Sedimentation in Reservoirs: Evaluation of Return Periods Related to Operational Failures of Water Supply Reservoirs with Monte Carlo Simulation

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Abstract: Sediment delivery to reservoirs causes a reduction in storage capacity, leading to emergency water conditions and difficulties in managing water resources and dams, especially on dry land. This paper presents a methodology for calculating the time period of sedimentation-induced operational failures of a water supply dam, based on the reservoir's daily water balance equation. The method applies a shot noise stochastic model to generate daily streamflow data calibrated with historical data, and accounts for sedimentation rates and the water volumes supplied to users. A Monte Carlo simulation was employed to generate different combinations of inflow and water supply release scenarios. The proposed methodology, which is completely generalizable, was applied in a case study of the Camastra reservoir in southern Italy. The results were in good agreement with the reservoir's historical operational data. **DOI: 10.1061/(ASCE)WR.1943-5452.0001307.** *© 2020 American Society of Civil Engineers.*

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Introduction

Dams are usually built to barricade rivers and create artificial reservoirs. The purposes of dam (water supply, hydropower generation, flood control) and reservoir operation can heavily affect river hydrology and flood frequency and, at the same time, influence solute and sediment transport in the regulated river (Molino et al. 2007; Tu et al. 2008; De Vincenzo et al. 2011; Pannone and De Vincenzo 2015; De Vincenzo et al. 2016; George et al. 2016; De Vincenzo et al. 2017). Most sediments transported by the flow settle into the reservoir, leading to a gradual reduction in water storage capacity and, in many cases, damaging water intake structures and reservoir outlets. In addition, the combination of sediment trapping and water regulation can modify the river morphology downstream of the reservoir, where bed degradation phenomena (Williams and Wolman 1984; Carling 1988; Brandt 2000; Stevens 2000; Grant et al. 2003; Molino et al. 2014) can affect the stability of fluvial engineering structures, the ecology of the regulated river (Ligon et al. 1995), and the river–coastline–sea sediment balance (Andredaki et al. 2014; Bergillos et al. 2016; De Vincenzo et al. 2018). The most common technique used for quantifying sedimentation in a reservoir is the bathymetric survey (Minear and Kondolf 2009). This knowledge is helpful in choosing measures for the rehabilitation of reservoirs and for prolonging their lifetime operation (Carone et al. 2006). A comparison between the most recent sequential surveys could provide useful indications of the sedimentation yield of the last few years and, consequently, of its future trend, assuming the watershed management, land use, and sediment control measures remain unchanged over time (Wu and Haith 1993; Molino et al. 2007; De Vincenzo et al. 2017, 2018; Covelli et al. 2020). Hydrological models are also available based on modeling the runoff and sediment supply from watersheds and their interactions, which are classified as empirical, conceptual, and distributed models (Wischmeier and Smith 1978; ASCE Task Committee on Quantifying Land-Use Change effects of the Watershed Management and Surface-Water Committees of Irrigation and Drainage Division 1985; Magar and Jothiprakash 2011). Moreover, analytical models have been proposed for the prediction of sedimentation in reservoirs (Patil and Shetkar 2016a, b).

According to ICOLD (2009), more than 0.5% of the world's total reservoir storage volume is lost annually as a result of upstream sedimentation. This process of reservoir storage capacity reduction is particularly concerning because the construction of new dams is becoming very uncommon for environmental, social, and economic reasons. Such a process could also have considerable impacts in dry regions, where all the negative implications could be exacerbated due to climate change (Abbaspour et al. 2009). In the related literature, the evaluation of water supply reservoir reliability has been approached by several authors, but the problem of storage capacity reduction due to sedimentation has been considered by very few. The storage–reliability–yield (SRY) relationship represents a tool that has traditionally been used for the estimation of the useful storage capacity required to deliver a specified quantity of water supply yield with a given level of reliability. Several works have been devoted to the SRY method, which can be divided into two types: (1) SRY methods in which the reservoir is fed by

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theoretical inflows, and (2) methods in which the reservoir is fed by recorded streamflow time series. In the first type, generalized SRY relationships are usually determined in graphical, tabular, or analytical form through Monte Carlo simulations using different stochastic models (Pegram 1980; McMahon and Mein 1978; Bayazit and Bulu 1991; Bayazit and Önöz 2000; McMahon and Adeloye 2005; McMahon et al. 2007b; Silva and Portela 2013). Concerning the second type, the reservoir system is simulated using recorded time series of streamflow (rather than using a stochastic model), and the SRY relationships are determined by multivariate regression (Adeloye et al. 2003; McMahon et al. 2007a, c; Adeloye 2009a, b). However, these models have several limitations: the SRY relationships of the first type are usually limited for use in over-year systems, in which the stochastic structure of annual streamflows is well approximated by the theoretical model of inflows assumed in the analysis. The second family of SRY relationships is usually limited to rivers with historical streamflow time series that possess similar statistics. In addition, SRY relationships are usually derived by employing annual or monthly streamflow series; sedimentation is not usually considered, and its application is more useful for design purposes. Araujo et al. (2006) attempted to consider the problem of storage capacity reduction in arid regions. In their paper, the behavior analysis (BA) of the reservoir—a simulation method widely used in this field (McMahon and Adeloye 2005)—was simulated by employing a continuity equation using synthetic streamflows, and reservoir reliability was determined by considering a loss of storage volume due to sedimentation. However, seasonal streamflows were considered, thus limiting the BA to a seasonal scale; fluctuations in municipal water release were not accounted for, and the sedimentation into the reservoir was not linked to the inflows. Bennett et al. (2013) assessed the storage capacity reduction of a flood-control reservoir due to sedimentation, but no estimation of the failures or reliability was performed. Wisser et al. (2013) used a dataset from a large-capacity reservoir to estimate storage capacity loss over time by employing several sedimentation models. In addition, their work computed the total reservoir storage and storage per person to assess the ability of the river basins to buffer changing conditions of water supply and demand with water storage.

Reservoir storage capacity reduction over time has unavoidable consequences on the beneficial uses of water supply, power generation, and flood control. Specifically, it could cause an increased frequency of water supply system failures, which are defined as situations in which the amount of water stored in a reservoir is not adequate to satisfy user demand. The prediction of water supply system failures and their return periods could be useful in sustainable management of existing reservoirs for future generations (Palmieri et al. 2003; Wang and Hu 2009); in addition, sedimentation and inflow rate forecasting methods represent an essential tool for engineers and management authorities.

The cited literature lacks studies in which the impact of sedimentation on reservoir capacity reduction over time and its influence on future failures of the water supply system are considered. Moreover, the concept of a return period associated with such situations has never been introduced.

A reservoir-water supply system operational failure is defined as the emptying of the reservoir below a minimum operational storage volume. This volume is the minimum reservoir capacity required to ensure proper functioning of water intake/outlet structures and good water quality in reservoirs affected by sedimentation. This work presents a new technique for the prediction of reservoir-water supply system operational failures. Moreover, a method capable of accounting for sediment deposition over time and fluctuations in municipal supply release was also used. The proposed methodology is based on a daily reservoir balance, in which different combinations of inflows and municipal water release scenarios are generated by a Monte Carlo simulation (Peres and Cancelliere 2016). In this study, a generalized shot noise model calibrated using the prediction-correction spectral and time-domain calibration (PCSTC) model proposed by Morlando et al. (2016) was used to generate a synthetic series of daily inflows to a reservoir. Finally, to estimate the accuracy of the proposed approach, the Camastra reservoir (Basilicata region, southern Italy) was used as a case study. An ample body of data are available on the Camastra reservoir's sediment volume, inflows, and user water releases (De Vincenzo and Molino 2013).

Materials

The methodology proposed herein is flexible and general and, to show its capability, a particular case study has been selected due to the availability of data. The case study as well as the available data are described in the present section. In particular, the return period was evaluated in accordance with the water deficit, taking into account sedimentation and fluctuations in municipal water release.

Study Area

The area under study is the Camastra basin, located in the Basilicata region in southeastern Italy. The Camastra watershed is an approximate leaf-shaped catchment bounded by hills with a surface area of 350 km^2. The Camastra River is a tributary of the main river of the Basilicata region, the Basento River. The location of the study area along with the Camastra watershed is shown in Fig. 1.

The dam was built between 1962 and 1967. The dam is 54-m high and has a reservoir storage volume of approximately $35.40 \cdot 10^6$ m^3. The initial dead volume is equal to $6.50 \cdot 10^6$ m^3, and thus the useful storage capacity is equal to $28.90 \cdot 10^6$ m^3. The reservoir is a multipurpose water resource, supplying municipal water to Potenza city and its environs, to Consorzio di Bonifica Bradano-Metaponto for irrigation, and to Matera city in the Basento Valley for industrial purposes.

Field Surveys and Average Annual Sedimentation Rates

Data were available from eight bathymetric surveys carried out over 25 years (a survey every 2 years, on average, between 1993 and 2005), which is quite a unique situation in the Italian context. From the available bathymetric data, it was possible to reconstruct the chronology of sediment delivery at the dam. In particular, an average annual sedimentation rate of 333,000 $m^3/year$ (Table 1; Fig. 2) occurred from 1967 to 1988. From 1988 to 1993, the annual average sedimentation increased to 1,390,000 $m^3/year$ due to superficial landslides confined to the right bank of the Camastra reservoir. The landslides were induced by several rapid reservoir drawdowns that occurred in the 1988–1990 period, when municipal water supply began. From 1993 to 1997, the annual average sedimentation rate gradually declined to its pre-landslide value, as the aforementioned landslides had stopped moving by 1993 (324,000 $m^3/year$). In the 1997–2017 period, the annual average sedimentation rate further declined to the current value of 87,000 $m^3/year$ because of the effectiveness of river training actions and soil conservation practices realized in the river network upstream of the Camastra reservoir (Molino et al. 2007).

The current sedimentation rate and the mean daily streamflows amounted to a total (water plus sediments) daily volume inflowing

Fig. 1. Camastra River basin.

Table 1. Temporal evolution of sedimentation in the Camastra reservoir (SC_0 = storage capacity)

Year	SC_0 (10^6 m^3)	W^{sed} (m^3)
1967	35.172	0
1988	28.712	7,001,000
1993	21.754	13,962,000
1995	20.776	14,942,000
1997	20.120	15,590,000
2005	19.421	16,289,000
2017	17.837	17,335,000

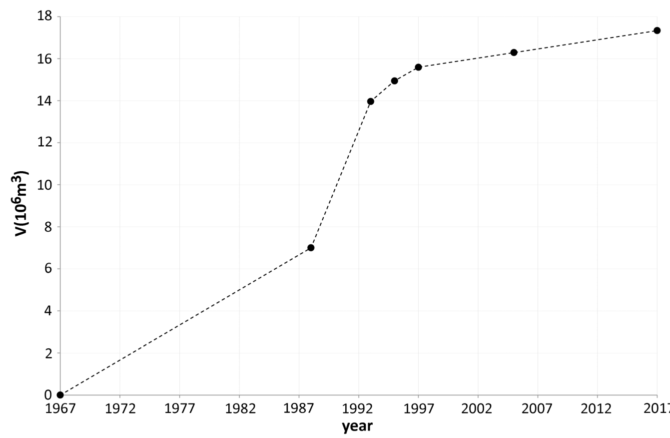

Fig. 2. Trend of bathymetric surveys in the Camastra reservoir.

to the dam of approximately 330,000 $m^3/year$ (obtained from the data), and the incidence of sediments was approximately $6.75 \cdot 10^{-4}$ m^3/m^3 (mean volumetric sedimentation rate). This estimate will be assumed in the following as a coefficient of proportionality between the daily volume inflow and sediment volume inflow at the dam. It was not possible to calibrate nonlinear models due to the lack of onsite turbidity data. Thus, a linear model for predicting daily sediment inflowing at the reservoir was assumed.

Historical Time Series of Daily Streamflow and User Release

A large quantity of reliable data, including more than 34 years of daily volume inflows and water supplied to different users, was available. The field data were provided by the Agency for Development of Irrigation and Land Transformation in Puglia, Lucania, and the Irpinia area (*Ente per lo Sviluppo dell'Irrigazione e la Trasformazione Fondiaria in Puglia, in Lucania e in Irpinia*). The daily inflow volumes were used to calibrate a stochastic model of the daily streamflow, while the water volumes provided to users were applied to build a stochastic model of the water release. Specifically, water supply release volumes varied according to the final category of use of the water resource (municipal, industrial, or irrigation). Moreover, the water course downstream of the dam requires a minimum ecological discharge E (Copertino et al. 1997), which was also taken into account in the present study. The demand time patterns, in terms of the daily water volume relative to irrigation users U^{irr} and industrial users U^{ind}, were constant over time, as were the time patterns relative to the daily volumes corresponding to the minimum ecological discharge E. Conversely, the data from the municipal water volume releases U^{mun} were not constant over time, and exhibited random fluctuations around seasonal average values. In addition, the time series of water losses (WL) due to overflows, releases, and infiltration were also reported and accounted for within the BA. The generation of the synthetic series of daily streamflow and output volumes is discussed in the next section.

Methods

Our methodology was based on a Monte Carlo simulation of equally likely scenarios of daily streamflows and municipal water releases. A BA of the reservoir system was performed with the solution of a water balance equation in which a synthetic series of streamflow and water supply releases represent the inputs and outputs. Sedimentation was accounted for through the mean volumetric sedimentation rate (see the "Field Surveys and Average Annual Sedimentation Rates" section), and it was proportional to the mean daily discharge. The synthetic streamflow series were generated by means of the stochastic model of Morlando et al. (2016), whose parameters were calibrated using historical flow data provided by the Reservoir Management Authority (see the "Field Surveys and Average Annual Sedimentation Rates" section). The historical data of different users, which were also provided by the Reservoir Management Authority (see the "Historical Time Series of Daily Streamflow and User Release" section), were used to generate the synthetic series of daily output volumes from the reservoir. The Monte Carlo simulation generates equally likely future scenarios and serves to extend the historical data.

Minimum Operational Storage Volume and Failure Conditions

Sedimentation into reservoirs can change the topography of the impounded area and the elevation–storage relationship, compromising the functioning of the water intake and outlet structure. As a consequence, the water supply system operator may need to adopt new management criteria for the minimum water operational volume requested by setting a minimum head needed to avoid air entrainment (to ensure good intake/outlet hydraulic functioning). In the presence of thermal stratification (Elçi 2008; Lu and Li 2014), the operator may need to withdraw water outside the anoxic zone (thermocline), especially for municipal use. This minimum volume ($W_{\min}$) (see the "Procedure for Return Period Estimation" section) can be established on the basis of the reservoir characteristics and specific operational needs.

Stochastic Model for Daily Streamflow Generation

To estimate the return period associated with reservoir operational failures as defined in the previous section, a stochastic model for daily streamflow generation is needed. In this study, the generalized shot noise (GSN) model calibrated using the PCSTC method by Morlando et al. (2016) was used. Here, the main steps of the PCSTC are briefly recalled; a more detailed description of its mathematical properties can be found in Morlando et al. (2016). The PCSTC is essentially a methodology for the calibration of a GSN model. The calibration of the GSN model requires identification of two model components: (1) the cumulative probability distribution of the input (physically interpreted with the rainfall probability), and (2) a transfer function model (physically interpreted as a runoff/infiltration model). It is worth noting that the cumulative distribution function (CDF) of the input does not represent the actual rainfall intensity CDF, but it is a distribution of the input that respects the hypothesis of the GSN model (see Morlando et al. 2016 for more details).

The model input (first component of GSN) was treated as an impulse train as follows:

$$z(t) = \sum_i c_i \delta(t - \tau_i) \tag{1}$$

where $z(t)$ = cumulative rainfall at time t; $\delta(\cdot)$ = Dirac's delta function; τ_i = Poisson process with density λ; and c_i = sequence of mutually independent and identically distributed random variables, with mean η_c and variance σ_c^2. In addition, c_i and τ_i are independent. Under the assumption that the effective precipitation during a single storm is distributed exponentially, the CDF of the daily effective rainfall z_d is given by the following equation:

$$F(z_d) = e^{-\lambda\Delta t}\left[1 + \sum_{\nu=1}^{\infty} \frac{(\lambda\Delta t)^\nu}{\nu!} P\left(\nu, \frac{z_d}{\eta_c}\right)\right] \tag{2}$$

where $\Delta t = 1$ day; and $P(\nu, z_d/\eta_c)$ = Pearson's incomplete gamma function. The expected value and the variance of the CDF in Eq. (2) are $\eta_{z_d} = \lambda\eta_c\Delta t$ and $\sigma_{z_d}^2 = 2\eta_{z_d}^2/(\lambda\Delta t)$, respectively.

To model the physical behavior of the watershed, the following transfer function $h(t)$ is considered as the second component of the GSN model, as follows:

$$h(t) = \begin{cases} t \geq 0, & \alpha_0\delta(t) + \frac{\alpha_1}{k_1} e^{-\frac{t}{k_1}} + \frac{\alpha_2}{k_2} e^{-\frac{t}{k_2}} \\ t < 0, & 0 \end{cases} \tag{3}$$

In Eq. (3), the delta function represents the surface runoff component, which is the portion of the effective rainfall that reaches the watershed outlet within a time interval smaller than the data aggregation interval (1 day). However, the two exponential functions were used to model the responses of two parallel linear reservoirs, with the lag times of k_1 and k_2 representing the daily and the monthly contributions, respectively. The coefficients α_0, α_1, and α_2 are the partition coefficients that weight the input among the parallel components. With the watershed being treated as a linear system, its response is given by the convolution integral between Eqs. (1) and (3), as follows:

$$q(t) = h(t) \times z(t) = \sum_i c_i h(t - \tau_i) \tag{4}$$

However, because the data aggregation time scale is 1 day, the input was modeled as a train of rectangular pulses $\{z_{d_k}\}$ of intensity equal to the daily rainfall, with the CDF given by Eq. (2). Then, the average value of the output daily discharge q_l was given by the following equation:

$$q_l = \sum_k z_{d_k} h_{k,l} \tag{5}$$

where $h_{k,l}$ = rectangular response of the watershed averaged over the lth time interval, whose expression is reported in Morlando et al. (2016).

The main steps of the PCSTC can now be summarized as follows:

- The parameters k_1 and k_2 in Eq. (3) were obtained by fitting the analytical power spectral density (PSD) relative to the theoretical model in Eq. (3) to the PSD estimate of the daily streamflow experimental data. During this step, a first estimate of α_0, α_1, and α_2 was also obtained.
- The rectangular pulses $\{z_{d_k}\}$ and the values of α_0, α_1, and α_2 were adjusted by fitting Eq. (5) to the observed daily streamflow data.
- Based on the knowledge of $\{z_{d_k}\}$, the average value of η_{z_d} and the variance $\sigma_{z_d}^2$ of the daily rainfall (parameters of the input CDF) were estimated for each month.

The PCSTC was calibrated with the data described in the "Field Surveys and Average Annual Sedimentation Rates" section, and the parameters of the probability distribution of the input and the transfer function are reported in Tables 2 and 3, respectively.

Table 2. Calibrated parameters of the watershed transfer function

α_0	α_1	α_2	k_1 (days)	k_2 (days)
0.201	0.799	—	38.431	33.720

Note: α_0, α_1 and α_2 = partition coefficients; k_1 and k_2 = characteristic linear reservoirs times.

Table 3. Calibrated parameters of the cumulative distribution function

Month	λ	η_c
1	0.0707	93.8420
2	0.1195	83.5171
3	0.1625	61.0562
4	0.0949	62.9453
5	0.0223	78.7795
6	0.0013	40.1870
7	0.0000	0.0000
8	0.0000	0.0000
9	0.0000	0.0000
10	0.0037	89.9786
11	0.0321	121.4535
12	0.0658	101.5331

Note: λ = density of the Poisson process, Eq. (2); and η_c = mean of the Poisson process, Eq. (2).

As shown in Table 2, the original hypothesized transfer function was reduced to only one surface runoff component and one reservoir. To assess the model, 1,000 years of synthetic daily rainfall series were generated using the CDF of Eq. (2), then the daily streamflow was generated using Eq. (5). The monthly comparisons of the first two statistical moments are provided in Fig. 3.

By inspection of Fig. 3, it is clear that the proposed stochastic model was able to capture the first two statistical moments of the observed data. The maximum differences occurred during February, March, and December, but they were consistent with the observed data because the maximum variability of the daily streamflow occurred during these three months. The *1*-standard deviation band, which attained its maximum width during the aforementioned months, also confirmed this outcome. Regardless, the statistics of the observed data fell within the *1*-standard deviation band in all months, except for the first-order moment of the observed data in July. This outcome occurred because, in that month, the observed series exhibited very low daily streamflow values.

Finally, the model performance is evaluated using the two indices (Morlando et al. 2016), that is, the model adequacy index I_1 as follows:

$$I_1 = 1 - \frac{s^2}{\sigma^2} \tag{6}$$

and the index I_2, which was introduced to test the correct reproduction of the annual maximum (AM) statistics of the recorded series—i.e., those discharges corresponding to the lowest frequencies in the flow duration curve were as follows:

$$I_2 = 1 - \frac{s_{AM}^2}{\sigma_{AM}^2} \tag{7}$$

In Eqs. (6) and (7), s = mean squared distance between the empirical frequency curve of the observed data and the corresponding curve for the generated discharges; σ^2 = variance of the observed data; s_{AM} = mean squared distance between the observed AM discharges and the generated AM discharges; and while σ_{AM}^2 = variance of the observed AM sample.

The obtained values for I_1 and I_2 were 0.92 and 0.87, respectively. The high values obtained for the two indices showed that the proposed model performed well in reproducing the time series of daily streamflows.

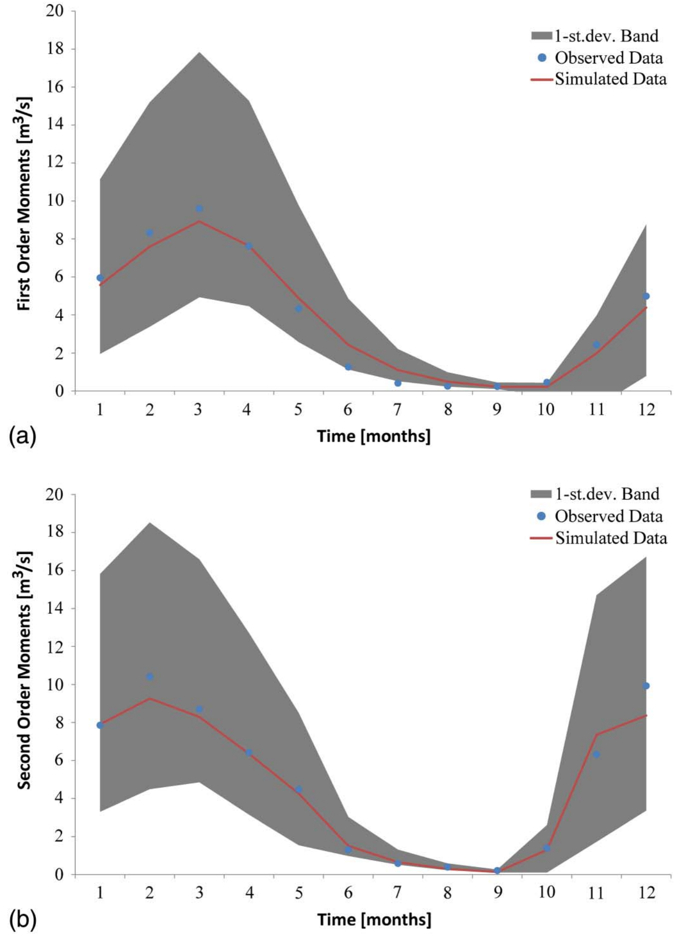

Fig. 3. Comparisons between: (a) first-order; and (b) second-order monthly statistical moments of observed and synthetic data.

Synthetic Series Generation of Daily Output Volumes

The daily output volumes were composed of the user release volumes U_i (municipal, industrial, and irrigation uses), the daily volume relative to the ecological discharge E, and daily volumes due to water losses WL_i. As already described in the "Historical Time Series of Daily Streamflow and User Releases" section, U_{ind} and U_{irr} vary on a monthly basis, while E is constant (see Table 4).

The time series of the municipal water release exhibited no trend, but it had seasonal variations. To work with a stationary time series, the original series U^{mun} was transformed as $Z = (U^{mun} - \mu_j)/\sigma_j$, where μ_j and σ_j are the seasonal mean and standard deviation of U^{mun} (Table 5), with the assumption of 12 seasonal intervals (one for each month).

The correlogram of the transformed time series (i.e., the autocorrelation function for all possible lags) showed no time correlation and a random dominant component (Fig. 4).

We assumed that the transformed series Z was distributed according to a normal CDF with zero mean and unitary standard deviation, which is written as follows:

$$F(y) = \frac{1}{2} + \frac{1}{2} erf\left[\frac{Z}{\sqrt{2}}\right] \tag{8}$$

where $erf(\cdot)$ = error function.

Table 4. Daily values of U^{ind} (industrial demand), U^{irr} (irrigation demand), and E (ecological flow) considered for the synthetic series generation model

Month	U^{ind} (m^3/s)	U^{irr} (m^3/s)	E (m^3/s)
1	0.000	0.000	0.010
2	0.000	0.000	0.010
3	0.000	0.000	0.010
4	0.000	0.000	0.010
5	0.052	0.018	0.010
6	0.037	0.040	0.010
7	0.049	0.087	0.010
8	0.036	0.075	0.010
9	0.031	0.057	0.010
10	0.021	0.003	0.010
11	0.012	0.000	0.010
12	0.000	0.000	0.010

Table 5. Estimated seasonal statistics of municipal demand time series, Eq. (8)

Month	μ_j	σ_j
1	0.392	0.162
2	0.346	0.162
3	0.294	0.145
4	0.227	0.109
5	0.225	0.098
6	0.262	0.117
7	0.355	0.122
8	0.437	0.123
9	0.472	0.116
10	0.478	0.110
11	0.491	0.115
12	0.470	0.142

Note: (μ_j = monthly mean; and σ_j = monthly standard deviation.

The hypothesis of a normal distribution was verified using the Kolmogorov–Smirnov test, which elicited a K–S statistic of 0.0134 and a critical value corresponding to 0.0156 at the 5% significance level.

To obtain more realistic output volumes, the total daily water loss from the reservoir was considered. This last component was evaluated based on the daily time series provided by the managing authority. It comprised all water losses due to overflows, infiltration, and releases due to the flooding alert system. Actually, the BA model can account for overflows from spillways [see Eq. (9) and the associated overflow condition], whereas it was difficult to introduce a specific mathematical condition accounting for the emergency releases from bottom outlets because historical operating rules and any deviations from those rules were not available. To simplify the approach, we have assumed that water losses due to infiltration and bottom releases WL_i were spread throughout the year as a constant daily value of 6,000 m^3, which was obtained by simply averaging the daily water losses from 1984 to 2017, without including the overflows from emergency spillways, which were already accounted for by the balance Eq. (9).

Finally, the generation of synthetic series of a daily output volume is conducted by generating N_y years of U^{mun} and summing, day by day, the generated series of U^{drink} with the corresponding daily values of U^{ind}, U^{irr}, WL_i, and E_i.

Procedure for Return Period Estimation

This section describes the proposed methodology for the estimation of the return period related to the operational failures of reservoir-water supply systems due to sedimentation. It was based on the reservoir daily water volume balance between the water inflow volumes (daily streamflows at the dam), water release volumes (for municipal, industrial and irrigation uses), ecological discharge volumes E, and water losses. The daily inflows to the dam were

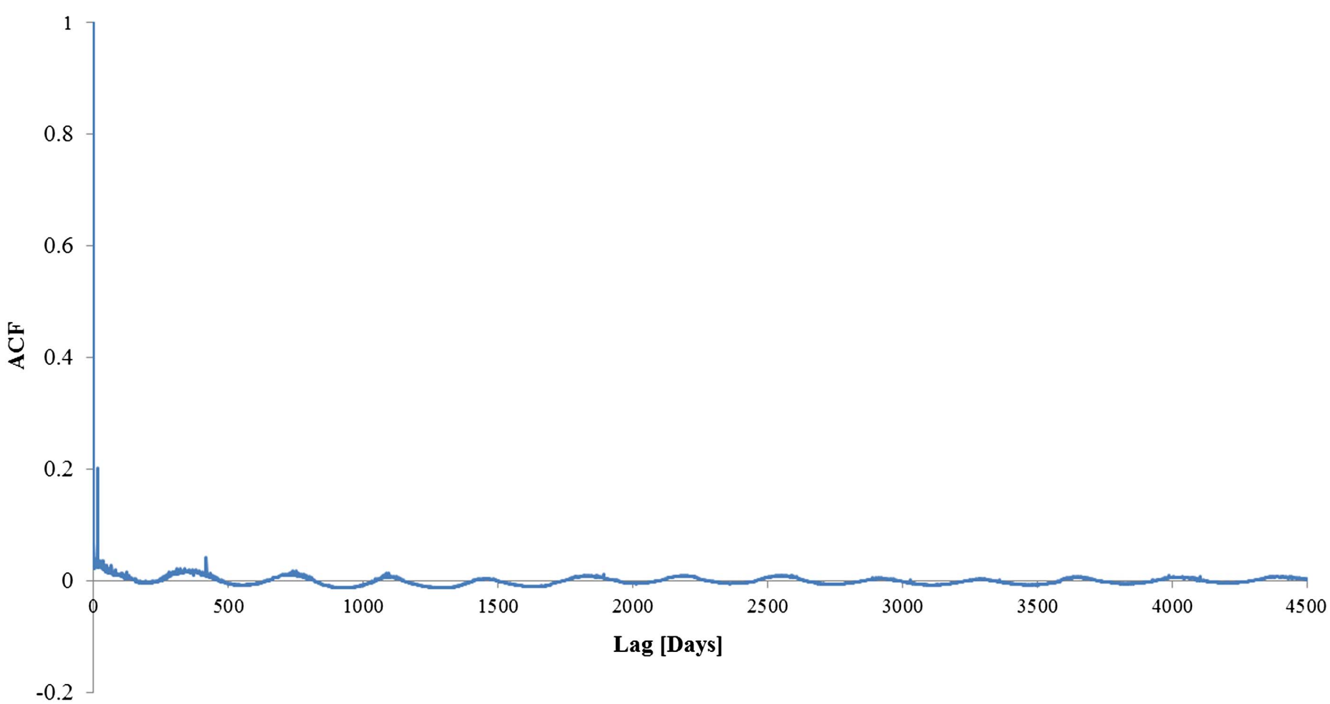

Fig. 4. Users release autocorrelation function (ACF) for all lags (correlogram).

generated by a shot noise model calibrated on historical data; water demand volumes for irrigation, industrial, and ecological needs were obtained from historical data. The methodology also took into account sedimentation through a mean volumetric sedimentation rate calibrated from bathymetric data. It expressed a linear proportionality between the water and sediment daily inflow volumes at the dam, which made it possible to estimate the evolution of the useful reservoir capacity over time. The proposed methodology consists of a Monte Carlo simulation in which different streamflow and user release scenarios are generated (using the methods described in the sections, "Stochastic Model for Daily Streamflow Generation" and "Synthetic Series Generation of Daily Output Volumes", respectively) and used as inputs to simulate the system with the following volume balance equations:

$$\begin{aligned} &W_i = W_{i-1} + I_i^* - O_i && \text{if } W_i <= SC_i \\ &W_i = SC_i && \text{if } W_i > SC_i \end{aligned} \tag{9}$$

where W_i and W_{i-1} = water volume in the reservoir at the ith and $(i-1)$th time intervals, respectively; $O_i = U_i^{mun} + U_i^{ind} + U_i^{irr} + E_i + WL_i$ = output volume from the reservoir at the ith time interval; and $I_i^* = I_i - W_i^{sed} = (1-\xi)I_i$ = net inflow volume at the ith time interval given by the water inflow volume I_i and the sediment inflow volume $W_i^{sed} = \xi I_i$ at the ith time interval. In particular, the inflow volume I_i is computed as the ith value of the daily streamflow (generated with the method described in the section, "Stochastic Model for Daily Streamflow Generation") times the number of seconds in a day; $\xi = 0.000675\ \mathrm{m^3/m^3}$ (see the "Field Surveys and Average Annual Sedimentation Rates" section); and SC_i = maximum storage capacity at the ith time interval, and it is evaluated as follows:

$$SC_i = SC_0 - \sum_{j=1}^{i} W_j^{sed} \tag{10}$$

where SC_0 = maximum storage capacity at the beginning of the simulation.

Note that in Eq. (9), the occurrence of a daily water volume W_i higher than the maximum storage capacity SC_i represents the condition of overflows from the spillways.

Then, the proposed methodology can be summarized in the following steps:

1. Assign a number of scenarios Ns, each of which has a length of N_y years. Then, set $s = 1$.
2. Generate N_y years of daily streamflows and daily supply releases.
3. Solve Eq. (9). If $W_i \le W_{\min}$ occurs during the solution of Eq. (9), set the number of years to failure $(TF)_s$ of the sth scenario, which is equal to $(TF)_s = ceiling(i/365)$, where $ceiling(\cdot)$ is the round-up function (Iverson 1962). The mathematical condition expressed by Eq. (9) corresponds to the operational failure of the reservoir water supply system, that is, the emptying of the reservoir storage volume below the minimum operational storage volume $W_{\min}$.
4. Set $s = s + 1$ and repeat from step 2 until $s = N_s$.
5. Set the return period T_{TF_s} associated with the emptying of the initial useful storage capacity equal to the following mean value:

$$T_{TF_s} = ceiling\left(\frac{1}{N_s}\sum_{s=1}^{N_s} TF_s\right) \tag{11}$$

The above-described procedure is summarized in the flow chart in Fig. 5.

The estimation of the return period related to the emptying of the useful storage volume is a very important parameter because it helps to define the intervention policies for the optimal management of the reservoir and its deposited sediments, considering that currently the lifespan of existing reservoirs needs to be much greater than that hypothesized in their original design.

The methodology is adaptable to different contexts and is modifiable in the presence of specific requirements. First, it permits us to define the minimum operational storage volume that ensures proper functioning of the water intake/outlet structures on the basis of the specific features of dams and their operational current and future requirements. Second, it may change the amount of water demand, which could remain unaltered or could be modified in the future on the basis of users' needs and political decisions.

Moreover, the proposed methodology takes into account current and future sedimentation, which will further reduce the useful capacity of the reservoir according to the incoming flow rates, thus affecting the capacity to meet water demand.

The model is also adaptable to modifications in inflows if the influence of climate change on water availability is highlighted. Depending on the area under study and the availability of data, the hydrological approach to the prediction of inflows could also be modified. The model approach would still be valid.

The proposed method also makes it possible to test the effectiveness of removal of a given volume of sediment from the reservoir bottom in terms of increasing the return period of the system operation. For this purpose, it is sufficient to modify the current useful capacity according to the recovery of capacity derived from the programmed sediment removal.

Results

In this work, a linear proportionality was assumed between the daily inflow volumes and the inflow sediment volume at the dam. The coefficient of proportionality ($6.75 \times 10^{-4}\ \mathrm{m^3/m^3}$) was calibrated based on bathymetric data of the last period (1997–2017). Currently, the yearly average sediment volume inflow at the dam was equal to $87{,}000\ \mathrm{m^3/year}$, and the results of numerical simulations seemed to confirm the validity of the adopted linear model. In fact, the calculated yearly sediment volumes ranged between a minimum of 40,000 $\mathrm{m^3}$ and a maximum of 120,000 $\mathrm{m^3}$, with an average of 81,254 $\mathrm{m^3}$, making them very similar to the current average yearly sediment yield volume.

For the application of the proposed methodology to the case of the Camastra dam, simulations were performed for a minimum operational storage volume $W_{\min}$ of $8{,}168{,}848\ \mathrm{m^3}$. In fact, in the specific case study, the first two (starting from bottom) water intakes were obstructed by sediments. According to the managing authority of the Camastra reservoir, to ensure good functioning of the third water intake, the minimum water elevation within the reservoir should be 515.91 m above sea level (a.s.l.), which corresponds to $W_{\min} = 5{,}532{,}690.3\ \mathrm{m^3}$; however, water quality problems occurred at this water elevation. Indeed, from the field observations obtained in September 2011 (after a very warm and dry summer), anoxic conditions occurred when the reservoir water level was 517.93 m a.s.l. and the corresponding storage volume was $7{,}204{,}885\ \mathrm{m^3}$, as highlighted by the results of the chemical analysis performed during the treatment process of water for municipal supply. For this reason, the reservoir operator decided to set the minimum water operational level at 519.0 m a.s.l. (far enough from the anoxic condition zone), and the $W_{\min}$ corresponding to this elevation was approximately $8{,}168{,}848\ \mathrm{m^3}$.

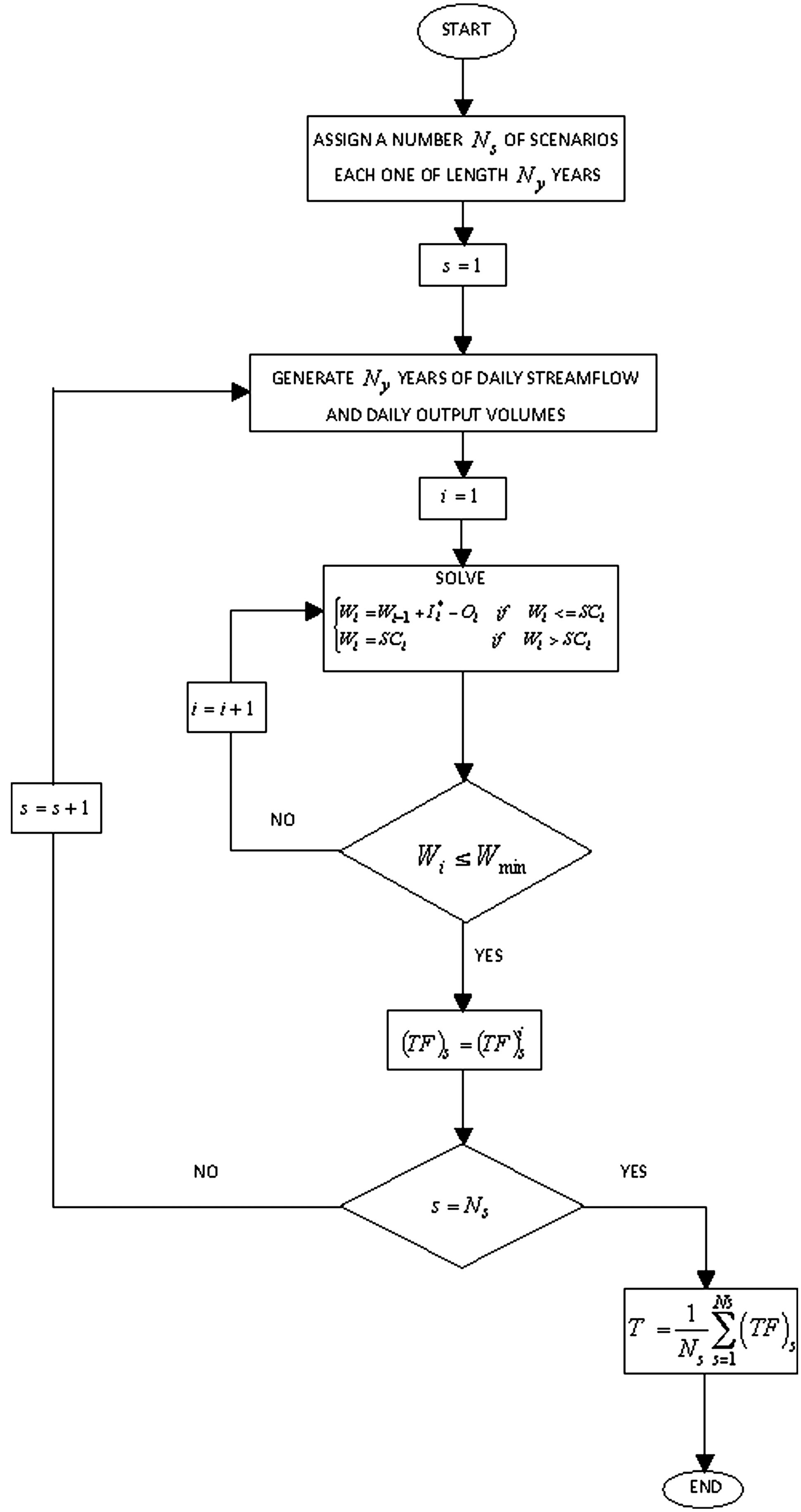

Fig. 5. Flow chart of proposed methodology.

The results of the simulations, with $N_s = 1{,}000$ (1,000 different initial seeds per 100 years of streamflows), are reported in Table 6 in terms of occurrences and frequencies of the TF_s obtained by the application of the methodology described in the section, "Procedure for Return Period Estimation of the Camastra basin."

The return period associated with the emptying of useful volume as, by definition, the mean value of the TF_s and its value was $T_{TF_s} = 3$ years (with actual mean value 2.1), while the estimated standard deviation of TF_s was 1.35 years.

In addition, the obtained value of the return period was consistent with the results obtained by Peres and Cancelliere (2016) for landslide triggering. They demonstrated that the use of simplified approaches may lead to an overestimation of the return period. Indeed, De Vincenzo and Molino (2013) obtained an estimated time to failure of 10 years using a deterministic approach in which the worst conditions in terms of municipal water release and daily streamflows were hypothesized. The result obtained by the proposed model was also confirmed by experimental data. In fact, between 1984 and 2011, the water level within the Camastra reservoir fell below 519.0 m a.s.l. 11 times (Table 7), with an average time to failure of 3 years.

To see how the return period behaves with different values of $W_{\min}$, the presented methodology was also applied with $W_{\min} = 7{,}204{,}885$ and $5{,}532{,}690.3\ \mathrm{m}^3$ (corresponding to the water levels of 517.93 and 515.91 m a.s.l., respectively), and $W_{\min} = 4{,}907{,}554\ \mathrm{m}^3$ (515 m a.s.l.). This last value can be considered under the hypothesis that approximately 600.000 m^3 of sediments would be removed from the specific sites affected by strong sedimentation, such as bottom outlets and water intake structures, with a more efficient functioning of reservoir manufacturers and a removal of anoxic conditions.

For comparison purposes, computations were also performed for a case where no sedimentation was considered. The results are summarized in Table 6, and in Fig. 6, the comparison among the observed and estimated return periods is depicted.

From inspection of Fig. 6, it is clear that T decreased as $W_{\min}$ increased, with a steep decrease between 515.91 and 517.93 m a.s.l. In Table 6, the obtained T values were compared with those observed. From the data registered between 1984 and 2017, the water levels within the reservoir decreased 6 times below 515.00 m a.s.l., 8 times below 515.91 m a.s.l., and 10 times below 517.93 m a.s.l. (Table 7). The results reported in Table 6 for the observed data were computed using Eq. (11). As seen from the comparison in Table 6, the proposed method can provide a good estimate of the return period.

Table 6. Simulated versus observed return periods T

$W_{\min}$	Estimated T (with sedimentation)	Observed T	Estimated T (no sedimentation)
8,168,848	3 (2.1)	3 (2.7)	4 (3.6)
7,204,885	3 (2.9)	3 (3.0)	5 (4.2)
5,532,690	6 (5.4)	4 (3.8)	12 (11.7)
4,907,554	6 (5.8)	6 (5.7)	15 (4.5)

Note: Values within brackets are pure average.

Table 7. Years of observed failures

Water level (m a.s.l.)	Corresponding $W_{\min}$ (m^3)	Years of failure occurrence
515.00	4,907,554.00	1984, 1985, 1988, 1989, 1990, 1993, 1994, 2001, 2002, 2008, 2011
515.91	5,532,690.30	1984, 1985, 1988, 1989, 1990, 1994, 2001, 2002, 2008, 2011
517.93	7,204,885.00	1984, 1985, 1988, 1990, 1994, 2001, 2002, 2011
519.00	8,168,848.00	1984, 1985, 1988, 1994, 2001, 2011

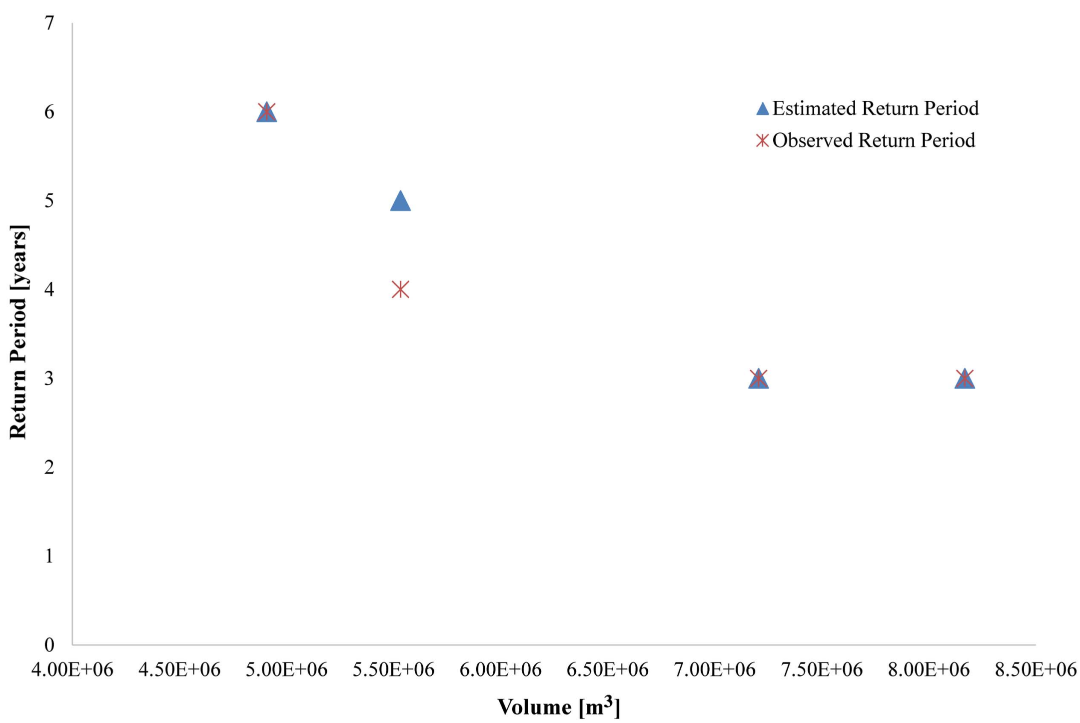

Fig. 6. Comparisons between estimated and observed return periods.

When no sediments were accounted for (Table 6), the estimated return periods were larger than those where sediments were considered as expected. In addition, the lower the volume threshold was, the greater the difference between the estimated T with and without the sediments. Indeed, the minimum level (519.0 m a.s.l.) during the study period was quite high, and was the result of several years of sedimentation with no management intervention aimed at preserving the initial useful storage volume. As a result, two of the three water intakes were completely obstructed by sediments, and anoxic conditions occurred at 517.93 m a.s.l. With such a high minimum level, the return period was mostly influenced by the yearly pattern of daily streamflow, as confirmed by the difference of just 1 and 2 years, for the levels 519.0 and 517.93 m, respectively (Table 6), between the return periods computed with and without sedimentation. The influence of sedimentation on the return period grew as the minimum operational level decreased. Indeed, when the minimum operational levels of 519.91 and 515 m a.s.l. were considered, the return periods estimated without considering sedimentation were more than twice as large as those estimated considering sedimentation.

The frequency distributions of the computed TF_s with and without sediments are depicted in Fig. 7, and are compared with the exponential distributions for the case $W_{\min} = 5{,}532{,}690$ (corresponding to a water level of 515.91 m). In particular, the exponential distribution parameters were estimated as the respective mean values of TF_s (i.e., 5.4 and 11.5). Similar results were obtained for the distribution of TF_s in the other cases.

Discussion

The study presented in this paper differs in several aspects from those found in the scientific literature. First, the concept of a return period relative to the emptying of the useful storage capacity has been introduced. In most of the studies available from the scientific literature, the concept of reliability associated with the delivery of a certain volume of water to the users is employed. Such a concept is more useful for design purposes rather than for management of existing reservoirs. Indeed, the reliability concept has typically been employed by various authors by identifying the probability of delivering a certain quantity of volume to the users for a given storage volume, while the method shown in this paper identifies the average number of years before a system failure would occur for a given storage capacity. This outcome is more helpful to management because it allows managing authorities to schedule their interventions based on the estimation of the mean time to failure (such as dredging, reservoir flushing, etc.). From Table 6, it is clear that the proposed method was able to estimate reasonably well the mean time between two emptyings of an assigned useful volume. The only overestimation occurred for the water level 515.91 m a.s.l. (6 versus 4 years); however, this outcome was still acceptable from a practical point of view because the number of observations was not large enough, and the observed and estimated return periods were quite small. In addition, the return periods have been estimated without sediment delivery, leading to an overestimation of T, with a difference that increased as the threshold volume decreased. Indeed, from the obtained results (Table 6), removing 600.000 m^3 of sediments from the reservoir would help to increase the return period from 3 to 6 years. Removal of larger sediment volumes would allow us to consistently reduce the frequency of anoxic conditions and, thus, to plan a more effective management of the reservoir and its manufacturers.

Interestingly, the simulated TF_s were described by an exponential distribution regardless of whether silting up was accounted for (Fig. 7). This result was consistent with the meaning of the return period and gives further validity to the proposed method. Indeed, exponential distributions are usually adopted to describe the time between two events, and in this specific case, it described the time between two failures.

Finally, the proposed method simulated the BA of the system on a daily scale. This is another important feature, because if the BA were performed on a monthly or seasonal scale, many system failures might have been not captured—for example, when the inflow is equal to the user requests during a month, but most user requests occur at the beginning of the month, while the inflow is available at the end. This effect would be enhanced if the user requests were considered constant and not modeled through a stochastic model.

Regarding the limitations of the proposed method, it requires a large body of field data for implementation, including data on daily streamflow, daily user requests, bathymetric measurements, and others. Currently, most of the data used in this study were usually available to the dam operator, with the possible exception of bathymetric surveys. The model used in this study to simulate sedimentation was rather simple. Although the results obtained were quite reliable, the actual sediment inflow rate should be a nonlinear function of the streamflow, but the calibration of such a model would

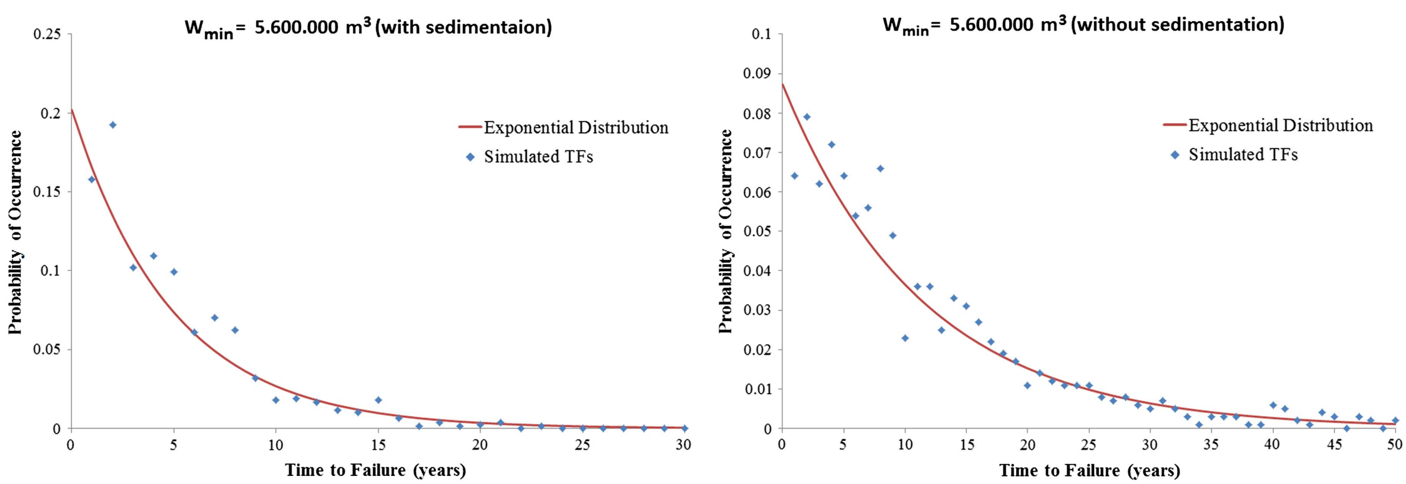

Fig. 7. Simulated TF_s statistics.

require an expensive campaign of measurements. Finally, the management rules about water releases from the dam's bottom outlet were not provided by the operator, because such releases occur due to various types of emergencies and are not easy to predict. Nevertheless, if the dam operator has defined management rules, they can be easily incorporated within the proposed procedure, leading to more realistic simulations.

Conclusions

Currently, the possibility of exploiting the storage capacity of reservoirs is more important than in past years, mainly due to the potential for drought periods that cause water shortages. Moreover, there are very few sites suitable for the large water volume needed to satisfy different user requests (e.g., irrigation, industrial, civil, hydroelectric), with catchment erosion and subsequent sedimentation significantly reducing their storage capacity and functionality. For this reason, to sustain the lifespans of reservoirs, it is essential to evaluate and manage reservoir sedimentation. In the present study, a methodology was used to calculate the return period of the sedimentation-induced operational failures of a reservoir-water supply system. Such methodology is a useful decision-making tool because it helps to define intervention policies for the optimal management of the reservoir and its deposited sediments. Unlike other works presented in the scientific literature, this method introduces the new idea of operational failures, which are defined as the emptying of the reservoir below the minimum operational storage volume required to ensure proper functioning of the water intake/outlet structures and a good quality of water. In addition, the proposed methodology is based on Monte Carlo simulation of equally likely scenarios of daily inflows and user releases, and estimates the time evolution of reservoir useful capacity through a mean volumetric sedimentation rate. It also allows the dam operator to estimate the minimum volume of sediment to be removed for an increase up to a given value of the return period of the system's operational failures.

The procedure was applied to a case study of the Camastra reservoir. The simulations of the reservoir showed a value of the return period associated with emptying the useful volume that was equal to $T = 3$ years. This outcome is consistent with the observed mean values of the times to failure that occurred during the last 34 years. Under the hypothesis that approximately 600.000 m^3 of sediments were removed from bottom outlets and water intake structures, the return period of the failures would increase from 3 to 6 years.

The application of the methodology—which is adaptable and modifiable in the presence of specific requirements—to reservoirs with different characteristics and problems would contribute to overcoming the limits of the proposed model, especially those related to the streamflows-sediment inflows linear relationship.

Data Availability Statement

The data about the case of study, the computer codes, and Excel™ files that support the findings of this study are available from the corresponding author upon reasonable request by email.

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