Comparative Assessment of Sediment Rating Curve Methods and Uncertainty Analysis for Reservoir Sedimentation Estimation in Dez Dam, Iran

Farnaz Karimi[1], Babak Lashkar-Ara[2*] and Hesam Seyed Kaboli[3]

1- Graduate Student, Water Engineering Department, Faculty of Civil Engineering, Jundi-Shapur University of Technology, Dezful, Iran.
2- Corresponding author's, Associated Professor, Water Engineering Department, Faculty of Civil Engineering, Jundi-Shapur University of Technology, Dezful, Iran. (Lashkarara@jsu.ac.ir).*
3- Associated Professor, Water Engineering Department, Faculty of Civil Engineering, Jundi-Shapur University of Technology, Dezful, Iran.

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Abstract

Accurate estimation of sediment inflow into reservoirs is essential for sustainable water resources management, reservoir operation, and long-term storage preservation. However, conventional sediment rating curve approaches are often associated with considerable uncertainty due to hydrological variability, limited sediment observations, and the nonlinear behavior of sediment transport processes. This study aims to evaluate the performance and uncertainty of seven sediment rating curve methods, including the USBR, FAO-USBR, Ferguson-USBR, Category Average, FAO-Category Average, Ferguson-Category Average, and Wet–Dry Period Separation methods, using 51 years of hydrological and sediment data from the Telezang hydrometric station upstream of Dez Dam, Iran. To quantify uncertainty in sediment volume estimation, two stochastic approaches, namely Monte Carlo Simulation (MCS) and Latin Hypercube Sampling (LHS), were implemented in the Python programming environment (NumPy and SciPy libraries). Probability distributions were assigned to the principal uncertain inputs, namely the annual discharge, the sediment-rating curve coefficients (sampled as correlated pairs) and the sediment composition (subject to a closure constraint). The estimated reservoir sedimentation obtained from the different rating curve methods was further compared with available hydrographic survey data from the Dez Dam reservoir. The results indicated that the USBR, Category Average, Ferguson-corrected Category Average, and Wet–Dry Period Separation methods produced estimates more consistent with the available hydrographic observations. Uncertainty analysis revealed that sediment-rating curve coefficients constituted the dominant source of uncertainty, followed by flow discharge, whereas sediment composition contributed the least to the overall uncertainty. With 10,000 realizations in each approach, the overall coefficients of variation of the cumulative sediment volume estimated by MCS and LHS were 0.42 and 0.41, respectively, while LHS converged with fewer realizations. The findings demonstrate the importance of integrating stochastic uncertainty analysis with sediment rating approaches to improve the reliability of reservoir sedimentation assessments.

Introduction

Reservoir sedimentation is recognized as one of the most critical challenges affecting the long-term sustainability and operational efficiency of hydraulic infrastructures worldwide. Progressive sediment accumulation reduces effective reservoir storage, disrupts flood-control performance, decreases hydropower efficiency, and threatens the reliability of water supply and irrigation systems. Consequently, accurate estimation of sediment inflow and deposited sediment volume is essential for sustainable

reservoir management and long-term planning. However, sediment transport and deposition processes are governed by complex interactions among hydrological, hydraulic, geomorphological, and sedimentological variables, making reliable prediction of reservoir sedimentation highly uncertain. One of the major challenges in water resources engineering is identifying and quantifying the variables controlling natural processes and understanding how uncertainties in these variables propagate through predictive models. In sedimentation studies, uncertainty arises from several sources, including temporal variability in river discharge, limited sediment observations, measurement errors, empirical assumptions, sediment characteristics, and reservoir trapping processes. These uncertainties significantly influence sediment yield estimation and may lead to considerable errors in reservoir design and operation. Therefore, uncertainty analysis is increasingly recognized as an essential component of sedimentation studies because it enables a better understanding of the relative importance of governing parameters and improves the reliability of predictive models.

Dams are constructed for multiple purposes such as flood control, hydropower generation, irrigation, urban and industrial water supply, and sediment management (Ferrari & Collins, 2006). Nevertheless, sediment accumulation remains one of the primary factors limiting reservoir performance and reducing reservoir lifespan. Reservoir sedimentation is controlled by a combination of watershed erosion, sediment transport rates, reservoir geometry, operational conditions, trapping efficiency, and sediment consolidation processes. Due to the stochastic nature of these factors, deterministic approaches alone are often insufficient for reliable sedimentation assessment. Recent investigations on Iranian reservoirs have further emphasized the importance of sediment transport dynamics, turbidity-current behavior, and sediment consolidation processes in long-term reservoir management and storage preservation (Aryaei & Lashkar-Ara, 2023; Goudarzi et al., 2021; Shadorvan et al., 2018).

Several empirical and semi-empirical methods have been developed to estimate reservoir sedimentation characteristics. Miller (1953) and Lane and Koelzer (1943) proposed empirical relationships for estimating the temporal variation of sediment bulk density and the unit weight of deposited sediments. These methods remain widely used because sediment consolidation directly affects the estimation of accumulated sediment volume and reservoir storage depletion. Similarly, Churchill (1948), Brune (1953), and Brown (1943) developed empirical approaches for estimating reservoir trap efficiency using observed reservoir data. Among these methods, the Brune (1953) trap-efficiency relationship is one of the most widely applied approaches for evaluating the proportion of incoming sediment retained within reservoirs. Accurate estimation of trap efficiency is therefore fundamental for predicting long-term reservoir sedimentation and storage reduction. In parallel with reservoir sedimentation studies, sediment rating curves have been extensively employed to estimate suspended sediment loads in rivers. Rating curve methods establish empirical relationships between river discharge and sediment discharge or sediment concentration. Conventional approaches such as the USBR method and its modified forms, including FAO-USBR and Ferguson-corrected methods, are commonly used because of their simplicity and low data requirements. Other approaches, such as category averaging and seasonal separation techniques, attempt to improve estimation accuracy by accounting for temporal variability and hydrological heterogeneity. Despite their widespread application, sediment rating curves are often associated with substantial uncertainty due to hysteresis effects, seasonal fluctuations, limited sampling during extreme events, and nonlinear sediment transport behavior. Consequently, different rating curve methods may produce considerably different sediment load estimates for the same watershed. Recent regional studies have also demonstrated the effectiveness of optimized sediment-rating relationships for improving suspended sediment estimation in Iranian river systems (Lashkar-Ara & Kiani, 2025).

Previous studies have attempted to incorporate uncertainty analysis into hydrological and

sedimentation modeling frameworks. Salas and Shin (1999) evaluated apparent reservoir sediment volume (ARSV) and accumulated reservoir sediment load (ARSL) using empirical sedimentation models for the Kani Reservoir on the White River. Uncertainty was analyzed using Monte Carlo Simulation (MCS) and Latin Hypercube Sampling (LHS), combined with sensitivity analysis. Their results demonstrated that water discharge and annual sediment inflow were the dominant factors controlling uncertainty in reservoir sedimentation. Papadopoulos and Yeung (2001) demonstrated the applicability of Monte Carlo simulation for uncertainty estimation in complex management systems, particularly under conditions involving relatively small uncertainties. Zou et al. (2002) proposed a Monte Carlo framework integrated with neural networks for uncertainty assessment in water quality modeling and demonstrated its effectiveness in handling stochastic variability in environmental systems. Ganji Norouzi (2006) applied Monte Carlo simulation and HAR methods to estimate uncertainty in inflow sediment volume for the Ekbatan Dam reservoir and concluded that sediment discharge and flow rate contributed most significantly to total uncertainty, whereas trap efficiency had comparatively minor influence. Lian and Yen (2003) compared several uncertainty analysis approaches, including HAR, Monte Carlo, Rosenblatt transformation, and LHS, for evaluating flood conveyance capacity through culverts. Their findings indicated that simplified sampling approaches such as LHS can achieve acceptable accuracy while requiring lower computational effort than conventional Monte Carlo simulation.

Recent studies have further advanced sediment-rating-curve estimation by explicitly accounting for temporal variability and improving the representation of sediment transport during different hydrological conditions. Salarijazi et al. (2024) demonstrated that temporal classification of discharge data, including seasonal, monthly, and wet–dry-flood periods, can improve the precision and consistency of suspended sediment rating curves in the Gorganrood Basin, Iran. Their results particularly highlighted the potential of wet–dry-flood classification for improving sediment-load estimation. Similarly, Daliri et al. (2025) evaluated established sediment-rating approaches, including the USBR and FAO-USBR methods, and proposed an improved rating-curve approach that accounts for flood-related sediment contributions and hysteresis effects.

While these studies highlight the importance of temporal and hydrological variability in sediment-rating relationships, the present study integrates alternative sediment-rating formulations with stochastic uncertainty propagation using both MCS and LHS for long-term reservoir sedimentation assessment.

Although previous investigations have significantly contributed to understanding uncertainty in hydrological and sedimentation systems, several research gaps remain. First, most studies have focused either on sediment rating curve development or on uncertainty analysis separately, while integrated frameworks combining multiple sediment estimation methods with stochastic uncertainty propagation remain limited. Second, comparative evaluation of sediment rating curve approaches under long-term reservoir sedimentation conditions has not been adequately investigated, particularly in semi-arid regions characterized by considerable hydrological variability. Third, many studies rely solely on statistical indicators without validating sedimentation estimates using reservoir hydrographic survey data. Finally, comparative assessment of Monte Carlo Simulation and Latin Hypercube Sampling for reservoir sedimentation uncertainty analysis remains relatively scarce in the literature.

To address these gaps, seven sediment-rating curve approaches, including USBR, FAO-USBR, Ferguson-USBR, Category Average, FAO-Category Average, Ferguson-Category Average, and Wet–Dry Period Separation methods, were evaluated using 51 years of hydrological and sediment data from the Telezang hydrometric station upstream of the Dez Dam reservoir. The resulting sediment-load estimates were used to assess long-term reservoir sedimentation and storage depletion and were validated against available hydrographic survey data. Stochastic uncertainty analysis was subsequently performed using Monte Carlo Simulation and Latin Hypercube Sampling in the Python programming

environment. The contributions of major uncertainty sources, including flow discharge, sediment-rating curve coefficients, sediment composition, and trap efficiency, were evaluated through probabilistic simulation.

Study Area and Methodology

Study Area

The Dez River watershed is located in the central Zagros Mountain range in southwestern Iran and extends between 48°10′–50°21′ E longitude and 31°35′–34°07′ N latitude. The basin is one of the major catchments draining into the Persian Gulf and plays an important role in regional water resources supply and hydropower generation. The Dez River constitutes the main river system within the basin, while the Dez Dam is situated approximately 23 km northeast of Andimeshk and 25 km north of Dezful. Hydrological and sediment data used in this study were obtained from the Telezang hydrometric station, located upstream of the Dez Reservoir at 48°46′ E longitude and 32°49′ N latitude, with an elevation of approximately 440 m above mean sea level. The contributing drainage area at this station is about 16,189 km². Telezang is classified as a first-order hydrometric station and is equipped with a 12-m measuring weir, limnimeter, and cableway system for discharge and sediment measurements. The station has been operated by the Khuzestan Water and Power Authority since 1955, and the recorded hydrological and sediment datasets are considered reliable for long-term sedimentation assessment and uncertainty analysis. Figure (1) presents the main tributaries of the Dez River basin and the spatial distribution of the watershed components.

Sediment Load Estimation

Sediment Rating Curve Framework

Long-term discharge and sediment records collected at the Telezang hydrometric station during 1968–2018 (51 years) were used to estimate sediment inflow into the Dez Dam reservoir. Sediment transport was evaluated using empirical sediment rating curves that relate river discharge to sediment load through power-law relationships. Because sediment transport increases nonlinearly with flow discharge, separate equations were adopted for suspended load and bedload estimation (Harrison, 2000):

$$Q_S = a_1 Q_W^{b_1} \quad (1)$$

$$Q_B = a_2 Q_W^{b_2} \quad (2)$$

where $Q_W$is river discharge (m³/s), $Q_S$is suspended sediment load (ton/day), $Q_B$is bedload discharge (ton/day), and a_1, b_1, a_2, and $b_2$are empirical regression coefficients. The total annual sediment load was obtained by summing suspended and bedload components:

$$QT_t = QS_t + QB_t \quad (3)$$

To improve estimation reliability, seven sediment-rating curve approaches were evaluated, including the USBR, FAO-USBR, Ferguson-USBR, Category Average, FAO-Category Average, Ferguson-Category Average, and Wet–Dry Period Separation methods.

USBR Method

The United States Bureau of Reclamation (USBR) method is one of the most widely used empirical approaches for estimating long-term sediment transport (USBR, 1987). This method establishes a regression relationship between measured river discharge and sediment load using observed hydrological and sediment data. Daily sediment discharge values were estimated from the rating curve and integrated over each hydrological year to determine annual sediment yield. Although the USBR approach provides a practical framework with limited data requirements, its application using a single regression equation for the entire annual record may not fully represent seasonal variability and nonlinear sediment transport behavior during extreme flow events. Nevertheless, due to its simplicity and broad applicability, the method remains a standard tool in reservoir sedimentation studies.

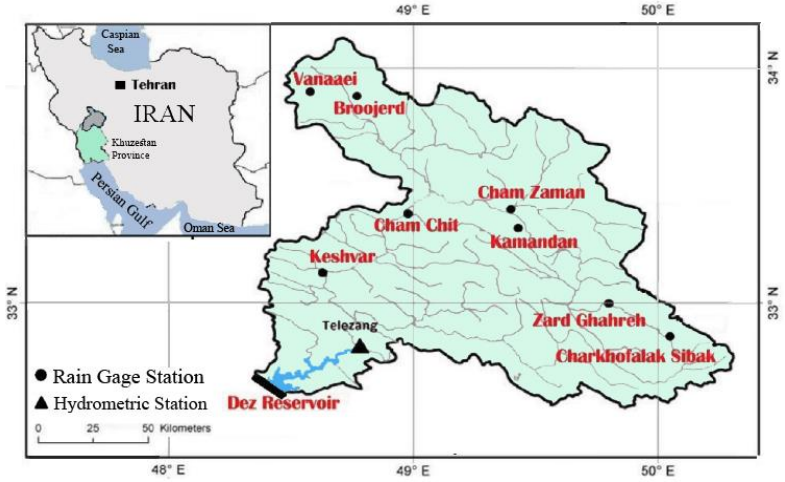


Fig. 1- Main tributaries of the Dez River basin in different parts of the watershed.

Wet–Dry Period Separation Method

Sediment transport processes are strongly affected by seasonal hydrological variability. Therefore, using a single sediment rating relationship for the entire year may introduce significant uncertainty. To address this issue, separate sediment rating curves were developed for wet and dry periods. Based on the hydrological characteristics of the Dez River basin, December–June was considered the wet season, whereas July–November represented the dry season. Independent discharge–sediment relationships were established for each period using corresponding observations. Daily sediment loads were then estimated separately and aggregated to calculate annual sediment discharge. This seasonal classification improves the representation of sediment transport processes under contrasting hydrological conditions and reduces uncertainty associated with highly variable discharge regimes.

Category Average Method

Conventional sediment rating curves are often biased toward low-flow conditions because sediment measurements during flood events are relatively limited. As a result, high-flow sediment transport may be underestimated despite its dominant contribution to annual sediment yield. To reduce this limitation, the Category Average method proposed by Miraboulaqasemi and Morid (1995) was employed. In this approach, river discharge data were divided into several discharge classes, and average discharge and sediment values were calculated for each category. A new regression relationship was subsequently developed between category-averaged discharge and sediment load values. This procedure improves the representation of high-flow sediment transport and generally produces more reliable long-term sediment load estimates.

FAO Correction Method

Sediment rating curves commonly underestimate sediment discharge because of logarithmic transformation and data dispersion effects. To reduce this systematic bias, the FAO correction method (FAO, 1981) was applied by modifying the regression coefficient a in Equations (1) and (2):

$$a' = \frac{\bar{Q_S}}{\bar{Q_W}^{\,b}} \quad (4a)$$

$$a' = \frac{\bar{Q_B}}{\bar{Q_W}^{\,b}} \quad (4b)$$

where a' is the corrected regression coefficient, $\bar{Q_S}$ and $\bar{Q_B}$ are average suspended and bedload discharges (ton/day), respectively, and $\bar{Q_W}$ is average river discharge (m³/s). The corrected coefficient replaced the original regression parameter in the sediment rating equations, and sediment loads were recalculated accordingly.

Ferguson Correction Method

Ferguson (1986) proposed a statistical correction method to reduce bias associated with

logarithmic regression models used in sediment rating analysis. In this approach, the correction factor is related to the variance of the regression residuals and is calculated as:

$$CF = \exp(2.651 S^2) \quad (5)$$

where S^2 is the variance of the residuals of the logarithmic (base-10) regression model It . was computed for each regression as the − residual mean square, $S^2 = \Sigma(\log_{10}Q_S,obs \log_{10}Q_S,est)^2/(n - ٢$, where n is the number of .observations used in the regression

The correction factor was multiplied by the regression coefficient $a$to obtain the adjusted coefficient a'. Similar to the FAO approach, the corrected coefficient replaced the original parameter in the sediment rating equations. The Ferguson correction method generally improves sediment load estimation under conditions characterized by high variability in sediment concentration data.

Trap Efficiency Estimation

Trap efficiency (TE) represents the percentage of incoming sediment retained within a reservoir and is a key parameter in reservoir sedimentation analysis. TE mainly depends on reservoir storage capacity, annual inflow volume, hydraulic conditions, and sediment grain-size characteristics. Reservoirs with higher storage-to-inflow ratios generally retain larger proportions of incoming sediment. Several empirical methods have been proposed for trap efficiency estimation, including the approaches of Churchill (1948), Brown (1943), and Brune (1953). In this study, Brune's (1953) method was adopted because of its widespread application and because it relates trap efficiency to the capacity-to-inflow ratio, which can be updated annually as the effective reservoir capacity decreases.

Brune's Trap Efficiency Curves

Brune's method was developed using empirical observations from 44 reservoir records in the United States (Brune, 1953). The method relates reservoir trap efficiency to the capacity-to-inflow ratio (C/IW), where C is the effective reservoir storage capacity and IW is the annual inflow volume. The C/IW ratio decreases over time as sediment accumulates and was therefore updated annually (Section 2.3.2). Brune (1953) presented a median curve together with upper and lower envelope curves; the upper envelope applies to coarse or highly flocculated sediments, whereas the lower envelope applies to fine-grained or colloidal sediments. Because Brune's curves are graphical, an analytical approximation of the form given in Equation (6) was used in this study, so that trap efficiency could be computed automatically for each year of operation and within the stochastic simulations. Although this functional form resembles the relationship originally proposed by Brown (1943), it is expressed here in terms of Brune's capacity-to-inflow ratio and is used only as a closed-form representation of Brune's curves. Because the deposits of the Dez Dam reservoir are dominated by fine-grained material (approximately 36% clay, 57% silt and 7% sand; Section 3.7), the adopted parameters (a = 100 and n = 1.5) were checked against Brune's lower envelope curve, which is the appropriate curve for fine sediments. For the capacity-to-inflow ratios of the Dez Dam reservoir during the study period (approximately 0.27–0.35), Equation (6) yields trap efficiencies of approximately 94.7–95.9%, which practically coincide with those of Brune's lower envelope curve (approximately 94.6–95.8%) and are only about 2% lower than those of the median curve. Consequently, the trap-efficiency estimates are consistent with the fine-grained composition of the deposits, and the choice among Brune's curves has only a minor effect on the estimated sedimentation.

Reservoir Sediment Retention Calculation

The trap efficiency in year t was calculated using the analytical approximation of Brune's (1953) trap-efficiency curve:

$$TE_t = 100\left(1 - \frac{1}{1+aX}\right)^n \quad (6)$$

where $TE_t$is the trap efficiency (%) in year t, $X = C_{t-1}/IW_t$, C_{t-1} is the effective reservoir capacity at the beginning of year t, $IW_t$is the annual inflow volume, and a and n are the empirical parameters of the selected trap-

efficiency curve. The values of $a = 100$ and $n = 1.5$ were used for the annual trap-efficiency calculations (approximating Brune's (1953) curves; see Section 2.3.1).

As sediment deposition progressively reduces the effective storage capacity of the reservoir, the C/IW ratio decreases over time, resulting in a gradual reduction in trap efficiency. Therefore, the effective reservoir capacity was updated annually to account for cumulative sediment deposition, and trap efficiency was dynamically evaluated for each year of reservoir operation. The resulting annual trap-efficiency estimates were subsequently used to calculate the annual sediment retained within the reservoir.

Sediment Bulk Density Estimation

Accurate estimation of sediment bulk density is essential for converting deposited sediment mass into sediment volume. Because deposited sediments gradually consolidate under reservoir conditions, sediment bulk density changes over time and depends on sediment composition, compaction, and reservoir operation conditions. In this study, the empirical relationships proposed by Lane and Koelzer (1943) together with Miller's (1953) modified formulation were used to estimate temporal changes in sediment bulk density (Miller, 1953).

Miller Method

Miller (1953) proposed an empirical relationship for estimating the average bulk density of deposited sediments after t years of reservoir operation:

$$W_t = W_1 + 0.4343K\left[\left(\frac{t}{t-1}\right)\ln(t) - 1\right],\ t > 1 \quad (7)$$

where W_t is the average sediment bulk density after t years (kg/m³), W_1 is the initial bulk density, and K is the sediment consolidation coefficient. The method accounts for the progressive consolidation of deposited sediments over time. The empirical coefficients corresponding to different sediment classes and reservoir operation conditions are summarized in Table (1).

Weighted Bulk Density Calculation

Because reservoir sediments consist of mixtures of clay, silt, and sand, weighted-average relationships were used to estimate representative bulk density and consolidation coefficients:

$$W_1 = 0.01\left[w_{1(c)}P_c + w_{1(m)}P_m + w_{1(s)}P_s\right] \quad (8)$$

$$K = 0.01\left[K_cP_c + K_mP_m + K_sP_s\right] \quad (9)$$

where $w_{1(c)}$, $w_{1(m)}$, and $w_{1(s)}$ are initial bulk densities of clay, silt, and sand, respectively; K_c, K_m, and K_s are consolidation coefficients; and P_c, P_m, and P_s are the percentages of clay, silt, and sand in the deposited sediment (Miller, 1953).

Reservoir Sedimentation Assessment

Reservoir sedimentation assessment was performed through an integrated framework including sediment load estimation, trap efficiency analysis, and sediment bulk density calculations. This framework enabled the evaluation of long-term sediment accumulation and reservoir storage depletion in the Dez Dam reservoir.

Table 1- Empirical coefficients for Miller's (1953) sediment bulk-density formulation.

Reservoir Operation Type	Clay K	Clay W_1	Silt K	Silt W_1	Sand K	Sand W_1
Sediments mostly submerged	256.32	208.26	91.31	1073.34	0	1409.76
Moderate water-level fluctuations	171.41	–	43.25	1217.52	0	1409.76
Reservoir usually empty	96.12	–	16.02	1297.62	0	1409.76
Riverbed sediment	0	–	0	1345.68	0	1409.76

Annual Sediment Load Calculation

The total annual sediment discharge entering the reservoir was estimated by combining suspended sediment and bedload transport:

$$QT_t = QS_t + QB_t \quad (10)$$

where QT_t is total annual sediment discharge, QS_t is suspended sediment discharge, and QB_t is bedload discharge.

The annual sediment retained within the reservoir was subsequently calculated using Brune's trap efficiency relationship:

$$RSL_t = 3.65QT_t \times TE_t \quad (11)$$

where RSL_t is annual retained sediment load (ton) and TE_t is trap efficiency (%).

Accumulated Reservoir Sediment Load

The cumulative sediment deposited within the reservoir after t years was estimated recursively as:

$$ARSL_t = ARSL_{t-1} + RSL_t \quad (12)$$

where $ARSL_t$ is cumulative sediment mass (ton).

The cumulative sediment volume was then determined using the corresponding sediment bulk density:

$$ARSV_t = \frac{1000ARSL_t}{W_t} \quad (13)$$

where $ARSV_t$ is cumulative deposited sediment volume (m^3).

Reservoir Storage Capacity Reduction

The remaining useful reservoir storage capacity after t years was calculated as:

$$C_t = C_0 - ARSV_t \quad (14)$$

where C_t is remaining reservoir capacity and C_0 is the initial useful storage volume.

By repeating these calculations annually, the long-term trend of reservoir capacity depletion and sediment accumulation was quantified (Salas & Shin, 1999).

Uncertainty Analysis

Because reservoir sedimentation processes involve considerable hydrological and sediment transport variability, uncertainty analysis was conducted using Monte Carlo Simulation (MCS) and Latin Hypercube Sampling (LHS). These probabilistic approaches enabled the propagation of uncertainty from model inputs to sedimentation predictions.

Sources of Uncertainty

The uncertainty analysis was carried out using the USBR monthly sediment-rating relationships as the reference model, and three groups of uncertain inputs were considered: annual river discharge (C1), the sediment-rating curve coefficients (C2), and the sediment composition (C3). For C1, the annual mean discharge of each year of the 1968–2018 record was treated as a random variable following the Log-Gamma distribution fitted to the 51 observed annual mean discharges, and the daily discharges of each year were scaled in proportion to the sampled annual mean, so that the seasonal pattern of the hydrograph was preserved. For C2, the coefficients of each monthly rating curve were sampled jointly from a bivariate normal distribution of ($\log_{10}a_1$, b_1), with the mean equal to the regression estimates Table (2) and the covariance matrix obtained from the corresponding least-squares regression; in this way, the strong negative correlation between the two coefficients (correlation coefficients of −0.99 to −1.00) was preserved. Because bedload was estimated as a fixed proportion (20%) of the suspended load, the bedload coefficients were not sampled independently but were derived as $a_2 = 0.2a_1$ and $b_2 = b_1$. For C3, the clay and silt fractions were sampled from uniform distributions centred on the reported composition, Pc ~ U[32.5, 39.5] and Pm ~ U[54.5, 59.5], and the sand fraction was obtained from the closure condition Ps = 100 − Pc − Pm, so that the three fractions sum to 100% in every realization. The effect of each group was evaluated by sampling that group while keeping the other inputs at their nominal values, and the overall uncertainty was evaluated by sampling all groups simultaneously. In all simulations, the

deposited sediment volume was limited to the available reservoir capacity.

Monte Carlo Simulation (MCS)

Monte Carlo Simulation is a probabilistic method based on repeated random sampling from predefined probability distributions (Jahangiri, 2002). In this study, uncertain input variables were represented using cumulative distribution functions (CDFs).

Random samples generated from these distributions were repeatedly introduced into the sedimentation model to obtain the distributions of the model outputs. In this study, 10,000 Monte Carlo realizations were generated for each uncertainty component and for the combined analysis. The number of realizations was selected on the basis of a convergence check, in which the coefficient of variation of the simulated cumulative sediment volume was monitored as a function of the number of realizations (see Section 3.9 and Figure (7c)).

Statistical indicators such as mean, standard deviation, and coefficient of variation were subsequently used to evaluate uncertainty in predicted sedimentation volumes.

Latin Hypercube Sampling (LHS)

Latin Hypercube Sampling is an efficient stratified sampling technique that improves sampling uniformity and reduces computational demand compared with conventional Monte Carlo approaches (Salas & Shin, 1999). In LHS, the probability distribution of each uncertain variable is divided into equiprobable intervals:

$$l_i = a_{i,0} < a_{i,1} < \cdots < a_{i,k} = u_i \quad (15)$$

such that:

$$P(a_{i,k} \le X_i \le a_{i,k+1}) = \frac{1}{K} \quad (16)$$

A random sample is selected from each interval, ensuring systematic coverage of the entire probability space (Figure 2). In the present study, 10,000 LHS samples were generated using 10,000 equiprobable strata for each uncertain input variable, so that MCS and LHS were compared at the same sample size. For the correlated rating-curve coefficients, LHS was applied to independent standard normal variables, which were then transformed using the Cholesky decomposition of the covariance matrix of each regression.

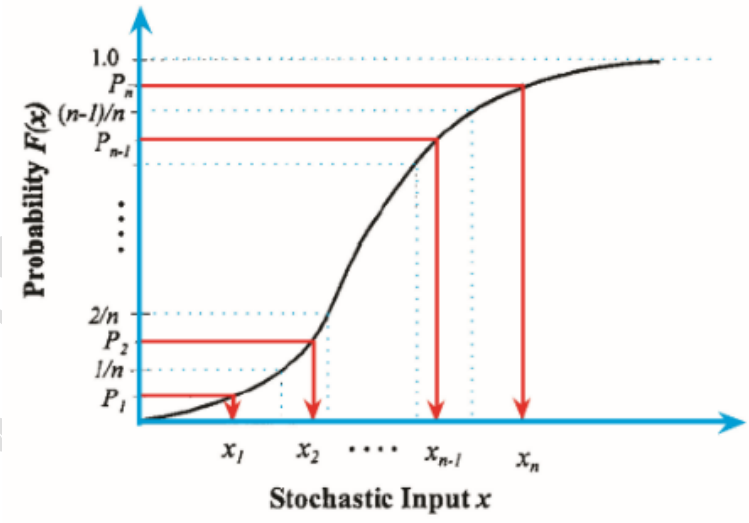


Fig. 2- Latin Hypercube Sampling (LHS) (Salas & Shin, 1999)

Table 2- Correlation coefficients between river discharge and sediment discharge at the Telezang hydrometric station using the USBR method.

Water Year	Month	Number of Samples	*a*	*b*	R^2
1968-2018	April	67	0.6713	1.7928	0.7057
1968-2018	May	62	0.0201	2.2988	0.7796
1968-2018	June	40	0.0054	2.5635	0.8266
1968-2018	July	41	0.0006	2.9819	0.6882
1968-2018	August	42	0.0006	3.0874	0.6984
1968-2018	September	32	0.0045	2.6572	0.5705
1968-2018	October	40	0.8631	1.5178	0.1203
1968-2018	November	37	0.0198	2.5373	0.447
1968-2018	December	55	0.4367	1.8734	0.4614
1968-2018	January	51	0.0496	2.2635	0.7873
1968-2018	February	60	1.3541	1.623	0.531
1968-2018	March	70	0.6993	1.7897	0.7339

Results and Discussion

The reduction in reservoir storage capacity at Dez Dam was evaluated using the seven sediment-rating approaches described in the methodology section. Incoming sediment load, trap efficiency, and sediment bulk density were estimated using long-term hydrometric and sedimentometric observations from the Telezang station over the 1968–2018 period. The obtained sediment inflow estimates were subsequently validated against reservoir hydrography data to identify the most reliable sediment-rating approach for long-term reservoir sedimentation assessment. A major limitation associated with sediment-rating approaches is the scarcity of sediment measurements during flood events, when a significant proportion of annual sediment transport occurs. Consequently, regression relationships between discharge and sediment load may underestimate high-flow sediment transport because the available observations are generally concentrated under low- and medium-flow conditions. Despite this limitation, exponential sediment-rating relationships remain among the most widely used empirical tools for long-term reservoir sedimentation analysis because they effectively represent the nonlinear interaction between discharge and sediment transport processes.

Sediment Rating Curve Results Using the USBR Method

The USBR method was applied by developing monthly sediment-rating curves relating water discharge to sediment discharge throughout the entire statistical period (1968–2018). Daily river discharge records were subsequently introduced into the derived equations to estimate daily sediment transport. Unlike the conventional USBR approach, which often relies on annual flow-duration curves, the present study therefore employed monthly separation of the statistical records to better capture seasonal sediment transport variability. The regression coefficients obtained for the monthly sediment-rating curves are presented in Table (2), while the corresponding graphical relationships are collectively illustrated in Figure (3).

The obtained results revealed substantial seasonal variability in the sediment–discharge relationships. The highest correlations were observed during June (R^2=0.8266) and January (R^2 =0.7873), whereas October exhibited the weakest correlation (R^2 =0.1203). The lower correlation observed during October is associated with greater scatter in the discharge–sediment relationship during transitional hydrological conditions. The monthly rating curves were not down-weighted based on their individual R^2 values; instead, each fitted monthly relationship was applied to the corresponding monthly discharge observations, while uncertainty in the rating-curve parameters was propagated through the stochastic uncertainty analysis. These empirical sediment-rating relationships are intended to represent the overall seasonal discharge–sediment behavior for long-term sediment estimation rather than to reproduce every individual sediment observation.

The exponent parameter *b* exceeded 2.0 during most months and approached values greater than 3.0 during July and August, indicating strong nonlinear sediment transport behavior under high-flow conditions. Such behavior suggests that relatively small increases in discharge during flood events can result in disproportionately large increases in sediment transport capacity.

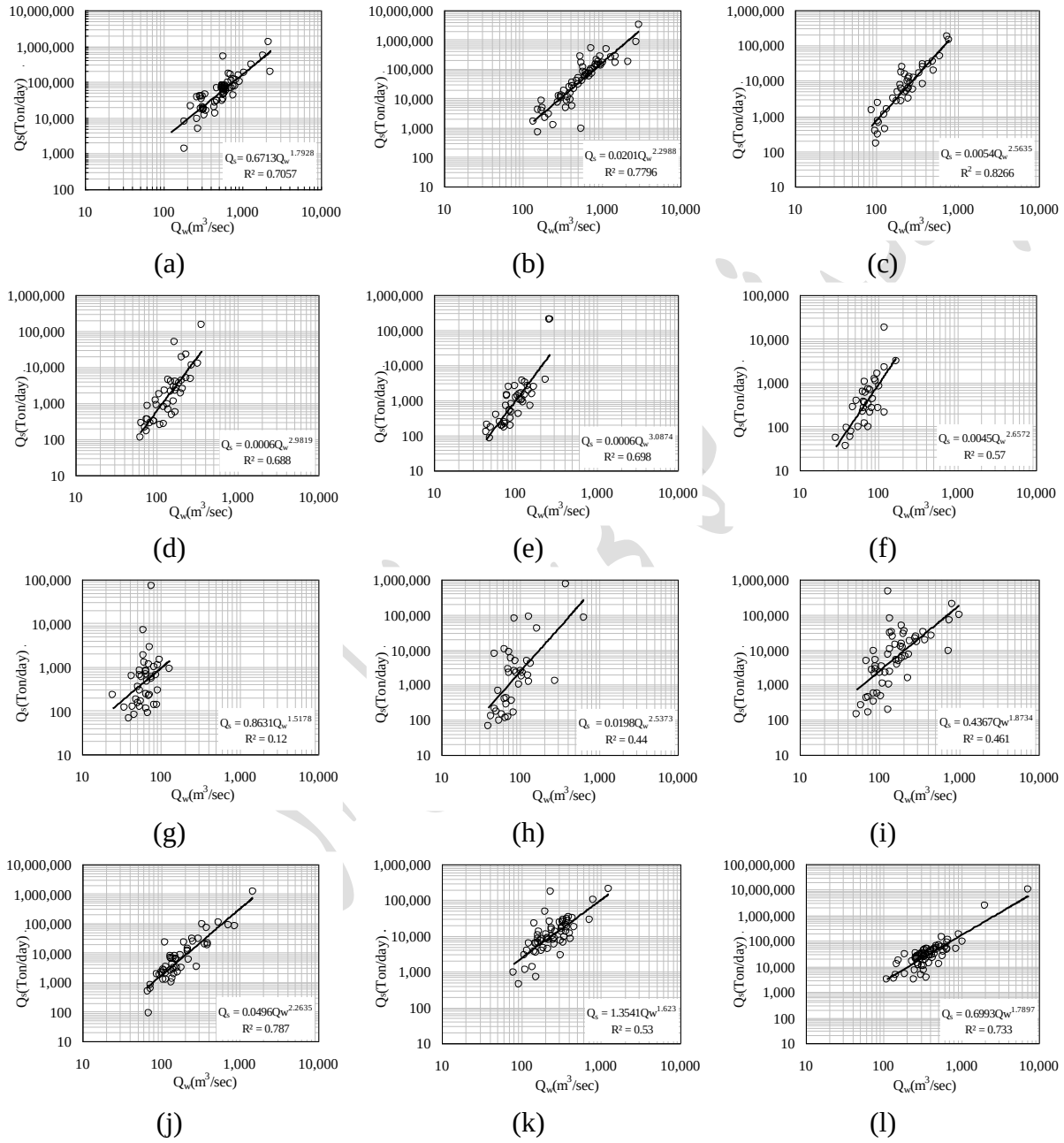


Fig. 3- Monthly sediment-rating relationships between streamflow and sediment discharge at the Telezang hydrometric station during 1968–2018: (a) April, (b) May, (c) June, (d) July, (e) August, (f) September, (g) October, (h) November, (i) December, (j) January, (k) February, and (l) March

Rating Curve Results Using Wet–Dry Period Separation

To account for seasonal hydrological variability, the statistical period was divided into wet and dry seasons. The wet season extended from December to June, while the dry season included the July–November period. Independent sediment-rating relationships were developed for each hydrological regime. The resulting sediment-rating curves are presented in Figure (4).

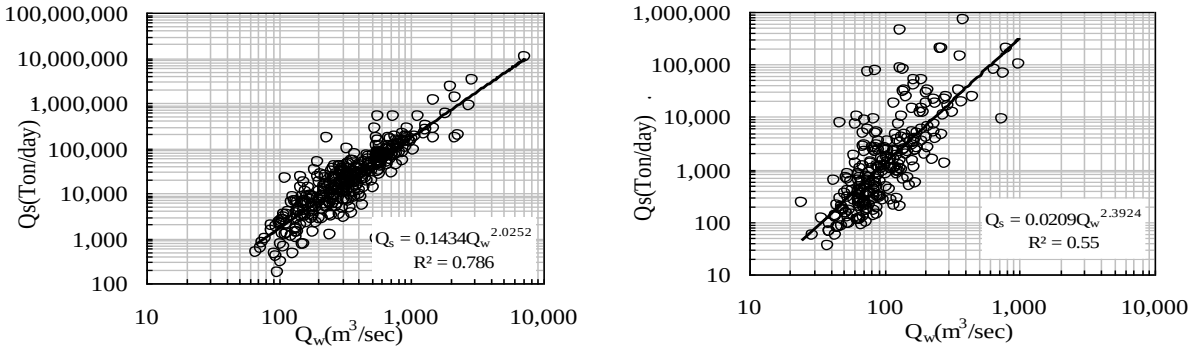
The seasonal separation substantially reduced the scatter associated with combining heterogeneous hydrological conditions into a single regression relationship. The results indicate that sediment transport in the Dez River basin varies substantially with seasonal runoff conditions, particularly during periods of snowmelt and intense precipitation. Therefore, separating the observations into wet and dry periods provides a more seasonally representative basis for estimating sediment transport than a single regression relationship applied to the entire statistical period.

Rating Curve Results Using the Category Average Method To improve the representation of high-flow sediment transport, river discharge observations were grouped into discharge classes of similar magnitude, and regression analysis was performed using class-averaged discharge and sediment load values. This approach reduces the dominance of low-flow observations in the regression process and increases the contribution of higher discharge classes, thereby increasing the contribution of higher discharge classes to the regression and improving their representation in the estimated sediment-rating relationship. Because the regression relationship is developed from category-averaged values rather than individual raw observations, the resulting regression statistics, including the coefficient of determination (R^2), should be interpreted as indicators of the goodness of fit of the aggregated sediment-rating relationship. Accordingly, the high R^2 value obtained for the Category Average method reflects the fit of the aggregated relationship and should not be interpreted alone as a direct measure of predictive accuracy for individual sediment observations. The resulting sediment-rating curve is illustrated in Figure (5).

The Category Average method produced a highly consistent regression relationship and improved the representation of high-discharge conditions. The high R^2 value reflects the goodness of fit of the regression developed from category-averaged observations. Therefore, the resulting relationship provides a more balanced representation of the discharge range, particularly for high-flow conditions.

Results of Applying the FAO Correction Method

The FAO correction factor was applied to both the USBR and Category Average approaches to reduce the bias associated with logarithmic transformation and regression dispersion effects. Corrected regression coefficients were calculated using Equations (4a) and (4b), and sediment loads were subsequently recalculated. The results are summarized in Tables (3) and (4).



(a) (b)

Fig. 4- Relationship between streamflow and sediment discharge using the wet–dry period separation method: (a) wet season and (b) dry season.

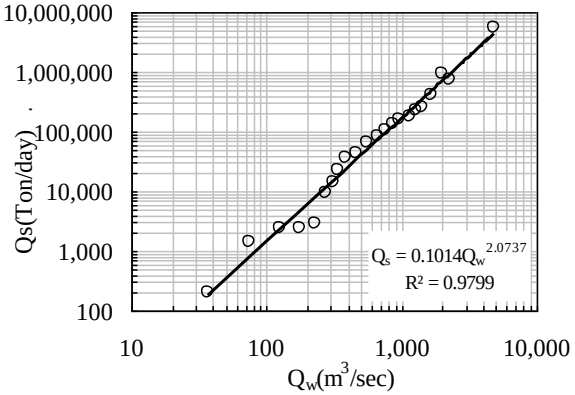


Fig. 5- Relationship between streamflow and sediment discharge using the Category Average method.

Table 3- Effect of the FAO correction coefficient on the USBR sediment-rating method.

Month	*a*	*b*	*a′*
April	0.6713	1.7928	0.9769
May	0.0201	2.2988	0.0462
June	0.0054	2.5635	0.0109
July	0.0006	2.9819	0.0023
August	0.0006	3.0874	0.0056
September	0.0045	2.6572	0.0115
October	0.8631	1.5178	4.4308
November	0.0198	2.5373	0.1889
December	0.4367	1.8734	1.1799
January	0.0496	2.2635	0.1707
February	1.3541	1.623	2.1297
March	0.6993	1.7897	3.1069

Table 4- Effect of the FAO correction coefficient on the Category Average method.

Time of Discharge Measurement	*a*	*b*	*a′*
Entire Statistical Period	0.1014	2.0737	0.2747

Application of the FAO correction significantly increased the estimated sediment transport values for nearly all months. The most substantial increases occurred during October and March, which also exhibited relatively large correction coefficients. Although the correction method theoretically compensates for logarithmic regression bias, the resulting sediment estimates were considerably larger than those inferred from hydrographic observations.

Results of Applying the Ferguson Correction Method

The Ferguson correction approach was also applied to the USBR and Category Average methods to account for regression variance effects. The correction factor CF was estimated using Equation (5), and adjusted regression coefficients were subsequently calculated.
The results are presented in Tables (5) and (6).

Table 5- Effect of the Ferguson correction coefficient on the USBR sediment-rating method.

Time of Discharge Measurement	*a*	*b*	S^2	CF	*a'*
April	0.6713	1.7928	0.0654	1.1892	0.7983
May	0.0201	2.2988	0.1355	1.4321	0.0288
June	0.0054	2.5635	0.0862	1.2568	0.0068
July	0.0006	2.9819	0.1575	1.5183	0.0010
August	0.0006	3.0874	0.1489	1.4839	0.0009
September	0.0045	2.6572	0.1466	1.4748	0.0066
October	0.8631	1.5178	0.3063	2.2524	1.9440
November	0.0198	2.5373	0.5286	4.0605	0.0804
December	0.4367	1.8734	0.3559	2.5690	1.1219
January	0.0496	2.2635	0.1122	1.3466	0.0668
February	1.3541	1.623	0.1213	1.3794	1.8678
March	0.6993	1.7897	0.0810	1.2394	0.8668

Table 6- Effect of the Ferguson correction coefficient on the Category Average method.

Time of Discharge Measurement	*a*	*b*	S^2	CF	*a'*
Entire Statistical Period	0.1014	2.0737	0.0242	1.0661	0.1081

The Ferguson correction factors ranged from 1.19 to 4.06 for the monthly USBR relationships and were largest in the months with the weakest regression fit (October–December), whereas the correction factor for the Category Average relationship was only 1.07 because of the small residual variance of the category-averaged regression. Consequently, the Ferguson method produced considerably more moderate increases in the estimated sediment transport than the FAO correction, which increased the coefficient a by factors of approximately 1.5–9.5 for the monthly relationships and 2.7 for the Category Average relationship. These findings indicate that the FAO correction may overestimate sediment transport under highly variable hydrological conditions, particularly when flood-event observations are limited, whereas the variance-based Ferguson correction results in a smaller adjustment.

Sediment Load Estimation and Trap Efficiency Analysis

The hydrographic survey data used for model validation are summarized in Table (7), while the average daily suspended load, bedload, and total sediment inflow to the Dez Dam reservoir estimated using the investigated methods are presented in Table (8).

Because direct bedload measurements were unavailable, bedload transport was estimated using the Karaushev (1977) empirical relationship based on the average riverbed slope at the Telezang station. The estimated bedload-to-suspended-load ratio of approximately 20% was consistent with previously reported values for mountain rivers with moderate slopes (Mosaedi & Hashemi Najafi, 2009). However, due to the lack of direct bedload observations at the Telezang station, the uncertainty associated with the empirical estimation of the bedload-to-suspended-load ratio could not be independently quantified and is recognized as a limitation of the present sediment estimation framework. The highest total sediment inflow values were obtained using the FAO-USBR and FAO-Category Average approaches, followed by the Ferguson-USBR approach, whereas the USBR, Category Average, Ferguson-Category Average, and Wet–Dry Period Separation methods produced relatively consistent sediment load estimates. The mean trap efficiency estimated using the seven methods ranged from 95.90% to 96.36%, indicating that the Dez Dam reservoir retains nearly all incoming sediment due to its high storage-to-inflow ratio. The corresponding mean trap-efficiency values are presented in Table (9). The limited variation in mean trap efficiency among the evaluated methods indicates that differences in trap-efficiency estimates have a relatively minor effect on the estimated sedimentation. In the stochastic uncertainty analysis, sediment-rating curve parameters represented the dominant source of uncertainty, whereas sediment composition contributed the least.

Table 7- Hydrographic survey results and sedimentation rates of the Dez Dam reservoir in 1962, 2002, and 2010 (Nekooianfar & Mehrbani, 2015).

Year	Reservoir Volume 1962	Reservoir Volume 2002	Reservoir Volume 2010	Volume Reduction 2002 vs 1962	Volume Reduction 2010 vs 1962	Volume Reduction 2010 vs 2002
Reservoir Volume (million m^3)	3465	2856	2705	609	760	155
Annual Sedimentation Rate (million m^3/year)	-	14.85	15.85	-	-	-

Note: The volume reduction of 155 million m^3 between 2002 and 2010 is reported as published by Nekooianfar and Mehrbani (2015). The difference between the published reservoir volumes for 2002 (2,856 million m^3) and 2010 (2,705 million m^3) is 151 million m^3, which is the value used in the calculations of the present study (Tables 10 and 11).

Table 8- Average daily sediment load entering the Dez Dam reservoir estimated using different sediment-rating methods (ton/day).

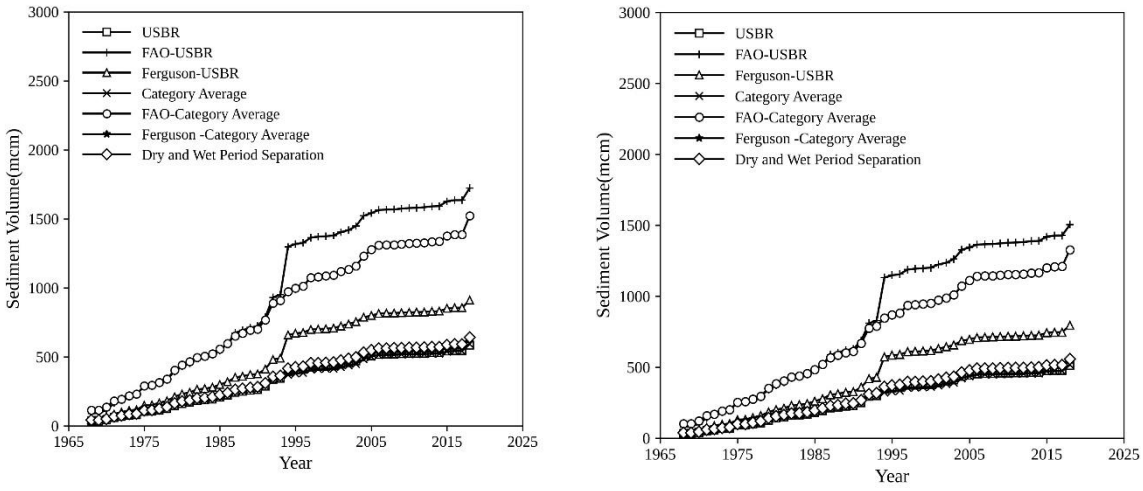
Method	Sediment Type		Reservoir Inflow
	Suspended Load	Bed Load	
USBR	26965	5393	32358
FAO-USBR	79534	15907	95441
Ferguson-USBR	41809	8362	50171
Category Average	27189	5438	32627
FAO-Category Average	70127	14025	84152
Ferguson -Category Average	28851	5770	34621
Dry and Wet Period Separation	29٣٦٥	5873	35238

Table 9- Mean trap efficiency estimated using the seven sediment-rating curve approaches over the study period.

Method	USBR	FAO-USBR	Ferguson-USBR	Category Average	FAO-Category Average	Ferguson -Category Average	Dry and Wet Period Separation
Mean Trap Efficiency (%)	96.36	95.90	96.25	96.36	96.00	96.35	96.34

Sediment Bulk Density and Reservoir Storage Reduction

The temporal evolution of sediment bulk density was evaluated using the Lane and Koelzer (1943) and Miller (1953) approaches. The initial bulk density of deposited sediments was estimated to range from approximately 785 to 898 kg/m^3, while the average bulk density after 51 years (1968–2018) increased considerably because of progressive consolidation processes. According to Samadi Boroujeni et al. (2011), the deposited sediments in the Dez Dam reservoir consist of approximately 36% clay, 57% silt, and 7% sand, indicating a predominance of fine-grained material. These findings are consistent with the field observations reported by Emamgholizadeh and Fathi-Moghadam (2014), who also reported a predominance of cohesive fine-grained sediments in the Dez Reservoir. Because the Dez Dam reservoir operates predominantly under submerged conditions and the deposited sediments are characterized by a high proportion of fine-grained material, Miller's method was selected for the final sedimentation analysis. The estimated remaining useful reservoir volumes after 51 years (1968–2018) for the investigated methods are illustrated in Figure (6).



(a) (b)

Fig. 6- Comparison of estimated cumulative reservoir sediment volume over time using different sediment-rating approaches: (a) Miller's (1953) bulk-density method and (b) Lane & Koelzer (1943) bulk-density method.

The results indicated that the FAO-corrected methods and, to a lesser extent, the Ferguson-USBR method tended to overestimate reservoir sedimentation and consequently underestimate remaining storage capacity. In contrast, the USBR, Category Average, Ferguson-Category Average, and Wet–Dry Period Separation methods showed closer agreement with the available hydrographic observations. However, the validation analysis is constrained by the limited number of available hydrographic survey epochs. Therefore, the comparison among sediment-rating approaches should be interpreted with caution, as the observed differences may partly reflect the uncertainty associated with hydrographic measurements.

Comparison of Reservoir Storage Reduction with Hydrographic Data

To assess the consistency of the investigated methods with observed reservoir sedimentation, the estimated reservoir storage depletion was compared with available hydrographic survey data. The comparison results are summarized in Tables (10) and (11).

Table 10- Reduction in active storage volume of the Dez Dam reservoir estimated using different sediment-rating approaches (MCM).

Year	Reservoir Volumes	USBR	FAO USBR	Ferguson USBR	Category Average	FAO Category Average	Ferguson Category Average	Dry and Wet Period Separation
Volume 1962	3465	3465	3465	3465	3465	3465	3465	3465
Volume 2002	2856	2842	1882	2562	2861	2166	2834	2812
Volume 2010	2705	2776	1722	2477	2781	1978	2750	2733
Volume Reduction 2002 vs 1962	609	623	1583	903	604	1299	631	653
Volume Reduction 2010 vs 1962	760	689	1743	988	684	1487	715	732
Volume Reduction 2010 vs 2002	151	66	160	85	80	188	84	79

Table 11- Comparative assessment of sediment-rating methods against reservoir hydrographic observations.

Year	Reservoir Hydrography	USBR	FAO USBR	Ferguson USBR	Category Average	FAO Category Average	Ferguson Category Average	Dry and Wet Period Separation
Reservoir Volume of Dez Dam in the Years 1962, 2002, and 2010								
1962	3465	3465	3465	3465	3465	3465	3465	3465
2002	2856	2842	1882	2562	2861	2166	2834	2812
2010	2705	2776	1722	2477	2781	1978	2750	2733
Deviation from Hydrography (MCM)								
1962	-	0	0	0	0	0	0	0
2002	-	-13.973	-974.450	-293.974	4.930	-690.229	-22.072	-44.207
2010	-	70.751	-983.319	-227.797	76.219	-727.478	44.984	27.515
Mean	-	18.926	-652.589	-173.924	27.050	-472.569	7.637	-5.564
Percentage of Reservoir Volume Deviation Relative to Hydrograph (%)								
1962	-	0	0	0	0	0	0	0
2002	-	-0.489	-34.119	-10.293	0.173	-24.168	-0.773	-1.548
2010	-	2.616	-36.352	-8.421	2.818	-26.894	1.663	1.017
Mean	-	0.709	-23.490	-6.238	0.997	-17.021	0.297	-0.177
Changes in Dez Reservoir Volume in the Years 1962, 2002, and 2010 (MCM)								
2002 vs 1962	-609.000	-622.973	-1583.450	-902.974	-604.070	-1299.229	-631.072	-653.207
2010 vs 1962	-760.000	-689.249	-1743.319	-987.797	-683.781	-1487.478	-715.016	-732.485
2010 vs 2002	-151.000	-66.275	-159.869	-84.824	-79.711	-188.248	-83.944	-79.277
Percentage Deviation of Reservoir Volume Changes Relative to Reservoir Hydrograph (%)								
2002 vs 1962	-	2.294	160.008	48.272	-0.810	113.338	3.624	7.259
2010 vs 1962	-	-9.309	129.384	29.973	-10.029	95.721	-5.919	-3.620
2010 vs 2002	-	-56.109	5.873	-43.825	-47.211	24.668	-44.408	-47.498

Among the evaluated approaches, the Wet–Dry Period Separation method showed the smallest mean deviation from the available hydrographic observations (−5.6 MCM), followed by the Ferguson-Category Average (7.6 MCM), USBR (18.9 MCM) and Category Average (27.1 MCM) methods. In contrast, the FAO-corrected methods and, to a lesser extent, the Ferguson-USBR method tended to overestimate reservoir sediment accumulation. These results are interpreted as comparative and confirmatory evidence of the consistency of the estimated reservoir sedimentation with the available hydrographic observations, rather than as an independent predictive or out-of-sample validation. The limited number of available hydrographic survey intervals also restricts the strength of predictive conclusions. Nevertheless, the closer agreement of the USBR, Category Average, Ferguson-Category Average, and Wet–Dry Period Separation methods with the observed hydrographic storage reduction indicates their

comparatively better performance under the conditions of the studied basin.

Uncertainty Analysis Using Monte Carlo Simulation (MCS)

The probability distributions assigned to the uncertain inputs are summarized in Table (12). The fitted distribution of the annual mean discharge, an example of the correlated sampling of the rating-curve coefficients, and the convergence of the simulations are illustrated in Figures 7(a) to 7(c), respectively. Because bedload was estimated as a proportion of the suspended sediment load, the bedload coefficients a_2-B and b_2-B were derived from a_1-S and b_1-S; they do not constitute independent uncertain inputs and were therefore not counted as separate sources of uncertainty.

The goodness of fit of the Log-Gamma distribution to the 51 annual mean discharges was assessed using the chi-square (χ^2) and Kolmogorov–Smirnov (KS) tests, and the distribution was not rejected at the 5% significance level ($\chi^2 = 4.41$, $P = 0.22$; $KS = 0.121$, $P = 0.41$). The uncertainty analysis was then performed using Monte Carlo Simulation (MCS) with 10,000 realizations for each uncertainty component and for the combined analysis, and the cumulative sediment volume after 51 years (ARSV in 2018) was used as the output variable. The deterministic value of this variable obtained with the nominal inputs was 574.8 MCM.

Table 12- Selected probability distributions for the parameters affecting uncertainty in reservoir sedimentation volume.

Uncertainty Factors	Mean	Standard Deviation (SD)	Statistical Distribution	χ^2 Statistic	P-value	Lower Bound	Upper Bound
Qw (annual mean)	249.73	104.70	Log-Gamma	4.41	0.220		
$\log_{10}$a1-S	Table 2	SE: 0.34–1.20	Bivariate normal with b1-S	–	–		
$b_{1\text{-}S}$	Table 2	SE: 0.13–0.67	Bivariate normal with $\log_{10}$a1-S	–	–		
$a_{2\text{-}B}$	0.2 × a1-S	–	Derived (not sampled)	–	–		
$b_{2\text{-}B}$	= b1-S	–	Derived (not sampled)	–	–		
$P_{(C)}$	36	2.02	Uniform	–	–	32.5	39.5
$P_{(m)}$	57	1.44	Uniform	–	–	54.5	59.5
$P_{(S)}$	7	2.48	Derived: 100 − P(C) − P(m)	–	–	1	13

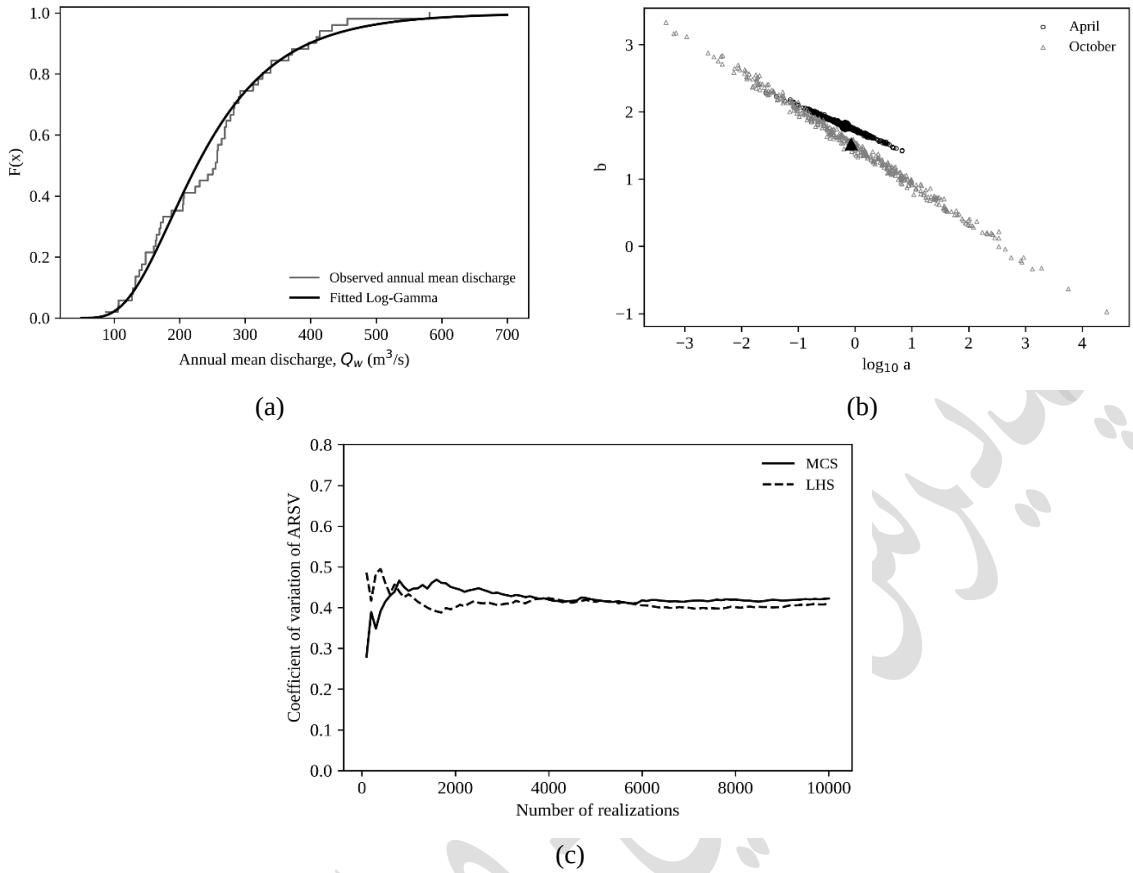


Fig. 7- Uncertainty-analysis inputs and convergence: (a) Log-Gamma distribution fitted to the annual mean discharge (Qw) at the Telezang station; (b) example of the correlated sampling of the rating-curve coefficients ($\log_{10}$a, b) for April and October (filled symbols show the regression estimates); and (c) convergence of the coefficient of variation of the cumulative sediment volume (ARSV) with the number of realizations for MCS and LHS.

Table 13- Uncertainty analysis results for cumulative reservoir sediment volume (ARSV, MCM) after 51 years (2018), based on 10,000 realizations, using Monte Carlo Simulation (MCS).

Uncertainty Factors	Mean	Standard Deviation	Coefficient of Variation
C1 (Flow discharge)	561.2	96.2	0.171
C2 (Rating-curve coefficients)	679.3	275.2	0.405
C3 (Sediment composition)	575.1	10.4	0.018
Overall (C1–C3 combined)	636.6	268.8	0.422

The uncertainty analysis demonstrated that sediment-rating curve coefficients constitute the dominant source of uncertainty in long-term reservoir sedimentation prediction. In the MCS framework, the coefficient of variation of the cumulative sediment volume was 0.405 for the sediment-rating coefficients (C2), 0.171 for the annual discharge (C1), and only 0.018 for the sediment composition (C3) (Table 13).

3.10 Uncertainty Analysis Using Latin Hypercube Sampling (LHS)

Latin Hypercube Sampling (LHS) was applied to improve sampling efficiency and reduce computational demand relative to conventional Monte Carlo Simulation. The uncertainty results obtained using both MCS and LHS are summarized in Tables (13) and (14).

Table 14- Uncertainty analysis results for cumulative reservoir sediment volume (ARSV, MCM) after 51 years (2018), based on 10,000 realizations, using Latin Hypercube Sampling (LHS).

Uncertainty Factors	Mean	Standard Deviation	Coefficient of Variation
C1 (Flow discharge)	562.5	95.5	0.170
C2 (Rating-curve coefficients)	675.8	273.7	0.405
C3 (Sediment composition)	575.0	10.4	0.018
Overall (C1–C3 combined)	635.2	260.4	0.410

The coefficients of variation presented in Tables (13) and (14) quantify the relative variability of the cumulative sediment volume after 51 years associated with each uncertainty component: annual flow discharge (C1), sediment-rating curve coefficients (C2), and sediment composition (C3). The overall uncertainty coefficients, obtained from the simulations in which all inputs were sampled simultaneously, were 0.422 for MCS and 0.410 for LHS. Because both methods were applied with the same number of realizations, these values are directly comparable, and the small difference between them indicates that the two sampling schemes provide consistent estimates of the propagated uncertainty. The convergence analysis (Figure 7c) showed that the coefficient of variation obtained with LHS remained within ±0.02 of its final value after about 1,800 realizations, whereas about 2,700 realizations were required with MCS, which confirms the higher sampling efficiency of LHS. The comparison between MCS and LHS in this study is therefore intended to evaluate the efficiency of the two sampling strategies rather than to suggest a reduction in the intrinsic physical uncertainty of reservoir sedimentation. In both approaches, the uncertainty associated with sediment-rating curve parameters remained the dominant uncertainty source, whereas sediment composition exhibited only a minor influence on overall sedimentation uncertainty.

Conclusions

This study presented a comprehensive framework for evaluating long-term sedimentation processes in the Dez Dam reservoir using empirical sediment-rating relationships, trap-efficiency analysis, sediment bulk-density estimation, and probabilistic uncertainty assessment. The comparison of seven sediment-rating approaches demonstrated that the USBR, Category Average, Ferguson-Category Average, and Wet–Dry Period Separation methods showed the closest agreement with the available hydrographic survey data. Among these methods, the Wet–Dry Period Separation approach exhibited the closest agreement with the observed reservoir storage depletion, which may be attributed to its explicit consideration of seasonal hydrological variability.The FAO correction substantially increased the estimated sediment loads and overestimated long-term reservoir sedimentation, whereas the variance-based Ferguson correction produced a much smaller adjustment; when applied to the Category Average relationship, it remained in close agreement with the hydrographic surveys, while the Ferguson-USBR method moderately overestimated sedimentation. These findings suggest that statistical bias-correction approaches should be applied with caution in basins characterized by highly variable sediment transport and limited flood-event observations. The uncertainty analysis further revealed that sediment-rating curve parameters constitute the dominant source of uncertainty in reservoir sedimentation prediction, while uncertainties associated with sediment composition exert comparatively minor influence. At the same sample size, MCS and LHS gave similar overall uncertainty coefficients (0.42 and 0.41, respectively), but LHS converged with fewer realizations (about 1,800 compared with 2,700), confirming its higher sampling efficiency. It should be noted that both Monte Carlo Simulation (MCS) and Latin Hypercube Sampling (LHS) propagate the same underlying uncertainty associated with reservoir sedimentation. Therefore, the advantage of LHS reflects improved sampling efficiency rather than a reduction in the intrinsic physical uncertainty of

the sedimentation process. Overall, the findings emphasize the importance of integrating hydrological seasonality, hydrographic validation, and probabilistic uncertainty analysis into reservoir sedimentation assessment frameworks. Future studies should focus on improving flood-event sediment monitoring, incorporating physically based sediment transport models, and integrating remote sensing and bathymetric data to improve the reliability of long-term sedimentation prediction under changing climatic and watershed conditions.

Conflict of Interest

The authors declared no potential conflicts of interest concerning the research, authorship, and publication of this article. Confirmation

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Data Availability Statements

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethical considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used Claude (Anthropic), an AI-assisted tool, to implement the copy-editor's comments, improve the language, format the manuscript and reference list according to the journal style, and draft the authorship contribution statement. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Authors' contribution(

First Author: F. Karimi: Investigation, data curation, formal analysis, software, visualization, and writing – original draft (M.Sc. thesis research).
Second Author: B. Lashkar-Ara: Conceptualization, methodology, supervision, validation, and writing – review & editing.
Third Author: H. Seyed Kaboli: Formal analysis (statistical analysis), validation, and writing – review & editing.

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