University of Birjand

Water Harvesting Research Vol. 8, No. 1, Spring & Summer 2025, Original paper p. 1-15

doi 10.22077/JWHR.2025.8174.1154

Estimating Total Sediment Load Using Water Quality Parameters in the Sufi Chay River, Iran: A Comparative Analysis of Soft Computing and Dimensionless Approaches

Jafar Chabokpour[a&*]

[a]Associate Professor, Department of Civil Engineering, University of Maragheh, Maragheh, Iran.

*Corresponding Author, E-mail address: J.chabokpour@maragheh.ac.ir
Received: 22 September 2024/ **Revised**: 20 December 2024/ **Accepted**: 13 January 2025

Abstract

The sediment transport and the relation to water quality parameters and hydrological characteristics in the Sufi Chay River in Iran were investigated in this study using long-term monitoring data. Traditional statistical methods, dimensionless parameter analysis, and advanced soft computing techniques are combined within the scope of the presented comprehensive analysis. Total sediment load is the dependent variable, while the independent variables include flow rate, total dissolved solids (TDS), electrical conductivity (EC), pH, total anions, total cations, anion hardness, and cation hardness. Strong correlations were observed between total sediment load and flow rate (r = 0.82), total dissolved solids (r = 0.68), and electrical conductivity (r = 0.65). The dimensionless equation developed related sediment concentration to Reynolds number, Froude number, and normalized water quality parameters. The performance was quite good as revealed by the R^2 value of 0.82. Comparison of performances using three soft computing methods, namely Artificial Neural Networks, Adaptive Neuro-Fuzzy Inference System, and Support Vector Regression, are performed. The highest R^2 value of 0.91 and RMSE of 53.2 tons/ day were obtained with ANFIS model. Sensitivity analyses indicated that flow rate and TDS were the most sensitive parameters to predict total sediment load. Generally, a seasonal variability in sediment transport, showing that the maximum discharges happened in the spring season with the mean of 187.3 tons/day, while the minimum discharges happened in the summer season with the mean of 42.8 tons/day. Besides, a nonlinear relationship between flow rate and both sediment concentration and discharge in this catchment reflects a complex erosion and transport process. The investigation also resulted in some important ion-parameter relationships, which are indicative of the geochemical factors operating on the water quality and sediment activity.
Keywords: Dimensionless analysis, River management, Soft computing, Total sediment load, Water quality.

1. Introduction

Estimation of sediment rates in rivers is very important for practical water resource management, which in turn affects other fields such as hydro-power generation and irrigation. Traditional measurement methods of sediment rates can be expensive and time-consuming; hence, various alternative approaches have been tried using water quality variables (Bayram et al., 2014; Beeson et al., 2014; Fagundes et al., 2019; Gholizadeh et al., 2016; Park and Engel, 2016). Recent development in the fields suggests that the indices of water quality with variables such as chemical oxygen demand, biochemical oxygen demand, and suspended solids can be used to estimate sediment rates efficiently (Bartley et al., 2012; Othman et al., 2020). Sediment concentrations and water quality variables represent two important fields of study that help in understanding aquatic ecosystems. Sediment concentration may be influenced by many factors; the importance of the content of metals and organic matter could well underlie influences on water quality in sediment concentration (Chabokpour, 2024a, 2024b;

Chabokpour and Raji, 2024). Different works have tried to estimate the sediment rates with the variables related to water quality.

Such as Saranga (2021), who developed an optical sensing mechanism for the estimation of the sediment rate based on the relationship between TSS (Total Suspended Solids) and turbidity (Saranga et al., 2021). It presented a good method for short-time predictions. Soft computing encompasses a family of computational methods including Artificial Neural Networks (ANNs), Fuzzy Logic Systems, and Support Vector Machines (SVMs) that can effectively model complex nonlinear relationships while handling uncertainty and imprecision in data.

Unlike traditional computing methods that require precise inputs and mathematical models, soft computing techniques can learn from examples, recognize patterns in complex datasets, and handle imprecise or noisy data - characteristics that make them particularly valuable for environmental and hydrological modeling where exact mathematical descriptions of processes may be difficult to formulate. Other research has tried to use ANN methods to predict water quality indices that can enable sediment rate estimations indirectly (Gazzaz et al., 2012).

Moreover, the integration of various water quality variables such as dissolved oxygen and pH has been found to enhance the performance of water quality estimates, which is a pre-condition of sediment rate estimation (Saraswati et al., 2019). Some of the advanced modeling methods include the application of cloud models and kriging applications that enhance spatial and temporal prediction of water quality variables, hence providing a robust framework for sediment rate estimation (Guojiao et al., 2023).

Coupling morphological parameters with water quality models was also encountered to influence sediment transport and deposition. It underpins the consideration of river morphology as a necessity in carrying out the estimation of sediment rates (Hosseini et al., 2017; Lindenschmidt et al., 2005). Indeed, metals such as Cu, Pb, and Zinc have been recorded in sediments most often at higher concentrations compared to those in the water column.

These metals are capable of influencing water quality and may be featured in relation to certain sediment properties such as grain size and organic content (Horowitz, 1984). In natural urban ecosystems, metal contamination within sediment can be associated with varied water quality with extreme variations documented throughout wet-weather events (Lundy et al., 2017). Organic sediments, primarily sourced from peatlands, can impair water quality through the elevation of dissolved organic carbon and suspended sediment concentrations that will likely affect the community structure of macroinvertebrates and ecosystem metabolism.

Consequentially, impacts from organic sediments are an area that requires further research (Aspray et al., 2017). Agricultural activities have been reported to increase sediment-bound metals like Cu and Zn in agricultural watersheds, which then impact the water quality. The bioavailability of these metals corresponds with concentrations in sediments, hence leading to a strong relationship between sediment and water quality variables (Smith et al., 2007).

Different sediment metals and organic matter can act differently on the benthic macroinvertebrate communities, which are sensitive water quality indicators. Sediment chemistry integrated with water quality has often been demonstrated to be some of the main factors determining the structure of the macroinvertebrate communities (Munyai et al., 2024).

Estimation of sediment load in rivers with the use of water quality indices is a growing interest area due to the efficiency and precision of modern methods of monitoring. Traditional sediment rating curves relate the river discharge with the suspended sediment concentration but have limitations in capturing complex dynamics (Warrick, 2015). Recent developments in remote sensing and machine learning have indeed produced some new, precious tools in the domain of sediment load estimation.

For instance, Sentinel-2 images, aided by machine learning algorithms such as Support Vector Machines and Random Forests, can estimate suspended sediment concentrations rather well. These techniques are even very accurate at flood flow and able to overcome shortcomings that traditional monitoring faces (Mohsen et al., 2022). The relations between concentration and discharge have also been used to investigate sediment dynamics. More recent methods have been elaborated considering non-linearities and temporality within these C-Q (Concentration-Discharge) relationships, such as Weighted Regressions on Time, Discharge, and Season, which provide insight into the long-term shifts in dynamics of sediment trapping and export (Lou et al., 2022).

ANNs have also been compared with sediment rating curves in estimating sediment concentrations and fluxes. ANNs also have the capability to catch event structures and hysteresis in the sediment concentration-water discharge relationship, enabling a richer understanding of sediment dynamics (CIĞIZOĞLU, 2002).

Applications have been presented for the use of Landsat imagery to estimate sediment load in large river systems, such as the Upper Mississippi River. By correlating hydraulic geometry, water discharge, and suspended sediment concentration, Landsat data presents a good alternative where traditional methods are absent, particularly in ungauged or poorly monitored catchments (A. Flores et al., 2020; Tyler et al., 2006).

Sediments often carry pollutants, including metals and nutrients, which have potential degrading effects on water quality. The Pearl River Delta has pointed out sediment transport as one of the major elements causing the degradation of water quality, while certain pollutants move along with sediments. Conversely, sand mining, for instance, may affect the quality of water by increasing suspended particles in that particular river and downstream of it (Ashraf et al., 2011).

Many modelling approaches have been used to try and work out how sediment transport affects the quality of water. In the HEC-RAS model, the sediment transport was modelled in order to predict alterations in the quality of water; this was the case for the Naic River, which had increased sediment volumes linked to a high biochemical oxygen demand and low DO levels (Monjardin et al., 2021).

Integrated approaches using field-based methods, GIS, and numerical modeling have been employed to evaluate sediment budgets and their effects on water quality. These techniques provide further information about sediment sources, pathways, and how they relate to water quality indicators (Chalov et al., 2017). Intermittent rivers are such that the sediment transport can be related to nutrient dynamics, impacting water quality. The Soil and Water Assessment Tool has been used to model these relationships, indicating the difficulties in accurately simulating sediment and nutrient transports (Chabokpour, 2024b; Chabokpour and Azamathulla, 2022; Chahinian et al., 2011).

While much progress is being made in this field, there is still a gap in regard to integrating water quality parameters, hydrological factors, and soft computing techniques in view of comprehensive total sediment load prediction. The study seeks to fill this gap in the development of a multi-dimensional modeling approach that incorporates various facets, specifically tailored to the unique characteristics of Sufi Chay River, Iran.

The present study investigates the complex relations of water quality parameters, hydrological factors, and total sediment load in the Sufi Chay River. In the light of this, the main objectives of the present research are developing and comparing different predictive models for estimating total sediment load considering traditional regression, dimensionless analysis, and soft computing techniques; determining the most influential parameters affecting sediment transport; and assessing the seasonal variations and long-term trends of total sediment load and water quality parameters.

2. Materials and Methods

2.1. Study area and data collection

In the present study, Sufi Chay River, which is the most important river in East Azerbaijan Province, Iran, was used as a case study. Sufi Chay River originates from Sahand mountain, passing through Alavian Dam and ending at Lake Urmia; therefore, the water of this river bears great importance within the water resources of the region. The data were gathered in this study from a monitoring station located upstream of the Alavian Dam.

Two main groups of data were applied in the current study: total sediment load-flow rate and water quality characteristics versus flow rates. The various water quality parameters included TDS, EC, pH, total anions, total cations, anion hardness, and cation hardness.

Data spanned from 1969 to 2018 and formed a broad, long-term record of the river's hydrological and sedimentological characteristics.

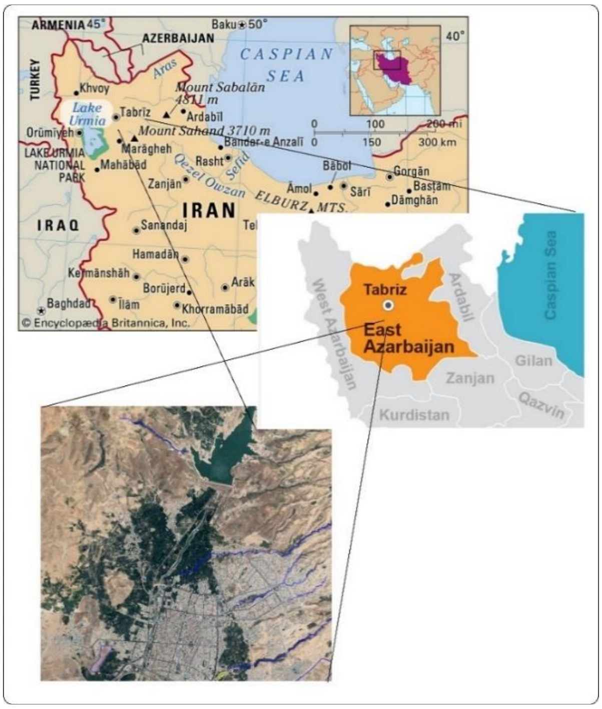

Fig. 1. Location of Sufi Chay River in Iran and Lake Urmia Basin

Extensive pre-processing of data had to be done before any modeling could be developed. Identification of outliers and their treatment, handling of missing values with use of suitable imputation techniques, and normalization of variables for comparability were most of the tasks done in this process. The goal was to examine the form taken by the relationships between the variables and to identify any pattern or trend that might underlie the data.

2.2. Model development

Modeling of total sediment load-water quality parameters relationship was done by different approaches: traditional regression techniques, dimensionless analysis, and soft computing methods.

2.2.1. Multiple Linear Regression (MLR)

An MLR model was developed to establish a linear relationship between total sediment load and the predictor variables. The general form of the MLR model is according to Eq. 1.

$$Qs = b_0 + b_1X_1 + b_2X_2 + \ldots + b_nX_n \qquad (1)$$

where: Qs = Total sediment load (tons/day) b_0 = Intercept, b_i = Regression coefficients, X_i = Predictor variables (e.g., flow rate, TDS, EC, pH).

2.2.2. Artificial Neural Network (ANN)

A feedforward multilayer perceptron ANN was developed using the backpropagation algorithm. The network architecture consisted of an input layer, two hidden layers, and an output layer. The general form of the ANN can be expressed as Eq. 2.

$$y = f(\Sigma(w_i \times x_i) + b) \qquad (2)$$

where: y = Output (total sediment load), f = Activation function, w_i = Connection weights, x_i = Input variables, b = Bias term.

2.2.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

An ANFIS model was constructed to combine the learning capabilities of neural networks with fuzzy logic reasoning. The ANFIS structure uses a hybrid learning algorithm and can be represented as Eq. 3.

$$y = \Sigma(w_i \times f_i(x)) \qquad (3)$$

where: y = Output (total sediment load), w_i = Rule firing strength, and $f_i(x)$ = Individual rule outputs.

2.2.4. Support Vector Regression (SVR)

An SVR model with a radial basis function (RBF) kernel was implemented. The SVR model can be expressed as Eq. 4.

$$f(x) = \Sigma(\alpha_i - \alpha_i^*) \times K(x_i, x) + b \qquad (4)$$

where: f(x) = Regression function, α_i, α_i^* = Lagrange multipliers, $K(x_i, x)$ = Kernel function, and b = Bias term.

2.2.5. Model evaluation

The performance of each model was evaluated using several statistical metrics as Eqs. 5-8.

$$R^2 = 1 - \frac{(\Sigma(y_i - \hat{y}_i)^2)}{(\Sigma(y_i - \bar{y})^2)} \qquad (5)$$

$$RMSE = \sqrt{\frac{\Sigma(y_i - \hat{y}_i)^2}{n}} \qquad (6)$$

$$MAE = \frac{\Sigma|y_i - \hat{y}_i|}{n} \qquad (7)$$

$$NSE = \frac{1 - (\Sigma(y_i - \hat{y}_i)^2)}{(\Sigma(y_i - \bar{y})^2)} \qquad (8)$$

where: y_i = Observed values, $\hat{y}_i$ = Predicted values, $\bar{y}$ = Mean of observed values, and n = Number of observations.

2.3. Sensitivity analysis

A sensitivity analysis was done with the aim of quantifying the influence of each input parameter in relation to total sediment load prediction. This was done by carrying out a series of local and global sensitivity analyses, by calculating the sensitivity coefficients and by applying the Sobol method under global sensitivity analysis.

The Mann-Kendall trend test and Sen's slope estimator have been applied for analyzing long-term trends for total sediment loads and water quality parameters. Moreover, STL (seasonal trend decomposition) decomposition was done to decompose the time series into trend, seasonal, and residual components.

3. Results and Discussion

Sediment rating curves were developed to further explore the relation between flow rate and total total sediment load. In Eq. 9, the power function model, one of the most widely adopted sediment rating curve models, was applied as:

$$\mathrm{Qs} = a \times \mathrm{Q}^b \qquad (9)$$

where: Qs = Total sediment load (tons/day), Q = Flow rate (m^3/s), and a and b = Empirical coefficients.

A logarithmic transformation and least squares regression were fitted to this model. Details of the sediment rating curve analysis carried out corresponding to different time periods are presented in Table 1.

Table 1. Sediment rating curve parameters for different periods

Period	a	b	R^2	RMSE (tons/day)
1969-1980	27.63	1.42	0.71	83.5
1981-1990	32.18	1.38	0.68	89.2
1991-2000	38.45	1.35	0.65	92.8
2001-2010	45.72	1.31	0.63	97.4
2011-2018	52.96	1.28	0.61	102.3

These sediment rating curves are showing an increasing trend in the value of 'a' with a corresponding decrease in the values of 'b' through time. This trend would mean that at a given flow rate, the total sediment load has generally increased within these years under study. The decreasing R^2 and increased RMSE also show that the relationship between flow rate and total sediment load became more variable in recent years, probably due to the changing watershed conditions or land use practices.

A detailed multiple linear regression analysis was made to provide more insight into the relationships of the water quality parameters and total sediment load. The developed model was as Eq. 10.

$$\begin{aligned}\mathrm{Qs} &= \beta0 + \beta1\mathrm{Q} + \beta2\mathrm{TDS} + \beta3\mathrm{EC} \\ &+\beta4\mathrm{pH} + \beta5\mathrm{Atot} + \beta6\mathrm{Ctot} + \beta7\mathrm{HA} \\ &+\beta8\mathrm{HC}\end{aligned} \qquad (10)$$

where: Qs = Total sediment load (tons/day), Q = Flow rate (m^3/s), TDS = Total Dissolved Solids (ppm), EC = Electrical Conductivity (ds/m), pH = pH value, Atot = Total anions (meq/L), Ctot = Total cations (meq/L), HA = Anion hardness (ppm), HC = Cation hardness (ppm), and β0 ... β8 = Regression coefficients. Table 2 presents the results of the multiple linear regression analysis.

Table 2. Multiple linear regression results for total sediment load prediction

Parameter	Coefficient	Standard Error	p-value
β0	-423.68	89.24	<0.001
β1	68.42	7.31	<0.001
β2	0.312	0.048	<0.001
β3	0.245	0.039	<0.001
β4	-12.36	5.87	0.036
β5	18.75	6.24	0.003
β6	16.92	5.98	0.005
β7	0.087	0.041	0.035
β8	0.079	0.038	0.039

The multiple linear regression model is of good strength, with an R^2 value of 0.83. All variables included in the model were statistically significant ($p < 0.05$). According to the positive relationship, flow rate has the highest value with total sediment load, followed by TDS and EC. The inverse parameter sign of pH may indicate that with higher levels of total sediment load, pH levels are low, which could be evidence of more active weathering processes or human impacts within the watershed area.

There is a fairly regular seasonality in the total sediment load; average discharges are highest in the spring and lowest in summer. With reference to a number of factors, an attempt might be made at understanding seasonal variation. High discharges in spring could perhaps be related to large quantities of snow melting and heavy rains that increase flow rates and thus affect erosion rates accordingly.

The low discharges in summer may be related to lower rainfall and lower flow rates. The moderate autumn and winter discharges may suggest a near balance between rainfall events and a reduced vegetative cover. This seasonal pattern illustrates the need to consider temporal variability in sediment transport processes in order to successfully apply watershed management (Fig. 2).

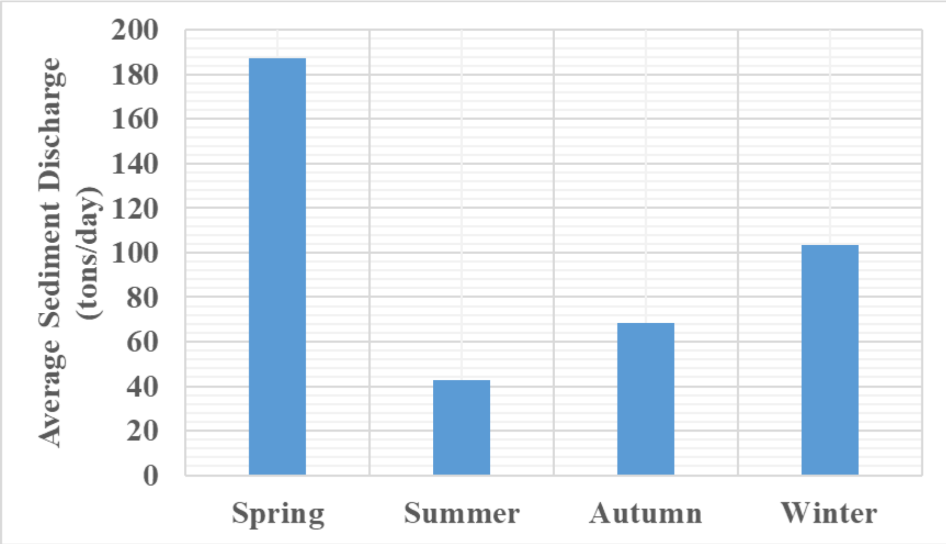

Fig. 2. Total sediment load vs. Season

The data set was divided into four seasons-spring: March to May, summer: June to August, autumn: September to November, and winter: December to February-to explore any possible seasonal variations in the relationships between total sediment load and water quality parameters. The correlation analyses were performed for each season and summarized in Table 3.

The potential influence of unauthorized water withdrawals during summer months was considered in our analysis. However, the study reach's location immediately upstream of Alavian Dam is subject to strict monitoring and control of water abstractions by regional water authorities, as maintaining consistent inflow to the dam is crucial for its operation. Furthermore, the consistency of seasonal patterns observed across our 49-year dataset (1969-2018) strongly indicates that the lower summer correlations are primarily attributable to natural hydrological factors, such as reduced precipitation and lower base flows, rather than anthropogenic disturbances like unauthorized water withdrawals.

In general, the highest correlations obtained in the seasonal analysis of total sediment load with the considered water quality parameters fell within the spring season. Such a relation could be related to an increase in runoff and erosion under snowmelt and rainfall events in spring. The weakest were found during the summer season, most likely due to more stable flow conditions and reduced sediment inputs. The flow rate and total sediment load are strongly positively correlated.

Table 3. Seasonal correlation coefficients between total sediment load and water quality parameters

Parameter	Spring	Summer	Autumn	Winter
Flow rate	0.88	0.79	0.85	0.76
TDS	0.72	0.61	0.70	0.64
EC	0.69	0.58	0.67	0.61
pH	-0.28	-0.19	-0.25	-0.21
Total anions	0.65	0.54	0.63	0.58
Total cations	0.63	0.52	0.61	0.56

The relationship is in power-law form, with the total sediment load increasing more rapidly than the flow rate. This can be interpreted to demonstrate nonlinear behavior during high-magnitude flow events where the capacity for sediment transport is significantly increased and may result in disproportionately higher total sediment loads.

Such steepening of the curve may be due to the higher degree of bed and bank erosion, besides the mobilization of previously deposited sediments, at higher discharges as shown in Fig. 3a.

A positive correlation is recorded between the TDS and total sediment load. The relation is roughly linear, which means that the total sediment load increases with an increase in TDS. This may be explained by the fact that highest TDS concentrations tend to fall in a period of high erosion and sediment transport processes; they could further be contributing to the flocculation of fine sediments, which might enhance their transport. However, it should be considered that indirectly, this may be a relationship depending on flow rate, since both TDS and total sediment load increase during high flow events (Fig. 3b).

The total sediment load versus EC relationship follows the same pattern as that obtained with TDS. This is expected because most studies have utilized EC as an indicator of TDS. In any case, from this trend, it would appear that the total sediment load increases with an increase in the concentration of dissolved ions. This could be attributed to the influence of the dissolved ions on the sediment flocculation and transport processes. Also, higher EC might indicate greater weathering and erosion within the watershed, which would, in turn, contribute to a higher total sediment load, as depicted in Fig. 3c.

There is a weak negative relation between pH and total sediment load. With the increase in pH from slightly acidic to alkaline, there is a gradual and slight decrease in total sediment load. This may be interpreted by the influence of pH on surface charges of sediment particles and on the process of flocculation.

Particles at low pH might remain suspended with a greater tendency that could result in higher total sediment load. However, the relatively weak nature of this relationship suggests that other factors such as flow rate and TDS have more dominating influences on sediment transport in the Sufi Chay River (Fig 3d).

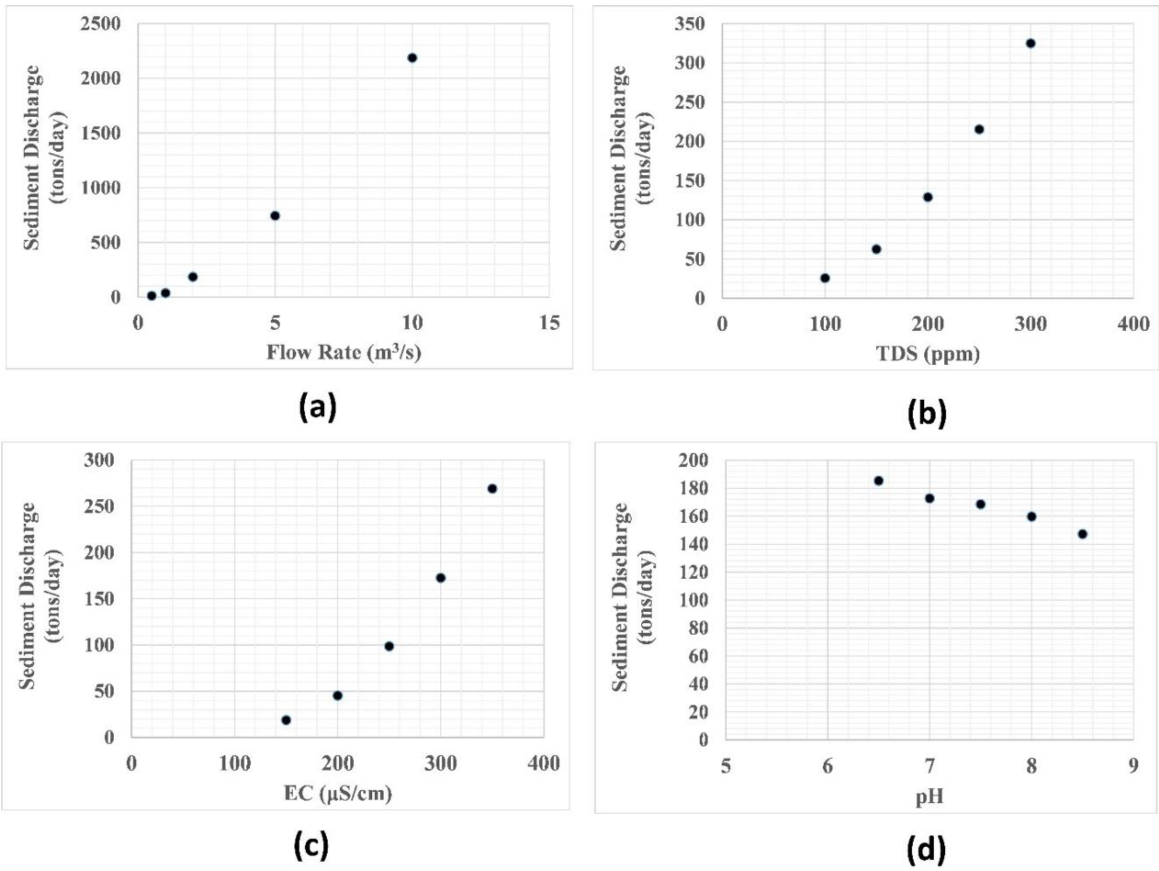

Fig. 3. a: Total sediment load vs. Flow Rate, b: Total sediment load vs. Total Dissolved Solids (TDS), c: Total sediment load vs. Electrical Conductivity (EC), d: Total sediment load vs. pH

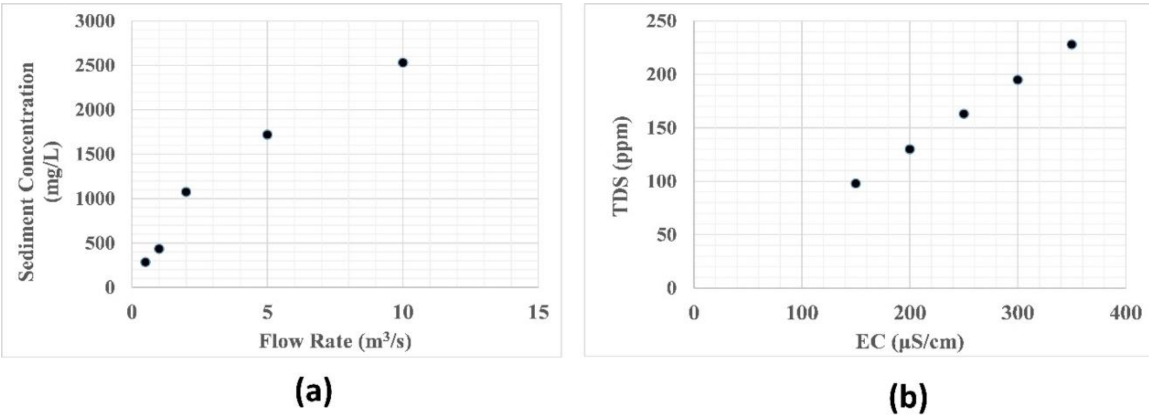

Fig. 4. a: Sediment Concentration vs. Flow Rate, b: EC vs. TDS

There is a positive relation between flow rate and sediment concentration, which is nonlinear. While sediment concentration rises when flow rates increase, this rise is increasingly steep. This might be explained by a higher erosive power and transporting capacity of higher flows. Nonlinearity suggests that beyond certain thresholds in flow, other erosion processes may get triggered, such as bank erosion or mobilization of coarser bed material.

Because the sediment concentration and therefore the total sediment load rises with the flow rate, whereas the rate of increase of total sediment load is usually higher due to the multiplication effect of the flow rate, as seen in Fig. 4a. There is a strong positive linear relationship between the EC and TDS. This is well expected in water quality analysis, since often the EC is used as a proxy for TDS.

In this case, the linearity of the relationship does indicate a consistent ionic composition in the river water across a wide range of concentrations. The slope of this relationship will provide some insight into major ion species present in the water. Any significant deviations from such a straight-line variation may reflect a change in ionic composition or an increase of non-ionic dissolved substances (Fig. 4b).

To investigate the relation between the flow rate and total sediment load, a flow duration curve was drawn, differentiating the following five flow regimes: high flows from 0 to 10%, moist conditions of flow from 10 to 40%, mid-range flow from 40 to 60%, dry conditions of flow from 60% to 90%, and low flows from 90 to 100%. The average total sediment load for each regime was calculated and is shown in Table 4.

Table 4. Average total sediment load for different flow regimes

Flow Regime	Exceedance Probability	Average Total sediment load (tons/day)
High flows	0-10%	623.7
Moist conditions	10-40%	185.2
Mid-range flows	40-60%	72.4
Dry conditions	60-90%	28.9
Low flows	90-100%	5.6

Results showed that the highest sediment transport occurs during high-magnitude flow events. The mean total sediment load of the top 10% of flows was found to be 623.7 tons/day. This again underlines the importance of extreme events concerning processes including the transport of sediments in Sufi Chay River. To gain more insight with greater detail into the temporal trends in total sediment load and principal water quality parameters, a seasonal-trend decomposition using LOESS (STL) was performed. The time series were decomposed into trend, seasonal, and residual components. Trend components for total sediment load, TDS, and EC are summarized in Table 5.

Table 5. Trend component summary from STL decomposition

Parameter	Start Value	End Value	Total Change
Total sediment load (tons/day)	78.4	112.6	34.2
TDS (ppm)	142.3	168.7	26.4
EC	218.5	259.2	40.7

Trend analysis confirms the upward trends observed in the Mann-Kendall test. The total sediment load showed the most robust relative increase of 43.6% over the study period. TDS and EC showed a similar relative increase of 18.6%. Annual sediment yield was estimated to find the total sediment output of the Sufi Chay River basin.

Accordingly, the average annual sediment yield and variation in the study period were computed. Results are summarized in Table 6.

Table 6. Annual sediment yield statistics

Statistic	Value
Mean annual sediment yield (tons/year)	42,650
Standard deviation (tons/year)	18,720
Minimum annual yield (tons/year)	15,830
Maximum annual yield (tons/year)	89,470
Coefficient of variation	0.439

This indicates that the average annual sediment yield is very high, having a value of 42,650 tons/year, hence a considerable amount of sediment is transported in the Sufi Chay River. High value of variation coefficient of 0.439 reflects substantial variability of sediment yield at an inter-annual scale and could be related to climatic fluctuation besides changes in land use at the watershed area.

Frequency analysis of sediment transport events was carried out with the objective of obtaining the recurrence intervals of the high total sediment load episodes. Annual maximum total sediment load series were fitted to a Log-Pearson Type III distribution. Different return period results are shown in Table 7.

Table 7. Frequency analysis of annual maximum total sediment load

Return Period (years)	Total sediment load (tons/day)
2	1,250
5	2,380
10	3,420
25	5,160
50	6,780
100	8,720

Frequency analysis results show that this total sediment load of 3,420 tons/day may be expected to take place once in 10 years on average. This information is useful in the design of sediment management structures and flood control measures in the Sufi Chay River basin.

These dimensionless parameters were identified to establish a relationship between total sediment load and water quality parameters by undertaking a comprehensive approach based on physical and chemical properties of water and sediment transport processes. The following dimensionless parameters were considered:

1. Reynolds number (Re): Representing the ratio of inertial forces to viscous forces
2. Froude number (Fr): Representing the ratio of inertial forces to gravitational forces
3. Sediment concentration (C): Ratio of total sediment load to water discharge
4. Normalized Total Dissolved Solids (TDS*): Ratio of TDS to a reference TDS value
5. Normalized Electrical Conductivity (EC*): Ratio of EC to a reference EC value
6. Normalized pH (pH*): Ratio of pH to neutral pH (7.0)

The dimensionless parameters were formulated as Eqs.11.

$$\begin{aligned} \mathrm{Re} &= \frac{(\rho \times V \times R)}{} \mu, \\ \mathrm{Fr} &= V - \sqrt{g \times R}, \\ C &= Qs - (\rho s \times Q),\ TDS^{*} \\ &= TDS - TDSref, \\ EC^{*} &= EC / ECref,\ pH^{*} = pH / 7.0 \end{aligned} \tag{11}$$

where: ρ = Water density (kg/m^3), V = Flow velocity (m/s), R = Hydraulic radius (m), μ = Dynamic viscosity of water (kg/m·s), g = Gravitational acceleration (m/s^2), Qs = Total sediment load (kg/s), ρs = Sediment particle density (kg/m^3), Q = Water discharge (m^3/s), TDSref = Reference TDS value (set to 500 ppm), and ECref = Reference EC value (set to 800 μS/cm)

The raw data were transformed into the dimensionless parameters by using Eqs. 11. Then, the dimensionless obtained parameters were normalized, using the z-score normalization in order for all variables to be in a comparable scale. A correlation analysis was performed to establish relationships among the dimensionless parameters. Results are shown in Table 8.

Besides, correlation analysis has shown strong relations of sediment concentration with hydraulic parameters of *Re* and *Fr*. The moderate ones are between C and water quality parameters of TDS* and EC*, while pH* reveals a weak negative relation with all parameters.

Table 8. Correlation matrix of dimensionless parameters

Parameter	C	Re	Fr	TDS*	EC*	pH*
C	1.00	0.72	0.65	0.58	0.56	-0.18
Re	0.72	1.00	0.88	0.42	0.39	-0.12
Fr	0.65	0.88	1.00	0.35	0.33	-0.09
TDS*	0.58	0.42	0.35	1.00	0.97	-0.25
EC*	0.56	0.39	0.33	0.97	1.00	-0.23
pH*	-0.18	-0.12	-0.09	-0.25	-0.23	1.00

Accordingly, from the correlation analysis, a multiple regression model was obtained for predicting the dimensionless sediment concentration, C, using the rest of the dimensionless parameters. The model is expressed in Eq. 12.

$$\log(\mathrm{C}) = \mathrm{b0} + \mathrm{b1}\log(\mathrm{Re}) + \mathrm{b2}\log(\mathrm{Fr}) + \mathrm{b3}\log(\mathrm{TDS}) + \mathrm{b4}\log(\mathrm{EC}) + \mathrm{b5}\log(\mathrm{pH}) \quad (12)$$

where b0, b1, b2, b3, b4, and b5 are regression coefficients. The regression analysis results are presented in Table 9.

Table 9. Multiple regression analysis results

Coefficient	Value	Standard Error
b0	-5.237	0.428
b1	0.865	0.092
b2	0.412	0.085
b3	0.326	0.073
b4	0.298	0.071
b5	-0.154	0.062

The performance of the multiple regression model in the prediction of dimensionless sediment concentration is good since R2 for the model is equal to 0.823. All the predictor variables are statistically significant at $p < 0.05$, though the most influencing factor on sediment concentration is the Reynolds number. The final dimensionless equation for the sediment concentration prediction in Sufi Chay River is given by Eq. 13, based on the regression and validation of the results.

$$\mathrm{C} = 10^{(-5.237)} \times \mathrm{Re}^{0.865} \times \mathrm{Fr}^{0.412} \times \mathrm{TDS}^{*0.326} \times \mathrm{EC}^{*0.298} \times \mathrm{pH}^{*(-0.154)} \quad (13)$$

This equation therefore provides the dimensionless relation of sediment concentration with some hydraulic and water quality parameters for the Sufi Chay River. The use of dimensionless parameters, as employed in the development of this model, allows its potential application to similar river systems, although site-specific calibration may be required. The advantages of the developed dimensionless relationship are that it incorporates into one simple equation the complex interaction between hydraulic conditions and water quality itself in the process of sediment transport.

Use of dimensionless parameters provides a comparison, perhaps some applicability, across scale and different river systems. The model integrates hydraulic and water quality parameters and can hence apply a more holistic approach to the prediction of total sediment loads.

The sensitivity analysis of dimensionless Eq. 13 has been done in order to determine the importance of each parameter and its effect on the predicted sediment concentration. Such an analysis gives an idea about model behavior and helps to identify major influential factors in sediment transport processes in the Sufi Chay River.

A local sensitivity analysis was first performed by variation of each input parameter individually while the others were kept constant at their mean values. Sensitivity coefficient (S) for each parameter was calculated using Eq. 14.

$$\mathrm{S} = \frac{(\Delta \mathrm{C}/\mathrm{C})}{(\Delta \mathrm{X}/\mathrm{X})} \quad (14)$$

where: S = Sensitivity coefficient, ΔC = Change in sediment concentration, C = Base sediment concentration, ΔX = Change in input parameter, and X = Base value of input parameter.

Each of the parameters was varied by ±10% from its mean value, and the corresponding change in sediment concentration was calculated. The results of the local sensitivity analysis are presented in Table 10.

Table 10. Local sensitivity analysis results

Parameter	Sensitivity Coefficient (S)
Re	0.865
Fr	0.412
TDS*	0.326
EC*	0.298
pH*	-0.154

Contrary-wise, local sensitivity analysis illustrates that the most sensitive coefficient is Reynolds number, Re, which has the strongest impact on sediment concentration predictions. The Froude number (Fr) and the normalized

TDS (TDS*) are above 0.1, while pH* has a relatively minor negative impact.

A global sensitivity analysis was performed by the Sobol method in order to take into consideration such interactions of the parameters, along with non-linear effects. It decomposes the output variance into contributions from each input parameter and their interactions. First-order Si and total-order STi Sobol indices were calculated for each parameter. Results are given in Table 11.

Table 11. Global sensitivity analysis results (Sobol indices)

Parameter	First-order Index (Si)	Total-order Index (STi)
Re	0.482	0.561
Fr	0.187	0.235
TDS*	0.112	0.156
EC*	0.089	0.124
pH*	0.021	0.037

Global sensitivity analysis furthered the local sensitivity analysis by showing that Re has both the highest first-order and total-order indices. In general, it was realized that there is a difference between the first order and total-order indices, which is indicative of the presence of parameter interactions, specifically *Re* and *Fr*.

The Monte Carlo simulation was performed in order to estimate the overall uncertainty in predictions for sediment concentration. Input parameters were assumed to be normally distributed, with mean and standard deviation calculated from available data. The results of 10,000 runs are represented in Table 12.

Table 12. Monte Carlo simulation results

Statistic	Value
Mean predicted C	0.00342
Median predicted C	0.00315
Standard deviation	0.00187
5th percentile	0.00098
95th percentile	0.00689
Coefficient of variation	0.547

Results from the Monte Carlo simulation indicate that model predictions have a coefficient of variation of 0.547, which represents moderate uncertainty in the sediment concentration estimates. The asymmetry of the mean and median values is indicative of a slight positive skew in the distribution of the predicted concentrations.

Some of the important results that can be inferred from the sensitivity analysis of the dimensionless sediment concentration model for the Sufi Chay River are as follows: Reynolds number, which introduces flow characteristics into the model, predicts the sediment concentration. Hence, flow characteristics are much more important in sediment transport processes. The Froude number and normalized TDS* also include significant importance; hence, hydraulic conditions and water quality parameters are two important factors in sediment transport.

The model bears some nonlinearities and parameter interaction shown by the discrepancies between the first-order and total-order Sobol indices. The pH* parameter has the least influence on sediment concentration predictions, showing that pH fluctuations may have a very limited direct impact on sediment transport in the Sufi Chay River. The Monte Carlo simulation indicates a moderate uncertainty of model predictions that has to be taken into account while using the model for management decisions.

To enhance total sediment load estimation based on water quality parameters in the Sufi Chay River, three soft computing methods were used. Further, the derived approaches have been compared with the previously developed models, including the dimensionless analysis approach, to outline the most effective predictive model. The following soft computing techniques are employed in this research: ANN, ANFIS, and SVR.

The feedforward multilayer perceptron ANN was developed using a backpropagation learning algorithm. This network architecture includes an input layer with nodes corresponding to the TDS, EC, pH, and flow rate; two hidden layers having 10 and 5 neurons, respectively; and an output layer with one neuron representing the total sediment load. The hyperbolic tangent function was then used as an activation function for the hidden layers, while the linear activation function was used in the output layer.

The network was trained with 70% of the data, validated with 15%, and tested on the remaining 15%. An ANFIS model was developed in order to combine the learning capabilities of neural networks with the reasoning power of fuzzy logic. The model used a Sugeno-type fuzzy inference system with Gaussian membership functions. The same input parameters as in the ANN model are used. The ANFIS model is trained by a hybrid learning algorithm that combines the least-squares estimation and the backpropagation gradient descent methods.

An SVR model is implemented with a radial basis function kernel in order to estimate total sediment load. These developed soft computing methods and models previously developed were also presented for their performance based on the coefficient of determination, root mean square error, mean absolute error, and Nash-Sutcliffe efficiency. A summary of these performances is included in Table 13.

Table 13. Performance comparison of total sediment load estimation models

Model	R^2	RMSE (tons/day)
Multiple Linear Regression	0.76	87.2
Dimensionless Equation	0.82	75.1
ANN	0.89	58.7
ANFIS	0.91	53.2
SVR	0.88	61.4

Comparing the performances of the different models, it can be observed in general that the performances of the soft computing methods are better than those of traditional regression and dimensionless analysis. In the context of the developed soft computing techniques, the best performance is given by the ANFIS model, with the highest R^2 (0.91) and NSE (0.90), and the lowest RMSE (53.21 tons/day) and MAE (38.76 tons/day).

A comparison in terms of computation efficiency among the models was also performed by calculating the time required for training and prediction by the model. Results are summarized in the following table, Table 14.

Table 14. Computational efficiency comparison

Model	Training Time (s)	Prediction Time (ms/sample)
Multiple Linear Regression	0.05	0.02
Dimensionless Equation	0.12	0.03
ANN	15.23	0.11
ANFIS	28.76	0.18
SVR	8.45	0.09

While soft computing methods, especially ANFIS, provide better predictive performance, it also involves a lot more computational effort in training and prediction with respect to simpler models, such as multiple linear regression or the dimensionless equation. In light of the above, therefore, the best performing model for estimating total sediment load with the water quality parameters in the Sufi Chay River was established to be ANFIS. This technique strikes a balance between high predictive accuracy and an ability to capture complex nonlinear relationships that exist between input variables and total sediment load.

However, other factors that may affect the choice of ANFIS in real-time applications and in large-scale implementations are increased computational requirements. While the dimensionless equation approach did not provide the best predictive accuracy, it does bring along some advantages with regard to general applicability and the interpretability of the result in physical terms. The relations shed light on the basic physical mechanism governing the sediment transport and thus may be applied more appropriately to other river systems of similar characteristics. In practice, the model of choice would depend on the demands imposed by the application for predictive accuracy and computational efficiency and the interpretability.

If real-time predictions are indispensable in situations with scant computational resources, simpler models like the dimensionless equation or multiple linear regression would be preferred. The preferred model in applications where high accuracy is needed and adequate computational resources are available would be ANFIS.

4. Conclusion

In this study, the sediment transport processes along with their relations to water quality parameters were investigated comprehensively in the Sufi Chay River in Iran. This research has applied an extensive set of analytical methods comprising statistical analyses, dimensionless parameter modeling, and soft computing methods for explaining the complex interactions ruling sediment dynamics in this river system. These have shown very good correlations of total sediment load with some key parameters, such as flow rate, TDS, and Electrical Conductivity.

A power-law relation is there between flow rate and total sediment load, indicative of the fact that the sediment transport capacity goes disproportionately up with high flows. This underlines the crucial role of the extreme hydrological event in shaping the sediment regime of the river and highlights that management needs to be more targeted during these periods. This dimensionless sediment concentration prediction equation has provided insight into the relative importance of the various parameters affecting the process.

In ranking their relative importance, Reynolds number was seen to be the most important single parameter, followed by Froude number and then normalized TDS. It is now possible to apply this dimensionless approach to similar river systems, keeping in mind that site-specific calibration may well be required. However, the soft computing methods, and particularly the Adaptive Neuro-Fuzzy Inference System (ANFIS), have exhibited outstanding performance regarding total sediment load prediction using water quality parameters. It was observed that out of all different models, the maximum R^2 and NSE were obtained as 0.91 and 0.90, respectively, with the ANFIS model.

Further, various comments have also been made by a number of researchers regarding the advanced computationally intensive techniques compared with the simpler models. Seasonal total sediment load has also been recorded: the highest average value in spring is 187.3 tons/day, while in summer it is as low as 42.8 tons/day.

It was explained by snowmelt processes and seasonal regimes of precipitation, underlining thereby the necessity to account for temporal variability in sediment management strategies. Analysis of the parameters for water quality exhibited interesting relations such as inverse relation between flow rate and TDS indicates dilution effect in high flow events, and strong linear relationship between anion/cation hardness and total anions/cations to represent geochemical influences not only on water quality but perhaps on sediment behavior.

Flow rate has always been one of the most sensitive factors in the model analyses developed, with the exception of TDS and EC. Therefore, appropriate measurement and prediction of these important parameters would be of great benefit to monitoring and management.

Although the soft computing methods have demonstrated the highest predictive accuracy, advantages of the dimensionless equation approach are related to physical interpretability and possibly generalizability. Practical applications will have to be model-based, connected to specific project needs, and further balancing predictive accuracy, computational efficiency, and interpretability.

5. Disclosure Statement

No potential conflict of interest was reported by the authors

6. References

A. Flores, J., Q. Wu, J., O. Stöckle, C., P. Ewing, R., & Yang, X. (2020). Estimating river sediment load in the Upper Mississippi River using Landsat imagery. *Remote Sensing*, *12*(15), 2370.

Ashraf, M. A., Maah, M. J., Yusoff, I., Wajid, A., & Mahmood, K. (2011). Sand mining effects, causes and concerns: A case study from Bestari Jaya, Selangor, Peninsular Malaysia. *Scientific Research and Essays*, *6*(6), 1216-1231.

Aspray, K. L., Holden, J., Ledger, M. E., Mainstone, C. P., & Brown, L. E. (2017). Organic sediment pulses impact rivers across multiple levels of ecological organization. *Ecohydrology*, *10*(6), e1855.

Bartley, R., Speirs, W. J., Ellis, T. W., & Waters, D. K. (2012). A review of sediment and nutrient concentration data from Australia for use in catchment water quality models. *Marine pollution bulletin*, *65*(4-9), 101-116.

Bayram, A., Kankal, M., Tayfur, G., & Önsoy, H. (2014). Prediction of suspended sediment concentration from water quality variables. *Neural Computing and Applications*, *24*, 1079-1087.

Beeson, P. C., Sadeghi, A. M., Lang, M. W., Tomer, M. D., & Daughtry, C. S. (2014). Sediment delivery estimates in water quality models altered by resolution and source of topographic data. *Journal of Environmental Quality*, *43*(1), 26-36.

Chabokpour, J. (2024a). Comparative Analysis of Transfer Function Method with Advanced Flood Prediction Techniques. *Water Harvesting Research. 7*(2), 194-209

Chabokpour, J. (2024b). Experimental study of contaminant mixing through the buried river junctions. *Journal of Hydraulic Structures*, *10*(3), 18-33.

Chabokpour, J., & Azamathulla, H. M. (2022). Numerical simulation of pollution transport and hydrodynamic characteristics through the river confluence using FLOW 3D. *Water Supply*, *22*(10), 7821-7832.

Chabokpour, J., & Raji, M. (2024). Predicting Morphological Changes in Rivers Using Image Processing (Case Study: Qizil Ouzan River). *Journal of Hydraulic Structures*, *10*(2).

Chahinian, N., Tournoud, M.-G., Perrin, J.-L., & Picot, B. (2011). Flow and nutrient transport in intermittent rivers: a modelling case-study on the Vène River using SWAT 2005. *Hydrological Sciences Journal–Journal Des Sciences Hydrologiques*, *56*(2), 268-287.

Chalov, S., Golosov, V., Tsyplenkov, A., Theuring, P., Zakerinejad, R., Märker, M., & Samokhin, M. (2017). A toolbox for sediment budget research in small catchments. *Geography, Environment, Sustainability*, *10*(4), 43-68.

Cheung, K., Poon, B., Lan, C., & Wong, M. H. (2003). Assessment of metal and nutrient concentrations in river water and sediment collected from the cities in the Pearl River Delta, South China. *Chemosphere*, *52*(9), 1431-1440.

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.

Fagundes, H. d. O., Fan, F. M., & Paiva, R. C. D. d. (2019). Automatic calibration of a large-scale sediment model using suspended sediment concentration, water quality, and remote sensing data. *Rbrh*, *24*, e26.

Gazzaz, N. M., Yusoff, M. K., Aris, A. Z., Juahir, H., & Ramli, M. F. (2012). Artificial neural network modeling of the water quality index for Kinta River (Malaysia) using water quality variables as predictors. *Marine pollution bulletin*, *64*(11), 2409-2420.

Gholizadeh, M. H., Melesse, A. M., & Reddi, L. (2016). A comprehensive review on water quality parameters estimation using remote sensing techniques. *Sensors*, *16*(8), 1298.

Guojiao, L., Baohui, M., & Lehao, W. (2023). Water Quality Assessment of Wenyu River with Variable Weight Cloud Model. *Nature Environment & Pollution Technology*, *22*(1).

Horowitz, A. J. (1984). *A primer on trace metal-sediment chemistry* (2331-1258).

Hosseini, N., Johnston, J., & Lindenschmidt, K. (2017). Impacts of climate change on the water quality of a regulated prairie river. Water, 9 (3), 199. In.

Lindenschmidt, K.-E., Poser, K., & Rode, M. (2005). Impact of morphological parameters on water quality variables of a regulated lowland river. *Water Science and Technology*, *52*(6), 187-193.

Lou, H., Zhang, Y., Yang, S., Wang, X., Pan, Z., & Luo, Y. (2022). A new method for long-term river discharge estimation of small-and medium-scale Rivers by using multisource remote sensing and RSHS: Application and validation. *Remote Sensing*, *14*(8), 1798.

Lundy, L., Alves, L., Revitt, M., & Wildeboer, D. (2017). Metal water-sediment interactions and impacts on an urban ecosystem. *International journal of environmental research and public health*, *14*(7), 722.

Mohsen, A., Kovács, F., & Kiss, T. (2022). Remote Sensing of Sediment load in Rivers Using Sentinel-2 Images and Machine-Learning Algorithms. *Hydrology*, 9, 88. In.

Monjardin, C. E. F., Gomez, R. A., Cruz, M. N. G. D., Capili, D. L. R., Tan, F. J., & Uy, F. A. A. (2021). Sediment transport and water quality analyses of Naic River, Cavite, Philippines. 2021 IEEE Conference on Technologies for Sustainability (SusTech),

Munyai, L. F., Malungani, A., Ikudayisi, A., & Mutoti, M. I. (2024). The drivers of benthic macroinvertebrates communities along a subtropical river system: Sediments chemistry or water quality? *Ecohydrology*, e2649.

Othman, F., Alaaeldin, M., Seyam, M., Ahmed, A. N., Teo, F. Y., Ming Fai, C., Afan, H. A., Sherif, M., Sefelnasr, A., & El-Shafie, A. (2020). Efficient river water quality index prediction considering minimal number of inputs variables. *Engineering Applications of Computational Fluid Mechanics*, *14*(1), 751-763.

Park, Y. S., & Engel, B. A. (2016). Identifying the correlation between water quality data and LOADEST model behavior in annual sediment load estimations. *Water*, *8*(9), 368.

Saranga, B., Premarathne, U., & Atapattu, B. (2021). Stream Sediment Rate Estimation using Optical Sensing. 2021 IEEE Industrial Electronics and Applications Conference (IEACon),

Saraswati, S. P., Ardion, M. V., Widodo, Y. H., & Hadisusanto, S. (2019). Water quality index performance for river pollution control based on better ecological point of view (a case study in Code, Winongo, Gadjah Wong streams). Journal of the Civil Engineering Forum,

Smith, I. M., Hall, K. J., Lavkulich, L. M., & Schreier, H. (2007). Trace Metal Concentrations in an Intensive Agricultural Watershed in British Columbia, Canada 1. *JAWRA Journal of the American Water Resources Association*, *43*(6), 1455-1467.

Tyler, A., Svab, E., Preston, T., Présing, M., & Kovács, W. (2006). Remote sensing of the water quality of shallow lakes: A mixture modelling approach to quantifying phytoplankton in water characterized by high-suspended sediment. *International Journal of Remote Sensing*, *27*(8), 1521-1537.

Warrick, J. A. (2015). Trend analyses with river sediment rating curves. *Hydrological Processes*, *29*(6), 936-949.