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Enhancing Long-Term Reservoir Inflow Forecasting: An Integrated Approach Combining Switch Prediction Method, Ensemble Rainfall Forecasts, and Machine Learning Techniques

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Abstract. This study makes a unique contribution by evaluating the effectiveness of the Switch Prediction Method (SPM) in integrating ensemble rainfall forecasts, significantly improving the accuracy of long-term inflow forecasting for reservoirs—a crucial aspect of hydrological forecasting. The proposed approach combines Numerical Weather Prediction (NWP) data with advanced machine learning techniques, specifically Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) models, to develop a robust forecasting framework. The study utilizes comprehensive datasets from the ShihMen Reservoir in Taiwan to assess the performance of the proposed model. The SPM dynamically integrates multiple meteorological forecasts to reduce uncertainty and improve rainfall input accuracy. These enhanced inputs are then used in multi-step forecasting (MSF) models with a 72-hour lead time. The results demonstrate that the LSTM-based model, combined with SPM-integrated forecasts, delivers accurate and stable inflow predictions. For instance, in the case of Typhoon Soudelor—the test event with the highest observed peak inflow (5,634.1 cms)—the proposed SPM-LSTM-MSF model achieved a Mean Absolute Error (MAE) of 178.8 cms and a Coefficient of Efficiency (CE) of 0.87, demonstrating superior accuracy and temporal stability compared to the SVM-based approach. These findings highlight the potential of SPM and machine learning techniques in enhancing reservoir management and flood control strategies, offering a robust and adaptable solution for complex hydrological forecasting tasks.

1. Introduction

Accurate long-term inflow forecasting is critical for effective reservoir management, particularly during extreme weather events such as typhoons. Over the past century, Taiwan has experienced an average of three to four typhoons annually, many of which bring intense rainfall and flood risks to mountainous regions(Lin et al., 2013a; Wang et al., 2019). While typhoon rainfall is an essential source of water, it also poses significant operational challenges. During the early phase of a typhoon—the rising limb—reservoir operators must regulate discharges through floodgates and hydropower systems to lower water

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levels in anticipation of incoming inflows. These actions not only protect dam infrastructure and downstream communities but also optimize hydropower efficiency(Li et al., 2010; Nohara et al., 2016; Wei and Hsu, 2008).

Following the peak inflow period, known as the recession limb, effective management of excess water is essential for implementing sediment flushing operations that preserve reservoir storage capacity. For example, (Morris and Fan, 1998)outlined comprehensive sediment management strategies to ensure long-term sustainability. (Kondolf et al., 2014) and (Lee et al., 2022) further emphasized the importance of integrating sediment flushing into routine operations to maintain the functionality of reservoirs across diverse hydroclimatic conditions.

Given these operational demands, inflow forecasts with lead times of up to 72 hours are invaluable for enabling timely and informed decision-making during typhoon events. Studies by (Hsiao et al., 2013) and (Yu et al., 2015) have demonstrated the utility of such forecasts in enhancing flood mitigation and optimizing water allocation. However, the complex, non-linear nature of rainfall–runoff processes and uncertainties in meteorological forecasts present ongoing challenges.

Numerical Weather Prediction (NWP) models have become indispensable tools for generating rainfall forecasts in advance of and during typhoon landfalls. Yet, a single NWP model may struggle to fully capture the spatiotemporal variability of typhoon-induced precipitation. To address this limitation, ensemble forecasting methods—which combine outputs from multiple models—have gained traction for their ability to represent a broader range of potential rainfall scenarios and reduce forecast errors (He et al., 2013; Hsiao et al., 2013; Yu et al., 2015) . (He et al., 2013) and (Wu et al., 2018; Wu and Lin, 2017) showed that ensemble approaches significantly improve short-term precipitation forecasts, particularly in rapidly changing weather conditions. Despite these advances, identifying the most accurate ensemble member or combination remains a central challenge. One promising direction involves applying probabilistic weighting techniques such as Bayesian Model Averaging (BMA). For example, (Mendes and Maia, 2023) introduced a multi-objective BMA framework that simultaneously optimizes forecast accuracy and reliability in typhoon-induced rainfall prediction. Their results highlight the value of adaptive, data-driven integration strategies for improving ensemble forecast performance.

Building upon this concept, the Switch Prediction Method (SPM) has been introduced as a dynamic ensemble integration strategy. Originally applied in landslide prediction (Lian et al., 2015; Utomo et al., 2019), SPM adaptively selects and combines forecast outputs based on real-time performance metrics, thereby enhancing predictive reliability. In hydrological applications, (Huang et al., 2021, 2022) successfully used SPM to improve the accuracy of sediment concentration and inflow forecasts. The adaptive nature of SPM makes it particularly well-suited to high-uncertainty environments such as typhoon-induced rainfall.

Concurrently, machine learning (ML) techniques have shown strong potential in modeling the non-linear relationships inherent in rainfall–runoff processes. Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) networks are particularly effective at capturing temporal dependencies and learning from historical data. (Lin et al., 2013b) and (Wu et al., 2014) demonstrated that SVM models can successfully model non-linear input–output relationships, leading to accurate forecasts of evaporation and streamflow when trained with high-quality data. (Lin et al., 2013c) applied SVM for tropical cyclone intensity forecasting, validating its capability in modeling meteorological–hydrological interactions. (Yang et al.,

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2018) developed a genetic algorithm-based predictor selection method for SVM-based typhoon rainfall forecasting, further improving input feature quality.

More recently, LSTM networks have surpassed traditional ML models in streamflow forecasting due to their ability to model sequential patterns and long-term dependencies. (Liang et al., 2018) demonstrated LSTM's effectiveness in modeling hydrodynamics of Dongting Lake and its interaction with the Three Gorges Dam. (Zhang et al., 2018) applied LSTM to enhance IoT-based monitoring of combined sewer overflows, while (Kaveh et al., 2021) utilized LSTM to predict daily suspended sediment concentrations under noisy input conditions. (Rahimzad et al., 2021) onfirmed that LSTM outperforms conventional ML models in streamflow forecasting, particularly under highly variable and uncertain conditions. (Zhou et al., 2025) further highlighted the advantages of LSTM-based models in flood forecasting for tidal river reaches. Their study showed that LSTM and stacked ensemble models were particularly effective in capturing the temporal dependencies of hydrological variables, leading to more reliable predictions under the complex interactions of tidal and riverine flows. (Luo et al., 2023) proposed an integrated approach combining LSTM-based preprocessing and post processing modules with a hydrological model. Their results demonstrated that such hybrid models not only effectively correct biases in physically-based forecasts but also outperform LSTM-only models when the training data is limited. This suggests that the integration of physical and data-driven models is particularly advantageous for improving multi-step inflow predictions under data-scarce conditions. In this study, SVM and LSTM are selected as representative models to evaluate their respective strengths in long-term inflow forecasting under uncertainty.

In Taiwan, conventional inflow forecasting is often limited to short lead times—typically six hours—due to the rapid watershed response and typhoon intensity (Yang et al., 2018). However, leveraging ensemble-based rainfall forecasts can significantly extend the forecasting horizon. (Huang et al., 2021) demonstrated that integrating forecasted rainfall with ML models improves long lead-time inflow prediction, which is critical for proactive reservoir operation. Moreover, (Guo et al., 2023) proposed a residual error correction and multiple-ahead adjustment technique to enhance inflow forecasts in mountainous catchments such as Shihmen and Feitsui Reservoirs. Their approach significantly improved prediction accuracy at 3–24 hour lead times, particularly under typhoon-induced heavy rainfall conditions. This further illustrates the value of post-processing techniques and data-driven corrections in improving reservoir forecasting performance under highly dynamic hydrological conditions.

This study aims to develop and evaluate a novel framework that integrates the SPM with advanced machine learning techniques to forecast reservoir inflows up to 72 hours in advance during typhoon events. The proposed methodology includes: (1) optimizing ensemble rainfall forecasts using SPM, (2) constructing inflow forecasting models using SVM and LSTM, and (3) applying these models with SPM-integrated rainfall inputs to generate long-term inflow predictions. By addressing both forecast uncertainty and hydrological modeling complexity, this framework seeks to enhance both scientific insight and practical resilience in reservoir inflow management.

The remainder of this paper is organized as follows: Section 2 introduces the methodology of the proposed SPM-integrated forecasting approach. Section 3 presents the case study of ShihMen Reservoir in Taiwan and the experimental design.

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Section 4 discusses forecasting results, uncertainty assessments, and model comparisons. Section 5 concludes with key findings and implications for future research and operational applications.

2. Methodology

2.1. Study area and data

2.1.1. Study area

ShihMen Reservoir, located in the middle reaches of the Dahan River in Taoyuan City, is one of Taiwan's most significant multi-purpose reservoirs. It was constructed with an earth-and-rock fill embankment. It currently has a storage capacity of approximately 199 million m3, reduced from its original designed capacity of 309 million m3 due to sedimentation issues. The reservoir plays a crucial role in providing agricultural irrigation, domestic water supply, and industrial water needs for the regions of Taoyuan City, New Taipei City, and Hsinchu County. Additionally, it serves multiple functions, including flood control, hydroelectric power generation, tourism promotion, and ecological environment preservation.

Figure 1 illustrates the location of the ShihMen Reservoir catchment area and the rain gauge stations. The catchment area of ShihMen Reservoir covers approximately 763 km2, with an annual average rainfall of about 2,600 mm. Over 60% of this precipitation occurs during the wet season from May to October, primarily due to heavy typhoon rains. These typhoons significantly impact the reservoir's operations and necessitate robust flood management strategies. Knowing the future inflow volume of the reservoir during typhoon periods in advance would greatly benefit the flood control operations of the reservoir. Accurate long-term inflow forecasting enables reservoir managers to make informed decisions regarding pre-emptive water release, optimizing storage capacity to mitigate flood risks while ensuring sufficient water supply for post-typhoon periods.

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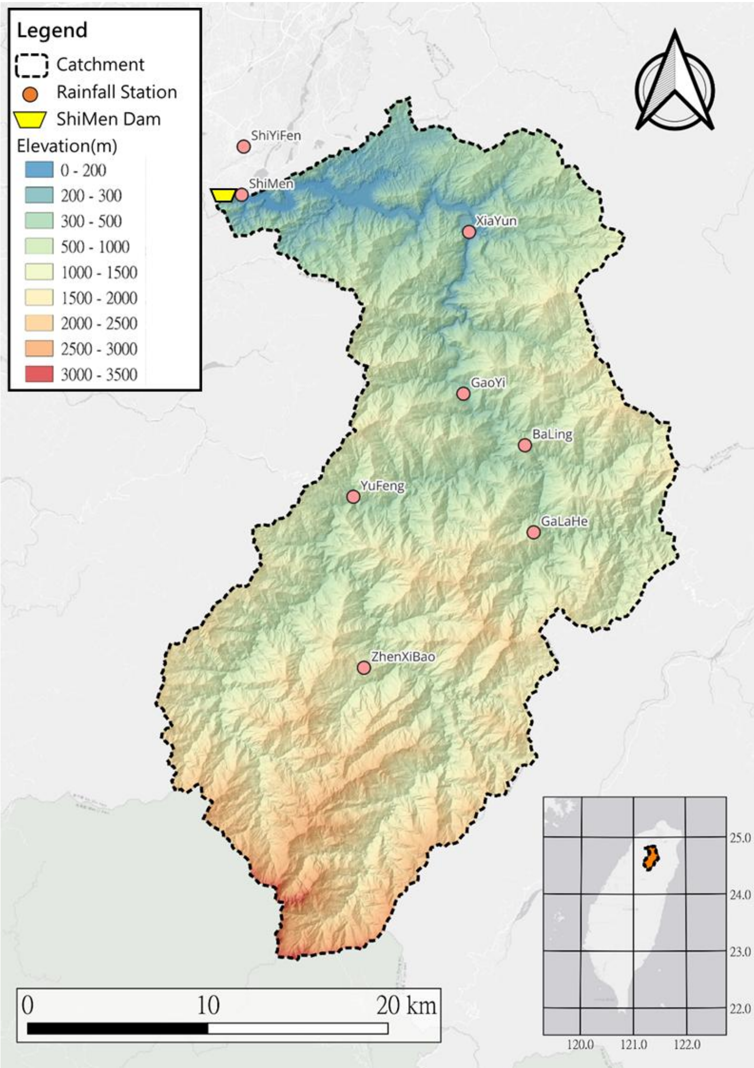

Figure 1 Map of the ShihMen Reservoir catchment showing the locations of rainfall stations used in the study. The spatial configuration is essential for understanding hydrological inputs and validating the forecast models. Data sources: Central Weather Administration and Water Resources Agency, Taiwan.

120 **2.1.2. Historical typhoon events**

This study collected reservoir inflow data from 18 typhoon events that occurred between 2004 and 2019. The duration of each typhoon event, the average peak hourly rainfall in the catchment area, and the peak inflow are listed in Table 1. The data were divided into training and test datasets in a 13:4 ratio based on the year of the typhoon events.

To ensure the model's generalization capability and to avoid extrapolation beyond the training range—a known limitation of machine learning approaches—the training dataset was deliberately selected to include typhoon events with both the highest

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(Typhoon Aere, peak inflow of 8,593.9 m³/s) and lowest (Typhoon Kammuri, peak inflow of 205.7 m³/s) inflow events. This approach ensures that the model is exposed to the full range of inflow variability during training.

The test dataset, while distinct in events, still falls within the range of the training data. For instance, Typhoon Soudelor in the test set recorded a peak inflow of 5,634.1 m³/s. The aim of this study is to evaluate the performance of the proposed forecasting framework under known but diverse hydrological conditions, rather than testing the model's extrapolation capability. A more detailed investigation of extrapolation beyond observed ranges is recognized as an important direction for future research.

Table 1 Summary of 18 historical typhoon events from 2004 to 2019 used for model training and testing. Includes event duration, peak hourly rainfall, and peak reservoir inflow.

Index	Typhoon event	Date (yyyy/mm/dd)	Duration (hr)	Peak hourly rainfall (mm/hr)	Peak inflow (m^3/s)
1	Aere	2004/08/23	96	53.4	8593.9
2	Krosa	2007/10/05	144	40.5	5300.4
3	Kalmaegi	2008/07/16	57	8.8	205.7
4	Fung-wong	2008/07/26	89	17.2	2039.8
5	Sinlaku	2008/09/11	313	30.8	3446.9
6	Jangmi	2008/09/26	150	31.4	3292.0
7	Morakot	2009/08/06	120	46.8	1837.5
8	Fanapi	2010/09/19	72	21.9	1056.2
9	Saola	2012/07/30	167	45.9	5385.1
10	Trami	2013/08/20	156	27.8	2410.1
11	Soulik	2013/07/11	135	38.7	5457.9
12	Dujuan	2015/09/29	106	36.4	3802.5
13	Meranti	2016/09/13	94	6.8	451.8
14	Soudelor	2015/08/06	73	47.4	5634.1
15	Megi	2016/09/26	94	41.0	4267.6
16	Maria	2018/07/09	23	23.2	1702.1
17	Lekima	2019/08/07	38	24.5	1166.4

2.1.3. Meteorological forecast products

This study utilized various meteorological forecast products, which are mainly categorized into NWP and ensemble forecasting. These include Quantitative Precipitation Estimation and Segregation Using Multiple Sensors (QPESUMS), Quantitative Precipitation Forecast (QPF), Ensemble Typhoon Quantitative Precipitation Forecast (ETQPF), Central

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Weather Bureau Weather Research and Forecasting model (CWB-WRF), WRF Ensemble Prediction System - Probability-Matched Rainfall Forecast (WEPS-PM) and Space and Time Multiscale Analysis System - WRF (STMAS-WRF).

QPESUMS is a platform that integrates observational data from radar, satellites, rain gauges, and lightning detection to provide real-time monitoring of severe weather, quantitative precipitation estimation, and short-term quantitative precipitation forecasting. QPF is the official quantitative precipitation forecast by the Central Weather Administration (formerly Central Weather Bureau). ETQPF uses ensemble model rainfall forecasts as a basis, combined with typhoon track forecasts and related meteorological parameters as selection criteria, to reassemble a new set of typhoon rainfall forecasts. CWBWRF is a mesoscale numerical model developed by the Central Weather Administration (formerly Central Weather Bureau) for atmospheric research and forecasting purposes. WEPS-PM is the best rainfall forecast product obtained by probabilistic matching and averaging of over 20 WRF products. STMAS-WRF is a short-term rainfall forecast product produced by integrating the WRF model with the Space-Time Multiscale Analysis System (STMAS) data assimilation technique. The temporal resolution, spatial resolution, and contents of each product are summarized in Table 2.

Due to differences in the availability and data provided by each meteorological forecast product, the meteorological forecast products obtained for each typhoon event in this study are summarized in Table 3. The precipitation forecast results from these meteorological forecast products can be used as input variables for the developed rainfall-runoff model to forecast long-term reservoir inflow.

Table 2 Characteristics of the meteorological forecast products used in this study, including data frequency, lead time, resolution, and data type.

Product	Data frequency	Lead time	Data type	Spatial resolution
QPF	6 hours	24 hours	6-hour accumulated rainfall	2.5 km
ETQPF	3 hours	72 hours	3-hour accumulated rainfall	0.04°
CWB-WRF	6 hours	72-120 hours	hourly rainfall	3.0 km
WEPS-PM	6 hours	72-108 hours	hourly rainfall	3.0 km
STMAS-WRF	3 hours	12 hours	hourly rainfall	3.0 km

Table 3 Availability of meteorological forecast products for each typhoon event in the test dataset. Indicates which products were used for ensemble integration via SPM.

Typhoon event	QPF	ETQPF	CWB-WRF	WEPS-PM	STMAS-WRF
Soudelor		√	√		
Megi	√	√	√	√	√
Maria	√	√	√	√	
Lekima	√	√		√	

2.2. Model development

A hybrid machine learning–based approach integrated with the Switch Prediction Method (SPM) is proposed to provide accurate 72-hour reservoir inflow forecasts. The flowchart of the proposed framework is presented in Figure 2. The development process consists of three main stages, each incorporating different data sources and computational components to enhance forecast accuracy and robustness.

In Stage 1, the SPM is used to optimize ensemble rainfall forecasts by dynamically selecting the most appropriate forecast product based on real-time observed rainfall. This adaptive integration of meteorological forecast products enhances the reliability of rainfall inputs by minimizing prediction biases and maximizing consistency with observed conditions. The output of this stage is the optimized ensemble rainfall forecast.

Stage 2 involves the construction of a data-driven rainfall–reservoir inflow model using observed rainfall and inflow data from historical typhoon events. Both SVM and LSTM are employed as predictive models to explore their respective strengths in capturing the nonlinear and temporal dynamics of hydrological processes.

In Stage 3, the optimized rainfall forecasts from Stage 1 are used as inputs to the trained models from Stage 2 to generate inflow predictions over a 72-hour lead time. This is achieved through a MSF approach, which allows the model to sequentially predict inflows for multiple future time steps. The outputs of this stage include both deterministic inflow predictions and, when ensemble rainfall inputs are used, associated confidence intervals representing forecast uncertainty.

This integrated framework provides a robust foundation for inflow forecasting and can be further enhanced for real-time operational deployment. The details of each stage are elaborated in the following subsections.

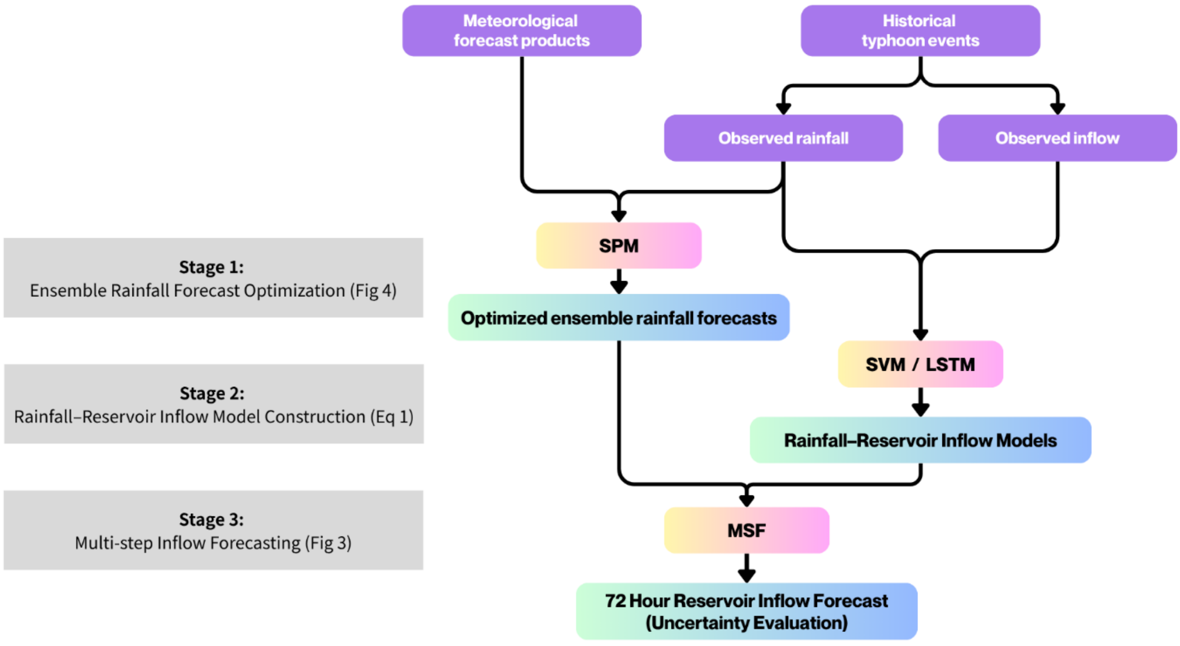

Figure 2 Schematic diagram of the proposed three-stage framework for 72-hour reservoir inflow forecasting, integrating ensemble rainfall forecasts with machine learning models (SVM and LSTM) via the Switch Prediction Method (SPM) and Multi-Step Forecasting (MSF).

2.2.1. Optimization of ensemble rainfall products using the switch prediction method

The first stage focuses on optimizing ensemble rainfall forecast products by applying the SPM. The SPM is a forecasting technique that dynamically switches between different predictive models based on specific criteria or conditions to improve accuracy. This approach is particularly useful in complex systems where different models show superior results under different circumstances.

In this study, the SPM is adopted to improve the accuracy and reliability of ensemble rainfall predictions by dynamically selecting the most suitable forecast from multiple ensemble members. This stage is shown in Figure 2, under the “Ensemble Rainfall Forecast Optimization” block. As noted by (Wu and Lin, 2017), forecast results can sometimes experience time delays. To address this issue, a parameter S can be set to shift the forecast results over time, thereby improving the delay problem and increasing the number of candidate models. Additionally, the SPM requires the determination of parameters N and M. These parameters are used to evaluate the performance of models from the current time t to t-N, selecting the best-performing M models as the output forecast.

The SPM effectively reduces the uncertainty inherent in ensemble forecasts by leveraging the strengths of various prediction models. By continuously integrating real-time rainfall observations, the method produces highly reliable and robust rainfall

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forecasts. These optimized forecasts form a solid foundation for the subsequent modeling stages, ensuring that the input data used in later stages is of high quality and reliability.

2.2.2. Construction of a rainfall-reservoir inflow model using observed data

In the second stage, observed data are employed to develop a rainfall-reservoir inflow model. This stage involves establishing a quantitative relationship between observed rainfall and reservoir inflow using historical rainfall and inflow data. As illustrated in Figure 2, historical typhoon events provide both rainfall and inflow observations for training the models. Statistical methods and machine learning algorithms are used to analyze the historical data and identify patterns and correlations. The model created in this stage serves as a critical tool for translating rainfall data into expected reservoir inflow, thus forming the basis for forecasting analysis. This step ensures that the model is tailored to the specific hydrological characteristics of the reservoir, improving the accuracy of inflow forecasts.

Machine learning methods offer significant advantages in rainfall-reservoir inflow modeling due to their ability to handle complex, non-linear relationships between input variables and inflow responses. Unlike traditional hydrological or statistical approaches, machine learning algorithms can automatically learn from data, capturing intricate patterns and dependencies that are often present in hydrological processes.

In this study, two advanced machine learning models are used: SVM and LSTM. SVM is chosen for its robustness in handling high-dimensional data and its effectiveness in regression tasks. It is particularly suited when the relationship between input variables and outputs is complex and non-linear. (Lin et al., 2013b, c; Lu et al., 2019; Wu et al., 2013, 2014) On the other hand, LSTM networks, a type of Recurrent Neural Network (RNN), are particularly well-suited for time series forecasting. (Kaveh et al., 2021; Liang et al., 2018; Zhang et al., 2018) LSTMs are capable of capturing long-term dependencies and temporal dynamics in sequential data, making them ideal for modeling the temporal patterns of rainfall and inflow. The general form of the nonlinear function approximator is given by:

$$Q_{t+1} = f\left(Q_t, Q_{t-1}, \cdots, Q_{t-(L_Q-1)}, R_{t-1}, \cdots, R_{t-(L_R-1)}\right) \qquad (1)$$

where is the predicted inflow at time +1, and represent the observed inflow and rainfall at time t and t-1, respectively. denotes the nonlinear function approximator constructed by the SVM or LSTM, and are the lag lengths of reservoir inflow and rainfall, respectively.

2.2.3. Forecasting 72-hour reservoir inflow using the optimized rainfall forecast input

The final stage integrates the optimized rainfall forecasts from Stage 1 and the trained machine learning models from Stage 2 to perform long-range inflow forecasting. This is achieved through a MSF approach, as indicated in Figure 2 and further illustrated in Figure 3. The MSF method is particularly effective for sequential prediction tasks, where the output of one

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prediction step is used as an input for the next step, thereby enabling more accurate and continuous inflow forecasting over extended periods.

The model dynamically integrates real-time rainfall data and optimized forecasts, ensuring that the input conditions reflect the most up-to-date information. As the forecast lead time increases, the model transitions from relying on observed data to utilizing its own sequentially generated forecasts and SPM-integrated rainfall inputs. Through 72 iterations, the MSF process produces a 72-hour reservoir inflow forecast. The integration of new rainfall data in real-time is particularly valuable for operational applications, such as adaptive water release strategies and flood control during typhoon events.

By incorporating these stages, the proposed model significantly improves the ability to forecast long-term reservoir inflows, thereby enhancing the overall management and operational efficiency of the reservoir. The integration of advanced meteorological products with cutting-edge modeling techniques ensures that the model remains robust and adaptable to various weather conditions and hydrological scenarios.

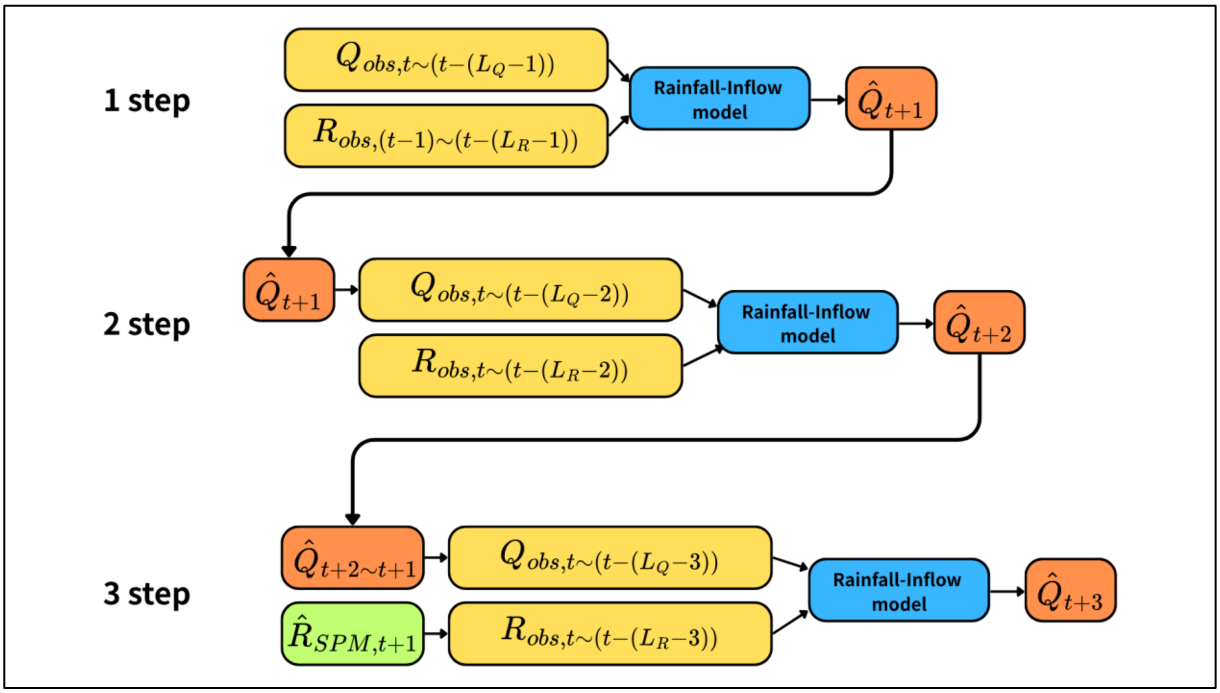

Figure 3 Flowchart of the Multi-Step Forecasting (MSF) procedure. This diagram demonstrates how sequential inflow predictions are generated by iteratively using previous outputs and SPM-optimized rainfall forecasts.

2.3. Performance measures

To evaluate the forecasting performance of proposed models in different stages, four criteria are used in this study and described as follows:

(1) Root mean square error (RMSE)

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(o_t - \hat{f}_t\right)^2} \qquad (2)$$

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RMSE measures the average magnitude of forecast errors, placing greater emphasis on larger errors. It is particularly useful for identifying models that generate significant outliers.

(2) Mean absolute error (MAE)

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left[o_t - \widehat{f_t}\right] \quad (3)$$

MAE represents the average of the absolute differences between forecasted and observed values, offering an intuitive measure of overall forecast accuracy.

where n is the number of data, and are the forecasted and the observed value at time t, respectively.

(3) Coefficient of correlation (CC)

$$\text{CC} = \frac{\sum_{t=1}^{n}(o_t-\bar{o})\left(\widehat{f_t}-\bar{\hat{f}}\right)}{\sqrt{\sum_{t=1}^{n}(o_t-\bar{o})^2\sum_{t=1}^{n}\left(\widehat{f_t}-\bar{\hat{f}}\right)^2}} \quad (4)$$

CC evaluates the strength and direction of the linear relationship between forecasted and observed values, indicating how well the predicted values follow the trend of the actual data.

(4) Coefficient of efficiency (CE)

$$\text{CE} = 1 - \frac{\sum_{t=1}^{n}\left(o_t-\widehat{f_t}\right)^2}{\sum_{t=1}^{n}(o_t-\bar{o})^2} \quad (5)$$

CE quantifies the proportion of variance in observed values explained by the forecast. A CE value closer to 1 indicates higher model efficiency, whereas a value less than zero suggests poor model performance.

where and are the averages of the forecasted and the observed value, respectively.

3 Results

3.1. The optimal inputs and parameters

The optimization algorithm used in this study was the grid-search method, which considered all parameter combinations within a reasonable range.

In the first stage, when integrating ensemble rainfall forecast products using the SPM, it was necessary to optimize the parameters S, N, and M. Through the grid-search method, the optimal parameters were determined as (S, N, M) = (1, 1, 2E), where E represents the number of provided meteorological forecast products (Table 3).

Fig 4 presents the illustration of the SPM stage for typhoon Megi. For this typhoon event, five meteorological forecast products were collected (E=5). Each product was shifted forward and backward by one unit (S=1), resulting in 15 candidate models. The forecast results from time t to t-1 (N=1) were compared with observed data to select the top-performing M models (M=2E=10). The average of M models at each lead time was then used as the rainfall forecasts.

The second stage, while constructing the rainfall-reservoir inflow model, concentrated on refining the input combinations for the model and the hyper-parameters of the machine learning-based models. Rainfall and reservoir inflow information were

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the critical input factors that must be determined for accurate reservoir inflow forecasting. The parameters and are crucial for the model's performance, as they determine the lag lengths of rainfall and reservoir inflow, which are essential for capturing the temporal dynamics needed in the forecasting. Additionally, the model's hyper-parameters significantly affect the model's learning and generalization abilities. The grid-search method ensured that the chosen hyper-parameters provided the best performance for the respective models, and these hyper-parameters were determined based on the use of training data and fixed during the test phase. The optimal parameter combinations for the SVM and LSTM models are shown in Table 4. The selection of these optimal inputs and parameters ensures that the models can capture the most relevant information for accurate inflow forecasting, taking into account the study area's temporal dependencies and hydrological characteristics.

Table 4 Optimal parameter settings and hyperparameters for the SVM and LSTM models used in reservoir inflow forecasting.

Model	Parameters and hyper-parameters							
SVM	L_R	L_Q	Kernal function	Gamma	Cos	Epsilon		
	6	7	RBF	2^{-1}	2^{1}	2^{-7}		
LSTM	L_R	L_Q	Hidden layer	Activation	Optimizer	Batch size	Dropout	Epoch
	6	7	{[64], [128]}	Relu	Rmseprop	32	1	150

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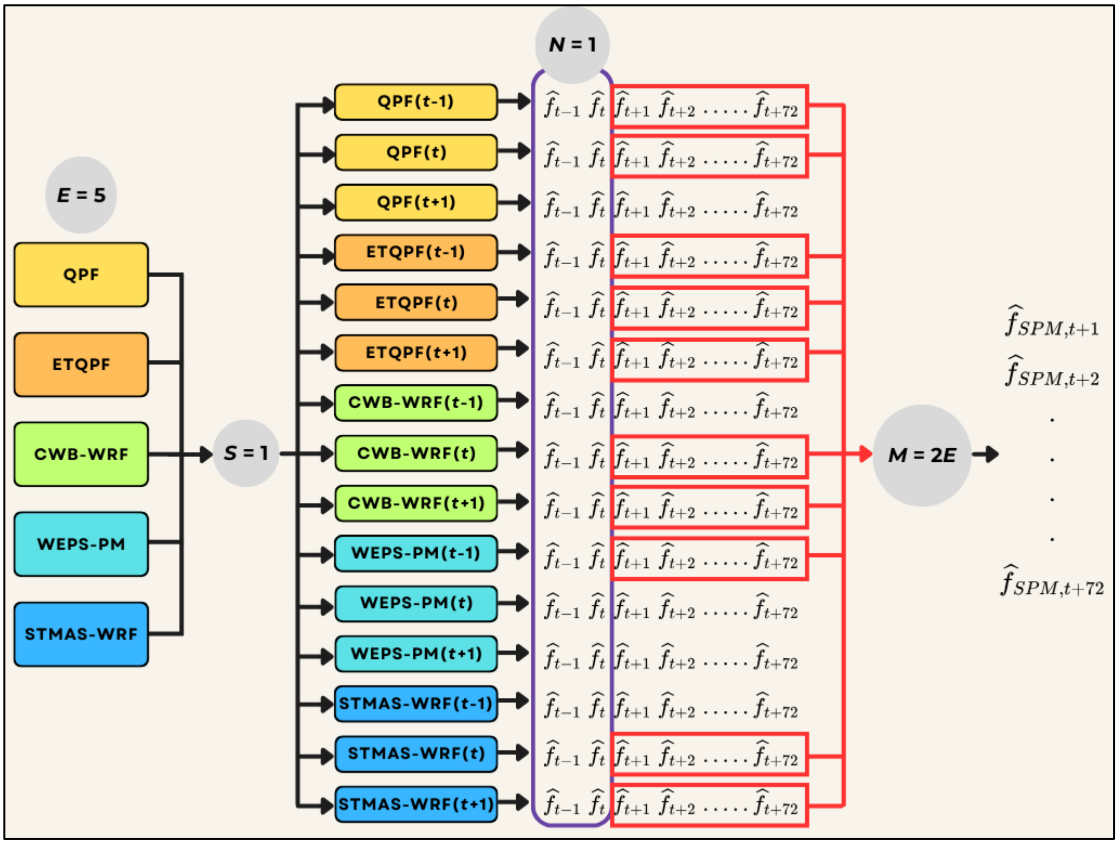

Figure 4 Illustration of the Switch Prediction Method (SPM) implementation for Typhoon Megi. It shows the selection of optimal forecasts by comparing multiple time-shifted rainfall forecasts against observations.

3.2. Model comparisons

3.2.1. Comparison of meteorological forecast products and the SPM

To evaluate the effectiveness of the SPM in enhancing the accuracy and reliability of rainfall forecasts, the performance of various meteorological forecast products with the results obtained using SPM are compared. Table 5 summarizes the results for four typhoon events using four evaluation metrics: RMSE, MAE, CC and CE.

For instance, during Typhoon Soudelor, the SPM achieved an RMSE of 4.70 mm, an MAE of 2.62 mm, a CC of 0.91, and a CE of 0.80, outperforming all individual forecast products, including ETQPF (RMSE: 8.53 mm, CE: 0.39) and CWB-WRF (RMSE: 6.31 mm, CE: 0.64). A similar pattern was observed for Typhoon Megi, where the SPM yielded an RMSE of 3.26 mm, an MAE of 1.85 mm, a CC of 0.93, and a CE of 0.82, again ranking first across all metrics.

In the case of Typhoon Maria, the SPM continued to demonstrate superior performance, producing the lowest RMSE (3.01 mm) and the highest CE (0.84). Even for Typhoon Lekima, where all models produced negative CE values due to

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considerable discrepancies in rainfall forecasts, the SPM still achieved the best relative performance, , with an RMSE of 5.45 mm. These results confirm that the SPM not only improves the accuracy of ensemble rainfall forecasts but also enhances the consistency and robustness of rainfall prediction under varying meteorological conditions.

The meteorological forecast products for each typhoon event and the integrated forecast results using the proposed SPM are shown in Figures 5 to 8. Due to the high temporal resolution of the ensemble forecasts, Figures 5 to 8 are presented to reflect the full variability and temporal spread among different forecast members. While individual lines may appear visually dense, this type of visualization is intended not for exact value identification but to highlight the degree of uncertainty across forecast initialization times. This approach realistically captures the variation and inconsistency commonly found in operational meteorological forecasts across different typhoon events.

As shown in Figure 5, it can be seen that for Typhoon Soudelor, the ETQPF model exhibited significant fluctuations in forecast results before the peak rainfall, leading to significant variations in forecasts at different times. On the other hand, the CWB-WRF model showed more stable forecast results with less variation in values over time. However, it significantly overestimated the peak rainfall, predicting a maximum rainfall of 90mm, whereas the actual observed rainfall was about 47mm. The proposed SPM, by integrating the advantages of both meteorological products, provided forecasts that did not exhibit significant fluctuations over time and had peak forecast values closer to the actual observations.

In Figure 6, the QPF model shows an overestimated rainfall after the peak rainfall. The ETQPF forecast results are consistent with the observed rainfall trends, but the peak rainfall is significantly underestimated. The CWB-WRF model tends to overestimate rainfall throughout the entire typhoon period, while WEPS-PM and STMAS-WRF showed relatively good performance regarding forecast error and trend alignment. The SPM combines the strengths of these models, resulting in stable forecast values over time with peak predictions closer to the observed values.

Figure 7 shows the performance of Typhoon Maria. The QPF model exhibits forecast fluctuations and overestimation of rainfall. In contrast, the CWB-WRF model underestimates rainfall throughout the typhoon period. ETQPF and WEPS-PM provide forecasts more consistent with the observed rainfall values and trends. The SPM integrates these forecasts to provide the most stable and accurate predictions, reducing errors and aligning more closely with observed data.

In Figure 8, it can be seen that QPF, ETQPF, and WEPS-PM all perform inadequately. Consequently, the performance of SPM was also limited, resulting in larger forecast errors compared to other typhoon events. However, the SPM still provide more stable forecasts than QPF and WEPS-PM, with better forecasts than ETQPF. This demonstrates that even under challenging conditions, the SPM offers superior overall error reduction and forecast stability.

The analysis shows that different meteorological forecast products have varying strengths and weaknesses across different typhoon events, making it challenging to identify a single best-performing product suitable for all situations. The SPM method proposed in this study addresses this issue by dynamically selecting and integrating forecasts based on real-time observational data. By filtering out unsuitable forecasts using specific criteria, the SPM method avoids directly impacting overall forecast performance. As a result, the rainfall forecasts generated by SPM exhibit lower uncertainty and better agreement with observed rainfall compared to individual meteorological forecast products. This demonstrates the robustness

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and adaptability of SPM in handling varying meteorological conditions and improving the reliability of typhoon rainfall forecasts.

Table 5 Performance comparison of individual meteorological forecast products and the SPM across four typhoon events using four statistical evaluation metrics.

Typhoon	Rainfall Product	Performance measures							
		Value				Rank			
		RMSE (mm)	MAE (mm)	CC	CE	RMSE	MAE	CC	CE
Soudelor	ETQPF	8.53	4.35	0.61	0.39	3	3	3	3
	CWB-WRF	6.31	3.10	0.90	0.64	2	2	2	2
	SPM	4.70	2.62	0.91	0.80	1	1	1	1
Megi	QPF	8.91	6.55	0.57	0.17	6	6	6	5
	ETQPF	5.01	2.86	0.93	0.72	4	4	1	2
	CWB-WRF	4.56	2.19	0.86	0.64	2	2	4	4
	WEPS-PM	4.73	2.60	0.90	0.68	3	3	3	3
	STMAS-WRF	6.10	4.72	0.72	-1.93	5	5	5	6
	SPM	3.26	1.85	0.93	0.82	1	1	1	1
Maria	QPF	8.91	6.55	0.57	0.17	5	5	5	5
	ETQPF	5.01	2.86	0.93	0.72	4	4	2	2
	CWB-WRF	4.56	2.19	0.86	0.64	2	1	4	4
	WEPS-PM	4.73	2.60	0.90	0.68	3	3	3	3
	SPM	3.01	2.39	0.94	0.84	1	2	1	1
Lekima	QPF	5.85	4.28	0.32	-4.50	2	2	4	4
	ETQPF	7.70	4.70	0.60	-2.57	4	4	1	1
	WEPS-PM	6.01	4.29	0.49	-2.94	3	3	3	3
	SPM	5.45	3.52	0.56	-2.86	1	1	2	2

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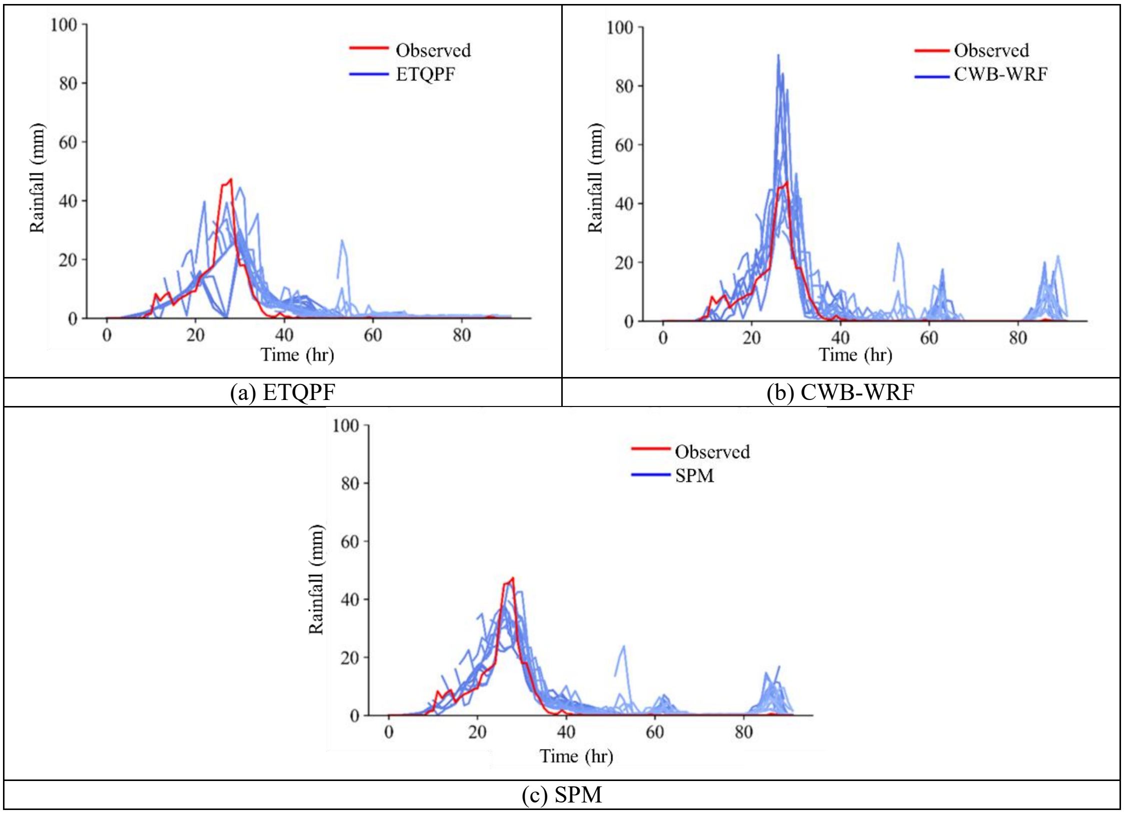
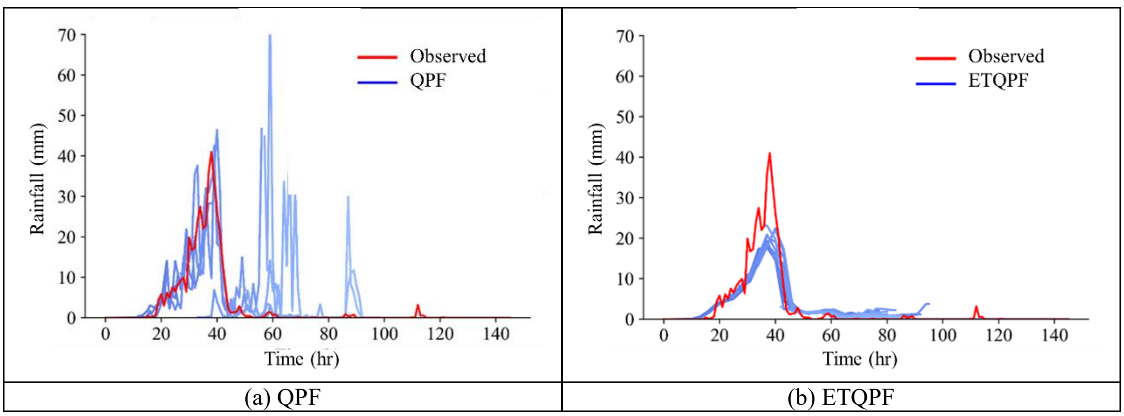


Figure 5 Comparison of meteorological forecast products (ETQPF and CWB-WRF) and the SPM-generated forecast for Typhoon Soudelor.



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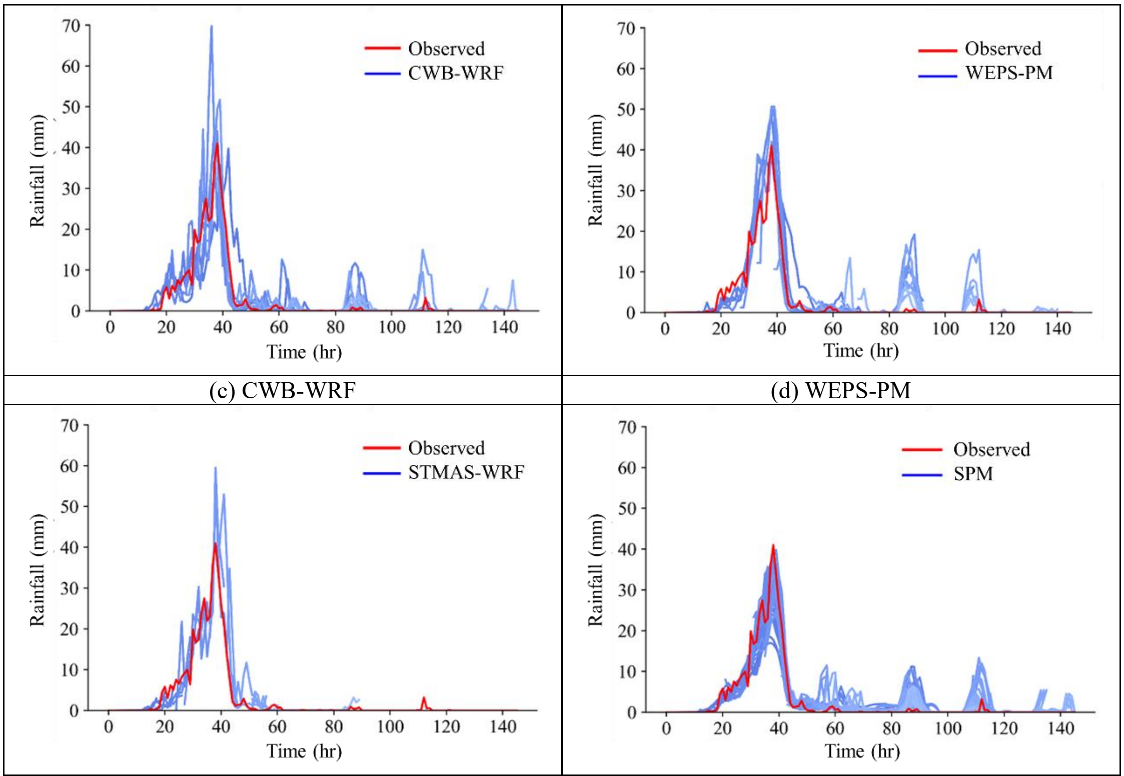
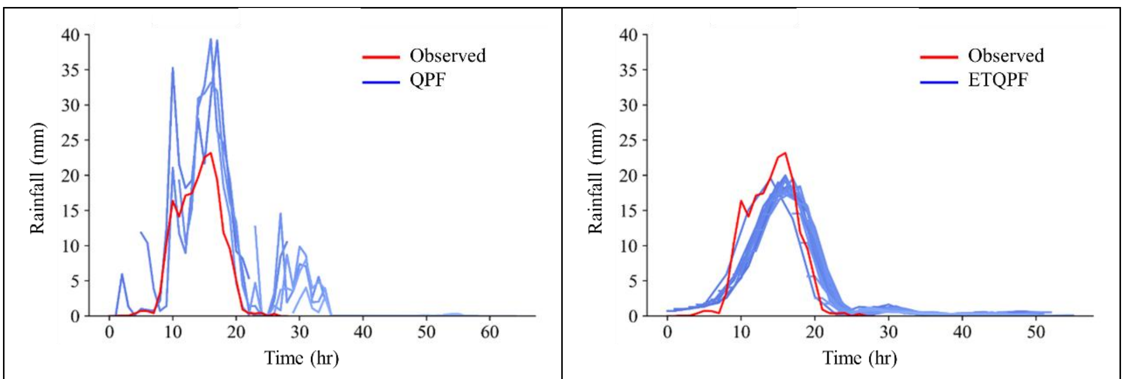


(c) CWB-WRF (d) WEPS-PM

(e) STMAS-WRF (f) SPM

345 **Figure 6 Comparison of meteorological forecast products (QPF, ETQPF, CWB-WRF, WEPS-PM and STMAS-WRF) and the SPM-generated forecast for Typhoon Megi.**



(a) QPF (b) ETQPF

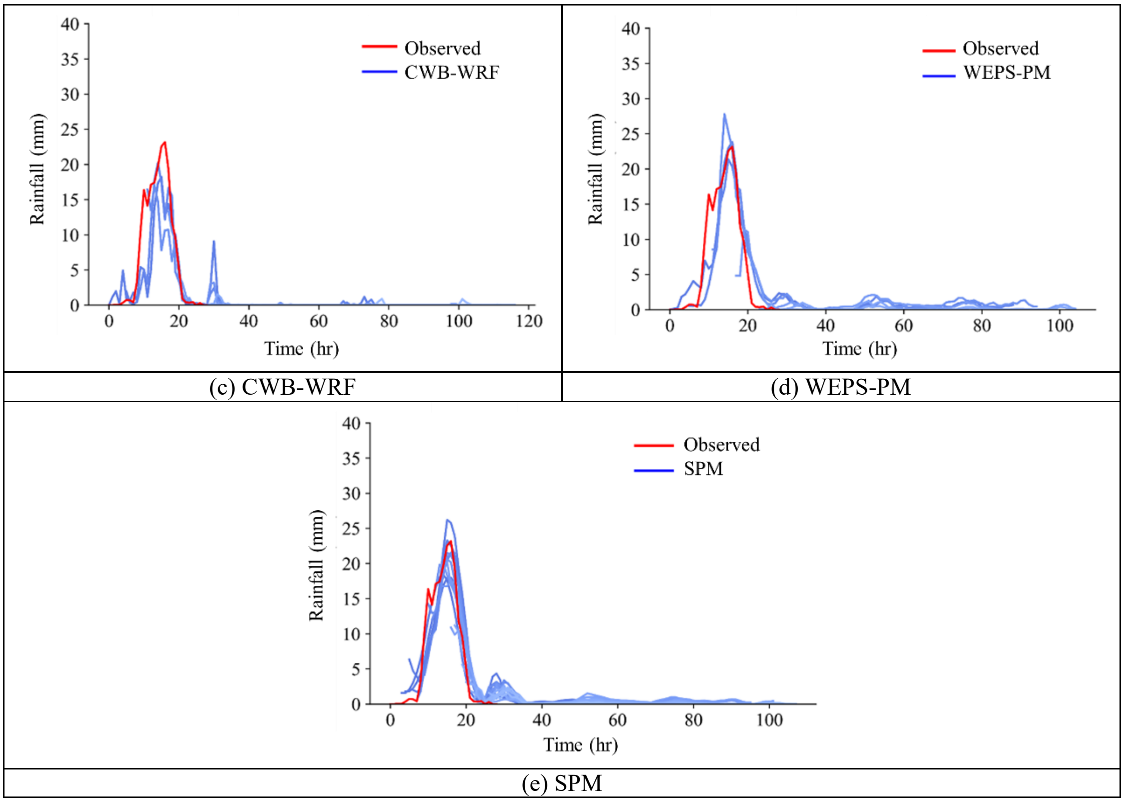
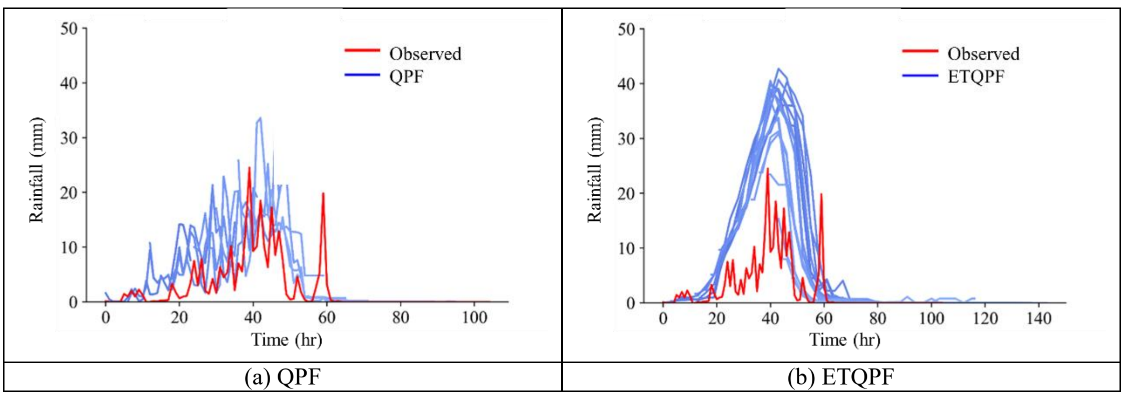


Figure 7 Comparison of meteorological forecast products (QPF, ETQPF, CWB-WRF and WEPS-PM) and the SPM-generated forecast for Typhoon Maria.



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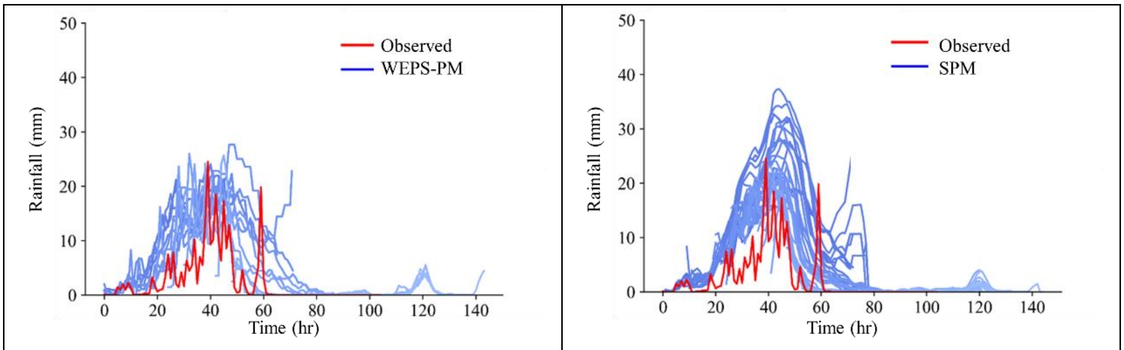

(c) WEPS-PM
(d) SPM

Figure 8 Comparison of meteorological forecast products (QPF, ETQPF and WEPS-PM) and the SPM-generated forecast for Typhoon Lekima.

3.2.2. Comparison of rainfall-reservoir inflow models

This section compares the performance of two machine learning-based rainfall-reservoir inflow models: SVM and LSTM. Both models were trained and tested using observed rainfall and inflow data, and their performance is summarized in Table 6 and illustrated in Figure 9.

During the training phase, the LSTM model demonstrated lower error values (RMSE: 56.75 cms, MAE: 26.83 cms) compared to the SVM model (RMSE: 60.63 cms, MAE: 31.46 cms), while also achieving a higher correlation coefficient (CC: 0.954 vs. 0.934). In the test phase, the SVM model exhibited slightly better RMSE (58.41 cms) than the LSTM model (59.95 cms), although the LSTM model had a marginally better CE (0.972 vs. 0.970). Both models achieved identical CC values of 0.928 in the test set.

These results suggest that while the SVM model showed slightly better overall generalization in terms of RMSE, the LSTM model maintained comparable performance and demonstrated stronger learning capability during training. Both models exhibited excellent predictive skill and reliability, with high CC and CE values in both phases, indicating their suitability for modeling complex, non-linear rainfall–inflow relationships. Given their consistent performance, both the SVM and LSTM models can be effectively used for long-term reservoir inflow forecasting, particularly when driven by SPM-integrated rainfall forecasts.

Table 6 Performance comparison between SVM-based and LSTM-based rainfall-inflow models during training and test phases.

Model		Performance measures			
		RMSE (cms)	MAE (cms)	CC	CE
SVM	Training	60.63	31.46	0.934	0.979
	Test	58.41	34.96	0.928	0.970
LSTM	Training	56.75	26.83	0.954	0.979
	Test	59.95	32.08	0.928	0.972

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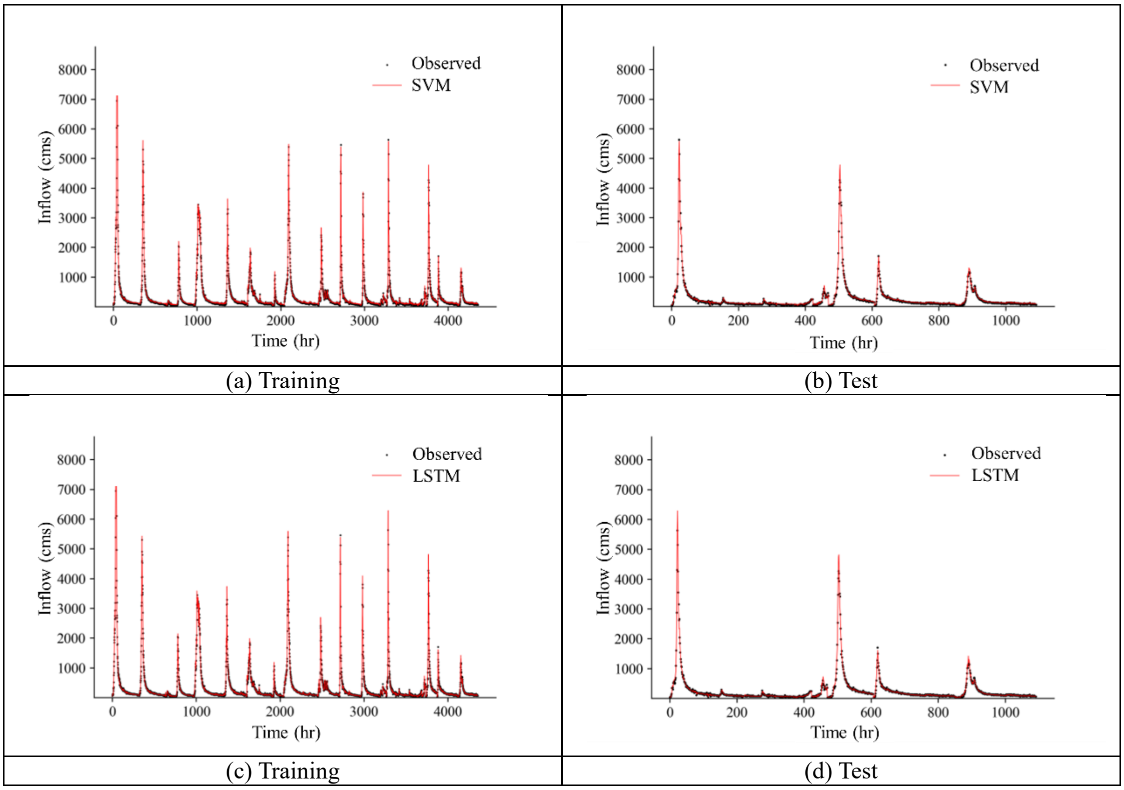

Figure 9 Performance comparisons of SVM-based and LSTM-based rainfall-inflow models using training and test datasets. The plots show both the accuracy and learning stability of each model.

3.2.3. Comparison of the performance of MSF with observed rainfall

This section primarily discusses the results of long-term inflow forecasting using the MSF method. Unlike the previous subsection, where inflow at time □+1 was forecasted using the information at time □, this section uses the MSF method. The MSF method iteratively calculates the forecasted inflow for the next time step, and then using it as the input for the subsequent step. This process is repeated 72 times to produce inflow forecasts from □+1 to □+72.

To evaluate the performance of the MSF method, the observed rainfall is used as input to examine the models' ability to forecast 72-hour inflows directly. Figure 10 shows the MSF forecasting results for the test events of Soudelor and Megi.

For Typhoon Soudelor, the SVM model initially underestimates the inflow. However, as time progresses and more observed inflow information at the rising limb becomes available, the MSF forecasts gradually become more accurate in forecasting the peak inflow. For Typhoon Megi, the SVM model accurately reflects the entire flood process, with forecasted peak inflows closely matching the observed values.

The LSTM model, on the other hand, captures the flood processes well for both Soudelor and Megi events. However, it tends to overestimate the peak inflow compared to the actual observed peak inflow.

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Overall, the results indicate that both SVM and LSTM models, when combined with the MSF method and accurate rainfall information, can reliably forecast reservoir inflows for up to 72 hours. This demonstrates the robustness and effectiveness of using MSF for long-term inflow predictions without significant oscillations or error accumulations.

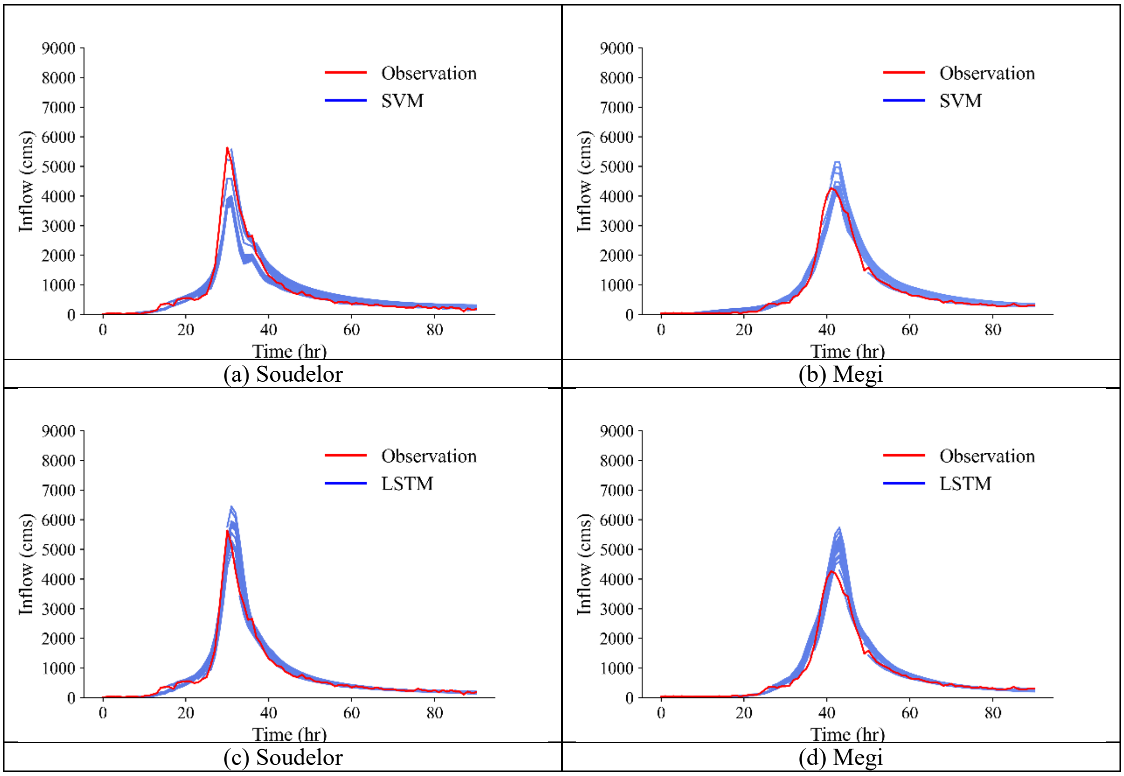

Figure 10 Multi-step inflow forecasts using observed rainfall for Typhoons Soudelor and Megi. The results validate both SVM and LSTM models for capturing temporal hydrological dynamics.

3.2.4. Comparison of the performance of MSF with forecasted rainfall

This section analyzes the results of long-term inflow forecasting using the MSF method with SPM-integrated forecasted rainfall data. The forecast performance for three test typhoon events—Soudelor, Megi, and Maria—is summarized in Table 7. The results show that the LSTM-based rainfall–inflow model outperformed the SVM-based model across all events and evaluation metrics. Specifically, for Typhoon Soudelor, the LSTM model achieved an RMSE of 285.2 cms, an MAE of 178.8 cms, a CC of 0.79, and a CE of 0.87, compared to the SVM model's RMSE of 321.3 cms and CC of 0.69. For Typhoon Megi, both models exhibited high correlation (CC: 0.98), but the LSTM model produced lower RMSE (183.9 cms) and MAE (118.0 cms) than the SVM model (RMSE: 214.4 cms, MAE: 164.5 cms), along with a higher CE (0.89 vs. 0.77). In the case of Typhoon Maria, the LSTM model again outperformed SVM, achieving a lower RMSE (185.2 cms) and MAE (155.6 cms), and higher CC (0.97) and CE (0.61) compared to the SVM model (CE: 0.43).

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These results confirm the superior performance of the LSTM model in forecasting long-lead reservoir inflows, particularly in capturing temporal dynamics and nonlinear rainfall–runoff relationships. The consistent advantage across multiple events highlights the LSTM model's robustness and its suitability for operational applications when combined with SPM-enhanced rainfall forecasts.

Figure 11 illustrates the MSF forecasting results using SPM-integrated forecasted rainfall data for the test events of Soudelor and Megi. Compared to using observed rainfall, the use of forecasted rainfall as input to the rainfall-inflow model leads to more pronounced fluctuations in the forecast results at different times due to the con-tinuous dynamic adjustments in the forecasted rainfall.

Table 7 Evaluation of forecasted inflows using SPM-integrated rainfall for three typhoon events. Comparison is based on RMSE, MAE, CC, and CE.

Typhoon	Model	Performance measures			
		RMSE (cms)	MAE (cms)	CC	CE
Soudelor	SVM	321.3	232.4	0.69	0.78
	LSTM	285.2	178.8	0.79	0.87
Megi	SVM	214.4	164.5	0.98	0.77
	LSTM	183.9	118.0	0.98	0.89
Maria	SVM	227.7	195.7	0.94	0.43
	LSTM	185.2	155.6	0.97	0.61

For Typhoon Soudelor, the SVM model tends to underestimate the peak inflow. The LSTM model's forecasts gradually align with the observed peak inflow as time approaches the peak inflow phase. However, after the peak, the LSTM model tends to overestimate the inflow. For Typhoon Megi, both models initially fail to accurately forecast the peak inflow due to underestimation the forecasted rainfall in the early stages of a typhoon. As a result, the predicted inflow to reservoirs may also have significant errors. As time progresses and the forecasted rainfall aligns more closely with the observed rainfall, both models start to capture the peak inflow more accurately. In this event, the LSTM model tends to overestimate the peak inflow, while the SVM model's forecasted peak inflow is more consistent with the observed values.

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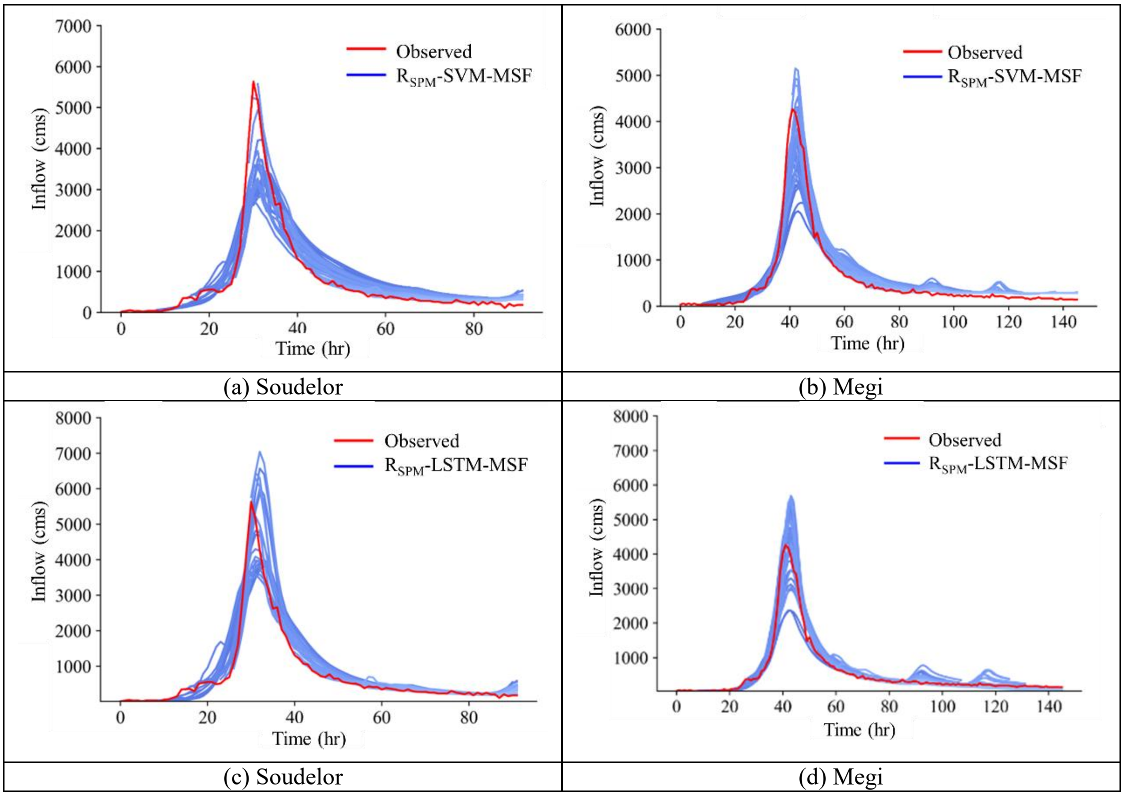

Figure 11 Inflow forecast comparisons using SPM-integrated rainfall inputs for Typhoons Soudelor and Megi. The plots show the effects of forecasted rainfall uncertainty on inflow prediction accuracy.

In addition to performing deterministic forecasts using SPM-integrated rainfall, the developed rainfall–inflow models can also be applied to generate probabilistic inflow forecasts based on multiple meteorological forecast products. By visualizing the ensemble spread and plotting corresponding confidence intervals, the uncertainty associated with inflow predictions can be quantified.

When the rainfall forecasts from different meteorological products vary substantially, the resulting inflow forecasts exhibit wider confidence intervals, reflecting increased uncertainty. This effect is evident in Figures 12(b) and 12(c) for Typhoons Megi and Maria, where broader confidence bands are observed near the flood peaks, indicating divergence among the ensemble forecasts. For Typhoon Lekima [Figure 12(d)], not only do the ensemble rainfall forecasts diverge significantly, but the SPM-integrated rainfall also overestimates the observed rainfall. This leads to inflated deterministic inflow predictions and larger uncertainty bounds, emphasizing the sensitivity of inflow forecasts to the accuracy and consistency of upstream rainfall inputs.

This issue highlights a fundamental limitation in the current inflow forecasting system—namely, that even a well-trained machine learning model remains highly dependent on the quality of its rainfall inputs. Figure 13 presents the inflow forecasting results for Typhoon Soudelor, initialized at 09:00 on August 7, 2015, with a 72-hour lead time. Compared to the observed inflow, the model underestimates the peak magnitude and predicts it with a clear delay. This discrepancy is largely

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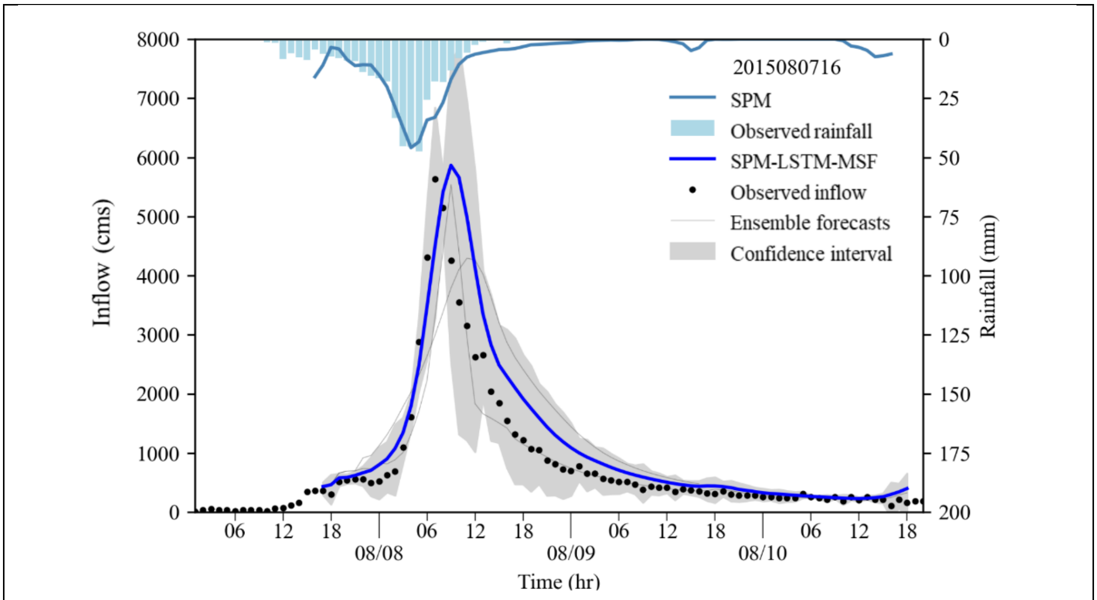
due to inaccuracies in the forecasted rainfall inputs, which—even after integration using the SPM—still show lower intensity and delayed onset relative to the observed rainfall. This example demonstrates that, while models such as LSTM are effective in capturing rainfall-inflow dynamics, their predictive performance is ultimately constrained by the accuracy of upstream meteorological forecasts, especially under extreme event conditions.

Notably, as shown in Figure 12(a), when the forecast was initialized at 16:00 on August 7, the predicted rainfall pattern became more consistent with observed data in both timing and magnitude. As a result, the inflow forecasts also improved significantly. These findings further underscore the critical role of accurate rainfall forecasts in long-lead inflow prediction and reservoir operation planning. Although the proposed forecasting framework demonstrates strong potential, its performance is expected to improve as meteorological forecasting technologies continue to advance.

Nevertheless, the use of the SPM enables dynamic integration of ensemble rainfall forecast products over time. When coupled with a machine learning-based model that captures the nonlinear rainfall-inflow relationship, this approach provides a viable means of generating long-term reservoir inflow forecasts. Such forecasts can serve as valuable references to support decision-making by reservoir management authorities.



(a) Soudelor

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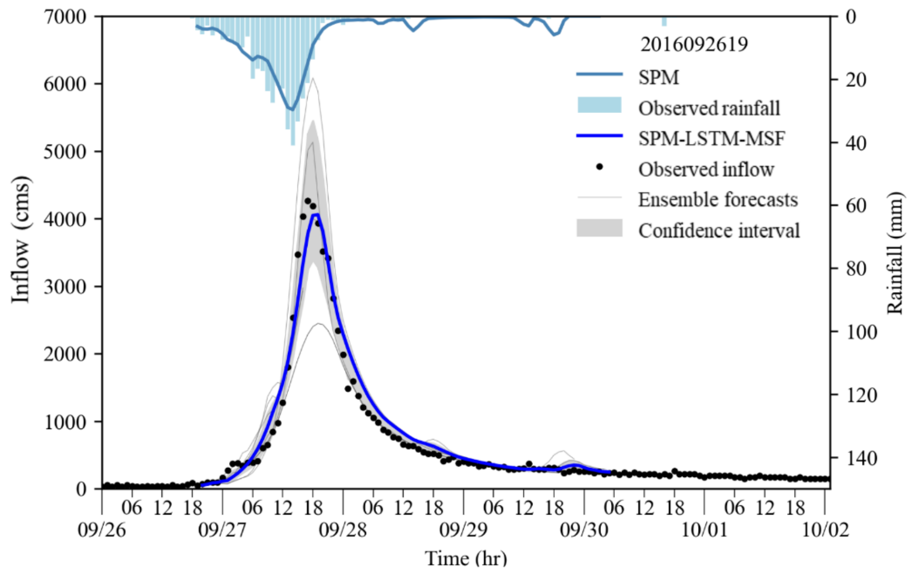
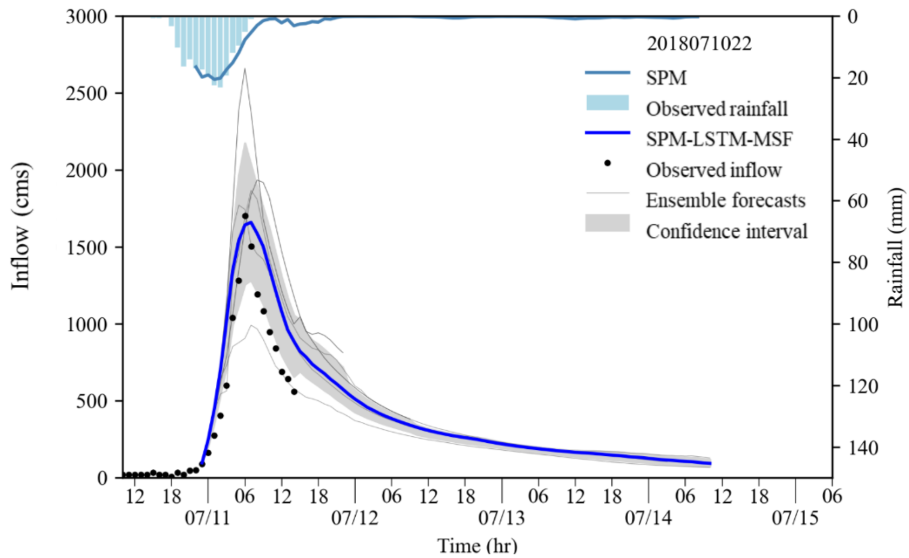


(b) Megi



(c) Maria

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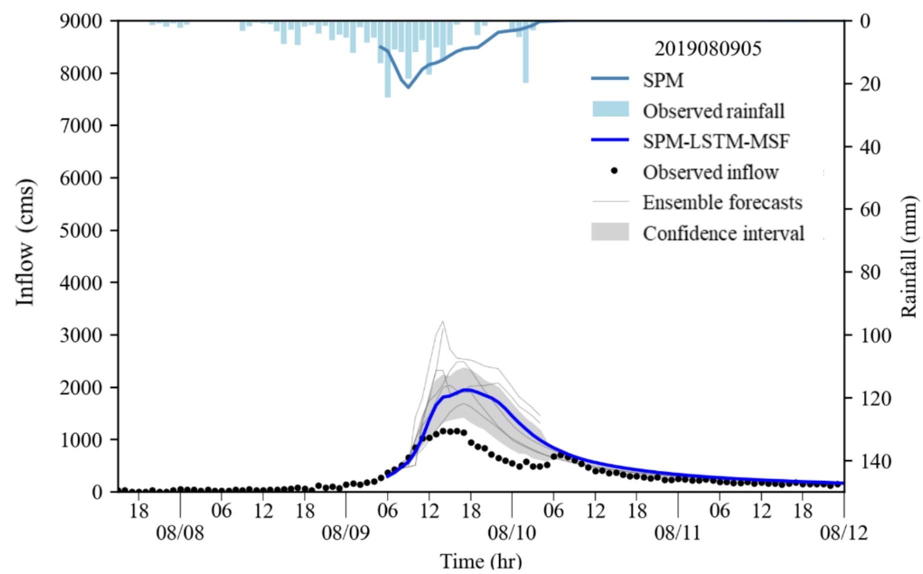
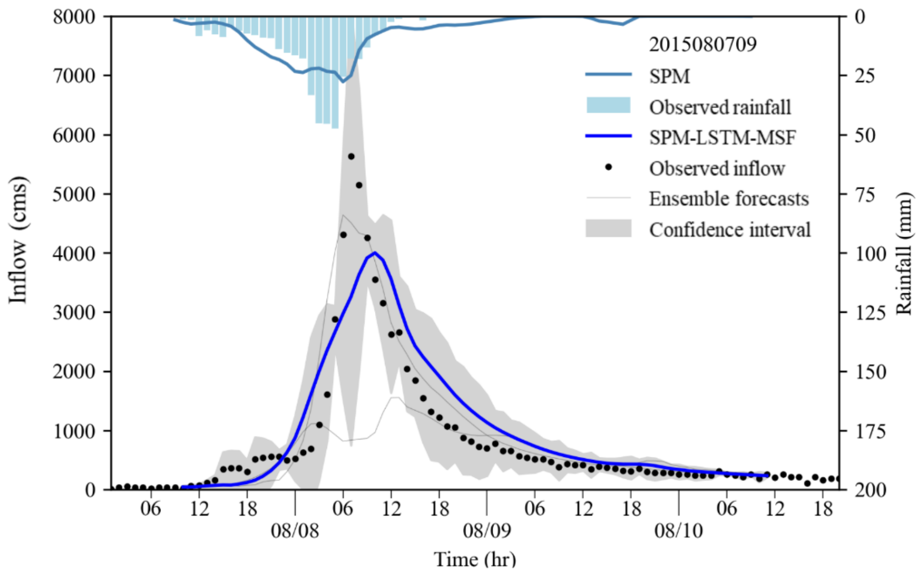


(d) Lekima

Figure 12 Probabilistic inflow forecasts for four typhoon events using ensemble rainfall inputs. Confidence intervals illustrate the uncertainty propagated from rainfall forecasts to inflow predictions.



455 **Figure 13 Early inflow forecast for Typhoon Soudelor using SPM and machine learning models. The figure highlights the effect of initialization timing and forecasted rainfall accuracy on peak prediction.**

4. Discussion

4.1. Performance superiority of LSTM over SVM

The comparative results of this study indicate that the LSTM-based model consistently outperforms the SVM-based model across various typhoon events and evaluation metrics. This performance advantage is largely attributed to LSTM's capability to capture temporal dependencies and non-linear dynamics inherent in hydrological processes.

LSTM, a specialized form of RNN, is designed to retain information over long sequences, making it particularly effective for time series modeling such as rainfall–runoff relationships. Its internal memory units allow it to learn sequential patterns and long-term influences of rainfall inputs on reservoir inflow. This is especially critical for flood forecasting where early rainfall events significantly affect downstream inflow volumes. Numerous studies have demonstrated LSTM's effectiveness in modeling complex hydrological time series, reinforcing its advantages observed in this study. In contrast, SVM is a static machine learning method that relies on mapping input features into higher-dimensional spaces using kernel functions. While effective in capturing non-linear relationships, SVM lacks the ability to model time-lagged dependencies, making it less suitable for sequential prediction tasks. Consequently, SVM exhibits inferior performance in capturing peak discharges and timing, particularly under highly variable rainfall conditions. The performance gap is evident in the quantitative metrics presented in Tables 6 and 7, where LSTM-based models achieved higher CE and lower RMSE values compared to SVM-based models. The advantage of LSTM becomes more pronounced under forecast-based rainfall scenarios, where input uncertainties amplify the need for temporal learning capabilities.

These findings align with previous studies in the literature. For instance, (Rahimzad et al., 2021) found that LSTM outperformed other models in daily streamflow forecasting across all evaluation criteria, demonstrating its robustness in hydrological modeling applications. Similarly, (Hu et al., 2020) showed that LSTM achieved superior results compared to SVM in small watershed flow prediction, particularly in capturing flood peaks and timing accuracy. Together, these results highlight the LSTM model's adaptability and robustness in hydro meteorological forecasting contexts, reaffirming its value in enhancing long-term reservoir inflow prediction frameworks.

4.2. Uncertainties in forecasting results

In hydrological forecasting, uncertainties arise from various sources, including input data inaccuracies, model structural limitations, and the inherent variability of hydrological processes. These uncertainties can significantly impact the reliability of reservoir inflow predictions, especially during extreme weather events.

Input Data Uncertainty: The accuracy of rainfall forecasts is a primary source of uncertainty in inflow predictions. Even with advanced integration methods like the SPM, discrepancies between forecasted and observed rainfall can lead to significant errors in inflow estimates. For instance, underestimating the intensity or delaying the onset of rainfall in forecasts can result in under predicted peak inflows and misaligned timing, as observed in the case of Typhoon Soudelor.

Model Structural Uncertainty: Machine learning models, such as LSTM and SVM, have demonstrated proficiency in capturing complex nonlinear relationships in hydrological data. However, their performance is contingent upon the quality and representativeness of the training data. Models trained on historical data may struggle to generalize to unprecedented events or changing climatic conditions, leading to increased prediction uncertainty.

Uncertainty Quantification in Machine Learning Models: Recent studies have emphasized the importance of incorporating uncertainty estimation within machine learning frameworks for hydrological forecasting. Techniques such as Monte Carlo dropout and mixture density networks have been employed to quantify predictive uncertainty, providing probabilistic forecasts that offer more comprehensive risk assessments. For example, (Klotz et al., 2022) demonstrated that deep learning models could produce statistically reliable uncertainty estimates in rainfall–runoff modeling by integrating such techniques.

Implications for Reservoir Management: Understanding and quantifying uncertainties in inflow forecasts are crucial for effective reservoir operation and flood risk management. By acknowledging the limitations of both input data and modeling approaches, reservoir managers can make more informed decisions, incorporating safety margins to accommodate potential forecast errors. Furthermore, ongoing advancements in uncertainty quantification methods will enhance the robustness of hydrological forecasts, contributing to more resilient water resource management strategies.

4.3. Research limitations and future directions

While this study demonstrates the effectiveness of integrating the SPM with machine learning techniques for long-term reservoir inflow forecasting, several limitations should be acknowledged.

Data Availability and Spatial Generalization: This study relies on data from a single reservoir—ShihMen Reservoir in Taiwan—which may limit the framework's applicability to other regions with distinct hydrological regimes. Although the SPM dynamically integrates multiple rainfall forecasts, its effectiveness might vary across regions depending on the availability and quality of meteorological forecast products.

Dependence on Rainfall Forecast Accuracy: The forecasting accuracy of inflow is fundamentally constrained by the precision of upstream rainfall forecasts. As observed in the case of Typhoon Soudelor, even with SPM integration, underestimation or delayed onset of rainfall forecasts can lead to significant biases in inflow prediction. Thus, improving the quality of rainfall forecasts—especially at longer lead times—remains a critical requirement.

Model Training and Extremes: Machine learning models like LSTM and SVM perform well within the range of training data but may struggle with extrapolation beyond observed extremes. While this study included typhoon events with diverse inflow magnitudes, future studies should further examine model robustness under changing climate conditions or previously unseen hydrometeorological extremes.

Operational Integration and Real-Time Applications: The proposed SPM-LSTM-MSF framework shows promise in a research setting, but further validation is needed under real-time operational conditions. This includes automated handling of real-time data streams, integration with decision-support systems, and user-centered interfaces for water resource managers.

Future Directions:

To address these limitations, future research should consider:

Expanding the dataset to include multiple basins with diverse hydrological regimes.

Evaluating the framework under real-time operational constraints.

Exploring hybrid models that integrate physical knowledge with data-driven approaches for improved interpretability and reliability.

By addressing these aspects, the proposed framework can evolve into a more comprehensive and adaptable tool for enhancing hydrological forecasting and water resource management under uncertainty. These enhancements will further bridge the gap between research innovation and practical decision-making in hydrological management.

5. Conclusions

This study presents a novel and robust framework for long-term reservoir inflow forecasting by integrating the SPM with advanced machine learning techniques, specifically SVM and LSTM models. The scientific contribution lies in two key innovations:

First, the study develops a dynamic ensemble rainfall integration approach (SPM), which systematically filters and combines multiple meteorological forecast products. This method significantly improves the temporal stability and accuracy of rainfall forecasts across diverse typhoon events, as evidenced by consistently higher correlation coefficients and lower RMSE and MAE values.

Second, by coupling SPM-integrated rainfall forecasts with data-driven inflow modeling techniques, the framework captures the complex non-linear and temporal dependencies inherent in hydrological processes. LSTM-based models, in particular, demonstrated strong generalization capabilities and superior performance over SVM-based models, especially under forecast-based scenarios with uncertain inputs.

Together, these components form a MSF system that effectively anticipates reservoir inflow up to 72 hours in advance. Quantitative evaluation confirms that the SPM-LSTM-MSF model offers improved accuracy. The ensemble flow forecasting can be generated using various meteorological forecast products with the proposed models, and the probabilistic forecasting approach enhances decision-making processes by providing information on forecast uncertainty. These findings contribute to the academic community by advancing the integration of dynamic ensemble forecasting and machine learning in hydrological modeling, paving the way for more adaptive and reliable decision-support tools for water resource management.

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