. (2018). Predicting the impact of drainage ditches upon hydrology and sediment loads using KINEROS 2 model: A case study in Ontario. *Canadian Biosystems Engineering, 60*(1), 1.1-1.15. https://doi.org/10.7451/CBE.2018.60.1.1

Heddam, S., Naghibi, A., Khosravi, K., & Singh, S. K. (2024). Suspended sediment load prediction and tree-based algorithms. In Remote Sensing of Soil and Land Surface Processes (pp. 257–269). Elsevier. https://doi.org/10.1016/B978-0-443-15341-9.00013-7.

Hoang, N. D., & Tran, V. D. (2023). Deep neural network regression with advanced training algorithms for estimatingthe compressive strength of manufactured-sand concrete. *Journal of Soft Computing in Civil Engineering, 7*(1), 114–134. https://doi.org/10.22115/scce.2022.349837.1485

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Hosseinian, S. M., Bazoobandi, P., Mousavi, S. R., & Karimi, F. (2023). Presentation of machine learning methods and multi-objective optimization of fracture indices for asphalt rubber mixtures containing wax-based warm mix additives modified by nano calcium carbonate. *Construction and Building Materials, 409*, Article 134136. https://doi.org/10.1016/j.conbuildmat.2023.134136

Hu, C., Wu, Q., Li, H., Jian, S., Li, N., & Lou, Z. (2018). Deep learning with a long short-term memory networks approach for rainfall–runoff simulation. *Water, 10*(11), 1543. https://doi.org/10.3390/w10111543

Jing, J., Li, R., Xiao, L., Shu, D., & Yang, P. (2024). Interpreting and modelling the daily extreme sediment events in karst mountain watersheds. *Science of the Total Environment, 926*, Article 171956. https://doi.org/10.1016/j.scitotenv.2024.171956

Joshi, B., Singh, V., Vishwakarma, D., Ghorbani, M., Kim, S., Gupta, S., & Mattar, M. (2024). A comparative survey between cascade correlation neural network (CCNN) and feedforward neural network (FFNN) machine learning models for forecasting suspended sediment concentration. *Scientific Reports*. https://doi.org/10.1038/s41598-024-61339-1

Kanga, S., Meraj, G., Das, B., Farooq, M., Chaudhuri, S., & Singh, S. K. (2020). Modeling the spatial pattern of sediment flow in lower Hugli estuary, West Bengal, India by quantifying suspended sediment concentration (SSC) and depth conditions using geoinformatics. *Applied Computing and Geosciences, 8*, Article 100043. https://doi.org/10.1016/j.acags.2020.100043

Karri, N., & Muntala, P. S. R. P. (2025). ML-Driven Performance Optimization. *International Journal of Artificial Intelligence, Data Science, and Machine Learning, 6*(2), 135–143. https://doi.org/10.63282/3050-9262.IJAIDSML-V6I2P115

Khajure, S., & Mohod, S. W. (2016). Future weather forecasting using soft computing techniques. *Procedia Computer Science, 78*, 402–407. https://doi.org/10.1016/j.procs.2016.02.081

Khanam, F., Munmun, F. A., Ritu, N. A., Saha, A. K., & Firoz, M. (2022). Text to speech synthesis: A systematic review, deep learning based architecture and future research direction. *Journal of Advances in Information Technology, 13*(5), 398–412. https://doi.org/10.12720/jait.13.5.398-412

Khennour, M. E., Bouchachia, A., Kherfi, M. L., & Bouanane, K. (2023). Randomising the Simple Recurrent Network: A lightweight, energy-efficient RNN model with application to forecasting problems. *Neural Computing and Applications, 35*(27), 19707–19718. https://doi.org/10.1007/s00521-023-08775-8

Khosravi, K., Golkarian, A., Melesse, A. M., & Deo, R. C. (2022). Suspended sediment load modeling using advanced hybrid rotation forest based elastic network approach. *Journal of Hydrology, 610*, Article 127963. https://doi.org/10.1016/j.jhydrol.2022.127963

Kılıç, E., & Yücel, N. (2021). Impact of nutrient load coming from göksu River on the northeastern Mediterranean. *Marine Science and Technology Bulletin, 10*(3), 295–305. https://doi.org/10.33714/masteb.963649

Kingsford, R., Bino, G., Finlayson, C., Falster, D., Fitzsimons, J., De, G., & Thomas, R. (2021). Ramsar wetlands of international importance–improving conservation outcomes. *Frontiers in Environmental Science*. https://doi.org/10.3389/fenvs.2021.643367

Kişi, O., Dailr, A. H., Cimen, M., & Shiri, J. (2012). Suspended sediment modeling using genetic programming and soft computing techniques. *Journal of Hydrology, 450*, 48–58. https://doi.org/10.1016/j.jhydrol.2012.05.031

Koutsovili, E., Tzoraki, O., Theodossiou, N., & Tsekouras, G. (2023). Early flood monitoring and forecasting system using a hybrid machine learning-based approach. *ISPRS International Journal of Geo-Information, 12*(11), 464. https://doi.org/10.3390/ijgi12110464

Latif, S. D., Chong, K. L., Ahmed, A. N., Huang, Y. F., Sherif, M., & El-Shafie, A. (2023). Sediment load prediction in Johor River: Deep learning versus machine learning models. *Applied Water Science, 13*(3), 79. https://doi.org/10.1007/s13201-023-01874-w

Li, X., Song, J., Yang, L., Li, H., & Fang, S. (2024). Source term inversion coupling Kernel Principal Component Analysis, Whale Optimization Algorithm, and Backpropagation Neural Networks (KPCA-WOA-BPNN) for complex dispersion scenarios. *Progress in Nuclear Energy, 171*, Article 105171. https://doi.org/10.1016/j.pnucene.2024.105171

Li, X., Yin, Y., Feng, R., Yu, J., Cao, D., Wu, X., & Wang, W. (2023). Double total variation (DTV) regularization and improved adaptive moment estimation (IADAM) optimization method for fast MR image reconstruction. *Computer Methods and Programs in Biomedicine, 233*, Article 107463. https://doi.org/10.1016/j.cmpb.2023.107463

Liu, X., Qi, H., Jia, S., Guo, Y., & Liu, Y. (2025). Recent advances in optimization methods for machine learning: A systematic review. *Mathematics, 13*(13), 2210. https://doi.org/10.3390/math13132210

Melesse, A. M., Ahmad, S., McClain, M. E., Wang, X., & Lim, Y. H. (2011). Suspended sediment load prediction of river systems:

An artificial neural network approach. *Agricultural Water Management, 98*(5), 855–866. https://doi.org/10.1016/j.agwat.2010.12.012

Nhu, V. H., Khosravi, K., Cooper, J. R., Karimi, M., Kisi, O., Pham, B. T., & Lyu, Z. (2020). Monthly suspended sediment load prediction using artificial intelligence: Testing of a new random subspace method. *Hydrological Sciences Journal, 65*(12), 2116–2127. https://doi.org/10.1080/02626667.2020.1754419

Nourani, V., Gokcekus, H., & Gelete, G. (2021). Estimation of suspended sediment load using artificial intelligence-based ensemble model. *Complexity, 2021*, 1–19. https://doi.org/10.1155/2021/6633760

Pan, C., & Huang, W. (2010). Numerical modeling of suspended sediment transport affected by tidal bore in Qiantang Estuary. *Journal of Coastal Research, 26*(6), 1123–1132. https://doi.org/10.2112/JCOASTRES-D-09-00024.1

Patel, M. H. (1995). Spherical minimax location problem using the Euclidean norm: Formulation and optimization. *Computational Optimization and Applications, 4*, 79–90. https://doi.org/10.1007/BF01299160

Pittock, J. (2021). Use of the Ramsar Convention to protect springs and other wetlands. *Conservation Biology, 35*(6), 1969–1971. https://doi.org/10.1111/cobi.13799

Platt, J. (1998). Sequential Minimal optimization: A fast algorithm for training support vector machines. Tech. Rep., Microsoft Research, Technical Report msr-tr-98-14.

Rajaee, T., & Jafari, H. (2020). Two decades on the artificial intelligence models advancement for modeling river sediment concentration: State-of-the-art. *Journal of Hydrology, 588*, Article 125011. https://doi.org/10.1016/j.jhydrol.2020.125011

Ranjan, A., & Roshni, T. (2024). Potential variability of discharge and suspended sediment load in the Sone River basin, Bihar. *Journal of Earth System Science, 133*(2), 62. https://doi.org/10.1007/s12040-024-02292-5

Rezaei, K., Pradhan, B., Vadiati, M., & Nadiri, A. A. (2021). Suspended sediment load prediction using artificial intelligence techniques: Comparison between four state-of-the-art artificial neural network techniques. *Arabian Journal of Geosciences, 14*(3), 215. https://doi.org/10.1007/s12517-020-06408-1

Roy, D. K., Paul, C. R., Munmun, T. H., & Datta, B. (2024). An automatic model selection-based machine learning approach to predict seawater intrusion into coastal aquifers. *Environmental Earth Sciences, 83*(9), 287. https://doi.org/10.1007/s12665-024-11589-z

Seyyedabbasi, A. (2023). Binary sand cat swarm optimization algorithm for wrapper feature selection on biological data. *Biomimetics, 8*(3), 310. https://doi.org/10.3390/biomimetics8030310

Stull, T., & Ahmari, H. (2024). Estimation of suspended sediment concentration along the Lower Brazos River using satellite imagery and machine learning. *Remote Sensing, 16*(10), 1727. https://doi.org/10.3390/rs16101727

Wang, Q., Chen, D., Li, M., Li, S., Wang, F., Yang, Z., & Yao, D. (2023). A novel method for petroleum and natural gas resource potential evaluation and prediction by support vector machines (SVM). *Applied Energy, 351*, 121836. https://doi.org/10.1016/j.apenergy.2023.121836

Yadav, A., Chithaluru, P., Singh, A., Albahar, M. A., Jurcut, A., Álvarez, R. M., & Joshi, D. (2022). Suspended sediment yield forecasting with single and multi-objective optimization using hybrid artificial intelligence models. *Mathematics, 10*(22), 4263. https://doi.org/10.3390/math10224263

Yadav, S., Ekbal, A., Saha, S., Kumar, A., & Bhattacharyya, P. (2019). Feature assisted stacked attentive shortest dependency path based Bi-LSTM model for protein–protein interaction. *Knowledge-Based Systems, 166*, 18–29. https://doi.org/10.1016/j.knosys.2018.11.020

Yu, L., Li, S., & Liu, S. (2023). Fast support vector machine training via three-term conjugate-like SMO algorithm. *Pattern Recognition, 139*, Article 109478. https://doi.org/10.1016/j.patcog.2023.109478

Yue, Z., Wang, N., Xu, B., Huang, X., Yang, D., Xiao, H., & Shi, Z. (2025). Toward trustworthy machine learning for daily sediment modeling in the riverine systems: An integrated framework with enhanced uncertainty quantification and interpretability. *Water Resources Research*. https://doi.org/10.1029/2024WR038650

Zena, K., Adugna, T., & Fufa, F. (2024). Climate and human activities impact on runoff and sediment yield in the central rift valley of Ethiopia. *Cogent Engineering, 11*(1), 2297511. https://doi.org/10.1080/23311916.2023.2297511

Zhang, S., Omar, A. H., Hashim, A. S., Alam, T., Khalifa, H. A. E. W., & Elkotb, M. A. (2023). Enhancing waste management and prediction of water quality in the sustainable urban environment using optimized algorithm of least square support vector machine and deep learning techniques. *Urban Climate, 49*, Article 101487. https://doi.org/10.1016/j.uclim.2023.101487

Zhang, W., Wei, X., Jinhai, Z., Yuliang, Z., & Zhang, Y. (2012). Estimating suspended sediment loads in the Pearl River Delta region using sediment rating curves. *Continental Shelf Research, 38*, 35–46. https://doi.org/10.1016/j.csr.2012.02.017

Zhou, H., Li, J., Zhang, S., Zhang, S., Yan, M., & Xiong, H. (2023). Expanding the prediction capacity in long sequence time-series forecasting. *Artificial Intelligence, 318*, Article 103886. https://doi.org/10.1016/j.artint.2023.103886

(Received December 7, 2025, revised February 26, 2026, accepted March 26, 2026)