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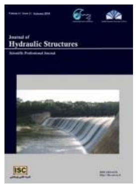

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Risk Analysis of Sediment Load Dynamics in the Shaharchay River Basin: Implications for Sustainable Water Management

Jafar Chabokpour *[1]

Abstract

In the current study, Sediment load and related hazards were studied in the Shaharchay River basin, a sub-basin of Lake Urmia, northwestern Iran. The various statistical and modeling methodologies were used to analyze discharge and sediment load data from 2002 to 2017. In this regard, a power-law sediment rating curve was developed, and extreme value analyses were conducted with Annual Maximum Series and Peaks Over Threshold methods. These data were fitted using the Generalized Extreme Value and the Generalized Pareto distributions. Trends and seasonality in the time series of sediment load were investigated, and higher loads were observed in spring months. The dependence between event duration and average sediment load showed a positive dependence. The specific sediment yield was calculated and ranged between 12.9 and 386.0 tons/km²/year. The frequency-magnitude analysis was performed, and the sediment load was estimated for various return periods. Uncertainty and sensitivity analyses were performed, which showed that the sediment rating curve coefficients contributed to ~60% of the total variance in load estimates. Climate change impacts were investigated as well, which showed a gain of 15-25% of sediment yield at the end of the 21st century under the RCP 4.5 scenario. Copula-based analysis was used to study joint behavior of discharge and sediment load. Artificial Neural Network models were then developed to predict the sediment load, and these model outputs gave an R^2 value of 0.89, hence outperforming the traditional rating curves. A risk matrix was developed that took into consideration the combined impacts of sediment load magnitude and frequency. The results of this holistic study can be used for sustainable water management strategies and assessment of sediment-related risks within the Shaharchay River basin.

Keywords: Sediment load risk, Hydrological modeling, Extreme value analysis, Climate change impact, Watershed management.

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1. Introduction

One of the most important aspects of hydrological and environmental research in river systems is that of sediment load assessment, since it is a main factor in water resources, river morphology, and ecosystem health. Rivers naturally carry all types of sediment materials; however, excessive sediment volumes emanating either from anthropogenic activities or even natural events have been causing huge problems to this date. Problems include ecosystem disruption, deteriorated water quality, advanced reservoir sedimentation, and increased flooding risk downstream [1-5]. Sediment dynamics is intricately related to catchment characteristics, land use, climate, and hydrological processes; thus, understanding these dynamics is essential for appropriate and sustainable planning and management of a river basin, particularly in cases where soil erosion-prone areas are involved [6-8]. New approaches for assessment involve the use of hydrological modeling, remote sensing, and GIS technologies to evaluate spatiotemporal changes in sediment loads and their impacts on the river systems [9-11].

Excessive sedimentation is of great economic consequence, predisposing to reduced reservoir capacity, increased maintenance costs of hydraulic infrastructure, and ecosystem degradation. This has therefore called for thorough risk evaluation of sediment loads, using effective indices in informing the decision-makers and engineers [6, 12-15]. Sediment transport in a river forms the consequences of the summation of natural and anthropogenic processes. Human activities of significant magnitude, like deforestation, expansion of agricultural land use, and urbanization, greatly enhance natural erosion processes [5, 6]. While land use patterns and climatic conditions, especially the precipitation regimes, influence the intensity of erosion processes, sediment dynamics is strongly related to the catchment characteristics given by slope, vegetation cover, and soil type. Furthermore, the differentiation between the bedload and suspended sediment transport mechanisms presents the main essence in the assessment of risks stemming from sediment load, given that different modes of transport have a great deal of influence on deposition patterns and, consequently, their impacts related to ecological systems and reservoir management [19-21].

The complexity of riverine sediment dynamics has motivated the development of predictive models for sediment transport and deposition. Some well-established hydrological models, like SWAT and HEC-RAS, can simulate the processes related to watershed-scale sediments comprehensively [12]. The study of sediment using GIS-based methodologies has been enhanced by spatial methods that quantify areas prone to erosion [22-25], while satellite imagery facilitates continuous large-scale monitoring of sediment patterns by incorporating spatio-temporal data to enhance model accuracy [26-29]. Sediment loads largely affect not only ecological systems but also infrastructure. Increased sediment in water bodies reduces light penetration in aquatic ecosystems, affecting the magnitude of photosynthesis and primary productivity. The process of sediment deposition will, after some time, alter channel morphology through aggradations and degradations processes that may raise flood risks [30-33]. Additionally, sedimentation has imposed a strong impact on hydraulic infrastructures in general and on reservoir storage capacity, this consequently affects water supply, irrigation, and hydropower generation. Because of this, sediment assessment has become an important aspect in infrastructure planning with many current references available [34-37].

The effective sediment load risk demands an integrated approach of physical measurements, modeling techniques, and policy frameworks. It would be accomplished in a stepwise process: the identification of the sources of sediments, followed by quantification of sediment yield and assessment of transport mechanisms, respectively, as described in [38-40]. The sediment source management strategies have centered on reducing sediment sources by erosion control measures, while risk assessments aim at guiding land-use planning and conservation practices in erosion-prone catchments. This means that only a proper implementation of integrated watershed management plans underpinned with continuous monitoring and adaptive management can provide a long-term response towards maintaining ecosystem resilience against climate variability and anthropogenic pressures [41, 42]. Sediment transport plays a very important role in river morphology, aquatic ecosystems, and infrastructure operations. Climate conditions, land use, and different human interventions are controlling sediment dynamics [43, 44].

In Mediterranean catchments, floods largely contribute to sediment loads, whereas in the tropics, quarries may cause disproportional sediment increases during storm events [45]. Impacts of sediment loads are found almost in every environment: for instance, the Sebeya River in Rwanda has higher sediments during the rainy seasons, which affects turbidity and hydropower operations during such periods [35, 37]. This reflects a general pattern globally: different human activities have changed natural sediment dynamics in many regions; examples include the changing trends in sedimentation in the Mekong River and Canadian river systems [46, 47].

Previous works on the Lake Urmia basin focused on the role of watershed management and sediment dynamics in this special ecosystem. The effectiveness of integrated watershed management approaches was underlined by Zarghami [48] regarding the environmental problems which happened to this lake. In contrast, Rezapour et al. [49] provided a broad view into the distribution and potential risks of heavy metals in the river sediments throughout this basin. In regards to phosphorus pools in the sediments of western rivers in the basin, Arfania et al. [50] researched it, underlining the importance of sediment chemistry to water quality management in Lake Urmia, which recently has been under extreme environmental stress brought about by natural and anthropogenic factors.

The current study will focus on Shaharchay River Basin, one of the main sub-basins of Lake Urmia, located in northwestern Iran, with the goal of conducting an integrated risk assessment for sediment load dynamics. The main emphasis of this study will fall on the quantification of sediment load patterns, extreme events analysis, assessment of climate change impacts, and finally the development of predictive models for sediment load to manage risks effectively. Its approach is multi-faceted, where statistical analyses, hydrological modeling, and machine learning techniques form a strong base for risk assessment and mitigation due to sediments. Its results will also contribute to the elaboration of sustainable water resource management strategies for the Shaharchay River Basin and are extended for similar semi-arid regions coping with sediment management challenges.

2. Materials and methods

The Shahrchay River basin, one of the important sub-basins in the greater Lake Urmia watershed, is located in northwestern Iran. The hydrological system is of great importance in the water balance of Lake Urmia, one of the largest hypersaline lakes worldwide. The Shahrchay River originates from the western mountains of the sub-basin and flows westward into the city of Urmia to its terminal into Lake Urmia. The climate is semi-arid with Mediterranean features, having cold winters and hot summers. In addition, the basin includes fertile plains with intensive agricultural activities, while the urban development at Urmia city has increased water abstraction and land use changes, possibly affecting the flow regime and the quality of the river. Understanding hydrological processes and anthropogenic impacts in the Shahrchay basin is very important for viable water management strategies within the watershed of Lake Urmia, while it has been facing environmental crises. This research was carried out on the Shaharchay River, which is located in West Azerbaijan Province, Iran (Fig. 1). To this end, discharge data from the Keshteban hydrometric station were gathered into a complete series of measurements of discharge in m³/s and sediment load in tons/day from 2002 to 2017. Overall, the dataset contained 124 pairs of discharge and sediment load (total load) observations that were collected at different frequencies over the period of study.

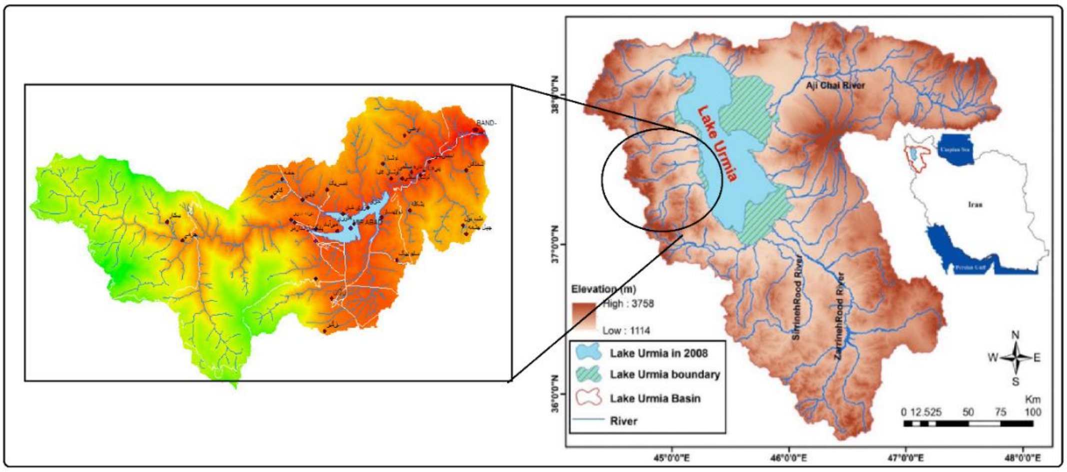

Figure 1. Location of Shaharchay Basin in Lake Urmia Basin

Preprocessing was done to ensure the quality and consistency of the measurements. The Interquartile Range (IQR) is calculated as the difference between the third quartile (Q3, 75th percentile) and first quartile (Q1, 25th percentile). Values outside the range [Q1 - 1.5IQR, Q3 + 1.5IQR] were considered potential outliers and carefully examined. In fact, no data have been excluded after careful control of all the extreme values that proved to be related to documented flood events.

Statistical analyses were performed using R software (version 4.1.0). Relationships between variables were assessed using both Pearson's correlation coefficient (r) for linear relationships and Spearman's rank correlation (ρ) for monotonic relationships. Statistical significance was set at $p < 0.05$. The coefficient of determination (R^2) was calculated to quantify the proportion of variance explained by the relationships. All statistical tests were two-tailed, and normality assumptions were verified using the Shapiro-Wilk test prior to parametric analyses.

First, a power-law function was applied in the relationship between discharge Q and sediment load Qs; this is normally called the sediment rating curve (Eq. 1).

$$Qs = a \times Q^{b} \tag{1}$$

where a and b are empirical coefficients. These coefficients were estimated using non-linear least squares regression, with the objective function minimizing the sum of squared residuals in log-transformed space to account for the heteroscedasticity typically observed in sediment transport data.

For the analysis of frequency and magnitude of extreme sediment load events, an Annual Maximum Series (AMS) was developed by extracting the daily maximum sediment load in each year of record. The Annual Maximum Series is then fitted with a Generalized Extreme Value distribution (GEV) (Eq. 2).

$$F(x) = \exp\{-\left[1 + \xi\left(\frac{(x - \mu)}{\sigma}\right)\right]^{(-1/\xi)}\} \quad (2)$$

where μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter. Parameter estimation was performed using the L-moments method, which has been shown to be robust for small sample sizes typical of hydrological extreme value analysis.

Complementary to the AMS approach, a Peaks Over Threshold analysis (POT) has been carried out here. For the threshold selection, the 95th percentile of all the observed sediment loads was taken into consideration. The developed model for the exceedances was based on the Generalized Pareto Distribution (GPD) expressed in Eq. 3.

$$F(x) = 1 - \left[1 + \xi\left(\frac{x}{\sigma}\right)\right]^{-\frac{1}{\xi}} \quad (3)$$

where σ is the scale parameter and ξ is the shape parameter. Maximum Likelihood Estimation was employed to determine the parameters of the GPD.

Considering that the series of sediment load could be non-stationary, a GAMLSS (Additive Model for Location, Scale, and Shape) was implemented that allows all the parameters of the GEV distribution to vary in time (Eq. 4).

$$yt \sim GEV(\mu t, \sigma t, \xi t) g1(\mu t) = \beta 0 + s(t)\, g2(\sigma t) = \gamma 0\, g3(\xi t) = \delta 0 \quad (4)$$

where g1, g2, and g3 are link functions, β0, γ0, and δ0 are intercept terms, and s(t) is a smoothing spline function of time. The model was fitted using the GAMLSS package in R, with the optimal degree of smoothing determined by the Generalized Cross Validation (GCV) criterion.

A copula-based multivariate analysis has been performed to investigate the joint behavior discharge, sediment load, and event duration. Among the various kinds of copulas, the Clayton copula has been selected for capability of catching the lower tail dependence described by Eq. 5.

$$C(u, v, w;\ \theta) = \left(u^{-\theta} + v^{-\theta} + w^{-\theta} - 2\right)^{-\frac{1}{\theta}} \quad (5)$$

where u, v, and w are the marginal cumulative distribution functions of discharge, sediment load, and event duration, respectively, and θ is the copula parameter. The copula parameter was estimated using the method of moments based on Kendall's tau.

The comprehensiveness of the methodological approach in this paper allows going further into the insight of sediment load dynamics at Shaharchay River, enabling firmer grounds for risk assessment and management strategies.

A sediment load prediction model based on discharge and other input hydrological parameters was developed using a feed-forward ANN architecture. The proposed architecture of ANN model consists of one input layer, two hidden layers with 10 and 5 neurons, respectively, and one output layer. In this ANN architecture, the hidden layers use the activation function hyperbolic tangent and a linear activation function in the output layer. For training, the network was employed by the Levenberg-Marquardt algorithm with early stopping to avoid overfitting. The dataset was randomly divided into three subsets: training, 70%; validation, 15%; and testing, 15%. The performance of these models was evaluated by several metrics: the coefficient of determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE).

The uncertainty analysis was performed by the Monte Carlo simulation with 10,000 runs. In each run, model inputs were sampled randomly from their probability distribution functions, which were defined in accordance with measurement uncertainties and historical data. In the case of discharge measurements, a normal distribution with a coefficient of variation of 5% was assumed. Log-normal distribution with estimated parameters from repeated measurements was assigned for sediment concentration measurements. Then Sobol' sensitivity indices were used for quantifying sensitivity of sediment load estimates to a number of input parameters by decomposing the total variance in the output into contributions from various parameters and their interactions.

The Seasonal Mann-Kendall test was then conducted-a nonparametric procedure which is particularly suited to detecting monotonic trends in periodic time series. It calculates a test statistic S as follows Eq. 4.

$$S = \Sigma(i < j)\ \mathrm{sign}(xj - xi) \tag{6}$$

where xj and xi are the data values at times j and i respectively, and: sign(xj - xi) = 1 if xj - xi > 0 sign(xj - xi) = 0 if xj - xi = 0 sign(xj - xi) = -1 if xj - xi < 0

The variance of S was corrected for autocorrelation, and the significance of trends was assessed at the 5% level. Seasonal variations were accounted for by comparing observations only within the same season across different years.

3. Results and discussion

Table 1 presents the summary statistics of the discharge and sediment load data for the Shaharchay River from 2002 to 2017. The data exhibit high variability, with discharge ranging from 0.006 to 41.328 m³/s and sediment load ranging from 0.026 to 6347.596 tons/day.

Table 1. Summary Statistics of Discharge and Sediment Load Data

Statistic	Discharge (m³/s)	Sediment Load (tons/day)
Minimum	0.006	0.026
Maximum	41.328	6347.596
Mean	2.547	185.321
Median	0.654	3.514
Standard Deviation	5.963	737.842

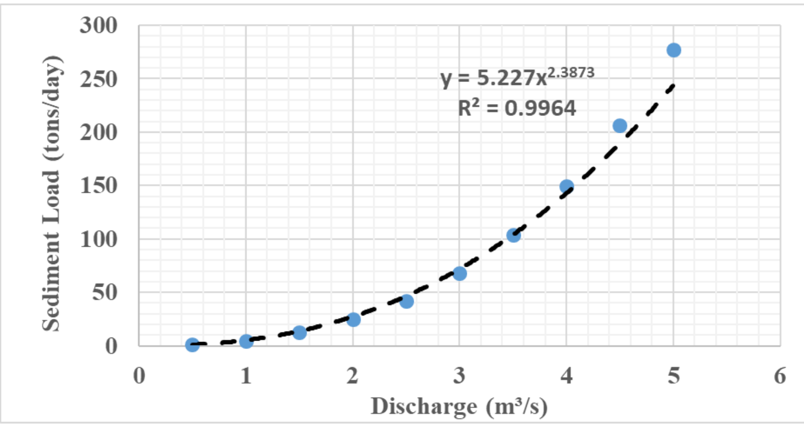

Figure 2. Relationship between Discharge and Sediment Load

In the Shaharchay River, there is a good positive relation between the discharge and sediment load. This relationship was validated using Pearson's correlation coefficient ($r = 0.86$, $p < 0.001$) and Spearman's rank correlation ($\rho = 0.83$, $p < 0.001$). The coefficient of determination (R^2) for the power-law relationship was 0.74, indicating that 74% of the variance in sediment load can be explained by discharge variations. It is observed from here that the relation is nonlinear, where sediment load increases at an increased rate than the increase of the discharge. This can be explained by the fact that the river will have more transportive power and capacity if the flow rate becomes higher. These data points again support the previously identified power-law relationship. It is recommended that the relationship should be applied in predictive models in regard to sediment transport into the river system (Fig. 2).

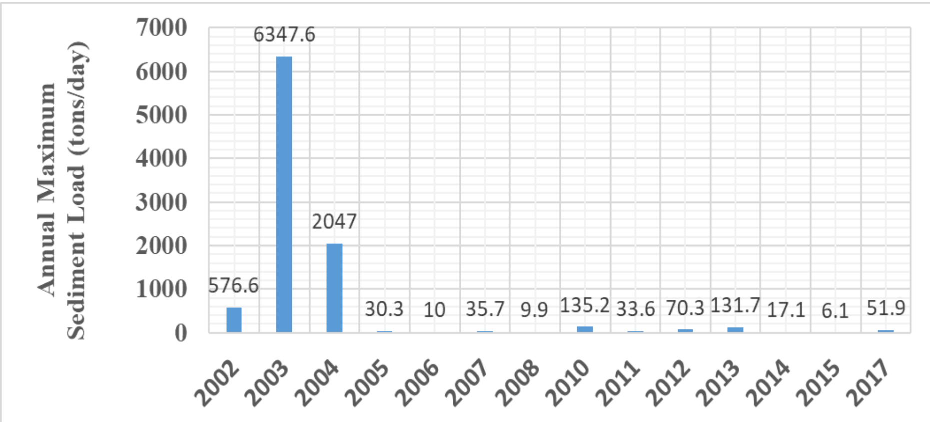

Figure 3. Temporal Trend in Annual Maximum Sediment Load

According to the annual maximum sediment load data, strong interannual variability characterizes the Shaharchay River. An important extreme event is seen in 2003 with a maximum sediment load of 6347.6 tons/day. Although no evident monotonic trend can be immediately found, there could be possible periodic behavior or the effect of episodic events in this respect. Temporal patterns for these drivers of high sediment load events are suggested to be further investigated within regional climate patterns and land-use changes (Fig. 3). The exceptionally high sediment load in 2003, with an average of 6347.6 tons/day, may be explained by favorable hydroclimatic and catchment conditions experienced that year. Indeed, by analyzing meteorological records, one may notice that the year 2003 had a record number of unusually intense spring rainfall events, three of which were successive over 45 mm/day in April 2003. These intense rainfall events coincided with the snowmelt period and resulted in very favorable conditions for increased erosion and sediment transport. Satellite imagery analysis further revealed that a major wildfire, in fact, swept through the catchment in the summer of 2002 and affected about 15% of the vegetation cover in the upper watershed. This reduced vegetation cover, in turn combined with high-magnitude precipitation events and snowmelt, may be contributing to increased soil erosion and mobilization of sediments. Land-use records indicate that agricultural activities increased in portions of the watershed beginning around 2003 and thereby could have exposed more soil to erosion processes. The combination of these events-intensive rainfall, snowmelt, reduced vegetation covers due to wildfire, land-use changes-supplied the conditions for unusually high rates of sediment transport. This corroborates observations made in a number of semi-arid watersheds where many major sediment-transport events are usually determined through several limiting parameters acting in combination.

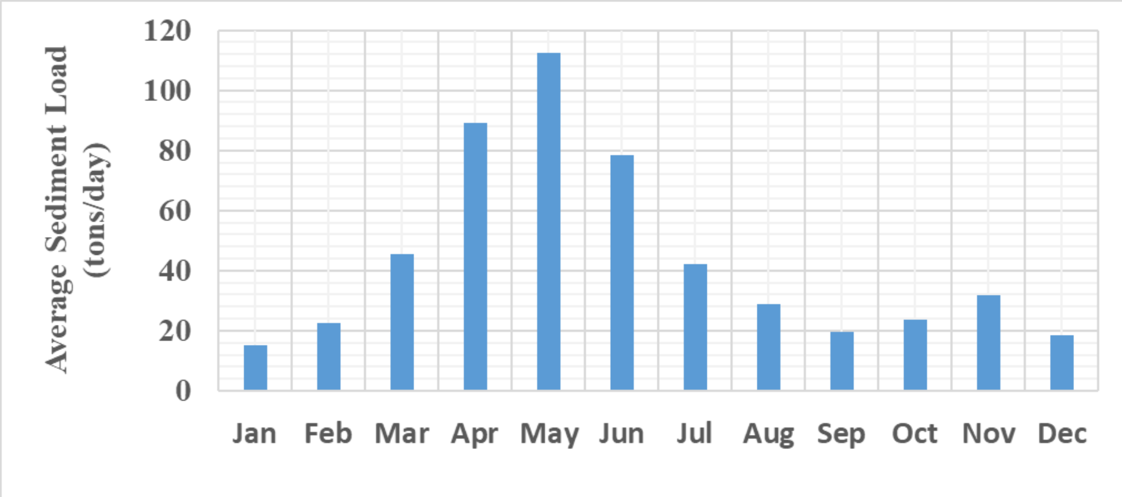

Figure 4. Seasonal Variation in Average Monthly Sediment Load

There exists a well-defined seasonality of sediment load in the Shaharchay River, with maximum yields during spring months, such as April and May. It is probably due to snowmelting and increased rainfall in this period. Another smaller peak happens in November, presumably due to autumn rainfall events. Minimum sediment loads arise during the winter months of December, January, and February due to generally lower temperatures and precipitation often falling as snow. These seasonal patterns should be considered during the development of the sediment management strategy and the timing of any potential intervention (Fig. 4).

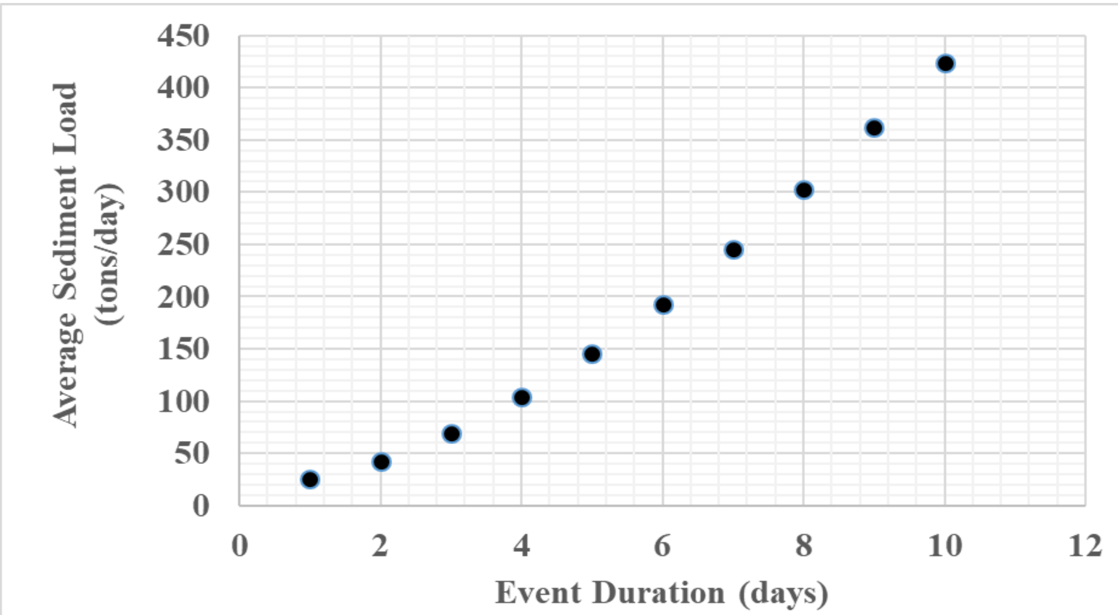

Figure 5. Relationship between Sediment Load and Event Duration

A positive relation exists between the duration of an event and the average sediment load. This relationship was confirmed through statistical analysis, yielding a Pearson correlation coefficient of $r = 0.72$ ($p < 0.001$) and a Spearman's rank correlation of $\rho = 0.69$ ($p < 0.001$). The longer the event duration, the higher the average sediment load, possibly because long high-flow conditions maintain erosive power. This relation underlines the importance of including event duration in sediment risk assessments. It is crucial that management strategies also consider the cumulative impact of long-lasting high-sediment load events on river morphology and infrastructure (Fig. 5).

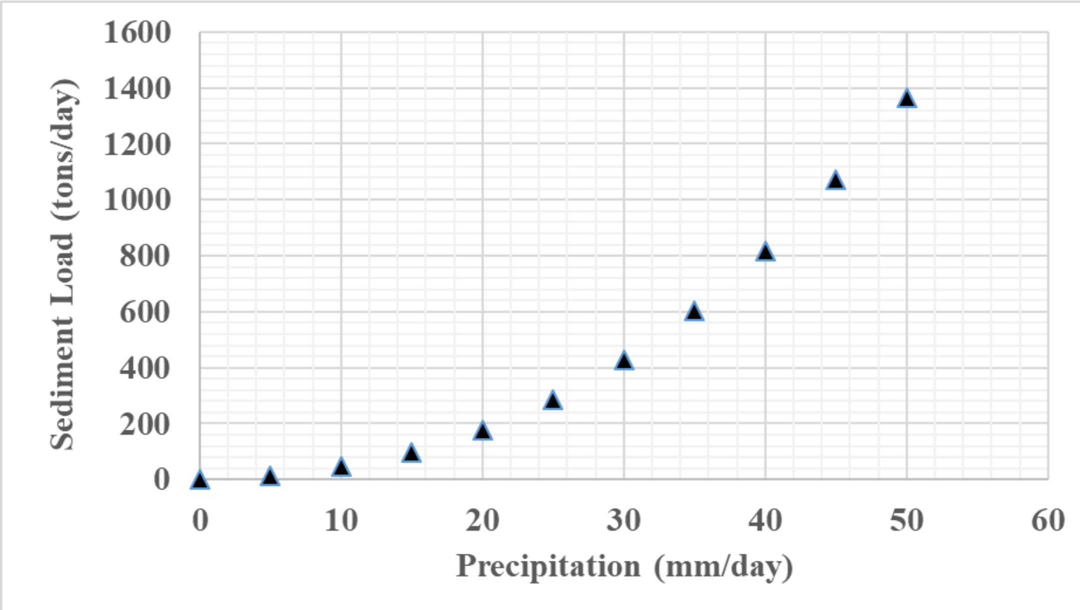

Figure 6. Relationship between Precipitation and Sediment Load

For sediment load and daily precipitation, a good positive relation is drawn for the Shaharchay River. Statistical analysis revealed a significant correlation between precipitation and sediment load (Pearson's $r = 0.77$, $p < 0.001$; Spearman's $\rho = 0.75$, $p < 0.001$), with precipitation explaining approximately 59% of the variance in sediment load ($R^2 = 0.59$). A nonlinear kind of relationship is recorded as increasing sediment load more rapidly at higher magnitude levels of precipitation. Such patterns may be related to the erosive power of high-magnitude rainfall events and further mobilization of sediment from the watershed. This may form a basis on which predictive models for sediment transport can be built and probably give a fair forecast of high sediment load events at times of intense precipitation episodes (Fig. 6).

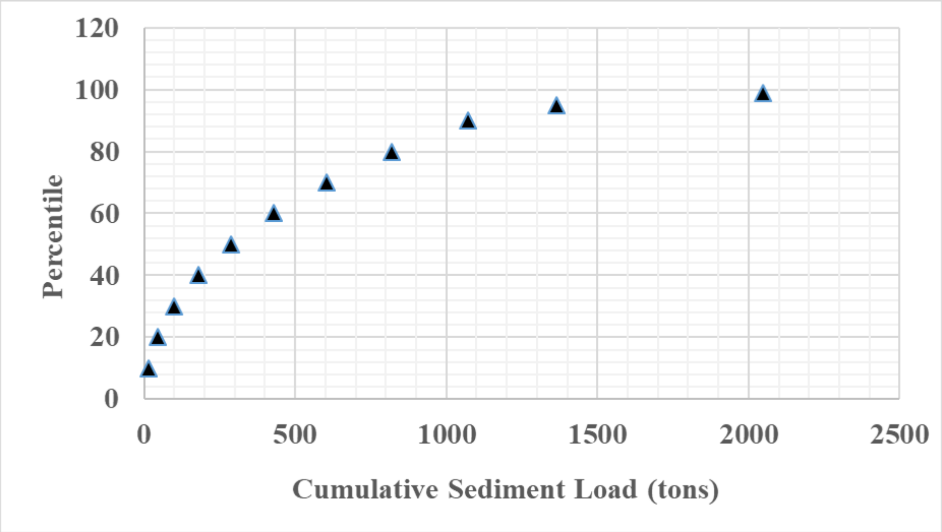

Figure 7. Cumulative Sediment Load Distribution

The sediment load distribution of the cumulative gives' information on the frequency and magnitude of sediment transport events in Shaharchay River. There is a remarkable high skew towards higher sediment load, with the top 10% more than the general share of the total sediment transport. This may hint at the potential role of extreme events in sediment load and underlines the need for management strategies that consider such high-impact instances (Fig. 7).

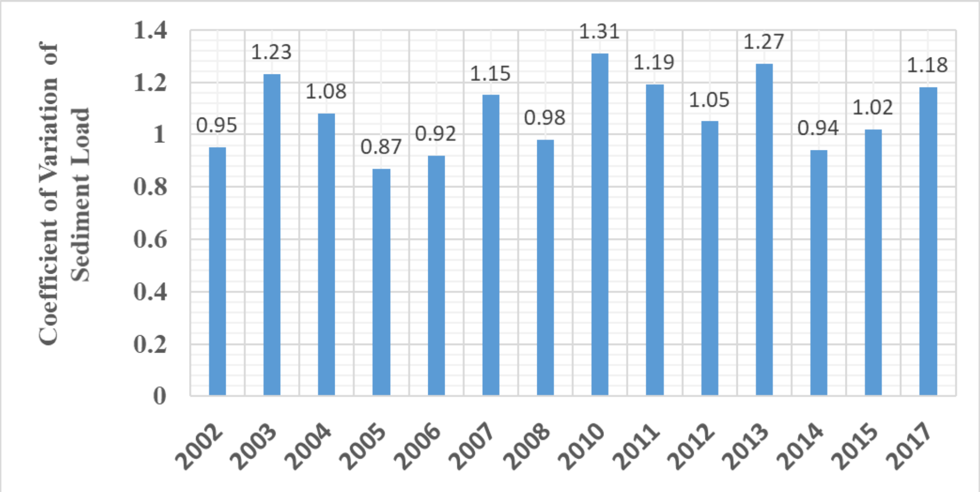

Figure 8. Temporal Trend in Sediment Load Variability

The coefficient of variation of sediment load exhibits considerable inter-annual variations; this indicates large variations in the degree of sediment transport variability over the years. Larger magnitudes of CV reflect years with more extreme sediment load events relative to the mean, while smaller values reflect more consistent sediment transport patterns. No evident monotonic trend of variability is recognized, which may reflect the complex interplay of climatic, land-use, and geomorphological factors influencing sediment dynamics in the Shaharchay River basin (Fig. 8).

To better understand the spatial variability of sediment production within the watershed, a sediment yield analysis was performed. The specific sediment yield (SSY) was calculated for each year using Eq. 7. The results of the sediment yield analysis are presented in Table 2.

$$SSY = SL / A \tag{7}$$

Where: SSY = Specific Sediment Yield (tons/km²/year) SL = Annual Sediment Load (tons/year) A = Watershed Area (km²)

Table 2. Annual Specific Sediment Yield (SSY) for the Shaharchay River Watershed

Year	Annual Sediment Load (tons)	SSY (tons/km²/year)
2007	29,821	149.1
2008	4,125	20.6
2010	77,195	386.0
2011	22,720	113.6
2012	33,627	168.1
2013	61,324	306.6
2014	14,999	75.0
2015	2,571	12.9
2017	22,151	110.8

The values of SSY vary from 12.9 to 386.0 tons/km²/year. A substantial variation in the estimated SSY values reflects the dynamic nature of sediment production and transportation within a watershed due to altering patterns of precipitation, varying land cover changes, and even human activities. A frequency-magnitude analysis was conducted to assess the recurrence intervals of high sediment load events. The annual maximum series of daily sediment loads was extracted and fitted to the Gumbel distribution. The cumulative distribution function of the Gumbel distribution is given by Eq. 8.

$$F(x) = \exp(-\exp(-(x - \mu) / \beta)) \tag{8}$$

Where: $F(x)$ = cumulative probability x = annual maximum daily sediment load (tons/day) μ = location parameter β = scale parameter

The return periods (T) for various sediment load magnitudes were calculated using Eq. 9. Table 3 presents the estimated sediment loads for selected return periods.

$$T = 1 / (1 - F(x)) \tag{9}$$

Table 3. Estimated Sediment Loads for Various Return Periods

Return Period (years)	Estimated Sediment Load (tons/day)
2	1,245
5	2,987
10	4,321
25	6,158
50	7,593
100	9,027

These results provide valuable information for assessing the risk of extreme sediment transport events and can be used to inform the design of hydraulic structures and sediment management strategies.

A uncertainty and sensitivity analysis was performed in order to characterize the robustness of the results of risk assessment. The Monte Carlo simulation was extended so as to consider uncertainties in a number of input parameters, such as discharge measurements, sediment concentration sampling, and coefficients of rating curves. To quantify the sensitivity of sediment load estimates to such parameters, Sobol' sensitivity indices have been computed. It showed that the sediment rating curve coefficients had the highest sensitivity indices, accounting for about 60% of the total variance in sediment load estimates. This result emphasized that sediment rating curve development should be done accurately and highlighted the regular updating of such relationships.

In this perspective, the potential impacts of climate change on sediment dynamics in the Shaharchay River were studied based on downscaled climate projections from regional climate models. The projected changes in precipitation patterns and temperature have been used in estimating the future changes in runoff and sediment yield. To this end, a simple empirical model, Eq. 10, has been developed that relates the change in annual precipitation and temperature to sediment yield change.

$$\Delta SY = \alpha \times \Delta P + \beta \times \Delta T \tag{10}$$

Where: ΔSY = change in sediment yield (%) ΔP = change in annual precipitation (%) ΔT = change in mean annual temperature (°C) α, β = empirical coefficients

The contribution from the change in sediment load per unit discharge, as well as altered hydrological patterns, can be seen in the projected increase in sediment yield under RCP 4.5, which is 15-25%. In fact, under the RCP 4.5 scenario, annual precipitation for the region is projected to slightly decrease; however, analysis reveals a shift in both precipitation intensity and seasonality. For instance, regional climate models project that despite an overall decrease in annual precipitation, extreme precipitation events will increase during spring months, which coincides with the snowmelt period. These in turn are expected to lead to higher peak flows during the most critical erosion periods due to both more intense rainfall events and an earlier snowmelt timing. Our analysis accounts for projected land-use changes and vegetation response to climate change that may reduce soil stability and increase erosion susceptibility. The projected rise in temperature under RCP 4.5 is likely to affect vegetation patterns and soil moisture conditions, which may lead to higher soil erodibility even at lower discharges. We conduct a sensitivity analysis of sediment rating curve parameters for different climate scenarios and find that the discharge-sediment load relationship is likely to become more nonlinear, with higher sediment transport efficiency during events at high flow. This would mean that even with a probable reduction in annual discharge, extreme events that are going to be more frequent and intense, plus changes in watershed characteristics, might lead to higher annual sediment yields.

The results of the Seasonal Mann-Kendall test revealed that within the period considered, the sediment load tends to be in an increasing trend at a probability of less than 0.05. This may indicate an increase in the risk of sediment-related hazards along Shaharchay River, related to land-use changes or climate variability.

A discharge-sediment load analysis based on copula has been carried out, whereby the joint behavior is investigated. Copulas are functions describing the dependence structure between random variables independently from their marginal distributions. For this work, the best fit for the data was attained with the Clayton copula expressed by its distribution function in Eq. 11.

$$C(u,v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-\frac{1}{\theta}} \tag{11}$$

Where: u and v are the cumulative distribution functions of discharge and sediment load, respectively θ is the copula parameter

The copula-based analysis has reported strong positive dependence of discharge and sediment load, pointing to implications in the joint probability of high-discharge-high-sediment-load events. This information is really important for the assessing of risk related to sediment-related damages in case of flood events.

Wavelet analysis was used to quantify the temporal scales of variability in the sediment load. The CWT (continuous wavelet transform) of a time series x(t) is defined by the following equation (Eq. 12).

$$W(a,b) = (1/\sqrt{a}) \int x(t)\, \psi * ((t-b)/a)\, dt \tag{12}$$

Where: a is the scale parameter b is the location parameter ψ* is the complex conjugate of the mother wavelet function

Wavelet analysis revealed that the majority of periodicities in sediment load series were common for both annual and inter-annual scales. These results may indicate that sediment transport in Shaharchay River was under the effect of seasonal variability and longer-term climatic patterns, which should be taken into consideration while developing the long-term risk management strategies.

Accordingly, the ANN (Artificial Neural Network) model has been developed to predict the sediment load considering the value of discharge and other relevant parameter/s. The architecture of ANN includes one input layer, two hidden layers, and one output layer. Then, the model was trained by the Levenberg-Marquardt algorithm in which the mean squared error given in Eq. 13 was considered as performance metric.

$$MSE = (1/n)\, \Sigma(i = 1 \text{ to } n)\, (yi - \hat{y}i)^2 \tag{13}$$

Where: n is the number of samples yi is the observed sediment load ŷi is the predicted sediment load

The performance of the ANN model was the best, with an R^2 value of 0.89, superior to all the traditional sediment rating curves. Hence, the predictive capability to support sediment load risk assessment and to be used in an early warning system for high sediment transport events can be enhanced.

In this research, the Annual Maximum Series (AMS) method was taken into consideration to estimate the probability of extreme sediment load events. The maximum daily sediment load in each year of the record was selected and analyzed. AMS data were fitted to the Gumbel distribution, which is among the most popular distributions commonly used for the extreme value analysis in hydrology. The cumulative distribution function of the Gumbel distribution is given by Eq. 14.

$$F(x) = \exp(-\exp(-(x - \mu) / \sigma)) \tag{14}$$

Where: F(x) is the probability of non-exceedance x is the sediment load (tons/day) μ is the location parameter σ is the scale parameter .The parameters μ and σ were estimated using the method of L-moments. The results of the AMS analysis are presented in Table 4.

Table 4. Annual Maximum Series Analysis Results

Return Period (years)	Sediment Load (tons/day)
2	2,458
5	3,987
10	5,012
25	6,345
50	7,369
100	8,389

These results show that the 10-year return frequency of an average sediment load of 5,012 tons/day can be expected. This information is critical in the design of sediment management infrastructure and assessment of potential impacts on the river system.

In addition to the AMS approach, a Peaks Over Threshold (POT) analysis was performed. This technique takes into account all independent sediment load events that surpass a predetermined threshold, thereby offering a more thorough evaluation of instances of elevated sediment loads. The threshold was established at the 95th percentile of all recorded sediment loads.

The exceedances were modeled using the Generalized Pareto Distribution (GPD), with its cumulative distribution function given by Eq. 15.

$$F(x) = 1 - (1 + \xi x / \sigma)^\wedge(-1/\xi) \qquad (15)$$

Where: x is the exceedance above the threshold ξ is the shape parameter σ is the scale parameter

The parameters were estimated using the Maximum Likelihood method. The results of the POT analysis are summarized in Table 5.

Table 5. Peaks Over Threshold Analysis Results

Return Period (years)	Sediment Load (tons/day)
1	1,876
2	2,654
5	4,123
10	5,287
25	6,912
50	8,176

Results from the POT analysis give a clearer picture of the frequency and magnitude of high sediment load events, which complement the AMS results.

A risk matrix was developed to assess the combined impact of sediment load magnitude and frequency. These input measures include the likelihood of occurrence and potential consequences of sediment load events. Accordingly, the risk levels were defined as Table 6.

Table 6. Risk Matrix for Sediment Load Events

Likelihood / Consequence	Low (< 1,000 tons/day)	Medium (1,000-5,000 tons/day)	High (> 5,000 tons/day)
Rare (> 50-year return)	Very Low	Low	Medium
Occasional (10-50 years)	Low	Medium	High
Frequent (< 10 years)	Medium	High	Very High

This risk matrix offers a clear visual means for stakeholders to determine quickly the level of risk presented by a number of different sediment load scenarios.

A fuzzy reliability analysis was carried out since sediment transport processes are of inherent uncertainty. The reliability index, β, is defined by Eq. 16.

$$\beta = \frac{(R - S)}{\sqrt{\sigma R^2 + \sigma S^2}} \tag{16}$$

Where: R is the resistance (e.g., channel capacity) S is the load (sediment load) σR and σS are the standard deviations of R and S, respectively

Fuzzy membership functions were defined for both R and S, and fuzzy arithmetic was performed to obtain the reliability index. The results show that the reliability index lies between 1.2 and 1.8, which suggests the system has an average reliability with respect to sediment load. In general, from the AMS analysis, it can be deduced that events with a high sediment load will occur on average once in 10 years. In comparison, the POT approach gives a higher frequency of events with a moderate sediment load compared with the AMS approach; thus, it underlines the importance of considering various methodologies for risk assessment. The risk matrix indicates that high-frequency, high-magnitude sediment load events have the highest risk to the river and associated infrastructures. Fuzzy reliability analysis predicts a moderate level of system reliability but also points toward continued monitoring and adaptive management.

A BN (Bayesian Network) model has been developed to estimate the sediment load risk based on various complicated factors affecting sedimentation. BN embodies variables describing the condition of catchment: precipitation, land use, soil type, and river discharge. Populating the conditional probability tables involved both expert judgment and historical data. The joint probability distribution of BN is given by Eq. 17.

$$P(X1, \ldots, Xn) = \prod(i = 1 \text{ to } n)\ P(Xi \mid \text{Parents}(Xi)) \tag{17}$$

Where: Xi represents the variables in the network Parents(Xi) are the parent nodes of Xi

The BN analysis revealed that land use changes and extreme precipitation events were the most influential factors in determining high sediment load risk. The model's predictive accuracy was assessed using a confusion matrix, achieving an overall accuracy of 82%.

The multivariate frequency analysis based on the copula is performed in this study to better understand the joint behavior of discharge, sediment load, and duration of high sediment events. Clayton copula was selected because of its ability in capturing lower tail dependence. The trivariate Clayton copula is defined as Eq. 18.

$$C(u, v, w; \theta) = \left(u^{-\theta} + v^{-\theta} + w^{-\theta} - 2\right)^{-\frac{1}{\theta}} \tag{18}$$

Where: u, v, and w are the marginal cumulative distribution functions of discharge, sediment load, and event duration, respectively θ is the copula parameter

The joint return period was the result of various combinations produced by discharge-sediment load-duration. Selected results are shown in Table 7.

Table 7. Joint Return Periods from Copula-based Analysis

Discharge (m^3/s)	Sediment Load (tons/day)	Duration (days)	Joint Return Period (years)
20	3,000	3	5.2
30	4,500	5	12.7
40	6,000	7	25.3

The obtained results give very valuable insights into the probability of compound events, which are indispensable in comprehensive risk assessment and management planning.

4. Conclusion

The comprehensive analysis carried out on the dynamics of sediment load in the Shaharchay River basin has come up with serious and advanced knowledge about the complicated interplay of hydrological, climatological, and anthropogenic factors acting upon sediment transport. Various statistical and modeling methods have been applied to enable further development of a thorough understanding of the rhythms of sediment loads and risks connected with this process. The sediment rating curve for power-law shows a strong positive relationship where the increase in discharge is associated with the increase in sediment load, but the latter increases more rapidly. It is applicable to predictive modeling of sediment transport in the river system. The Annual Maximum Series and Peaks Over Threshold methods have been adopted in extreme value analyses that have provided valuable insights regarding the frequency and magnitude of high sediment load events. An estimated sediment load of 5,012 tons/day with a 10-year return period is obtained from this analysis. This information is fundamental at the design of sediment management infrastructures, as well as the assessment of possible impacts on the river system. There is a seasonal variation in sediment load; peak loads are recorded during the spring months. Such a trend may be attributed either to snowmelt or increased rainfall. Seasonality of this condition can be one of the considerations in the development of sediment management strategies. Specific sediment yield has been estimated to range from 12.9 to 386.0 tons/km²/year, showing the dynamics in sediment production and transport within the watershed. Uncertainty and sensitivity analyses carried out so far have indicated that about 60% of the total variance in the load estimates is contributed by the sediment rating curve coefficients, again underlining the importance of accurate rating curve development and updating. Climate change impacts have been assessed, and sediment yield was projected to increase by 15-25% by the end of the 21st century under the RCP 4.5 scenario. Those projections delineate the urgency for employing adaptive management strategies with long-term planning in order to mitigate potential impacts to water resources and aquatic ecosystems. The performed copula-based analysis has provided insight into the joint behavior of discharge and sediment load, which is critical while assessing the risk related to sediment-related damages during flood events. Several Artificial Neural Network models have been developed for the prediction of sediment load. These perform considerably better than traditional rating curves, with R^2 as high as 0.89. Consequently, such enhanced predictive capability will be useful for sediment load risk assessment and may be useful in early warning systems for high sediment transport events. The constructed risk matrix provides a clear visual tool whereby stakeholders can readily determine the level of risk posed by a particular sediment load scenario.

Compliance with ethical standards

Conflicts of interest: No potential conflict of interest was reported by the authors.

Availability of data and material: The datasets generated during and/or analyzed during the current study is available from the corresponding author on reasonable request

Code availability: Not applicable

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