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ORIGINAL ARTICLE

Real-time flood forecasting using time-varying parameter hydrological model: case study for Ta Trach reservoir

Chau Kim Tran[1,3] · Nguyen Dong Dang[1] · Dang Mai Nguyen[2] · Bac Thi Ngoc Nguyen[1] · Binh Thi Hoa Le[1] · Hoang Cong Vo[1] · Hien Phu La[1,3]

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Abstract

Flood forecasting for reservoir operation is a complex and challenging subject. It is, however, fundamental for minimizing damage and maximizing economic efficiency in reservoir management. Currently, real-time flood forecasting represents an essential trend on a global scale. This study introduces a real-time flood forecasting approach using a time-varying parameter hydrological model, applied to forecast inflows to Ta Trach reservoir in the historical flood season in 2020. The model dynamically updates parameters to reflect basin conditions in every time steps. Notably, the study's method achieves high accuracy with Nash–Sutcliffe Efficiency values of 99.32, 95.7, and 89.14% for 1-h, 3-h, and 6-h lead times, respectively. Results surpass traditional fixed parameter and artificial intelligence models. Moreover, requiring only updated rainfall and inflow data, the model is computationally efficient, compatible with existing infrastructure in research area. With these advantages, the method presented in the study has opened a new approach and is suitable for broader applications in flood flow forecasting.

Keywords Real-time flood forecasting · Time-varying parameters · Inflow discharge · Hydrological model · Ta Trach reservoir

Introduction

Nowadays, real-time flood forecasting plays an essential role in the operation of reservoirs (He et al. 2022). In order to meet the requirements of socio-economic development, reservoirs are now under increasing pressure to operate safely and effectively. Maintaining high water level in the reservoir will increase the efficiency of power generation as well as ensure water supply safety during the dry season. However, this also brings risks to the reservoir. Reasonable flood discharge not only ensures the safety of the structure but also reduces the risk for the downstream systems (Yi & Yi 2024). Timely and accurate information on flood forecasting results will help reservoir owners make effective and accurate operational decisions. Therefore, improving flood forecasting accuracy is the main goal of many studies (Callaghan et al. 2021).

There are many flood forecasting techniques, but they can basically be divided into two main groups, namely black box models and deterministic models (Lohani et al. 2014; WMO 2011; Yi & Yi 2024). Each approach has its own advantages and disadvantages. Firstly, black box models do not attempt

✉ Chau Kim Tran
kimchau_hwru@tlu.edu.vn

Nguyen Dong Dang
dang@tlu.edu.vn

Dang Mai Nguyen
nguyendd@tlu.edu.vn

Bac Thi Ngoc Nguyen
191800155@e.tlu.edu.vn

Binh Thi Hoa Le
binhlth@tlu.edu.vn

Hoang Cong Vo
hoangvc@tlu.edu.vn

Hien Phu La
laphuhien@tlu.edu.vn

[1] GIS and Remote Sensing Application Group, Thuyloi University, 175 Tay Son, Dong Da, Ha Noi, Vietnam

[2] School of International Education, Thuyloi University, 175 Tay Son, Dong Da, Ha Noi, Vietnam

[3] Water Resources Engineering, Thuyloi University, 175 Tay Son, Ha Noi, Việt Nam

to simulate the physical processes involved but based on statistical or empirical principles. They primarily use the collected data and seek to describe the system's response from that data. In recent years, a new trend of this type is the artificial intelligence (AI) application. AI tools, especially machine learning models such as artificial neural networks, have become an integral part of forecasting systems in recent years (Byaruhanga et al. 2024). Some authors even applied deep learning techniques to flood forecasting (Mosavi et al. 2018; Nevo et al. 2022; Xiang et al. 2020). In fact, black box models can be very good at simulating available events, but they often perform poorly in forecasting extreme cases that have never occurred (Toth & Brath, 2002). This means that the approach requires a large amount of input data to cover all situations for training. The second group of techniques is deterministic models. The essence of these models is to simulate physical processes in the basin. The deterministic models simulate flood events via flood-producing and flood routing process (Byaruhanga et al. 2024). In flood-producing process, the mathematical formulas are used to simplify the physical processes occurring on the basin (Deng et al. 2016; Xiong et al. 2019). Meanwhile, the hydraulic models such as Hec Ras, Mike 11, LISFLOOD, which solve shallow water equations, are used to route flood along the river (Mustamin et al. 2024). According to Byaruhanga et al (2024), among the 20 popular techniques for flood forecasting, the number of hydraulic and hydrological models accounts for one-third. Among them, a popular hydrological model that can be mentioned is HEC-HMS. Many authors have used this model in flood forecasting issue. Goodarzi et al (2024) integrated the weather research and forecasting (WRF) with HEC-HMS model to the flood forecasting for Talesh basin. Similarly, in China, Oleyiblo & Li (2010) applied HEC-HMS model for Misai and Wan'an basin. HEC-HMS can be integrated with Hec RAS to become a complete tool for flood forecasting. In this case, the HEC-HMS model transfers the rainfall in the basin into input boundaries for the Hec Ras model to route the river flow. Despite their wide application in flood forecasting, the deterministic models still exit some limitations. Some basin characteristics cannot be accurately determined from the available data. They become model parameters which are usually determined through the calibration and validation process. However, this is not always possible. Moreover, the model parameters are usually fixed, while the actual conditions of the basin change strongly, especially during the flood season. Therefore, it is difficult to accurately represent basin conditions with these models (Beven 2000; Broersen & Weerts 2005; Pathiraja et al. 2016).

Over the years, although flood forecasting field has reached a mature stage, this is still a complex issue. First of all, the relationship between precipitation and river flow is the nonlinear dynamic (Hejazi et al. 2008; Lai et al. 2022). This presents an even greater challenge because of the time-varying physical processes occurring on the basin, such as infiltration, transformation from effective rainfall to flow, and groundwater. These challenges are cumbersome and non-trivial, especially when some issues are beyond of human understanding (Deng et al. 2016; Xiong et al. 2019). Considering the influence of climate change in the current condition in which floods are becoming more frequent and complicated, this topic becomes even more urgent than ever (Callaghan et al. 2021). The second challenge, which is very common, is related to infrastructure constraints. In the past, there were few stations of the hydrometeorological network, and most of them only measured daily precipitation. For example, the entire Thua Thien Hue province has an area of more than 5000 km2, but there are only 3 meteorological stations to measure hourly rainfall data. In addition, these data are not generally accessible. So far, there has been less evidence of real-time forecasting in Vietnam.

Given the aforementioned reasons, developing a novel approach to flood forecasting is imperative. Such an approach should ensure applicability to atypical extremely events, which are likely to occur more frequently in the future due to climate change impacts, while simultaneously maintaining the forecast accuracy in the context of dynamic basin conditions. According to Zhang et al (2024), time-varying parameters deterministic model has been promising in improving runoff forecasting. It overcomes the shortcomings of the black box models when simulating the historical flood events. Their study determines the model's parameters for each period in the past and uses these parameters to forecast the future flows. Young (2002) used historical rainfall and runoff data to predict future runoff under similar conditions in the future. In his study, the parameters of the model are allowed to be modified to capture the effects of changes on the watershed over time. Lian et al (2024) applied differentiable parameter learning to identify the time-varying parameter model. In this case, the influence of climate factors, soil conditions, and vegetation change were considered. The result of this study showed that time-varying parameters can enhance the accuracy of streamflow estimation. Meanwhile, in the study of Jeong & Kim (2023), the instantaneous unit hydrograph (UHG) is continuously updated using the effective rainfall following a power–law relationship. In fact, when there is high rainfall intensity, the concentration time is short and vice versa. Although this approach is successful in explaining the relationship between time of concentration and rainfall intensity, insufficient attention has been paid to other phenomena. An expansion of the method to include other hydrological processes such as loss calculation and based flow is required to improve the precision of forecast results. In conclusion, time-varying parameter hydrological model should be a potential approach in real-time flood forecasting to reservoirs. Consequently, this approach presents a viable method for enhancing the accuracy of flood

forecasting. This perspective is also supported by Refsgaard (1997) in his research. With above discussion, time-varying parameter hydrological model should be a potential approach in real-time flood forecasting to reservoirs.

In addition to improving forecasting quality, forecasting tools must also adapt to existing infrastructure conditions while meeting real-time forecasting requirements. In flood season, rapid flow variations result in short forecasting intervals, typically ranging from a few dozen minutes to an hour. Using detailed hydraulic models or distributed ideological parameter models requires high-performance computing systems to meet these demands. However, given Vietnam's limited infrastructure, deploying such complex models on a large scale remains challenging. Therefore, selecting a simple model with fast computation capabilities and minimal input data requirements is a crucial consideration. According to Sahu et al (2020), HEC-HMS is a useful tool for flood forecasting due to its fast processing speed and low cost. This model is freely provided by the U.S. Army Corps of Engineers (Scharffenberg 2016) and features a flexible structure that allows easy interaction through CSV-formatted files. A notable advantage of HEC-HMS is the availability of optimization algorithms (Feldman 2000), which facilitates real-time parameter adjustments. For these reasons, HEC-HMS has been selected for application in this study.

To address the critical challenges posed by unusual weather phenomena and infrastructure limitations, this study introduces a novel approach to flood forecasting. Our method leverages a time-varying parameter hydrological model, which dynamically updates basin conditions through continuous parameter adjustments. This innovation offers new insights for enhancing real-time flood prediction accuracy. A key novelty of our research lies in its high applicability and adaptability, even in data-scarce environments, thanks to its minimal input data requirements. To validate this approach, we applied the model to the Ta Trach basin in Thua Thien Hue province, Vietnam, focusing on the 2020 historical flood season to forecast reservoir inflow. The following section provides a detailed description of the study area, while the methodology outlines the core technologies employed. Subsequently, we present the advantages of our proposed results and discuss potential limitations to guide future research.

Methods

Research area

The study area is the Ta Trach reservoir. Ta Trach reservoir was built on the mainstream of Ta Trach river, located in Duong Hoa commune, Huong Thuy town, Thua Thien—Hue province. This is an area frequently affected by major floods. In recent years, according to statistics from the Central Steering Committee for Disaster Prevention and Control, Thua Thien Hue province has often been impacted by 2 to 3 storms and tropical depressions. A notable example is the historic 2020 floods, which marked an extremely severe flood season in the study area due to consecutive heavy rains caused by 9 storms and tropical depressions (Ortiz Vargas & Sebesvari 2021). From October to November 2020, the sudden influence of storms caused many heavy rainfall events. The total rainfall at Nam Dong station during this period was up to 4730 mm, and the rain intensity sometimes reached 75 mm/h (Watec 2016). This caused severe consequences for the region. According to reports from the Central Steering Committee for Natural Disaster Prevention and Control and the Thua Thien Hue Provincial People's Committee, during the historic 2020 floods, the province recorded 43 fatalities and total damages of approximately USD 90 million (The Central Steering Committee for Disaster Prevention and Control, 2020).

The study watershed was chosen due to the significant role of the Ta Trach Reservoir. About 24 km downstream from Ta Trach reservoir is Hue City, the ancient capital of Vietnam—the cultural heritages recognized by UNESCO. This is not only a densely populated area but also has historical and cultural significance. The operation of Ta Trach reservoir directly affects the water level of the river in Hue City. Therefore, accurately forecasting the flow to the reservoir will determine the flood safety for this city, which is an essential task of this reservoir.

The issue of accurate reservoir inflow forecasting is a prerequisite for the effective reservoir operation. Nevertheless, this matter encounters numerous difficulties in implementation. The catchment area is 717 square kilometers with the basin topography ranges in elevation from 200 m to over 1,000 m above sea level. The terrain has relatively steep slopes, averaging about 25–35%, with some areas exceeding > 40% gradient, particularly along sheer mountain slopes. This results in a short concentration time for runoff across the watershed. As a result, the inflow to the reservoir fluctuated strongly. Based on Ta Trach reservoir operation data in 2020, the flood flow to the reservoir has about 8 flood peaks with values above 2000 m^3/s compared to the flood season's base flow value of about 50 m^3/s. The highest peak reaches 4023 m^3/s (Vietnam Disaster and Dyke Management Authority 2017).

In order to minimize future flood losses, a more accurate flood forecasting tool that is suitable for the basin conditions needs to be established. In the recent years, new rainfall systems are available in Vietnam (Watec 2016; Weather Plus 2017). These systems provide short-term, online available, and continuously updated rainfall data. This is the fundamental basis for the development of a real-time flood forecasting system. Hourly or even shorter interval rainfall

data from these systems will be useful information as the input of the time-varying parameter hydrological model. In this study, there are 3 automated rainfall stations around research basin, namely Nam Dong, Ho Truoi, and Ho Thuy Yen (Fig. 1). Rainfall data from these three stations are used as input to estimate inflow to Ta Trach reservoir. Furthermore, observed reservoir inflow data can also be updated in real time. This condition is also essential for applying the subsequent forecasting methodology.

Methodology

The study's process is presented in the flow chart in Fig. 2. The proposed hydrological modeling and flood forecasting framework employs an iterative, self-optimizing approach to enhance prediction accuracy. The process begins with continuous updates of observed rainfall data and initial parameter calibration, followed by model simulation and comparison between observed and simulated discharge. If discrepancies arise, the system automatically performs parameter optimization until satisfactory alignment is achieved. Crucially, the model integrates updated rainfall data to enable proactive flood prediction, while a feedback mechanism evaluates forecast performance and further refines parameters for subsequent cycles. This closed-loop system offers key advantages, including dynamic adaptability to real-time and predicted rainfall, reduced reliance on manual intervention through automated calibration, and sustained improvement via continuous evaluation. This framework is an advanced solution for reliable, adaptive flood risk assessment and early warning systems.

In this study, the HEC-HMS model for the Ta Trach basin is established. This is a large basin, so the spatial distribution of basin characteristics and rainfall needs to be considered. In order to be applicable to a large basin, the study divides the Ta Trach basin into 4 sub-basins. These basins are linked together by 02 channels, as shown in Fig. 3. This approach has also been applied by many authors in their studies (Ahmed et al. 2021; Tran et al. 2021). With the division of sub-basins, the model has more parameters, which makes the parameters optimization process become more flexible. However, the computational volume is also increasing. There are a lot of methods in the HMS model in each process (loss, transform, and base

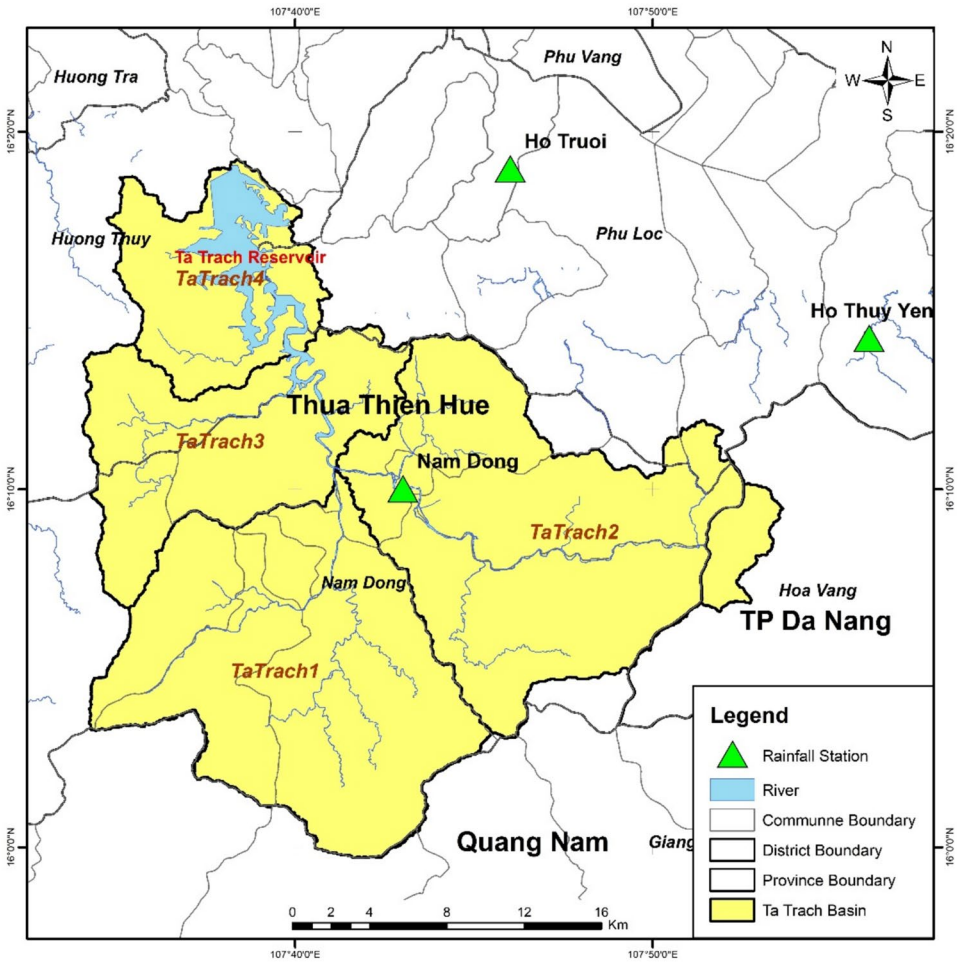


Fig. 1 Research area

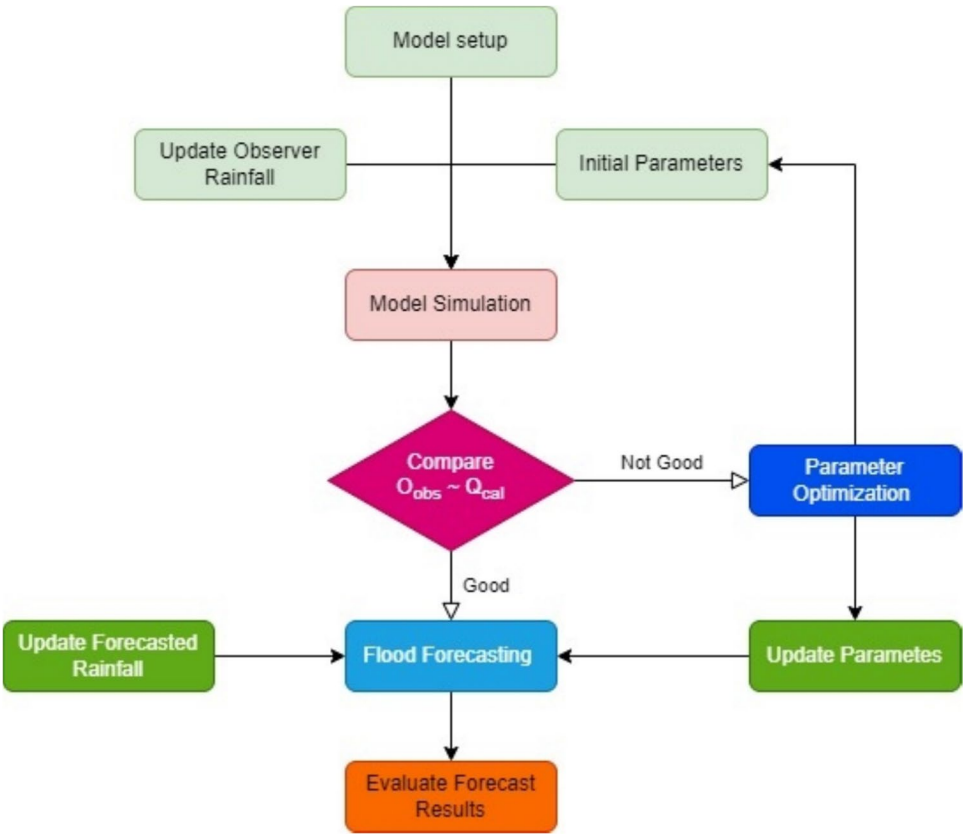


Fig. 2 Flow chart of study

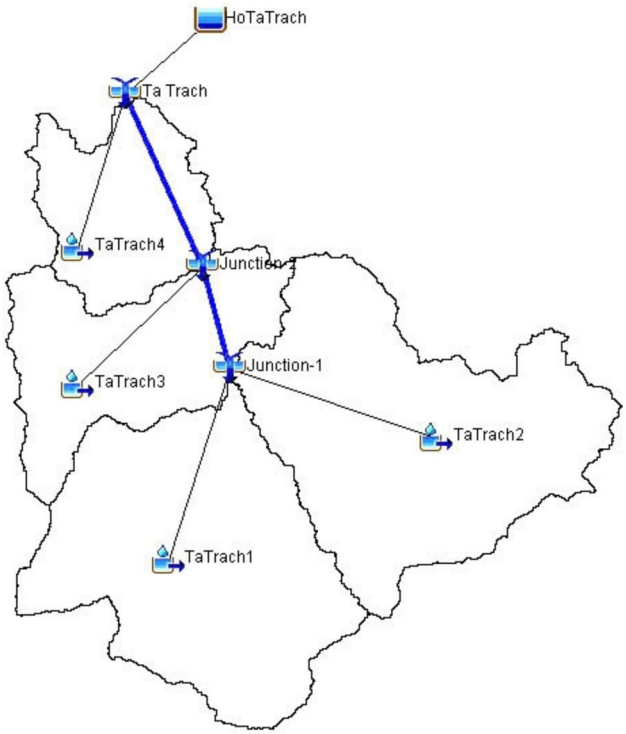


Fig. 3 HEC-HMS model structure for Ta Trach basin

flow). Each method has a different number of parameters. In this study, the authors have selected the methods which have the least number of parameters. First, the CN coefficient method, which has 8 parameters, is used to estimate water loss. Second, the SCS dimensionless hydrograph transform method with 4 parameters is used to convert rainfall to flow. The regression method, which has 12 parameters, is selected to estimate base flow. The 2 reach components are calculated by Muskingum method with a total of 6 parameters. There are a total of 30 parameters in the model of our study. Table 1 describes the methods and the parameters used in our study. In this table, the parameter range and the initial parameter for the first run are also updated. This initial parameter has been calibrated with actual measurement data of a large flood in the past (Flood event in 2019). The calibration result for this flood is also quite good with NSE = 0.9. This parameter set will be used for the fixed parameter model in the following section.

At each time i, the observed rainfall data are updated up to the current time. The research used data from 3 automatic rainfall stations, which are Truoi, Thuy Yen, and Nam Dong (Fig. 1). These are automatic rainfall stations that continuously update rainfall data at 1-h interval. These rainfall data are used as input for the 4 sub-basins in the model. In this study, the Thiessen polygon method

Table 1 Parameters in HMS model

ID	Process	Element	Method	Unit	Range	Initial value
1	Loss	TaTrach1	SCS Curve Number—Curve Number		60–99	60
2		TaTrach2	SCS Curve Number—Curve Number			60
3		TaTrach3	SCS Curve Number—Curve Number			60
4		TaTrach4	SCS Curve Number—Curve Number			60
5		TaTrach1	SCS Curve Number—Initial Abstraction	mm	1–50	20
6		TaTrach2	SCS Curve Number—Initial Abstraction	mm		20
7		TaTrach3	SCS Curve Number—Initial Abstraction	mm		20
8		TaTrach4	SCS Curve Number—Initial Abstraction	mm		20
9	Transform	TaTrach1	SCS Unit Hydrograph—Lag Time	min	100–1000	250
10		TaTrach2	SCS Unit Hydrograph—Lag Time	min		250
11		TaTrach3	SCS Unit Hydrograph—Lag Time	min		250
12		TaTrach4	SCS Unit Hydrograph—Lag Time	min		250
13	Baseflow	TaTrach1	Recession—Recession Constant		0.1–1	250
14		TaTrach2	Recession—Recession Constant			0.3
15		TaTrach3	Recession—Recession Constant			0.3
16		TaTrach4	Recession—Recession Constant			0.3
17		TaTrach1	Recession—Ratio to Peak		0.1–0.99	0.2
18		TaTrach2	Recession—Ratio to Peak			0.2
19		TaTrach3	Recession—Ratio to Peak			0.2
20		TaTrach4	Recession—Ratio to Peak			0.2
21		TaTrach1	Recession—Discharge per Area	$m^3/s/km^2$	0–50	0.25
22		TaTrach2	Recession—Discharge per Area	$m^3/s/km^2$		0.25
23		TaTrach3	Recession—Discharge per Area	$m^3/s/km^2$		0.25
24		TaTrach4	Recession—Discharge per Area	$m^3/s/km^2$		0.25
25	Routing	Reach-1	Muskingum—K	hr	1–10	0.1
26		Reach-2	Muskingum—K	hr		0.1
27		Reach-1	Muskingum—x		0.1–0.5	0.1
28		Reach-2	Muskingum—x			0.1
29		Reach-1	Muskingum—Number of Subreaches		1–100	1
30		Reach-2	Muskingum—Number of Subreaches			1

(Thiessen 1911) is applied to calculate the weights of rain stations for each sub-basin.

To perform the simulation process, the initial set of parameters is based on the set of parameters at the previous time i-1. This set of parameters is continuously updated with each calculation time step. With the initial set of parameters and observed rainfall, the model calculates the inflow to Ta Trach reservoir at the current time. Then, the program will compare the calculated and observed flows. The purpose of the comparison process is to check the suitability of the parameters with the current situation of the basin. According to QCVN 18: 2019/BTNMT (Vietnamese MONRE, 2019), the tolerable error in individual forecast S_{cf} is defined by Eq. (1):

$$\sigma_{\text{tolerable}} = 0.674\sigma_{\Delta} \tag{1}$$

where σ_{Δ} is the standard deviation of the forecast variable change from its mean change during the forecast period. It can be estimated by Eq. (2):

$$\sigma_{\Delta} = \sqrt{\frac{\sum_{i=1}^{k}(\Delta Q_i - \Delta\overline{Q})^2}{n-1}} \tag{2}$$

$\Delta Q_i = Q_i^{cal} - Q_{i+\Delta t}^{cal}$ is the change in forecast discharge during the forecast period Δt

$\Delta\overline{Q}$ is the corresponding mean change.

Q_i^{cal} is the forecast discharge at time step i.

Q_i^{obs} is the observed discharge at time step i.

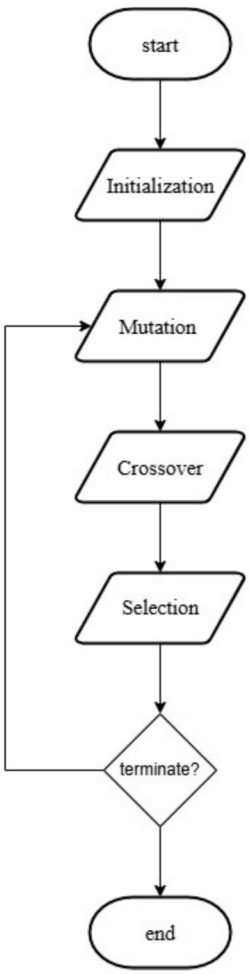
k is the data series selected from at least 5 years historical data.

n is the total number of data points.

Based on the historical data of flood inflow to Ta Trach reservoir, the value $\sigma_{\text{tolerable}}$ is 74.4 m^3/s. In each time step, if the error of calculated inflow by the model is within the allowable range, the model parameter set is kept. If the error is out of the allowable range, the optimization process is performed. The aim of the process is to find the best set of parameters for the current time. Since HEC-HMS version

4.9, several optimization algorithms have been integrated into the software including differential evolution, univariate gradient, and simplex search methods. This facilitates the rapid search for optimal parameters when using the HEC-HMS model. Compared with univariate gradient and simplex search methods, the differential evolution search method is more robust (Scharffenberg 2016). In this study, the optimization trial is run using the differential evolution (DE) search method (Storn & Price 1997). This is a search and optimization algorithm based on the principle of natural evolution. Natural evolution shows optimality in that the next generation is always better than the previous generation through three key components crossover, mutation and selection. The processes of these operators are described as flow chart in Fig. 4.

In the initialization process, the (DE) algorithm aims to evolve target vectors at generation G, defined as $X_i^G = (X_{i,j}^G)$, i = 1,…, NP, j = 1,…,D, where NP is population size (default value is 30 as suggested by the HEC-HMS model). D is the dimension of search space. According to Feldman (2000) the range of D is presented in Table 1. The values of the parameters are selected within the range between the maximum and minimum values in Table 1 to ensure their physical significance. The mutation operation products mutant vector V_i^G via mutation strategies is shown in Fig. 4, where r1, r2, r3 are the distinct integers randomly generated from the range of [1, NP] which are also different from the index i. The scaling factor F is a positive control parameter for scaling the difference vector, which is generally restricted in the range of [0, 1]. Following the mutation phase, a crossover operation is applied to each pair of X_i^G and V_i^G to generate a trail vector U_i^G. In this process, the crossover rate CR is a user-specified real value within the range [0,1]; j_{rand} is a uniformly distributed random integer in the range of [1, D]. Subsequently, a selection procedure is performed. The objective function value of each trial vector fit(U_i^G) is compared to that of its corresponding target vector fit(X_i^G) of the current population. The comparison result will determine the value of target X_i^{G+1} for the next generation as shown in Fig. 4. In this study, the period for comparing calculated and observed inflows during the optimization process is typically 3–6 h prior to the present time. This relatively short period



$$X_i^G = (X_{i,1}^G, X_{i,1}^G, \ldots X_{i,D}^G)$$

$$V_i^G = X_{r1}^G + F(X_{r2}^G - X_{r3}^G)$$

$$U_i^G = \begin{cases} V_i^G \; if(rand_{i,j}(0,1) \le CR \; or \; j == j_{rand}) \\ X_i^G \; otherwise \end{cases}$$

$$X_i^{G+1} = \begin{cases} U_i^G \; if(fit(U_i^G) \le fit(X_i^G)) \\ X_i^G \; otherwise \end{cases}$$

Fig. 4 The flow chart of differential evolution algorithm

aims to capture the instantaneous trend of the inflow. Consequently, the mean absolute error (MAE) index is selected as the objective function. The formula for determining the MAE value is presented in Eq. (5) and will be presented in the following section. This objective function is appropriate for short data series due to its simplicity. The parameter optimization process is carried out with the goal of finding the smallest MAE index. In this study, after each search, the smallest MAE value is compared with $\sigma_{\text{tolerable}}$ which is defined in Eq. (1), to determine the termination condition. If the condition is not met, the searched parameters, such as computation time interval, Max Iteration, Population Size, and Seed Value, will be adjusted through a trial-and-error approach to satisfy the termination condition.

After the model set of parameters has been detected, the two processes will be executed in parallel. First, that set of parameters is used to forecast inflow for the next few time steps. Secondly, the values of the parameter set will be updated to the initial value for calculation for the next calculation loop. Assuming that the parameter set does not change significantly compared with the previous time step, the desired parameter set value is close to the value at the initial time. Therefore, the selection of the initial set of parameters helps reduce the optimization time.

The last step of the research project is the assessment of the forecast quality. According to QCVN 18: 2019/BTNMT (Vietnamese MONRE, 2019), the forecast lead time for the Ta Trach reservoir is 6 h. Therefore, the 1-h, 3-h, and 6-h forecast lead times is evaluated in this research. To quantify the accuracy of the study, the study compares the ΔQ_i value with the $\sigma_{\text{tolerable}}$ value for every individual forecast turn. The overall accuracy (OA) index formulas are as follows:

$$OA = \frac{\text{the number of accurate forecast}}{\text{the total number of forecasts}} \tag{3}$$

Moreover, the study uses several error measurement criteria (Nash & Sutcliffe 1970) to compare the consistency of the forecast result with the observed inflow. It includes Nash–Sutcliffe Model Efficiency Coefficient NSE (Nash & Sutcliffe 1970) (Nash & Sutcliffe 1970). It is a statistic that determines the relative magnitude of the residual variance compared to the observed data variance. It is a popular goodness-of-fit statistic that is widely used in hydrology research. NSE index can be estimated by Eq. (4). The value of NSE is in the range $(-\infty, 1]$. NSE = 1 represents a perfect prediction.

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(Q_i^{cal} - Q_i^{obs}\right)^2}{\left(Q_i^{obs} - \overline{Q_i^{obs}}\right)^2} \tag{4}$$

The other common measure of forecast error in time series analysis is mean absolute error (MAE) (Hyndman & Koehler 2005). It is the average of the magnitude of difference between the predicted values and the actual values. MAE is always non-negative, and a lower MAE is better than higher one. It is defined as Eq. (5).

$$MAE = \frac{\sum_{i=1}^{n}\left|Q_i^{cal} - Q_i^{obs}\right|}{n} \tag{5}$$

The other index which is more appropriate to represent model performance than the MAE is root-mean-square error (RMSE) (Chai & Draxler 2014). This is the standard deviation of the residuals. It measures how far between the prediction discharge and the actual discharge. RMSE is always non-negative and a lower RMSE is better than higher one. The RMSE is defined as Eq. (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_i^{cal} - Q_i^{obs}\right)^2} \tag{6}$$

Furthermore, statistical indicators including the coefficient of determination (R2—Eq. 7) and normalized standard deviation (σ_{nor} − equation 8) were computed to assess the prediction model's performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Q_i^{cal} - Q_i^{obs}\right)^2}{\sum_{i=1}^{n}\left(Q_i^{cal} - \overline{Q^{obs}}\right)^2} \tag{7}$$

$$\sigma_{nor} = \frac{\sigma^{cal}}{\sigma^{obs}} \tag{8}$$

All notations used in Eqs. 4–8 are defined in Eq. 2.

Results and discussion

The study was conducted to forecast the inflow to Ta Trach reservoir during the flood season from September 17 to November 31, 2020. Based on the observed flow in Fig. 7a (blue line), the hydrograph showed a very complicated process. The first peak arrived on September 18th. This was a rapid flood event. The rising and falling limbs also occurred in a short period. The flow increased suddenly from 40 m^3/s up to 2700m^3/s in only 10 h. In the main flood season in October, floods occurred one after the other. While the previous flood had not ended, the next flood had occurred. The flood peaks had exceeded 3500m^3/s many times. The highest flood appeared on October 10th. There were 2 peaks flood event with both values reaching 4000m^3/s. These values were the historical flood value and had never happened before. In addition to large floods, some small floods with peak flood values of a few hundred m3/s were also common. The 2020 flood season in Thua Thien Hue can be considered as a representative flood season. Flood patterns are very diverse and flood peaks cover a wide range. This leads to a high level of difficulty in predicting flooding in 2020. If it

is possible to accurately predict this flooding season, the approach is reliable to make forecasts for the study area.

The study also compares our result with other results archiving from 2 different approaches. The first approach is the traditional way which uses a fixed parameter model which is the initial parameter set in Table 1. The second approach is artificial intelligence technique. In this study, Lightgbm algorithm is used. All models are calibrated and validated/tested with historical data to ensure the reliability. Figure 5 presents a box plot comparing observed data with forecasted results using different methods across various forecast periods. From this plot, a similar trend is presented across all forecast periods. For the time-varying parameter model, the mean value as well as the upper and lower quartiles of the forecasted results aligns closely with the observed data. The length of the whiskers is also well-matched, indicating that the distribution of forecasted values using this method is highly consistent with the observed data. The forecast results of other remain methods, however, are not as good as expected. The whisker length is longer in the fixed parameter model, suggesting that the peak flood forecasts of this model tend to be overestimated, while the AI model exhibits the opposite trend. The data distribution in these two models is not entirely reasonable, as indicated by the significant differences in interquartile ranges compared to the observed values. The study also compares forecast accuracy using a Taylor diagram (Fig. 6). Visual results indicate that data point from the variable-parameter model cluster closest to the reference point. This analysis suggests that the parameter-varying model provides better forecast results than the other two models. The comparative statistical indices demonstrating this are also presented in Table 2.

The study also presents the hydrographs for the observed and forecasted flow using the time-varying parameter model. The inflow forecast result with 1-h forecast time is shown in Fig. 7a. In this figure, the forecasted inflow hydrograph is consistent with the observed discharge. All flood peaks are forecasted very well, especially the big flood peaks. Large errors mostly appear at the end of falling limbs, when the flow is relatively small. The NSE index in this case reaches 99.35%. In more than 1,100 forecasts, only 51 times have the forecast error ΔQ larger than the tolerable error S_{cf}. The OA index is 94.74%. The very good results above show that using the hydrological model with time-varying parameters is a very potential approach. Due to the continuous update of the model parameters, the current condition of the catchment area is shown more realistically. Figure 7b and c shows the moving average forecasted inflow for the next 3 and 6 h. As the forecasted time increases, the accuracy of the forecasted results slightly decreases. The NSE indexes of average forecasted inflow in the next 3 h and 6 h are 96.36% and 90.91%, respectively. According to Mccuen et al (2006) these indexes are in the very good level. Note that there is a significant discrepancy in some places, such as the 4th flood peak on October 11th. However, the forecasted hydrographs are matched with the observed data. Most flood peaks are fairly well forecasted. The OA indexes in both cases are very high with values reaching 93.10% and 90.88%, respectively.

As it can be seen in Table 2, the result of our approach is much better than those of the other two in all cases. A popular explanation of the difference is that the variation of model parameters responds better to the current state of the basin than using a fixed parameter set in the traditional approach. In fact, the infiltration capacity of the basin for rainfall events is different. Even within a rainfall event, it is not uniform. That may be due to changes in the surface cover, moisture content in the surface layer. Similarly, the concentration time in the basin is also not the same with different rainfall intensity. Therefore, a simple mathematical formula with fixed parameters can only give reasonable results globally but cannot give good results in detail. The study has segmented the whole flood season process into

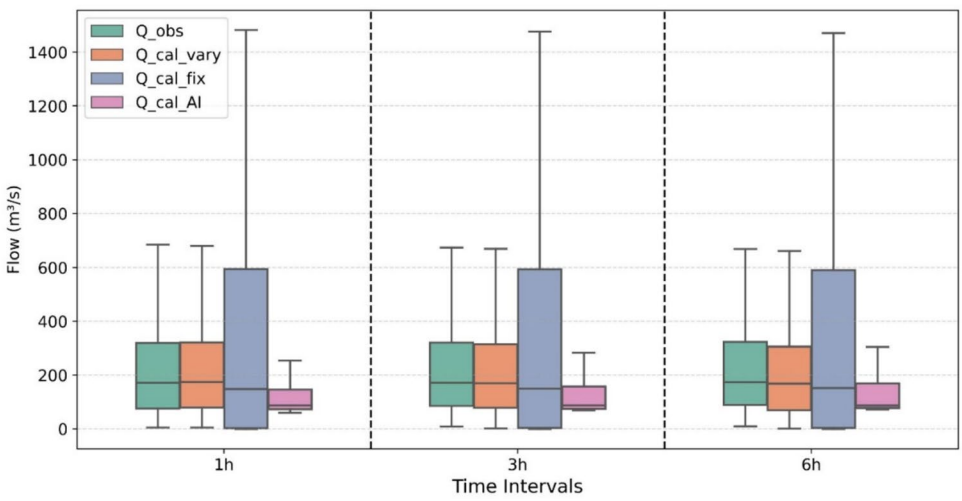


Fig. 5 The violin plot of observed and forecasted data using different methods

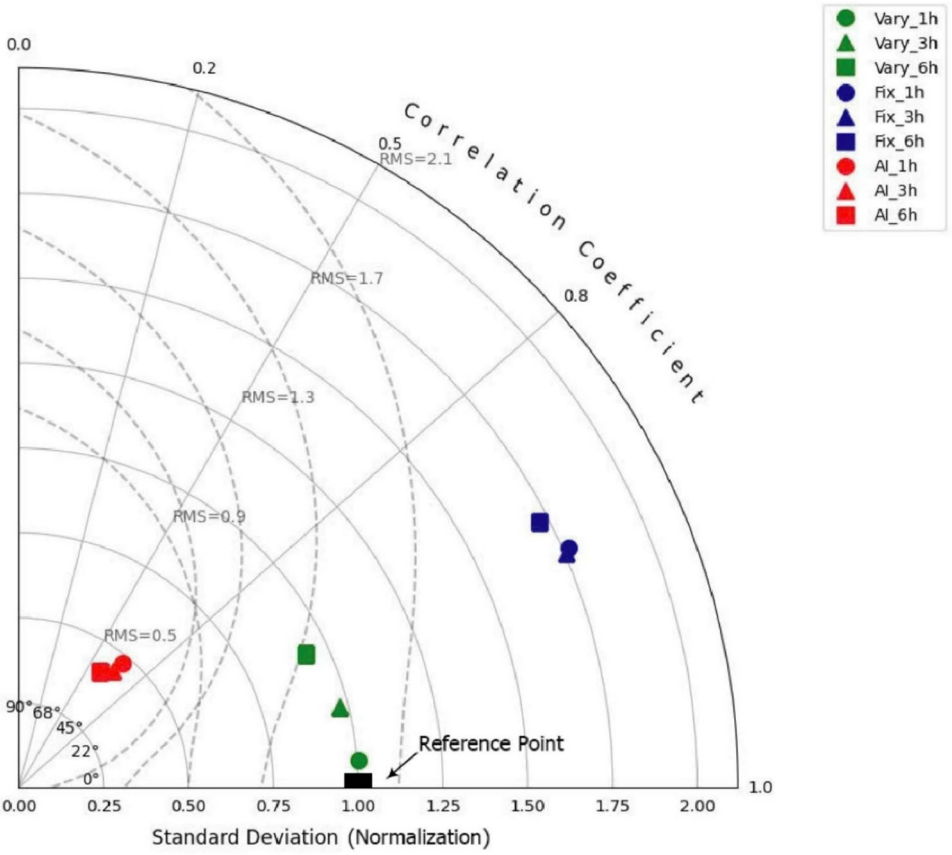


Fig. 6 The Taylor diagram to compare forecasted result using different methods

Table 2 The results of 3 approaches for 2020 flood season

Forecasted time	Index	Time-varying parameter model	Fixed parameter model	Artificial intelligence model	Unit
1 h	OA	95	40	50	%
	NSE	99	15	30	
	MAE	21	246	216	m3/s
	RMSE	43	499	452	
	R^2	0.99	0.81	0.41	–
	σ_{nor}	1.00	1.77	0.48	
3 h	OA	93	41	50	%
	NSE	96	15	26	
	MAE	25	270	212	m3/s
	RMSE	101	557	436	
	R^2	0.96	0.86	0.48	–
	σ_{nor}	0.99	0.45	0.44	
6 h	OA	91	41	50	%
	NSE	91	16	34	
	MAE	36	265	208	m3/s
	RMSE	156	536	416	
	R^2	0.91	0.88	0.54	–
	σ_{nor}	0.97	1.79	0.43	

small periods and finds the suitable parameters for each moment. That explains why our study results are better than the traditional approaches. Moreover, our approach still simulates the physical processes occurring in the basin via hydrological model. Even with the historical floods, the model still responds well to the transformative process from rainfall to discharge. This overcomes the weakness of the artificial intelligence approach. Which struggles when the model has to deal with historical flood events that fall outside the range of data used for training.

Another striking feature of this approach is simple. The simplicity of the approach is reflected in both the input data requirements and the structure of the model. The model does not need historical data to validate the model. The only requirement that needs to be met is that the upstream rainfall and inflow data to the reservoir are continuously updated. This is a possible condition to adapt in Vietnam or other parts in the world. The selection of using a free, popular model with built-in optimization algorithms has simplified the calculation process. In this study, the Ta Trach basin is divided into 4 sub-basins with a total of 32 parameters. For this simple structure, the calculation time including the parameter optimization process each time is negligible (< 5 min) compared to the shortest forecasted time step (1 h). For larger basins, however the model structure will become

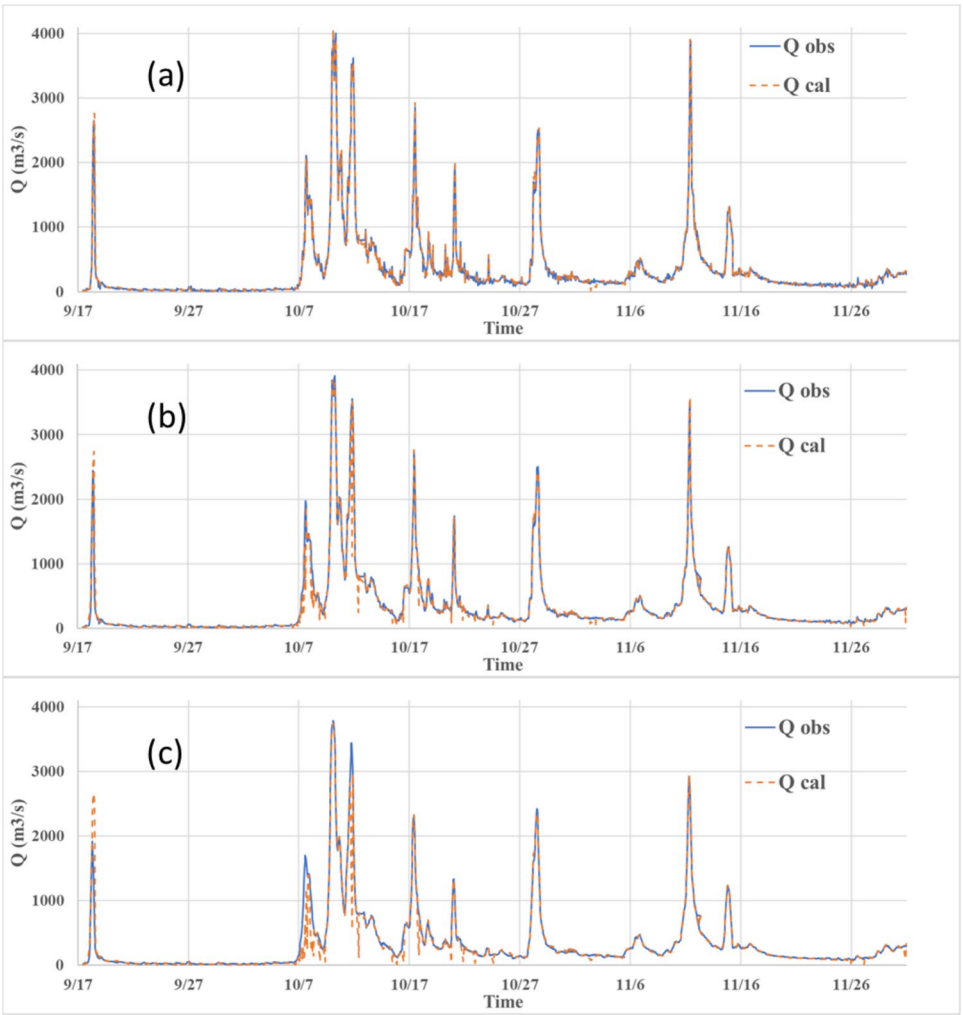


Fig. 7 The forecasted and observed inflow hydrographs with (a) 1 h, (b) 3 h và, (c) 6 h ahead

more complex with more parameters. Therefore, the calculation time may increase. However, the concentration time on the basin will also increase too. Thus, the calculation process still ensures to adapt the requirements for real-time forecasting. This shows the superiority of the approach.

In forecasting, the indispensable input component is forecasted rainfall. The precision of the forecasted rainfall greatly affects the forecast results. Therefore, choosing the appropriate rainfall forecast model for each region is a very complex topic. This topic is beyond the scope of the present study. This is the limitation of our study. This means that in the practical forecasting applications, the possible results are not as well as our present result. However, this error is minimized by continuously updating both observed and forecasted rainfall data. In the future, the authors will conduct further research to select the most appropriate forecasted rainfall source for the study area. Another suggestion is we can assemble data from many forecasted rainfall sources to find the most appropriate percentile.

In this study, the lumped model is used due to resource constraints (computer configuration, distributed rainfall data, etc.), also considering that the research basin is not large and the number of parameters is not too many. For larger and more complex areas, the same approach can be applied to distributed models or hydro-hydraulic integrated models. As more complex systems are adopted, more resources are also required. Other optimization algorithms also need to be tested for evaluation. Many studies have applied Kalman filter as an effective tool in determining the model's parameters in variation conditions of the research area (Deng et al. 2016; Pathiraja et al. 2016; Xiong et al. 2019). This is also a development direction of future research.

Another potential future research direction could be to combine physical process-based models with artificial intelligence models to become a hybrid model (Li et al. 2024), in which the parameters that have produced good forecast results in the past will be saved for training. In the future, when similar conditions occur, the model will automatically find the optimal parameters corresponding to the same conditions. Thus, the parameter finding process will be reduced, making the forecast processing speed faster. However, this

approach also requires a large amount of data for training and testing artificial intelligence models.

Conclusions

This study developed a real-time flood forecasting approach using a time-varying parameter hydrological model, which was applied to predict flood inflows to the Ta Trach reservoir. By dynamically updating model parameters to reflect real-time basin conditions, the approach aimed to enhance forecasting accuracy and support reservoir operations during flood events.

The results demonstrated superior predictive performance, even during the unprecedented 2020 flood. The model achieved NSE values of 99.32, 95.7, and 89.14% for 1-, 3-, and 6-h lead times, respectively. Compared to traditional fixed parameter models and a pilot artificial intelligence model, the proposed approach consistently outperformed in all forecasted time steps.

This approach holds significant practical value due to its simplicity, rapid computational speed, and minimal data requirements. Additionally, it aligns well with the current infrastructure conditions in Vietnam, making it feasible for practical applications. The use of a free, easily configurable model further enhances its scalability for application in other regions. The approach is expected to be particularly advantageous in large, complex basins or multi-reservoir systems.

Despite these strengths, the study has a notable limitation. This research relies on past flood event data, which excludes the evaluation of forecasted rainfall accuracy. Since rainfall forecasts are a critical input for real-time flood forecasting, this remains an important aspect to address.

Future research will focus on integrating reliable forecasted rainfall sources to improve the model's real-time applicability. Additionally, testing in larger basins with complex inter-reservoir systems will help assess the model's effectiveness in more intricate hydrological settings. Moreover, hybrid modeling techniques could be explored to further enhance forecasting accuracy.

In conclusion, the time-varying parameter hydrological model presents a promising direction for real-time flood forecasting, offering high accuracy, fast computation, and broad applicability.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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