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RELIABILITY ASSESSMENT OF CALIBRATED CHIRPS-BASED WATER BALANCE MODELING ACROSS TWO TROPICAL RESERVOIR CATCHMENTS

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ABSTRACT: Seasonal rainfall variability in tropical irrigation systems complicates reservoir operation by affecting inflow reliability and long-term storage sustainability. Although CHIRPS is useful for data-scarce basins, most studies remain limited to single-catchment evaluation. This study assesses reliability in calibrated CHIRPS-based water balance modeling in two tropical reservoir catchments characterized by contrasting spatial scales and irrigation requirements. CHIRPS rainfall data for 2004-2023 were statistically calibrated against observed data and assessed using the correlation coefficient (R), Nash-Sutcliffe Efficiency (NSE), and RSR. Corrected rainfall inputs were employed in the F.J. Mock rainfall-runoff model with Genetic Algorithm parameter optimization. Dependable discharge (Q20, Q50, and Q80) was estimated using Weibull probability analysis, while long-term surplus-deficit dynamics were evaluated through water balance modeling. The findings indicate that both catchments have steady discharge modeling performance (NSE > 0.70) and strong calibration reliability (R > 0.75). Although the overall frequencies of surplus deficits were comparable, watershed size and irrigation demand influenced dry-season resilience and the seasonal concentration of water deficits. These results show that satellite-based hydrological modeling combined with demand-aware reservoir management can support seasonal water security and adaptive reservoir operation in tropical data-scarce environments. Beyond site-specific performance evaluation, this study proposes a cross-catchment reliability assessment framework to examine the transferability of calibrated CHIRPS-based water balance modeling across heterogeneous tropical reservoir systems.

Keywords: CHIRPS Precipitation Dataset, Water Balance Modeling, Rainfall-Runoff Simulation, Dependable Discharge, Tropical Reservoir Catchments

1. INTRODUCTION

Reservoirs play a key role in water security for tropical irrigation systems where the variability in monsoonal rainfall has a strong influence on inflow availability, storage stability and operational reliability [1,2] . Because rainfall is concentrated within a short-wet season followed by prolonged dry periods, reservoir systems often experience alternating surplus and shortage conditions. Hydrological responses also vary with watershed scale, as small catchments tend to generate rapid runoff, whereas larger basins generally show delayed runoff and stronger groundwater buffering [3]. These conditions increase the need for reliable rainfall data to support water balance assessment and discharge estimation [4].

In data-scarce tropical regions, sparse and incomplete rain-gauge networks limit conventional hydrological analysis [5]. Satellite-derived precipitation products therefore provide an important alternative for rainfall-runoff modeling and water resources assessment [6]. CHIRPS offers long-term rainfall estimates at 0.05° × 0.05° resolution by integrating satellite observations and station-based measurements [7]. Previous studies show that bias-corrected CHIRPS can support rainfall-runoff modeling, irrigation planning, and dependable discharge estimation in data-limited basins [8]. However, most applications remain site-specific, leaving the reliability of CHIRPS-based hydrological modeling across catchments with different watershed scales and irrigation intensities insufficiently understood.

In Indonesia, CHIRPS-F.J. Mock applications remain dominated by single-reservoir studies, providing site-specific evidence but limited insight into cross-catchment reliability. The key gap is whether calibrated CHIRPS-based water balance modeling remains consistent and interpretable across reservoirs with contrasting watershed scales, runoff responses, and irrigation demand structures.

In this study, reliability is defined as the capacity of a calibrated satellite-based hydrological modeling framework to produce consistent and decision-relevant performance across analysis stages. It is evaluated through four dimensions: rainfall-input reliability, assessed by the agreement between corrected CHIRPS and observed rainfall; runoff-model reliability, assessed by the model's ability to reproduce observed discharge; hydrological supply reliability, assessed through dependable discharge and surplus-deficit behavior; and cross-catchment reliability, assessed by comparing these indicators under different watershed and irrigation-demand conditions. Thus, reliability is treated as an integrated framework, not a single metric.

This study evaluates calibrated CHIRPS-based water balance modelling across two tropical reservoir catchments with contrasting watershed scales and irrigation demands. The assessment integrates rainfall correction, F.J. Mock rainfall-runoff simulation, dependable discharge, surplus-deficit analysis, and a Reliability Difference Index (RDI) to quantify cross-catchment consistency.

The remainder of this article presents the research significance, describes the study areas, data preparation, rainfall correction, rainfall-runoff modeling, dependable discharge estimation, water balance analysis, and cross-catchment reliability assessment, followed by the discussion of model performance, surplus-deficit behavior, comparative reliability indicators, and the main conclusions of the study.

2. RESEARCH SIGNIFICANCE

Although calibrated CHIRPS-based hydrological modelling has been applied in tropical catchments, previous studies have mainly focused on local applicability and cross-catchment reliability has not been widely evaluated. The study extends the evaluation to a structured inter-catchment assessment framework to evaluate model stability under contrasting watershed scales and irrigation demands. The present study contributes to a more transparent methodological approach to test transferability and robustness for data-scarce tropical reservoir systems by integrating rainfall correction, runoff simulation, dependable discharge, deficit-pattern analysis, and RDI.

3. METHODOLOGY

3.1 Study Area

3.1.1 Krisak Reservoir (Small Catchment)

Krisak Reservoir is in the upstream part of a tropical monsoonal river system in Central Java, Indonesia (Figure 1). It has a small catchment area of approximately 7.05 km² and a river length of about 4.37 km, resulting in limited storage buffering and rapid runoff response during rainfall events. The watershed is dominated by cultivated agricultural land, while the soil moisture capacity was represented by a lumped value of 200 mm based on regional soil characteristics, previous F.J. Mock applications, and calibration adjustment.

3.1.2 Pacal Reservoir (Medium Catchment)

Pacal Reservoir is in East Java, Indonesia, within the Bengawan Solo River system (Figure 1). It drains a larger catchment of more than 84 km² and serves an irrigation area of approximately 16,633 ha. Compared with Krisak, its larger contributing area and stronger hydrological buffering produce a more gradual runoff response. Rainfall-runoff simulation was conducted over the 2004-2023 period at a 10-day interval, and the main characteristics of both reservoirs are summarized in Table 1.

3.2 Data Description

This study used 20-year data (2004-2023), including CHIRPS and observed rainfall, climatological variables for evapotranspiration estimation, observed inflow discharge for model evaluation, and irrigation demand data from reservoir operation plans.

CHIRPS rainfall data for 2004-2023 were extracted from the 0.05° gridded dataset by overlaying grid cells with each reservoir catchment boundary and averaging the intersecting cells to obtain catchment rainfall. The extracted series were checked for temporal consistency, aligned with observed rainfall, cleaned of unmatched records, and aggregated into 15-day intervals for Krisak and 10-day intervals for Pacal. Bias correction was then performed using the selected catchment-specific regression model, and the corrected CHIRPS rainfall series were used as final inputs in the F.J. Mock rainfall-runoff simulation.

3.3 Data Quality Assessment

Satellite rainfall data from CHIRPS were calibrated against observed rainfall using separate regression-based correction models for each reservoir catchment. Five functional forms were tested, namely linear, exponential, logarithmic, polynomial, and power regression, as expressed in

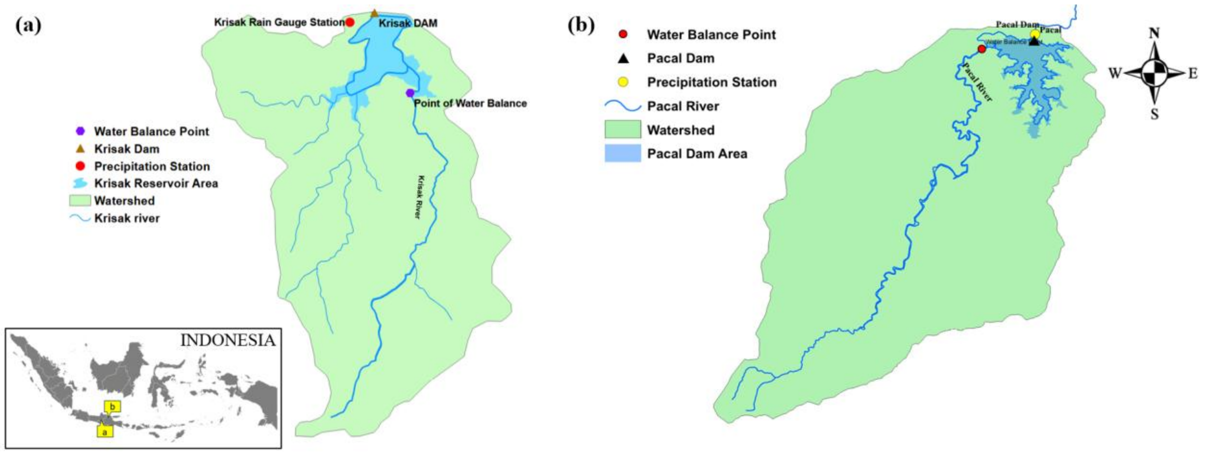

Fig. 1 Map of (a) Krisak Reservoir and (b) Pacal Reservoir.

Table 1. Comparative Catchment Characteristics and Basis of Parameter Interpretation.

Parameter	Krisak Reservoir (Small Catchment)	Pacal Reservoir (Medium Catchment)	Basis of Interpretation
Catchment Area	7.05 km²	84 km²	Delineated from watershed boundary and reservoir catchment data
Irrigation Area	340 ha	16,633 ha	Obtained from reservoir irrigation service area/operation records
Simulation Interval	15-day	10-day	Adjusted to the available hydrological and reservoir operation data interval
Dominant Land Use	Agricultural	Agricultural-mixed	Interpreted from catchment-scale land-cover information and reservoir documentation
Soil Moisture Capacity	200 mm	200 mm	Adopted as an effective lumped SMC parameter based on regional soil characteristics, prior F.J. Mock applications, and calibration consistency
Rainfall Regime	Tropical monsoon	Tropical monsoon	Based on the seasonal rainfall pattern of the study region

Eq. (1)-Eq. (5). Model calibration and validation were performed using temporally aligned CHIRPS and observed rainfall datasets:

$$Linear: y = a + bx \tag{1}$$

$$Exponential: y = ae^{bx} \tag{2}$$

$$Logarithmic: y = a + b.ln(x) \tag{3}$$

$$Polynomial: y = a + bx + cx^2 \tag{4}$$

$$Power: y = ax^b \tag{5}$$

where x is CHIRPS rainfall, y is corrected rainfall, and a, b, and $c$are empirical regression coefficients. The best correction model for each reservoir was selected based on validation performance.

Model performance was evaluated using R, NSE, and RSR [9,10]. The correction model for each reservoir was selected based on the best validation performance, namely higher R and NSE and lower RSR, to reduce overfitting and ensure transferability to independent data [11]. The 2004-2023 paired rainfall data were temporally aggregated and chronologically divided into calibration and validation subsets. This split preserved time-series structure, avoided information leakage, and captured interannual variability. All candidate regression models were summarized in a comparative table to support model selection. Based on validation accuracy and stability, the linear model was selected for Krisak, while the polynomial model was selected for Pacal (Table 2).

3.4 Rainfall-Runoff Modeling Using the F.J. Mock Method

Rainfall-runoff transformation was conducted using the F.J. Mock water balance model, which estimates discharge from rainfall, evapotranspiration, soil moisture storage, groundwater storage, infiltration, and runoff components [12,13].

Table 2. Candidate regression models and calibration-validation performance metrics for CHIRPS rainfall correction (S = Selected, NS = Not Selected, C = Calibration, V = Validation)

Reservoir	Model Form	R (C)	NSE (C)	RSR (C)	R (V)	NSE (V)	RSR (V)	Decision
Krisak	**Linear**	**0.60**	**0.65**	**0.51**	**0.85**	**0.69**	**0.55**	**S**
Krisak	Exponential	0.45	0.25	1.49	0.77	0.38	0.78	NS
Krisak	Logarithmic	0.59	0.09	0.95	0.79	0.59	0.64	NS
Krisak	Polynomial	0.62	0.14	1.02	0.84	0.66	0.59	NS
Krisak	Power	0.59	0.19	1.04	0.85	0.72	0.53	NS
Pacal	Linear	0.81	0.66	0.58	0.78	0.54	0.68	NS
Pacal	Exponential	0.64	-0.28	1.13	0.58	-0.22	1.10	NS
Pacal	Logarithmic	0.80	0.64	0.60	0.73	0.49	0.72	NS
Pacal	**Polynomial**	**0.84**	**0.70**	**0.55**	**0.78**	**0.58**	**0.65**	**S**
Pacal	Power	0.82	0.65	0.59	0.76	0.55	0.67	NS

The model was selected because it is widely used in Indonesian data-scarce reservoir catchments, requires limited input parameters, and still represents key tropical water balance processes. Other models were not compared because this study focused on cross-catchment reliability assessment of calibrated CHIRPS rainfall within an established operational framework, not model-structure benchmarking.

Potential evapotranspiration was calculated using the Modified Penman method based on local climatological parameters. Soil moisture capacity (SMC) was set at 200 mm for both catchments, consistent with regional soil characteristics. The core discharge equation is expressed in Eq. (6).

$$Q_n = \frac{A \times 1000}{n \times 86400} \times Runoff \quad (6)$$

where Q_n is discharge (m³/s), A is watershed area (km²), n is number of simulation days, and Runoff represents total effective runoff depth [13].

The F.J. Mock infiltration coefficient (*i*) and groundwater recession factor (*k*) were independently optimized for each reservoir using a Genetic Algorithm (GA) to minimize discharge simulation error [14]. consistent with recent applications of metaheuristic optimization in reservoir studies under variable inflow conditions [15].

3.5 Dependable Discharge Estimation

Dependable discharge was estimated using the Basic Month Method based on simulated discharge series. Ten-day (or fifteen-day) discharge values were ranked in descending order and probability of exceedance was calculated using the Weibull [16]. The formula shows as in Eq. (7).

$$P = \frac{m}{n+1} \times 100\% \quad (7)$$

where *P* is the probability of exceedance (%), *m* is the rank order of the discharge value after sorting the data in descending order, and *n* is the total number of observations.

Three reliability levels were analyzed; Q20 (wet-year condition); Q50 (normal condition) and Q80 (dry-year condition). These dependable discharge values were used to assess low-flow reliability and reservoir vulnerability under different hydrological scenarios [17].

3.6 Water Balance Modeling

Reservoir water balance was evaluated using the mass balance equation in Eq. (8).

$$\Delta S = Q_{inflow} - Q_{outflow} \quad (8)$$

where ΔS is the change in reservoir water storage or water balance condition over a given simulation period, Q_{inflow} represents modeled catchment inflow and $Q_{outflow}$ represents irrigation water demand [18].

A positive balance indicates water surplus, whereas a negative balance indicates deficit conditions [19-21]**.** Surplus-deficit frequency was calculated over the 20-year simulation period to quantify system reliability. Seasonal distribution of deficit occurrence was also analyzed to identify critical vulnerability periods within the monsoonal cycle.

3.7 Cross-Catchment Reliability Assessment

Modeling robustness was evaluated through four reliability dimensions: rainfall-input reliability using R, NSE, and RSR; runoff-model reliability using simulated-observed discharge agreement; hydrological supply reliability using Q20, Q50, Q80, and surplus-deficit frequency; and cross-catchment reliability using performance deviations between Krisak and Pacal Reservoirs.

A RDI (Eq. 9) was introduced to quantify performance deviation between reservoirs as an indicator of cross-catchment reliability. It serves as a comparative robustness measure after other reliability dimensions are evaluated. Lower RDI indicates stronger modeling consistency, while higher RDI reflects greater catchment-dependent model behavior.

$$RDI = \frac{|NSE_A - NSE_B|}{NSE_{mean}} \tag{9}$$

Lower RDI values indicate stronger modeling consistency across catchment scales.

This cross-catchment assessment framework enables evaluation of whether calibrated CHIRPS-based modeling remains reliable under contrasting watershed sizes and irrigation intensities.

4. RESULTS AND DISCUSSION

4.1 CHIRPS Calibration Performance Across Catchments

The selected correction equations were retained because they produced the best validation performance and cross-period stability; therefore, the resulting statistics were used as indicators of rainfall-input reliability before runoff simulation. Calibrated CHIRPS rainfall agreed well with observed rainfall in both reservoirs, with high correlation coefficients ($R > 0.75$) and acceptable validation NSE values, as summarized in Table 3. Linear regression was selected for Krisak, while polynomial regression was selected for Pacal, indicating that CHIRPS bias was corrected differently according to catchment characteristics. Figure 2 shows that most corrected rainfall values were concentrated around the 1:1 line, confirming improved agreement after calibration. However, Krisak showed wider scatter under high rainfall intensity because its smaller catchment and shorter flow path make rainfall variability more sensitive to local extremes, resulting in higher residual uncertainty at peak rainfall magnitudes.

4.2 Rainfall-Runoff Simulation Reliability

The calibrated CHIRPS dataset showed good rainfall-runoff performance in both reservoirs, with correlation coefficients above 0.80 and NSE values in the good to very good category. This supports its use for inflow simulation, consistent with recent reservoir studies showing that hydrological modeling can improve inflow prediction for monsoonal reservoir operation under climate uncertainty [22]. As shown in Figure 3, the agreement between simulated and observed hydrographs indicates runoff-model reliability, namely the ability of corrected rainfall inputs to reproduce observed discharge behavior.

Krisak generated faster runoff with sharper hydrograph peaks because its small catchment and limited storage reduce hydrological buffering. In contrast, Pacal showed smoother hydrograph variation and longer dry season baseflow due to its larger catchment and stronger groundwater storage. The different optimized infiltration coefficient (i) and groundwater recession factor (k) confirm this scale dependence: Krisak required greater parameter adjustment to capture peak flows, while Pacal showed stronger recession buffering. Thus, the F.J. Mock structure remained reliable across contrasting catchments, although optimized parameters were site-specific.

4.3 Dependable Discharge Characteristics

Dependable discharge analysis revealed different hydrological behavior under dry, normal and wet conditions, indicating consistency of flow availability as an index of hydrological supply reliability. The results of the comparison are shown in Table 4.

Krisak Reservoir has a lower Q80 than Pacal Reservoir (0.0337 versus 0.993 m^3/s), indicating less reliable dry season flow. This is also reflected in the low-flow retention ratios, Q80/Q50 is 0.194 for Krisak and 0.495 for Pacal, and Q80/Q20 is 0.060 and 0.248, respectively. The results show that Pacal is more persistent in low flows because of its larger catchment and groundwater buffering capacity, while Krisak is more sensitive to reduction of rainfall, which leads to more abrupt depletion of discharge.

Krisak has a more variable discharge regime, while Pacal shows a more buffered response (see figure 4). The Q80 discrepancy may also be a function of methodological factors, including different simulation intervals (15-day for Krisak and 10-day for Pacal) and residual CHIRPS rainfall uncertainty during high intensity events. This difference should be considered as a total effect of hydrological scale, model configuration and rainfall-input uncertainty.

Table 3. Calibration and Validation Performance Indicators (C = Calibration, V = Validation)

Indicator	Reservoir A	Reservoir B
R (C)	0.8545	0.7768
NSE (V)	0.6948	0.5765
RSR	0.5524	0.6508
Selected Model	Linear	Polynomial

Table 4. Dependable Discharge

Reliability Level	Krisak Reservoir (m^3/s)	Pacal Reservoir (m^3/s)
Q80	0.0337	0.993
Q50	0.1733	2.006
Q20	0.5621	4.000

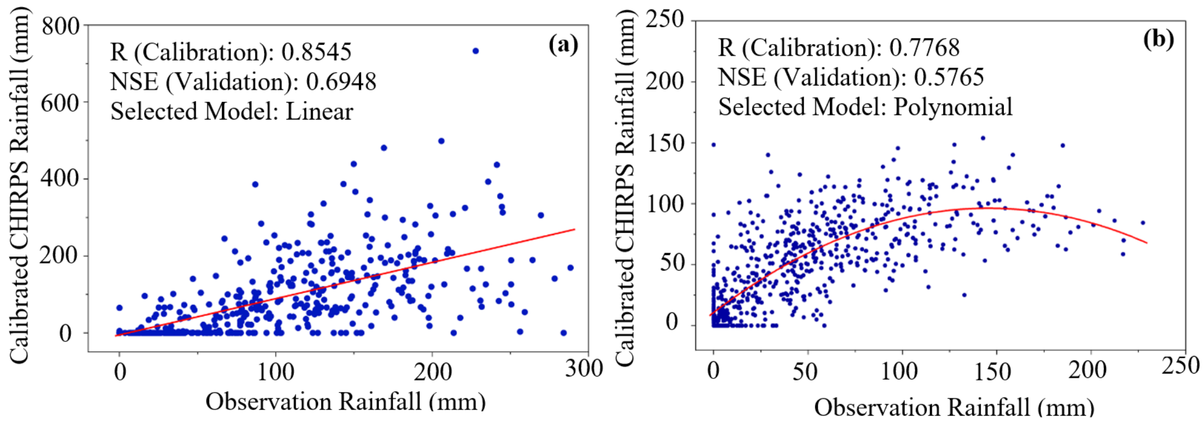

Fig. 2 Scatter plot of calibrated CHIRPS rainfall against observed rainfall for (a) Krisak Reservoir and (b) Pacal Reservoir.

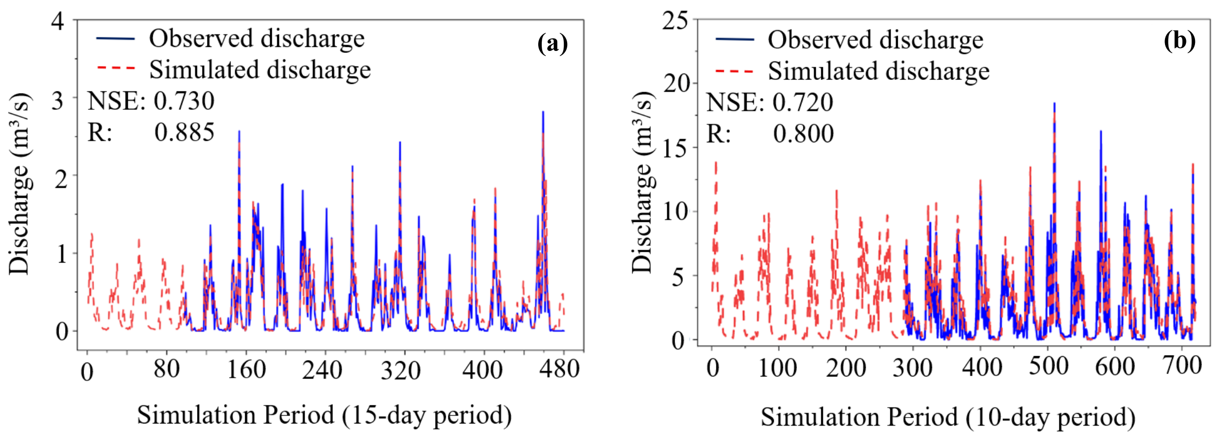

Fig. 3 Observed and simulated discharge hydrograph for (a) Krisak Reservoir and (b) Pacal Reservoir during 2004-2023

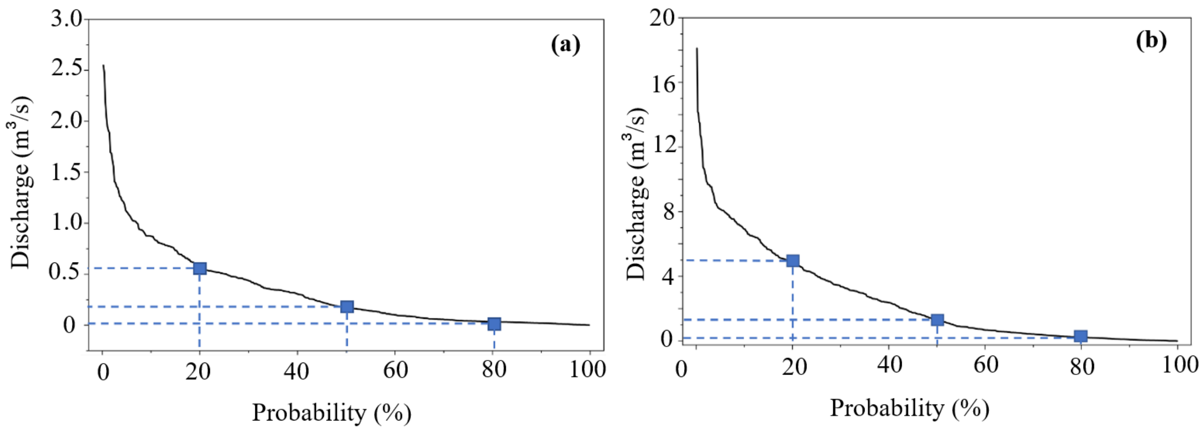

Fig. 4 Dependable discharge curves for Krisak Reservoir and Pacal Reservoir based on Weibull probability distribution.

4.4 Water Balance Reliability and Deficit Structure

Simulation of the water balance for the 20 years shows alternate surplus and deficit in both reservoirs. Reservoir reliability is not only controlled by inflow availability but also by long-term storage degradation, since sedimentation may reduce storage capacity, trap efficiency, and water-supply reliability [23]. The surplus-deficit frequency was adopted as a measure of hydrological supply reliability, because it shows the temporal consistency of water adequacy to the irrigation demand. Table 5 shows the comparative frequency of surpluses and deficits.

Seasonal deficit patterns differed between reservoirs, although surplus deficit frequencies were similar. The seasonal deficit occurrence is shown in Figure 5. Krisak deficits were concentrated in the peak dry season, July-September, while Pacal had a broader deficit window, March to June (Figure 5). This suggests that they have different dry-period responses, where Krisak has a more concentrated seasonal deficit while Pacal has a longer but more distributed deficit pattern, likely related to watershed scale, storage buffering, and timing of irrigation demand.

4.5 Cross-Catchment Reliability Assessment

The RDI was calculated based on the deviation of the NSE among reservoirs to quantify the consistency of the modelling. The RDI was low (<0.15), indicating low divergence of performance across catchment scales. The comparative reliability indicators are presented in Figure 6.

Figure 6 shows that rainfall calibration performance is relatively similar between reservoirs, while low-flow reliability has a strong variation. Pacal has a much higher Q80 than Krisak (0.993 versus 0.0337 m^3/s) and higher normalized ratios of Q80/Q50 (0.495 versus 0.194) and Q80/Q20 (0.248 versus 0.060). This indicates a higher persistence of the dry season flow in Pacal. The difference is probably due to groundwater and catchment scale buffering in Pacal, more rapid runoff depletion in Krisak, different simulation intervals, and residual uncertainty in rainfall correction. Thus, dry-year reliability is less transferable than would be expected from calibration performance alone.

These findings have broader implications for tropical monsoon reservoir systems, where hydrological resilience is controlled by rainfall concentration, watershed scale, and irrigation demand. Small catchments are more vulnerable to rapid dry-season depletion because limited storage reduces flow buffering, whereas larger systems are more influenced by operational water allocation. Therefore, calibrated satellite-based hydrological modelling can support adaptive reservoir operation in heterogeneous and data-scarce tropical basins. From a risk-management perspective, reliability assessment is also important because hydrological failure and dam-related hazards may cause significant downstream economic losses [24].

While the modelling performance was consistent between the two catchments, there were some limitations to acknowledge. First, the calibration of rainfall depended on the available ground-based rain gauge stations, and the relatively sparse spatial distribution may not fully represent the localized rainfall variability, especially during extreme monsoonal events. Second, the irrigation demand data were obtained from operational planning records, which may contain uncertainties in real water allocation on the field and use at the farmer level. These factors may introduce yet more variability in deficit estimation and reliable discharge interpretation. Thus, although the cross-catchment reliability framework gives useful comparative insight, more studies with denser rainfall networks, real-time irrigation monitoring and distributed hydrological modelling could improve robustness assessment.

Table 5. Surplus-Deficit Frequency Distribution

Condition	Krisak Reservoir (%)	Pacal Reservoir (%)
Surplus	49%	49%
Deficit	51%	51%

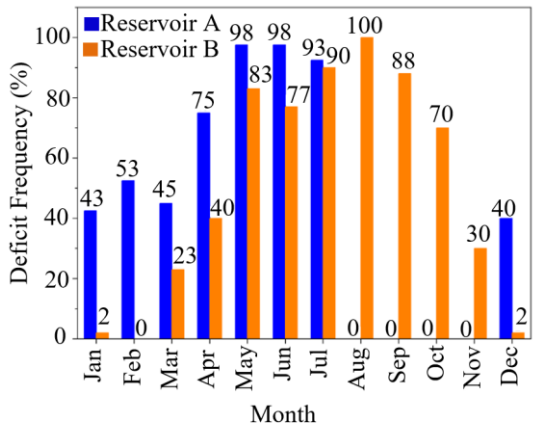

Fig. 5 Monthly deficit occurrence frequency (%) for Krisak Reservoir (A) and Pacal Reservoir (B) over the 2004-2023 simulation period.

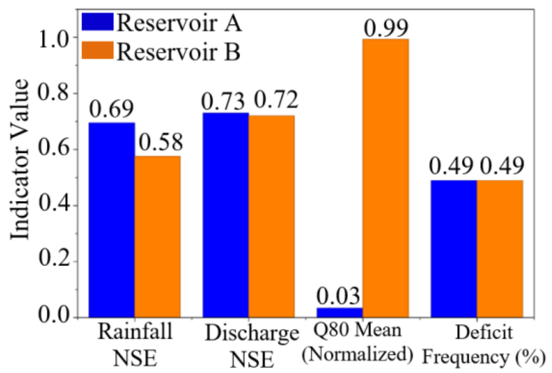

Fig. 6 Comparative reliability indicators for Krisak Reservoir and Pacal Reservoir.

5. CONCLUSION

This study evaluated the reliability of calibrated CHIRPS-based water balance modelling in two tropical reservoir catchments with contrasting scales: Krisak Reservoir (7.05 km²) and Pacal Reservoir (84 km²). The corrected CHIRPS rainfall showed reliable agreement with observed rainfall, with validation R values of 0.85 for Krisak and 0.78 for Pacal, and validation NSE values of 0.69 and 0.58, respectively. The F.J. Mock rainfall-runoff simulation also showed good discharge prediction performance, with correlation coefficients above 0.80. Dependable discharge analysis revealed scale-dependent hydrological behavior, where Pacal had much higher Q80 than Krisak, 0.993 m^3/s compared with 0.0337 m^3/s, supported by higher Q80/Q50 ratios of 0.495 and 0.194, respectively. Although both reservoirs showed similar surplus and deficit frequencies, 49% and 51%, their seasonal deficit patterns differed: Krisak deficits were concentrated in July-September, while Pacal deficits extended from March to June. The low RDI value (<0.15) indicates that the calibrated CHIRPS-F.J. Mock framework is generally consistent across catchments, although dry-season reliability remains more catchment-dependent. These findings confirm the potential of calibrated satellite rainfall for reservoir water balance assessment in data-scarce tropical basins, although denser rainfall networks and improved irrigation data are still needed to enhance model robustness and transferability.

6. ACKNOWLEDGMENTS

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