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A Coupled Framework of Reservoir Operation and SAC-SMA Hydrological Model for River Basin Simulation

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Abstract

This paper aims to design and integrate a reservoir operation module into the SAC-SMA hydrological model to simulate flood flows in the Ban Chat reservoir region in Vietnam. The SAC-SMA model is automatically calibrated using a series of stages, including sensitivity analysis by the Sobol method and parameter optimization by the Harmony Search algorithm, while the reservoir simulation is generated based on inter-reservoir operation rules. Optimization of SAC-SMA configuration, validated through two significant flood events in 2023 and 2024 in the area, yields a Nash–Sutcliffe Efficiency value of approximately 0.70-0.79, with peak flow errors of 10.2% for the peak flood season and 16.3% for the late flood period. Additionally, the introduced reservoir operation module effectively simulates the actual management procedures of the Ban Chat reservoir. Computation of the 2024 flood event demonstrates minimal discrepancies in reservoir water levels and total outflow. Although the module showed limited accuracy in reproducing downstream releases during the 2023 flood due to complex multi-objective operations in the Red River system, the coupling demonstrates strong potential for simulating and forecasting reservoir operations.

Keywords

Reservoir operation; SAC-SMA model; Flood simulation; Ban Chat reservoir; Vietnam.

1. Introduction

Reservoirs have major impacts on society and the environment, including water supply, electricity production and flood control (He et al., 2024; Li et al., 2024). Consequently, their operation plays an important role in water management strategies (Lee et al., 2025). For instance, operational rules commonly target ensuring reasonable flood control volume by opening spillway gates, yet may cause water shortages during the post-flood season (Liu et al., 2006). In hydrology, therefore, effective representation in reservoir simulation is essential for demonstrating the flow regulation and assessing its effects on downstream areas. A wide range of literature describes techniques for estimating reservoir releases, of which data-driven and process-based approaches are popular (Li et al., 2025). Due to the rapid development of computational resources, reservoir discharges can now be predicted using historical data through multiple machine learning and artificial intelligence models. In particular, a study assesses the efficacy of seven machine learning models on outflow estimation of Sirikit Reservoir in Thailand (Wannasin et al., 2024), while a combination of Long short-term memory (LSTM) networks and an explainable machine learning method, namely Shapley additive explanations (SHAP), is applied to evaluate hydrological effects on reservoir discharge (Fan et al., 2023). However, this data-driven method depends on the availability of observation records, thus, it encounters challenges in regions where a shortage of monitoring exists. On the other hand, the process-based approach focuses on emulating human intervention in reservoir operations, replacing the need for historical observations with methods ranging from empirical equations to discharge policy-based techniques. The first one determines reservoir outflows by practically derived stage–discharge curves or storage-discharge relationships (Hughes et al., 2021; Zhang et al., 2012). Omran (2025) enhances the approach to utilize a numerical solution to solve outflow governing equation defined by reservoir's area elevation. The second method extends to the integration of operating policies or rules described in multiple literature sources. A study (Ludwig, 2006) shows that the combination of reservoir water level – release relationship with policies can achieve optimal reductions in reservoir levels and discharge while guaranteeing adaptable target storage capacities. Liu et al. (2012) evaluate multiple optimal solutions to appropriately distribute load in hydropower reservoirs. Liu and Luo (2019) introduce a novel dynamic multi-objective optimization model tailored for real-time reservoir flood control that explicitly solves both uncertainty in flood prediction and decision-making process.

Recently, reservoir operational algorithms have often been coupled with hydrological models to bring about a holistic understanding of the interactions between natural inflows and managed releases. In particular, hydrology modelling represents rainfall-runoff process and reservoir operation models are responsible for simulating man-made regulated decisions (Vora et al., 2024). The linkage between two models is established through the exchange of key variables, primarily including inflow, outflow, storage, and water levels at each simulation time step. This target can be achieved through water mass balance equations combined with the aforementioned reservoir factors' curves, which have been widely pronounced in a series of well-known models like HEC-HMS, SWAT, WEAP, VIC (Dang et al., 2020; Feldman, 2016; Neitsch et al., 2011; Raskin et al., 2007). The more advanced simulation could be applied along with the incorporation of detailed infrastructure components such as leakage, outlet configurations and pump operation schedules (Masdaf et al., 2025; Neluwala, 2023). This integrated approach forms the basis for accurate estimations of streamflow and overall water balance in areas downstream of reservoirs (Yassin, 2019).

Among various types of hydrological models available, Sacramento – Soil Moisture Accounting (SAC-SMA), first introduced by Burnash (1973), is one of the most popular conceptual lumped models. The versatility and efficiency of this model are successfully described through diverse application grounds, including river flow prediction (Kratzert et al., 2019), water allocation planning (He et al., 2016), flood operation (Wijayarathne & Coulibaly, 2020), and across distinctive locations such as the United States (Botterill & McMillan, 2023), Canada (Darbandsari & Coulibaly, 2020) and China (Wang et al., 2023). In this paper, motivated by the above successful rainfall-runoff and reservoir-integrated models, we upgrade the SAC-SMA model by integrating it with a reservoir operation module to enable customization of operational rules and facilitating validation and comparison across different flow scenarios. The Ban Chat reservoir's catchment in northern Vietnam is selected as a case study. Remarkably, a set of sixteen model parameters contained in SAC-SMA requires significant effort on calibration, especially parameter selection and optimization (Uliana et al., 2019; Wang et al., 2023). Therefore, the implementation of the research includes (1) simulation of reservoir inflow through SAC-SMA model, of which model configuration is achieved by parameter sensitivity analysis and optimization, and (2) developing and validating the reservoir operation simulation of Ban Chat reservoir.

2. Methodology

2.1. SAC-SMA model

The conceptual SAC-SMA model utilizes the principle of water balance in upper and lower layers of soil to estimate different components of flow in a basin, namely direct, surface, subsurface, primary and supplementary flows as well as to represent the water storage at separate soil layers. Each depth zone is occupied by free water moving under gravity and tension water whose movement is slowly driven by evaporation and diffusion (Figure 1). The change and movement of water components in SAC-SMA are described through a number of parameters as shown in Table 1. Basin's average precipitation and potential evapotranspiration (PET) are required inputs for the SAC-SMA model. Due to shortage of the case study area's monitoring meteorology data related to wind speed and relative humidity, the PET can be derived only from temperature data through Hargreaves method (Hargreaves & Allen, 2003) whose applicability has been pronounced in Vietnam conditions (Hong Ngoc & Khanh, 2021).

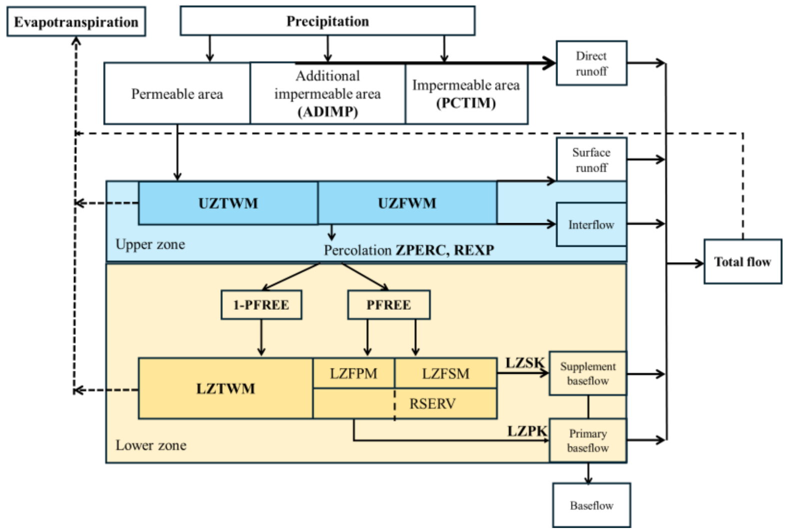


Figure 1: Schematic processes in SAC-SMA model (adopted from (Bournas & Baltas, 2021; Uliana et al., 2019))

Table 1: Description of parameters in SAC-SMA model (adopted from (Bournas & Baltas, 2021))

Parameter Category	Parameter	Description	Reference range
Storage capacity	UZTWM	Upper zone tension water maximum storage (mm)	1 - 150
	UZFWM	Upper zone free water maximum storage (mm)	1 - 150
	LZTWM	Lower zone tension water maximum storage (mm)	1-1000
	LZFSM	Lower zone free water supplement maximum storage (mm)	1-1000
	LZFPM	Lower zone free water primary maximum storage (mm)	1-1000
Runoff depletion rate	UZK	Upper zone free water lateral depletion rate (1/day)	0.1-0.5
	LZPK	Lower zone primary free water depletion rate (1/day)	0.0001-0.25
	LZSK	Lower zone supplement free water depletion rate (1/day)	0.01-0.25
Percolation rate	ZPERC	Maximum percolation rate	1-250
	REXP	Exponent of the percolation equation	0-5
Impervious area	ADIMP	Additional impervious area	0-0.4
	PCTIM	Impervious fraction of the watershed	0.000001 - 0.1
	PFREE	Percentage of water percolation directly to lower zone free water storage	0-0.6
Minor parameter	RIVA	Riparian vegetation fraction	0
	SIDE	Ratio of deep recharge to channel baseflow	0
	RESERV	Percentage of lower zone free water not transferable to lower zone tension water	0.3

2.2. Automatic Calibration procedure

2.2.1. Sensitivity analysis

Aiming at narrowing parameter dimensions, sensitivity analysis is an important approach to evaluate and identify the prior parameters dominating the modelling response (Acero Triana et al., 2025). This strategy has been proving its efficiency in either ranking or shortlisting significantly influential parameters in pre-processing for model calibration, as discussed across a spectrum of studies (Anand et al., 2025; Elgendy et al., 2025; Zambrano-Bigiarini & Rojas, 2013). In this study, a global sensitivity analysis method, particularly Sobol, is used to determine the most influential parameters of the SAC-SMA model. Sobol is widely used to explore the importance of parameters for multiple hydrology models (Heldmyer et al., 2022; Kumar et al., 2025). The underlying principle of this method involves decomposing the total variance in modeling outcomes into distinct components consisting of variances attributed to individual parameters and variances deriving from interactions among parameters. The relative contribution of each component is quantified through sensitivity indices. First-order indices denote primary impact of individual parameters, while higher-order indices capture combined effects from collective parameters. The total-order index demonstrates the comprehensive influence of each parameter and its interactions with entire other parameters. The total variance of the model output F(x) is mathematically described in equation (1):

$$F(x) = \sum_{i=1}^{N} F_i + \sum_{i \le j \le n}^{N} F_{ij} + \cdots + \sum_{i \le n}^{N} F_{1 \ldots N} \tag{1}$$

The first-order, the second-order, and total-order sensitivity indices can be accordingly stated as follows:

$$S_i = \frac{F_i}{F(x)} \tag{2}$$

$$S_{ij} = \frac{F_{ij}}{F(x)} \tag{3}$$

$$S_{Ti} = 1 - \frac{F_{\sim i}}{F(x)} \tag{4}$$

Where:
N – definition of number of model parameters,
F_i - definition of the first-order variance contributed by parameter I,
F_{ij} – definition of interactive effect between the parameter i and parameter j.

2.2.2. Parameter optimization

Another integral part of model calibration is parameter tuning. This study applies Harmony Search (HS) algorithm, which is a simple optimization technique replicating musicians in performing notes in an orchestra (Geem et al., 2001). The theory behind this method is that in order to fit the audience's favourite, the musicians train and play by adjusting different notes to form the best. The algorithm considers the optimal solutions as the finest notes and the optimization process as harmony generation. The optimization algorithm depends on a range of operators such as Harmony Memory Size (HM), Harmony Memory Considering Rate (HMCR), Pitch Adjusting Rate (PAR) and Bandwidth (BW). To evaluate a new harmony, the HM stores a set of existing harmonies for comparison. The HMCR then defines the chance that the newly generated harmony will be adapted from one of these stored harmonies (HMCR $\in$ [0, 1]). The PAR is the probability of range adjustment assigned in the BW (PAR $\in$ [0, 1]). Particularly, the implementation of the HS is described in the following stages:

- Step 1: Set up parameters of HS including HMS, HMCR, PAR, BW and additional parameters such as the maximum number of iterations, upper and lower bounds of variables.
- Step 2: Randomly generate the harmony memory (HM) in the search domain and determine the objective function.
- Step 3: Improvising a new harmony based on HMCR and PAR operators.
    - Produce a random number $k_1 \in [0, 1]$. If k_1 < HMCR, the new harmony is randomly selected from HM: $\vec{X}_{new} = \vec{X}_a$ where a is an arbitrary index selected from HMS
    - Generating a random number $k_2 \in [0, 1]$. If k_2 < PAR, the new harmony selected based on HMCR is adjusted in a BW

$$\vec{X}_{new} = \begin{cases} \vec{X}_{new} \pm rand \times BW & if\ k_2 < PAR \\ \vec{X}_{new} & otherwise \end{cases} \quad (5)$$

- If k_1 >= HMCR, the new harmony is randomly generated in the search space.

- Step 4: Updating the HM: If the objective function of the new harmony $\vec{X}_{new}$ is better than that of the worst harmony in the HM, the worst one is replaced.

- Step 5: Repeat Step 3 and Step 4 until the stopping criteria are satisfied.

2.3. Study Area and Data

The study area is located in the Nam Mu River basin, a sub-basin of the Red River, one of the principal river systems in Vietnam. The basin is controlled by the Ban Chat Hydropower Reservoir, one of the seven major reservoirs in the Red River system, with a catchment area of 1,929 km^2. The study area lies entirely within the mountainous region of Northwest Vietnam, characterized by deeply dissected terrain and steep slopes. The average elevation of the basin ranges from 800 to 1,200 m, while the headwater areas include several mountain ranges exceeding 1,500–2,000 m. The main river channel extends in a northwest–southeast orientation, consistent with the geological structure of the Hoang Lien Son range (Figure 2).

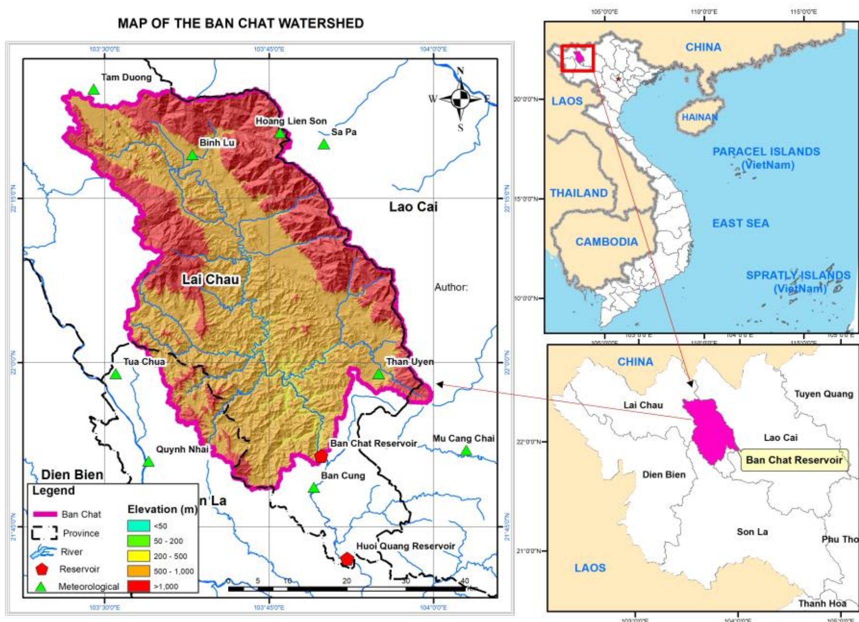


Figure 2: Map of the Ban Chat watershed (Source: Author elaboration)

The basin receives an average annual rainfall of 1,700–2,800 mm, with mean annual temperature ranging between 18–21°C, relative humidity around 80%, and average annual evaporation of 842 mm. The hydrological regime is characterized by two distinct seasons: the flood season, typically from May to September, and the dry season, from October to April of the following year. Flood season lasts from June to October and contributes an average of 83.4% of the annual discharge, while the dry season accounts for only 16.6%. The mean annual inflow to Ban Chat Reservoir is about 133.6 m^3/s, corresponding to a runoff modulus of 69.3 L/s/km^2 and an annual runoff depth of 2,184 mm (Anh & Thao, 2021; Luong, 2024).

To develop and validate a reservoir operation module coupled with the SAC-SMA model for the Ban Chat basin, two representative flood events in 2023 and 2024 were selected for simulation. The 2023 flood occurred from 4th to 16th

August, reaching a peak discharge of 2,404.4 m^3/s. This event coincided with the major flood season in the Nam Mu basin, in particular from 20th July to 21st August (Government of Vietnam, 2019, June 17), with maximum daily rainfall recorded at 113.3 mm and a total flood volume of approximately 833.7 million m^3 flowing to Ban Chat Reservoir. The 2024 flood occurred from 7th to 18th September under the influence of Typhoon Yagi, representing a late-season event in the Nam Mu basin. The flood peak reached 1,970 m^3/s, with maximum daily rainfall of 103.5 mm and a total inflow volume of about 381.3 million m^3. In this study, the August 2023 flood was used for automatic calibration of the SAC-SMA model, while the September 2024 flood was employed for parameter validation. These two events were also selected to evaluate the effectiveness of integrating the reservoir operation module into SAC-SMA, capturing different operational phases of flood regulation, i.e., the 2023 flood shows the case in the major flood season when reservoir water level was lowered before incoming floods, and the 2024 flood happened in late-season flood when reservoir level was close to the normal water level.

The datasets used in this study include:

- **Topographic, land cover, land use, and soil type data** for basin characterization, obtained from (Vietnam Ministry of Natural Resources and Environment, 2020).
- **Meteorological and hydrological data** adopted from Vietnam's National research project report implemented by Luong (2024). Hourly rainfall and daily mean temperature are collected at Tam Duong, Than Uyen, and Mu Cang Chai stations during the representative flood events in 2023 and 2024, while hourly inflow and outflow data are observed at Ban Chat hydropower reservoir (Figure 3).
- **Reservoir data** for Ban Chat Reservoir, including parameters and operation rules, are obtained from the operation procedures (Government of Vietnam, 2019, June 17; Vietnam Ministry of Industry and Trade, 2016, August 23).

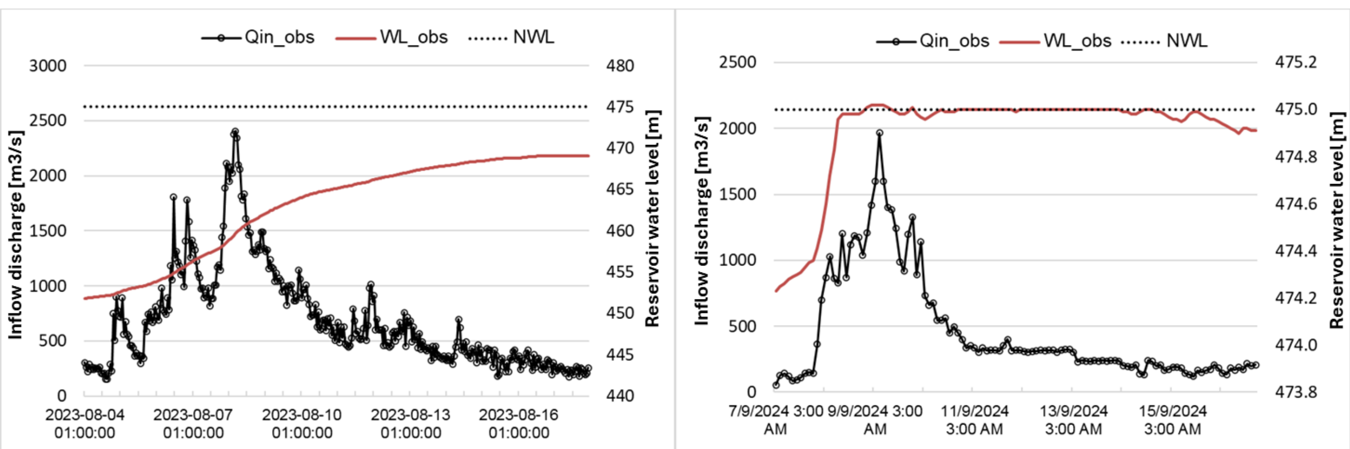


Figure 3: Hydrological data at the Ban Chat reservoir

Note: Qin=inflow discharge to the reservoir, NWL= normal water level of the reservoir, WL= water level of the reservoir during flood event

Table 2: Major parameters of the Ban Chat reservoir

Parameters	Unit	Value
Total storage	[10^6 m^3]	2150
Active storage	[10^6 m^3]	1900
Flood control storage	[10^6 m^3]	1045
Installed capacity	[MW]	220
Normal water level (NWL)	[m]	475
Dead water level (DWL)	[m]	431

Parameters	Unit	Value
Crest elevation	[m]	482
Spillway crest elevation	[m]	460
Design of spillway	[m]x[m]	15x15
Number of spillways	[-]	4

Note: The normal water level (NWL) is the level at which the reservoir is safely operated to balance water supply, flood control, and power generation. This water level represents the upper safety limit for flood regulation and downstream flood control operations, and is typically defined prior to the onset of the major flood season.

2.4. Reservoir Simulation

The study basin's flow is regulated by the Ban Chat hydropower reservoir, which has a total storage capacity of 2.15 billion m^3, of which 1.045 billion m^3 is dedicated to flood control (Table 2). This reservoir is one of the key infrastructures contributing to flood management in the Da River basin and the downstream Red River region in Vietnam. According to the inter-reservoir operation procedure for the Red River system (Government of Vietnam, 2019, June 17), Ban Chat, in coordination with Huoi Quang, Son La, Lai Chau, and Hoa Binh reservoirs, plays a vital role in joint operations to ensure downstream safety, particularly for Hanoi capital and the Red River Delta during the flood season. Owing to its substantial flood control storage, Ban Chat significantly contributes to peak flow attenuation, prolonging flood arrival time, and provides critical support for flood reduction in downstream areas.

The operation of the Ban Chat reservoir follows the inter-reservoir operation procedure of the Red River system (Government of Vietnam, 2019, June 17) and its own operation rules (Vietnam Ministry of Industry and Trade, 2016, August 23). The critical operation rules of the Ban Chat reservoir are summarized as follows.

- The reservoir manager should maintain the release discharge is not higher than the inflow while the water level is smaller than 475m (NWL). In the case of the water level at 475m, outflow is equal to inflow.
- When the water level is at NWL while inflow is forecasted to increase and the reservoir is at a safe level, the Ban Chat reservoir is supposed to operate following its own regulation procedures and using the storage upper the NWL. The detailed critical scenarios are:
    - When inflow to Ban Chat reservoir is below 850 m3/s: maintain water level in the range of 469m to 472m to prepare for flood control storage.
    - When inflow to Ban Chat reservoir from 850 to 2100 m3/s (small flood): gradually increase the release discharge up to the inflow discharge. Water level should be in the range of 472m and 475m (NWL).
    - When inflow to Ban Chat reservoir from 2100 to 3000 m3/s (big flood): gradually increase the release discharge up to the inflow discharge. Priority is given to ensuring dam safety, with releases regulated according to the maximum discharge capacity of the spillway. Water level should not exceed 475m (NWL).
    - When the inflow to Ban Chat reservoir is greater than 3000 m3/s (extreme flood): Priority is given to ensuring dam safety, with releases regulated according to the maximum discharge capacity of the spillway. Coordinate with Huoi Quang reservoir (downstream of Ban Chat reservoir) to maintain downstream flow fluctuations within ±30%.

2.5. Coupling SAC-SMA model and reservoir operation

To simulate the operation of the Ban Chat Reservoir, this study employed the reservoir water balance method. The governing equation is expressed as:

$$\frac{dS}{dt} = Q_{in}(t) - Q_{out}(t) - E(t) \tag{5}$$

Where:

S - is the reservoir storage,

t - is the time step,

Qin(t) - is the inflow,

Qout(t) - is the outflow,

E(t) - is the evaporation loss on the reservoir surface.

Since the focus of this study is on flood event operation, evaporation loss was considered negligible. The precipitation on the reservoir surface was included in the total inflow to the reservoir. The inflow (Qin(t)) was computed and simulated using the SAC-SMA model for the catchment areas controlled by Ban Chat reservoir. The reservoir outflow equation is described as:

$$Q_{out}(t) = Q_{turbine}(t) + Q_{spill}(t) \tag{6}$$

Where:

$Q_{turbine}(t)$ is the hydropower plant discharge, determined by the electricity demand of the entire interconnected system. In practice, power demand fluctuates during the day, with peak and off-peak periods. Since Ban Chat Reservoir operates in coordination with other reservoirs in the Red River system, the turbine discharge does not follow a fixed pattern. Therefore, in this study, turbine discharge was approximated using the long-term mean of observed discharge data from 2012–2025.

$Q_{spill}(t)$ represents spillway release, which was computed using an empirical formula based on the spillway crest width corresponding to the reservoir water level *Z(t)* (Vietnam Ministry of Industry and Trade, 2016, August 23) and is formulated as below:

$$Q_{spill}(t) = \begin{cases} 0 & , \quad if\ Z(t) < 460 \\ 161.74 \times Z(t) + 22.885 & , \quad if\ Z(t) < 470 \\ 7.4 \times Z(t) + 1515 & , \quad if\ Z(t) \geq 470 \end{cases} \tag{7}$$

The reservoir operation module is coupled with SAC-SMA model following the procedure given in Figure 1 and provided in Python programming language.

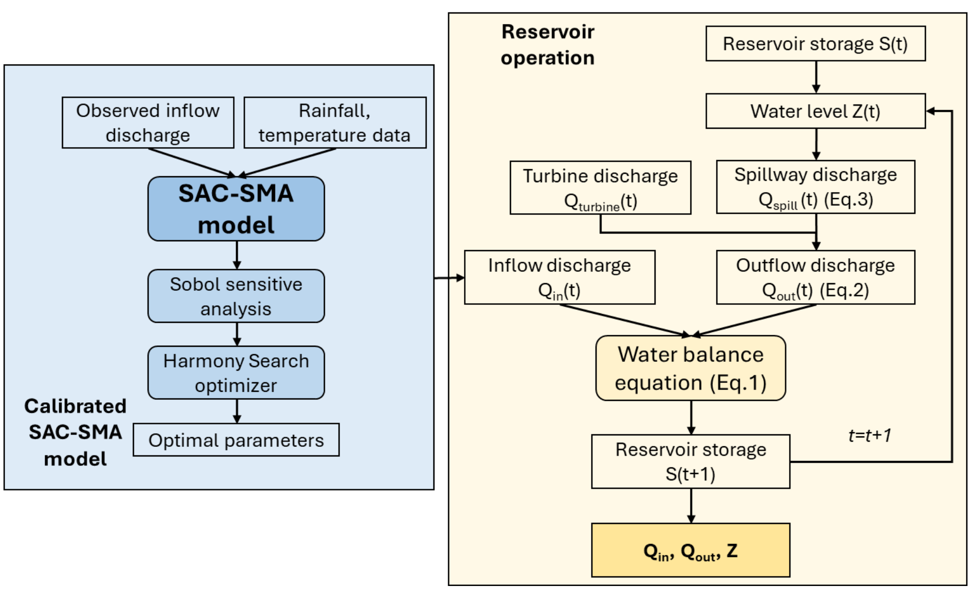


Figure 1: Flowchart of coupled reservoir operation with SAC-SMA model

3. Discussion and Results

3.1. Implementation of SAC-SMA model

The model is modified for hourly flood simulation and for the Ban Chat watershed. In this study, modules of evaporation and surface runoff are considered, other modules such as snow and river routing are not simulated. The main parameters are initially set up as in Table 3 and the results are given in **Chyba! Nenašiel sa žiaden zdroj odkazov.**.

Table 3: Major parameters of the SAC-SMA model

UZTWM	UZFWM	LZTWM	LZFPM	LZFSM	ADIMP	UZK	LZPK	LZSK	ZPERC	REXP	PCTIM	PFREE
[mm]	[mm]	[mm]	[mm]	[mm]	[-]	[-]	[-]	[-]	[-]	[-]	[-]	[-]
48.521	85.415	461.136	1000	937.222	0.081	0.1	0.001	0.01	250	2	0	0.5

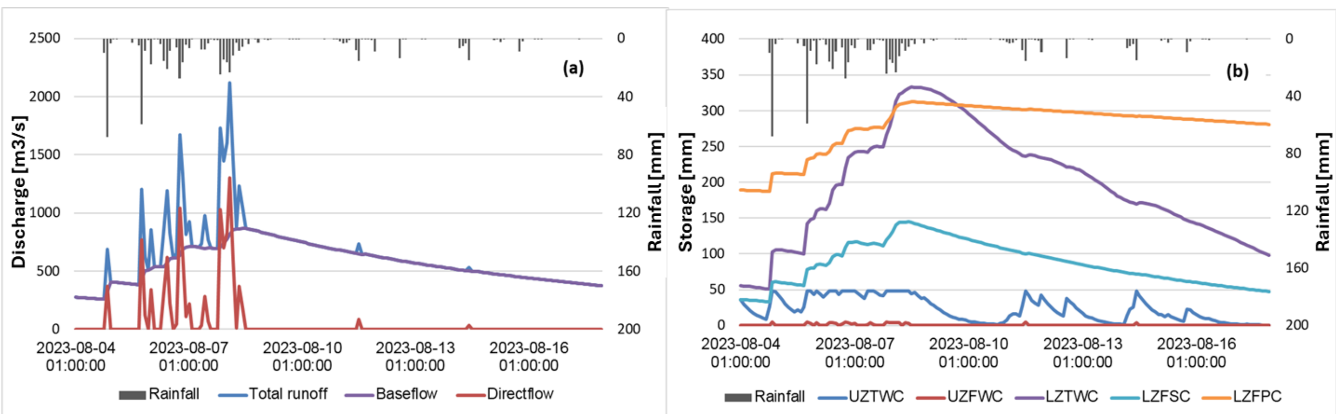


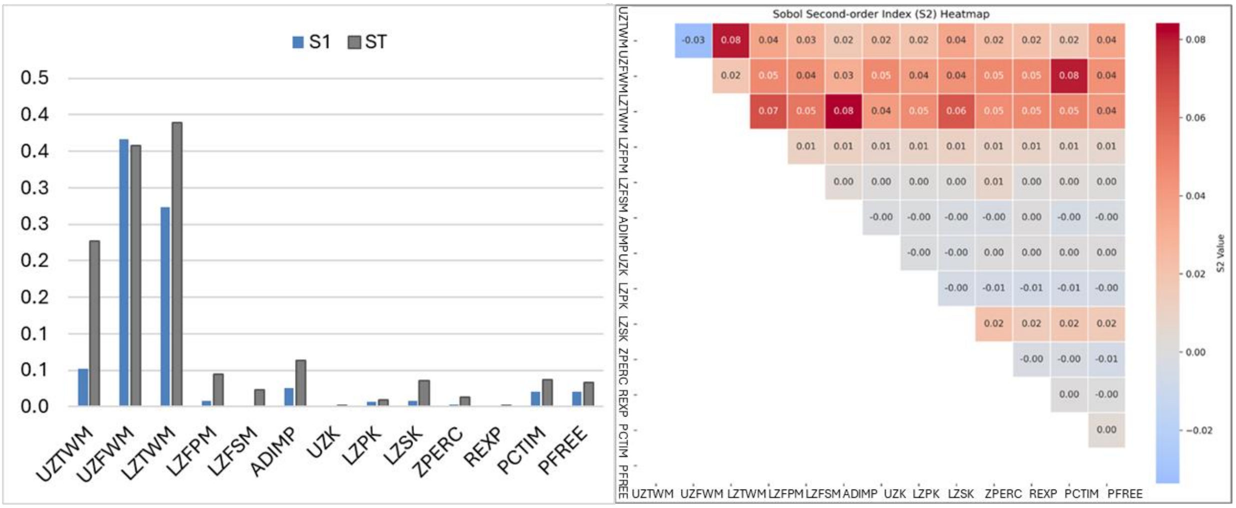
Figure 2: Simulation of flows (a) and storages (b) using SAC-SMA model

The simulated total flow is the sum of baseflow and direct flow, subtracting evaporation which is negligible in flood simulation (**Chyba! Nenašiel sa žiaden zdroj odkazov.**a). In which the baseflow is a response of lower zone primary and s upplemental storages, while the direct runoff is from upper zone free storage and impervious area. The variation of storages in **Chyba! Nenašiel sa žiaden zdroj odkazov.**b presents the fast response of upper storages (UZTWC and U ZFWC) during flood event. This response function is more obvious in the late stage of the flood event, i.e., from 10-14 August 2023. The moisture level of lower storages (LZTWC, LZFSC and LZFPC) demonstrates increasing and decreasing trends corresponding to rising and recession stages of flood.

3.2. Automatic Calibration results

3.2.1. Sensitivity of parameters in SAC-SMA model

The Sobol technique is applied to analyse the global sensitivity of SAC-SMA's parameters. The number of Saltelli's samples (Saltelli et al., 2010) is 14,336 for a 512 base sample size and 13 main parameters. The Sobol sensitivity analysis assesses parameter contributions to model performance as measured by Nash–Sutcliffe Efficiency (NSE). The first-order Sobol index (S1) illustrates the direct impact of a single parameter on model response. The total-order Sobol index (ST) presents both individual and interaction of SAC-SMA's parameters. The sensitive analysis also estimates the pair-interaction of parameters through second-order index (S2). The results of Sobol sensitive analysis are given in Figure 3.



(a) **(b)**

Figure 3: Sobol's index: (a) First-order and (b) Second-order

The first-order and total-order indices show a strong impact of UZTWM, UZFWM and LZTWM in model response (Figure 3a). In which the UZFWM parameter has an independent role (ST equal to S1) whereas the UZTWM and LZTWM become important when combined with other parameters i.e. ST>>S1. The LZFPM and ADIMP parameters also slightly contribute to the model simulation. The pair-parameter importance is evaluated by S2 index (Figure 3b). It can be seen that all combinations of UZTWM, UZFWM and LZTWM with other parameters significantly contribute to NSE performance. The combination of LZSK and the remaining parameters also plays a minor role in model response. Therefore, the most sensitive SAC-SMA parameters are UZTWM, UZFWM, LZTWM, PCTIM, ADIMP, LSPK and LZSK. These parameters are then used as pivotal variables for the optimization process.

3.2.2. Optimal of SAC-SMA's parameters

The optimization process determines the best-fit parameters of the SAC-SMA model for simulating flood flow in the Ban Chat reservoir watershed. The Harmony search algorithm is implemented with parameters of HMS=50, HMCR=0.95, PAR=0.1, BW=0.01 and a total iteration of 5000. The objective function is generated by considering of both NSE and flood peak error by involving a penalty function.

The optimal solution given in Table 4 demonstrates the major parameters of SAC-SMA model to obtain the NSE = 0.70 and peak error = 10.2% (

Table 5). The optimal hydrograph shows an accurate simulation of flood flow, especially in capturing the peaks. The peak error is less than 20% and the model correctly identifies the peak period on 8 August. There are some errors in flood simulation during the early stage of flood flow when rainfall reaches its first and second peaks (Figure 4). In this period, the rainfall intensity reaches 35.7 mm/hour and 53.7mm/hour, while the observed flow has no clear peaks. The simulated flow, thus, overestimates and fails to mimic the observation. The reason for this failure might be explained by the small threshold of the upper storages (1-5 mm, see Table 4) that represents the immediate response in flood flow generation.

Table 4: Optimal SAC-SMA parameters

Parameters	UZTWM	UZFWM	LZTWM	ADIMP	LZPK	LZSK
Unit	[mm]	[mm]	[mm]	[-]	[-]	[-]
Value	1.441	31.349	67.585	0	0.01	0.1

Table 5: The model performance

Index	NSE	Peak discharge		
		Observation [m3/s]	Simulation [m3/s]	Error [%]
Auto calibration	0.70	2404.4	2649.1	10.2
Validation	0.79	1966.1	1645.7	16.3

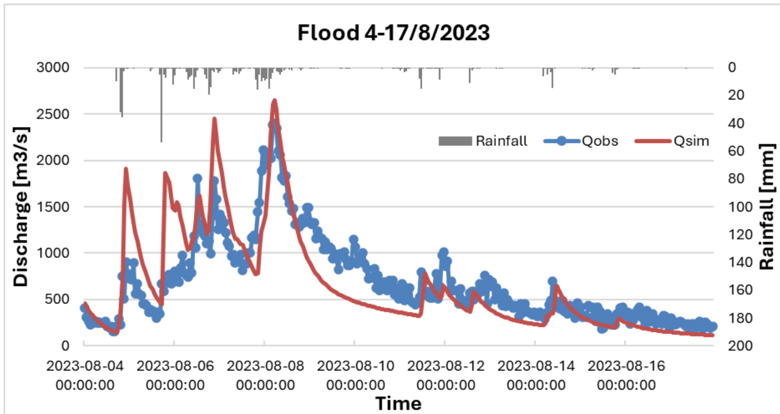


Figure 4: Simulated and observed hydrograph at the Ban Chat reservoir in optimized flood event

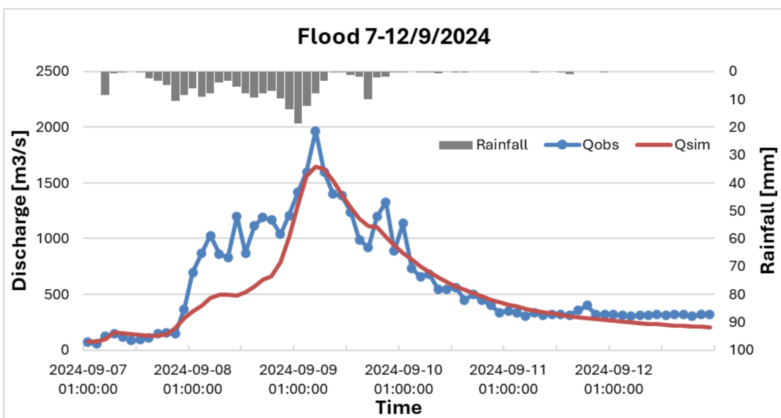


Figure 8: Simulated and observed hydrograph at the Ban Chat reservoir in validated flood event

The performance of optimal parameters is evaluated using a validated flood event in September 2024. This is a flash flood event with intense rainfall from 8th to 9th of September. The optimal SAC-SMA model results are NSE=0.79 and peak error=16.3%. The simulated flood flow represents the accurate peak time and hydrograph shape but fails in identifying peaks in the early stage (Figure 8). This trend shows the opposite error compared to the flood event of 2023. It can be seen that these two flood events illustrate distinct basin responses to the heavy rainfall events. Therefore, the optimal parameter set harmonising the NSE performance for the typical floods would successfully simulate the other flood events. Generally, this parameter set is applicable for further simulation.

3.3. Reservoir Operation in the SAC-SMA model

The reservoir operation module, programmed in Python based on the operational procedures described in Section 2.4, is integrated into the SAC-SMA hydrological model following the schematic diagram presented in Figure 4. The inflow to the Ban Chat Reservoir simulated by the automatically calibrated SAC-SMA model is used as input to Equation (1) to compute the reservoir water balance.

The simulation of reservoir operation is validated using two flood events - the August 2023 flood and the September 2024 flood corresponding to two distinct initial water level conditions. The August 2023 event began on August 4, when the reservoir water level was WL = 451.81 m, below the spillway crest elevation (460 m); at this time, Ban Chat Reservoir still retained considerable flood storage capacity and was in a flood-receiving condition. In contrast, the September 2024 flood occurred when the water level was close to the normal water level (WL = 475 m), meaning the reservoir was nearly full and the operation procedure had to be implemented to ensure dam safety.

To evaluate the performance of the developed reservoir operation module, two inflow scenarios are considered:

- Scenario 1: Using *observed inflow data* to validate the reservoir operation module.
- Scenario 2: Using *simulated inflow data* from the SAC-SMA model to assess the performance of the integrated model.

Table 6: Performance of reservoir operation module

Criteria	Observation		Simulation (Scenario 1)		Simulation (Scenario 2)	
	Flood 2023	Flood 2024	Flood 2023	Flood 2024	Flood 2023	Flood 2024
Water level at the end of flood event [m]	469.1	474.9	469.1	475.0	468.9	474.9
Error of water level [m]			0.0	0.1	-0.2	0.0
Total water volume released downstream [$10^6 m^3$]	25.6	380.3	17.9	372.6	5.4	324.5
Error of total release water volume [%]			-29.9	-2.0	-78.8	-14.7

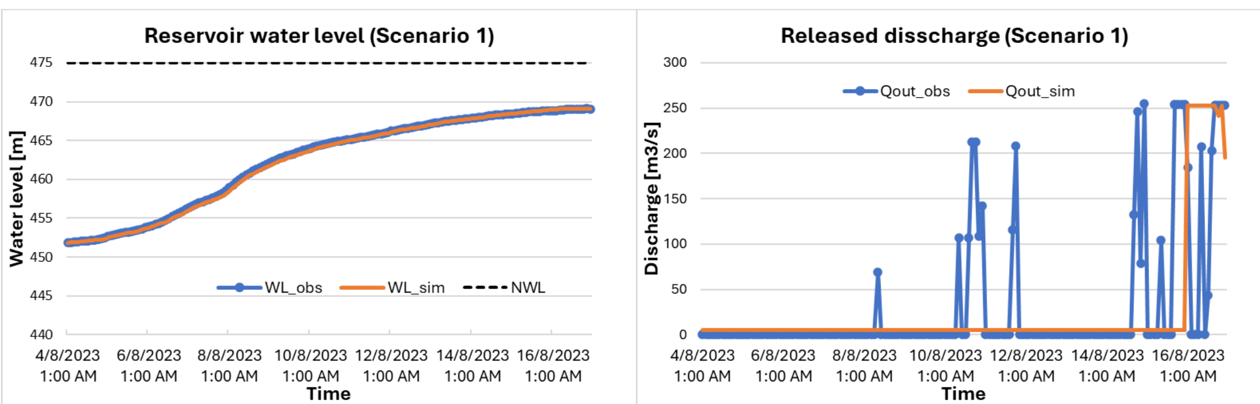


Figure 9: Operation results of Ban Chat reservoir in flood 2023 (Scenario 1)

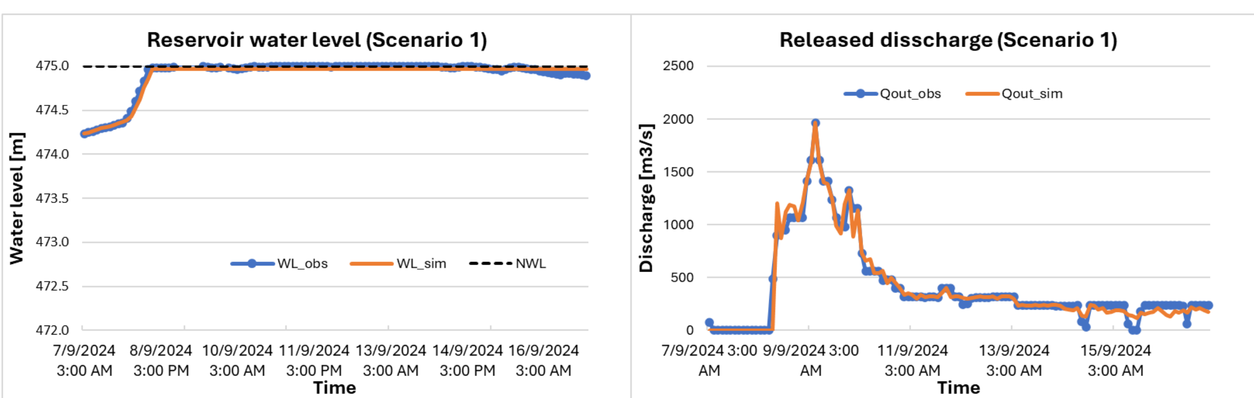


Figure 10: Operation results of Ban Chat reservoir in flood 2024 (Scenario 1)

It can be observed that the developed reservoir operation module successfully reproduces the actual operation of the Ban Chat Reservoir during two flood events: August 2023 (main flood season) and September 2024 (late flood season). In both events, the simulated reservoir water levels closely match the observed values, with errors of only 0.1 m in flood 2024 (Scenario 1) (Table , Figure and Figure). For the downstream release discharge, the simulation of the 2023 flood results in a total release volume error of up to 29.9%, whereas this error is only 2.0% for the 2024 event.

Under the operation scenario based on simulated inflows (Scenario 2), the deviations in reservoir water level for both floods are insignificant, approximately 0-0.2 m. However, the errors in the total downstream release volumes reach 78.8% in the 2023 flood and 14.7% in the 2024 flood (Table , Figure and Figure). Although the accuracy of the simulation in Scenario 2 is lower than that of Scenario 1, it still shows promising applicability in flood reservoir stage forecasting.

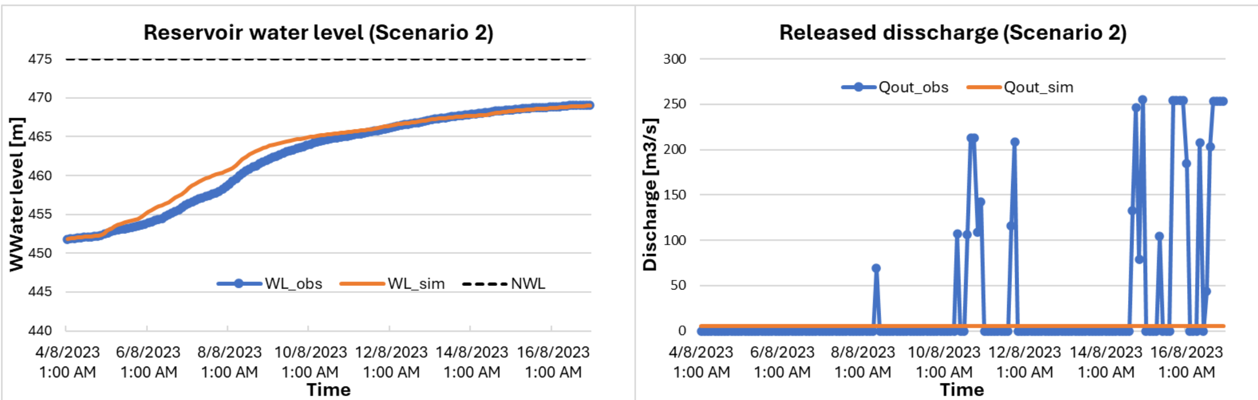


Figure 11: Operation results of Ban Chat reservoir in flood 2023 (Scenario 2)

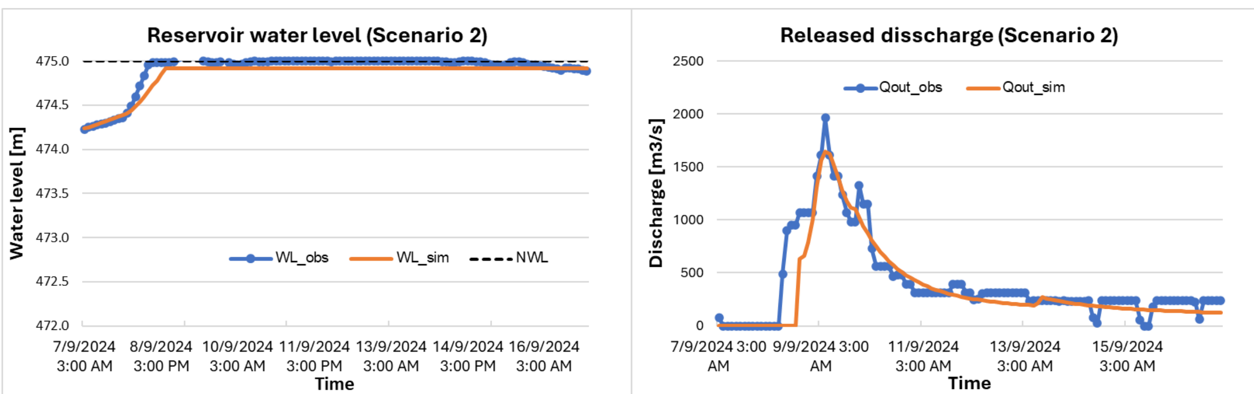


Figure 12: Operation results of Ban Chat reservoir in flood 2024 (Scenario 2)

Thus, it can be concluded that the reservoir operation module integrated with the SAC-SMA model successfully captures the overall operational trends of the Ban Chat Reservoir. The discrepancy between simulated and observed reservoir water levels is relatively small, ranging from 0-0.2m. However, the integrated module is unable to accurately replicate the actual downstream release process.

This limitation arises because the Ban Chat Reservoir operates under a multi-objective scheme. During the main flood season, when the reservoir water level remains within the safe range, water is released primarily for hydropower generation to ensure energy security for the entire Red River system. Consequently, the reservoir operation during this period is influenced not only by the internal characteristics of Ban Chat itself but also by the power generation schedules and regulation capacities of other major reservoirs such as Hoa Binh and Son La. Therefore, the actual operation of Ban Chat is strongly interconnected with the operation of these upstream and downstream reservoirs. It should be highlighted that the present study did not include a simulation of the inter-reservoir interactions within the Red River basin.

4. Conclusion and Recommendations

In this study, a reservoir operation module is developed and integrated with the SAC-SMA hydrological model to simulate flood flows in the Ban Chat Reservoir basin. The open-source SAC-SMA model is programmed in Python with modifications to simulate hourly inflow to the Ban Chat Reservoir. The sensitivity analysis of the model's parameters indicates that UZTWM, UZFWM, LZTWM are the most dominant, with consideration of PCTIM, ADIMP, LSPK and LZSK parameters. An automatic calibration process is also conducted using the Harmony Search optimization algorithm. The optimized parameter set is validated against two major flood events: August 2023 (peak flood season) and September 2024 (late flood season). The validation results show NSE of 0.70-0.79, with peak flow errors of 10.2% for the 2023 flood and 16.3% for the 2024 flood. Given the extreme characteristics of these flood events, the obtained parameter set can be considered acceptable.

The study also develops a reservoir operation module that reproduces the actual operational procedures of the Ban Chat Reservoir. The simulation results for the two flood events indicate negligible errors in reservoir water level (<20 cm) and in the total outflow during the 2024 flood event (14.7%). Despite its limitations in reproducing downstream releases during peak flood conditions, the coupled SAC-SMA framework demonstrates clear practical value for operational flood management. The direct linkage between simulated inflows and reservoir release decisions allows the model to be used for scenario-based flood routing, testing alternative operating rules, and examining their implications for downstream flood mitigation. Owing to its open-source and modular structure, the framework can be readily implemented in data-scarce basins and provides a flexible foundation for future integration with real-time forecasting and decision-support systems.

Further improvements of the framework should focus on several key aspects. A primary priority is the extension of the reservoir operation module to represent coordinated multi-reservoir operations within the Red River system, where operational constraints and downstream flood control objectives are of paramount importance during peak flood periods. The turbine outflow from the reservoir also needs to be assessed. In addition, inflow simulation performance could be post-processed using machine learning techniques to reduce residual systematic errors and improve flood peak representation under extreme conditions.

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Author Contributions

T.T.N conceived and designed the study. **T.T.L.** conducted the Python code scripts of SAC-SMA and manuscript drafting. **H.D.L.** performed the reservoir operation rules. **T.H.V.** contributed to data preparation and reservoir operation rules. All authors critically reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Disclosure of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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