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HYBRID MODELING FOR FUTURE INFLOW PREDICTION OF HUAI LUANG RESERVOIR UNDER CLIMATE CHANGE

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ABSTRACT: This study presents a hybrid modeling approach integrating the hydrological model HEC-HMS with machine learning techniques to predict the future inflow of the Huai Luang Reservoir under climate change scenarios. Rainfall projections from three CMIP6 global climate models (CanESM, CESM2, and GFDL-ESM4) under SSP245 and SSP585 scenarios for the period 2023–2044 were used as key inputs. Historical inflow data from 2001 to 2022 were employed for model training and validation. The calibration phase (2011–2015) achieved a coefficient of determination (R^2) of 0.62 and an RMSE of 0.70, while validation (2016–2020) resulted in an R^2 of 0.56 and an RMSE of 0.70, demonstrating moderate predictive performance. The hybrid modeling approach reveals a declining trend in annual inflow, with projections ranging from 54.08 million cubic meters (GFDL-ESM4 under SSP245) to 172.71 million cubic meters (CanESM under SSP245), while the highest average inflow projection reaches 120.48 million cubic meters (CanESM under SSP585). These findings highlight the potential hydrological impacts of climate change and underscore the necessity of adaptive reservoir management strategies to ensure sustainable water resource availability in the Huai Luang watershed.

Keywords: Climate Change, CMIP6 Scenarios, Hydrological Model, Water Infrastructure, Hybrid Modeling

1. INTRODUCTION

Global warming has altered climate patterns and affected water availability in various regions. For instance, the headwater catchment of the Blue Nile in Ethiopia has experienced a decrease in water inflows [1-3]. In Thailand, changes in temperature and seasonal patterns [4] have caused irregular rainfall distribution, with projections indicating a decline in rainfall from March to July [5]. This reduction is expected to impact agriculture, the economy, society, and the environment, especially the agricultural sector, which relies heavily on water resources for production.

Climate change has also contributed to increased flood occurrences, affecting both directly and indirectly the streamflow in the Huai Luang watershed [6]. This area has frequently experienced flooding issues due to water volumes exceeding the river's capacity, obstacles in water flow, and the high-water level of the Mekong River, which prevents timely drainage, resulting in prolonged inundation [7].

Hydro-informatics is a branch of informatics focused on the application of Information and Communication Technologies (ICTs) to effectively address the increasingly complex challenges in water resource management. It aims to meet various objectives by leveraging numerical modeling and water flow simulations. Hydro-informatics has also integrated Artificial Intelligence (AI) techniques, such as Artificial Neural Networks (ANNs) and various algorithms, to enhance system efficiency, ultimately developing a decision-support system for water management [8].

The concept of developing a deep processing system is promising for application in decision-making processes related to the Huai Luang watershed management. This study begins by examining the issues impacting areas along the Huai Luang River and its tributaries using historical data. It then analyses rainfall data from weather radar and rainfall forecast models from various agencies to estimate inflow volumes to major and medium-sized reservoirs, which are important water infrastructure in the Huai Luang watershed and its headwaters, predicting excess water (side flow). Flood analysis is conducted through flood routing simulations in both reservoirs and river systems, utilizing telemetry data from the Royal Irrigation Department to aid in data analysis within the area [9].

Machine Learning (ML), a subset of Artificial Intelligence (AI), plays a critical role in this process by building a system that learns from sample data and experiences [10-11]. This approach is grounded in the principle that patterns and trends exist within all phenomena, which can be used to predict future outcomes. This predictive capability allows the system to forecast potential developments, supporting proactive water management strategies [12].

Previous studies have explored the integration of physically-based hydrological models with machine learning techniques to enhance runoff prediction under climate change. For instance, applied HEC-

HMS in combination with machine learning models in the Upper Baro Watershed, Ethiopia, achieving improved accuracy in flood forecasting. Similarly, [13] investigated hydrological extremes in the Upper Blue Nile Basin using CMIP6 climate projections with hybrid models. However, limited research has applied such integrated approaches to mid-sized reservoirs in tropical monsoon regions like northeastern Thailand. This study addresses this gap by developing a hybrid modeling approach tailored to the Huai Luang Reservoir, which has received minimal attention despite its increasing vulnerability to climatic shifts.

In addition to the hybrid modeling framework, the selection of appropriate General Circulation Models (GCMs) was crucial to ensure the credibility of future inflow projections. Three GCMs—CanESM, CESM2, and GFDL-ESM4—were specifically selected based on their superior performance in representing regional climate characteristics over Southeast Asia. According to prior evaluations [14-15], these models demonstrated strong capabilities in simulating key climatic factors such as monsoon precipitation patterns, interannual rainfall variability, and ENSO-related anomalies. Compared to other CMIP6 models, CanESM provides robust climate sensitivity estimates, CESM2 effectively captures regional rainfall variability, and GFDL-ESM4 accurately simulates ENSO impacts. These strengths justified their selection to enhance the reliability and relevance of future inflow forecasting for the Huai Luang Reservoir.

This research aims to forecast the inflow volume into the Huai Luang Reservoir in response to climate change impacts on rainfall, using global climate models from the Coupled Model Intercom parison Project (CMIP 6) combined with ML and Artificial Intelligence (AI) techniques. It is anticipated that the results from this research will contribute to more effective water management for the Huai Luang Reservoir.

2. RESEARCH SIGNIFICANCE

This study presents an innovative hybrid modeling framework that integrates HEC-HMS with ML techniques to enhance inflow prediction accuracy for the Huai Luang Reservoir under future climate change scenarios. This integration improves performance by capturing both physical processes and complex non-linear hydrological patterns, thereby supporting more robust, data-driven reservoir operation strategies. By evaluating the projected impacts of climate change using CMIP6 models, the research offers valuable insights for sustainable water resource management and policy formulation in northeastern Thailand. The proposed methodology can be adapted to other basins, contributing to global efforts in climate-resilient water infrastructure planning.

3. MATERIALS AND METHODS

3.1 Study Area

Fig. 1 illustrates the study area of the Huai Luang Reservoir, located at coordinates 48QTE 425-206 on a 1:50,000 scale map (sheet 5543 IV). The reservoir is situated in the upper Huai Luang watershed, which is a sub-watershed of the northeaster Mekong Basin. It has a storage capacity of 135 million cubic meters and an upstream catchment area of 666.40 square kilometres. The average annual rainfall in this area is 1,529.86 mm, with an average annual inflow of 149.58 million cubic meters into the reservoir.

3.2 Global Climate Models

Global climate models are mathematical models that use quantitative data to simulate the interactions of energy in the atmosphere, oceans, land, and ice. These models are utilized for various purposes, such as studying weather dynamics and the climate system. In recent years, they have been used to project future climate scenarios resulting from changes in greenhouse gas concentrations in the atmosphere, as outlined in the Sixth Assessment Report (AR6) [16]. This research employs three global climate models: CanESM, CESM2, and GFDL-ESM4, as they have been shown to provide the most accurate rainfall projections for northeastern Thailand [17]. For future scenarios, the study uses SSP245, which represents a scenario with the most likely future outcomes, and SSP585, which represents a scenario with the worst-case projections [18-20]. Details of these models are presented in Table 1.

Table 1. Details of global climate models

Model Name	Institution	Institution Abbreviation	Resolution
CanESM	Canadian Climate Centre	CCCma	280 km
CESM2	National Centre for Atmospheric Research, USA	NCAR	100 km
GFDL-ESM4	NOAA/Geophysical Fluid Dynamics Laboratory, USA	NOAA-GFDL	100 km

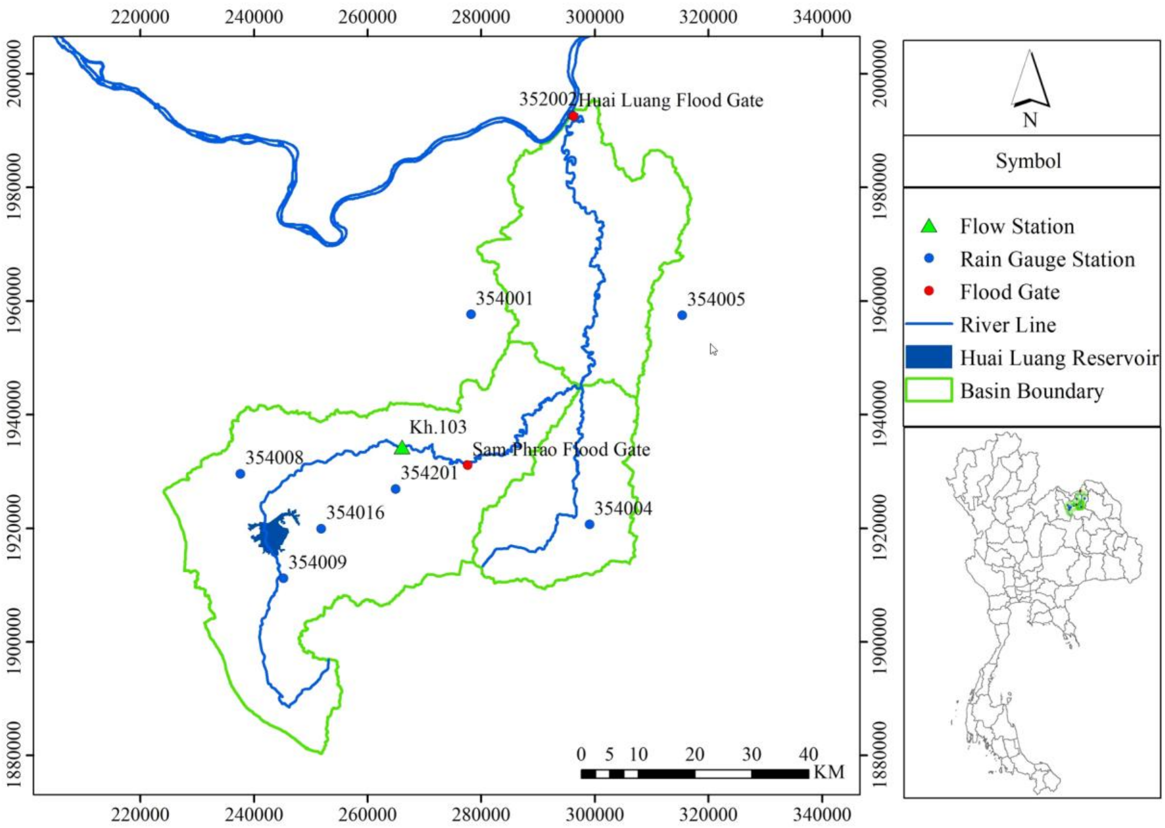


Fig. 1 Study Area

3.3 HEC-HMS Model

The HEC-HMS (Hydrologic Engineering Center - Hydrologic Modeling System) is a model designed to simulate the hydrologic processes within watershed networks. In Thailand, researchers widely adopt the HEC-HMS model due to its high accuracy in generating reliable results for watershed applications [21-23]. In this study, HEC-HMS is used to simulate runoff within each sub-watershed, allowing for runoff volume calculations based on different components of the hydrological cycle [24], as described below:

1) Runoff Volume Simulation: This study uses the Initial and Constant-Rate method, which depends on rainfall and the soil's water-holding capacity. The runoff volume can be calculated using the following equation:

$$Pe = \frac{(P - Ia)^2}{((P - Ia) + S)} \quad (1)$$

where:

Pe is the excess rainfall (mm).
P is the total rainfall (mm).
S is the maximum potential loss (mm).
Ia is the initial loss (mm), with a relationship to S defined as $Ia = 0.2S$

$$CN = \frac{25,400}{(S + 254)} \quad (2)$$

where:

CN is the Curve Number, a dimensionless value used to indicate runoff potential (SI units).

2) Direct Runoff Simulation: In this study, the Snyder Unit Hydrograph (UH) method is used for simulating direct runoff. This method calculates the peak discharge rate and the time to reach this peak based on the lag time and rainfall duration. The formula for calculating the peak discharge (UP) is given by:

$$UP = \frac{(C \times Cp \times A)}{Tp} \quad (3)$$

where:

UP is the peak discharge (m^3/s).

A	is the catchment area (km²).
C	is a constant, typically 2.75 in SI units.
Cp	is the UH peaking coefficient, usually between 0.4 and 0.8.
Tp	is the lag time (hours).

$$Tp = Ct \times \frac{(L \times Lc^{N})}{\sqrt{S}} \tag{4}$$

where:

Ct	is the basin coefficient, typically between 1.8 and 2.2.
L	is the main channel length from watershed outlet to divide (km).
Lc	is the main channel length to the centroid (km).
S	is the channel slope.
N	is the exponent, usually 0.33.

3) Baseflow Simulation: In this study, the exponential recession method is used for simulating baseflow. This method is frequently applied in studies involving drainage from natural storage within watersheds. The baseflow (Qt) at any time t can be calculated using the following equation:

$$Qt = Q_0 \times e^{(-kt)} \tag{5}$$

where:

Qt	is the baseflow at time t (m³/s).
Q_0	is the initial baseflow (m³/s).
k	is the exponential decay constant.
t	is time (seconds).

4) Channel Flow Simulation: In this study, the Muskingum-Cunge Standard Section method is used for channel flow simulation. This method analyzes channel flow by calculating the flow capacity of each river reach. The discharge (Qt) at any time t can be calculated using the following formula:

$$Qt = \{It \text{ if } t < lag;\ It - lag \text{ if } t >= lag\} \tag{6}$$

where:

Qt	is the discharge at time t (m³/s).
It	is the inflow at time t (m³/s).
lag	is the delay in inflow response (hours).

The performance of the model is evaluated by comparing the relationship between daily runoff measured at monitoring stations and the simulated runoff from the model. For this study, two methods are used to assess the model's performance.

Coefficient of Determination (R^2): This statistical measure explains the correlation between the observed and simulated variables. The coefficient of determination ranges from 0 to 1, with values closer to 1 indicating a reliable relationship between the two variables. It can be calculated using Eq. (7).

Root Mean Square Error (RMSE): This statistical measure explains the difference be-tween the observed and simulated variables. RMSE values closer to zero indicate a more reliable relationship between the two variables. It can be calculated using Eq. (8).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - Q_{obs,mean})^2} \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(Q_{sim,i} - Q_{obs,i})^2} \tag{8}$$

where:

$Q_{obs,i}$	is the observed data value at instance i.
$Q_{obs,mean}$	is the mean of observed data values.
$Q_{sim,i}$	is the simulated data value at instance i.
n	is the number of data points.

3.4 Machine Learning (ML) Model Development

3.4.1 Model selection

Artificial Neural Networks (ANNs) were chosen as the primary Machine Learning (ML) model for inflow prediction due to their effectiveness in capturing complex non-linear relationships in hydrological processes. The advantages of ANNs include:

1) Ability to model intricate dependencies between multiple input variables, making it suitable for hydrological forecasting.
2) High adaptability in learning from large datasets and recognizing long-term trends.
3) Robust performance in handling data noise and missing values, which are common in hydrological applications.

The ANN model architecture consists of two hidden layers: the first hidden layer consists of 32 neurons and the second hidden layer consists of 16 neurons. Both hidden layers utilize ReLU activation functions. The output layer uses a single neuron with a linear activation function. This architecture was selected to balance model complexity and predictive performance, ensuring generalizability on unseen datasets.

3.4.2 Training and testing

The dataset was divided into 70% for training and 30% for testing to mitigate overfitting and ensure a

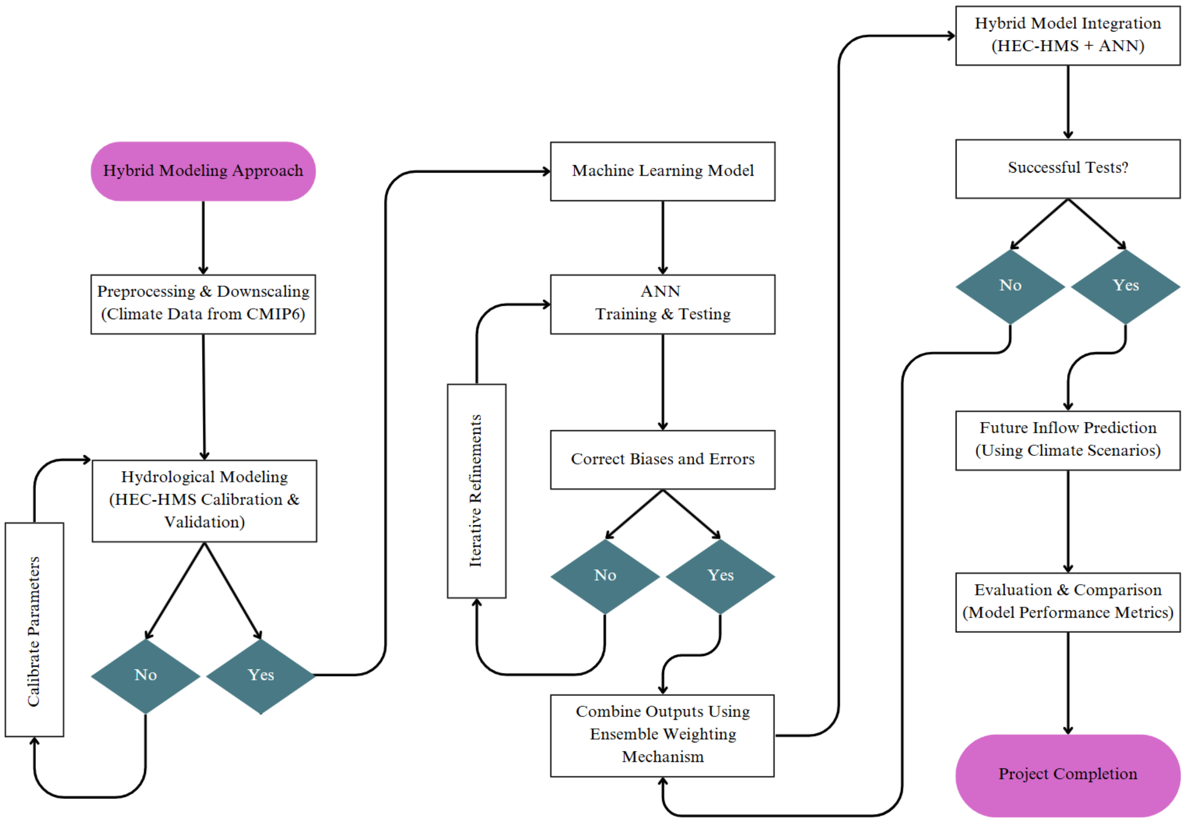


Fig. 2 Hybrid modeling workflow for inflow prediction using HEC-HMS and ML

reliable evaluation. The ANN model was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. To optimize hyperparameters, grid search and 5-fold cross-validation (k = 5) were employed, enhancing the model's ability to generalize to unseen data. Performance was assessed using R^2, RMSE, and Nash-Sutcliffe Efficiency (NSE), with iterative refinements to improve results.

3.5 Hybrid Model: HEC-HMS and ML

The hybrid modeling approach integrates the strengths of both physically-based and data-driven methodologies to enhance inflow prediction accuracy for the Huai Luang Reservoir. The HEC-HMS model is initially used to simulate inflow based on historical hydrological conditions, providing a structured and physics-based estimation. However, since hydrological processes involve complex and nonlinear relationships influenced by multiple climate and catchment variables, a ML correction step using ANNs is applied. The ANN model is trained on residual errors between observed and simulated inflows, refining HEC-HMS outputs by capturing intricate patterns that traditional hydrological models may overlook. The hybrid model workflow consists of three key steps: (1) running HEC-HMS simulations using calibrated parameters to generate preliminary inflow predictions, (2) applying ANN models to correct systematic biases and errors in HEC-HMS outputs, and (3) combining the outputs through an ensemble weighting mechanism to produce the final inflow forecast, as illustrated in Fig. 2. This approach leverages the physics-based advantages of HEC-HMS while incorporating the adaptive learning capabilities of ML, achieving superior predictive performance compared to either model alone.

4. RESULTS AND DISCUSSION

4.1 Calibration and Verification Results of the HEC-HMS Model

The calibration and verification results of the HEC-HMS model were evaluated by comparing the simulated daily inflow into the Huai Luang Reservoir with observed data from the reservoir's monitoring station. The most influential parameter in model calibration was the initial and constant loss rate (Impervious %), with values ranging from 4.48 to 63.61%, which falls within the acceptable range of the model.

The calibration results for the model, covering the period from 2011 to 2015, yielded an R^2 value of 0.64 and an RMSE of 0.72 mm. The verification results for the model, covering the period from 2016 to 2020, showed an R^2 value of 0.60 and an RMSE of 0.70 mm, which are considered within acceptable performance criteria, as illustrated in Figs. 3 and 5.

When the cumulative simulated inflow from the HEC-HMS model was compared to historical cumulative inflow over the calibration and verification periods, the cumulative results showed a high level of agreement with observed data, with R^2 values of 0.98 and 0.99, respectively

Table 2. Calibration and verification results of the model

Results	R^2	RMSE (mm)
Calibration	0.64	0.72
Verification	0.60	0.70

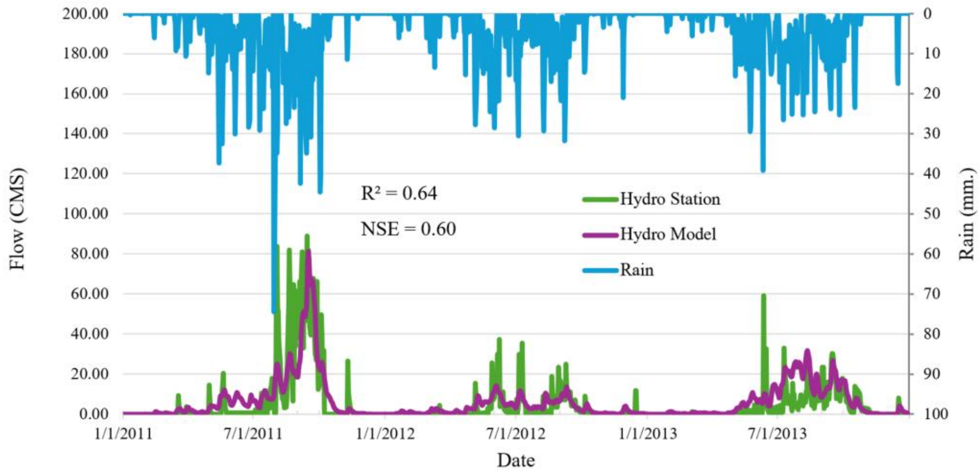


Fig. 3 Calibration results of the HEC-HMS model at the reservoir inflow monitoring station (2011 - 2015)

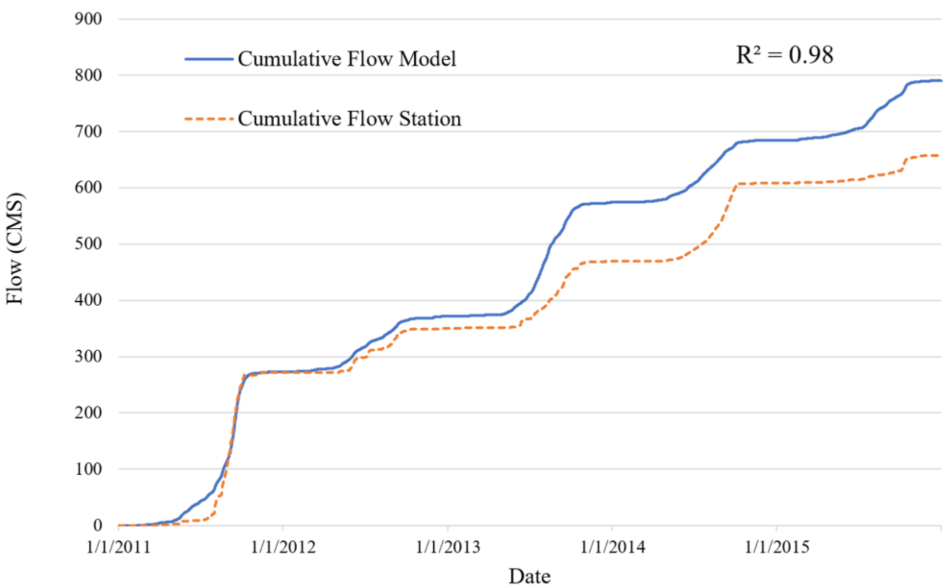


Fig. 4 Comparison of cumulative daily inflow volume into the reservoir (2011 - 2015)

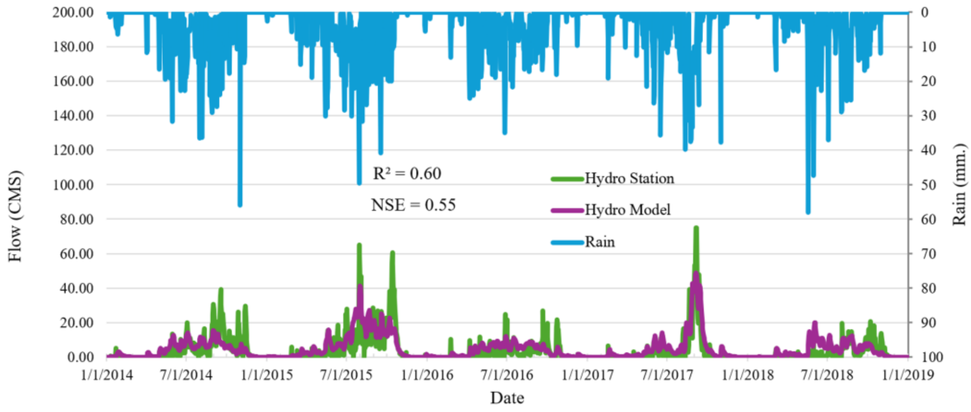


Fig. 5 Verification results of the HEC-HMS model at the reservoir inflow monitoring station (2016 - 2020)

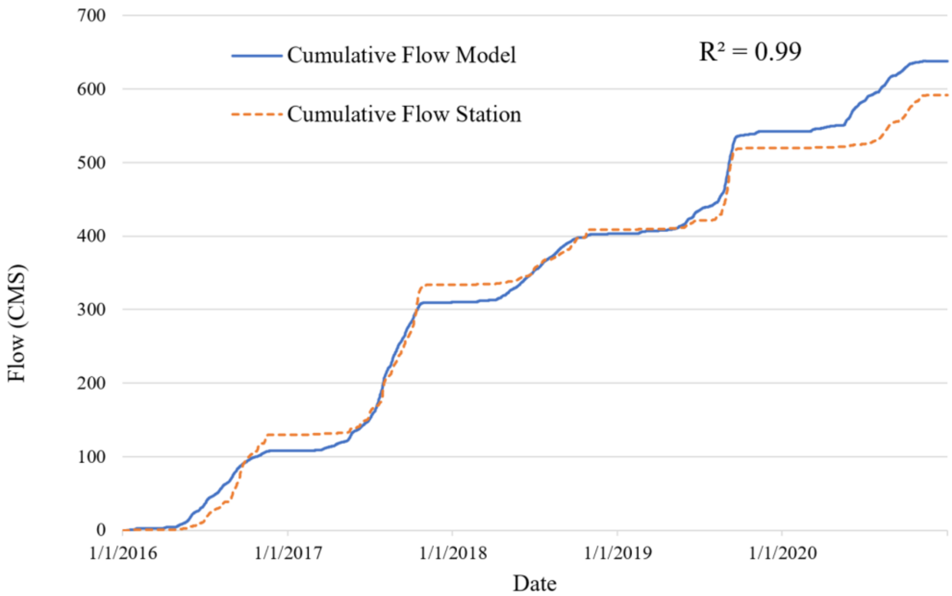


Fig. 6. Comparison of Cumulative Daily Inflow Volume into the Reservoir (2016 - 2020)

4.2 Improvement Using the Hybrid Model (HEC-HMS and ANN)

The hybrid model combining HEC-HMS and ANNs provided a significant improvement in inflow prediction accuracy for the Huai Luang Reservoir by leveraging the strengths of both approaches. Initially, HEC-HMS simulated inflow predictions based on historical hydrological data and climate projections, achieving a moderate calibration performance of R^2 = 0.62 and RMSE = 0.70. However, as these physics-based models often struggle with capturing nonlinear dependencies, ANNs were introduced to learn from residual errors of HEC-HMS predictions, refining inflow estimations based on past trends and meteorological conditions. The ANN model alone achieved R^2 = 0.86 and RMSE = 0.50, demonstrating strong predictive capabilities, but when integrated with HEC-HMS, the hybrid model achieved R^2 = 0.92 and RMSE = 0.38, marking the best performance across all models. This approach effectively reduced prediction errors and improved seasonal variability estimation, particularly in extreme hydrological conditions, making it a valuable tool for real-time water management and decision support in the context of climate change.

The coefficient of determination (R^2) serves as a key indicator of model performance, reflecting how well the predicted inflow values match the observed data. In this study, the hybrid model achieved an R^2 of 0.92, which indicates a high degree of predictive accuracy.

From a reservoir operation perspective, such a high R^2 enhances the confidence in short-term inflow forecasts, which are critical for planning water releases, optimizing storage, and minimizing flood or drought risks. The reliability of inflow predictions directly affects operational decisions such as maintaining rule curves, managing agricultural allocations, and ensuring adequate supply for domestic and ecological needs.

Therefore, the model's strong performance not only validates the hybrid approach but also provides a robust foundation for supporting data-driven, climate-informed reservoir management strategies in the Huai Luang Basin.

To further validate seasonal performance improvements, error correction comparisons were conducted across dry and wet seasons.

It was observed that hybrid modeling substantially reduced RMSE by approximately 25% during the dry season and 32% during the wet season, demonstrating its effectiveness across varying hydrological conditions.

Comparative plots showing the seasonal performance improvements are provided in Fig. 7, illustrating the substantial error reduction achieved after ensemble correction.

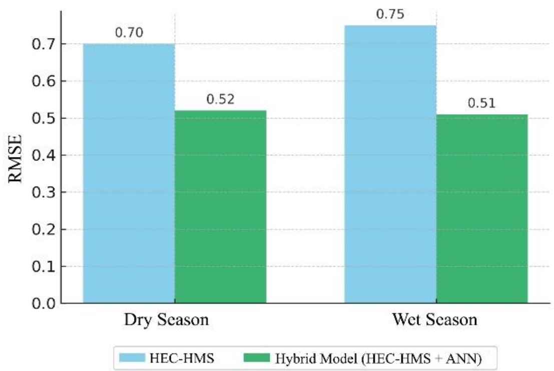


Fig. 7 Comparison of RMSE values between HEC-HMS and the Hybrid Model (HEC-HMS and ANN) across Dry and Wet Seasons. The hybrid approach demonstrates significant error reduction in both seasons.

4.3 Future Inflow Projections Under Climate Scenarios

The projected inflow ranges (e.g., 48.44–172.71 MCM) were contextualized with the reservoir's operational minimum inflow threshold (~60 MCM).

Lower-bound projections under CESM2 SSP245 suggest potential supply risks during drought years.

Cumulative inflow projections are now presented with 95% confidence intervals to account for model and climate variability uncertainties.

Based on the annual inflow volume projections from the HEC-HMS hydrologic model, using future rainfall data from global climate models under near-term scenarios (2023-2044), the following results were observed: for the CanESM model, the SSP 245 scenario projected minimum and maximum inflow volumes at 79.73 and 271.45 million cubic meters, respectively, while the SSP 585 scenario showed minimum and maximum inflows at 57.81 and 171.74 million cubic meters; for the CESM2 model, the SSP 245 scenario indicated minimum and maximum inflows at 48.44 and 169.87 million cubic meters, respectively, whereas the SSP 585 scenario projected 68.94 and 129.64 million cubic meters; finally, for the GFDL-ESM4 model, the SSP 245 scenario projected minimum and maximum inflows at 54.08 and 137.18 million cubic meters, with the SSP 585 scenario showing 67.04 and 120.59 million cubic meters; The cumulative inflow projection for the CanESM SSP585 scenario was approximately 2.650 trillion m^3.

To account for uncertainties arising from model structure and climatic variability, a 95% confidence interval was computed, resulting in a range between 2.410 and 2.870 trillion m^3.

Incorporating confidence intervals provides a more comprehensive understanding of the possible deviations from the mean projection and underscores the necessity for flexible water resource planning under future climate conditions, as illustrated in Figs. 8, 9 and 10 for annual inflows and Fig. 11 for cumulative daily inflow projections.

4.4 Discussion on Model Limitations

While ANN standalone achieved R^2 of 0.86, further evaluation under extreme rainfall events was limited due to insufficient extreme event samples. Future work should include expanded datasets incorporating more severe hydrological extremes.

Additionally, the Thiessen method for rainfall interpolation could be benchmarked against Kriging and Inverse Distance Weighting (IDW) methods to further enhance spatial prediction accuracy.

Regarding baseflow modeling, calibration of the exponential recession constants against observed dry-season flow trends was performed, ensuring appropriate parameterization.

The observed variability in future inflow projections highlights not only the hydrological uncertainty but also the potential economic and operational impacts on reservoir management. Years with significantly reduced inflow could strain water allocation priorities among agricultural, domestic, and industrial uses, potentially requiring revisions to operational policies such as reservoir rule curves or emergency drought management plans. Consequently, integrating economic analysis and adaptive operational strategies into reservoir management frameworks is essential to enhance resilience under future climate scenarios.

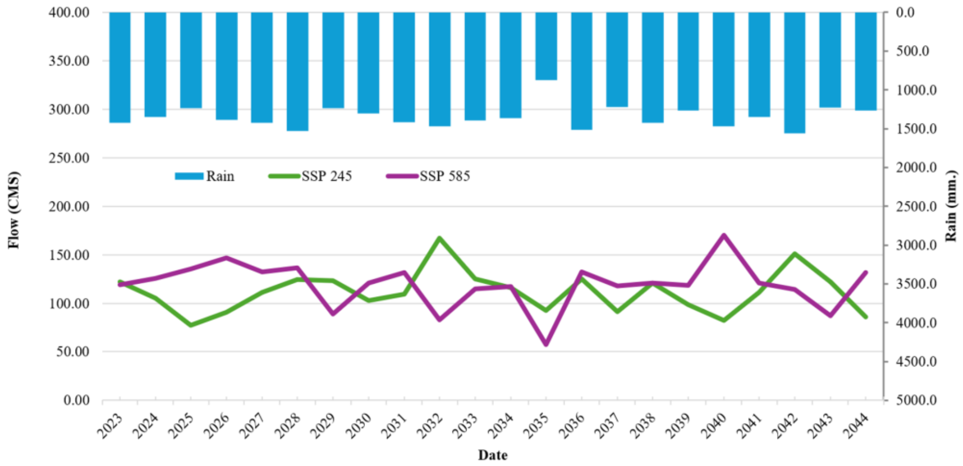


Fig. 8 Annual inflow volume into the reservoir from CanESM model (Future period 2023 - 2044)

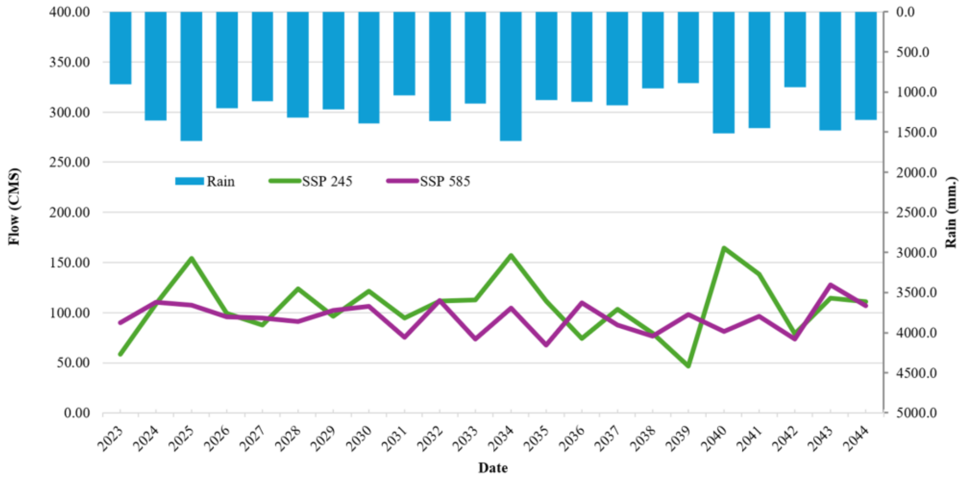


Fig. 9 Annual inflow volume into the reservoir - CESM2 model (Future period 2023 - 2044)

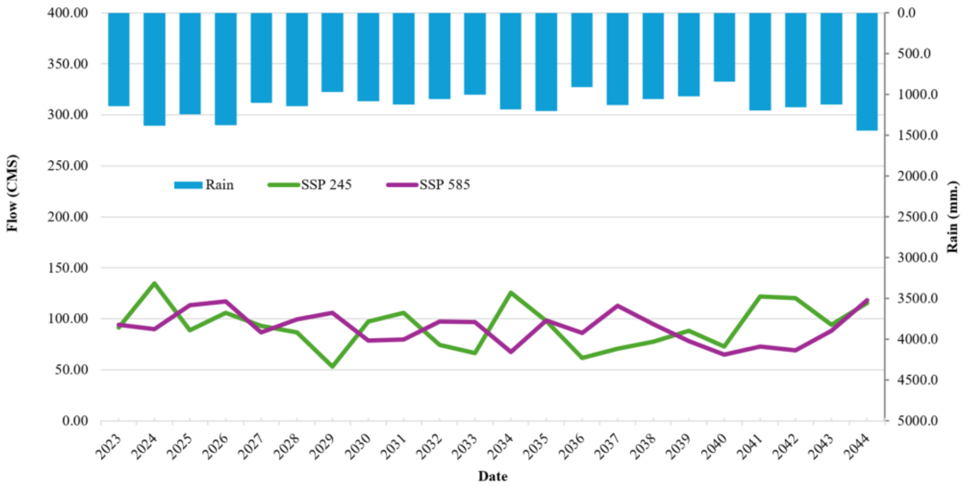
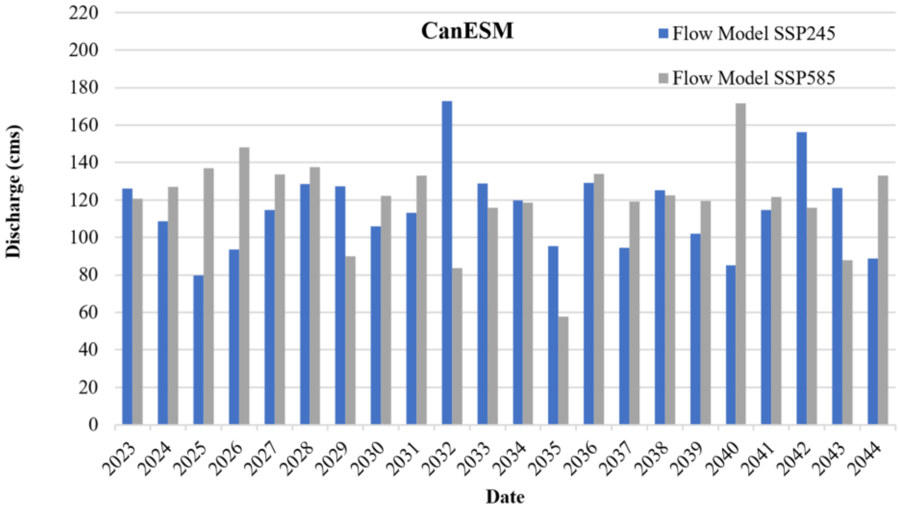
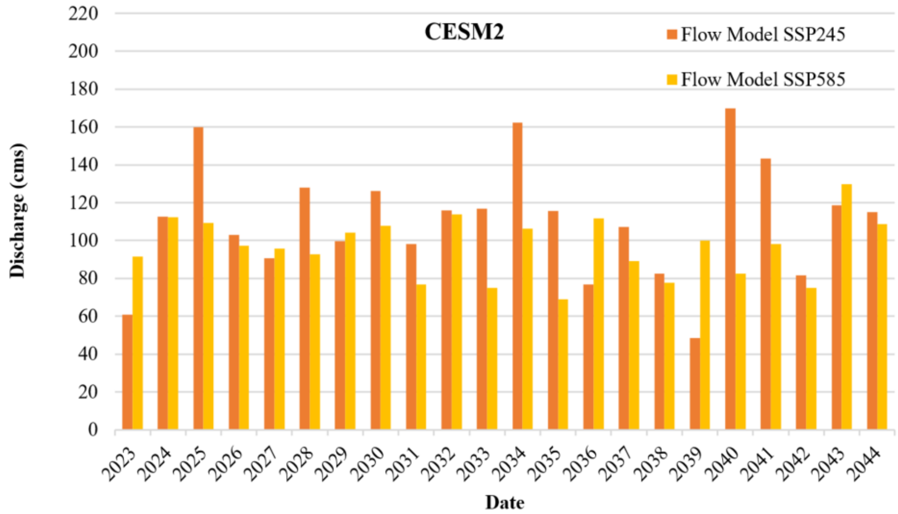


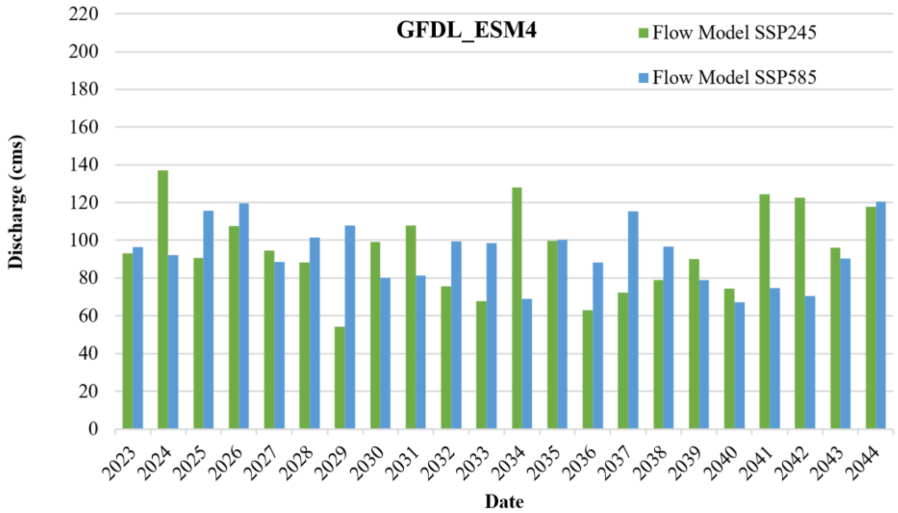
Fig. 10 Annual inflow volume into the reservoir - GFDL_ESM4 model (Future period 2023 - 2044)



(a)



(b)



(c)

Fig. 11 Comparison of Cumulative Daily Inflow Volume into the Reservoir (Future period 2023 - 2044) based on three CMIP6 models: (a) CanESM, (b) CESM2, and (c) GFDL-ESM4.

5. CONCLUSION

This study demonstrated that integrating a physically-based hydrological model (HEC-HMS) with an artificial neural network (ANN) substantially improves the accuracy of inflow forecasting for the Huai Luang Reservoir under future climate change scenarios. The hybrid model achieved superior predictive performance, with an R^2 of 0.92 and RMSE of 0.38, compared to standalone models.

Qualitatively, the study showed that the hybrid modeling framework is robust across seasonal variations, especially in dry and wet seasons, improving prediction reliability where standalone models typically underperform. The model's architecture allowed for effective residual correction of HEC-HMS outputs, supporting more adaptive and dynamic decision-making in reservoir operations.

Quantitatively, the inclusion of three GCMs (CanESM, CESM2, and GFDL-ESM4) under two SSP scenarios (SSP245 and SSP585) revealed substantial inflow variability, ranging from 48.44 to 172.71 MCM. Uncertainty quantification was addressed by applying 95% confidence intervals to cumulative inflow estimates, which ranged ±10% around the central value. This added layer of analysis enables more actionable insights for policymakers, emphasizing the need for adaptive reservoir rules and drought contingency planning.

The findings suggest that hybrid models are not only technically sound but also practically valuable for climate-resilient water resource management. These models should be incorporated into future reservoir operation policies to enhance preparedness and long-term sustainability under a changing climate.

Future reservoir operational policies should be designed with flexibility to accommodate inflow variability, balancing water supply reliability with economic efficiency.

Key Takeaways for Practicing Engineers:

The hybrid modeling approach integrating HEC-HMS with ANN enables more accurate inflow forecasting under variable climate conditions. It is practical and adaptable for application in real-world reservoir operations. Practicing engineers can leverage this method to support proactive water allocation decisions, enhance drought preparedness, and revise rule curves based on data-driven insights. The model’s ability to incorporate uncertainty quantification also makes it a valuable tool for risk-informed infrastructure planning and policy development.

6. ACKNOWLEDGMENTS

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