ENHANCING FLOOD CONTROL STRATEGIES VIA RESERVOIR SYSTEM MODELING: CASE ANALYSIS OF RASI SALAI AND HUA NA DAMS, THAILAND

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ABSTRACT

Effective reservoir management requires the ability to navigate the uncertainties of natural and human-induced factors, such as fluctuating rainfall, variable inflows, and evolving water demand. This study focuses on optimizing the operations of Rasi Salai Dam, Hua Na Dam, and That Noi Dam in the Mun and Chi River Basins to reduce flood risks in Sisaket and Ubon Ratchathani provinces, Thailand. By employing the HEC-RAS model, we developed a comprehensive simulation of the watershed, integrating data from key water measuring stations (M.5, M.7, M.9, M.182, and E.20A) collected between 2019 and 2022. The study modeled water retention and release strategies, comparing the efficiency of new rule curves against existing ones. Results indicate that the proposed model enhances the efficiency of flood management, demonstrating better water release control and coordination among the dams. The findings underscore the importance of integrated reservoir management in mitigating flood risks and ensuring sustainable water resources for the region.

Keywords: reservoir operation, HEC-RAS model, optimization techniques, flood control, integrated water management.

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INTRODUCTION

The Khong-Chi-Mun Project is one of the most significant initiatives aimed at addressing both drought and flood problems in northeastern Thailand. The project primarily involves the Mun River, which originates from Chumphon Buri District in Surin Province and flows into Sisaket Province. Here, it intersects with Huai Thap before continuing through Rasi Salai District. Further south, Huai Khyung joins the Mun River, which is controlled by several weirs and other hydraulic structures in Sisaket Province. This area also serves as a confluence point for the Chi River and the Mun River, with additional tributaries such as Lam Se Bai and Lam Se Bok joining the Mun River in Ubon Ratchathani Province [1-2]. These regions frequently encounter challenges in water management due to varying water levels caused by seasonal changes and infrastructure limitations [3-4].

Previous studies on the Mun River Basin have predominantly focused on predictive models for estimating water levels and flow rates. For instance, research has examined the relationships between water measuring stations and employed simulation models like MIKEFLOOD to predict flood-prone areas [5-6]. However, many of these studies have not incorporated detailed information on the floodgate operations of the Rasi Salai Dam and Hua Na Dam, which are crucial for effective water management [7-8].

In contrast, there has been limited research into the economic, social, and environmental aspects of water management at the Rasi Salai and Hua Na dams. Some studies have focused on the lower Mun River Basin, particularly behind Hua Na Dam, investigating impacts, forecasting, and management strategies to mitigate flood and drought problems in Ubon Ratchathani Province [9-10]. These studies often utilize multiple models to forecast water levels and apply various algorithms to determine optimal reservoir control curves [11-12].

Recent advancements in optimization techniques, including stochastic dynamic programming and genetic algorithms, have been increasingly applied to find optimal reservoir control curves [13-14]. These techniques take into account the complexities of multi-reservoir systems and the constraints posed by risks, addressing the rising water demand due to economic and social development [15-16]. For example, stochastic dynamic programming allows for the handling of uncertainties in inflows and demands by considering the probabilistic nature of these variables over multiple time stages [17-18]. This method optimizes reservoir operations by evaluating different scenarios and determining the best decision policy that minimizes risks and maximizes benefits over time [19]. Genetic algorithms, inspired by natural selection and genetics, have proven useful in solving large, complex optimization problems with multiple objectives and constraints [20-21]. These algorithms generate a population of potential solutions and use operators such as selection, crossover, and mutation to evolve the population toward better solutions over successive generations [22]. For instance, Qingwen Lu *et al*. (2021) applied stochastic programming to optimize floodwater utilization in a complex multi-reservoir system, demonstrating significant improvements in reservoir management [23].

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Given the dynamic and uncertain nature of water inflows, the application of dynamic reservoir operating rules can enhance the consistency and efficiency of reservoir management [24-25]. The HEC-RAS model widely recognized for its reliability and accuracy, has been extensively used to analyze water impacts, optimize reservoir operations, and improve land use planning [26-27]. Studies have shown that integrating real-time data and historical records from various water measuring stations can lead to more comprehensive models for sustainable reservoir management and flood risk reduction [28-30].

This study aims to use the HEC-RAS model to simulate the watershed and determine optimal water depletion strategies for the Rasi Salai Dam, Hua Na Dam, and That Noi Dam. By incorporating real-time data and historical records, the research seeks to develop a robust model that enhances flood risk management and supports sustainable water resource management in the region.

MATERIALS AND METHODS

This study employs the HEC-RAS model to develop a representative watershed to determine the maximum volume of water that can be released from three reservoirs while ensuring that downstream economic areas remain within tolerable water level limits. This methodology is crucial for identifying appropriate parameters related to the topography and the representative area of the study basin [5]. The maximum flow volume calculated from the model was subsequently evaluated using the HEC-RAS model to identify potential flood zones.

Two primary scenarios were considered in this research: (1) a simulation of water conditions during the period from September to October 2022, and (2) a scenario where runoff levels are adjusted in 0.50-meter increments, ranging from 115.00 to 120.00 meters above mean sea level. The process steps undertaken in this study are depicted in Figure-1.

Figure-1 illustrates the operational process and tools selected for this research. A comprehensive review of previous studies has shown that the HEC-RAS model is widely trusted and accepted within the research community. The model’s capabilities have been continually enhanced, establishing it as a reliable and freely accessible tool. It has been extensively utilized in the analysis of water impacts, water resource management, and land use planning. Data were collected as input for the model, followed by an evaluation of the model's performance, calibration, and verification to ensure the selection of appropriate parameters. The performance of the model was then assessed through simulations of the two scenarios, leading to the determination of the maximum volume of water that can be safely released.

Simulating the river network based on the physical characteristics of the study area provides a realistic representation of hydrological behavior. This approach allows for the generation of data that can be measured and validated, facilitating accurate analysis and interpretation of water dynamics by hydraulic principles.

This section provides a detailed overview of the study area and the data sources used in this research. The focus is on the river network influenced by the three reservoirs and their subsequent impact on downstream economic regions. The description of the water measurement stations utilized in this study is presented in Table-1.

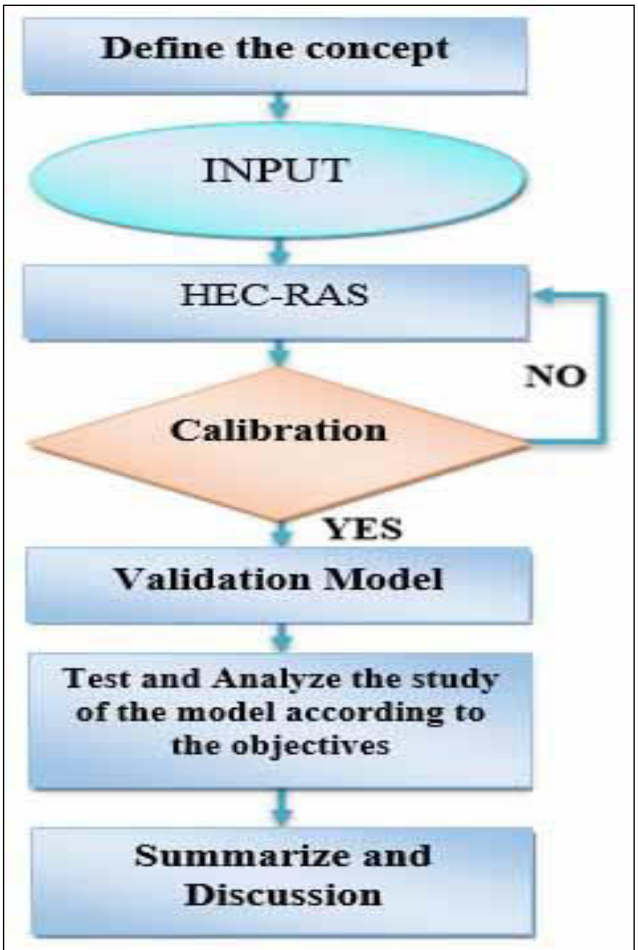

Figure-1. Study framework.

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Table-1. Description of water station in the study.

River Code	Approx. Lat.N-Long.E	D.A. Sq.Km	Water Level Period	Discharge Data
Chi				
E.20A	15° 31' 59" 104° 15' 24"	47,818	1973-Cont'd	1974-Cont'd
Mun				
M.5	15°20'20.6" 104°08'59.3"	45,295	1969-Cont'd	1969-Cont'd
M.7	15°13'24.7" 104°51'33.2"	107,345	1966-Cont'd	1966-Cont'd
M.182	15°07'55.7" 104°29'18.6"	49,778	1973-Cont'd	1974-Cont'd

USING HEC-RAS PROGRAM

a. HEC-RAS Model Calibration

The calibration of the HEC-RAS model was conducted using runoff data collected from water measuring stations M.5, M.182, and M.7 over the period from 2019 to 2022. This time frame included both flood and non-flood conditions, allowing for a comprehensive calibration process. The calibration was performed by testing various water level scenarios, which were divided into three distinct data sets, each containing specific test cases as outlined by the data entry algorithm.

b. HEC-RAS Model Validation

Following the calibration, the model validation was carried out using maximum water level data from the years 2019 to 2022, a period marked by significant flooding as well as drought conditions. For validation, daily water level data from 2019 and 2022 (covering September to December) were utilized, encompassing periods of low, normal, and high water levels. At the upstream boundary, located at km 72+000, the flow rate data was initialized with the maximum flow rate in cubic meters per second. The downstream boundary was established at Rasi Salai Dam (km 0+000); with the downstream flow regulated by the normal depth at water measuring station M.7.

Once the river map and the required river cross-sections were obtained, the model underwent calibration to adjust the roughness coefficient, known as Manning's n. This step is critical for ensuring the model accurately simulates the hydraulic behavior of the river. Further details on the calibration of Manning's n will be provided in the subsequent section. The data from water measuring stations M.5, M.182, and M.7, which were used during the calibration and validation processes, are depicted in Figures 2-9.

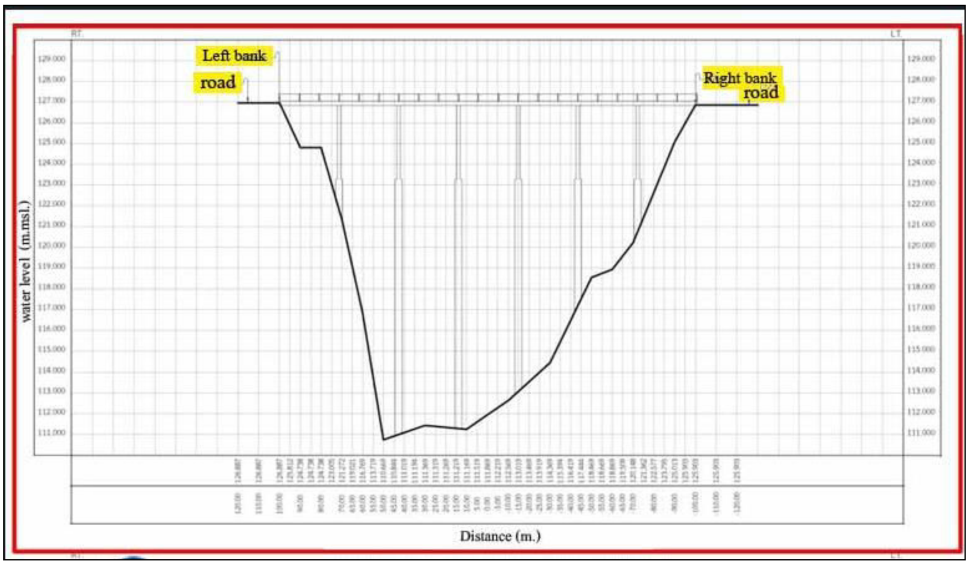

Figure-2. Description Thatnoi Dam (Cross section KM.133+331).

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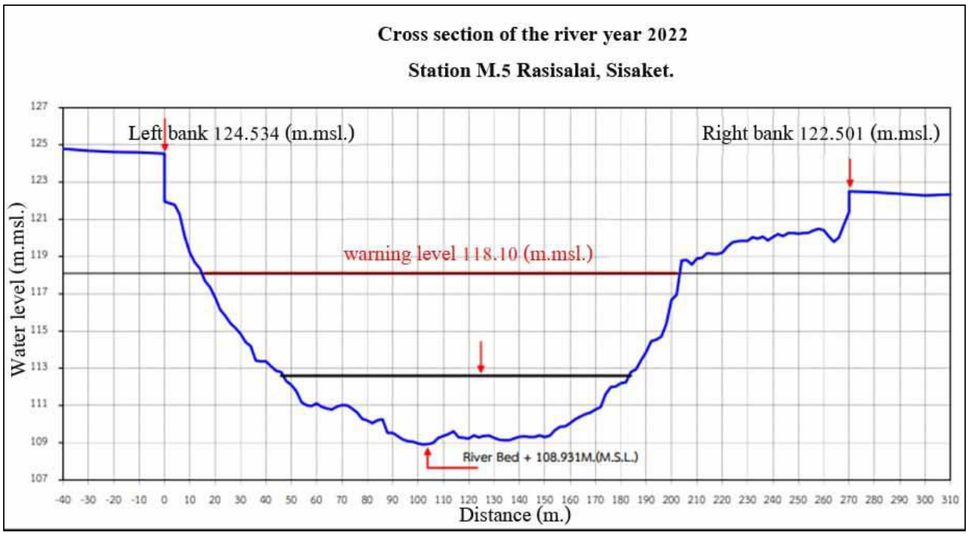

Figure-3. Description M.5.

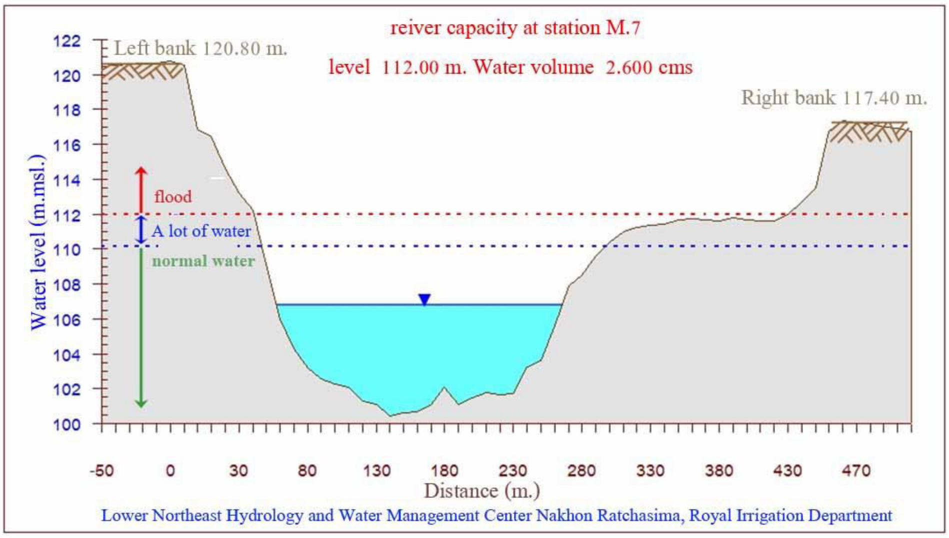

Figure-4. Description M.7.

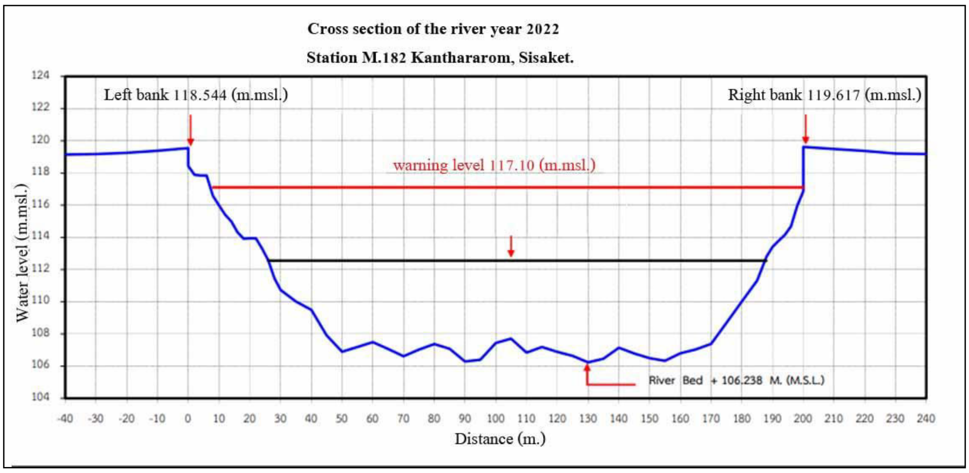

Figure-5. Description M.182.

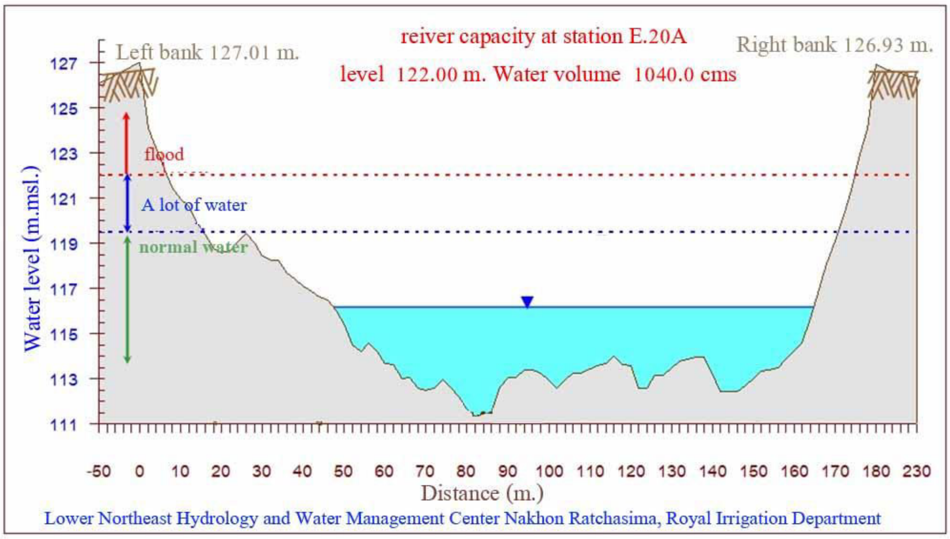

Figure-6. Description E.20A.

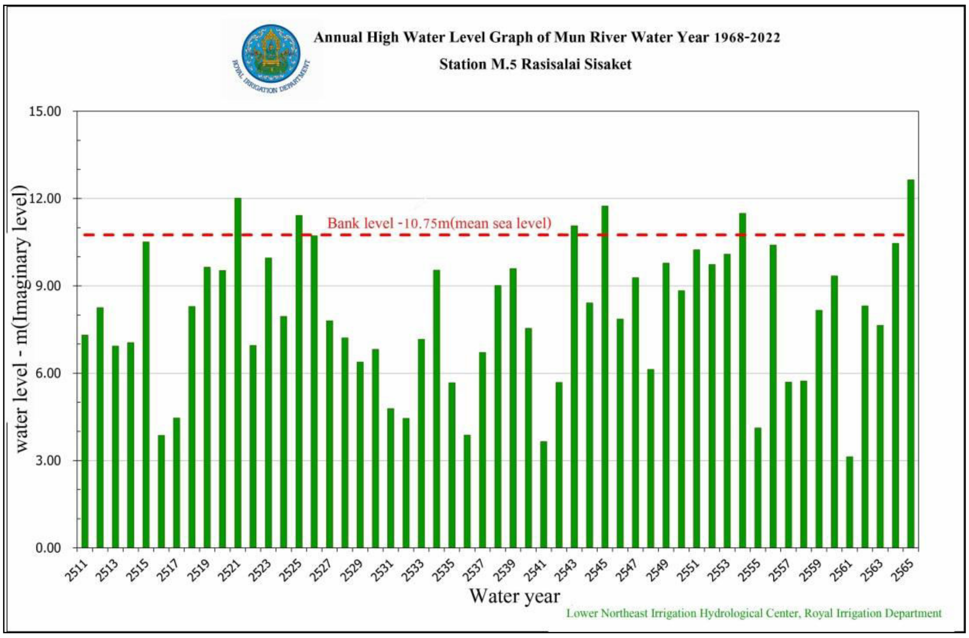

Figure-7. Graph showing the maximum waterlevel in the water year 1968-2022 at M.5 of the Mun River Basin.

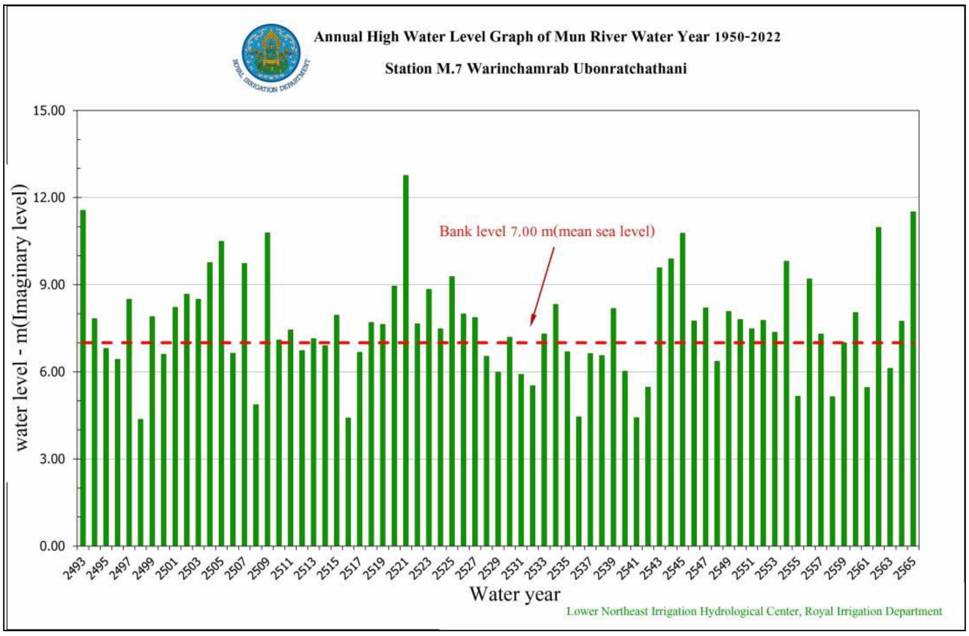

Figure-8. Graph showing the maximum waterlevel in the water year 1950-2022 at M.7 of the Mun River Basin.

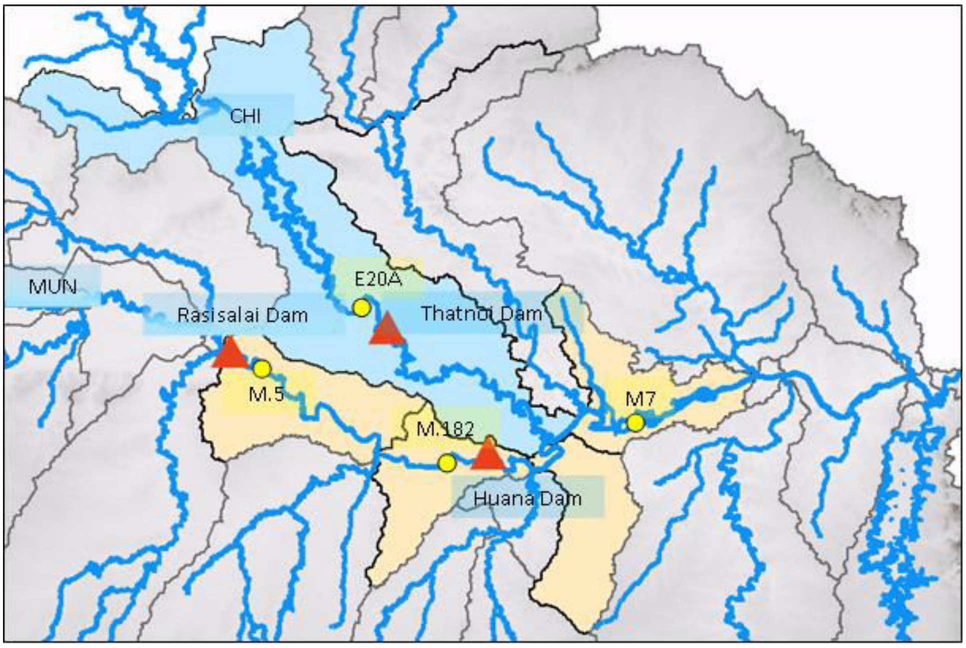

Figure-9. Study Area.

HEC RAS MODEL CALIBRATION RESULTS

a. Calibration Results Using Roughness Coefficient (Manning's n)

The calibration of the HEC-RAS model was performed by adjusting Manning's n roughness coefficient through a trial-and-error process. The goal was to achieve accurate water level simulations in the Mun River. This involved collecting flood stain data along the riverbanks, particularly in areas that experienced significant flooding in 2019 and 2022. The calibration focused on the highest water levels and maximum flow rates recorded at water measuring stations M.5 and M.7, which are situated within the flood-prone zone, covering a total distance of 85 kilometers. This stretch starts from the Rasi Salai Dam and extends through the M.5 water measurement station to the M.7 and E.20A runoff measurement stations in the Chi River, as depicted in Figure-12.

The collected data were then compared with simulated water levels to determine the appropriate Manning's n value for the HEC-RAS simulation. Initially, the basic Manning's n roughness coefficient values were

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set based on comparisons from previous studies [7, 18], aerial photographs, and actual field surveys. The roughness coefficients used were n = 0.04 for both the riverbank and the riverbed. Subsequently, Manning's n value was adjusted incrementally within the range of 0.010 to 0.015 to minimize the RMSE (Root Mean Square Error) and improve the model's accuracy. The Steady Flow Analysis tool was used to run the data in steady flow mode, with detailed output results being saved for further analysis.

b. HEC RAS Model Calibration Results

The model calibration was further validated using maximum water level data from the years 2019 to 2022, a period marked by significant flooding and drought conditions. The calibrated model was then tested against daily water level data from 2019 and 2022 (covering September to December), which included instances of flooding at the Upstream Boundary, particularly at Rasi Salai Dam in Rasi Salai District, Sisaket Province. The flow rate at the starting point (Initial Flow) was set to the maximum recorded flow rate in cubic meters per second. The downstream boundary was designated at the runoff measurement station M.7 (km. 0+000), with downstream flow controlled by normal depth.

The calibrated Manning's n values derived from the initial calibration process were applied to six sets of water data from 2019 and 2022. This step was undertaken to ensure consistency and accuracy across different flood scenarios, as demonstrated in the subsequent sections.

RESULTS

A. Model Calibration Results

The calibration results are presented in a graph that tracks water levels (in meters above mean sea level, msl) over a period from July 31 to November 28, 2019. This graph includes multiple lines representing different scenarios or models, specifically for the M7 station. The scenarios vary based on different roughness coefficients (Manning's n) with values ranging from 0.025 to 0.040, and riverbank roughness set at 0.080. The graph's R^2 value of 0.8733 indicates a strong correlation between the model predictions and the actual observed data. An R^2 value close to 1 suggests that the models account for a large portion of the variance in the observed data, demonstrating the effectiveness of the calibration process as shown in Figure-10.

B. Model Validation Results

The validation process was conducted using the calibrated model to compare the predicted water levels against actual observed data at the M7 station. Figures 11-13 provide detailed visual representations of the validation results.

Figure-11 illustrates the comparison of water levels at the M7 station during the flood events in 2019. The figure shows both the observed data and the predicted water levels from the model. The close alignment of the two sets of data in the graph indicates that the model accurately predicts water levels under the conditions tested. The variations in water levels due to different Manning's n values are also highlighted, showing the model's sensitivity to this parameter.

Figure-12 presents a time series of water levels at the M7 station during the 2022 flood event. Similar to Figure-14, this Figure compares the observed water levels with those predicted by the model. The results demonstrate the model's robustness in predicting water levels across different years with varying hydrological conditions. The graph also shows that the model successfully captured the peak flood levels, further validating its accuracy.

Figure-13 offers a comprehensive comparison of the cumulative distribution of water levels at the M7 station, based on both observed and modeled data. This figure is crucial as it not only validates the model's predictions across different time frames but also emphasizes the model's performance in capturing the full range of water level variations. The close match between the cumulative distributions of observed and modeled data confirms the model's reliability in predicting water levels during flood events.

These figures collectively demonstrate that the calibrated HEC-RAS model is effective in predicting water levels in the Mun River, providing a reliable tool for flood management and planning. The close agreement between the observed and modeled data across different scenarios and periods underscores the robustness of the calibration and validation processes according to the previous studies [26-29].

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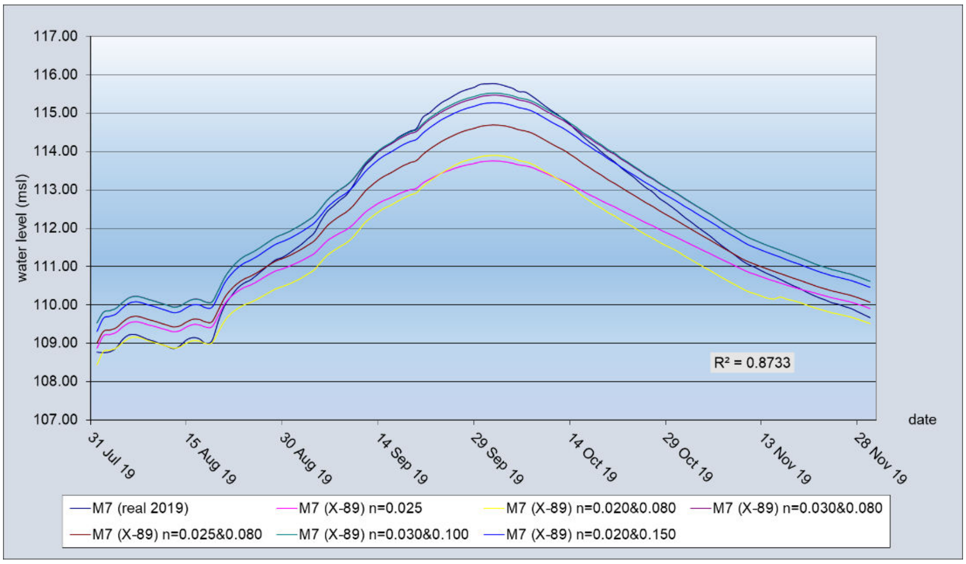

Figure-10. Result calibrate Manning's model at station M.7.

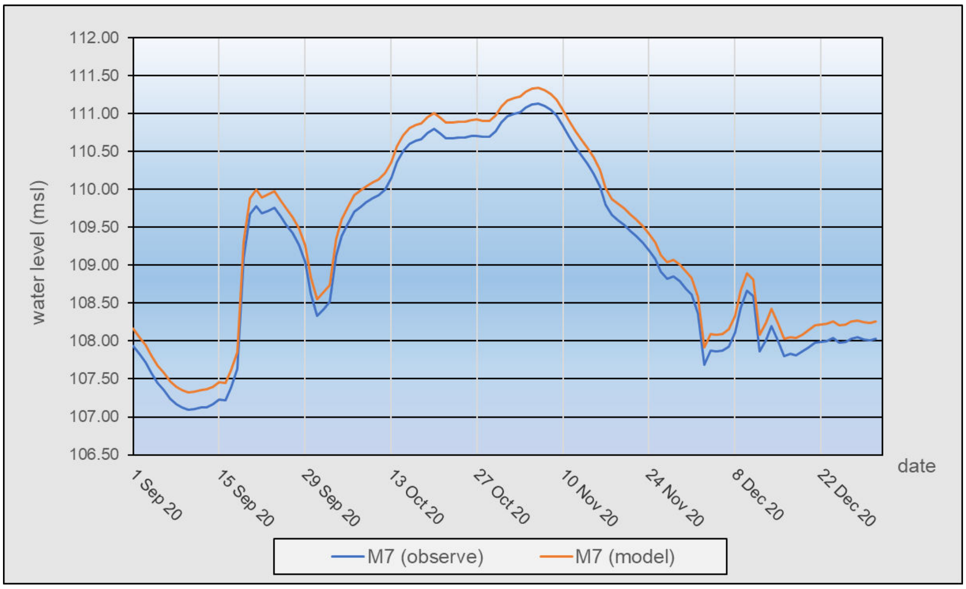

Figure-11. Water year 2020(Sep-Dec)

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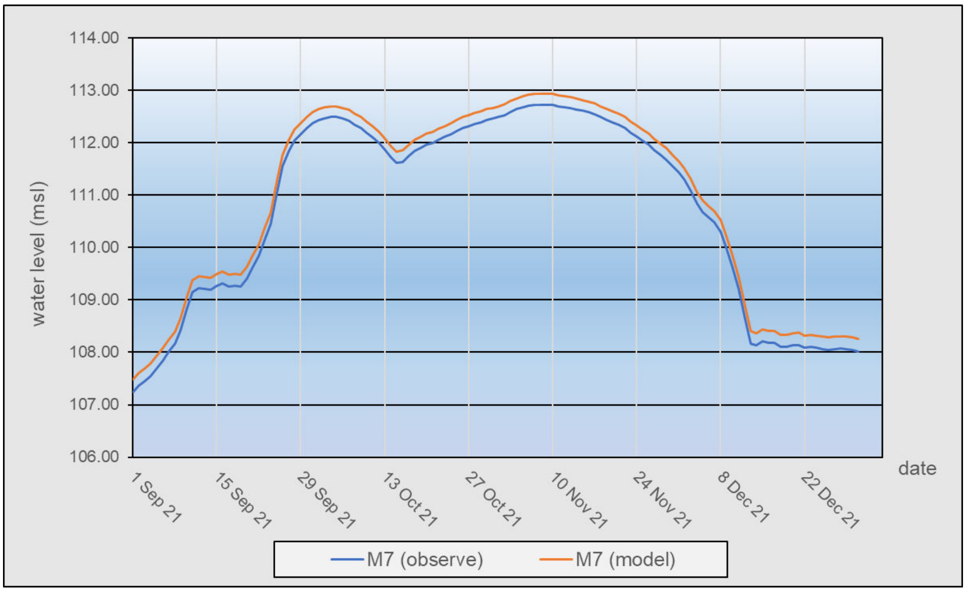

Figure-12. Water year 2021(Sep-Dec).

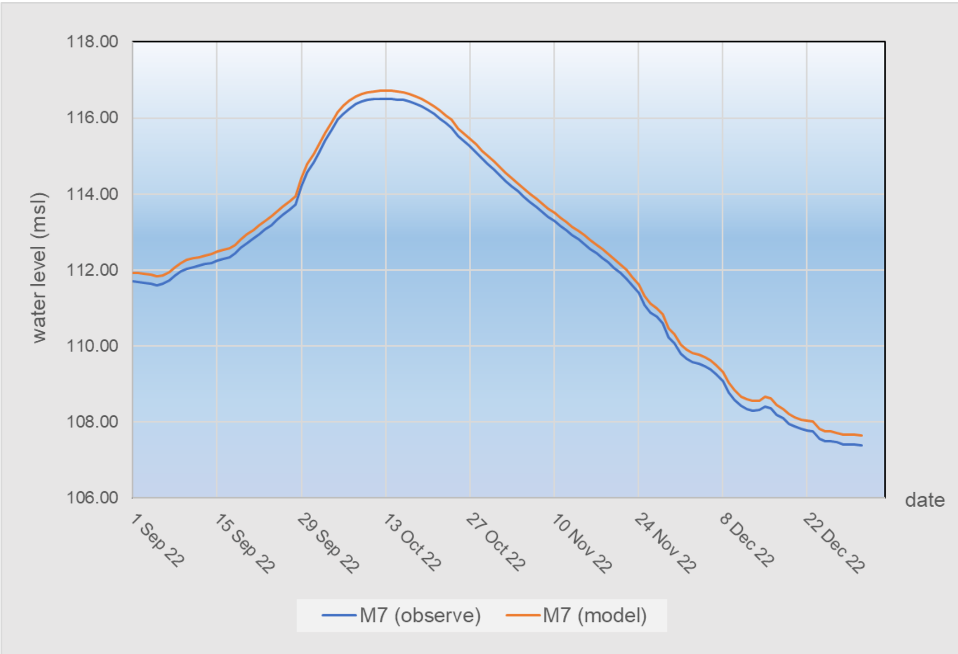

Figure-13. Water year 2022(Sep-Dec).

CONCLUSIONS

This study successfully utilized the HEC-RAS model to simulate and optimize water release strategies for three key reservoirs-Rasi Salai Dam, Hua Na Dam, and That Noi Dam-within the Mun and Chi River Basins in northeastern Thailand. The comprehensive calibration and validation of the model, using real-time data from multiple water measuring stations, confirmed the model's robustness in predicting water levels and assessing flood risks. The findings highlight the effectiveness of the proposed model in enhancing flood management strategies, particularly in maintaining tolerable water levels in downstream economic areas.

The integration of dynamic reservoir operation rules with the HEC-RAS model has proven to be a valuable approach for managing the complexities of multi-reservoir systems. By adjusting Manning's n roughness coefficient and other model parameters, the study achieved high accuracy in simulating water behavior under various hydrological conditions. The statistical measures obtained as high R^2 values and low RMSE and PBIAS values demonstrate the model's capability to replicate observed water levels, ensuring reliable predictions for future flood events.

Moreover, the research underscores the importance of using advanced simulation tools like HEC-

RAS in conjunction with real-time data to support sustainable water resource management. The findings can inform policymakers and water resource managers in developing more effective flood mitigation strategies, ultimately contributing to the resilience of the region's water infrastructure.

In conclusion, this study not only advances the application of hydraulic modeling in flood risk assessment but also provides a framework for optimizing reservoir operations in the face of increasing water demands and climate variability. Future research should continue to refine these models, incorporating more diverse data sets and exploring their application in other regions with similar hydrological challenges.

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