

Climate driven water balance stress in a reservoir using ANN corrected CORDEX-SEA projections

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Abstract: Reservoir water balance assessment is essential for understanding how climate variability and climate change affect water availability and operational performance in monsoon regions. This study evaluates baseline (2006–2023) and projected (2024–2050) water balance stress in Wonogiri Reservoir, Indonesia, using bias-corrected Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA) projections under representative concentration pathways (RCP4.5 and RCP8.5). The main contribution is an integrated reservoir-scale framework linking artificial neural network (ANN)-corrected precipitation and potential evapotranspiration with hydrological inflow simulation and differentiated forecasting of turbine and hollow jet valve (HJV) outflows to assess intra-annual storage stress under an operational constraint. An ANN was applied for bias correction and coupled with the F.J. Mock model for inflow simulation, while singular spectrum analysis (SSA) was used for outflow forecasting. Water balance was evaluated under probabilistic hydrologic conditions with a minimum intake elevation of 128 m. Baseline results indicate a monsoon-driven surplus–deficit regime with high inflow variability ($0.04\text{--}221.93\text{ m}^3\cdot\text{s}^{-1}$) and strong dry-season vulnerability due to elevated evapotranspiration. The SSA shows higher predictability for turbine outflows ($NSE = 0.76$) than for HJV outflows ($NSE = 0.58$). Although dependable inflow increases in both scenarios, these gains do not translate into higher effective storage. Instead, additional inflow is largely discharged during wet periods, while dry-season storage declines because of unfavourable inflow timing and increased evaporation. Thus, climate change may intensify seasonal operational stress, requiring adaptation strategies focused on seasonal timing, evaporation losses, and release pathways rather than annual water availability alone.

Keywords: artificial neural network, climate change, Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA), reservoir water balance, singular spectrum analysis

INTRODUCTION

Climate change is modifying both the timing of wet-dry transitions and the amount of water lost through evaporation. This means that the amount of water in reservoirs is not just based on the total amount of water that comes in each year (Nur *et al.*, 2021). In regions where the monsoon delivers the majority

of precipitation, the annual rainfall significantly influences the efficacy of reservoirs (Tian *et al.*, 2022). Research indicates that monsoon precipitation in Indonesia is shifting, accompanied by a temperature increase of approximately 0.8°C , heightening concerns for water security. This is particularly applicable to Java Island, where there is a significant demand for water and reservoir systems are crucial (Sipayung, Nurlatifah and Susanti,

2019; Kementerian PPN/Bappenas, 2021). Evaporation has become a significant loss factor in reservoir water balance, especially during extended dry seasons, and should not be regarded as a residual element in climate effect evaluations (Enkhili *et al.*, 2023). Even if annual inflows go up, higher evaporative losses can make effective storage much smaller and limit operational margins. Recent studies indicate that future reservoir vulnerability is often influenced by intra-annual variability and seasonal misalignment between supply and demand, rather than only by mean annual water availability (Wilby and Harris, 2006; Ngai *et al.*, 2022). The Wonogiri Reservoir is a substantial water body in Central Java utilised for several purposes, including flood mitigation, agricultural irrigation, electricity production, and potable water supply. Because the dry seasons are getting longer, the rainy seasons are getting wetter, and more water is evaporating, Wonogiri Reservoir is becoming more vulnerable to hydroclimatic stress (Sipayung, Nurlatifah and Susanti, 2019).

Previous studies in the region have investigated rainfall patterns or input variability; however, these analyses have predominantly focused on isolated components, thereby limiting their ability to explain integrated reservoir-scale responses to climate change. There remains a significant gap in assessments that simultaneously examine bias-corrected climate forcing, hydrological inflow generation, evaporative losses, and multiple operational outflow pathways within a single water balance framework for tropical monsoon reservoirs (Tangang *et al.*, 2020). Satellite and model-derived hydroclimatic datasets often exhibit systematic bias and scale-dependent uncertainty, underscoring the imperative for validation and rectification prior to hydrological application, as demonstrated by hybrid machine-learning analyses juxtaposing Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) satellite products with ground station data (Wahyuni, Sisingih and Dewi, 2021; Holthuijzen *et al.*, 2022). Bias correction is essential for dependable hydrological applications, as correction alternatives significantly affect projected means and extremes in Southeast Asia and may also influence the consistency of downstream water-balance interpretation (Nguyen *et al.*, 2023). Recent research indicates that exposure to heightened rainfall and temperature variations in Java is expected to increase, leading to more intra-annual variability and impacting existing reservoir operation protocols (Hendrawan *et al.*, 2024).

Reservoir water balance outcomes depend not only on inflow magnitude, but also on how inflow variability propagates through operational release pathways. In multipurpose reservoirs, outflows often consist of policies or components constrained by capacity (such as turbine releases) and event-based components, such spill or routing devices. To comprehend the future evolution of storage, it is crucial to understand the behaviour of these routes, particularly in climate scenarios where increased input does not necessarily equate to enhanced usable storage due to operational constraints and release regulations (Okkan *et al.*, 2023; Wahyuni *et al.*, 2024).

The purpose of this study is to analyse the water balance of the Wonogiri Reservoir from 2006 to 2023 and from 2024 to 2050, a timeframe projected for climate change. It will use Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA) forecasts for the representative

concentration pathways (RCP4.5 and RCP8.5) scenarios. Precipitation and potential evapotranspiration are bias corrected using an ANN and applied to inflow simulation with the F.J. Mock hydrological model, while turbine and hollow jet valve (HJV) outflows are forecast using singular spectrum analysis (SSA). By explicitly accounting for seasonal timing, evaporative losses, and differentiated outflow pathways under fixed operational constraints, this study provides an integrated reservoir-scale assessment of climate-driven intra-annual water balance stress in a monsoon-influenced system. Unlike previous studies that focus on annual metrics, this study demonstrates how intra-annual redistribution governs operational risk. Although climate projection, bias correction, hydrological simulation, and reservoir analysis have each been widely used, fewer studies have integrated these components at the reservoir scale in a way that explicitly resolves intra-annual storage stress in monsoon systems. Most previous studies emphasise annual inflow change, rainfall trends, or generalised reservoir response, while giving less attention to how bias-corrected climate forcing, evaporative losses, and differentiated outflow pathways jointly determine usable storage under operational constraints. In addition, widely used statistical correction approaches such as quantile mapping are effective for distributional adjustment but do not always address nonlinear local relationships between modelled and observed hydroclimatic variables, especially when multiple forcing variables are used in subsequent impact modelling (Nguyen *et al.*, 2023; Wang and Tian and Carroll, 2023; Wang and Tian, 2024). Therefore, the contribution of this study is not merely the combination of standard tools, but the development of an integrated reservoir-scale assessment that (i) applies artificial neural network (ANN)-based correction to both precipitation and potential evapotranspiration (*PET*) forcing from CORDEX-SEA, (ii) separates policy-constrained and event-driven outflow pathways through turbine and HJV forecasting, and (iii) evaluates how seasonal redistribution of inflow and evaporation affects storage stress under fixed intake constraints in a monsoon-influenced reservoir.

STUDY MATERIALS AND METHODS

STUDY AREA AND DATA

Wonogiri Reservoir is in Danuarjo Village, Wonogiri Regency, Central Java Province (7°50'13.48"S, 110°55'42.95"E) (Fig. 1). Constructed in 1981 and operational since 1982, the reservoir is a multipurpose system serving flood control, irrigation, hydro-power generation, and raw water supply. The reservoir drains a 1,326 km² catchment and has a surface area of approximately 90 km², making it one of the major reservoirs in Java. Hydroclimatic data used in this study includes precipitation, potential evapotranspiration (*PET*), inflow, outflow (turbine and hollow jet valve – HJV), and reservoir storage for the period 2006–2023, which were obtained from operational records. These datasets were used for baseline analysis, model calibration, and validation. All observed hydroclimatic and operational records were subjected to basic quality control prior to analysis. The screening process included consistency checks for unit conversion, inspection of missing or duplicated monthly records, comparison of seasonal patterns across variables, and verification

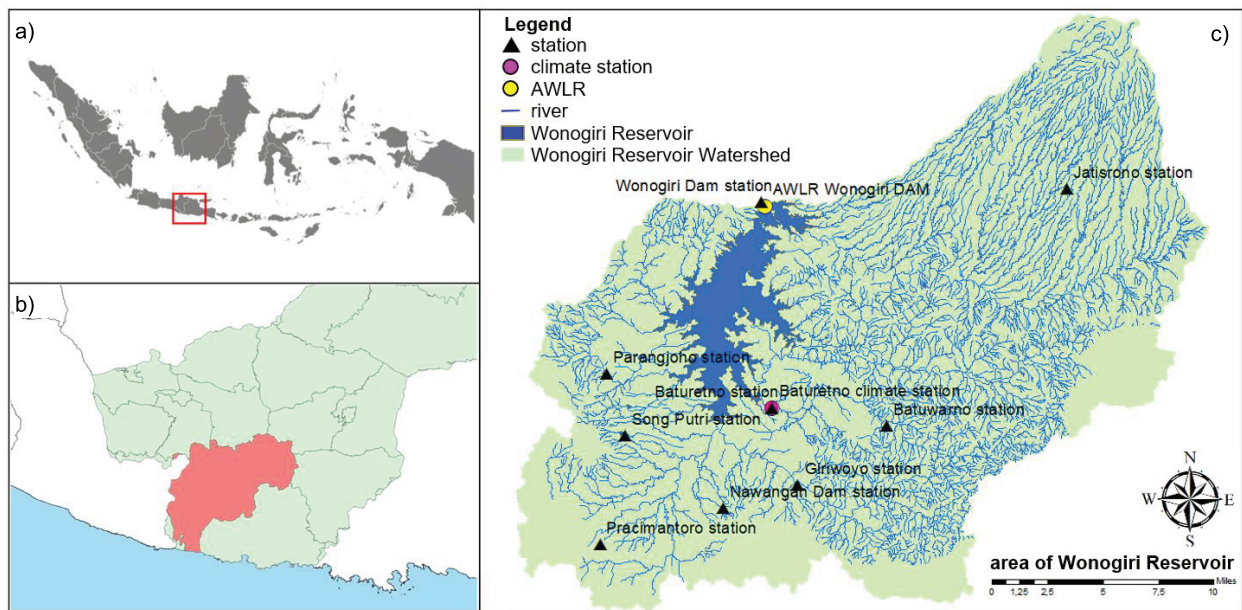


Fig. 1. Map of: a) Indonesian archipelago, b) Wonogiri Regency, c) Wonogiri Reservoir and watershed; source: own elaboration

of temporal alignment among inflow, outflow, storage, precipitation, and *PET* series. Because the analysis is conducted at monthly time scale, short-duration operational fluctuations are not explicitly represented. The main data limitation is that historical reservoir operation records reflect realised management decisions and infrastructure constraints during the observation period; therefore, they may not fully represent future adaptive operating policies. In addition, the use of a single climate model chain limits the characterisation of inter-model spread, so the results should be interpreted as scenario-based system response rather than a complete probabilistic envelope.

METHOD

The overall methodological framework consists of five main stages (Fig. 2):

- (i) preparation of observed and climate model data;
- (ii) bias correction of precipitation and *PET* using ANN;
- (iii) climate projection under RCP4.5 and RCP8.5 scenarios;
- (iv) inflow simulation using the F.J. Mock hydrological model and outflow forecasting using singular spectrum analysis (SSA);
- (v) reservoir water balance simulation for baseline and future periods.

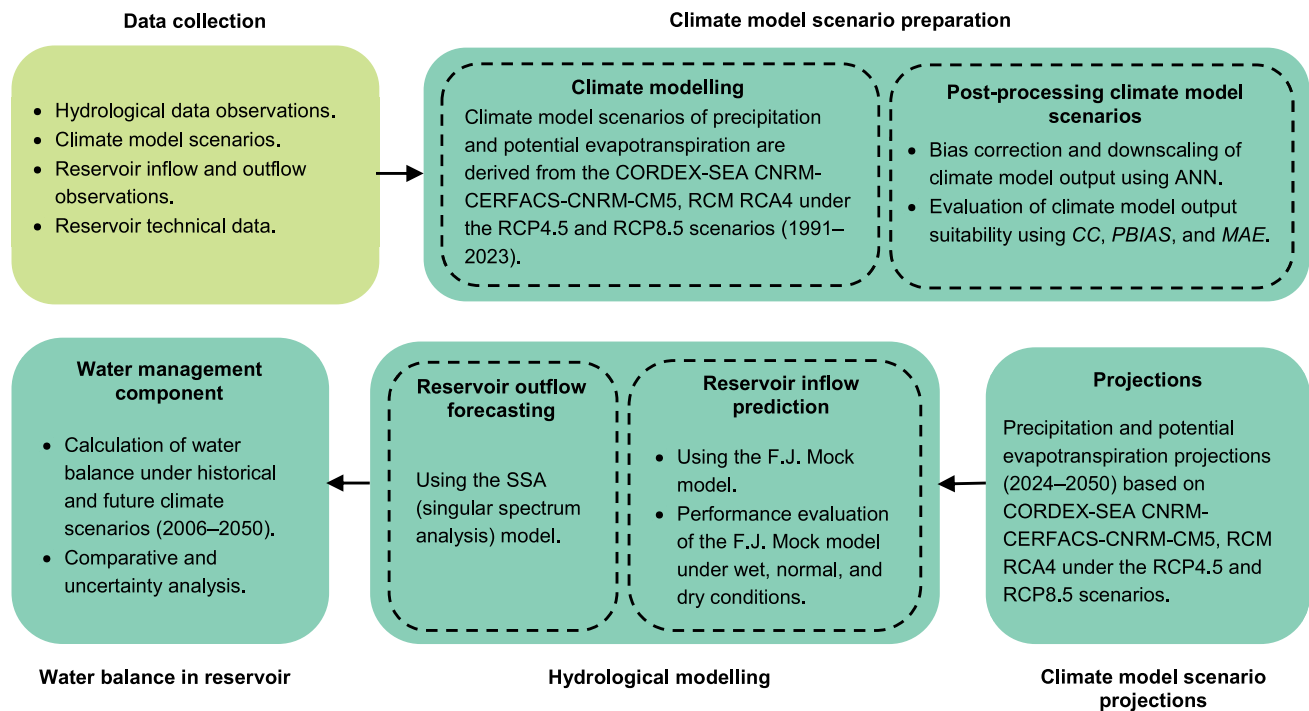


Fig. 2. Methodological framework; CORDEX-SEA = Coordinated Regional Climate Downscaling Experiment for Southeast Asia, CNRM = Centre National de Recherches Metereologiques, CM5 = Climate Models version 5, RCM = Regional Climate Model, RCP = representative concentration pathways, ANN = artificial neural network, CC = correlation coefficient, PBIAS = percent bias, MAE = mean absolute error, CERFACS = Centre European de Recherche et de Formation Avancee en Calcul Scientifique, RCA4 = Rossby Centre Regional Atmospheric 4; source: own study

RESERVOIR WATER BALANCE

Reservoir water balance was evaluated using the mass conservation principle, accounting for inflow (I , in $\text{m}^3\cdot\text{s}^{-1}$), outflow (O , in $\text{m}^3\cdot\text{s}^{-1}$), evaporation loss volume (E_t , in m^3), and storage change (S_t) (Latif *et al.*, 2021). Mathematically, the continuity Equation (1) according to Song, Her and Kang (2022) is:

$$\frac{dS}{dt} = I - O \quad (1)$$

$$S_t = S_{t-1} + (I_t - O_t - E_t) \Delta_t \quad (2)$$

where: S = reservoir storage (m^3), t = time, Δ_t = time interval (86,400 s).

CLIMATE CHANGE SCENARIO DATA SETS

Climate projections were obtained from the CORDEX-SEA framework at $0.25^\circ \times 0.25^\circ$ spatial resolution, using the CNRM-CERFACS CNRM-CM5 global climate model dynamically down-scaled by RCA4 under RCP4.5 and RCP8.5 scenarios (Vuuren *et al.*, 2014). Monthly precipitation and PET data were extracted for baseline (2006–2023) and projection (2024–2050) periods, with detailed model information summarised in Table 1.

Table 1. Climate models and scenarios used for 1991–1050: CNRM-CERFACS-CNRM-CM5 and the RCA4 Model developed by the Swedish Meteorological and Hydrological Institute (SMHI)

Experiment	Variable
RCP 8.5	precipitation
RCP 4.5	
RCP 8.5	potential evapotranspiration
RCP 4.5	

Explanations: CNRM, CERFACS, CM5, RCP as in Fig. 2.
Source: own elaboration.

BIAS CORRECTION AND MODEL EVALUATION

Raw CORDEX-SEA precipitation and PET outputs were statistically bias-corrected using an ANN implemented in RapidMiner. The ANN has been widely applied to address nonlinear relationships in hydroclimatic time series and improve predictive performance (Shafaei *et al.*, 2016). The ANN was selected in this study because the relationship between modelled and observed hydroclimatic variables in tropical monsoon environments is often nonlinear, seasonally dependent, and variable specific. Compared with simpler approaches such as delta change, which mainly preserves mean change signals, ANN provides greater flexibility to learn nonlinear departures in both magnitude and seasonality. Compared with conventional quantile mapping, ANN can better accommodate nonlinear predictor-target relationships across variables, although it does not automatically guarantee trend preservation and therefore must still be interpreted cautiously under future climate conditions (Nguyen *et al.*, 2023; Wang, Tian and Carroll, 2023; Wang and Tian, 2024).

Monthly observed and modelled climate data for 1991–2005 were used for training, while 2006–2023 data were used for evaluation. The ANN was configured as a feed-forward multilayer perception with one hidden layer, sigmoid activation in the hidden layer, and linear output activation. Separate networks were trained for precipitation and PET . Model training was performed iteratively until validation error stabilised, and the final model was selected based on minimum prediction error on withheld data. The ANN was used to reduce systematic local bias in CORDEX-SEA forcing prior to hydrological application rather than to replace physically based climate interpretation.

Model performance was evaluated using the correlation coefficient (CC), percentage bias ($PBIAS$), and mean absolute error (MAE), following Equations (3)–(5) (Moriassi *et al.*, 2007). These metrics were jointly used to assess temporal agreement, systematic over- or underestimation, and absolute error magnitude. Because subsequent inflow simulation is sensitive to both rainfall amount and evaporative demand, improvement in both rainfall amount and evaporative demand, improvement in both precipitation and PET forcing was considered necessary before hydrological application.

$$CC = \frac{N \left(\sum_{i=1}^N P_i Q_i \right) - \sum_{i=1}^N P_i \cdot \sum_{i=1}^N Q_i}{\sqrt{\left[N \sum_{i=1}^N P_i - \left(\sum_{i=1}^N P_i \right)^2 \right] \cdot \left[N \sum_{i=1}^N Q_i - \left(\sum_{i=1}^N Q_i \right)^2 \right]}} \quad (3)$$

$$PBIAS = \frac{\sum_{i=1}^N (P_i - Q_i)}{\sum_{i=1}^N P_i} 100\% \quad (4)$$

$$MAE = \frac{\sum_{i=1}^N (P_i - Q_i)}{N} \quad (5)$$

where: N = number of samples, P_i = observed data, Q_i = model/corrected estimate.

INFLOW SIMULATION USING THE F.J. MOCK MODEL

Reservoir inflow was simulated using the F.J. Mock hydrological model, which applies a monthly water balance approach incorporating rainfall, evapotranspiration, soil moisture, ground-water storage, and runoff components in Equation (6) (Jayanti *et al.*, 2023). The model was selected because its monthly conceptual structure is consistent with the temporal resolution of the available hydroclimatic and reservoir operation datasets, it is parsimonious and suitable for data-constrained basins, and it has been widely used in Indonesian and monsoon-influenced catchments for operational water-resources assessment. Therefore, the model is appropriate for reservoir-scale seasonal inflow simulation rather than event-scale flood representation. Evapotranspiration was computed using the modified Penman method, and discharge was estimated as:

$$Q = f(R, ET, SM, G) \quad (6)$$

where: Q = discharge ($\text{m}^3\cdot\text{s}^{-1}$), R = rainfall, ET = evapotranspiration (mm), SM = soil moisture storage (mm), G = groundwater storage (mm).

Model performance was validated against observed inflow using the Nash–Sutcliffe efficiency (NSE) and correlation coefficient (CC) formula as shown in Eq. (7) (Moriassi *et al.*, 2007).

$$NSE = 1 - \frac{\sum_{i=1}^N (Q_o - Q_m)^2}{\sum_{i=1}^N (Q_o - \bar{Q}_o)^2} \quad (7)$$

where: Q_o = observed discharge ($\text{m}^3 \cdot \text{s}^{-1}$), Q_m = modelled discharge ($\text{m}^3 \cdot \text{s}^{-1}$), and $\bar{Q}_o$ = mean of observed discharge ($\text{m}^3 \cdot \text{s}^{-1}$).

Model calibration was conducted against observed inflow by iteratively adjusting effective soil moisture, groundwater recession, and runoff response parameters to maximise agreement between simulated and observed monthly discharge during the calibration period. Validation was then performed on an independent evaluation period. In this study, the F.J. Mock model is used as a reservoir-inflow generator on a monthly scale; therefore, its suitability should be interpreted in relation to seasonal water-balance behaviour rather than detailed event hydrograph reproduction. A limitation of the F.J. Mock model is that it simplifies watershed heterogeneity and may under-represent process-level dynamics during extreme hydrological transitions. Accordingly, the model is appropriate for assessing climate-driven seasonal inflow response and water balance stress, but less suitable for high-frequency runoff extremes or physically explicit watershed diagnosis.

DEPENDABLE DISCHARGE ESTIMATION

Dependable discharge was estimated using the basic month method combined with the Weibull probability approach, producing Q80 (dry), Q50 (normal), and Q30 (wet) discharge conditions (Ramadhani, 2017; Sejati and Akbar, 2024), is in Equation (8):

$$P = \frac{m}{n+1} 100\% \quad (8)$$

where: m = the debit data sequence number, n = the total number of data.

OUTFLOW FORECASTING USING SINGULAR SPECTRUM ANALYSIS

Reservoir outflows (turbine and HJV) were forecast using SSA, a nonparametric time series decomposition technique suitable for nonstationary and seasonal data (Hassani and Thomakos, 2010). The SSA consists of embedding, singular value decomposition, grouping, and reconstruction stages (Movahedifar, Hassani and Kalantari, 2023). This study chose SSA because it does not need a lot of training data and does a good performance of capturing seasonal operational patterns. Forecasting was performed using linear recurrent formulation (LRF) using Equation (9) (Dani *et al.*, 2024). In this study, SSA was used to represent dominant seasonal and medium-term operational structure rather than to reproduce every event-driven release precisely. This distinction is important for the HJV series, which is partly controlled by episodic operational responses to high inflow or routing conditions. Therefore, lower predictive skill for HJV outflow is interpreted as higher uncertainty in the event-driven outflow component, whereas turbine outflow is expected to be more predictable because it is constrained by operational policy and capacity. The SSA outputs were thus used as scenario-consistent operational inputs to the reservoir water balance model, with

greater interpretive confidence assigned to turbine releases than to HJV releases.

$$\hat{f}_t^{(h)} \begin{cases} \hat{f}_t^{(h)} & \text{for } t = 1, 2, \dots, n \\ \sum_{j=1}^{L-1} r_j^{(h)} \hat{f}_{t-j}^{(h)} & \text{for } t = n+1, \dots, n+M \end{cases} \quad (9a)$$

$$\hat{f}_t = \sum_{h=1}^m \hat{f}_t^{(h)} \quad \text{for } t = n+1, \dots, n+M \quad (9b)$$

where: $\hat{f}_t^{(h)}$ = reconstructed or forecasted value of the h^{th} SSA component at time t , $\hat{f}_{(t-j)}^{(h)}$ = previous reconstructed or forecasted value of component h , observed at lag j , $r_j^{(h)}$ = linear recurrent coefficient for lag j of the h^{th} SSA component, L = SSA window length or embedding dimension, $L-1$ = number of lagged component values included in the recurrence equation, j = lag index, $j = 1, 2, \dots, L-1$, h = index of an SSA component or reconstructed group, m = total number of retained SSA components or groups, $(\hat{f})_t$ = final aggregated forecast of reservoir outflow at time t , t = time index, n = number of observed data points in the original series, M = number of future time steps forecast, or forecast horizon, $n+1, \dots, n+M$ = future forecasting period, $\hat{}$ = an estimated, reconstructed or forecasted value, (h) = SSA-component index, not a mathematical exponent.

UNCERTAINTY CONSIDERATIONS

Uncertainty in this study arises from four main sources. First, climate uncertainty originates from the selected GCM-RCM chain and emissions scenario, which affects the magnitude and timing of projected precipitation and *PET*. Second, bias-correction uncertainty arises because ANN correction reduces systematic historical bias but does not eliminate all future non-stationarity or extreme-event errors. Third, hydrological-model uncertainty arises from the structural simplification of the F.J. Mock model and from parameter equifinality in transforming climate forcing into inflow. Fourth, operational uncertainty arises from SSA-based outflow forecasting, especially for HJV releases, which are more episodic and less predictable than turbine releases.

These uncertainty sources were not propagated through a full multi-model ensemble or formal probabilistic framework in the present study. Instead, uncertainty was addressed through cautious interpretation of model skill, separation of more reliable and less reliable operational components, and comparison of directional responses across two climate scenarios. The consistency of the major findings across RCP4.5 and RCP8.5 namely stronger intra-annual mismatch, higher evaporation burden, and reduced dry-season storage effectiveness suggests that the identified stress pattern is directionally robust, even though the exact magnitude of projected change remains uncertain.

RESULTS

BIAS CORRECTION PERFORMANCE FOR PRECIPITATION AND POTENTIAL EVAPOTRANSPIRATION

The ANN-based bias correction significantly enhanced the concordance of Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA) precipitation

and potential evapotranspiration (*PET*) with observational data during the evaluation period (2006–2023), validating its efficacy for hydrological forcing (Hastina, Wahyuni and Harisuseno, 2025). The raw CORDEX-SEA precipitation underestimated the observed precipitation by 29.5% (RCP4.5) and 26.4% (RCP8.5). Similarly, the raw *PET* underestimated the observed *PET* by approximately 13% under both scenarios. After bias correction, the mean annual precipitation and *PET* closely matched the observed values, with the remaining biases falling within $\pm 2\%$ (Tab. 2).

Model performance measures show a significant improvement: the correlation coefficients for precipitation went up by around 15%, from almost zero to over 0.84 for *PET*, and the mean absolute error (*MAE*) went down by more than 60% (Tab. 2). These results show that ANN bias correction works to reduce systematic errors in both size and variability, making it possible to use credible climate data for inflow and water balance simulations (Fig. 3).

The improvement of performance is hydrologically meaningful because the corrected forcing reduces two major sources of downstream error simultaneously: underestimation of effective rainfall input and underestimation of evaporative demand. The large *CC* improvement for *PET* indicates that the ANN correction substantially improved seasonal co-variation with observations, which is particularly important for reservoir systems where dry-

season storage loss is strongly controlled by atmospheric demand. Although the improvement in precipitation *CC* is more moderate, the marked reduction in *MAE* and *PBIAS* indicates that the corrected series is substantially more suitable for monthly inflow simulation than the raw CORDEX-SEA output.

BASELINE WATER BALANCE ANALYSIS

The baseline monthly water balance shows a clear pattern of surplus and deficit caused by the monsoon. During the rainy season (November to April), there is a lot of excess water, and during the dry season (May to October), there is a lot of storage stress (Fig. 4). Inflow varies a lot from year to year, going from 0.04 to 221.93 $\text{m}^3\cdot\text{s}^{-1}$. This mostly controls how much water is released and when spills happen.

Outflow patterns reflect differentiated operational pathways. Turbine releases remain relatively stable (0–60 $\text{m}^3\cdot\text{s}^{-1}$), indicating policy and capacity constrained operation, while hollow jet valve (HJV) discharges contribute a smaller and more variable component (maximum 31.55 $\text{m}^3\cdot\text{s}^{-1}$). Dry season vulnerability is amplified by elevated *PET* (86–306 $\text{mm}\cdot\text{month}^{-1}$), which accelerates storage drawdown when inflow is suppressed, highlighting that low storage conditions arise from the combined effect of reduced inflow and increased evaporative demand rather than rainfall deficits alone (Tab. 3).

Table 2. Evaluation model result

Data	Evaluation statistic	RCP4.5		RCP8.5	
		before corrected	after corrected	before corrected	after corrected
Precipitation	<i>CC</i>	0.58	0.66	0.56	0.65
	<i>PBIAS</i>	21.63	8.41	16.94	6.80
	<i>MAE</i>	35.17	13.67	27.54	11.06
Potential evapotranspiration	<i>CC</i>	0.05	0.84	−0.15	0.86
	<i>PBIAS</i>	−12.75	1.45	−13.31	1.25
	<i>MAE</i>	254.82	102.69	256.43	91.02

Explanations: *CC* = correlation coefficient, *PBIAS* = percentage bias, *MAE* = mean absolute error, RCP = representative concentration pathway. Source: own study.

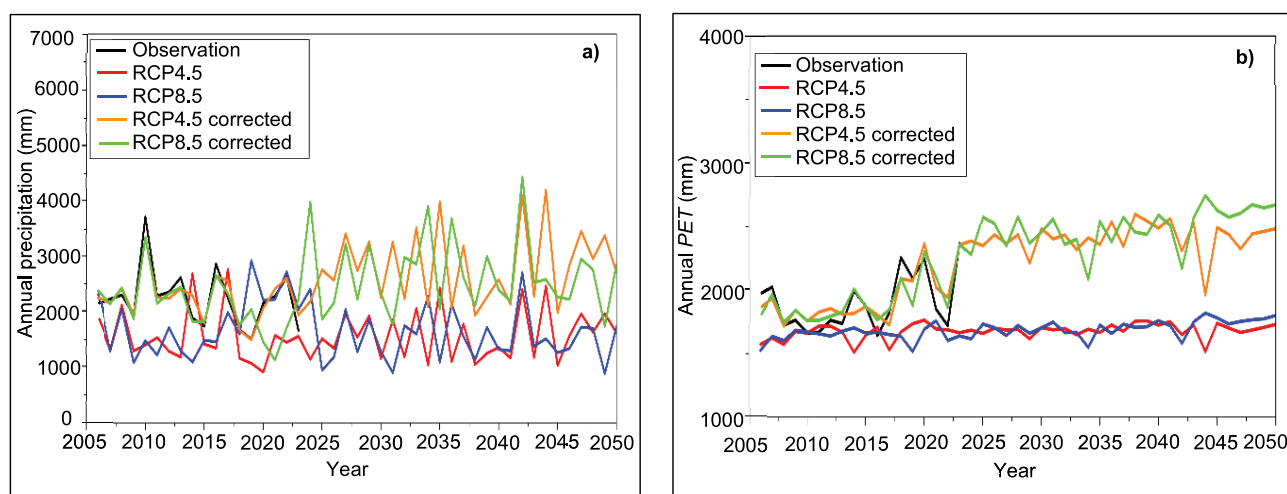


Fig. 3. Artificial neural network bias corrected annual values of: a) precipitation, b) potential evapotranspiration (*PET*); RCP = representative concentration pathway; source: own study

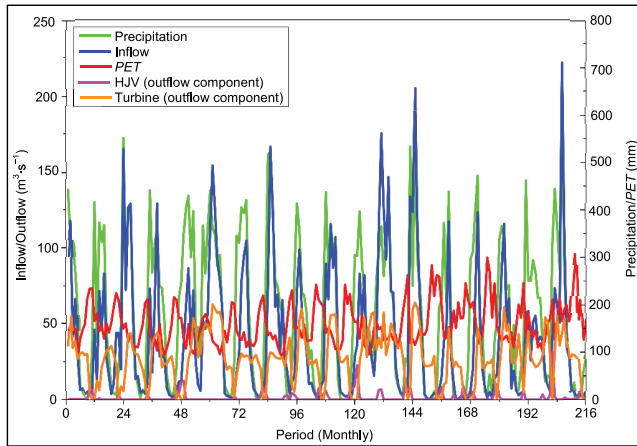


Fig. 4. Baseline (historical) water balance components: inflow, outflow, potential evapotranspiration (*PET*) and precipitation; HJV = hollow jet valve; source: own study

PROJECTED INFLOW SIMULATION AND MODEL VALIDATION

Future inflow was simulated using the F.J. Mock model under RCP4.5 and RCP8.5 scenarios for 2006–2050, incorporating bias-corrected precipitation and *PET*. Model validation against observed inflow demonstrates satisfactory to good performance, with *NSE* values of 0.64 (RCP4.5) and 0.66 (RCP8.5), and strong correlations ($CC > 0.80$) – Table 4. These results confirm the reliability of the F.J. Mock model for subsequent dependable discharge and water balance analysis.

Table 3. Baseline hydroclimatic summary

Component	Baseline range / key statistic	Seasonal implication (wet: Nov–Apr; dry: May–Oct)
Inflow	0.04–221.93 $\text{m}^3\cdot\text{s}^{-1}$	wet season peaks drive surplus and spill; dry season minima define the critical drawdown period
Turbine outflow	0–60 $\text{m}^3\cdot\text{s}^{-1}$	operation constrained releases; relatively insensitive to short term inflow extremes
Hollow jet valve outflow	max. 31.55 $\text{m}^3\cdot\text{s}^{-1}$	minor component; supports baseflow/environmental regulation
Potential evapotranspiration	86–306 $\text{mm}\cdot\text{month}^{-1}$	higher in dry season due to higher evaporative demand ($T\uparrow$, $RH\downarrow$, radiation $\uparrow$)
Precipitation	0–671.42 $\text{mm}\cdot\text{month}^{-1}$	strong seasonality; wet month concentration controls inflow generation

Explanations: T = temperature, RH = relative humidity.

Source: own study.

Table 4. Validation of F.J. Mock simulated discharge against observed discharge

Scenario	Evaluation statistic	
	<i>NSE</i>	<i>CC</i>
RCP 4.5	0.64 (satisfactory)	0.80 (very good)
RCP 8.5	0.66 (good)	0.82 (very good)

Explanations: *NSE* = Nash–Sutcliffe efficiency, *CC* = correlation coefficient, RCP = representative concentration pathway.

Source: own study.

At monthly scale, *NSE* values of 0.64–0.66 indicate satisfactory to good performance for climate-impact-oriented reservoir inflow simulation, especially given the conceptual structure of the model and the use of bias-corrected climate forcing. The *CC* values above 0.80 further indicate that the model captures the temporal dynamics of wet and dry periods well. These statistics suggest that the model is adequate for seasonal water balance assessment, although some uncertainty remains for extreme transitions and peak-flow months.

DEPENDABLE DISCHARGE ANALYSIS USING BASIC MONTH

Dependable discharge analysis indicates an overall increase in inflow availability under both climate scenarios, particularly for wet and normal conditions (Tab. 5). Relative to the baseline period (2006–2023), Q_{80} increases from 18.13 to 25.12 $\text{m}^3\cdot\text{s}^{-1}$ under RCP4.5 and to 21.19 $\text{m}^3\cdot\text{s}^{-1}$ under RCP8.5, while Q_{30} increases from 49.70 to 63.63 $\text{m}^3\cdot\text{s}^{-1}$ (RCP4.5) and 61.50 $\text{m}^3\cdot\text{s}^{-1}$ (RCP8.5). Despite these increases, dependable discharge gains alone do not guarantee improved storage reliability, as operational constraints and evaporation losses strongly influence net water balance outcomes.

OUTFLOW FORECASTING USING SINGULAR SPECTRUM ANALYSIS

The SSA successfully captures the seasonal structure and medium-term variability of reservoir outflows, particularly for turbine releases (Fig. 5). The chosen window length ($L = 8$)

Table 5. Mean dependable discharge under dry (Q_{80}), normal (Q_{50}), and wet (Q_{30}) flow ($\text{m}^3\cdot\text{s}^{-1}$) conditions

Period	Scenario	Condition		
		Q_{80}	Q_{50}	Q_{30}
2006–2023	baseline	18.13	35.83	49.70
2024–2050	projection RCP 4.5	25.12	44.78	63.63
	projection RCP 8.5	21.19	43.33	61.50

Explanations: RCP = representative concentration pathway.

Source: own study.

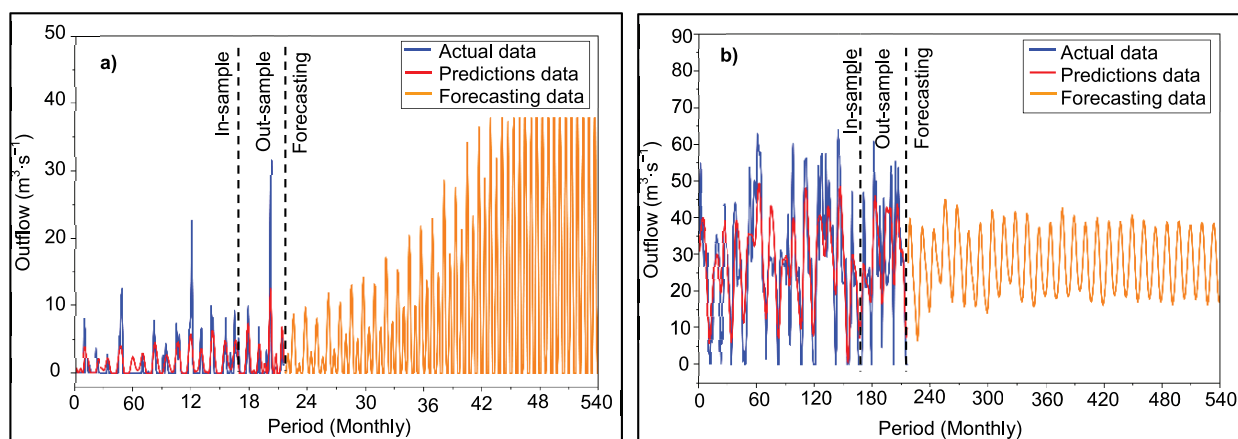


Fig. 5. Outflow discharge projection using the singular spectrum analysis method: a) hollow jet valve outflow, b) turbine; source: own study

provides superior predictive accuracy for turbine discharge ($NSE = 0.76$; $RSR = 0.49$) compared to HJV discharge ($NSE = 0.58$; $RSR = 0.65$) – Table 6. This discrepancy shows the difference between policy-constrained turbine operation and event-driven HJV releases. The latter are more uncertain during peak inflow periods.

The contrast in predictive skill between turbine and HJV outflows releases is also conceptually consistent with reservoir operation logic. Turbine outflow releases follow a more regular and capacity-constrained pattern, so their seasonality is easier to reconstruct using SSA. In contrast, HJV outflow releases are activated under more episodic and operationally contingent conditions, which makes them less stationary and more difficult to forecast. Therefore, the HJV series contributes greater uncertainty to projected water balance than the turbine series and should be interpreted as an indicator of stress-responsive release behaviour rather than a highly deterministic forecast.

Table 6. Singular spectrum analysis (SSA) skill summary

Series	Best SSA parameter	Skill metrics (out of sample)	Interpretation for uncertainty
HJV outflow	$L = 8$	$NSE = 0.58$, $RSR = 0.65$	moderate skill; higher uncertainty near extreme peaks
Turbine outflow	$L = 8$	$NSE = 0.76$, $RSR = 0.49$	good skill; seasonal structure robust and more predictable

Explanations: HJV = hollow jet valve outflow, L = window length, NSE = Nash–Sutcliffe efficiency, RSR = $RMSE$ -observations standard deviation ratio. Source: own study.

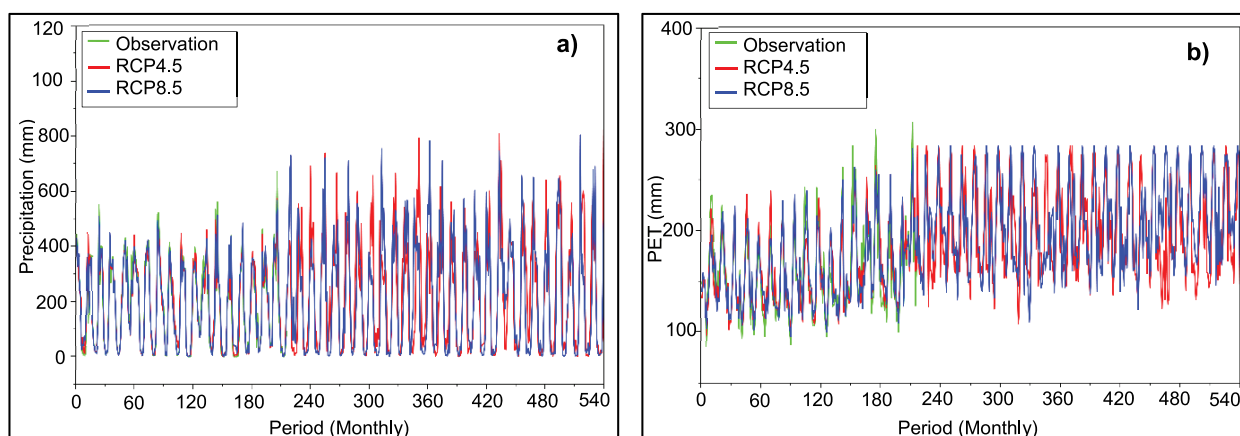


Fig. 6. Climate projection comparison chart in trends of: a) precipitation, b) potential evapotranspiration (PET); RCP = representative concentration pathway; source: own study

PROJECTED CHANGES IN INFLOW, EVAPORATION, AND STORAGE

Climate forecasts suggest more intra-annual variability instead of consistent annual alterations. According to RCP4.5, inflow increases happen mostly in the middle of the year (June–September), and big drops happen during the usual recharging periods (October–February) (Fig. 6). The RCP8.5 makes this pattern stronger by making inflow rises bigger in some months and drops sharper in others. This makes it more likely that inflow availability and storage recovery will not match seasonally (Fig. 7b).

Evaporation losses rise in all scenarios, especially near the conclusion of the dry season, which is in line with higher atmospheric evaporative demand (Fig. 7a). Storage models show that more water coming in does not mean more water being kept, because gains during rainy periods are mostly canceled out by more discharges and evaporation, while storage during dry periods drops by up to 82% under RCP8.5 (Fig. 7e–g).

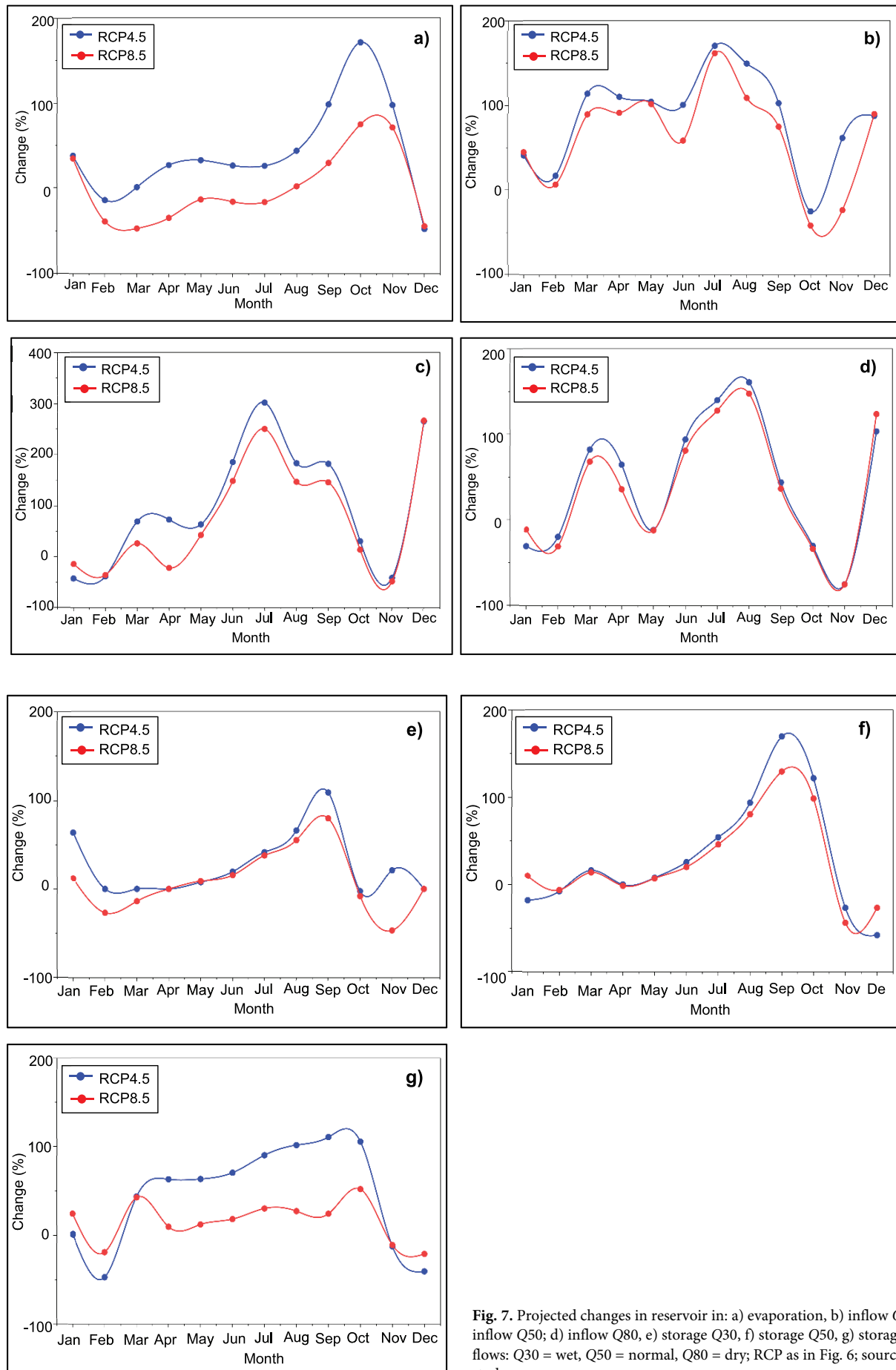


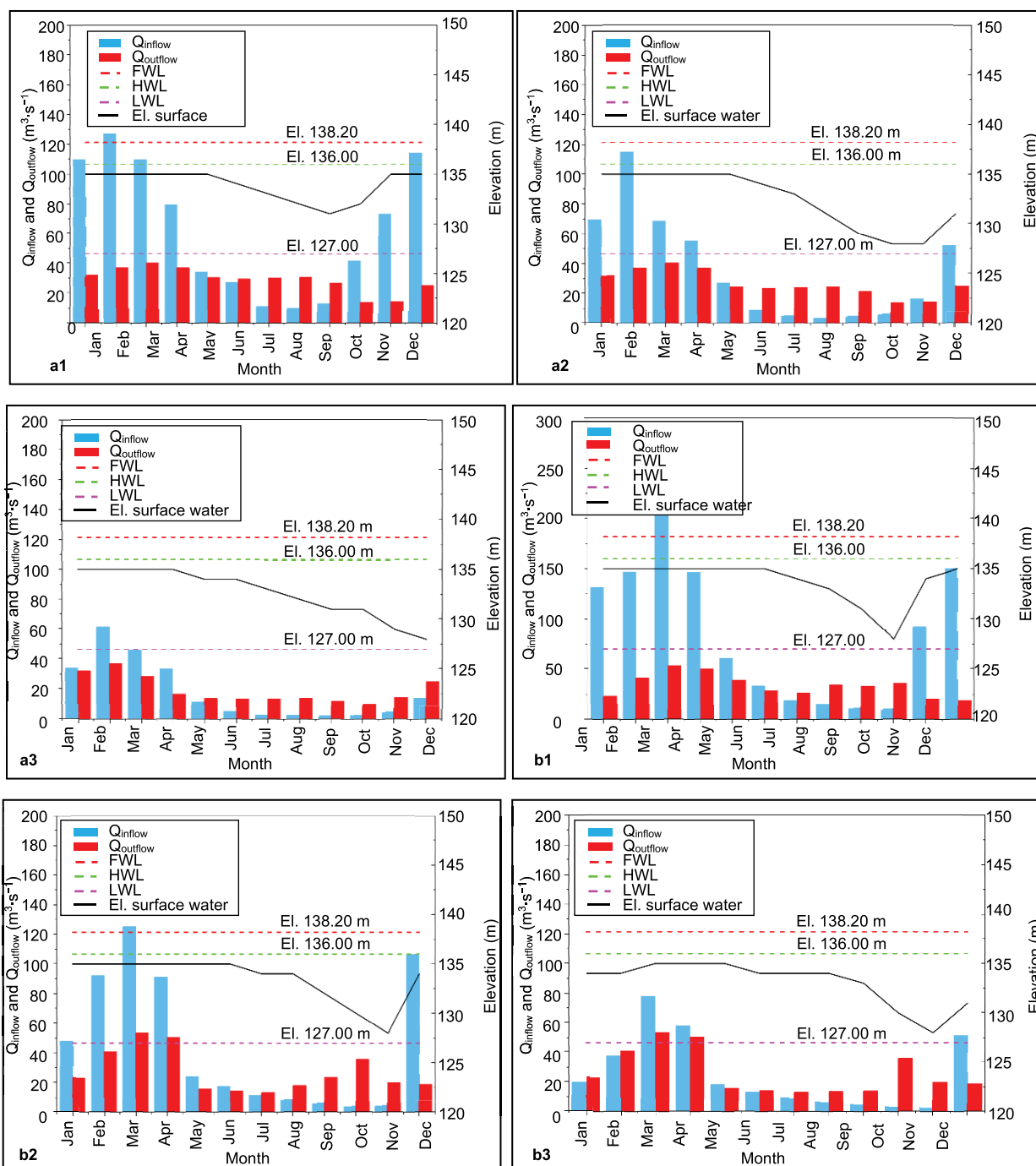
Fig. 7. Projected changes in reservoir in: a) evaporation, b) inflow Q30; c) inflow Q50; d) inflow Q80, e) storage Q30, f) storage Q50, g) storage Q80; flows: Q30 = wet, Q50 = normal, Q80 = dry; RCP as in Fig. 6; source: own study

COMPARATIVE WATER BALANCE OUTCOMES

Monthly water balance simulations enforcing a minimum intake elevation of 128 m highlight increasing operational stress under future climates (Fig. 8). The 128 m intake elevation was treated as a fixed screening constraint to evaluate climate-induced storage stress under a consistent operating threshold. This assumption does not represent a fully dynamic rule curve and therefore should be interpreted as a simplified operational benchmark rather than a complete simulation of adaptive reservoir management. Compared to baseline conditions, RCP4.5 exhibits more frequent dry-season drawdown toward the intake threshold, while RCP8.5 produces the strongest stress signal, characterised by

prolonged dry periods, delayed storage recovery, and sharper declines in reservoir elevation. Annualised water balance components (Tab. 7) confirm that increased inflow under both scenarios is largely transmitted as higher outflow, particularly during wet periods (+108% under RCP4.5, +119% under RCP8.5), while dry-period storage change declines substantially (up to -85%), indicating heightened vulnerability to seasonal water shortages despite higher mean inflow.

These outcomes indicate that future operational stress is governed by transmission inefficiency rather than absolute inflow shortage alone. In other words, the reservoir receives more water on average in some projected conditions, but a larger fraction of that water becomes unavailable for dry-season storage support



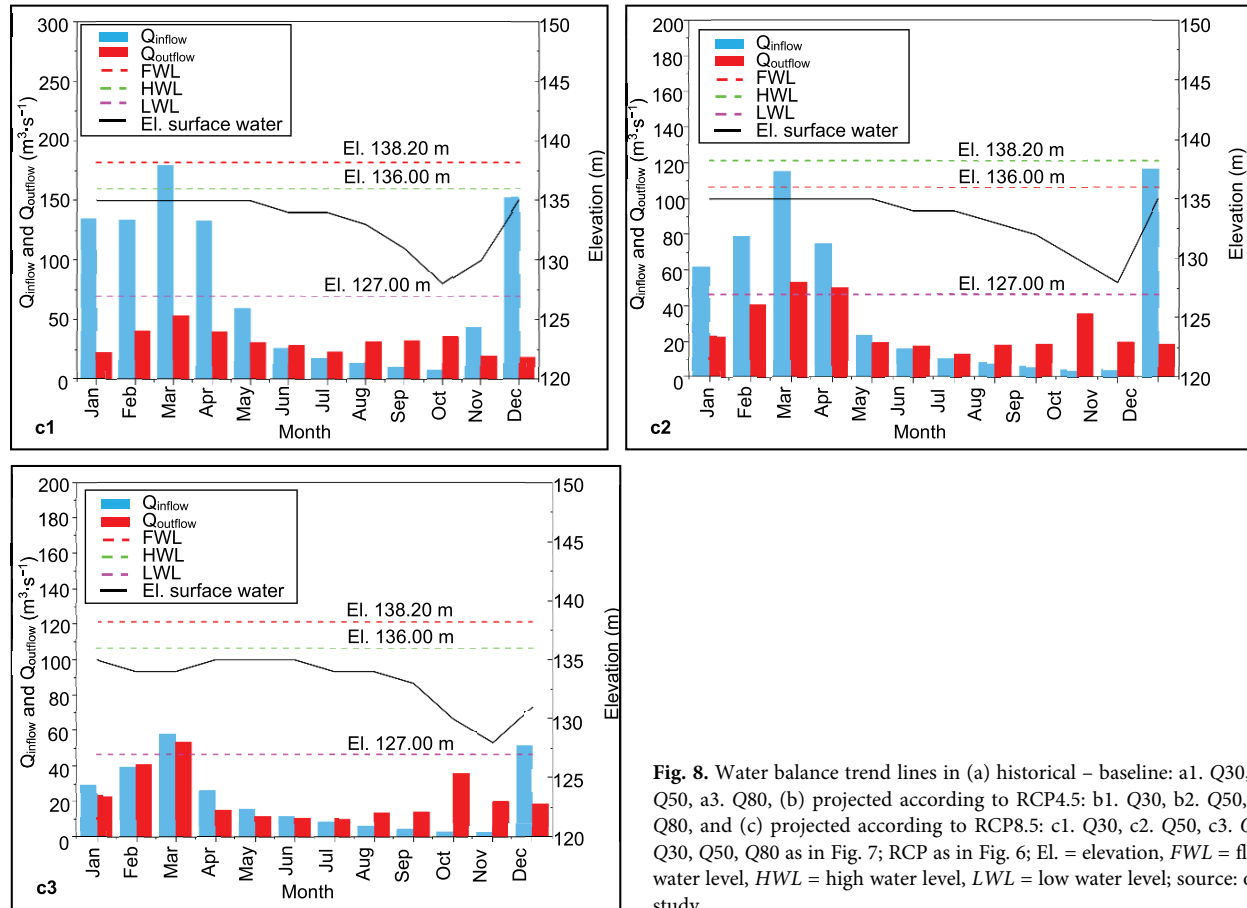


Fig. 8. Water balance trend lines in (a) historical – baseline: a1. Q30, a2. Q50, a3. Q80, (b) projected according to RCP4.5: b1. Q30, b2. Q50, b3. Q80, and (c) projected according to RCP8.5: c1. Q30, c2. Q50, c3. Q80; Q30, Q50, Q80 as in Fig. 7; RCP as in Fig. 6; El. = elevation, FWL = flood water level, HWL = high water level, LWL = low water level; source: own study

Table 7. Quantitative summary of water balance components

Component		Baseline	RCP4.5	Δ (%)	RCP8.5 (MCM·y ⁻¹)	Δ (%)
		MCM·y ⁻¹				
Inflow	dry period	563	791	+40	667	+18
	normal period	1,115	1,405	+26	1,363	+22
	wet period	1,552	2,659	+71	2,383	+54
Evaporation	dry period	44	72	+64	61	+40
	normal period	61	90	+47	93	+51
	wet period	67	96	+43	90	+34
Outflow	dry period	480	713	+49	583	+22
	normal period	889	1,082	+22	1,161	+31
	wet period	888	1,843	+108	1,943	+119
Change in storage	dry period	+40	+6	−85	+22	−44
	normal period	+164	+44	−73	+109	−33
	wet period	+278	+278	0	+278	0

Explanations: RCP as in Fig. 6, Δ = percentage change.

Source: own study.

because it arrives outside the most beneficial recharge window, is lost to higher evaporation, or is released through intensified wet-period outflow. This explains why rising inflow and declining storage can coexist within the same climate scenario.

DISCUSSION

The results demonstrate that climate change impacts on Wonogiri Reservoir are governed primarily by changes in intra-annual timing, variability, and loss amplification rather than by increases in mean annual inflow. Under both representative concentration pathways (RCP4.5 and RCP8.5) scenarios, annual inflow increases are projected; however, these gains do not translate into enhanced usable storage, highlighting the limitations of assessments based solely on annual water availability. This finding reinforces evidence from monsoon-dominated reservoir systems showing that seasonal redistribution of inflow often exerts stronger control on storage performance than mean inflow magnitude (Espanmanesh and Tilmant, 2022). Projected inflow increases are unevenly distributed across the year and frequently occur outside the critical storage recovery window, while inflow during key recharge months weakens. Consequently, surplus inflow is predominantly discharged via spill or operational outflows instead of being conserved, especially when subjected to fixed capacity and rule-curve limitations. This mechanism elucidates the paradox of rising input alongside diminishing dry-season storage, a behaviour similarly noted in other highly seasonal reservoir systems. These results highlight that assessments relying solely on annual inflow figures may overstate future water supply if seasonal alignment is not explicitly addressed. Evaporation becomes a significant aggravating factor of dry-season susceptibility. Even moderate reductions in rainfall can trigger substantial storage losses when combined with increased atmospheric evaporative demand. The projected rise in evaporation toward the end of the dry season accelerates storage drawdown, narrowing operational margins and increasing the probability of approaching intake elevation thresholds. This result is consistent with global assessments showing that reservoir evaporation losses are increasing under climate warming and significantly reducing effective storage, particularly in water-stressed regions (Jansen and Teuling, 2020). Differentiation between outflow pathways provides further insight into how climate-driven inflow changes propagate through the reservoir system. Turbine outflow releases are still predictable and limited by operating policy. On the other hand, hollow jet valve (HJV) discharges are more variable and uncertain since they happen when anything happens. So, unless operating regulations or structural capacity are changed, future increases in inflow are more likely to make spill and routing pressure worse than improve controlled releases. Similar differences between outflows that are limited by policy and those that are dominated by spills have been found in climate impact studies of multipurpose reservoirs that are affected by changing hydrologic regimes (Bees and Mooy, 2024).

The lower predictive skill of the HJV series therefore does not invalidate the broader water-balance signal, but it does require cautious interpretation of the exact magnitude of event-responsive releases. For this reason, the most defensible conclusion is that future hydroclimatic change is likely to increase routing and spill pressure more than it improves regulated storage effectiveness.

From a management perspective, the findings suggest that static operation may become increasingly inefficient under future climate conditions. Adaptation options may include seasonally adjusted rule curves, pre-emptive wet-season release strategies, hedging policies for dry-season supply protection, and stronger consideration of evaporation losses in storage planning. Recent reservoir operation studies indicate that climate-tailored allocation and hedging rules can improve system performance under altered hydrologic regimes, particularly where timing shifts are as important as changes in annual totals (Okkan *et al.*, 2023; Espanmanesh *et al.*, 2024). Accordingly, the present results should be interpreted as evidence that Wonogiri Reservoir may require more flexible seasonal operation in the future.

Several uncertainties should also be emphasised. First, the study uses one general circulation model–regional circulation model (GCM-RCM) chain, so inter-model spread is not fully represented. Second, ANN bias correction improves historical agreement but cannot eliminate uncertainty associated with future non-stationarity. Third, the F.J. Mock model is a parsimonious conceptual model and therefore simplifies watershed processes, especially for extreme runoff generation. Fourth, the HJV outflow forecast exhibits only moderate skill, which introduces uncertainty into the event-driven release component. Therefore, the conclusions are strongest at the level of direction and mechanism, greater intra-annual mismatch, stronger evaporation burden, and lower dry-season storage effectiveness rather than exact monthly values. Future work should extend this framework using multi-model climate ensembles, formal uncertainty propagation, and adaptive rule-curve simulation.

The results indicate that climate change is likely to exacerbate the risk of spills during the wet season and increase the burden on storage during the dry season at Wonogiri Reservoir. This is due to more variability throughout the year, alterations in the timing of inflow, and elevated evaporative losses, rather than merely fluctuations in the average inflow. This underscores the necessity of reservoir water balance evaluations that explicitly incorporate seasonal timing, loss mechanisms, and distinct release paths, especially for monsoon-affected systems where operational limitations significantly influence climatic effects. The lessons learnt can be applied to other reservoirs that are affected by monsoon and have similar constraints on how they can be used.

CONCLUSIONS

This study assessed the baseline (2006–2023) and projected (2024–2050) water balance of Wonogiri Reservoir using an integrated framework combining Coordinated Regional Climate Downscaling Experiment for Southeast Asia (CORDEX-SEA) climate projections, artificial neural network (ANN)-based bias correction, F.J. Mock inflow simulation, and singular spectrum analysis (SSA)-based outflow forecasting. The main scientific contribution is the explicit demonstration that climate impacts on this monsoon-influenced reservoir are controlled more by intra-annual redistribution of inflow, evaporation increase, and differentiated release pathways than by changes in annual inflow alone. The baseline analysis confirms that reservoir operation is governed by a monsoon-driven surplus-deficit regime, in which dry-season vulnerability arises from the combined effects of

suppressed inflow and elevated evaporative demand rather than from rainfall deficits alone.

Under both representative concentration pathways (RCP4.5 and RCP8.5) scenarios, mean dependable inflow increases across all hydrologic conditions; however, these increases do not translate into enhanced usable storage. Instead, water balance simulations show that additional inflow is largely transmitted as increased outflow, particularly during wet periods, while dry-season storage declines substantially due to intensified evaporation and unfavourable inflow timing. Wet period outflow increases by over 100% relative to baseline, whereas dry period storage change decreases by up to 85% under future climate scenarios, highlighting growing seasonal operational stress. Outflow forecasting reveals a clear contrast between policy constrained turbine outflow releases and event hollow jet valve discharges, with the latter exhibiting higher uncertainty and greater sensitivity to climate induced inflow variability. This distinction demonstrates that future inflow increases are more likely to exacerbate spill and routing pressure than to improve regulated water supply reliability, unless operational rules or infrastructure capacity are adjusted.

Overall, the results indicate that climate change impacts on Wonogiri Reservoir are dominated by intensified intra annual variability, shifted inflow timing, and rising evaporative losses rather than by changes in mean annual inflow. This study contributes an integrated reservoir scale assessment that explicitly accounts for seasonal timing, loss processes, and differentiated release pathways, providing insights that extend beyond conventional annual water balance evaluations. The results highlight the importance of integrating intra annual dynamics into reservoir management and adaptation strategies for monsoon affected systems in a changing climate. Overall, the results indicate that reservoir vulnerability in monsoon systems cannot be inferred from annual inflow change alone. Reservoir adaptation should therefore prioritise seasonal operating flexibility, explicit treatment of evaporation losses, and operational strategies that account for intra-annual storage stress.

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CONFLICT OF INTERESTS

All authors declare that they have no conflict of interests.

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