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RESEARCH ARTICLE - HYDROLOGY

Development of a relationship between hydrometric and hydrographic observations to predict reservoir capacity loss

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Abstract

Accuracy of reservoir capacity loss estimation on daily timescale is dependent on the certainty of sediment load prediction, density estimate and capacity observed by consecutive hydrographic surveys. Data-scarce and uncertain data conditions restrict the development of a relationship between hydrographic surveys and hydrometric observations. The present study has been carried for Ukai Reservoir, India. A novel sediment rating curve fitting approach by optimization technique has been proposed in order to accurately predict sediment load from low-frequency sampled discharge and sediment concentration observations. The study demonstrates the validation of the bulk density estimate using statistical hypothesis testing and identifies the correctness of the hydrographic survey results. Application of the developed hydrometric and hydrographic relationship indicated that about 50% of the capacity loss of a year might occur during a single extreme event. The proposed approach can serve as a decision support system to monitor and manage sedimentation for the reservoir having uncertain data conditions.

Keywords Hydrometric observations · Hydrographic survey · Sediment rating curve · Representative sediment density · Reservoir capacity loss

Introduction

Rivers are the carrier channels for both water and sediment transported by the flow. Impoundment of water in the reservoir is a prime objective, but in doing so silting of sediments carried with the flow needs to be checked. Understanding that reservoirs are non-renewable resources drives the research on their capacity loss (Kondolf et al. 2014). Initially, defining the rate of storage loss over a period of the dam's operation was the sole interest. However, of late, attention is also being paid to augment the life of the reservoirs despite the sediment inflow experienced by them (Chaudhuri 2006; Kondolf et al. 2014; Palmieri et al. 2001; Sumi and Hirose 2009). For achieving this goal, the inflowing sediment load has to be associated with reservoir capacity loss (RCL). Marineau and Wright (2017) quoted that a model that can relate the hydrological history to the reservoir sedimentation rates, at shorter timescales, can give precise estimates of the economic life of the reservoir.

The transportation and deposition of sediments in the reservoir can be studied by hydrometric observations and hydrographic surveys. Capacity loss noticed between two hydrographic surveys can be related to the suspended sediment concentration (SSC) observed at the hydrometric gauging station (Marineau and Wright 2017; Tebbi et al. 2012; Verstraeten and Poesen 2002); however, there are multiple practical limitations to it (Salas and Shin 1999).

If the bed load is unmeasured, then the use of empirical formulations and approximations may bring uncertainty to the predicted total sediment load (Swamee and Ojha 1991; Vanoni 1979). A low-frequency sampling (once a day) of the discharge and the SSC may generate an inaccurate sediment load estimate (Arabkhedri et al. 2010; Bussi et al. 2017; Harrington and Harrington 2013; Walling 1977a, b). In other words, hydrological sampling plan based on rising and falling limb of the hydrograph requires a couple of samples per day, while sampling once a day (time-based sampling) will bring inaccuracy in sediment load estimation. Statistically, a fixed time-based sampling plan to measure SSC will limit the sensitivity of RCL analysis, as

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the variation in the hydrograph and sediment graph is not captured adequately. In such instances, a sediment rating curve (SRC) can predict the continuous record of concentration to estimate the sediment load. Yet, a stable SRC relationship can only be developed from high-frequency sampled data, (Bussi et al. 2017; Crawford 1991; Horowitz 2003) and in its absence, different grouping and fitting procedures can be tested to identify a profound rating relationship. SRC can be obtained by grouping the data based on either time or the stage of the river (Walling 1977a, b). Seasonal variations in the SSC can be detected by time-based grouping, while grouping based on the stage of the river (rising and falling limb of the hydrograph) incorporates the fluctuations resulting from the hysteresis effect (De Girolamo et al. 2015).

The power form of relationship, as an SRC model, relates SSC and discharge by means of nonlinear curve fitting. A nonlinear (power) form of relationship can be converted to a linear form by logarithmic data transfer (Heidarnejad et al. 2006). Thus, ordinary least square (OLS) regression technique can be used to fit the linearized relationship of SSC and discharge. However, regression faces a limitation since the fitted model will possess the least square of residuals only for the concentration. Besides, regression between the suspended sediment load and discharge as an alternative to SSC and discharge is also considered to be a wrong practice. The suspended sediment load includes discharge in its computation and generates a nonexistent superficial correlation (Annandale et al. 2016). Hence, to achieve the minimum difference of load estimates and to fit the suspended SRC such that the value of the coefficient of determination for SRC remains high, an optimization model approach is developed which further calibrates the SRC.

In the absence of the observed trap efficiency (TE), its estimation using empirical equations and curves (Brune 1953) may cause uncertainty in the computation of reservoir-deposited sediments. The bulk density of the complete reservoir is hard to identify as no theoretical base has been established to obtain the reservoir density from the sample-point densities. Bussi et al. (2013) found the predictability of the Lane and Koelzer (1943) empirical formulation to be satisfactory. For a small check dam, the authors validated the predicted dry bulk density using five sampled measurements. Yet, the complex distribution of sediments over the reservoir and neglecting the organic matter content compromised its validity (Verstraeten and Poesen 2001). Small et al. (2003) collected over 30 sediment samples from the Crombie Reservoir to determine the wet and dry densities. The researchers documented that the basal region had high density values (up to 2200 kg/m^3) while the surface region had low density (500 kg/m^3). Thus, the bulk density sampling might not give a representative value for the whole deposit and is usually estimated and not sampled. Tebbi et al. (2012) estimated a typical value of dry bulk density (1400 kg/m^3) by considering the composition of the sediments.

The objective of this paper is to predict RCL (on a daily time step) from the hydrometric observations using low-frequency (once a day) suspended sediment sampled data. The impact of the grouping and fitting procedures on the SRC for estimating the sediment load has been assessed, and a novel SRC model fitting approach by optimization technique has been proposed. A matrix of RCL is computed, using the SRC models and bulk density estimates, to assess the uncertainty of the predictions.

Study area and data collection

Ukai Reservoir, India, is chosen for the study, as it is equipped with an upstream gauging station having a long period of SSC record, reservoir sediment sampling data are available (for density estimate) and multiple hydrographic surveys are carried out on the reservoir. Ukai Dam reservoir lies in the middle of the Tapi basin (Fig. 1). Tapi River originates near Multai, Betul district, Madhya Pradesh, India, at an elevation of 752 m and drains in the Arabian Sea. The length of the Tapi River is 724 km; Purna (length of 274 km) and Girna (length of 260 km) are two major tributaries of the river. Tapi basin lies between 72°33′ and 78°17′ east longitudes and 20°9′ to 21°50′ north latitudes. The basin is surrounded by the Satpura Range (from the north), Mahadev Hills (from the east) and Ajanta Range (from the south). Tapi basin is covered with agriculture, forest and water bodies by 66.19%, 25% and 2.99%, respectively, of the total area. The basin majorly consists of black cotton soil. The annual rainfall in the Tapi basin is 830 mm.

The first impoundment of the reservoir occurred in 1972. The gross reservoir capacity at the time of the first impoundment was 8510×10^6 m^3. The full reservoir level (FRL) is at 105.15 m from the mean sea level, and its water spread area is 520 km^2. The catchment area up to the dam wall is 62,225 km^2. As per the last hydrographic survey report (2003), the total loss observed in reservoir capacity is 1095.71×10^6 m^3, the existing storage capacity is reduced to 7414.29×10^6 m^3 and the distribution of loss is 51% in dead live and 49% in live storage.

Sarangkheda gauging station (21º25′55″N, 74º31′37″E) is the nearest upstream suspended sediment and discharge gauging station of the Central Water Commission (CWC). The discharge and sediment concentration data are available from 1984 at the gauging station. Discharge is measured at the station gauge line by the velocity-area method. The depth of flow in the cross section is measured at verticals of the segmented station gauge line, and observations of velocity are obtained with a current meter at 0.6 m depth point. The widths, depths and velocities observed

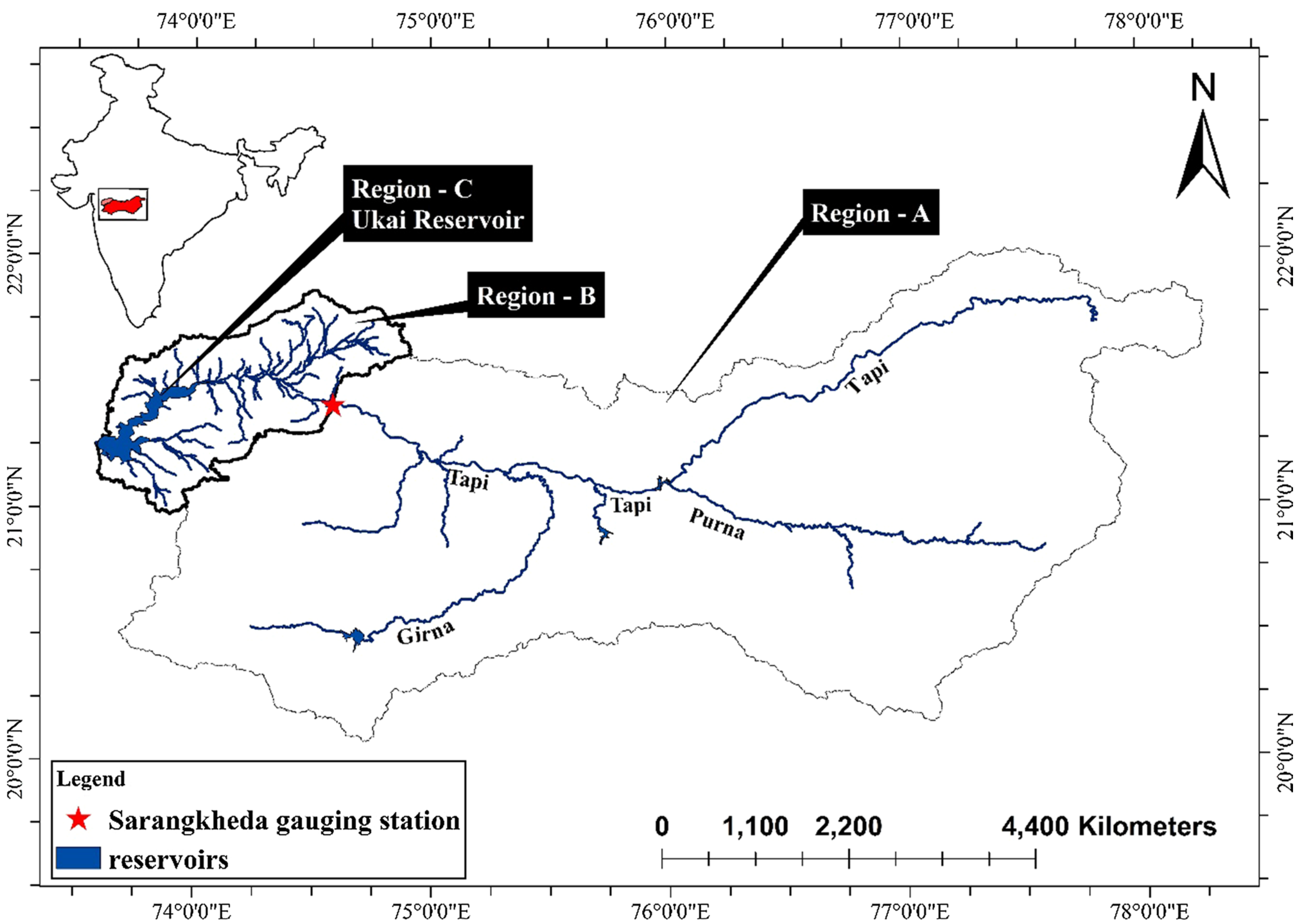

Fig. 1 Location of Ukai Reservoir in Tapi basin

are used to compute discharge for each segment of the cross sections. Summation of these segmental discharges is the total discharge observed at the station gauge line. The Punjab-type bottle sampler is used to collect suspended sediment at 0.6 m depth. The frequency of discharge and sediment measurement at station gauge is once per day, whereas the water surface elevation is measured every hour (CWC 2014).

Sedimentation surveys (hydrographic surveys) of the Ukai Reservoir were conducted in 1979, 1983, 1992, 2001 and 2003. A schematic representation of the Tapi basin up to the Ukai Dam is given in Fig. 2. Region A (58,400 m^2)

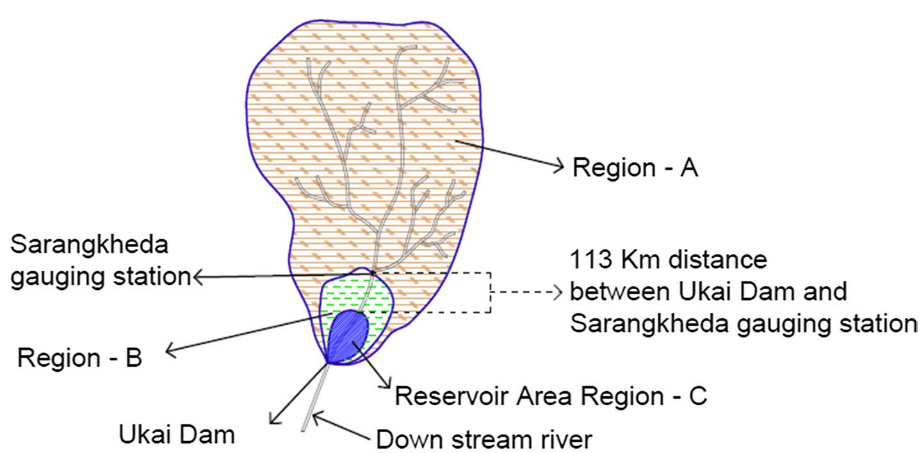

Fig. 2 Schematic representation of the reservoir its upstream gauging station and ungauged catchment

is the Tapi basin area up to the Sarangkheda gauging station. The ungauged region B (3825 m^2) is the area of the Tapi basin between the Ukai Dam and the gauging station. The distance between the reservoir's tail and Sarangkheda is 113 km. The reservoir area at its full level (105.15 m) is 520 m^2, as depicted in region C (Fig. 2). The mean of daily discharge and sediment concentration observed at the gauging station (period 1984–1992) is 276 m^3 and 0.45 kg/m^3, respectively, while the maximum value of discharge and sediment concentration observed at the gauging station (period 1984–1992) is 13,750 m^3 and 17.09 kg/m^3, respectively. Grain size analysis of the deposited sediment in the Ukai Reservoir at varying distances from the dam wall is provided in Table 1.

Methodology

Quantitative RCL is computed by converting the reservoir-inflowing sediment load to the deposited sediment volume. Sediment load inflowing the reservoir can be predicted using a stable SRC, which can be then converted to deposition volume using the estimated reservoir sediment density. The predictability of the capacity loss from different SRC models and density estimates is checked in three phases (Fig. 3). In the first phase, emphasis has been made for the precise prediction of the reservoir-inflowing sediment load. The second phase of the work deals with the estimation of sediment bulk density for the conversion of the inflowing sediment load to deposition volume. Four data grouping approaches and two fitting procedures are used to develop eight types of rating curve relationships. The predictions of these rating curves are subjected to three density estimates.

Table 1 Grain size analysis of Ukai Dam Reservoir

Sample no.	P_C^a	P_M^b	P_s^c
1	0.36	0.56	0.08
2	0.35	0.59	0.06
3	0.37	0.56	0.07
4	0.34	0.57	0.09
5	0.39	0.56	0.05
6	0.36	0.56	0.08
7	0.00	0.02	0.98
8	0.35	0.58	0.07
9	0.35	0.55	0.08
10	0.34	0.56	0.10
Average	0.32	0.51	0.17

The data were abstracted from the publication of the CWC (2015)

[a] P_C, Percentage of clay/100 (particle size less than 0.002×10^{-3} m), [b] P_M, Percentage of silt/100 (particle size 0.002 to 0.075×10^{-3} m), [c] P_S, percentage of sand/100 (particle size 0.075 to 4.75×10^{-3} m)

It is to be noted from phase three that if the RCL predicted is not equivalent to observed RCL, the best sediment load-estimating model (Phase 1) is to be used to fill the data gaps and inconsistencies. Then, an assessment of the estimated bulk density should be done to correct the predicted RCL. From the above process, the established temporal-lumped relationship is utilized to disintegrate the capacity loss on daily time step.

Computation of daily RCL is done from the daily trapped inflowing load (predicted using the SRC model) and estimated sediment densities. Gross reservoir capacity at the end of the period is obtained by deducting the inflowing sediment volume from the gross capacity at the beginning of the period (Eq. 1):

$$\mathrm{GRC}_t = \mathrm{GRC}_{t-1} - \left[\frac{L_t * \mathrm{TE}}{\mathrm{BD} * 10^6}\right] \tag{1}$$

where GRC_{t-1} = gross reservoir capacity at the beginning of period ($10^6\times m^3$), GRC_t = gross reservoir capacity at the end of period ($10^6\times m^3$), L_t = predicted sediment load inflowing the reservoir during period t (Kg), TE = trap efficiency of the reservoir, BD = bulk reservoir density of the reservoir (kg/m^3).

SRC model development

The gauged data were observed to be inconsistent with data gaps in the SSC measurements. In such a situation, the missing data were filled using suspended SRC (Walling 1977a, b). The available instantaneous daily time-stepped data may not reveal the hysteresis effect. Thus, in the present study, the SRCs are developed using time-based grouping, that is, daily, monthly average and yearly average data. Data grouping was carried out to reconnoiter a relationship between discharge and concentration, while the application of the developed relationship was utilized to predict the concentration on a daily time step. Fitting of the rating curve to the data was achieved by two methods, namely ordinary least square (OLS) linear regression and fitting using optimization.

Data grouping

For developing the daily SRC model, directly available data were utilized. The monthly model was developed by grouping the data for the months in different years and calculating the average value of discharge and concentration for each month's group in a year. A yearly average model was developed by categorizing the data according to the calendar year and then establishing the average value of discharge and concentration. Month-wise models were obtained by clustering the daily data of all the similar months.

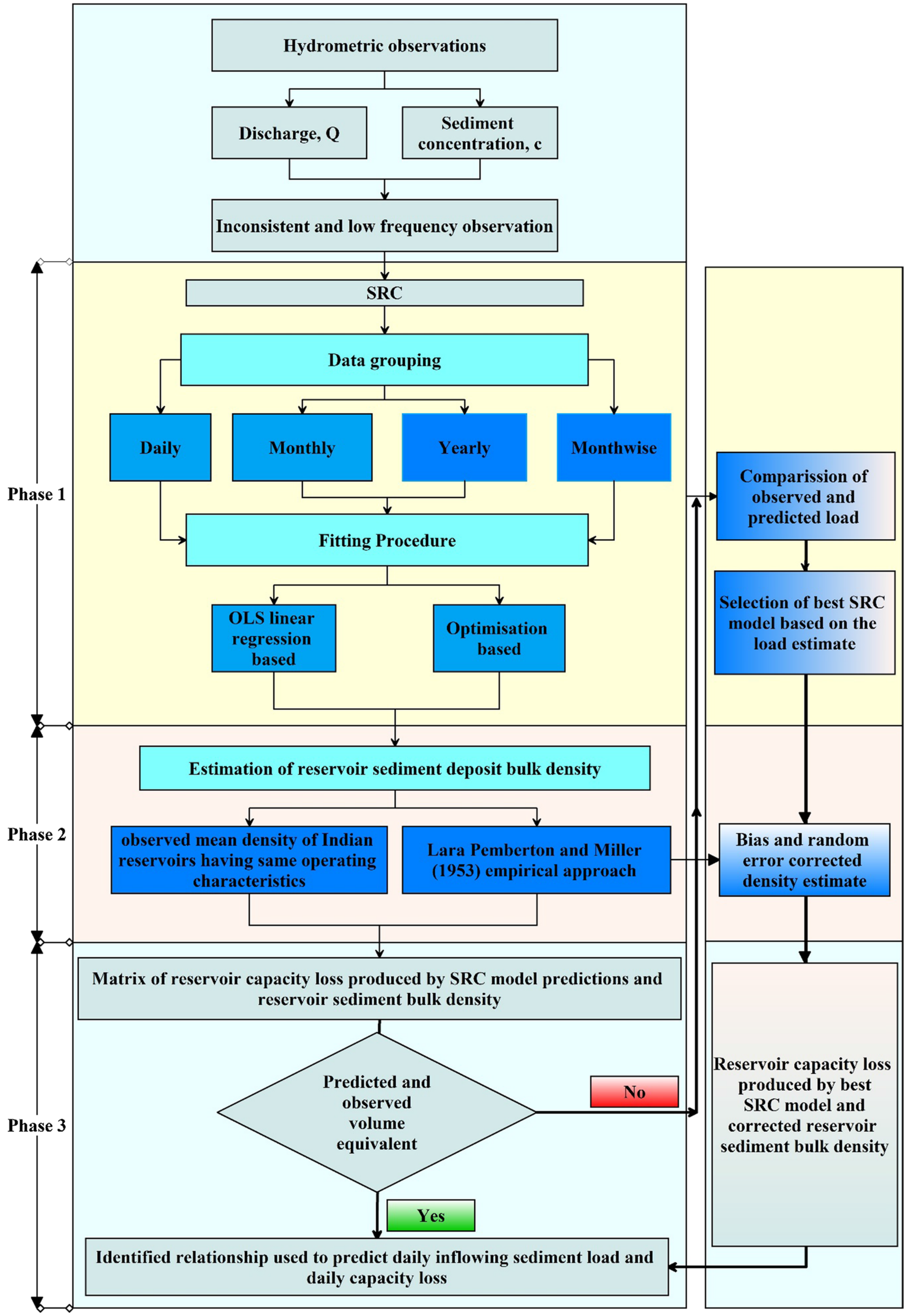

Fig. 3 Methodology adopted for identification of reservoir capacity loss

Curve fitting by OLS regression and proposed optimization

After grouping, the conversion of the values to logarithms of base ten was performed for transforming the model from the power form (Eq. 2) to the linear form (Eq. 3). The scaling coefficient, a, is transferred to the intercept ($\log a$), and the exponent, b, becomes the slope of the transferred linear relationship:

$$c = aQ^b \tag{2}$$

$$\text{Log}\, c = b * (\log Q) + (\log a) \tag{3}$$

Fitting a curve to the data is done by two methods, viz. ordinary least square (OLS) regression (linear fitting) and optimization technique. Both the fitting procedures are optimization techniques that minimize a particular statistical error function (objective) with respect to certain constraints. OLS linear regression is derived from calculus while optimization obtains solution numerically. The OLS regression would give a good relationship between discharge and concentration but may not necessarily produce a good sediment load estimate. On the other hand, the correlation between suspended sediment load and discharge is of interest; however, sediment load includes discharge in its computation and regression between them may generate a nonexistent superficial correlation (Annandale et al. 2016). The novel approach proposed in the present research is to calibrate the SRC coefficients in such a way that no significant change is observed in the coefficient of determination (obtained from OLS regression fitting procedure) between discharge and SSC relationship. Yet, the predictive accuracy of the accumulated suspended sediment load is increased. That is, the SRC models developed using OLS regression are further calibrated to have a minimum difference in load estimates. In order to fit the SRC models by optimization, the coefficient of determination (obtained using the OLS regression) between discharge and SSC relationship is considered as a benchmark. The lower bound of the coefficient of determination (for the SRC model fitted by optimization technique) is selected as 5% lower than the benchmark value, while the upper bound for the coefficient of determination is given as one. Similarly, the upper and lower bounds of the scaling coefficient, a, and the exponent, b were selected such that the range of bound was maintained between ± 5% of the SRC coefficients obtained using the OLS regression (Eq. 3). The objective of the daily, monthly average and yearly average SRC models fitted by optimization was to minimize the absolute percentage error in the suspended sediment load accumulated over a period (1984–1992) and is expressed mathematically in Eq. 4. On the other hand, the objective of the month-wise SRC was the minimization of the absolute percentage error in the load accumulated over the period of analysis for the respective month only:

$$\text{Percentage error} = \frac{L_\mathrm{p} - L_\mathrm{o}}{L_\mathrm{o}} * 100 \tag{4}$$

The observed (L_o) and predicted (L_p) sediment loads (ton/day) were obtained using Eqs. 5 and 6, respectively, by summing the product of the SSC, c_i, with the daily mean discharge, Q_i, for the study period (n days):

$$L_\mathrm{o} = \sum_{i=1}^{n} \left(c_{i\,\mathrm{observed}} * Q_i * \frac{24 * 60 * 60}{1000} \right) \tag{5}$$

$$L_\mathrm{p} = \sum_{i=1}^{n} \left(c_{i\,\mathrm{predicted}} * Q_i * \frac{24 * 60 * 60}{1000} \right) \tag{6}$$

where average observed discharge Q_i (m^3/s) of a particular day is obtained from the gauge-discharge curve and the water surface elevation (observed every hour). The predicted concentration $c_{i\,\mathrm{predicted}}$ ($\mathrm{kg/m}^3$) is obtained as per Eq. 2, and observed concentration $c_{i\,\mathrm{observed}}$ ($\mathrm{kg/m}^3$) is the observed SSC for a given day. It is to be noted that observed sediment concentration does not represent the average sediment load of the day but is a single temporal-point measurement. Sediment transport rate throughout a day is majorly dependent on the variation in precipitation. Hence, the measured concentration value is not aligned with the hydraulic and hydrological factors. Using such measurement brings intrinsic uncertainty in the load prediction (Singh et al. 2013).

Optimization of the objective function for the constraints is done utilizing Excel Solver optimization tool. The solver is a spreadsheet-based optimization tool that provides nonlinear generalized reduced gradient (GRG) and evolutionary method to optimize nonlinear problems. The GRG method starts with an initial solution. It looks at the gradient of the absolute percentage error (Eq. 4) as the SRC coefficients are changed and stops as the first derivatives equal zero. The evolutionary method starts with random values of the coefficients (parent population) and evaluates them by a fitness function (Eq. 4). The population is mutated, a new set of SRC coefficients are created as offspring, the individual fitness of each SRC coefficient is evaluated and the least fit is replaced with new values.

Using both methods one after another, it is assured that a global optimal solution of the SRC coefficients is reached. In GRG method and evolutionary method, the convergence is given as 0.0001. In the evolutionary method, the population size is given as 100 and the mutation rate is given as 0.075. The limiting time bound in the evolutionary method is selected as 30 s; i.e., the optimization process is to be stopped if maximum time without improvement of the solution is more than 30 s.

The statistical function of the Nash–Sutcliffe model efficiency factor *NSMEF* (Nash and Sutcliffe 1970) and the index of agreement *d* (Willmott 1981) signify the model efficiency and are used for comparing the observed and predicted suspended sediment loads. The *NSMEF* scores range from negative infinity to one. A value equal to or less than zero denotes that the developed model should be disregarded, while the value of unity indicates a perfect prediction. The index of agreement *d* is a non-dimensional and bounded measure. It is bounded from zero to one, with one suggesting a perfect match and zero connoting a lack of match between the observed and predicted values.

Computation of the sediment volume

Analyzing the observed SSC and discharge data obtained on daily time step (period 1983–1992), it has been found that about 33% of SSC data were not measured but can be predicted by SRC. By applying the SRC, the spatial and temporal data gaps were filled and the time series of daily suspended sediment load was obtained. The daily suspended sediment load records were summed up for the period between the two consecutive hydrographic surveys. The total load cannot be estimated if the bed load is not included in the predicted suspended load. The bed load was not measured during the study period; therefore, considering the grain size distribution of the sediment, it was assumed to be 20% of the measured load (BIS-12182 1987; Waikhom and Yadav 2017). Besides, the calculated sediment load was adjusted as per the reservoir TE, which was estimated from the Brune (1953) median curve. The mathematical relationship of Brune (1953) median curve (Eq. 7) proposed by Garg and Jothiprakash (2008) was employed:

$$\mathrm{TE} = \frac{\frac{C_\mathrm{o}}{I}}{0.00013 + 0.01\left(\frac{C_\mathrm{o}}{I}\right) + 0.0000166\sqrt{\frac{C_\mathrm{o}}{I}}} \tag{7}$$

where TE = trap efficiency (%), C_o = storage capacity of the reservoir (10^6 m^3), I = inflow of water in the reservoir (10^6 m^3).

The total load (kg) can be converted to volume (m^3) based on the deposited sediment bulk density (hereafter merely referred to as density), which can be acquired by sampling the deposited sediment or by using empirical formulae. In the present analysis, sediment sampling was not a feasible approach due to the depth of the reservoir. Furthermore, point densities recorded in different locations need to be converted into representative density (Annandale et al. 2016). The sediment volume was computed from the density based on the Lara and Pemberton (1963) and Miller (1953) (i.e., empirical approach), the observed mean density of Indian reservoirs and the typical value of density as per Tebbi et al. (2012).

Reservoir-submerged sediment density

Lara and Pemberton (1963) and Miller (1953) empirical approach is used for the estimation of the submerged sediment bulk density. The initial density was calculated using the Lara–Pemberton method (Strand and Pemberton 1982) as shown in Eq. 8:

$$W_\mathrm{i} = W_\mathrm{c}P_\mathrm{c} + W_\mathrm{m}P_\mathrm{m} + W_\mathrm{s}P_\mathrm{s} \tag{8}$$

W_i = density in kg/m^3, P_c, P_m and P_s = clay, silt and sand percentages of the incoming sediment, respectively. W_c, W_m and W_S = clay, silt and sand coefficients of the incoming sediment, respectively.

Miller's (1953) approach was applied to determine the average sediment density deposited in T years of the reservoir's operation, as provided in Eq. 9:

$$W_T = W_i + 0.4343K\left[\frac{T}{T-1}\left(\log_e T\right) - 1\right] \tag{9}$$

W_T = average density in kg/m^3, after T years of reservoir operation, W_i = initial density in kg/m^3, as derived from Eq. 8, K = constant, based on compacting characteristics of sediment and reservoir operation.

The value of K relates the compacting characteristics of the sediment based on the sediment size analysis. The bulk densities obtained from the Lara and Pemberton (1963) and Miller (1953) (cited in Strand and Pemberton 1982) approach depend on the grain size analysis.

In addition to the density computed by Lara and Pemberton (1963) and Miller (1953) approach, the typical value of density (1400 kg/m^3; Tebbi et al. 2012) and the mean of observed sediment densities (i.e., 1191 kg/m^3; CWC 2015) were utilized for the computation of sediment volume. Natural variability of the arithmetic mean sediment densities observed from 21 Indian reservoirs ranged from 780 to 1555 kg/m^3.

Results and discussion

SRC models

An SRC can represent flow and sediment transport relationship for a location under a certain range of environmental, climatic and land use conditions. In other words, the relationship of sediment load and discharge together should be consistent during the period of analysis

(Asselman 2000; Warrick 2015). Before the development of SRCs, trend analysis was performed by nonparametric tests, which showed that discharges and suspended sediments have trend during the study period. However, the obtained trend between observed discharges is similar to the trend in observed concentrations; i.e., both the discharge and SSC are found consistent with each other. Hence, SRCs by different data grouping and curve fitting procedures were developed at Sarangkheda gauging station for the period 1984–1992.

SRC developed by OLS regression

Figure 4 illustrates the SRC fitted with daily, monthly and yearly groups of data utilizing the OLS regression fitting procedure. The month-wise data-grouped SRC models fitted by OLS regression are illustrated in Figs. 5 and 6. It is inferred from Figs. 5 and 6 that only the monsoon months' discharge and SSC are correlated, while the non-monsoon months' data exhibit no connection whatsoever. Statistical significance of the log of discharge and concentration data used in the regression model was checked by hypothesis testing (P values). It was found that all the SRCs produced in Figs. 4, 5 and 6 are statistically significant except the month-wise SRCs of the months February, April, May and

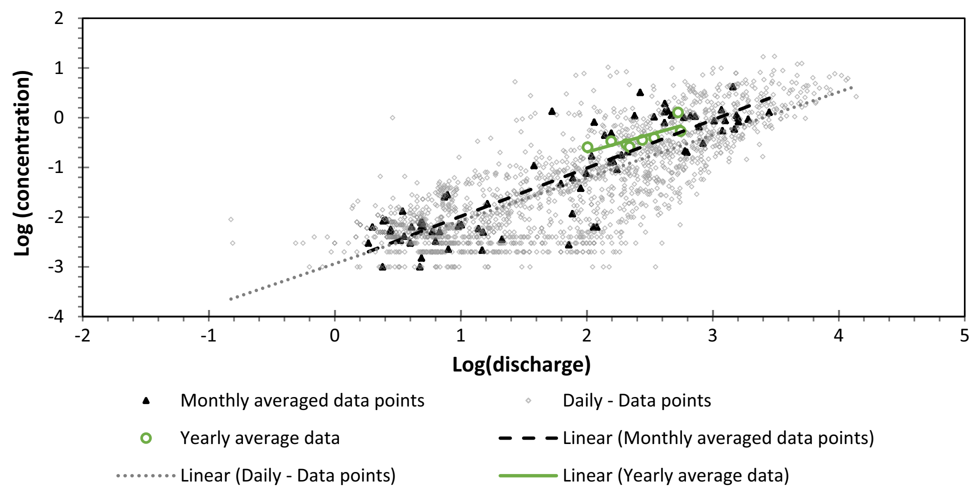

Fig. 4 SRC fitted using OLS regression

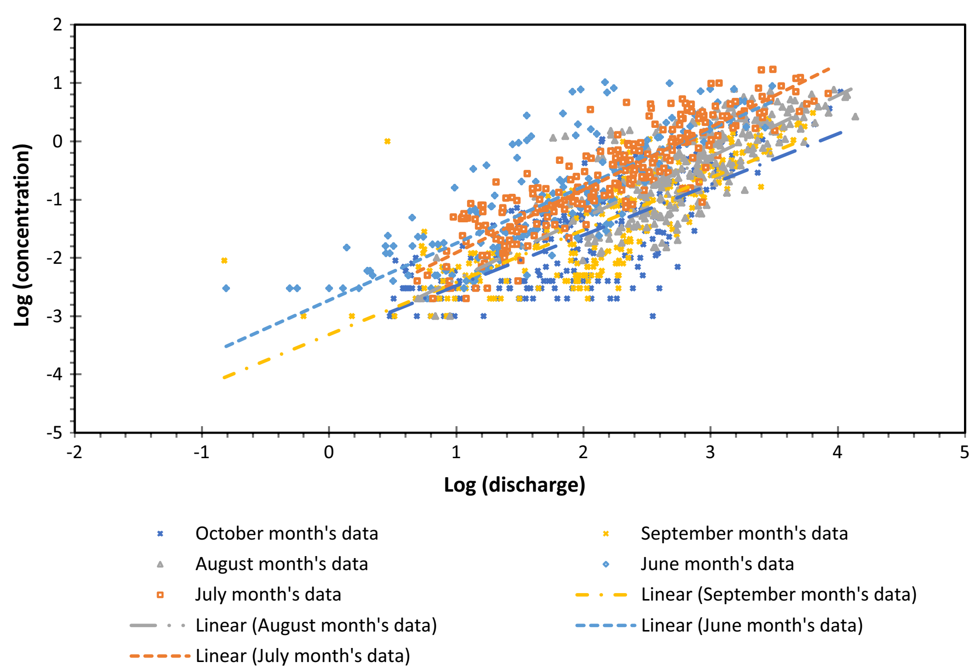

Fig. 5 SRC fitted using OLS regression for monsoon months (month-wise SRC)

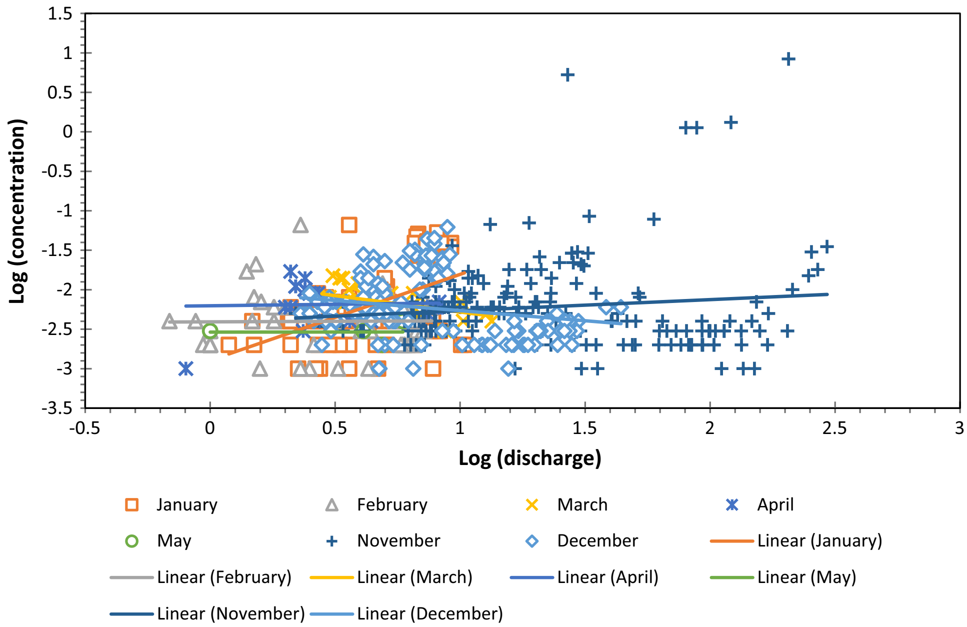

Fig. 6 SRC fitted using OLS regression for non-monsoon months (month-wise SRC)

November. It is to be noted that during these months, very lean flow is observed and the sediment load contribution is less than 0.2%. Scaling (intercept) and exponent (slope) coefficients along with the coefficient of determination for the SRCs which are shown in Figs. 4, 5 and 6 are presented in Table 2. By conversion of the intercept [Log(a)] (presented in Table 2) to scaling coefficient (a), it is understood that for one unit of discharge, the concentration (kg/m^3) will be its thousandth part.

SRC developed by optimization

The information of the relationship obtained between discharge and SSC was utilized to fit SRC models by optimization. Selected bounds for the SRC models to be fitted by optimization technique are listed in Table 3. The coefficient of determination (r^2) between SSC and discharge was considered as one of the constraining conditions, and the lower limit of r^2 was provided. The curves obtained for daily, monthly and yearly data by optimization are presented in Fig. 7. For the month-wise SRC model fitting by optimization, only the monsoon months were considered, as they exhibited a good correlation between the discharge and concentration. Fitted month-wise SRCs are portrayed in Fig. 8. By considering the objective function as per Eq. 4 along with the constraints as mentioned in Table 3, SRC fitted by the optimization technique is presented in Table 4.

Table 2 SRC models developed using OLS regression

SRC model		Log (a)	b	Coefficient of determination, R^2
Group of data	No. of data points			
Daily data-based SRC model	1889	−2.9349	0.8628	0.6476
Monthly averaged data-based SRC model	76	−2.9542	0.9701	0.7801
Yearly averaged data-based SRC model	9	−2.1072	0.7076	0.6122
Month-wise data-based month-wise SRC models				
June	217	−2.9349	0.8628	0.6476
July	260	−2.9862	1.0757	0.7900
August	279	−3.4197	1.0514	0.5947
September	268	−3.3142	0.8962	0.6430
October	240	−3.3467	0.8688	0.5916

Here, a, scaling coefficient of the sediment rating curve [(kg/m^3)/(m^3/s)]; b, exponent coefficient of rating curve (unitless)

Table 3 Range of upper and lower bounds

Group of data	Coefficient log (*a*)		Coefficient *b*		Coefficient of determination, R^2	
	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound
Daily data-based SRC model	−2.79	−3.08	0.91	0.82	1	0.62
Monthly averaged data-based SRC model	−2.81	−3.10	1.02	0.92	1	0.74
Yearly averaged data-based SRC model	−2.00	−2.81	0.74	0.67	1	0.58
Month-wise data-based month-wise SRC models						
June	−2.79	−3.08	0.91	0.82	1	0.62
July	−2.84	−3.14	1.13	1.02	1	0.75
August	−3.25	−3.59	1.10	1.00	1	0.56
September	−3.15	−3.48	0.94	0.85	1	0.61
October	−3.18	−3.51	0.91	0.83	1	0.56

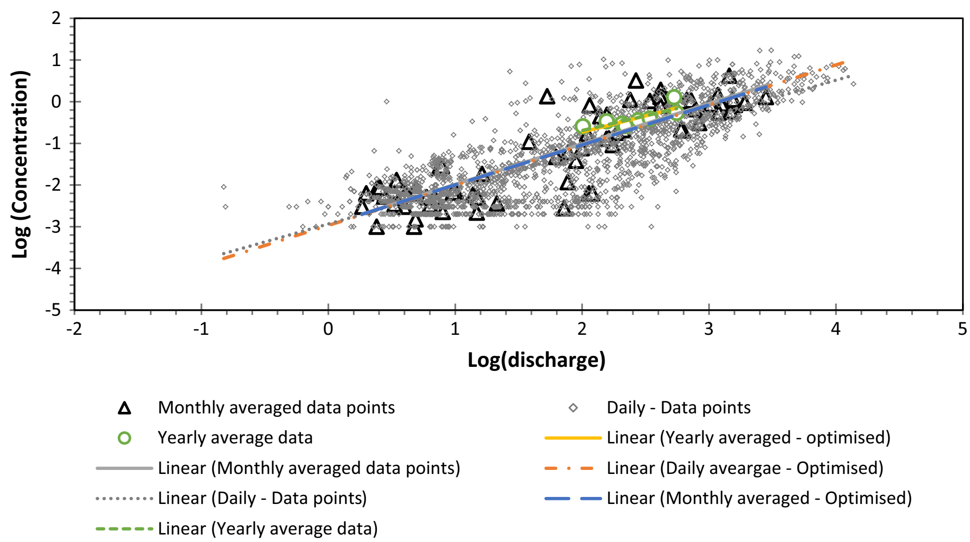

Fig. 7 SRC fitted by optimization and OLS regression

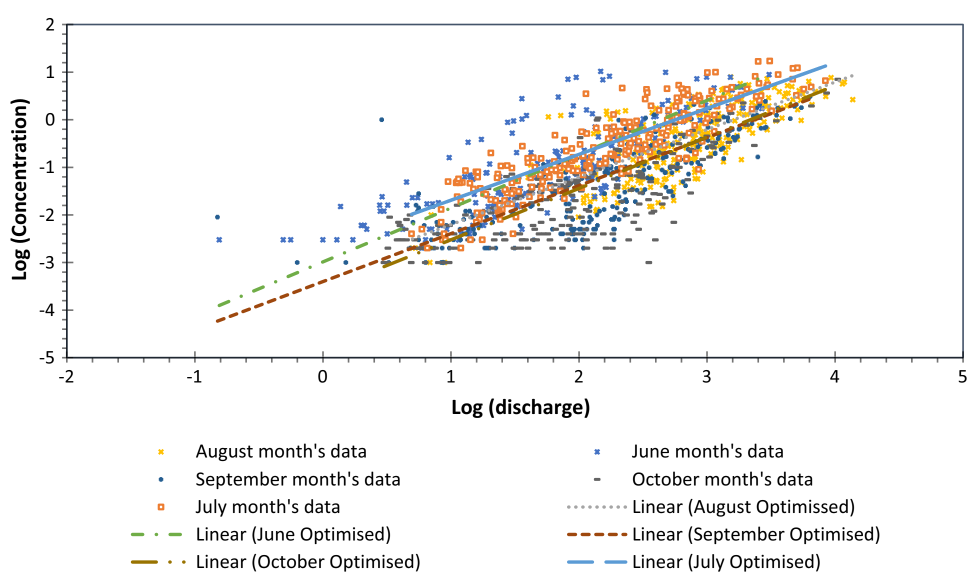

Fig. 8 Month-wise SRC fitted by optimization and OLS regression

Table 4 SRC models developed using optimization technique

SRC model		Log (a)	b	Coefficient of determination, R^2
Group of data	No. of data points			
Daily data-based SRC model	1889	−3.0131	0.9016	0.6268
Monthly averaged data-based SRC model	76	−2.9571	0.9593	0.7796
Yearly averaged data-based SRC model	9	−2.1733	0.6751	0.6048
Month-wise data-based month-wise SRC models				
June month	217	−2.9862	0.9031	0.6340
July month	260	−2.8546	1.0642	0.7751
August month	279	−3.5000	1.0980	0.5851
September month	268	−3.4000	0.9078	0.6114
October month	240	−3.5000	0.8785	0.5615

Comparison of SRC developed by OLS regression and optimization

SRC models were obtained from different groups of data, i.e., daily, monthly, yearly and month-wise though they were applied to daily time step data (discharge) to predict daily concentration and sediment load. Comparison of observed and predicted sediment load passing Sarangkheda gauging station for the period 1984–1992 disclosed that SRC fitted by optimization gave better prediction than OLS regression-fitted SRCs (Fig. 9). Table 5 shows the percentage error, NSMEF and *d* computed between observed and predicted load. The NSMEF scores of the yearly, monthly and daily models fitted by optimization are 0.4603, 0.4813 and 0.6240, respectively. The coefficient of determination obtained for the monthly SRC model fitted by optimization is 0.7796 and is the highest of all.

Despite this close agreement of the optimization-fitted SRCs with predicted sediment load for the entire 9-year period, yearly sediment load predictability was investigated. Not surprisingly, the accuracy of the yearly predictions decreased. The percentage error ranged from −79.87 to 82.65% for optimization-fitted models while for OLS regression-fitted model the error ranged from −88.24 to 98.64%. The dissimilarity of the percentage error between the entire 9-year period and yearly sediment load prediction demonstrates the competence of the SRCs fitted by optimization to round the error associated with longer periods.

The variability of predictions for yearly accumulated sediment loads with respect to data grouping was observed less for models fitted by optimization (Fig. 10), as compared to the models fitted by OLS regression (Fig. 11). This shows that the SRC models fitted by OLS regression are highly susceptible to data grouping and resolution, while those designed by the optimization technique are less influenced by the resolution of the data. This is due to the fact that the OLS regression models were further calibrated using the optimization technique by considering an objective function for minimizing the error between the observed and the predicted loads. From the results of the SRC models devised using the diversified approaches, it could be legitimated that the ones that were developed using optimization were the best.

The composition of the SRC fitting data significantly impacts the SRC produced (Horowitz 2003). Though results of the study have revealed that sediment load predictions obtained from SRCs fitted by optimization is independent of the composition of the dataset and hence, the coefficients of the obtained SRCs were analyzed. A negative correlation between the regression coefficients of the fitted SRCs is evident if the sediment flow regime is consistent (e.g., Asselman

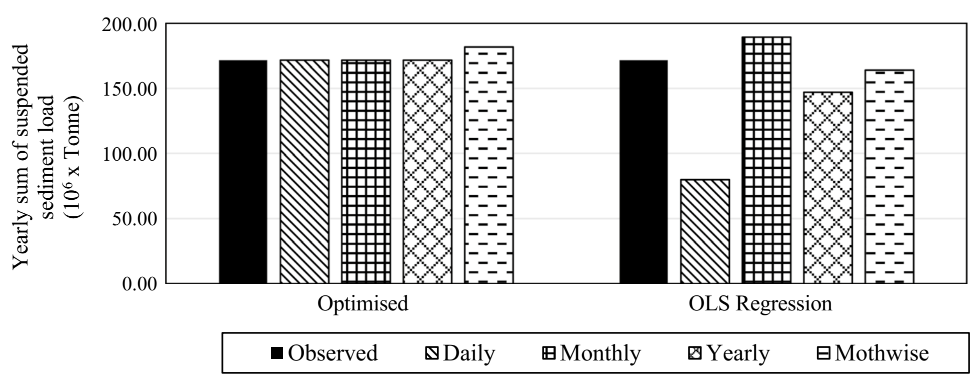

Fig. 9 Differences between actual and sediment rating curve-derived sediment load passing Sarangkheda gauging station during 1984–1992 period

Table 5 Statistical summary of developed SRC models

SRC model		Percentage Error	Nash–Sutcliffe model efficiency factor	Index of agreement, *d*
Group of data	Fitting procedure used for fitting an SRC			
Daily data-based SRC model	OLS regression	−53.42	0.5892	0.9964
	Optimization technique	−3.52E–07	0.4603	0.9953
Monthly averaged data-based SRC model	OLS regression	13.32	0.3478	0.8699
	Optimization technique	*−1.33E–07*	*0.4813*	*0.8834*
Yearly averaged data-based SRC model	OLS regression	−14.29	0.6872	0.9018
	Optimization technique	−2.01E–08	0.624	0.9031
Month-wise data-based month-wise SRC models				
June	OLS regression	−84.24	0.1988	0.3991
	Optimization technique	3.78E–07	0.6438	0.9148
July	OLS regression	17.24	0.0653	0.8324
	Optimization technique	−3.48E–05	0.4406	0.8713
August	OLS regression	−4.08	0.5757	0.9106
	Optimization technique	1.60E–11	0.579	0.9124
September	OLS regression	−49.98	0.6557	0.8387
	Optimization technique	−1.54E–07	0.9143	0.9779
October	OLS regression	−71.19	0.3879	0.5945
	Optimization technique	−7.90E–08	0.9371	0.9821

Italic values show the best performing model

The observed load is computed from the observed discharge and sediment concentration while the predicted load is computed using observed discharge and predicted sediment concentration

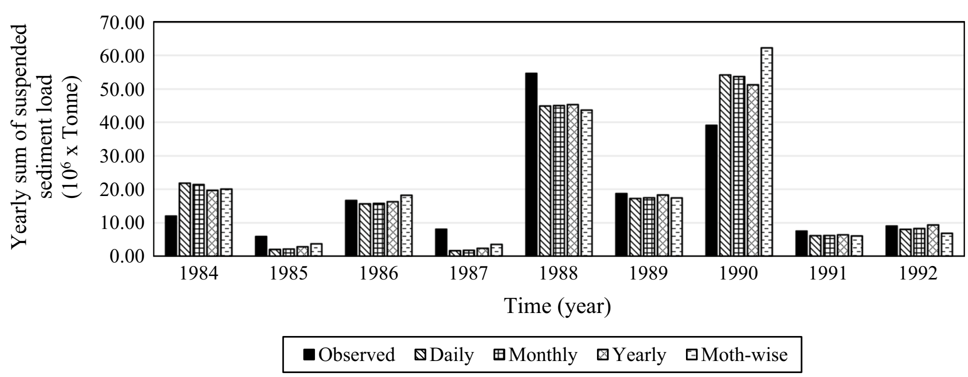

Fig. 10 Comparison of observed and predicted sediment load for the sediment rating curve fitted by optimization

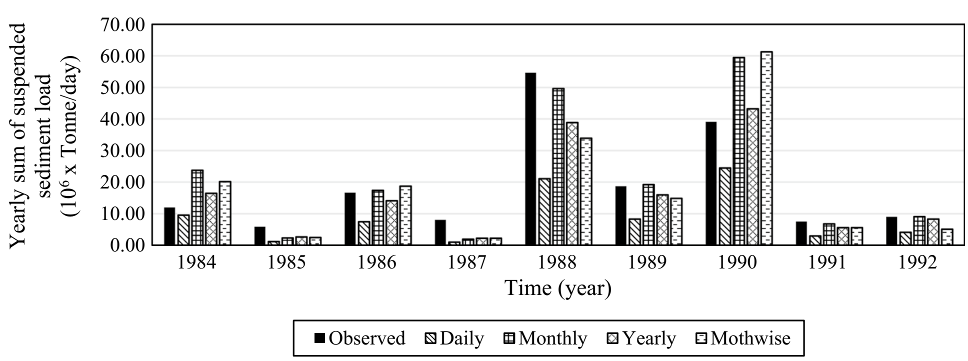

Fig. 11 Comparison of observed and predicted sediment load for the sediment rating curve fitted by OLS regression

2000; Syvitski et al. 2000). Sediment flow regime in the river reach of Sarangkheda gauging station is consistent during the 1984–1992 period, as no major activity has occurred in the upstream catchment area. Furthermore, the SRCs are obtained by grouping the observed data at a fixed location and period. Therefore, it is likely that the SRC coefficients should exhibit a good relationship. SRC coefficients obtained from daily, monthly, yearly and month-wise groups of data were plotted and are presented in Fig. 12. July and August month fitted SRCs from the month-wise models were only used to assess the relationship of the coefficients because they contribute 79% of the sediment load from a hydrological year. The coefficient of determination was found to be 0.7651 between SRC coefficients fitted by OLS regression, while for the coefficients of the SRCs fitted by optimization approach, it increased to be 0.8197. The upturn of the relationship between SRC coefficients indicates that the SRC fitted by optimization represents the flow and sediment transport regime in a better way, as compared to OLS regression-fitted SRCs.

Application of the SRC model to predict reservoir-inflowing sediment load by filling spatial and temporal data gaps

The availability of temporal and spatial data from the hydrometric observations pertaining to two consecutive hydrographic surveys is presented in Table 6. The surveys were undertaken in 1983 and 1992. Since the Sarangkheda gauging station was established only in 1984, hydrometric observations of the entire catchment area for the preceding year were missing. Moreover, the gauging station's observed data (1984–1992) do not account for the suspended sediment from region B (Fig. 2). Hence, the model was applied to bridge the spatiotemporal data gap. The SRC models developed at the Sarangkheda gauging station were transferred to the Ukai Reservoir head. Discharge inflow to the reservoir was identified from a water budget model in the form of a spreadsheet program. Elevation storage curve was utilized to obtain the storage volume. Daily inflow ($I_{t=1\,\text{day}}$) was computed from the change in storage volume in accordance with the downstream release by the spillway, as well as the hydropower plant and reservoir water loss by evaporation (Eq. 10). Volume of evaporation was estimated using the observations of pan evaporimeter:

$$I_t = S_t - S_{t-1} + \left(\mathrm{VR_{ph}} + \mathrm{VR_{ULBMC}} + \mathrm{VR_{SPILLWAY}} + \mathrm{VR_{EV}}\right) \tag{10}$$

I_t = inflow at the end of the period, S_{t-1} = storage at the beginning of the period, S_t = storage at the end of the period, $\mathrm{VR_{ph}}$ = volume of release through powerhouse during period t, $\mathrm{VR_{ULBMC}}$ = volume of release through Ukai left bank main canal during period t, $\mathrm{VR_{SPILLWAY}}$ = volume of release

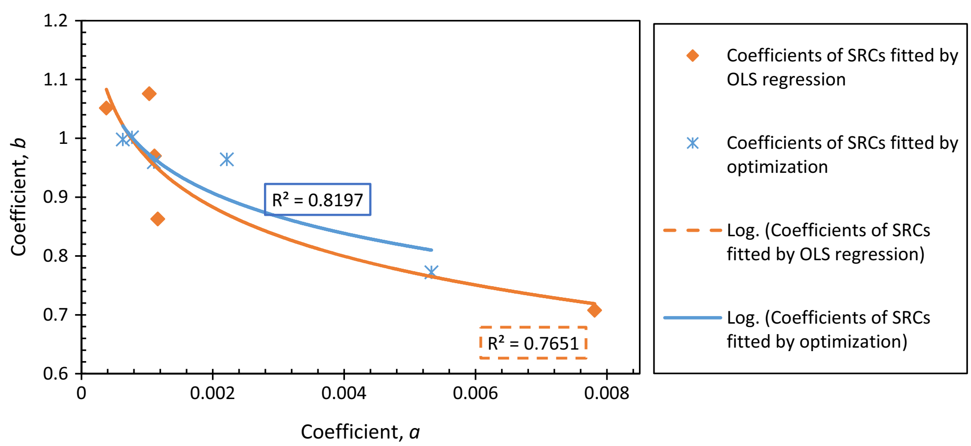

Fig. 12 Correlation between the coefficients of the SRC obtained from OLS regression and optimization fitting

Table 6 Spatial and temporal suspended sediment concentration and discharge data gaps and inconsistency

Year		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
Hydrometric observation data for regions A and B (Fig. 2)	A	Missing data	Present but inconsistent								
	B		Missing data (ungauged catchment area)								
Hydrographic survey		Survey done	–	–	–	–	–	–	–	–	Survey done

Regions A and B are as shown in Figs. 1 and 2, region B is ungauged region and data are missing for the period 1983–1992. The Sarangkheda gauging station was established in 1984, and so data of 1983 are missing through radial gates (spillway) during period t, VR_{EV} = volume of water lost by evaporation during period t.

For the year 1983, discharge inflow was directly used as input in the SRC models to estimate the suspended sediment load contributed by the complete reservoir upstream catchment. As per the monthly SRC fitted by optimization, sediment inflowing the reservoir in the year 1983 was computed to be 23.56×10^6 tonnes. For the period 1984–1992, the daily water volume contributed by region B was discerned and it was converted into the daily discharge contribution of the region. The discharge contributed by region B was thus used as input in the SRC models to ascertain the suspended sediment load contribution of the region. Region B (ungauged catchment area, 3825 km^2) which includes the reservoir rim catchment contributes about 5% (8.36×10^6 tonnes) of sediment load of the region A (gauged catchment area) (Table 7). The suspended sediment load received by the reservoir during the study period is furnished in Table 7.

Ukai Reservoir-trapped sediments

Reservoir-trapped sediment is derived from the product of trap efficiency (TE) and total sediment load (suspended load and bed load). TE was predicted by Brune median curve, which ranged from 96.9 to 99.4% (period 1983–1992).

Reservoir-deposited sediment density and deposition volume

Three approaches of sediment bulk density were used to compute deposition volume. First, density was computed using empirical approach (Lara and Pemberton 1963; Miller 1953), second, based on the mean observed densities of Indian reservoirs having similar operational characteristics, density was computed (i.e., 1191 kg/m^3) and third, typical value of density (i.e., 1400 kg/m^3) was considered (Tebbi et al. 2012).

Estimation of the density by empirical approach was carried out in two steps. The initial sediment density was computed (Lara and Pemberton 1963), which was further processed for the effect of consolidation (Miller 1953). Sediment sampling of the submerged deposited sediments showed that the clay, silt and sand content of the sediment is 32%, 51% and 17%, respectively (Table 1). According to the reservoir operation, the sediment always remains submerged in the reservoir and is never exposed to sunlight or air. The mean initial density obtained through Eq. 8 was 963.82 kg/m^3. The average density after 9 years of compaction (final density) as inferred from Miller (1953) was 966.07 kg/m^3.

The three densities (viz. empirical approach based, mean observed density and typical density value) and sediment load trapped by the reservoir (obtained from different SRC models) were used to convert the sediment mass inflow to volumetric terms. RCL observed by two consecutive hydrographic surveys performed in the years 1983 and 1992 is 466.200×10^6 m^3. Table 8 demonstrates the difference in the observed and predicted volumes. The percentage error noticed in Table 8 urged further investigation on the certainty of the estimated density.

Empirical density estimate

The RCL predicted from the density estimated by empirical formulation resulted in an underprediction ranging from

Table 7 Total suspended load contributed by catchment

SRC model (1)		SSL_A^a (2)	SSL_{A+B}^b (3)	SSL_B^c (4)	SSL_A^d (5) (2) + (3) + (4) = (5)
Group of data used for SRC model development	Fitting procedure used for fitting an SRC				
Observed data		171.595	–	–	–
Daily data-based SRC model	OLS regression	80.788	11.546	4.349	96.682
	Optimization technique	173.379	23.021	7.771	204.171
Monthly averaged data-based SRC model	OLS regression	191.286	25.840	8.936	226.062
	Optimization technique	173.383	23.559	8.215	205.157
Yearly averaged data-based SRC model	OLS regression	148.701	22.888	9.844	181.433
	Optimization technique	173.409	25.911	10.531	209.850
Summation of month-wise SRC model	OLS regression	157.993	12.551	6.238	176.782
	Optimization technique	174.970	16.497	10.991	202.457

[a]Total suspended load contributed by region A in million tonnes for the period 1984–1992

[b]Total suspended load contributed by entire catchment in million tonnes for the year 1983

[c]Total suspended load contributed by region B in million tonnes for the period 1984–1992

[d]Total suspended load contributed by entire catchment in million tonnes for the period 1983–1992

Table 8 Percentage error between observed and computed sediment volume

SRC models		PE_a (%)	PE_b (%)	PE_c (%)
Data group	Fitting technique			
Daily data-based SRC model	OLS regression	−74.24	−79.1	−82.22
	Optimization technique	−45.6	−55.87	−62.46
Monthly averaged data-based SRC model	OLS regression	−39.77	−51.14	−58.44
	Optimization technique	−45.34	−55.66	−62.28
Yearly averaged data-based SRC model	OLS regression	−51.66	−60.79	−66.64
	Optimization technique	−44.09	−54.65	−61.42
Summation of month-wise SRC model	OLS regression	−52.9	−61.79	−67.50
	Optimization technique	−46.06	−56.24	−62.78

PE, percentage error computed between observed and predicted reservoir-deposited sediment volume. Suffix *a, b* and *c* stands for the density estimate used to derive the volume prediction, *a* implies volume computed using the empirical formula of bulk density, *b* implies volume computed using density of Indian reservoirs having similar operational characteristics and *c* implies volume computed using typical value of density (1400 kg/m^3)

39.77 to 74.24%. Such obtained underprediction cannot be considered for the estimation of daily RCL (Table 8), and uncertainty of the density estimate is assessed. The density estimated by the Lara and Pemberton (1963) and Miller (1953) approach using the sampled sand, silt and clay content depends on the particular specimens in the sample. Since these values can vary from sample to sample, particular samples can produce misleading values resulting in incorrect density estimates. The possibility of estimating a wrong density, on the basis of the collected sand silt and clay content, cannot be absolutely rejected except complete reservoir area is accurately sampled. This is, of course, physically and economically challenging as the dam rises to a maximum height of 70 m above the river bed level (Ukai Dam authority). Generally, in reservoir sediment sampling, the depth of water becomes one of the major hindrances for sample collection. Hence, due to limited samples in the spatial domain, the density representing the complete reservoir area has to be inferred from the sample-obtained mean density. In order to obtain an objective or subjective bias correction factor, which can be multiplied to the sample-estimated density, to infer reservoir representative density, the major sediment density influencing factors and the sampling program-related biases have to be evaluated. The inadequacy of such data limits us while deriving the bias correction factor. Nevertheless, in order to derive the corrected density estimate, the SRC that stood best for load prediction during SRC development stage (month-wise data-grouped SRC fitted by optimization, Table 4) is considered as the best SRC and a submerged sediment density of the reservoir is derived as a ratio of accumulated sediment load to the observed RCL (observed from hydrographic surveys conducted during 1983 and 1992). The computed representative density is found to be 528.075 kg/m^3; such low value of computed density questions the validity of the derived sediment load or the 1992 hydrographic surveyed reservoir capacity.

Statistical evaluation of the density estimated by the empirical approach (Lara and Pemberton 1963; Miller 1953) and density obtained by equating sediment load (gravimetric) with hydrographic surveyed RCL (volumetric) is performed. Assuming that the statistical population of density follows a normal distribution and considering the empirical-derived density estimate as mean of statistical sample and the density obtained by equating gravimetric sediment load with volumetric RCL as statistical-population mean, two-tailed t test is performed to compare the mean of statistical sample and population for the known standard deviation of the sample (for ten sampled specimens).

T test statistic (t) is a standardized value calculated from the mean of sample and population, which incorporates both the sample size and its variability. The null hypothesis is exactly sufficed if t is found to be zero; as the absolute t is increased, the significance of accepting the null hypothesis is decreased (Johnson 2017). For the present study, the null hypothesis (H_0) proposes that the statistical-sample mean is not significantly different than the statistical-population mean, and on the other hand, the alternative hypothesis (H_a) states that the statistical-sample mean is significantly different than the population mean. The critical T value ($t_{\alpha/2,\,\mathrm{df}}$) for significance level (α) as 95% with nine degrees of freedom (df) is found to be 2.262, and t is calculated as 6.784. As t is higher than $t_{0.975,9}$, it is determined from hypothesis testing that H_0 is rejected in favor of H_a. This does not necessarily mean that H_a is true; it only suggests that there is not sufficient evidence to accept the null hypothesis suggesting alternative hypothesis may become true. However, the statistical test clearly rejected the statistical significance of the two densities to be equal. Hence, the correctness of the reservoir capacity (observed during the hydrographic survey of 1992), the derived sediment load and the density estimate remains a question. Therefore, four scenarios of RCL between the period 1983 and 2003 are generated using the month-wise data-grouped SRC fitted by optimization and different density estimates. It was expected that if the sediment load predictions are accurate, then the capacity loss predicted from one scenario will be in good agreement with the difference between the reservoir capacity observed during the hydrographic surveys of 1983 and 2003, resulting in one true reservoir sediment density. Densities of 528.075 kg/m^3, 966.07 kg/m^3, 1191 kg/m^3 and 1400 kg/m^3 are used to generate scenarios 1, 2, 3 and 4, respectively. Comparing the observed and predicted RCL, an overprediction of 82.10% is reported from scenario 1 while an underprediction of 0.46% is reported from scenario 2. However, scenarios 3 and 4 have produced an underprediction of 19.26% and 31.31%, respectively. The discrepancy ratio of these estimates is presented in Table 9. The density estimated from the empirical approach (966.07 kg/m^3) showed least deviation between observed and predicted capacity loss. A lower value of the error from scenario 2 validates the SRC model to produce sediment load and the density obtained by empirical approach.

In order to relate hydrometric and hydrographic observations for the prediction of reservoir capacity loss on daily timescale, correct prediction of sediment load has to be done, density estimate has to be accurate and the uncertainty from the hydrographic survey should be narrowed. The present research has highlighted major problems, which can hinder the linking of the hydrometric observations with the RCL. Uncertainties of the predicted sediment load, density estimate and hydrographic survey are interlinked. The proposed approach is beneficial as it assesses the correctness of the observed data by statistical evaluation of density estimates and generation of the capacity loss scenarios. The result of the study demonstrates the prediction of daily RCL in uncertain data conditions. It is necessary to discuss here that, in the future, more consideration should be given to ensure the correctness of the hydrographic surveys. RCL obtained from hydrographic surveys should be cross-verified with the RCL derived from the hydrometric observation, using the present approach. In addition to it, from the ongoing research, few

Table 9 Reservoir capacity loss with respect to estimated densities for the period 1983–2003

Scenario	Sediment density	RCL_o^a (10^6 m^3)	RCL_p^b (10^6 m^3)	DR^c (%)
Scenario 1	528.05	548.71	999.22	1.82
Scenario 2	966.07		546.20	1.00
Scenario 3	1191.00		443.05	0.81
Scenario 4	1400.00		376.91	0.69

[a]RCL_o, reservoir capacity loss derived from the gross reservoir capacity observed in 1983 and 2003 hydrographic surveys

[b]RCL_p, reservoir capacity loss computed from the sediment load trapped by the reservoir and different density estimates

[c]DR, discrepancy ratio between RCL_o and RCL_p

essential points identified for quality control, minimization of the surveying error and the uncertainty are listed here: (1) Hydrographic surveys should be carried out on standardized operating procedures providing a uniform method of planning, collecting, processing and analyzing data. (2) Before the execution of the hydrographic survey, by examining the reservoir bathymetry obtained from previous surveys, critical locations should be identified, so that a comparison overlay for those particular locations can be prepared. (3) The main survey lines directions (perpendicular to the general direction of contours) and their spacing should be identified from the previous surveys experience. (4) Crossline direction, i.e., at right angles to mainline direction, should be selected as a vital quality regulation measure. So when any interpolation algorithm is used, the results can be verified with such control lines. (5) Surveying vessel speed has to be assessed for the expected range of depths in the survey area and the type of echo sounder in use to reduce the measurement and observation uncertainty. (6) A consistent datum must be used throughout all hydrographic survey projects, or the data has to be adjusted if comparison has to be made.

Gross reservoir capacity loss prediction

The temporal lumped relationship established between the hydrometric observations of the reservoir upstream gauging station and the reservoir capacity derived from hydrographic surveys were utilized to disintegrate the observed phenomena on a daily time step.

Employing the SRC model, daily depositing sediment volume and continuous timeline of gross reservoir capacity are obtained (Fig. 13). Though the model is based on a simple approach, the validity of the developed relationship to predict the RCL was found considerable. The relationship was thus utilized to estimate the action of the extreme hydrological events to RCL (Table 10). During a flood event on August 08, 2006, about 1991×10^6 m^3 of water flowed into the reservoir in a single day, which brought about 42.16×10^6 tonnes (estimated) of sediment load causing 43.64×10^6 m^3 (estimated) of RCL (Fig. 14). This model estimate is 0.59% of 2003 surveyed reservoir capacity. The average RCL from its first impoundment in 1972 to the last bathymetry survey carried out in the year 2003 was 35.35×10^6 m^3/year. The results have shown that about 50% of the capacity loss of a year may occur during a single extreme event. The design siltation rate of the Ukai Dam is 0.149×10^3 m^3/km^2/year, whereas the observed rate in the reservoir is 0.568×10^3 m^3/km^2/year (CWC 2015), which shows that the rate of siltation was underestimated by 73.77%.

Ten extreme flood events observed in the history of the Ukai Reservoir were analyzed for the inflowing sediment load and RCL (Table 10). With respect to initial reservoir capacity, RCL of 0.512% to 0.081% was observed. Through all these

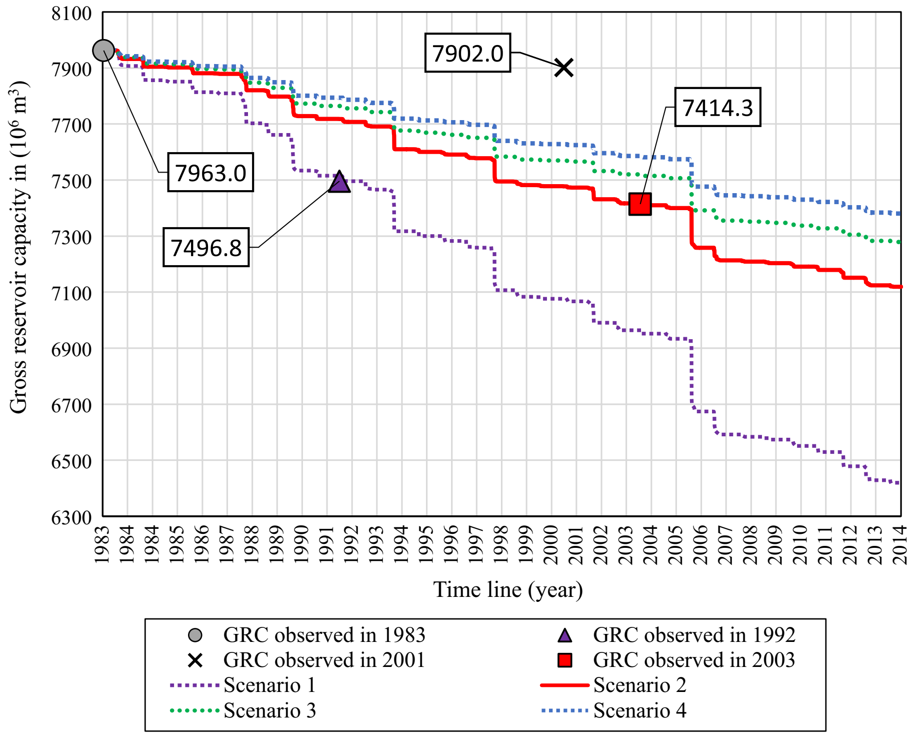

Fig. 13 Time series of predicted reservoir capacity loss

Table 10 Extreme events in reservoir catchment and its impact on capacity loss

S. no.	Date	Amount of water received by reservoir ($10^6 \times m^3$)	Estimated sediment inflow ($10^3 \times$ ton)	Estimated capacity loss ($10^6 \times m^3$)
1	08-08-2006	1991.00	42.16	43.64
2	16-09-1998	1839.63	36.11	37.38
3	07-09-1994	1350.09	19.69	20.39
4	20-08-1984	1188.00	15.33	15.87
5	17-08-1990	1022.80	11.43	11.83
6	09-07-2007	1021.88	11.41	11.81
7	04-10-1988	909.02	9.07	9.39
8	07-09-2012	905.56	9.01	9.32
9	20-08-1989	803.52	7.12	7.37
10	02-08-2013	779.93	6.72	6.96

ten events, about 173.96×10^6 m^3 of sediment volume settled in the reservoir, which reduced the capacity of the reservoir by 2.04%. It is to be noted that the estimated RCL by such hydrometric and hydrographic relationship may only provide a first-order capacity loss estimate. Yet, in data-scarce condition, it may stand as a very useful tool to understand the response of hydrological events directly on the RCL.

Conclusions

The certainty of the predicted sediment load trapped by the reservoir, estimated bulk density of the deposited sediment and the hydrographic survey observed reservoir capacity limits the accuracy of the reservoir capacity loss (RCL) prediction. Accurate prediction of sediment load using sediment rating curve (SRC) has been emphasized in the present study. A novel SRC fitting approach by means of optimization technique is proposed to predict sediment load using low-frequency (once a day) suspended sediment sampled data. Use of SRCs to produce sediment load predictions by different grouping and fitting procedures has produced the following learnings.

- Data grouping (composition of data) and curve fitting procedures adopted for the SRC model development will change the exponent and scaling coefficient of the SRC models.

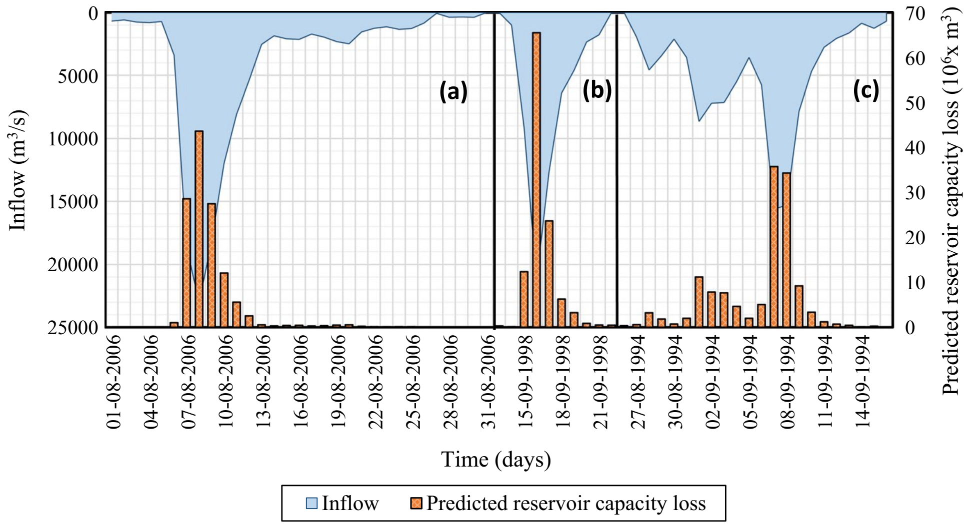

Fig. 14 Inflow and reservoir capacity loss. Three extreme events which occurred during 2006 (**a**), 1998 (**b**) and 1994 (**c**) are presented

- Degree of accuracy of the predicted load from low-frequency observations varies with the composition of the data in case of SRCs fitted by ordinary least square regression, whereas the effect of data composition to predict sediment load was observed to be low in the case of SRCs fitted by the proposed optimization approach.
- The percentage error observed between the entire period and yearly sediment load prediction demonstrated that the competence of the SRCs fitted by optimization to round the error associated with longer periods is high.
- Assessment of the relationship between the SRC coefficients has suggested that the SRCs fitted by optimization represent the flow and sediment transport regime in a better way.

Hence, if the sampling frequency is low and observations are made independent of the hydrograph (as instantaneous temporal point measurement), then the observed data can be utilized effectively by employing the fitting procedure based on optimization.

The approach developed in this paper provides a means to validate the estimate of reservoir-submerged sediment density obtained from the sampled sediment sand, silt and clay content and the empirical density predicting models. Statistical hypothesis testing (*P* value or *T* value) is required to be performed between the mean density estimated from sediment samples and the density obtained by equating sediment load prediction to the observed capacity loss. The result of the hypothesis tested should prove that both of these densities do not differ. If they differ, further investigation of the estimated density, as well as the hydrographic surveys, is required, before utilizing it to derive RCL.

Application of the developed relationship between the hydrographic and hydrometric observations to disintegrate the RCL on a daily scale will enhance the understanding of event-based capacity loss, which may stand as a useful approximation to devise a sediment management strategy.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding authors state that there is no conflict of interest.

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