



## Incorporating Storage-Dependent Losses into Reservoir Water Balance Modeling: A GLUE-Based Uncertainty Assessment of Seymareh Dam

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### Abstract

Accurate reservoir water balance modeling is critical for sound water resources management, yet conventional models often simplify unresolved closure terms (e.g., net evaporation, unmonitored seepage, and bank storage exchange) as static or negligible. This study incorporates a storage-dependent loss formulation into the annual water balance of the Seymareh Dam reservoir (Iran) over a 13-year period (2011–2023) and evaluates parameter uncertainty using the Generalized Likelihood Uncertainty Estimation (GLUE) methodology with 10,000 Monte Carlo simulations. The baseline zero-loss assumption produced significant balance closure errors, whereas the storage-dependent linear parameterization yielded a statistically robust fit ( $R^2 \approx 0.60, p < 0.05$ ). Under the GLUE framework with a behavioral threshold of  $NSE \geq 0.5$ , approximately 18.2% of parameter sets were retained, identifying optimal parameters ( $a_{opt} = 0.2055, b_{opt} = -252.89$  MCM) with a peak  $NSE = 0.5973$ . The 95% prediction uncertainty (95PPU) interval successfully bracketed 69.2% of observed annual storage variations. Leave-one-year-out cross-validation and non-parametric bootstrap resampling confirmed the stability and non-spurious nature of the positive storage-loss dependency. A strong compensatory equifinality was identified between the slope and intercept ( $r \approx -0.98$ ), demonstrating that parameter uncertainty governs the first-order response surface of reservoir water balance errors. The proposed framework provides a parsimonious, uncertainty-aware diagnostic tool for improving operational decision-making in large-scale impoundments.

**Keywords:** GLUE, Reservoir water balance, Seymareh Dam, Storage-dependent loss, Uncertainty analysis

### 1. Introduction

Reservoirs and dams control river flows and manage water supplies across entire regions. They handle domestic and agricultural water needs, generate hydropower, prevent flooding, manage droughts, and regulate environmental flows. By storing water during wet periods and releasing it when needed, reservoirs boost water security and economic growth. They also help communities adapt to unpredictable climate patterns and water shortages (Carlino et al. 2024; He et al. 2024; Tang et al. 2025). Global expansion of dam infrastructure is expected to continue in response to population growth, economic development, increasing

water demand, and the transition toward renewable energy systems (Fan et al. 2024). However, many existing and future reservoirs are located in regions characterized by high hydrological variability, particularly semi-arid and arid environments, where accurate estimation of reservoir water balance is essential for effective operation and sustainable management.

The reliability of reservoir operation largely depends on the ability to accurately quantify temporal changes in storage and identify the major components controlling the water balance. A reservoir water balance is generally formulated based on the relationship between

inflow, outflow, storage variation, and additional gains or losses associated with internal hydrological processes. Accurate estimation of these components is required for operational decision-making, water allocation, drought assessment, and long-term planning (Jain and Singh 2023; Loucks and Van Beek 2017; Wurbs 2005). Although the mathematical structure of a reservoir water-balance equation is relatively simple, its practical implementation remains challenging because several components cannot be directly observed or continuously measured.

Processes such as evaporation, seepage, groundwater exchange, unmeasured operational transfers, and measurement uncertainty may contribute substantially to discrepancies between observed and simulated storage changes. In many reservoir applications, these unresolved processes are commonly represented through an aggregated residual term or simplified loss component. This approach is often necessary because detailed measurements of individual water-balance components are rarely available, particularly at annual time scales. Consequently, many operational and research models assume that the aggregated residual remains constant over time or can be represented by a lumped parameter estimated during calibration (Dingman 2015; Shaw et al. 2011; Tripathy and Mishra 2024). Although such assumptions improve model simplicity and reduce data requirements, they may introduce structural limitations when unresolved components vary systematically with reservoir conditions. In particular, a constant residual assumption implicitly assumes that the combined effects of evaporation, seepage, groundwater interactions, operational influences, and measurement uncertainties remain independent of reservoir storage conditions (Clark et al. 2015; Gupta et al. 2012; Khatakho et al. 2026). This assumption may not always be valid because reservoir storage can influence several physical and operational processes contributing to the overall water balance. Variations in storage directly affect water-surface area, hydraulic gradients, reservoir elevation, and potentially the exchange processes between surface water and

surrounding geological formations. For example, higher storage levels may increase evaporation losses through larger exposed water surfaces, modify seepage conditions through changes in hydraulic head, and influence operational decisions regarding water releases. Therefore, even when individual processes cannot be independently quantified, their aggregated effect may exhibit systematic dependence on observable reservoir states, such as initial storage. Several studies have highlighted the importance of improving the representation of dynamic processes in hydrological and reservoir models. Dynamic formulations of evaporation, groundwater interaction, and other hydrological processes have demonstrated that assuming constant parameters may not adequately represent long-term water-balance behavior (Alsumaiei 2026; Kratzert et al. 2022; Nearing et al. 2021).

Alongside structural improvement of hydrological models, uncertainty analysis has become an essential component of reliable water-resources modeling. Hydrological simulations are affected not only by parameter uncertainty but also by uncertainties associated with limited observations, simplified process representation, and model structural assumptions. Therefore, evaluating model performance based solely on a single calibrated parameter set may not fully capture model reliability. Among available uncertainty analysis approaches, the Generalized Likelihood Uncertainty Estimation (GLUE) framework has been widely applied to quantify parameter uncertainty and investigate equifinality in hydrological systems (Herrera et al. 2022; Montanari 2007). GLUE identifies behavioral parameter sets based on predefined performance thresholds rather than assuming the existence of a single optimal solution.

By evaluating ensembles of acceptable parameter combinations, the framework provides probabilistic bounds for model simulations and allows characterization of predictive uncertainty. Its flexibility, conceptual transparency, and ability to represent parameter equifinality make GLUE particularly suitable for data-limited environments and conceptual hydrological models (Blasone et al. 2008; Haddad 2025; Onur Onen et al. 2025; Vrugt et al. 2009).

Despite extensive applications of uncertainty analysis in watershed-scale hydrological models, fewer studies have investigated the role of uncertainty and parameter equifinality in simplified reservoir water-balance formulations where unresolved components are represented through alternative residual structures.

In particular, the question of whether a storage-dependent formulation of the aggregated residual can provide additional explanatory capability compared with conventional constant-residual assumptions remains insufficiently explored. Addressing this research gap is particularly important for reservoirs located in regions with strong interannual variability, where changes in storage conditions may systematically influence unresolved water-balance components.

Understanding whether storage information can improve representation of aggregated residual behavior may provide a practical pathway toward improved reservoir simulations without requiring extensive additional monitoring infrastructure.

Therefore, this study aims to investigate whether the aggregated water-balance residual of Seymareh Dam, Iran, exhibits systematic dependence on initial reservoir storage and whether incorporating this dependence improves the representation of annual storage changes during the period 2011–2023. Two alternative model structures are evaluated: (1) a conventional formulation assuming a constant residual component and (2) a storage-dependent formulation in which the aggregated residual varies as a function of initial reservoir storage. The storage–residual relationship is quantified using regression analysis, while parameter uncertainty, equifinality, and predictive uncertainty are evaluated using the Generalized Likelihood Uncertainty Estimation (GLUE) framework.

By integrating empirical relationship analysis, structural model comparison, and uncertainty assessment, this study proposes a parsimonious and uncertainty-aware framework for improving reservoir water-balance representation in data-limited environments.

## 2. Materials and Methods

### 2.1. Study area

The Seymareh Dam is located in western Iran on the Seymareh River, one of the main tributaries of the Karkheh River basin. The dam site lies in Ilam Province, approximately 30 km northwest of Darreh Shahr County and about 3 km upstream of Talkhab Village. The geographic coordinates of the dam are approximately 704,550 m Easting and 3,686,000 m Northing.

The dam is constructed within a narrow U-shaped gorge characterized by steep valley walls. The Seymareh Dam is a large storage reservoir primarily developed for hydropower generation, flood control, and improving downstream flow regulation. The height of the dam from the riverbed is approximately 130 m, while the height from the bedrock foundation reaches about 179 m.

The crest elevation of the dam is 730 meters above mean sea level, and the normal operating water level is 723 m. At the normal operating level, the reservoir has a storage capacity of approximately 2.8 billion cubic meters (BCM), making it one of the largest reservoirs in Iran.

Reservoir impoundment began in April 2011, marking the start of operational water storage in the system. From a geological perspective, the study area is located within the Folded Zagros Zone, specifically in the southwestern sector of this tectonic province. The regional geological structure is dominated by anticlines that generally follow the northwest–southeast orientation of the Zagros mountain range.

These geological characteristics influence the geomorphology of the reservoir valley and may also affect processes such as seepage and groundwater interaction within the reservoir system. In this study, the annual water balance of the Seymareh reservoir was analyzed for the period 2011–2023 using observed data on reservoir storage, inflow, and outflow to evaluate the performance of water balance models with different representations of reservoir losses (See Fig. 1).

### 2.2. Data collection

The hydrological and operational data used in this study were obtained from the Water Research Institute (WRI) of the Ministry of

Energy of Iran. These datasets originate from the annual monitoring program of the Seymareh Dam reservoir, conducted systematically by WRI as part of its national reservoir monitoring activities. The dataset covers 13 hydrological years (2011–2023), capturing the reservoir behavior from its initial impoundment in April 2011 to recent operational conditions. The monitoring records include key hydrological and operational variables required for reservoir water balance analysis.

The primary annual variables compiled for this study include:

1. Inflow ( $Q_{in}$ ): Total annual volume of water entering the reservoir from the upstream catchment (MCM).

2. Outflow ( $Q_{out}$ ): Total annual volume of water released from the reservoir through power generation, environmental flows, and spillway discharges (MCM).

3. Storage levels ( $S_{start}$  and  $S_{end}$ ): Reservoir storage at the beginning and end of each hydrological year (MCM).

4. Observed Storage Change ( $\Delta S_{obs}$ ): The annual change in reservoir storage calculated as (Jain and Singh 2023; Wurbs 2016):

$$\Delta S_{obs,i} = S_{end,i} - S_{start,i} \quad (1)$$

where  $i$  represents the hydrological year. To provide an overview of the hydrological characteristics of the Seymareh reservoir during the study period, the descriptive statistics of the compiled variables are summarized in Table 1.

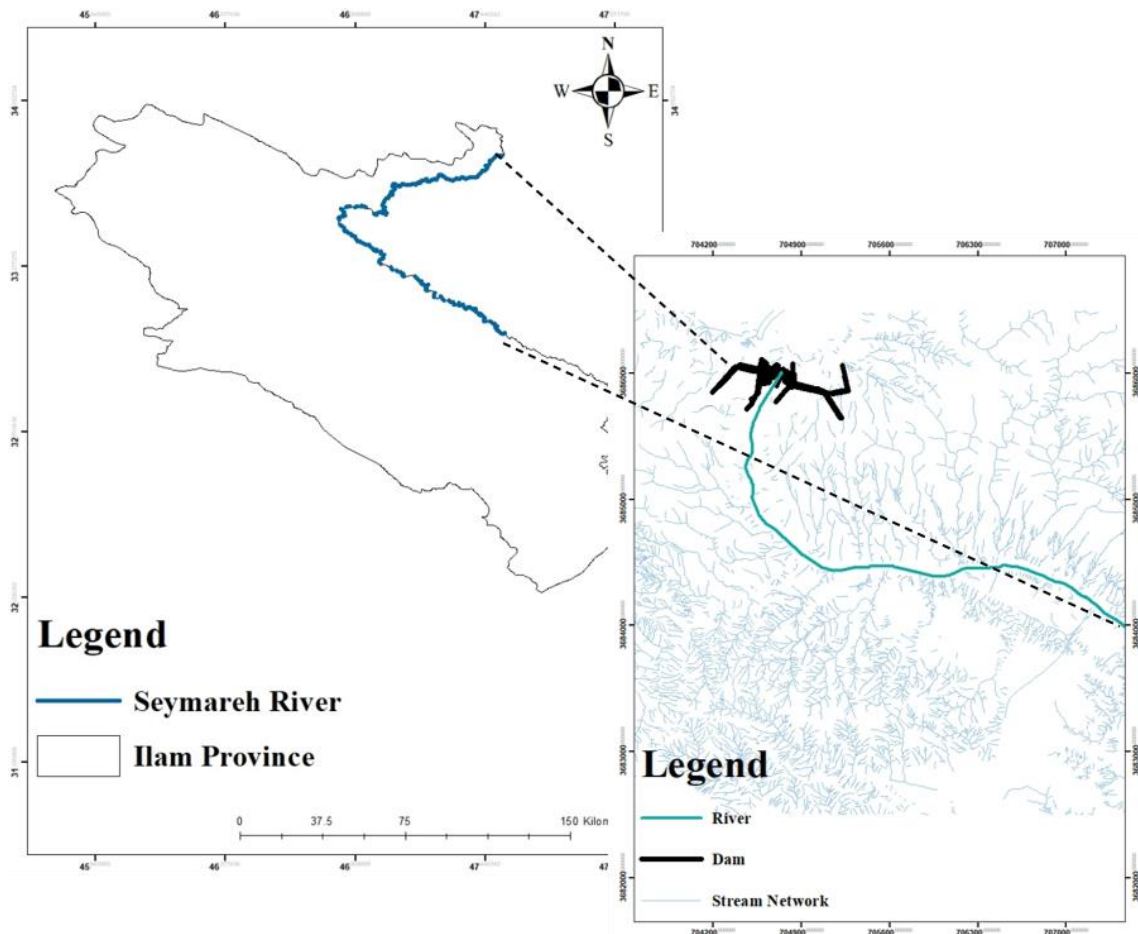


**Fig. 1.** Location of Seymareh Dam

**Table 1.** Descriptive statistics of the annual hydrological and operational data of Seymareh Reservoir (2011–2023)

| Parameter              | Mean    | Std. Dev | Min     | Max     | CV   |
|------------------------|---------|----------|---------|---------|------|
| $Q_{in}$ (MCM)         | 1780.12 | 1416.22  | 544.62  | 5643.68 | 0.80 |
| $Q_{out}$ (MCM)        | 1684.62 | 1492.64  | 245.66  | 5601.10 | 0.89 |
| $S_{start}$ (MCM)      | 1020.90 | 617.18   | 0.08    | 1591.20 | 0.60 |
| $S_{end}$ (MCM)        | 1158.08 | 571.31   | 57.00   | 1812.70 | 0.49 |
| $\Delta S_{obs}$ (MCM) | 137.17  | 290.48   | -233.23 | 668.76  | 2.12 |

As shown in Table 1, the Seymareh River basin exhibits a highly dynamic hydrological regime. The annual inflow ( $Q_{in}$ ) varied dramatically, ranging from a minimum of 544.62 MCM to a peak of 5643.68 MCM, with a high coefficient of variation ( $CV=0.80$ ). This extreme variability is also reflected in the annual outflow ( $Q_{out}$ ,  $CV=0.89$ ), which mirrors both wet-season flood regulations and dry-season operational releases.

The initial reservoir storage ( $S_{start}$ ) showcases the filling phase and subsequent drawdown cycles, ranging from nearly empty (0.08 MCM in the first year of impoundment) to a maximum of 1591.20 MCM. The extremely high variability in observed annual storage changes ( $\Delta S_{obs}$ ,  $CV=2.12$ ) underscores the complex water balance dynamics of the reservoir. Such pronounced fluctuations in water levels and storage volumes strongly justify the integration of a dynamic, storage-dependent loss function over traditional constant-loss models.

### 2.3. Classical reservoir water balance

The behavior of reservoir storage is governed by the principle of mass conservation, commonly referred to as the reservoir continuity equation. This equation states that the change in water storage within a reservoir over a given time period is equal to the difference between incoming and outgoing water fluxes (Song et al. 2016; Zhu et al. 2022). The general form of the reservoir water balance can be expressed as:

$$\Delta S_t = Q_{in,t} - Q_{out,t} - L_t \quad (2)$$

where  $\Delta S_t$  represents the change in reservoir storage during time step  $t$ ,  $Q_{in,t}$  is the inflow entering the reservoir,  $Q_{out,t}$  is the released outflow, and  $L_t$  represents the total water losses occurring within the reservoir system. For computational purposes, the storage variation

can also be expressed in terms of consecutive storage states:

$$S_{t+1} = S_t + Q_{in,t} - Q_{out,t} - L_t \quad (3)$$

where  $S_t$  and  $S_{t+1}$  denote the reservoir storage at the beginning and end of the time step, respectively. The loss term  $L_t$  represents the combined effects of several hydrological and operational processes, including evaporation from the reservoir surface, seepage through the reservoir bed and abutments, and other unmeasured losses. In many reservoir studies, these loss components are difficult to measure directly due to limited observational data and spatial variability.

As a result, they are often represented as an aggregated loss term within the water balance framework. This continuity equation provides the fundamental basis for reservoir simulation and water balance modeling, and it has been widely applied in hydrological and water resources studies for analyzing reservoir dynamics and operational behavior.

### 2.4. Constant loss model

In simplified reservoir water balance analyses, the total loss term is frequently represented by a constant parameter that aggregates all unmeasured loss components. These losses typically include evaporation from the reservoir surface, seepage through the reservoir bed and abutments, bank storage exchanges, and other operational uncertainties that are difficult to quantify individually. When detailed measurements of these processes are unavailable, they are often approximated by an average loss value over the simulation period (Lai et al. 2022; Yeh 1985):

$$S_{t+1} = S_t + Q_{in,t} - Q_{out,t} - L_t - C \quad (4)$$

where  $C$  is a constant parameter representing the average reservoir loss during the simulation period. This formulation assumes that the combined effect of evaporation, seepage, and other losses remains approximately constant over time.

The constant-loss assumption is widely adopted in reservoir balance studies due to its simplicity and parsimony, particularly when the primary objective is to capture the overall storage dynamics rather than to explicitly simulate individual physical processes (Yeh 1985). In such cases, the parameter  $C$  effectively compensates for unknown or unmeasured components of the water balance and is typically estimated through model calibration.

However, this simplification may introduce limitations in representing the actual behavior of reservoir systems. In reality, several loss components are influenced by reservoir storage conditions. For example, evaporation losses are strongly related to the water surface area, which generally increases with storage volume. Similarly, seepage rates may vary with hydraulic head and reservoir water level, particularly in reservoirs constructed in fractured or permeable geological formations (Zhu et al. 2022).

Consequently, representing reservoir losses as a constant value may not adequately capture the temporal variability of these processes under changing hydrological conditions. As a result, constant-loss models may produce biased estimates of storage variations, especially during periods of significant storage fluctuations. These limitations highlight the need for alternative formulations that allow reservoir losses to vary dynamically with storage conditions.

## 2.5. Storage-dependent loss model

To better represent the physical behavior of reservoir losses, this study introduces a storage-dependent loss formulation, in which the magnitude of reservoir losses varies as a function of the reservoir storage. This formulation aims to overcome the limitations of the constant-loss assumption by allowing the loss term to dynamically respond to changes in reservoir conditions.

The modified reservoir water balance equation can therefore be written as:

$$S_{t+1} = S_t + Q_{in,t} - Q_{out,t} - L(S_t) \quad (5)$$

where  $L(S_t)$  represents the reservoir loss term expressed as a function of storage at time  $t$ .

In natural reservoir systems, several loss processes are strongly influenced by the reservoir water level and storage volume. For example, evaporation losses are closely related to the exposed water surface area, which generally increases with rising reservoir storage. Similarly, seepage losses through the reservoir bed and abutments may vary with hydraulic head and reservoir pressure conditions. Because of these physical dependencies, representing reservoir losses as a function of storage can provide a more realistic description of reservoir water balance dynamics.

In this study, the storage-dependent loss function is represented using a linear relationship with reservoir storage, which provides a parsimonious yet physically meaningful formulation:

$$L(S_t) = aS_t + b \quad (6)$$

where  $a$  is the storage-dependent loss coefficient, representing the rate at which losses increase with reservoir storage,  $b$  is the baseline loss component, representing the storage-independent portion of reservoir losses.

The parameter  $a$  captures the variability of losses associated with changes in storage conditions, while the parameter  $b$  accounts for background losses that occur regardless of storage level. The use of a linear formulation offers a balance between model simplicity and physical interpretability, allowing the loss term to vary with storage while avoiding unnecessary model complexity.

Such storage-dependent parameterizations have been increasingly adopted in simplified reservoir modeling frameworks, particularly when detailed measurements of evaporation area dynamics or seepage fluxes are unavailable (Fayaed et al. 2013). By incorporating storage variability into the loss representation, the proposed formulation provides a more flexible and realistic approximation of reservoir water balance processes.

## 2.6. Generalized Likelihood Uncertainty Estimation (GLUE)

To account for the inherent uncertainties in reservoir loss estimation and parameter identification, this study employs the

Generalized Likelihood Uncertainty Estimation (GLUE) framework, proposed by (Beven and Binley 1992). The GLUE methodology is founded on the concept of equifinality, which suggests that multiple parameter sets may perform equally well in representing the observed behavior of a complex hydrological system (Beven 2006). This approach moves away from the search for a single optimal parameter set and instead focuses on identifying a population of behavioral models that adequately simulate the system dynamics. The implementation of the GLUE framework in this study involves the following systematic steps:

### 2.6.1. Parameter sampling and prior distributions

A large number of parameter sets for the proposed storage-dependent loss model (a and b) were generated using Monte Carlo sampling. In the absence of detailed prior information regarding the seepage and evaporation characteristics of the Seymareh reservoir, uniform prior distributions were assumed for both parameters. The sampling ranges were defined to cover a wide physically plausible space: the storage-dependent coefficient ( $a$ ) was sampled within  $[0, 0.5]$ , and the baseline loss component ( $b$ ) was sampled within  $[-500, 0]$  MCM. A total of 10,000 independent simulations were performed to ensure a robust exploration of the parameter space.

### 2.6.2. Likelihood metric and behavioral criteria

To evaluate the performance of each parameter set, the Nash-Sutcliffe Efficiency (NSE) was utilized as the likelihood measure. The NSE is a widely accepted metric in hydrological modeling that quantifies the agreement between observed and simulated storage dynamics (Moriassi et al. 2007):

$$NSE = 1 - \frac{\sum_{i=1}^n (S_{obs,i} - S_{sim,i})^2}{\sum_{i=1}^n (S_{obs,i} - \bar{S}_{sim,i})^2} \quad (7)$$

where  $S_{obs,i}$  and  $S_{sim,i}$  are the observed and simulated reservoir storage for year  $i$ , and  $\bar{S}_{obs}$  is the mean of the observed storage. Following the GLUE protocol, a threshold (cutoff) value was established to distinguish

between behavioral and non-behavioral models. Parameter sets yielding an  $NSE \geq 0.50$  were classified as behavioral, while those falling below this threshold were discarded.

### 2.6.3. Uncertainty quantification and prediction limits

The likelihood values of the behavioral parameter sets were rescaled to ensure that their sum equals unity, effectively transforming them into a cumulative subjective probability distribution. These weights were then used to derive the uncertainty bounds for the simulated reservoir storage. Specifically, the 95% Prediction Uncertainty (95PPU) was calculated at each time step by identifying the 2.5th and 97.5th percentiles of the weighted cumulative distribution of the simulated storage values. This provides a rigorous measure of the model's reliability and the range within which the true reservoir storage is expected to fall given the parametric uncertainty (Abbaspour et al. 2007).

The 95% prediction uncertainty (95PPU) interval was defined using the 2.5th and 97.5th percentiles of the behavioral simulation ensemble at each time step (Abbaspour 2004):

$$\begin{aligned} PPU_{2.5, t} &= Q_{0.025}(S_{sim,t}^{beh}) \\ PPU_{97.5, t} &= Q_{0.975}(S_{sim,t}^{beh}) \end{aligned} \quad (8)$$

where  $Q_{0.025}$  and  $Q_{0.975}$  denote the 2.5th and 97.5th quantiles, respectively, of the simulated annual storage changes generated by the behavioral parameter sets. The proportion of observed annual storage changes enclosed within the 95PPU interval was quantified using the P-factor (Abbaspour 2015):

$$P = \frac{N_{inside}}{N_{obs}} \quad (9)$$

where  $N_{inside}$  is the number of observed annual storage changes falling within the corresponding 95PPU bounds and  $N_{obs}$  is the total number of available observations.

In the present study, the resulting uncertainty band was interpreted specifically as parameter-induced predictive uncertainty, conditional on the adopted model structure, parameter ranges, behavioral acceptance criteria, and available observations.

It was therefore not considered a complete representation of total hydrological predictive uncertainty, which may additionally arise from

input-data errors, observational uncertainty, model structural deficiencies, and parameter uncertainty.

#### 2.6.4. Model performance evaluation

To rigorously compare the predictive accuracy of the proposed storage-dependent loss model against the baseline constant-loss model, three statistical performance metrics were employed:

1. Nash-Sutcliffe Efficiency (NSE): As described in Section 2.6.2, used to evaluate the overall fit of the storage trajectories.

2. Root Mean Square Error (RMSE): Used to quantify the magnitude of the residuals in units of volume (MCM).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_{obs,i} - S_{sim,i})^2} \quad (10)$$

3. Mean Absolute Error (MAE): Used to assess the average absolute difference between observations and simulations, providing a metric less sensitive to outliers than RMSE (Hodson 2022).

$$MAE = \frac{1}{n} \sum_{i=1}^n |S_{obs,i} - S_{sim,i}| \quad (11)$$

By evaluating these metrics for both models, the study quantifies the improvement gained by incorporating the storage-dependency into the reservoir water balance framework.

#### 2.7. Robustness and sensitivity analysis

Given the constrained observational record ( $N = 13$  annual observations), additional sensitivity analyses were conducted to evaluate the robustness and stability of the inferred storage–loss relationship. First, a leave-one-out cross-validation (LOOCV) approach was implemented by iteratively omitting one annual observation and refitting the linear regression model (Kirchner 2009):

$$L_{obs,t} = aS_{start,t} + b \quad (12)$$

The parameter estimates ( $a$  and  $b$ ) were recorded for each subset iteration to examine whether the positive storage dependence was disproportionately governed by individual high-leverage years or outliers. Second, non-parametric bootstrap resampling was employed to quantify parametric uncertainty.

A total of 10,000 bootstrap replicates were generated via random sampling with replacement from the empirical dataset. The regression model was fitted independently to each synthetic sample, yielding empirical parameter distributions from which percentile-based confidence intervals were derived.

It should be noted that these procedures do not constitute an independent external validation, as they inherently rely on the same underlying sample. Instead, they serve to verify that the derived empirical relationships are structurally stable against sampling variability and specific observational artifacts.

### 3. Results and Discussion

#### 3.1. Interannual variability of the water-balance residual

To quantify the unmeasured components of the water budget over the 2011–2023 observation period, the annual water-balance residual was determined as the discrepancy between total inflow, outflow, and the observed annual change in storage:

$$L_{obs,t} = Q_{in,t} - Q_{out,t} - \Delta S_{obs,t} \quad (13)$$

where  $Q_{in,t}$ ,  $Q_{out,t}$ , and  $\Delta S_{obs,t}$  denote the annual inflow, outflow, and observed change in storage, respectively.

The resulting residual displayed marked interannual fluctuations, spanning from  $-698.99$  to  $+288.37$  MCM. The alternating positive and negative values imply that the residual is not a monotonic loss mechanism, but rather an integrated response encompassing unquantified fluxes (e.g., evaporation, subsurface exchange, operational lags) alongside observational errors. Consequently, representing the residual as a time-invariant parameter is physically unrealistic. To explore potential state-dependent patterns, we examined the correlation between the annual residual and the initial reservoir storage.

#### 3.2. Storage–residual relationship

To evaluate the state-dependent behavior of the residual, an ordinary least-squares (OLS) linear regression was established between the annual water-balance residual and the initial (beginning-of-year) reservoir storage (Duan and Bastiaanssen 2013):

$$L_{obs,t} = aS_{start,t} + b - \varepsilon_t \quad (14)$$

where  $S_{\text{start},t}$  is the reservoir storage at the start of year  $t$ ,  $a$  and  $b$  are the regression slope and intercept, respectively, and  $\varepsilon_t$  represents the random error term.

The estimated parameters were  $a = 0.2061$  and  $b = -252.08$ , with the fitted model accounting for roughly one-third of the observed residual variance ( $R^2 = 0.323$ ). The

slope parameter  $a$  was positive and statistically significant at the 5% significance level ( $p = 0.043$ ; 95% CI: [0.008, 0.404]). As depicted in Fig. 2, the positive slope indicates that higher antecedent storage levels are systematically associated with larger net water-balance residuals.

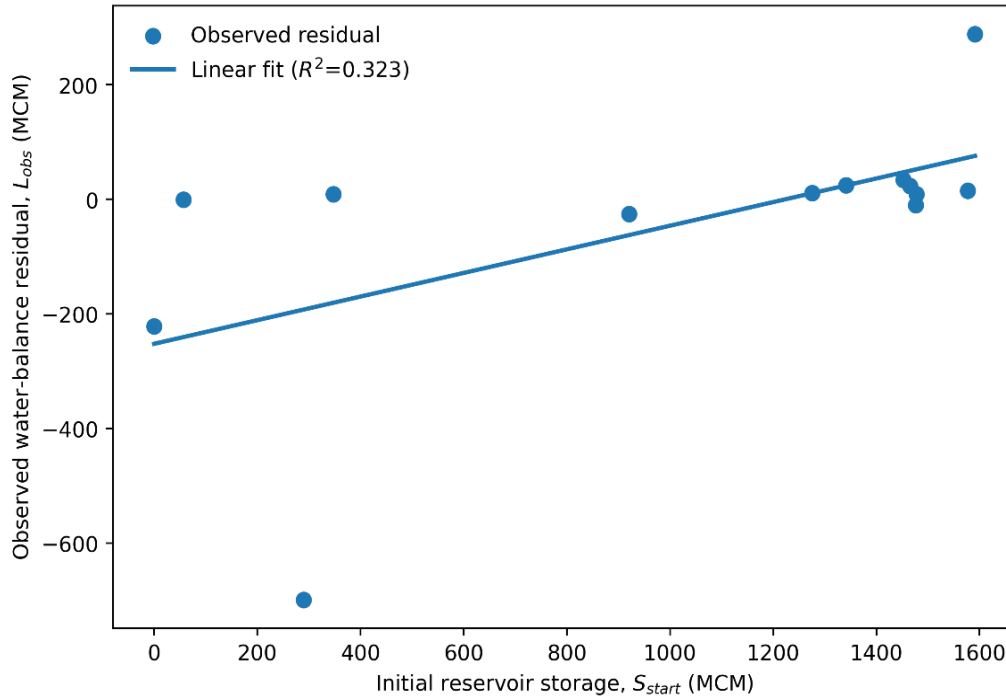


**Fig. 2.** Relationship between beginning-of-year reservoir storage and the observed annual water-balance residual

While this empirical link confirms storage dependence, the moderate  $R^2$  suggests that initial storage alone does not capture the full spectrum of interannual variability, pointing to other unmodeled climatic, operational, and hydrogeological forcings. Crucially, the slope coefficient ( $a$ ) must be interpreted as an effective, system-scale empirical parameter rather than a direct physical descriptor of a single mechanism (such as stage-dependent seepage or surface-area-driven evaporation). Due to the aggregated nature of  $L_{\text{obs}}$ , the individual physical fluxes and measurement errors cannot be uniquely partitioned based on the available bulk observations.

### 3.3. Calibration of the constant-residual baseline

To provide a fair structural benchmark for the proposed storage-dependent formulation, a calibrated constant-residual model was included in the analysis. The constant residual

term  $C$  was estimated as the arithmetic mean of the observed annual water-balance residuals (Song et al. 2022) over the 2011–2023 study period:

$$C = \frac{1}{n} \sum_{t=1}^n L_{\text{obs},t} \quad (15)$$

Based on Eq. 15, the calibrated value was determined to be  $C = -41.67$  MCM. Consequently, the constant-residual benchmark model is formulated as:

$$\Delta S_{CL,t} = Q_{\text{in},t} - Q_{\text{out},t} - C \quad (16)$$

Here,  $C$  is interpreted as an effective aggregate residual rather than a direct physical estimate of reservoir loss, as the observed water-balance residual inherently integrates unmeasured hydrological fluxes, operational dynamics, and observational uncertainties.

### 3.4. Predictive performance

To assess the diagnostic and predictive utility of incorporating state-dependent residuals, the proposed formulation was benchmarked against the standard no-loss baseline model. The baseline storage change ( $\Delta S_{sim,t}^{base}$ ) assumes conservation of mass driven solely by monitored surface fluxes:

$$\Delta S_{sim,t}^{base} = Q_{in,t} - Q_{out,t} \quad (17)$$

whereas the storage-dependent (SD) formulation ( $\Delta S_{sim,t}^{SD}$ ) explicitly integrates the empirical closure correction:

$$\Delta S_{sim,t}^{SD} = Q_{in,t} - Q_{out,t} - (aS_{start,t} + b) \quad (18)$$

Model evaluation was performed using NSE, RMSE, and MAE, as summarized in Table 2.

The storage-dependent formulation demonstrated a notable performance enhancement over the baseline, with the NSE increasing by 0.214 (a relative improvement of approximately 55.8%) and the RMSE decreasing by 19.2% (from 219.17 to 177.10 MCM). Given that this gain is achieved via only two additional empirical

parameters ( $a$  and  $b$ ), the proposed modification represents a parsimonious yet effective refinement to the conventional reservoir water balance.

A nuanced contrast emerges between the quadratic (RMSE, NSE) and absolute (MAE) error metrics. While the SD formulation markedly suppressed peak deviations and enhanced variance tracking, its MAE exhibited a minor increase (from 105.50 to 109.18 MCM). This discrepancy is inherently tied to the OLS optimization objective, which penalizes large residual outliers more heavily than moderate deviations. Consequently, the storage-dependent formulation should be interpreted as an enhanced representation of the macro-scale temporal dynamics and extreme anomalies rather than a strictly monotonic reduction of absolute errors across all individual hydrological years. The observed versus simulated interannual storage trajectories for both formulations are illustrated in Fig. 3.

**Table 2.** Performance metrics of the baseline and storage-dependent water-balance formulations

| Model                        | a     | b (MCM)  | C(MCM) | NSE    | RMSE (MCM) | MAE (MCM) |
|------------------------------|-------|----------|--------|--------|------------|-----------|
| No-loss baseline             | -     | -        | 0      | 0.3832 | 219.1729   | 105.49    |
| Storage-dependent regression | 0.206 | -252.077 | -      | 0.5973 | 177.1022   | 109.17    |
| Calibrated constant-residual | -     | -        | -41.67 | 0.4056 | 215.1756   | 128.82    |

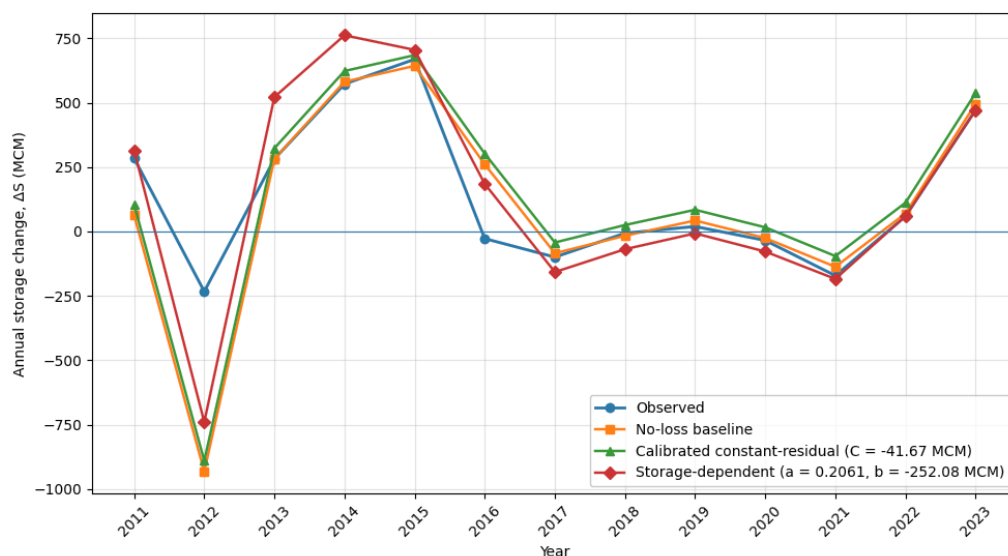


**Fig. 3.** Observed versus simulated annual storage changes ( $\Delta S$ ) for baseline and storage-dependent models.

### 3.5. Parameter uncertainty analysis via GLUE

To account for parameter equifinality and evaluate parameter identifiability, the Generalized Likelihood Uncertainty Estimation (GLUE) was applied to the storage-dependent formulation. A uniform Monte Carlo sampling of  $N = 10,000$  parameter sets was conducted within the predefined prior parameter space:  $a \in [0, 1]$  and  $b \in [-500, 500]$  MCM.

Parameter sets meeting the behavioral cutoff criterion of  $NSE \geq NSE_{\text{baseline}}$  (yielding  $NSE \geq 0.383$ ) were retained. Out of the sampled space, 772 realizations (7.72%) were classified as behavioral. The optimal (maximum-likelihood) parameter set yielded:

$a_{\text{opt}} = 0.2055$ ,  $b_{\text{opt}} = -252.89$  MCM ( $NSE = 0.5973$ )

These values show remarkable consistency with the deterministic OLS regression estimates ( $a = 0.2061$ ,  $b = -252.08$  MCM;  $NSE = 0.5970$ ).

This close agreement provides an important cross-methodological verification. While OLS regression directly minimizes the residual sum of squares between  $L_{\text{obs}}$  and  $S_{\text{start}}$ , the GLUE framework evaluates parameter sets based on their holistic ability to reproduce the target storage trajectory ( $\Delta S_{\text{obs}}$ ) under a likelihood formulation.

The convergence of both independent methodologies toward virtually identical parameter optima confirms the robust identifiability of the storage-dependent relationship and demonstrates that the inferred parameters are not artifacts of the fitting procedure. A detailed summary of the GLUE posterior distributions and performance metrics is provided in Table 3.

### 3.6. Parameter equifinality and structural trade-offs

An evaluation of the behavioral parameter ensemble revealed a strong inverse correlation between the slope ( $a$ ) and intercept ( $b$ ) ( $r_{a,b} = -0.858$ ). The geometry of the behavioral parameter space is depicted in Fig. 4.

This strong inverse correlation reflects a direct compensatory trade-off between the model parameters across the historical storage envelope: an increment in the storage-dependent slope ( $a$ ) is balanced by a

corresponding downward shift in the intercept ( $b$ ) to maintain equivalent closure adjustments. Consequently, distinct parameter pairs can yield near-identical simulation performance over the observed storage domain.

This trade-off exemplifies the classical issue of parameter equifinality in hydrological inverse modeling. The observational data tightly constrain the macro-scale response surface (i.e., the net storage-dependent trend) rather than uniquely resolving each coefficient independently. Therefore, while the empirical evidence robustly supports a positive storage-residual dependency, treating the deterministic regression solution as a unique physical parameterization would be physically unjustified.

**Table 3.** GLUE parameter uncertainty and behavioral parameter statistics

| Metric                             | Value     |
|------------------------------------|-----------|
| GLUE samples                       | 10000     |
| Behavioral sets ( $NSE \geq 0.5$ ) | 772       |
| Behavioral proportion (%)          | 7.72      |
| Best NSE                           | 0.5972    |
| Best a                             | 0.2054    |
| Best b (MCM)                       | -252.8929 |
| Regression a                       | 0.2061    |
| Regression b (MCM)                 | -252.0777 |
| Behavioral a median                | 0.2111    |
| Behavioral a 2.5%                  | 0.0796    |
| Behavioral a 97.5%                 | 0.3336    |
| Behavioral b median (MCM)          | -252.9237 |
| Behavioral b 2.5% (MCM)            | -404.4706 |
| Behavioral b 97.5% (MCM)           | -102.2477 |
| $r(a,b)$                           | -0.8583   |
| P-factor (%)                       | 69.2307   |

Crucially, the posterior distributions reinforce the stability of the inferred relationship: the median behavioral parameters closely coincide with both the OLS regression and the optimal GLUE estimates, confirming that the preferred parameterization resides in the high-density core of the behavioral manifold rather than near peripheral or degenerate boundaries.

### 3.7. Predictive uncertainty quantification and 95PPU analysis

To quantify the predictive uncertainty stemming from parameter equifinality, the 772 behavioral parameter sets were propagated through the storage-dependent water-balance model to construct the 95% prediction uncertainty (95PPU) bounds. For each hydrological year, the upper and lower limits of the 95PPU envelope were delineated by the 97.5<sup>th</sup> and 2.5<sup>th</sup> percentiles of the simulated storage changes, respectively. The resulting uncertainty envelope bracketed 69.23% of the observed annual storage variations, yielding a *P*-factor of:  $P=0.692$ . The detailed annual 95PPU intervals and ensemble characteristics

are summarized in Table 4, and the temporal evolution of the predictive envelope is illustrated in Fig. 5.

A *P*-factor of 69.23% indicates that parameter uncertainty alone accounts for a substantial fraction of the observed interannual variability. However, the fact that nearly 30% of the observations fall outside the 95PPU bounds demonstrates that parameter equifinality does not fully capture the total systemic uncertainty. This outcome aligns consistently with the moderate regression explanatory power ( $R^2 = 0.323$ ) and simulation efficiency (NSE = 0.597).

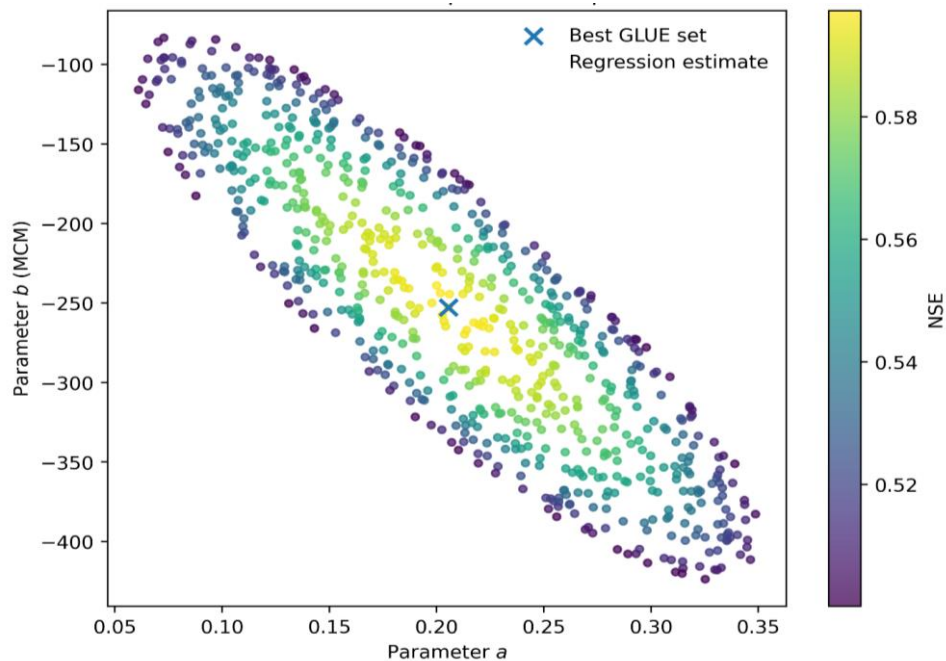


Fig. 4. Distribution of behavioral parameter pairs (*a*, *b*) obtained from the GLUE uncertainty assessment

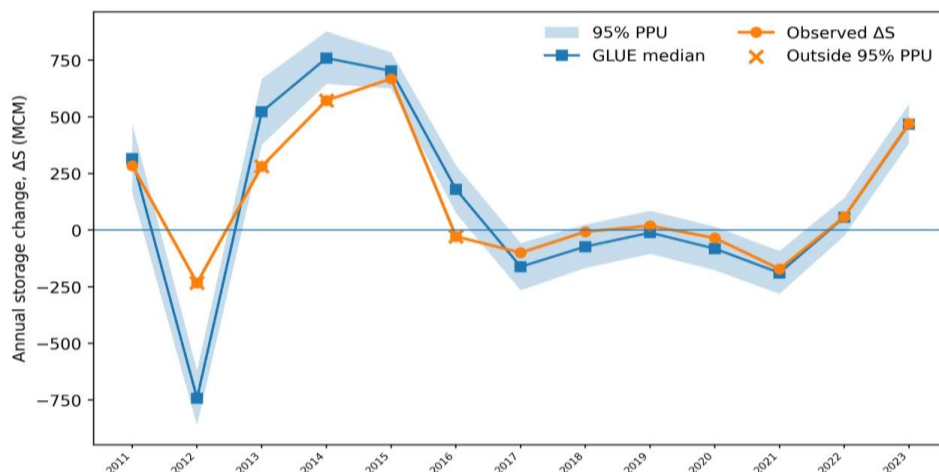


Fig. 5. Observed annual storage changes and the GLUE-derived 95% prediction uncertainty envelope

**Table 4.** Annual observed storage changes and GLUE-derived 95PPU limits

| Year | Observed $\Delta S$ (MCM) | 95PPU lower (MCM) | GLUE median (MCM) | 95PPU upper (MCM) | Inside 95PPU |
|------|---------------------------|-------------------|-------------------|-------------------|--------------|
| 2011 | 284.1                     | 164.6892          | 315.3590          | 466.8960          | TRUE         |
| 2012 | -233.23                   | -860.9408         | -742.2235         | -620.6154         | FALSE        |
| 2013 | 281.74                    | 377.4620          | 522.5346          | 667.7384          | FALSE        |
| 2014 | 572.66                    | 645.8884          | 759.7976          | 876.8920          | FALSE        |
| 2015 | 668.76                    | 625.6004          | 703.0663          | 784.1884          | TRUE         |
| 2016 | -27.8                     | 75.3983           | 180.2929          | 285.9745          | FALSE        |
| 2017 | -99.6                     | -265.7627         | -161.5704         | -57.3050          | TRUE         |
| 2018 | -6.7                      | -167.3331         | -72.6352          | 24.0782           | TRUE         |
| 2019 | 19.3                      | -104.7535         | -10.9794          | 85.2901           | TRUE         |
| 2020 | -34.8                     | -176.5888         | -81.7558          | 14.9778           | TRUE         |
| 2021 | -171.5                    | -280.9906         | -188.5374         | -92.2848          | TRUE         |
| 2022 | 58.8                      | -25.4075          | 56.6878           | 141.5300          | TRUE         |
| 2023 | 471.5                     | 383.7104          | 467.3995          | 556.5759          | TRUE         |

While the storage-dependent correction effectively captures the first-order systematic dynamics of the unmonitored residual, the remaining unexplained variance is likely driven by unmodeled structural dynamics—such as transient hydrodynamic lags, unmeasured interannual climatic variations in evaporation/seepage rates, and observational noise in inflow–outflow monitoring.

### 3.8. Sensitivity and robustness analysis of the storage–residual relationship

To assess whether the inferred storage dependency was disproportionately driven by isolated leverage points or extreme hydrological anomalies, a Leave-One-Year-Out (LOYO) cross-validation analysis was conducted. The OLS regression was iteratively refitted across sub-samples, systematically omitting one observation year at a time.

As summarized in Table 5, the estimated slope coefficient ( $a$ ) remained strictly positive across all LOYO iterations, confirming that the positive directionality of the storage–residual relationship is an intrinsic feature of the system dynamics rather than an artifact of a single anomalous year. Nonetheless, the magnitude of  $a$  exhibited moderate variability across the cross-validation folds, reflecting the sampling uncertainty associated with the relatively limited decadal observational record ( $N = 13$  years).

Consequently, the robustness assessment firmly corroborates the qualitative finding of a positive, state-dependent water-balance residual, while appropriately acknowledging that the precise numerical value of the sensitivity coefficient ( $a$ ) remains subject to sample-size constraints.

**Table 5.** Leave-one-year-out sensitivity of the storage–residual regression

| Year | $a$    | $b$ (MCM)  |
|------|--------|------------|
| 2011 | 0.2158 | -265.41865 |
| 2012 | 0.1056 | -101.1670  |
| 2013 | 0.2765 | -349.6467  |
| 2014 | 0.2399 | -304.3491  |
| 2015 | 0.2069 | -256.0053  |
| 2016 | 0.1749 | -239.4930  |
| 2017 | 0.2143 | -255.28093 |
| 2018 | 0.2131 | -253.8389  |
| 2019 | 0.2090 | -252.7552  |
| 2020 | 0.2110 | -253.3147  |
| 2021 | 0.2074 | -252.3591  |
| 2022 | 0.2060 | -252.0871  |
| 2023 | 0.2060 | -252.0790  |

#### 4. Conclusion

This study investigated whether the unmeasured annual water-balance residual of a reservoir exhibits systematic state dependence on antecedent storage conditions, and whether incorporating such dependency enhances the diagnostic fidelity and predictive simulation of annual storage changes. Utilizing a multi-year observational record (2011–2023), an empirical storage-dependent residual formulation was developed and rigorously evaluated through both OLS regression and GLUE framework. The results confirmed a statistically significant positive relationship between the beginning-of-year reservoir storage ( $S_{\text{start}}$ ) and the annual water-balance residual ( $L_{\text{obs}}$ ):

$$L_{\text{obs},t} = 0.2061 S_{\text{start},t} - 252.08 \quad (R^2 = 0.323, p = 0.043)$$

This empirical relationship indicates that initial storage accounts for approximately one-third of the interannual variance in the water-balance closure error, while the remaining unexplained variability stems from unmodeled climatic drivers, transient operational dynamics, and observational uncertainties. Integrating this storage-dependent term into the annual water-balance formulation yielded marked performance enhancements over the conventional no-loss baseline. The Nash–Sutcliffe Efficiency (NSE) increased from 0.383 to 0.597 (a 55.8% relative improvement), alongside a 19.2% reduction in RMSE (from 219.17 to 177.10 MCM). These improvements demonstrate that explicitly accounting for storage dependence retrieves substantial explanatory information regarding storage trajectory dynamics without resorting to an over-parameterized model structure.

The GLUE uncertainty analysis provided an independent, cross-methodological validation of parameter identifiability and model equifinality. Out of 10,000 Monte Carlo samples, 772 parameter sets (7.72%) met the behavioral threshold ( $\text{NSE} \geq \text{NSE}_{\text{baseline}}$ ). The maximum-likelihood parameter set ( $a = 0.2055$ ,  $b = -252.89$  MCM;  $\text{NSE} = 0.5973$ ) converged remarkably close to the deterministic OLS estimates. This robust convergence between independent analytical frameworks reinforces the credibility of the inferred storage dependence. Nonetheless, a

strong inverse correlation between parameters ( $r_{a,b} = -0.858$ ) highlighted a distinct compensatory mechanism (equifinality), demonstrating that bulk water-balance observations constrain the net storage-dependent response surface rather than resolving unique, decoupled physical parameters. Propagation of behavioral parameter sets demonstrated that the 95% prediction uncertainty (95PPU) envelope bracketed 69.23% of the observed annual storage changes ( $P\text{-factor} = 0.692$ ). This bracketed proportion affirms that parameter uncertainty captures the primary first-order dynamics of the system, while the unbracketed observations point to the influence of structural model limitations and measurement noise in inflow–outflow monitoring.

A fundamental implication of these findings is that the residual term must be interpreted as an effective, system-scale empirical flux rather than an explicit physical parameterization of a single mechanism (e.g., stage-dependent seepage or open-water evaporation). In reality, the observed residual integrates the synergistic effects of surface area expansions, evaporation rates, bank storage exchange, groundwater seepage, and operational routing lags. Isolating these discrete physical processes remains fundamentally unidentifiable from bulk inflow–outflow–storage observations alone. The core contribution of this work is the establishment of a parsimonious, two-parameter diagnostic framework for addressing systematic closure errors in data-scarce reservoir systems. This approach is particularly advantageous in operational settings where continuous, direct monitoring of evaporation or subsurface fluxes is absent, but reliable surface hydrological records are maintained. Several caveats and research avenues warrant consideration:

1) **Sample Size and In-Sample Calibration:** The findings are grounded in a 13-year decadal record. Although Leave-One-Year-Out (LOYO) cross-validation verified the directional stability of the positive slope, the reported performance metrics primarily reflect in-sample explanatory skill. Extended time series are required for rigorous split-sample predictive validation.

2) Linearity vs. Nonlinear Dynamics: While a linear formulation was adopted for parsimony, higher-order non-linearities (governed by reservoir stage–area–capacity geometry or non-linear seepage gradients) could provide further refinements if longer observational records become available.

3) Process-Level Partitioning: Future investigations should combine remote-sensing-derived water surface areas, satellite altimetry, stable isotope signatures, and hydro-meteorological datasets to decompose the bulk residual into physically explicit components (e.g., evaporation vs. net groundwater flux).

In conclusion, incorporating antecedent reservoir storage into the water-balance residual formulation bridges the operational gap between simplistic no-loss models and data-intensive, fully distributed process models, providing a robust, parsimonious basis for enhanced reservoir storage accounting.

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## 6. Conflict of interest

No potential conflict of interest was reported by the authors.

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