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José-Luis Molina

jlmolina@usal.es

Universidad de Salamanca

Maria Carmen Molina

Universidad de Sevilla

Carmen Patino-Alonso

Universidad de Salamanca

Fernando Espejo

Universidad de Salamanca

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Bayesian Bed-Load Transportation modelling (BBLT) method: a novel predictive approach to quantifying and managing bed load transportation and reservoir sedimentation.

J. L. Molina^{1*}, M. C. Molina², C. Patino-Alonso³, and F. Espejo⁴

¹ IGA Research Group, Hydraulic Engineering Area, High Polytechnic School of Engineering of Ávila, University of Salamanca, Av. de los Hornos Caleros 50, 05003 Ávila, Spain. E-mail: jlmolina@usal.es

² IGA Research Group, Department of Aerospace Engineering and Fluid Mechanics, High Technical School of Engineering, University of Sevilla, Camino Descubrimientos, s/n- Isla Cartuja, 41092 Sevilla, Spain. E-mail: mmolina11@us.es

³ IGA Research Group, Department of Statistics, University of Salamanca, Campus Miguel de Unamuno, C/ Alfonso X El Sabio s/n, 37007 Salamanca, Spain. E-mail: carpatino@usal.es

⁴ IGA Research Group, Hydraulic Engineering Area, High Polytechnic School of Engineering of Ávila, University of Salamanca, Av. de los Hornos Caleros 50, 05003 Ávila, Spain. E-mail: espejo@usal.es

*Corresponding author: jlmolina@usal.es

Abstract

Bed-load transport and reservoir sedimentation constitute major sources of uncertainty in fluvial hydraulics and reservoir management largely due to the nonlinear relationship between hydraulic forcing conditions and sediment transport generation. This study develops a Bayesian probabilistic framework for predictive sediment transport and reservoir sedimentation assessment under variable hydraulic conditions within the Rules Reservoir catchment (Granada, SE Spain). The proposed methodology integrates Meyer-Peter and Müller (MPM)-type transport formulations with probabilistic dependency structures linking liquid discharge, instantaneous sediment transport, cumulative bed-load transport, and reservoir sedimentation response.

Observed liquid-discharge temporal series were incorporated as the principal hydraulic predictor within the Bayesian Bed-Load Transport (BBLT) framework. The obtained logarithmic relationship between liquid discharge and instantaneous sediment transport confirmed the strong nonlinear dependency between hydraulic forcing and sediment transport generation under natural flow conditions. The obtained results revealed that high-flow scenarios substantially increased sediment transport intensity and reservoir sedimentation response. Under maximum hydraulic forcing conditions ($Q_L = 20\text{--}35 \text{ m}^3/\text{s}$), instantaneous sediment transport became concentrated within the highest transport interval ($0.08\text{--}0.1 \text{ kg/s}$), while estimated reservoir sedimentation volumes shifted toward the upper intervals between 13 and 15 Mm^3 . In contrast, low-flow conditions ($Q_L = 0\text{--}1 \text{ m}^3/\text{s}$) generated limited sediment transport activation and reduced sedimentation response.

The implemented framework enabled uncertainty-aware propagation of hydraulic variability throughout the complete sediment transport chain, supporting probabilistic scenario simulation and reservoir sedimentation assessment under variable hydrological conditions. The proposed methodology therefore provides a physically interpretable and operationally applicable approach for uncertainty-aware sediment-management strategies, reservoir sedimentation assessment, and predictive support for reservoir management in Mediterranean mountain catchments and comparable fluvial systems.

Keywords: BBLT method, Bayesian modeling; reservoir management; bed-load

transport; reservoir sedimentation; uncertainty modelling.

1. Introduction

Bed-load and bed-material sediment transport exert a first-order control on the morphodynamic evolution of gravel- and sand-bed rivers. Yet, despite more than a century of theoretical, experimental, and field-based research, predicting bed-load transport remains one of the most uncertain components of fluvial hydraulics. This uncertainty arises from the nonlinear interaction between turbulent flow, bed resistance, grain-size distribution, sediment supply, hiding and exposure effects, bed forms, and the intermittent character of particle motion under natural flow conditions.

The problem is particularly relevant in regulated rivers and reservoirs, where sediment continuity is interrupted and uncertainty in sediment inflow, transport capacity, and deposition patterns directly affects active storage, hydropower production, flood-control performance, and downstream sediment deficits. Reliable reservoir sedimentation assessment requires coupling catchment sediment production, river sediment transport,

and in-reservoir morphodynamics, while accounting for uncertainty in sediment yield, boundary conditions, and model parameters (Ateeq-Ur-Rehman et al. 2018; George et al. 2017; Mouris et al. 2023; Pesci et al. 2023). Consequently, improving bed-load transport predictions is not only a theoretical problem but also a practical requirement for sediment management strategies such as flushing, sluicing, bypassing, and sediment routing in reservoirs (Petkovšek et al. 2025).

Classical formulations such as those of Meyer-Peter and Müller (MPM), Einstein, van Rijn, and Parker typically express transport as a function of excess shear stress, stream power, or dimensionless mobility parameters. Despite its wide adoption for coarse-bed rivers, MPM was developed from controlled flume experiments and its limited transferability to natural rivers — where bed forms, armoring, sediment-supply limitation, and unsteady conditions often dominate — is well documented. Systematic evaluations have repeatedly confirmed that no single bed-load formula performs consistently well across field and flume datasets (Barry et al. 2004; Gomez and Church 1989; Recking 2010). A major source of uncertainty is the representation of the threshold for incipient motion: natural rivers frequently display partial transport, intermittent entrainment, and bed armoring that blur the transition between no motion and measurable transport, causing threshold-based formulas to perform particularly poorly near incipient-motion conditions (Barry et al. 2004; Sidiropoulos et al. 2021).

These limitations have motivated growing interest in data-driven and machine-learning approaches. Artificial neural networks, adaptive neuro-fuzzy inference systems, symbolic regression, and ensemble tree methods such as Random Forests and XGBoost have reported high predictive accuracy and introduced explainability tools such as SHAP values to identify dominant predictors (Bhattacharya et al. 2007; Khosravi et al. 2024; Mir et al. 2024). However, purely data-driven models remain difficult to adopt

operationally unless their predictions are interpretable and reliable outside the calibration domain. This has led to hybrid strategies that preserve the structure of established transport equations while enhancing their flexibility through optimization. Sidiropoulos et al. (2021) proposed an enhanced MPM formulation that outperformed the original formula and was competitive with Gaussian process regression (GPR), placing probabilistic machine learning in direct comparison with a physically interpretable extension of a classical formula.

Bayesian and probabilistic approaches provide a complementary route for improving empirical sediment transport models. Bayesian inference offers a formal framework for estimating uncertain parameters, incorporating prior knowledge, propagating uncertainty, and producing prediction intervals rather than single deterministic estimates. Schmelter et al. (2011) demonstrated that critical shear stress and transport parameters can be inferred as posterior distributions from observations, while Beckers et al. (2020) showed that Bayesian updating can provide realistic parameter ranges for sensitive morphodynamic model parameters. From a reservoir-management perspective, Bayesian recalibration of MPM-type relations provides an intermediate level of complexity between deterministic empirical equations and computationally intensive hydro-morphodynamic models, particularly relevant under multiple interacting uncertainties such as limited bathymetric surveys, uncertain grain-size distributions, and imperfect transport equations (Mouris et al. 2023; Pesci et al. 2023).

A central challenge therefore remains unresolved: how to improve bed-load transport prediction while retaining the explanatory value of classical hydraulic formulations and providing uncertainty estimates useful for operational sediment management. This challenge is especially acute in reservoir catchments where continuous liquid-discharge observations are available but sediment transport measurements are limited, intermittent,

or highly uncertain. Within this context, the present study develops and evaluates a Bayesian framework for uncertainty-aware prediction of sediment transport dynamics using physically based MPM-type formulations under field-relevant hydraulic conditions, combining hydraulic descriptors, sediment transport relationships, and probabilistic parameter inference to improve estimation of sediment transport response and associated reservoir sedimentation processes.

2. Materials and Methods

2.1 Study area and dataset

The selected case study corresponds to the Rules Reservoir system, located within the Guadalfeo River basin in southern Spain (Fig. 1). The basin is characterized by Mediterranean hydroclimatic conditions, steep mountainous topography, and episodic high-intensity rainfall events that strongly influence runoff generation and sediment transport dynamics throughout the drainage network. Hydrological response within the basin is commonly associated with marked temporal variability in flow conditions and sediment mobilization processes, particularly during high-flow events.

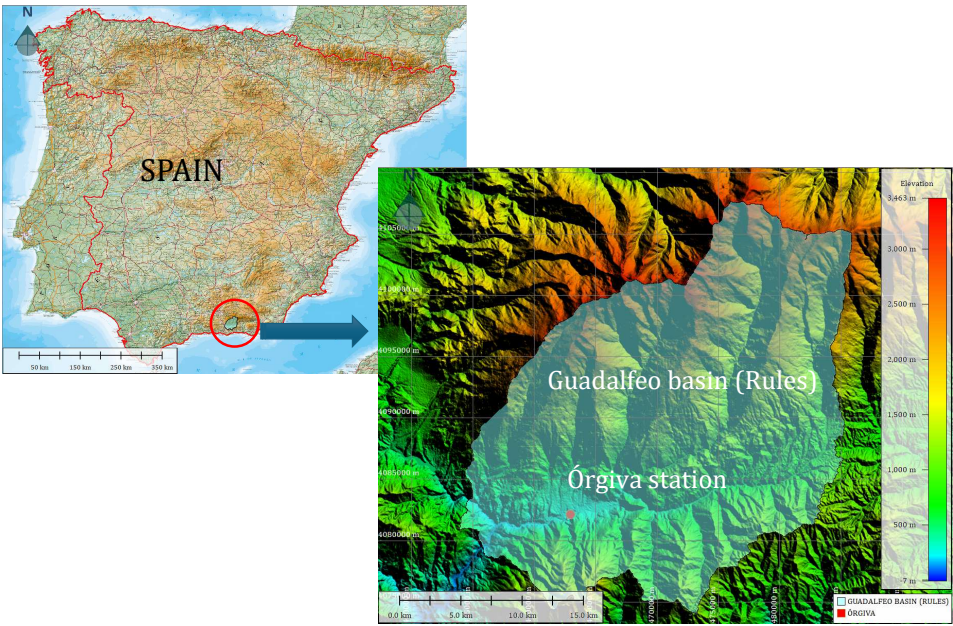


Fig. 1. Study area corresponding to the Rules Reservoir system in the Guadalfeo River basin (southern Spain) and location of the analyzed hydraulic and sediment transport monitoring sectors.

The analyzed dataset consisted of hydraulic and sediment-related variables associated with bed-load transport characterization and predictive sediment transport modelling. The available information included liquid discharge (Q_L , m³/s) and sediment transport rate (Q_s , kg/s) obtained under different hydraulic conditions within the analyzed monitoring sectors. Continuous liquid-discharge records from the Órgiva hydrological station were additionally incorporated to characterize temporal hydraulic variability and its relationship with sediment transport response. Within this framework, liquid discharge at the Órgiva station was considered the primary hydraulic predictor driving sediment transport estimation. The observed relationship between hydraulic forcing and sediment transport generation constituted the basis for the subsequent predictive and Bayesian modelling framework.

The dataset included both sector-based transport observations and aggregated transport series derived from the monitored hydraulic conditions. Cumulative sediment transport representations were also evaluated in order to characterize temporal transport persistence and transient sediment mobilization phases associated with variable hydraulic forcing. The analyzed information was subsequently used to support the hydraulic characterization, physically based transport modelling, Bayesian calibration procedure, and uncertainty-aware evaluation framework developed in this study.

2.2 Hydraulic and sediment-transport characterization

The hydraulic and sediment-transport characterization was based on the coupled analysis of flow conditions and bed-load response under variable hydraulic forcing. The

framework focused on the relationship between liquid discharge Q_L and sediment transport rate Q_s , as discharge-driven hydraulic forcing controls sediment entrainment and transport generation in alluvial and gravel-bed channels. This relationship is particularly relevant because bed-load transport commonly exhibits nonlinear, intermittent, and temporally variable behavior under field conditions (Barry et al. 2004; Buffington and Montgomery 1997; Recking 2010)

Hydraulic conditions were characterized using liquid discharge, hydraulic radius, channel slope, boundary shear stress, and the Shields parameter. Boundary shear stress was estimated using the classical depth–slope formulation:

$$\tau = \rho g R S$$

where τ is boundary shear stress, ρ is water density, g is gravitational acceleration, R is hydraulic radius, and S is energy slope. Sediment mobility was described through the dimensionless Shields parameter:

$$\theta = \frac{\tau}{(\rho_s - \rho) g D}$$

where ρ_s is sediment density and D is the representative grain diameter. These descriptors provided a physically consistent basis for evaluating sediment mobility under variable discharge conditions.

Continuous discharge records from the Órgiva hydrological station were incorporated to represent temporal hydraulic variability and support sediment-transport prediction under uncertainty. In addition to instantaneous transport rates, cumulative sediment transport was considered to account for persistence and transient mobilization phases:

$$Q_{s,acc}(t) = \int_0^t Q_s(\tau) d\tau$$

This cumulative representation is relevant because natural gravel-bed transport is rarely an instantaneous equilibrium process and may vary substantially under comparable hydraulic conditions due to turbulence, bed heterogeneity, armoring, and intermittent entrainment (Einstein 1950; Gomez and Church 1989; Pähtz et al. 2020; Wilcock and McArdell 1993). Overall, this characterization established the hydraulic and sedimentological basis for the physically based modelling and Bayesian predictive framework developed in the following sections.

2.3 Physically based characterization of bed-load transport formulations

Bed-load transport was represented using physically based formulations commonly applied in fluvial hydraulics and morphodynamic modelling. Particular attention was given to excess-shear-stress approaches derived from Meyer-Peter and Müller and to stochastic interpretations of transport variability introduced by Einstein, since both frameworks remain central to the physical interpretation of sediment entrainment in gravel-bed rivers (Einstein 1950; Meyer-Peter and Müller 1948).

The classical Meyer-Peter and Müller formulation relates dimensionless bed-load transport to excess Shields stress:

$$q_b^* = 8(\theta - \theta_c)^{3/2}$$

where q_b^* is dimensionless bed-load transport, θ is the Shields parameter, and θ_c is the critical Shields stress for incipient motion. Although widely used because of its simplicity and physical interpretability, classical excess-stress formulations may perform poorly under natural conditions due to sediment heterogeneity, armoring, partial transport, threshold variability, and unsteady hydraulic forcing (Anczyk 2020; Gomez and Church 1989; Recking 2010).

To provide greater flexibility, a generalized power-law formulation was adopted:

$$q_b^* = \alpha(\theta - \theta_c)^\beta$$

where α is the transport coefficient, β controls the nonlinear transport response, and θ_c represents the critical Shields stress. This structure preserves the threshold-based physical interpretation of sediment mobility while allowing the transport response to adapt to field-scale variability.

In parallel, Einstein's probabilistic interpretation was used to frame sediment transport as an intermittent process influenced by turbulence and temporal hydraulic fluctuations. Accordingly, α , β , and θ_c were treated as the main calibrable parameters in the subsequent Bayesian framework.

2.4 Bayesian predictive framework

A Bayesian framework was implemented to quantify uncertainty and predict sediment transport response under variable hydraulic conditions. Instead of treating transport parameters as fixed deterministic coefficients, the governing parameters of the physically based formulations were represented as probabilistic variables conditioned on observed hydraulic and sediment-transport data. This approach is suitable for sediment transport because field-scale predictions are affected by nonlinear response behavior, threshold uncertainty, sediment heterogeneity, equifinality, and measurement error (Beven and Binley 1992; Fenicia et al. 2018; Vrugt et al. 2003).

Liquid discharge records from the Órgiva hydrological station were used as the primary hydraulic predictor. The probabilistic framework linked hydraulic forcing, mobility descriptors, and sediment transport response through Bayesian-network-based dependency structures implemented in Hugin Expert. This allowed uncertainty propagation and conditional inference among hydraulic and sedimentological variables, which is particularly relevant in environmental systems characterized by nonlinear

interactions, causal dependence structures, and incomplete information (Molina et al. 2019).

Bayesian inference was based on Bayes' theorem:

$$P(X | D) = \frac{P(D | X)P(X)}{P(D)}$$

where $P(X | D)$ is the posterior distribution of the predictive variables conditioned on the observed dataset D , $P(D | X)$ is the likelihood, and $P(X)$ is the prior distribution. The main inferred variables were the transport coefficient α , transport exponent β , and critical Shields stress θ_c .

Observed and predicted sediment transport rates were related through a residual-error model:

$$Q_{s,obs} = Q_{s,pred} + \varepsilon$$

where ε represents residual variability associated with hydraulic fluctuations, intermittent transport, measurement uncertainty, and model structural limitations. This error term was represented through a Gaussian distribution with zero mean and variance σ^2 . Recent developments in stochastic hydrology and Bayesian causal modelling have highlighted the importance of probabilistic frameworks for representing temporal dependence, predictive uncertainty, and uncertainty propagation in complex environmental systems (Vrugt et al. 2003; Zazo et al. 2022).

Thus, the Bayesian framework integrated physically based sediment-transport equations with probabilistic inference, enabling uncertainty-aware prediction of sediment transport under variable discharge conditions relevant to reservoir sedimentation and siltation-susceptibility assessment.

2.5 Predictive performance evaluation and uncertainty assessment

Model performance was evaluated by combining deterministic goodness-of-fit metrics with probabilistic uncertainty assessment. This dual approach allowed both predictive accuracy and parameter robustness to be assessed under field-relevant hydraulic variability.

The agreement between observed and predicted sediment transport rates was quantified using the Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_{s,obs,i} - Q_{s,pred,i})^2}$$

and the Nash–Sutcliffe Efficiency coefficient:

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{s,obs,i} - Q_{s,pred,i})^2}{\sum_{i=1}^n (Q_{s,obs,i} - \bar{Q}_{s,obs})^2}$$

where $Q_{s,obs}$ and $Q_{s,pred}$ are observed and predicted sediment transport rates, respectively, n is the number of observations, and $\bar{Q}_{s,obs}$ is the mean observed transport rate. Positive NSE values indicate better performance than the observed mean, whereas low or negative values indicate limited predictive skill (Knoben et al. 2019; Nash and Sutcliffe 1970).

Uncertainty was assessed through the Bayesian dependency framework, which enabled evaluation of predictive variability associated with threshold uncertainty, intermittent transport, hydraulic fluctuations, and model structural limitations. Therefore, model evaluation was not restricted to identifying a single optimal parameter set, but focused on assessing the physical consistency, predictive robustness, and uncertainty representation of the proposed framework.

Overall, this evaluation supported the interpretation of sediment-transport predictions in relation to sediment routing, reservoir sedimentation, and siltation susceptibility under variable hydrological conditions.

2.6 Methodology

2.6.1 General Framework

The methodological framework comprises four sequential stages: (1) acquisition of observed liquid discharge data, (2) computation of bed-load transport using a physically based model, (3) catchment-scale aggregation and analysis, and (4) development of a probabilistic predictive tool (BBLT).

This approach integrates deterministic sediment transport modeling with probabilistic inference to evaluate reservoir sedimentation under variable hydraulic forcing.

Hydraulic Data Acquisition

Time series of instantaneous liquid discharge (m³/s) for all sub-basins were obtained from *Sevillana de Electricidad S.A.(Endesa)*. These data provide the primary forcing input for sediment transport estimation.

Sediment Transport Modeling

Bed-load transport was computed using the Meyer-Peter and Müller (MPM) equation, selected for its applicability to gravel-bed rivers:

$$q_b = 8(\theta - \theta_c)^{3/2} \sqrt{(s - 1)gd_{50}^3}$$

where q_b is bed-load transport rate per unit width, θ is the Shields parameter, θ_c is the critical Shields stress, s is relative density, g is gravitational acceleration, and d_{50} is median grain diameter.

Hydraulic parameters (shear stress and Shields parameter) were derived from observed discharge data. The resulting relationship between instantaneous liquid and solid discharge was used as input for subsequent stages.

Catchment-Scale Aggregation

Liquid and solid discharges were aggregated over the entire reservoir catchment to account for cumulative sediment transport effects and reduce bias associated with localized sediment flushing processes affecting finer materials (≤ 30 mm).

A logarithmic relationship between liquid discharge (Q_L) and instantaneous solid transport ($Q_{S,inst}$) was obtained:

$$Q_{S,inst} = 0.0199\ln(Q_L) + 0.0275 (R^2 = 1)$$

This relationship indicates a strong nonlinear dependence between flow conditions and sediment transport (Fig. 2), supporting its use in predictive modeling.

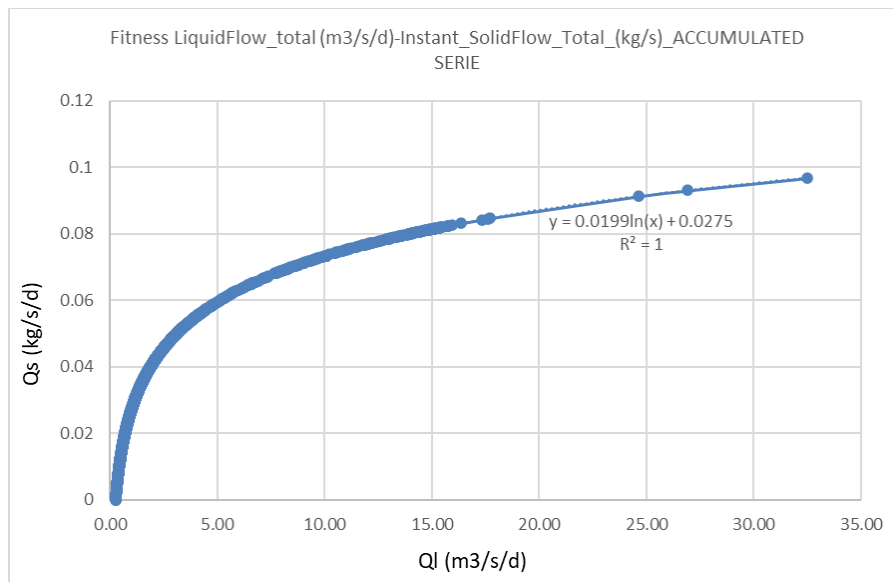


Fig. 2. Logarithmic best-fit relationship between observed liquid discharge (Q_L) and instantaneous solid transport response ($Q_{s,inst}$) derived from the accumulated temporal-series dataset used within the BBLT probabilistic predictive framework.

2.6.2 BBLT Predictive Model

The BBLT model was developed as a probabilistic framework for predicting bed-load transport and reservoir sedimentation. It integrates hydraulic forcing, sediment transport generation, and reservoir response through a Bayesian causal structure.

Causal Structure

A directed causal chain (Fig. 3) was defined linking five variables: total liquid discharge, instantaneous solid transport, cumulative solid transport, global bed-load transport, and reservoir sediment volume. This structure enables propagation of uncertainty across the system.

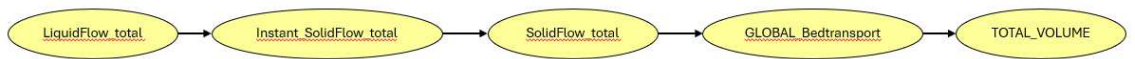


Fig. 3. BBLT modelling tool. Application to Rules Reservoir (Granada, SE Spain)

Variable Definition and Discretization

Each variable was discretized into interval states to enable Bayesian inference and scenario analysis (Table 1). Discretization allows representation of system variability and supports probabilistic predictions.

Table 1. Variables incorporated within the BBLT probabilistic predictive framework.

Variable name	Causal role	CPT	Type	Interval range	Units
		population			
		method			
<i>LiquidFlow_total</i>	Parent	Machine	Interval	0–1; 1–2; 2–3;	m ³ /s
		Learning		3–4; 4–5; 5–7;	

				7–10; 10–20;	
				20–35	
<i>Instant_SolidFlow_Total</i>	Intermediate	Machine	Interval	0.01–0.02;	Kg/s
		Learning		0.02–0.03;	per day
				0.03–0.04;	
				0.04–0.05;	
				0.05–0.06;	
				0.06–0.08;	
				0.08–0.1	
<i>SolidFlow_total</i>	Intermediate	Mathematical	Interval	–inf–0; 0–40;	Kg/s
		Expression		40–80; 80–	TOTAL
				100; 100–120;	
				120–140; 140–	
				160; 160–inf	
<i>GLOBAL_Bedtransport</i>	Intermediate	Mathematical	Interval	–inf–0; 0–	Tn
		Expression		10×10^6;	
				10×10^6–	
				15×10^6;	
				15×10^6–	
				20×10^6;	
				20×10^6–	
				25×10^6;	
				30×10^6–	
				35×10^6;	
				35×10^6–	

				40×10 ⁶ ;
				40×10 ⁶ –
				45×10 ⁶
<i>TOTAL_VOLUME</i>	Final	Mathematical	Interval	0–1; 1–2; 2–3; Mm ³
	Objective	Expression		3–4; 4–5; 5–6;
				6–7; 7–8; 8–9;
				9–10; 10–11;
				11–12; 12–13;
				13–14; 14–15

Dependency Modeling and CPT Population

A hybrid approach was adopted:

- The relationship between LiquidFlow_total and Instant_SolidFlow_Total was derived using machine learning based on MPM model outputs. The learning process used time-series data and interval discretization.
- The remaining dependencies were defined using deterministic expressions:

$$SolidFlow_{total} = Instant_SolidFlow_Total \times 3188$$

where 3188 is the number of records in the time series. The total sediment mass transported (in tonnes) was then derived as:

$$GLOBAL_Bedtransport = \frac{SolidFlow_{total} \times (60 \times 60 \times 24 \times 365 \times 8)}{1000}$$

$$TOTAL_VOLUME = \frac{GLOBAL_Bedtransport}{3 \times 10^6}$$

where TOTAL_VOLUME (Mm^3) represents the volume of sediment deposited in the reservoir, and 3 is the assumed bulk density for mass-to-volume conversion.

Overall, the proposed framework enables consistent propagation of hydraulic variability through the sediment transport chain, providing probabilistic estimates of bed-load transport and reservoir sedimentation. The complete workflow is summarized in Fig. 4.

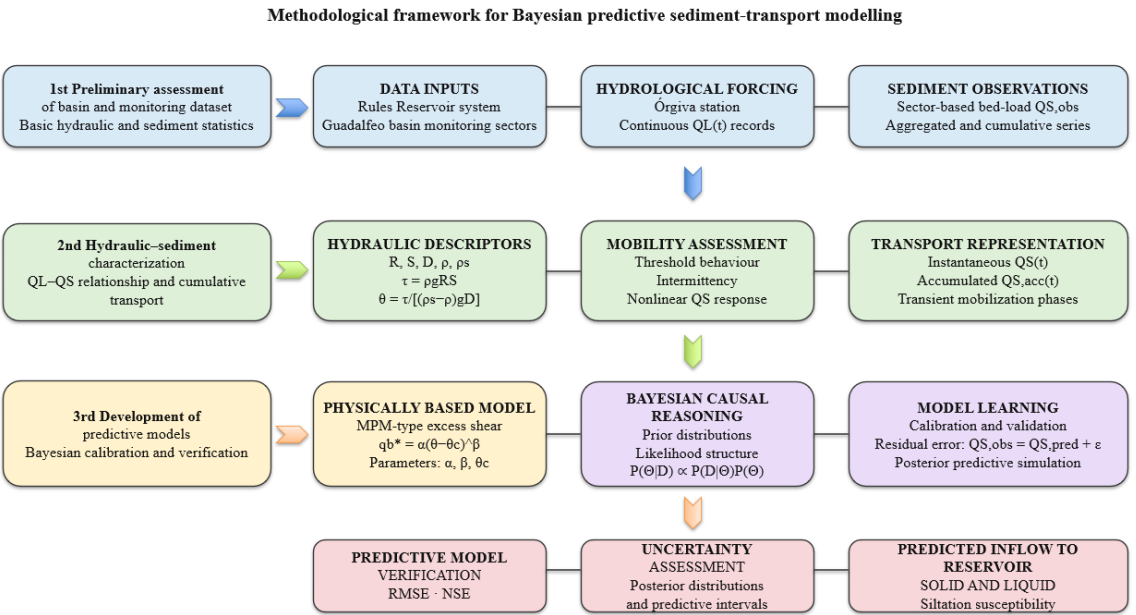


Fig. 4. Methodological framework for (BBLT) method.

3. Results

3.1 Scenarios Simulation

3.1.1 Business as Usual (B.A.U) scenario

The Business as Usual (B.A.U.) probabilistic simulation scenario represented the baseline hydraulic and sediment transport conditions observed within the study catchment (Fig. 5). Under these conditions, observed liquid discharge (LiquidFlow_total, Q_L) presented a

mean value of $\mu = 2.03 \text{ m}^3/\text{s}$ and a standard deviation of $\sigma = 9.51$, reflecting substantial temporal variability in hydraulic forcing conditions.

The probabilistic response of instantaneous sediment transport (Instant_SolidFlow_Total, QS, inst) yielded a mean value of $\mu = 0.02$, indicating predominance of low-to-moderate sediment transport conditions throughout the analyzed temporal series. Accumulated sediment transport (SolidFlow_total, Q_s ,total) presented a mean value of $\mu = 85.83$, while estimated global bed-load transport (GLOBAL_Bedtransport) yielded a mean value of $\mu = 2.19 \times 10^7 \text{ t}$.

Finally, the estimated reservoir sedimentation volume (TOTAL_VOLUME) presented a mean value of $\mu = 7.31 \text{ Mm}^3$ and a standard deviation of $\sigma = 2.57 \text{ Mm}^3$, indicating intermediate sedimentation conditions under observed hydraulic forcing variability.

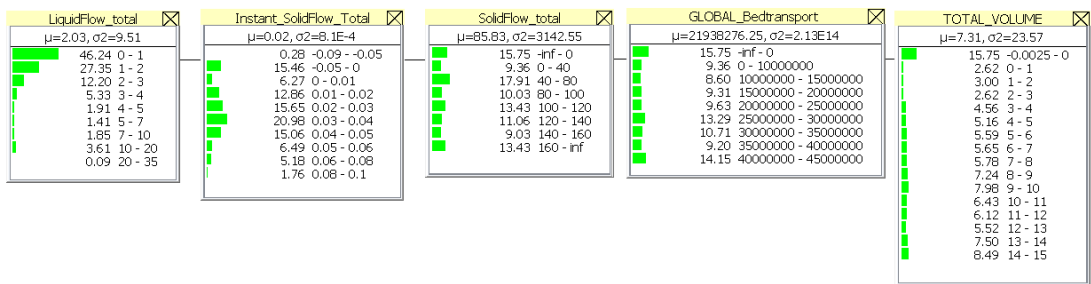


Fig. 5. Business as Usual (B.A.U.) probabilistic simulation scenario within the Bayesian predictive framework showing the dependency structure between hydraulic forcing conditions, sediment transport response, cumulative bed-load transport, and reservoir sedimentation estimation.

3.1.2 Hydraulic Forcing Conditions

Maximization of Liquidflow conditions

The maximization of LiquidFlow conditions produced a substantial increase in sediment transport response and reservoir sedimentation estimation (Fig. 6a). Under this scenario, the hydraulic forcing variable (LiquidFlow_total, Q_L) became fully concentrated within the highest discharge interval (20–35 m³/s).

The probabilistic response of instantaneous sediment transport (Instant_SolidFlow_Total, $Q_{s,inst}$) shifted completely toward the highest transport interval (0.08–0.1), while accumulated sediment transport (SolidFlow_total, $Q_{s,total}$) became fully concentrated within the maximum transport state (160–inf).

Similarly, estimated global bed-load transport (GLOBAL_Bedtransport) shifted toward the highest transport interval between 4.0×10^7 and 4.5×10^7 . The propagated probabilistic response additionally produced a strong increase in reservoir sedimentation estimation (TOTAL_VOLUME), with dominant probabilities concentrated within the 13–15 Mm³ intervals.

These results indicate that extreme hydraulic forcing conditions may substantially amplify sediment transport generation and reservoir sedimentation response within the analyzed catchment system.

Minimization of LiquidFlow conditions

The minimization of hydraulic forcing conditions produced a substantial reduction in sediment transport generation and reservoir sedimentation response throughout the probabilistic framework (Fig. 6b). Under this scenario, the liquid discharge variable (LiquidFlow_total, Q_L) became fully concentrated within the minimum discharge interval (0–1 m³/s), representing low-flow hydraulic conditions within the analyzed system.

The propagated probabilistic response of instantaneous sediment transport (Instant_SolidFlow_Total, $Q_{s,inst}$) shifted predominantly toward low transport intervals,

particularly between 0–0.01 (33.45%), 0.01–0.02 (27.82%), and 0.02–0.03 (24.56%).

Lower transport intervals below zero also presented non-negligible probabilities,

particularly the –0.05–0 interval (13.57%), indicating reduced sediment mobility under

minimum hydraulic forcing conditions

Accumulated sediment transport ($Q_{s,total}$) exhibited dominant

probabilities within low-to-intermediate transport intervals. In particular, the intervals

–inf–0, 0–40, and 40–80 represented 34.06%, 20.24%, and 33.91% of the probabilistic

response, respectively, while the 80–100 interval accounted for 11.79%. This distribution

reflects a substantial reduction in cumulative sediment transport generation compared

with high-flow scenarios.

Similarly, estimated global bed-load transport (Q_{GLOBAL}) shifted toward

low and intermediate transport intervals, with negligible probabilities in the highest

transport states. The propagated response additionally produced relatively low reservoir

sedimentation estimation (V_{TOTAL}), with the highest probability in the near-

zero interval (–0.0025–0 Mm^3 ; 34.06%) and most remaining probabilities distributed

between 0 and 7 Mm^3 .

Overall, the minimization of liquid discharge conditions demonstrated that low hydraulic

forcing substantially reduces sediment transport activation, cumulative bed-load

transport, and reservoir sedimentation response within the analyzed probabilistic

framework.

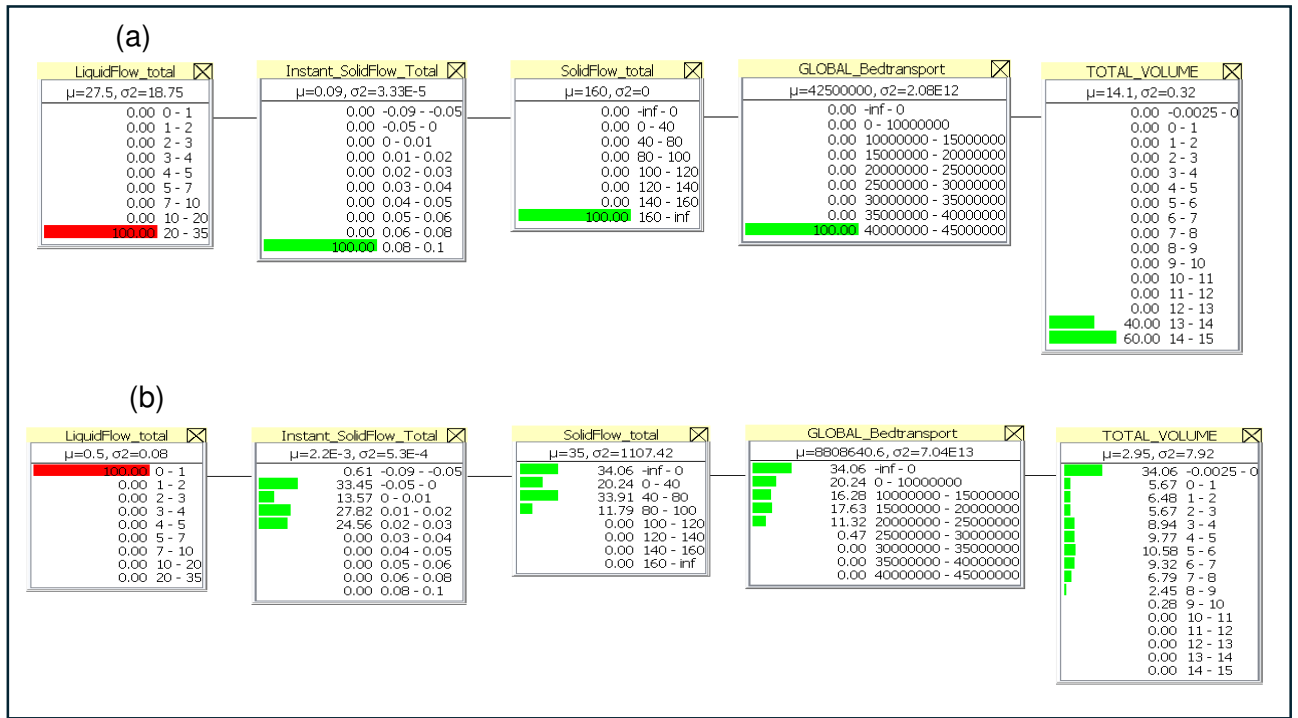


Fig. 6. Probabilistic simulations under extreme hydraulic forcing conditions within the Bayesian predictive framework: (a) maximization of LiquidFlow conditions; (b) minimization of LiquidFlow conditions.

3.1.3 Instantaneous Sediment Transport Conditions

Maximization of Instant_SolidFlow_Total

The maximization of instantaneous sediment transport conditions produced a strong propagated response throughout the complete hydraulic–sediment transport chain (Fig. 7a). Under this scenario, the probabilistic distribution of instantaneous sediment transport (Instant_SolidFlow_Total, $Q_{s,inst}$) became fully concentrated within the highest transport interval (0.08–0.1), representing maximum instantaneous sediment transport activation within the analyzed probabilistic framework.

The propagated probabilistic response produced elevated hydraulic forcing conditions, with observed liquid discharge (LiquidFlow_total, Q_L) concentrated predominantly

within the 10–20 m³/s interval (94.64%), while a secondary contribution was associated with the 20–35 m³/s interval (5.36%). This behavior indicates that high instantaneous sediment transport conditions are primarily associated with sustained high-flow hydraulic regimes.

Accumulated sediment transport (SolidFlow_{total}, Q_{s,total}) became fully concentrated within the highest transport interval (160–inf), indicating substantial amplification of cumulative sediment transport generation. Similarly, estimated global bed-load transport (*GLOBAL_Bedtransport*) shifted entirely toward the maximum transport interval between 4.0×10^7 and 4.5×10^7 .

The propagated response additionally produced high reservoir sedimentation estimation (*TOTAL_VOLUME*), with probabilities concentrated within the upper volumetric intervals of 13–14 Mm³ (40%) and 14–15 Mm³ (60%). These results indicate that maximum instantaneous sediment transport conditions may generate substantial cumulative sediment transport and reservoir sedimentation response under elevated hydraulic forcing conditions.

Minimization of Instant_SolidFlow_Total

The minimization of instantaneous sediment transport conditions produced a generalized reduction in cumulative sediment transport and reservoir sedimentation response throughout the probabilistic framework (Fig. 7b). Under this scenario, the variable representing instantaneous sediment transport (Instant_SolidFlow_Total, Q_{s,inst}) became fully concentrated within the minimum transport interval (–0.09 to –0.05), indicating extremely limited sediment transport activation under the imposed probabilistic conditions.

The propagated probabilistic response strongly affected cumulative sediment transport generation (SolidFlow_total, $Q_{s,total}$), which became entirely concentrated within the minimum transport interval below zero. Similarly, the estimated global bed-load transport (GLOBAL_Bedtransport) shifted completely toward the minimum transport state, indicating negligible cumulative sediment transport propagation through the analyzed system.

The resulting reservoir sedimentation response (TOTAL_VOLUME) also exhibited complete concentration within the minimum sedimentation interval ($-0.0025-0 \text{ Mm}^3$), reflecting negligible sediment accumulation under minimum instantaneous sediment transport conditions. The obtained probabilistic response therefore demonstrated a direct dependency between instantaneous sediment transport activation and cumulative reservoir sedimentation generation within the implemented predictive framework.

Overall, the minimization of instantaneous sediment transport conditions demonstrated that reduced sediment mobility substantially limits cumulative bed-load transport propagation and reservoir sedimentation susceptibility within the analyzed probabilistic structure.

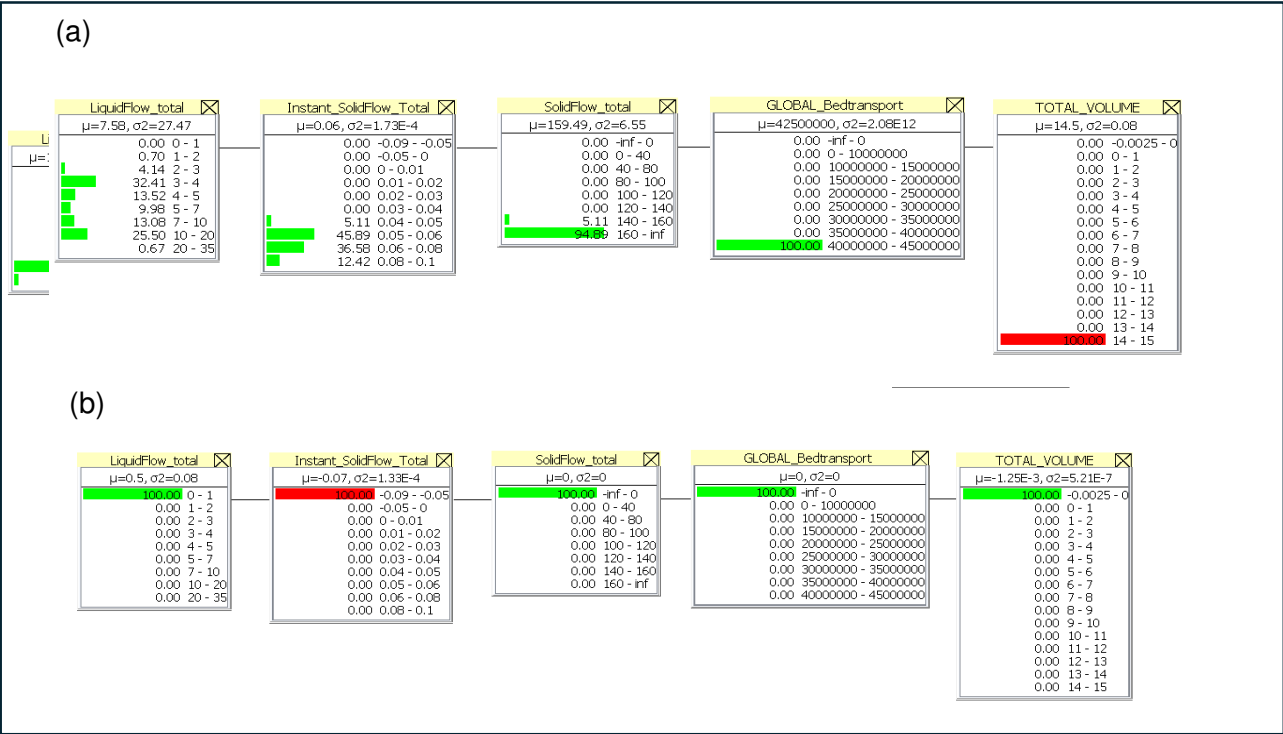


Fig. 7. Probabilistic simulations under extreme Instant_SolidFlow_Total conditions within the Bayesian predictive framework: (a) maximization of instantaneous sediment transport conditions; (b) minimization of instantaneous sediment transport conditions.

3.1.4 Reservoir Sedimentation Volume Conditions

Maximization of Total Volume

The maximization of reservoir sedimentation volume produced a propagated response characterized by moderate-to-elevated hydraulic forcing conditions and substantial sediment transport generation throughout the analyzed probabilistic framework (Fig. 8a). Under this scenario, the reservoir sedimentation variable (TOTAL_VOLUME) became fully concentrated within the highest volumetric interval (14–15 Mm³), representing maximum reservoir sedimentation conditions within the simulated system.

The propagated hydraulic response showed that liquid discharge (LiquidFlow_total, Q_L) was mainly associated with moderate-to-high discharge intervals, particularly 3–4 m³/s (32.41%), 5–7 m³/s (19.98%), 10–20 m³/s (15.50%), and 7–10 m³/s (13.08%). These results indicate that maximum reservoir sedimentation conditions are associated with sustained moderate-to-high discharge regimes rather than exclusively extreme flow events.

Instantaneous sediment transport (Instant_SolidFlow_Total, $Q_{s,inst}$) exhibited dominant probabilities within the upper transport intervals, particularly 0.04–0.05 (45.19%), 0.05–0.06 (36.58%), and 0.06–0.08 (12.42%). This probabilistic distribution indicates persistent activation of elevated sediment transport conditions associated with reservoir sedimentation generation.

Accumulated sediment transport (SolidFlow_total, $Q_{s,total}$) became strongly concentrated within the highest transport interval (160–inf), which represented 94.8% of the

probabilistic response, with the remaining probability mainly located in the 140–160 interval. Similarly, estimated global bed-load transport (GLOBAL_Bedtransport) shifted entirely toward the upper transport interval between 4.0×10^7 and 4.5×10^7 , indicating substantial cumulative sediment transport propagation throughout the reservoir catchment.

Overall, the maximization of reservoir sedimentation volume demonstrated that sustained moderate-to-high hydraulic forcing conditions combined with elevated instantaneous sediment transport may produce substantial cumulative sediment transport and significant reservoir sedimentation response within the analyzed system.

Minimization of Total Volume

The minimization of reservoir sedimentation volume produced a generalized reduction in hydraulic forcing conditions, sediment transport generation, and cumulative bed-load transport throughout the probabilistic framework (Fig. 8b). Under this scenario, the reservoir sedimentation variable (TOTAL_VOLUME) became fully concentrated within the minimum volumetric interval (0–1 Mm³), representing negligible to very low reservoir sedimentation conditions within the analyzed system.

The propagated hydraulic response showed that liquid discharge (LiquidFlow_total, QL) became entirely concentrated within the lowest discharge interval (0–1 m³/s), indicating minimum hydraulic forcing conditions associated with reduced sediment transport activity.

Instantaneous sediment transport (Instant_SolidFlow_Total, $Q_{s,inst}$) shifted predominantly toward the lower transport intervals, particularly between 0–0.01 (67.02%) and 0.01–0.02 (32.98%). Negative or higher transport intervals exhibited

negligible probabilities, indicating very limited sediment transport activation under minimum sedimentation conditions.

Accumulated sediment transport (SolidFlow_total, $Q_{s,total}$) became fully concentrated within the 0–40 interval, while estimated global bed-load transport (GLOBAL_Bedtransport) shifted completely toward the minimum positive transport interval between 0 and 1.0×10^7 . These results indicate that negligible to very low reservoir sedimentation conditions are directly associated with low hydraulic forcing and strongly reduced sediment transport generation throughout the catchment system.

Overall, the minimization of reservoir sedimentation volume demonstrated that reduced hydraulic forcing conditions substantially limit sediment transport activation, cumulative bed-load transport, and reservoir sedimentation response within the analyzed probabilistic framework.

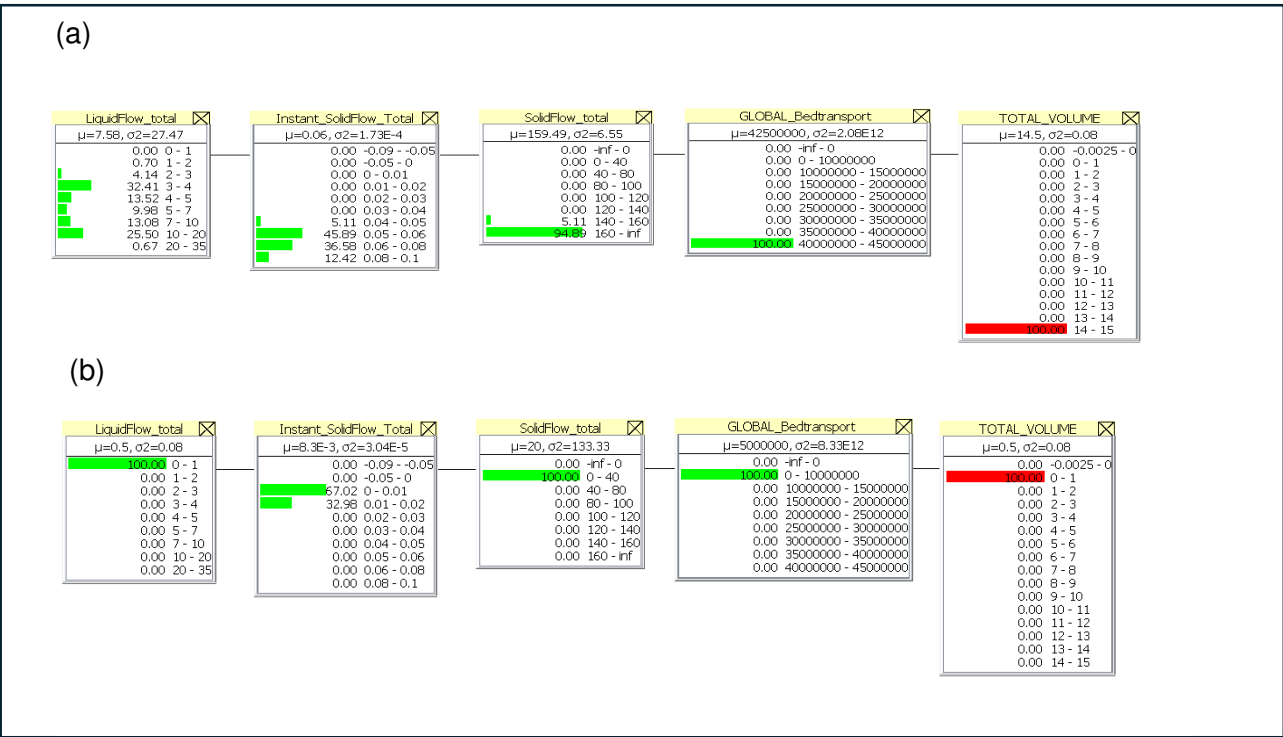


Fig. 8. Probabilistic simulations under extreme TOTAL_VOLUME conditions within the Bayesian predictive framework: (a) maximization of reservoir sedimentation volume; (b) minimization of reservoir sedimentation volume.

3.2 Reservoir management implications

Based on the obtained probabilistic sedimentation scenarios, different preventive, corrective, and mitigation-oriented reservoir-management strategies may be proposed according to the estimated sedimentation susceptibility and hydraulic forcing conditions (Table 2). These measures are intended to reduce sediment accumulation, improve sediment continuity, and preserve reservoir storage capacity under variable hydrological conditions.

Table 2. Preventive, corrective, and mitigation-oriented reservoir-management strategies associated with probabilistic sedimentation scenarios.

Management category	Management strategy	Main objective	Potential application
Preventive	Check dams and ravine stabilization	Reduce upstream sediment generation and sediment delivery	Highly erosive sub-basins and mountain ravines
Preventive	Sediment routing and bypass strategies	Improve sediment continuity and reduce reservoir deposition	Sediment-laden flood events
Preventive	Hydraulic monitoring and	Identify critical hydraulic periods	Real-time reservoir-

	early-warning systems	associated with management elevated sediment support transport
Preventive	Forest hydrological-l restoration (FHR)	Restore degraded Tributary landscapes and subcatchments and regulate the water whole catchment. cycle within a river Limited to soil, basin through isolation and terrain targeted conditions (high reforestation and slopes) erosion control active actions
Corrective	Sediment flushing operations	Reduce High-flow periods accumulated associated with sediment volume elevated sediment within the reservoir transport
Corrective	Dredging of reservoir deposits	Recover effective Advanced reservoir storage sedimentation capacity conditions
Mitigation-oriented	Construction of upstream retention structures	Retain coarse Tributary inflow sediment before sectors entering the reservoir system

Mitigation-oriented	Periodic	Evaluate long-term	Reservoir
	sedimentation	sedimentation	maintenance and
	assessment	evolution and	operational
		storage-capacity	planning
		reduction	

562

563 Overall, the proposed probabilistic framework provides a physically interpretable and
564 operationally applicable approach for uncertainty-aware reservoir sedimentation
565 assessment and sediment-management planning under variable hydraulic forcing
566 conditions.

567

568 **4. Discussion**

569 The probabilistic simulations demonstrated strong sensitivity of sediment transport
570 generation and reservoir sedimentation response to variations in hydraulic forcing
571 conditions. High-flow scenarios produced substantial increases in instantaneous sediment
572 transport, cumulative bed-load transport, and estimated reservoir sedimentation volume,
573 indicating that relatively short periods of elevated discharge may contribute
574 disproportionately to long-term reservoir sedimentation processes. In contrast, low-flow
575 conditions generated reduced sediment transport activation and limited sedimentation
576 response, highlighting the dominant influence of hydraulic forcing variability on
577 sediment generation dynamics within the analyzed catchment system.

578 The implemented probabilistic framework additionally demonstrated the capability to
579 estimate sediment transport response directly from observed liquid-discharge conditions.

580 This characteristic is particularly relevant for reservoir-management applications because

liquid discharge observations are generally more accessible and continuously monitored than sediment transport measurements in most operational reservoir systems. The resulting probabilistic dependency structure therefore enables uncertainty-aware estimation of sediment transport generation and reservoir sedimentation susceptibility under variable hydrological conditions.

The propagated probabilistic structure further enabled uncertainty-aware estimation of sediment transport and reservoir sedimentation response under variable hydraulic conditions. Instead of providing single deterministic predictions, the framework generated probabilistic distributions associated with sediment transport generation and reservoir sedimentation scenarios. Such probabilistic characterization may support risk-informed reservoir-management strategies under uncertain hydrological conditions, particularly in Mediterranean mountain catchments characterized by strong hydrological variability and episodic sediment transport activation.

From an operational perspective, the proposed framework may support preliminary assessment of sedimentation susceptibility, identification of critical hydraulic periods associated with elevated sediment transport, and uncertainty-aware evaluation of reservoir sedimentation response. Potential applications include support for sediment-routing strategies, flushing-operation planning, reservoir maintenance prioritization, and long-term storage-capacity assessment under variable hydraulic forcing conditions.

5. Conclusions

The obtained results indicated a clear probabilistic dependency between hydraulic forcing, sediment transport generation, and reservoir sedimentation within the analyzed catchment. The implemented framework identified liquid discharge as the main hydraulic predictor for sediment transport activation and cumulative sedimentation. Scenario-based

simulations showed that elevated discharges produced substantial increases in instantaneous transport, accumulated bed-load, and estimated reservoir sedimentation volume, whereas low-flow conditions generated limited responses. This aligns with the well-documented nonlinear, threshold-controlled behavior of sediment transport in gravel-bed rivers and stochastic entrainment mechanisms under natural flows (Barry et al. 2004; Furbish et al. 2017; Recking 2010). Consequently, simulations suggested high sensitivity to hydraulic variations; under high-flow scenarios, the response shifted toward maximum transport intervals. This disproportionate increase in transport intensity confirms the threshold-controlled nature of sediment entrainment, consistent with field-scale studies (Buffington and Montgomery 1997; Wilcock and McArde11 1993) and interpretations emphasizing uncertainty propagation in sediment-routing dynamics (Czuba 2018).

The framework demonstrated the potential of physically interpretable Bayesian probabilistic structures for uncertainty-aware sediment transport prediction. Unlike purely deterministic formulations, this approach explicitly represents uncertainty propagation throughout the hydraulic–sediment transport chain. This is particularly relevant under natural flow conditions affected by temporal hydraulic variability, sediment heterogeneity, armoring processes, and intermittent entrainment dynamics. The resulting probabilistic characterization may therefore provide a more flexible representation of sediment transport response under field-relevant conditions. Comparable Bayesian-network approaches have previously demonstrated robust applicability for environmental systems characterized by nonlinear interactions, causal dependence structures, and uncertainty propagation (Aguilera et al. 2011).

Methodologically, the proposed framework represents an intermediate approach between classical deterministic equations and purely data-driven machine-learning models.

Conventional MPM-type formulations often exhibit limited predictive capability under natural river conditions due to threshold uncertainty and sediment heterogeneity (Gomez and Church 1989; Sidiropoulos et al. 2021). At the same time, although machine-learning approaches can provide high predictive accuracy, their physical interpretability and extrapolation capability under changing hydraulic conditions may remain limited depending on data availability, model structure, and the calibration domain. In this context, the implemented Bayesian framework preserves the physically interpretable structure of classical formulations while successfully incorporating uncertainty-aware prediction and probabilistic dependency analysis.

The results highlight the framework's applicability for preliminary reservoir-management and sedimentation-assessment purposes. Propagating hydraulic variability toward reservoir sedimentation enables the estimation of sedimentation susceptibility under variable discharges. This supports uncertainty-aware management strategies, including sediment-routing assessment, maintenance prioritization, and long-term storage-capacity evaluation under fluctuating hydrological conditions. This aspect is particularly relevant for Mediterranean mountain catchments, where episodic high-flow events and temporal hydraulic variability dominate sediment dynamics, reinforcing the need to integrate sediment continuity within sustainable reservoir-management strategies (Kondolf et al. 2014).

In conclusion, the proposed Bayesian probabilistic framework successfully integrated physically based MPM-type sediment transport formulations with uncertainty-aware prediction and probabilistic dependency analysis. The study confirms that liquid discharge variability exerts major control over sediment transport generation and reservoir sedimentation within the analyzed catchment. High-flow conditions produced substantial increases in sediment transport intensity and estimated sedimentation

volumes, whereas low-flow conditions generated limited responses. By explicitly characterizing the relationship between liquid discharge, cumulative bed-load transport, and reservoir sedimentation, the methodology provides a physically interpretable and operationally relevant approach for predictive sediment transport estimation. Furthermore, the framework enables robust, uncertainty-aware prediction under variable hydrological conditions. This makes it highly applicable for preliminary reservoir sedimentation assessment and the development of sustainable sediment-management strategies, particularly in Mediterranean fluvial environments.

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