

**Real-time flood forecasting and uncertainty analysis: A case study of
the Krong H’rang hydropower reservoir**

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Abstract: Early and reliable flood forecasting is crucial for mitigating the impacts of floods and ensuring the safe operation of irrigation and hydroelectric facilities. Traditional methods often use a calibrated event-based rainfall-runoff model with a limited number of simulations, making it difficult to measure parameter uncertainties accurately. This paper introduces a new method for estimating the parameters of the HEC-HMS model and evaluating the uncertainties in real-time flood forecasting. First, the Latin Hypercube Sampling (LHS) procedure is used to efficiently sample the parameter values throughout the feasible parameter space. Next, thousands of parameter sets are simulated using a deterministic rainfall-runoff model, generating numerous initial solutions for the Shuffled Complex Evolution (SCE-UA) algorithm to search and evolve. Additional parameter sets are then generated as the search evolves, leading to new simulations until the algorithm reaches the convergence criteria. The optimal solutions are selected based on predefined multiple objective functions. Uncertainty of the forecast results is also computed using the Generalized Likelihood Uncertainty Estimation (GLUE) method and represented as confidence intervals. The method was applied to forecast flood hydrographs at the Krong H’rang hydropower reservoir in Vietnam, using data from 33 flood events from 2016 to 2021. The results demonstrate that the program can effectively forecast the flood hydrograph up to 4 hours in advance (the Kling-Gupta efficiency $KGE > 0.8$ and the absolute relative volume error $|VE| < 10\%$). The observed values fall within the uncertainty range of $Q_{5\%}$ - $Q_{95\%}$. Compared to the conventional method, which uses a fixed parameter set value, this approach is superior and therefore can assist policymakers and operators in more effectively managing reservoir operations.

Keywords: HEC-HMS; flood forecasting; uncertainty analysis; auto-calibration; SCE-UA; Krong H’rang.

1. Introduction

Vietnam is a country highly prone to disasters, especially in its central region, which is particularly susceptible to extreme tropical storms and flooding (WB and ADB, 2020). In recent years, these events have become more severe and frequent due to the impact of

climate change (NOAA, 2021). The country has experienced heavy rainfall over short periods, and there will be likely more extreme precipitation (Nguyen et al., 2017). According to a report from the Vietnam Government, an extreme flood event occurred in the Central Region on October 23rd, 2020, which was categorized as a level IV disaster, surpassing the highest alert level III. This flood resulted \$1.5 billion in damages, and the deaths or disappearances of more than 243 people (IFRC, 2020). In 2021, another flood event caused the loss of 18 lives and inundated almost 60,000 houses, while also inflicting significant damage on extensive agriculture areas (ECHO, 2021).

Numerous hydropower reservoirs have been constructed in the Central Region of Vietnam. However, the current forecasting and operational system pose potential risks to downstream areas (Nguyen et al., 2023). Specifically, the reservoir inflows are determined according to predefined schedules, requiring the tools and synchronized technical systems to operate effectively according to the government-approved process (EVN Vietnam, 2019). Therefore, it is crucial to have a reliable and accurate forecast of potential flood peaks, flood volume, and arrival time to assist stakeholders and decision-makers in planning and ensuring the safe and optimal operation of hydropower dams and reservoirs during flood periods (To et al., 2022). Flood forecasting information is also crucial for providing early warnings to residents in flood-threatened areas as well as for assisting reservoir operators in managing flood-control structures, such as spillway systems and turbines to maintain dam safety and flood protection in downstream areas (Reig et al., 2020).

Rainfall-runoff models are widely used worldwide to simulate and forecast floods. Many different rainfall-runoff models are available, and the choice of model depends on the specific application and the level of accuracy required (EPA, 2017). The Hydrologic Engineering Center - Hydrologic Modeling System (HEC-HMS), developed by the

USACE, is one of the most popular tools for flood forecasting (USACE, 2000). It can produce results quickly, which is important for real-time updates (Chu & Steinman, 2009). The HEC-HMS is a physically based, semi-distributed, and deterministic multi-purpose model, used for various purposes such as rainfall-runoff transformation process, urban drainage, and flood forecasting (USACE, 2024).

Many case studies have been conducted using the HEC-HMS for hydrologic modelling at different scales using various data sources including radar and satellite precipitation (Azam et al., 2017; Grek & Zhuravlev, 2020). Some studies have compared the accuracy of the HEC-HMS with that of other hydrology models. For example, Joo et al. (2014) compared the accuracy of the HEC-HMS with the Revitalised Flood Hydrograph (ReFH) rainfall-runoff model on 14 flood events and found that the HEC-HMS performed better in peak flow prediction. Filianoti et al. (2020) compared the performances of four physical-based and conceptual models (HEC-HMS, SWMM, MIKE11-NAM, and WEC-FLOOD) for flood prediction and concluded that the HEC-HMS was the best model overall.

However, the HEC-HMS model also has several limitations when applied in practice. First, the model does not have the feature of automatic execution setup, and all procedures must be manually executed by the users, which is very time-consuming and prone to error (USACE, 2024). Second, the HEC-HMS model uses the HEC Data Storage System's data format (HEC-DSS) to store and manage data, which is not accessible by common text-reading or data-processing programs (USACE, 2009). Third, setting up and running the HEC-HMS model requires the users to have a deep knowledge of hydrological mathematical models and a good understanding of the precipitation and flood characteristics of the basin (Nguyen et al., 2022). This is particularly important for

setting up, calibrating, and validating the model to fit with the characteristics of each actual flood and forecast inflow.

The HEC-HMS model versions 4.11 and 4.12 (released on May 8, 2024) help the modelers to find the best parameters value by running the algorithms, such as Univariate-Gradient, or Nelder and Mead, via the Trial Run function (USACE, 2024). However, finding the best parameter set is time-consuming, as it is currently done manually. A modified version of the Gauss-Marquardt-Levenberg technique based on the SCE-UA developed by Duan et al. (1992) is suggested in an internal USACE study (Skahill, 2006) but has not yet been officially integrated. Consequently, only some studies have focused on enhancing the HEC-HMS performance by automatically calibrating parameters (Albo-Salih & Mays, 2021; Chu & Steinman, 2009; Şensoy et al., 2018).

Several techniques exist to find the global optimum solution, with the SCE-UA algorithm being considered a powerful and successful method for the parameter calibration of hydrological and hydraulic models (Duan et al., 1992; Vrugt et al., 2003; Yapo et al., 1998). It has been successfully applied to many models, including MIKE NAM (Zakermoshfegh et al., 2008), SWAT (Eckhardt & Arnold, 2001), SWMM (Lee & Kang, 2016), and HEC-RAS (Tong & Komma, 2017). Some developers, such as SWAT-CUP (Abbaspour, 2015) or MIKE-Auto CAL (DHI, 2020), have integrated the SCE-UA algorithm into their automatic model parameter tools.

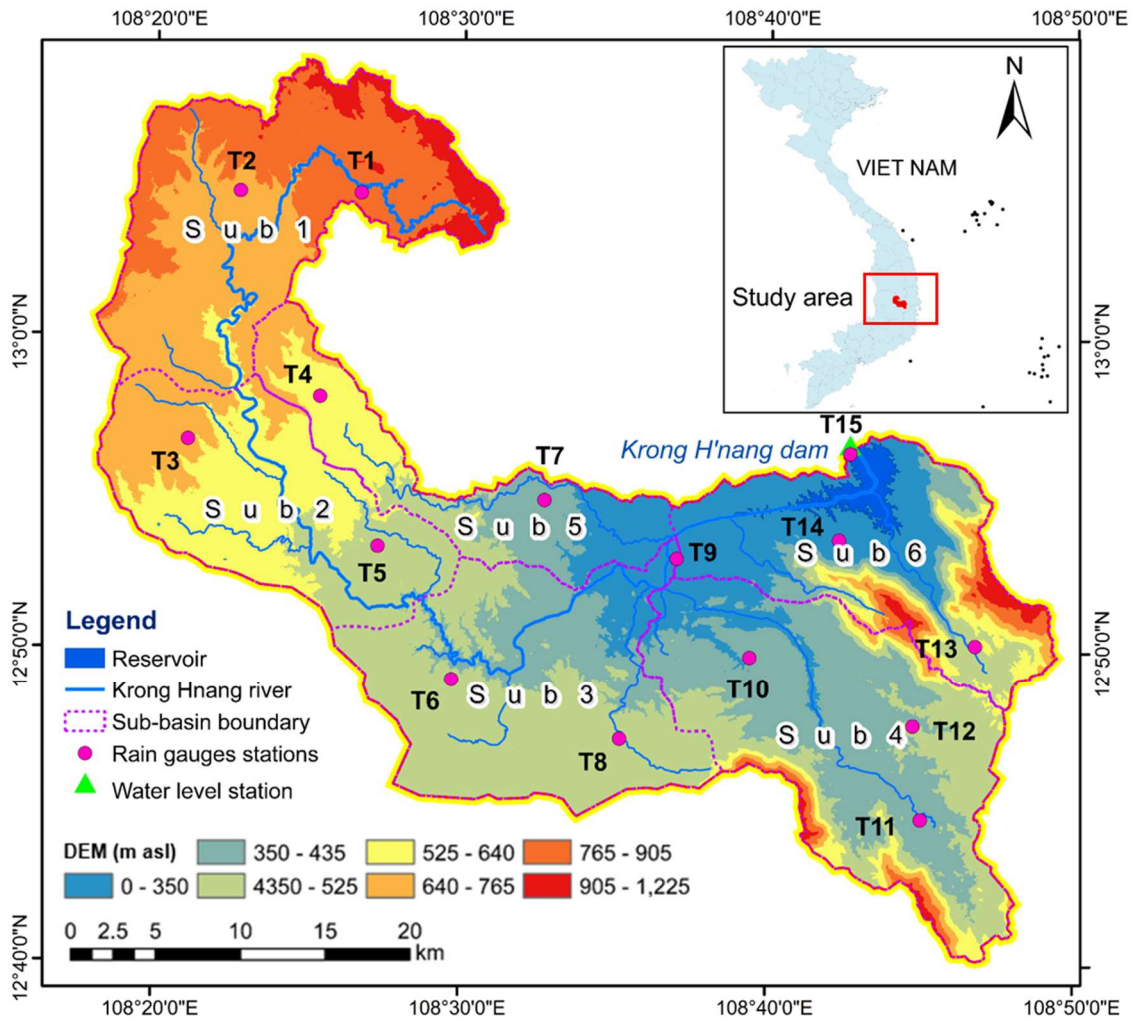
Another key consideration is parameter sensitivity, which is important for accurate model interpretation, calibration, and application (Cooper et al., 1997, 2007). Some current methods involve changing parameters at 5% intervals within a $\pm 30\%$ range from the average value (Yu & Zhang, 2023; Zelelew & Melesse, 2018). However, there has been no research to determine the combined effects of different parameters.

In response to these issues, our research aims to develop a novel real-time flood forecasting and uncertainty analysis application. The main purpose is to use Python scripting to automatically drive and update the HEC-HMS rainfall-runoff model for a large number of simulations to forecast flow and quantify model uncertainty in real-time based on continuous observations of rainfall and discharge data. The feasible domain is sampled using the Latin Hypercube Sampling (LHS) algorithm. For the first time, the SCE-UA algorithm is adapted to the HEC-HMS model to automatically search for the optimal parameters set. Simulation results are used in the evolutionary process to achieve the global optimal solution, and the Generalized Likelihood Uncertainty Estimation (GLUE) method is used for the uncertainty analysis. The output data are stored and displayed on the Graphic User Interface (GUI) for monitoring and control. The procedure has been applied to forecast flood hydrographs at the Krong H'nang hydropower reservoir in Vietnam's Central Highlands. This program is an important part of the reservoir operation decision support system, providing early forecasting information, and efficient reservoir inflow predictions to help policymakers and operators better manage reservoir operations.

2. Study area and dataset

2.1. Study area

The Krong H'nang dam was constructed on the Krong H'nang River in Dak Lak Province (see Figure 1). This river is a major tributary of the Ba River, the largest river basin in the South-Central region of Vietnam (Decision No. 878 Vietnam Gov, 2018). The Krong H'nang reservoir basin covers an area of 1,168 km², with a total volume of 165.78 x 10⁶ m³, and an active volume of 108.5 x 10⁶ m³. The dam was designed with a design flood of 8.234 m³/s, corresponding to a 1,000-year return period (EVN-PECC4, 2007).



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Figure 1. Map of the Krong H'ngang River basin.

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Figure 1 shows the location of the study area. We divided the main basin into six subbasins (Sub1 to Sub6). The locations of 15 automatic rain gauges (T1 to T15) are indicated by the star markers. The green triangle represents the location of the Krong H'ngang dam and the automatic water level gauges. The color indicates the elevation from low (blue color) to high (red color) values. The upper part of the Krong H'ngang basin (including Sub1, Sub2, and a part of Sub5) is located in the climate-affected area west of the Truong Son Mountain range, with an average terrain elevation of 670 m. The rainy season is from May to November. The average daily maximum rainfall for 28 years (1978-2006) varies between 100 and 130 mm (EVN-PECC4, 2007). The lower part of

the Krong H’nam basin is in the climate-affected area of East Truong Son, with an average topographic elevation of 350 m. Typhoons and weather disturbances from the East Sea (Vietnam) strongly influenced this region. The flood season often occurs from October to December. The average daily maximum rainfall for 28 years is 250-350 mm (EVN-PECC4, 2007).

2.2. Dataset

Observed data from the Krong H’nam hydropower reservoir monitoring system, covering the period from September 2016 to December 2021 and containing 33 flood events were used in this study. These data are plotted in Figure 2 (note that data between floods are not displayed). Among them, approximately 55% of the dataset (the first 18 flood events) were used for estimating the feasible range of each parameter in the HEC-HMS model based on manual calibration with trial-and-error. The next five events (15% of the dataset) from #19 to #23 were used for testing the auto-calibration of the Krong H’nam flood forecast program, and the remaining (#24 to #33) were used for real-time flood forecasting.

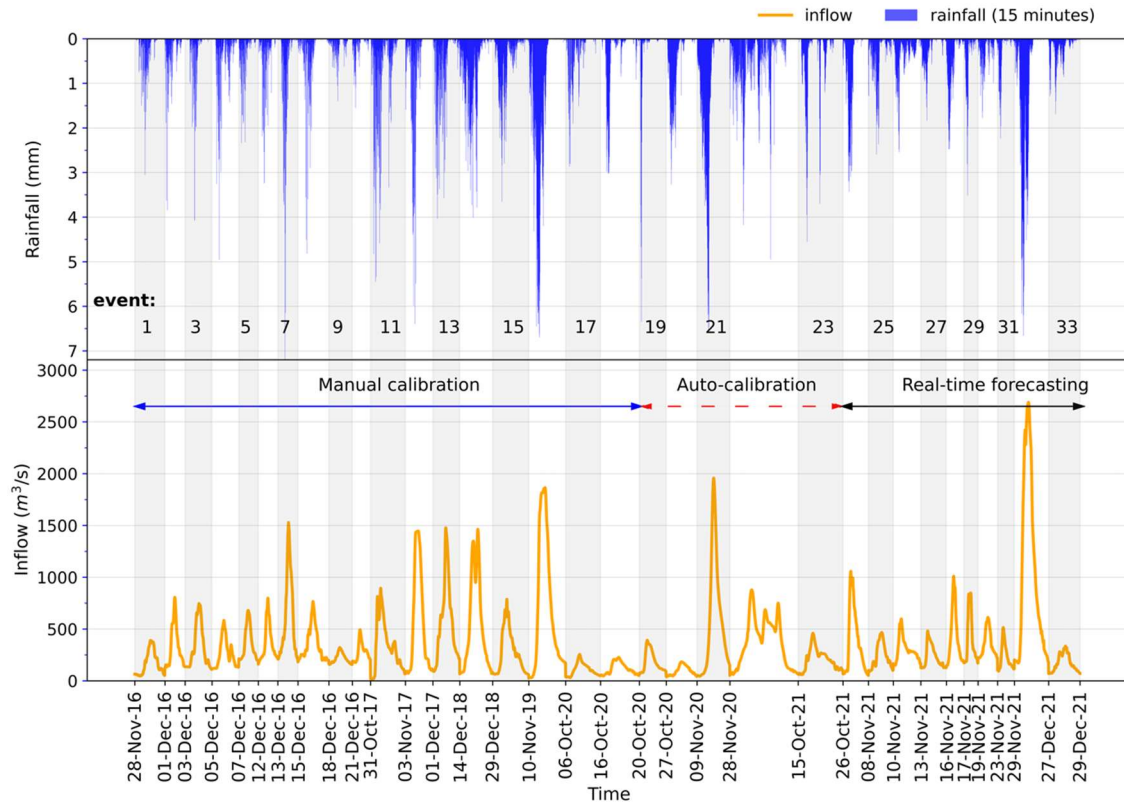


Figure 2. Observed rainfall and flood data from the 33 flood events.

Several statistics of the storm events including rainfall duration, depth, intensity, and time to peak are presented in Table 1. A rainfall event can peak within a few hours to a day and lasts from one to four days with a total depth between 18 mm and 278 mm. Note that for the Krong H'ngang reservoir, the threshold value of inflow discharge, which is considered a flood to the reservoir, is not specified in the design documents or the operation procedure. In this study, the authors used all rainfall-runoff events based on the live database with a rainfall duration of more than 12 hours and complete flood graphs (base flow, rising limb, flood peak, and receding limb). Regular floods last approximately 42 hours on average and up to 102 hours, the time to flood peak varies from 8.5 hours to 32.8 hours. The average peak discharge is about 850 m³/s, while the maximum one is 2,710 m³/s. The average total flood volume is about 55 x 10⁶ m³, and the largest is 192 x 10⁶ m³. In addition, several other statistics on the intensity of flood events are detailed in Table 1.

Table 1. Statistics of the intensities of the 33 flood events from 2016 to 2021.

Statistics	Min	Mean	Max
Duration (h)	21.0	42.0	102.0
Total rainfall depth (mm)	18.0	82.7	278.0
Rainfall intensity (mm/ h)	0.63	1.86	5.00
Time to rainfall peak (h)	3.0	9.9	20.0
Flood peak (m ³ /s)	182.3	849.0	2.710
Total flood volume (10 ⁶ m ³)	16.5	54.6	192.0
Time to flood peak (h)	8.5	18.3	32.8
Lag time (h)	1.0	8.0	15.5
Baseflow Q ₀ (m ³ /s)	20.0	110.0	221.0

In addition to the basic statistics, the correlations between total rainfall, total flood volume, peak discharge, and peak rainfall are also presented in Figure 3. Typically, the relationship between rainfall and runoff is nonlinear because it depends on various factors related to the basin characteristics and the antecedent conditions. However, if we approximate the relationship between total rainfall and flood volume in the Krong H'ngang River basin by a linear regression model, the results show that the correlation is quite strong with a coefficient of determination of $R^2 = 0.768$. This relationship is useful for a rough estimation of the flood volume coming to the reservoir when knowing the forecasted amount of total rainfall.

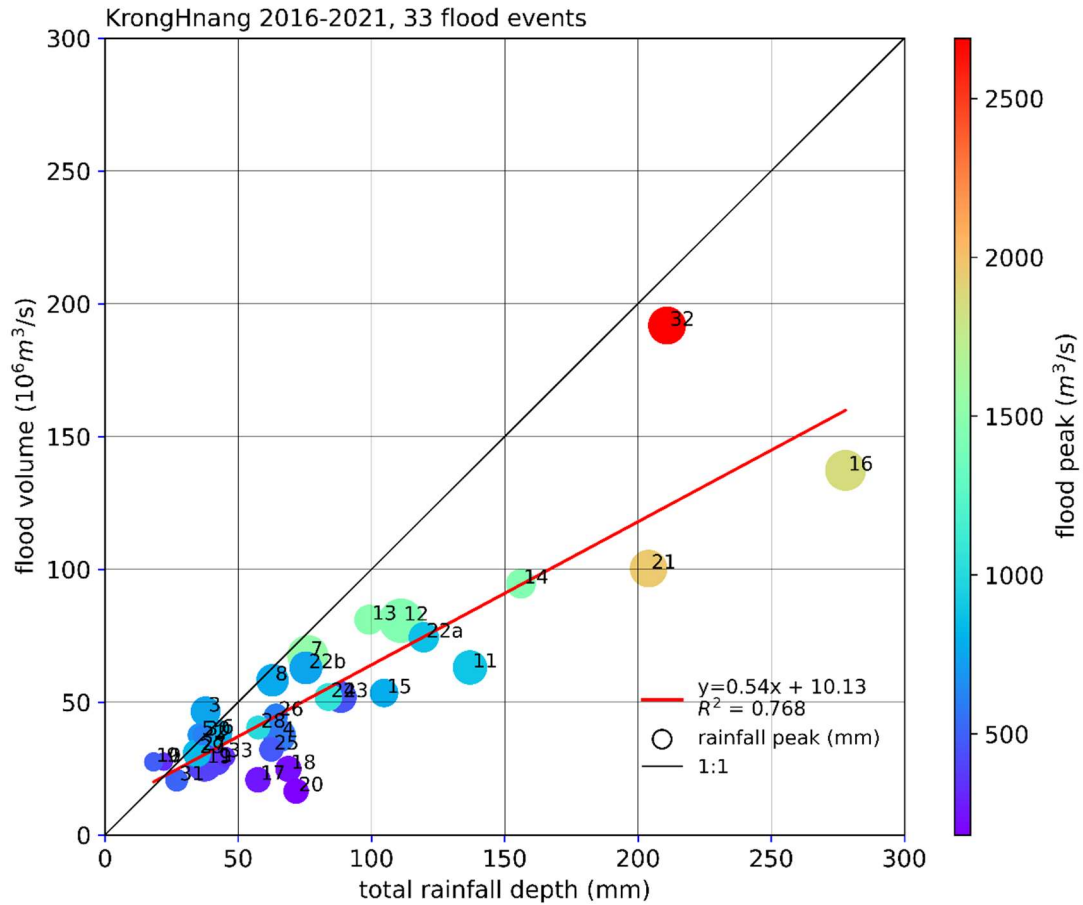


Figure 3. Relationships between total rainfall depth (horizontal axis), flood volume (vertical axis), flood peak (color range), and rainfall peak (point size). The straight red line shows the linear relationship between the total rainfall depth and the flood volume.

3. Methodology

3.1. Model structure and descriptions

KrongHnang-RTFF (Krong H’ang Real-Time Flood Forecasting) is a real-time operated program with inputs and outputs updated every 15 minutes, which is similar to the observed frequency of rain gauges. The program is developed using the Python language and relies on the HEC-HMS as the core rainfall-runoff component for real-time flood simulation and forecasting for the Krong H’ang hydropower reservoir. The main components of the program are shown in Figure 4, including: (1) a live database, (2) input data, (3) model parameter configuration, (4) calling and implementing the HEC-HMS

model, (5) auto-calibration or global optimum search, (6) forecast flood hydrograph and confidence interval, (7) output and model performance, and (8) update for the next time step. The details of each step are as follows:

3.1.1 Live database

The database consists of observed data, parameters, and output data. Several functions and scripts have also been developed to collect and synchronize data from observing devices or those retrieved from other sources. For the Krong H'ngang River basin, real-time observed rainfall data from 15 automated rain gauged stations, reservoir water level, reservoir inflow, and release (through spillways and turbines) data are automatically stored on an SQL Server (an online database).

3.1.2 Input data format and conversion

In order to meet the HEC-HMS data format requirements, we developed a library that seamlessly converts standard time-series data stored in the live database to the HEC-DSS format and vice versa using the Python language. This library can efficiently handle different data formats in less than a second, making it ideal for real-time data access.

3.1.3 Model setup and parameters configuration

The setup parameters for the HEC-HMS hydrological model include parameters describing the hydraulic properties of the basin, meteorological models, and real-time updates. These parameters are stored in the system files in "ASCII text" format, which can be accessed by external programs. As this is an important part, further details of the HEC-HMS model setup for the Krong H'ngang basin are presented separately in Section 3.2.

3.1.4 Automatically implementing the HEC-HMS model

The HEC-HMS model has no automatic function. Consequently, to simulate a flood event, users need to utilize function buttons manually, which requires a lot of time and effort. It is therefore inappropriate for flood forecasting. Therefore, we developed a submodule using the Python language that can automatically control the HEC-HMS model in real-time.

3.1.5 Automatic calibration

The KrongH'ang-RTFF program uses the SCE-UA algorithm (Duan et al., 1992) implemented in the SPOTPY library (Houska et al., 2015) to evolve and search for the optimal solution of different model parameters within the feasible domain from the initial solutions. To create the initial solutions, we used the Latin Hypercube Sampling (LHS, McKay et al., 1979) method to efficiently sample the parameter values throughout the feasible domain. Depending on the computer's strength, the number of repetitions (i.e., the repeat of the search and evolution) can be set to a few thousand or more to maintain a balance between computation cost, efficiency, and the accuracy of the search results. In this study, we used a workstation computer with the following configuration: AMD Ryzen 64 cores, 128 threads, 4.3 GHz CPU, and 64 Gb RAM. The search for the optimal solution is divided into two phases (or two stages) to enhance the search speed and accuracy while accommodating for the time constraints (i.e. updated data and results every 15 minutes). Phase 1 uses 1,000 repetitions to search for the optimal solution and is served as the raw solution for the next phase. In phase 2, the optimal result of Phase 1 is used as the centre for re-sampling the initial solutions (30% of margin to each side and not to exceed the limit of each parameter) and 5,000 repetitions are used to evolve and search for the final optimal solution. As this is the core of the parameter optimization,

further details on the LHS procedure as well as the SCE-UA algorithm are presented in Section 3.3.

3.1.6 Output data

The output results, including the optimal solution and different confidence interval bands, are computed based on the simulation results of the HEC–HMS model in the evolutionary process governed by the SCE–UA algorithm. The optimal solution is selected on the Pareto front of a predefined multi-objective function. The uncertainty of prediction results (presented as confidence ranges of $Q_{5\%}$ - $Q_{95\%}$ and $Q_{25\%}$ - $Q_{75\%}$.) are estimated using the Generalized Likelihood Uncertainty Estimation (GLUE, Beven et al., 2001) method. Further details on the objective functions and the GLUE method are presented in Section 3.4.

3.1.7 Results visualization and data storage

To support the managers and decision-makers in operating the Krong H’rang hydropower dam, the program displays the results through a Graphic User Interface (GUI). This helps to visualize the observed rainfall-runoff process occurring in real-time as well as the goodness-of-fit, the trend of the forecasted results, and the uncertainty of the model prediction. All the parameter values and the forecasted results of the current time step are exported and stored in the SQL Server database.

3.1.8 Update for the next time

After 15 minutes, the live database is updated with the new rainfall data, reservoir water level, inflow, and outflow. The entire process is then repeated.

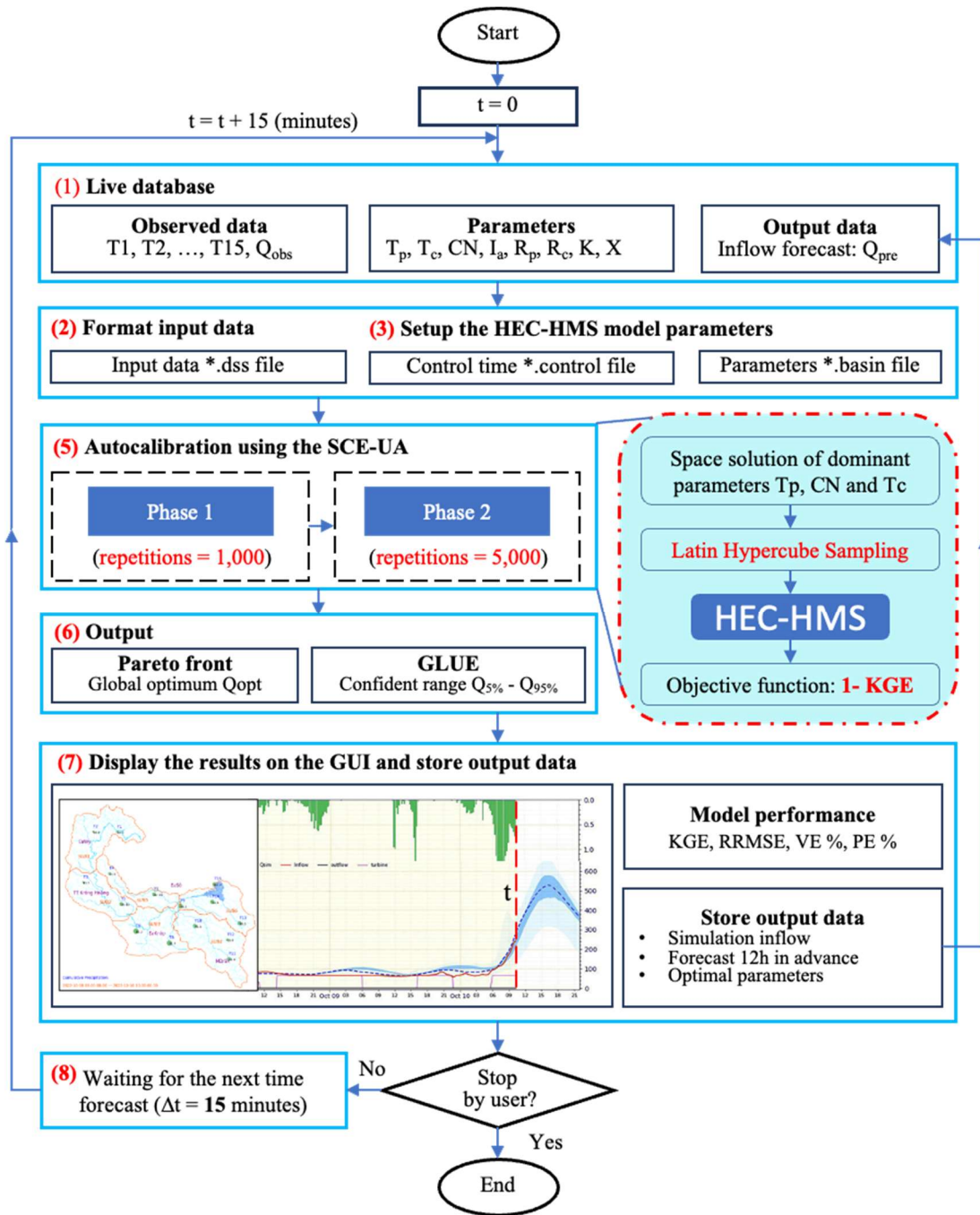


Figure 4. Model structure of the Krong H'ngang-RTFF program.

3.2. The HEC-HMS model for the Krong H'ngang River basin

The HEC-HMS model of the Krong H'ngang River basin (Figure 5) contains six subbasins from Sub1 to Sub6. The main river from the outlet of Sub1 to the Krong H'ngang reservoir is composed of four river segments from Reach1 to Reach4 (see the details in *Appendix A1*). To represent the Krong H'ngang basin hydrologic conditions in the HEC-HMS, the

initial and constant rate (Ia) and Curve Number (CN) were selected for the loss model, the Snyder's unit hydrograph (Snyder's UH) was selected for direct runoff, the exponential recession mode was selected to calculate baseflow and the Muskingum method was chosen for the channel routing method. The subbasin average precipitation of the meteorological model was calculated using the Thiessen polygons method.

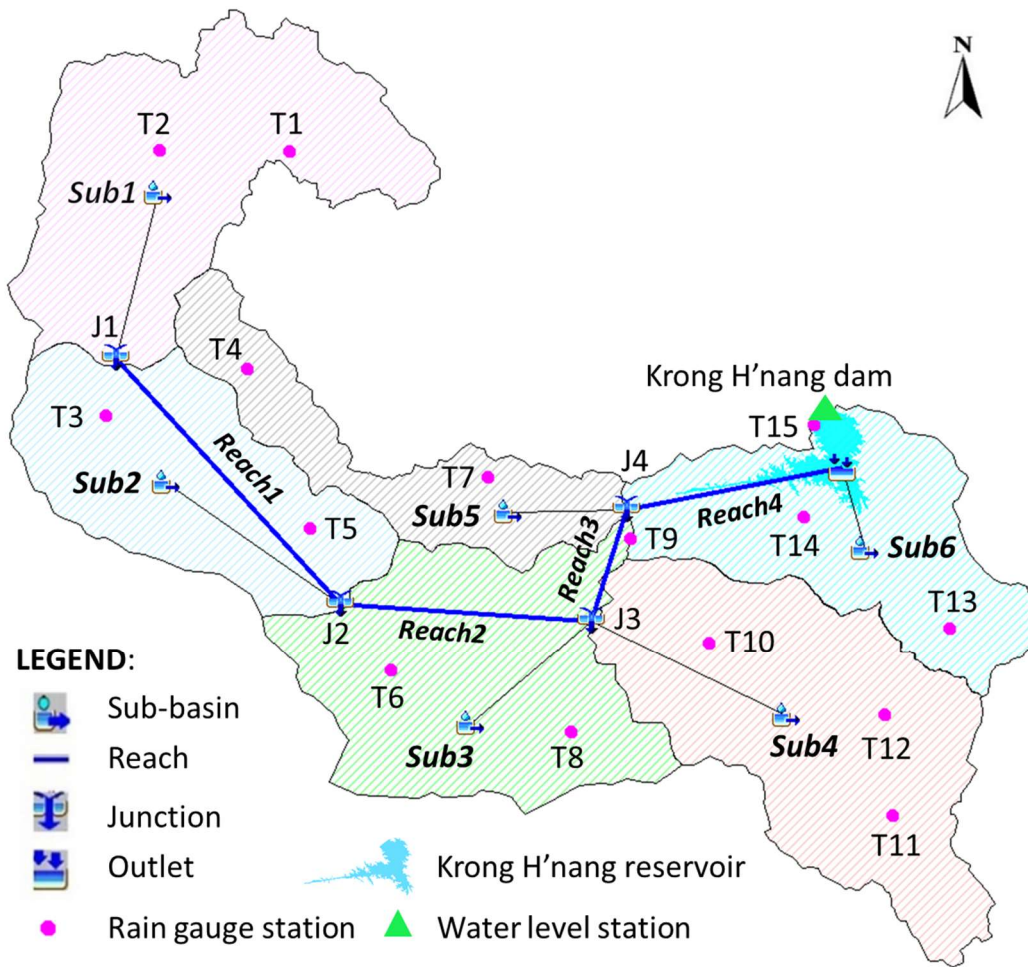


Figure 5. The HEC-HMS model for the Krong H'ngang River basin.

The number of parameters is quite large for the Krong H'ngang basin. A total of 50 parameters are required (7 parameters for each of the 6 subbasins plus 2 parameters for each of the 4 river sections). This can cause different problems when searching for the global optimal values of different model parameters. To enhance the search speed and accuracy, two things can be done: (i) by shortening the feasible range for each parameter, and (ii) by reducing the number of dimensions of the parameter space. The former is done

based on the observed data and the experience playing with the HEC-HMS model for the area of interest during the manual calibration of the first 18 flood events. The latter is done by performing a sensitivity analysis of model parameters. Some parameters are much less sensitive than others. In this sense, an average value can be used for these parameters instead of varying them and searching for the optimal values.

3.3. Automatic calibration using the LHS method and the SCE-UA algorithm

After determining the feasible domain of the parameters for the study basin, we used the SCE-UA algorithm to search for the global optimum solution (see Figure 4). The first step is to generate initial solutions by sampling the parameter values throughout the feasible domain using the LHS method. Since it considers the previously generated sample points, this approach is much more efficient than the traditional random sampling one because the number of samples used to cover the solution space is reduced by approximately 50% (McKay et al., 1979).

After seeding the sample with s initial parameter combinations, the SCE-UA algorithm will then divide these parameter sets into different search groups (known as different complexes). Each parameter set is then passed to the HEC-HMS model to simulate the rainfall-runoff process. Each simulated flow is then evaluated by comparing it with the observed data using the Kling-Gupta efficiency (KGE) index. The SCE-UA algorithm will then shuffle the parameter sets between different complexes to exchange information and avoid being trapped within the local optimum. New parameter sets are then generated in a good search direction (evolution). This evolution and shuffling will be repeated until the convergence condition is satisfied or the number of iterations specified by the user is reached (e.g., repetition n , $pcento$, $ppeps$ values in the SCE-UA algorithm). Details of the SCE-UA algorithm (by Duan et al., 1992) and how we adapted

the HEC-HMS as a simulation component within the algorithm can be found in *Appendix A2*.

Since the SCE-UA algorithm in the SPOTPY library is limited to only one objective function, we chose the KGE index as the criterion for the program to shuffle and evolve the complexes. The good thing about the KGE is that it also includes the coefficient of determination R , standard deviation, and mean value. However, this is not the case in selecting the final optimum solution, as we can use a multi-objective function by adding another objective function in addition to the current KGE index. It is noted that no single index can account for all aspects of the flood path (such as flood shape, peak discharge, timing, and total flood volume), multiple indices are needed to evaluate model performance effectively (Beven, 2010). For the flood forecasting of the reservoirs for operation, the total flood volume is another key factor in decision-making (Nguyen et al., 2022). Therefore, the final solution is selected on the Pareto front which show the best trade-off relations between two objectives (Mays & Tung, 2002). Here, it is the minimization of both $(1-KGE)$ and the absolute relative volume error $|VE|$ functions. The equations for computing the KGE and $|VE|$ indices are provided in *Appendix A3*.

3.4. Model prediction uncertainty analysis using the GLUE method

The authors use the GLUE method (Beven & Freer, 2001) to analyze the reliability of the forecasted results. The model parameter sets (the solutions) are evolved by the SCE-UA algorithm, with 1,000 times in Phase 1 and 5,000 times in Phase 2, respectively. The model parameter sets are extracted and divided into the accepted and non-behavioural regions. A cut-off threshold is defined by a certain allowable deviation of the maximum likelihood value occurring in the sample. In this study, we used a $KGE = 0.65$ as a common threshold to divide the sample space. The good solutions are retained for calculating the Cumulative Distribution Function (CDF) of the model results. The

CDF of variable KGE is defined as equation (1). For all x where the right-hand side represents the probability that the variable KGE takes on a value less than or equal to the threshold $KGE = 0.65$.

$$F_{KGE}(x) = P(KGE \leq x) \quad (1)$$

The CDF is then used to compute different confidence intervals (5% to 95%) as well as the probability distribution (posterior) of the parameters.

4. Results and Discussion

4.1. Manual calibration and parameter ranges

To assess the model performance, in addition to the two indices (KGE and VE) mentioned in Section 3.3, the relative root mean square error ($RRMSE$) and the relative peak error (PE) of the simulation results were also computed. The equations for computing their values are provided in *Appendix A3*. The results of the manual calibration are shown in Table 2. It can be seen that the model performs very well. On average, KGE is 0.88 and VE is 6.40 %. The lowest KGE is 0.66 and the worst value of VE is 14.27 %.

Table 2. Model performance from manual calibration of 18 floods (from #1 to #18).

No.	KGE	RRMSE	PE %	VE %	No.	KGE	RRMSE	PE%	VE%
1	0.868	0.189	7.48	10.50	10	0.849	0.158	-2.97	4.78
2	0.815	0.253	-19.47	8.89	11	0.776	0.293	16.12	5.56
3	0.934	0.138	-1.40	-6.03	12	0.936	0.146	5.93	5.72
4	0.872	0.257	-0.30	7.52	13	0.929	0.190	-8.16	4.90
5	0.925	0.104	-8.16	2.61	14	0.915	0.213	-0.79	6.53
6	0.660	0.285	2.66	14.27	15	0.947	0.183	4.54	-1.72
7	0.905	0.159	-2.78	-6.04	16	0.977	0.106	4.20	-0.54
8	0.744	0.191	-0.67	-0.63	17	0.934	0.142	-11.19	4.16
9	0.958	0.054	-0.25	-3.64	18	0.875	0.139	9.53	1.34

Based on the results of the manual calibration, the feasible ranges of different HEC-HMS model parameters for the Krong H'ng basin are defined as shown in Figure 6. Compared to the original suggested values in the HEC-HMS manual, the parameter ranges of several parameter types are reduced significantly (see *Appendix A1*). This plays

an important role in narrowing down the parameter search space and leads to an enhancement of search speed and accuracy. For example, the time of concentration T_p range is shortened from 0-500 hours to 0.5-16 hours only. The Muskingum travel time K is only a few hours instead of the maximum value of 150 hours. Similarly, the ranges of curve number CN , the ratio to peak coefficient R_p , and the Muskingum adjustment coefficient X , are reduced by about 50% or more.

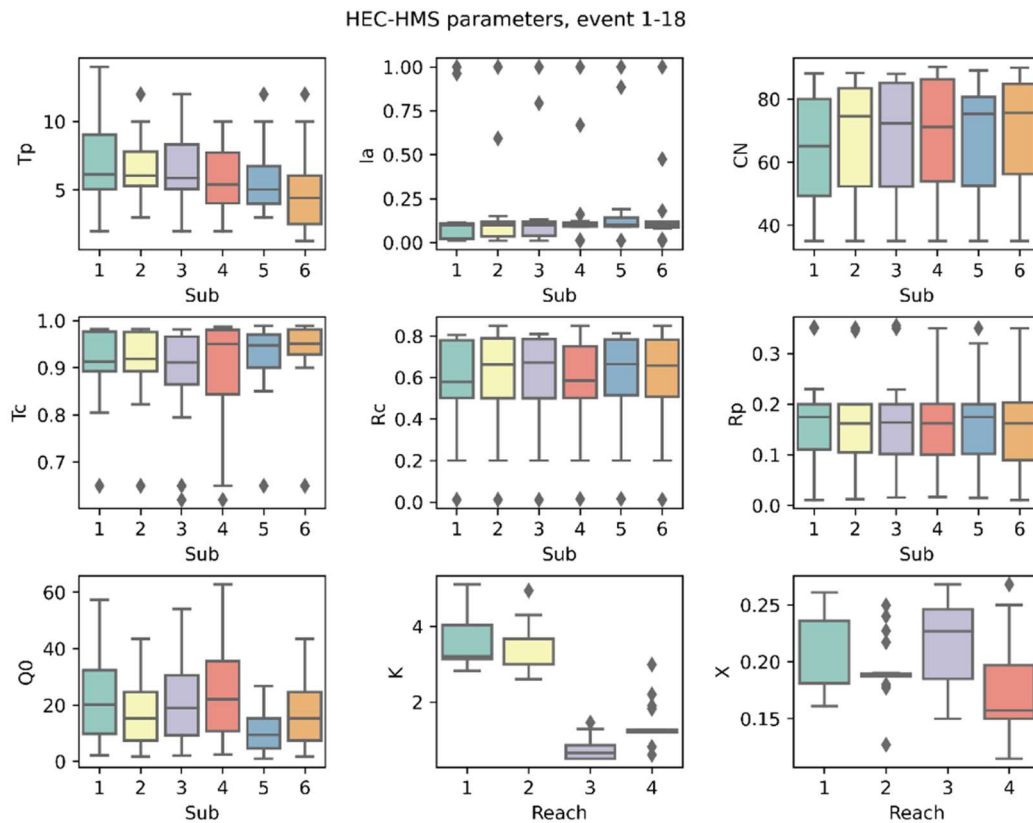


Figure 6. The parameter space of the HEC-HMS model in the Krong H'nang reservoir basin is based on the results of the manual calibration of 18 floods (from #1 to #18).

4.2. Parameter sensitivity analysis

Among the nine parameter types of the HEC-HMS model as described in Section 4.1 above, five types of them are more sensitive than the others. These five types of parameters include: standard lag T_p , coefficient T_c in the Snyder's UH method, curve number CN , initial loss I_a in the SCS Curve Number method, and the time travel K in

the Muskingum routing method. To understand the sensitivity of each parameter type and the effect of different parameter combinations, all possible combinations of these parameter types based on their min and max values were simulated in the HEC-HMS.

For example, for the three most sensitive parameters, Tp , CN , and Tc (based on manual calibration experience), a combination of $2^3 = 8$ parameter sets were simulated (see Figure 7).

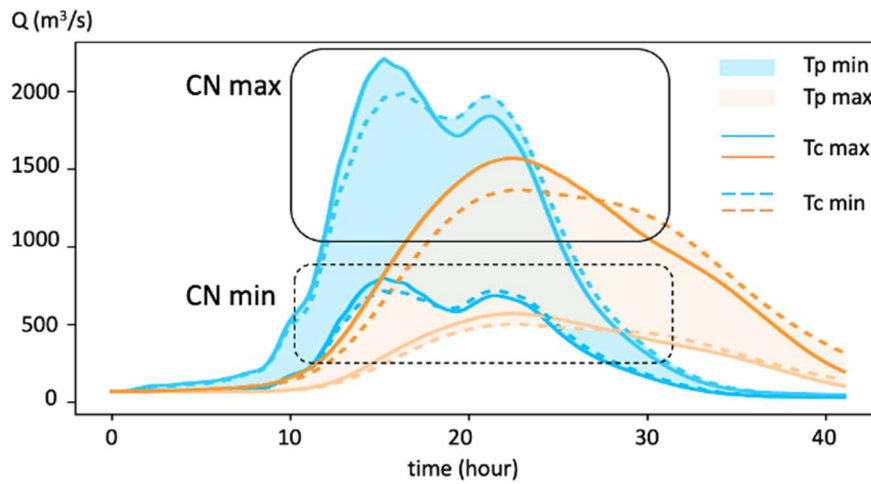


Figure 7. Sensitivity analysis of eight parameter set combinations based on the minimum and maximum values of Tp , CN , and TC , as illustrated for flood event #12.

The results show that when the time of concentration Tp changes from the minimum value (represented by blue) to the maximum value (represented by orange), the flood shape changes drastically. For a small Tp value (i.e., fast concentrated flood), the flood quickly increases to the peak value and then decreases, whereas a large Tp causes flood peaks to appear much slower, flattening out and declining much slower. For the same Tp value, if CN is changed from a minimum value to a maximum value, the peak discharge and the total flood volume increase sharply. The CN_{max} corresponds to a larger flood peak and a larger flood volume, whereas CN_{min} significantly reduces the flood peak and decreases the flood volume. The parameter Tc is much less sensitive than Tp and CN are, but Tc also affects the magnitude and shape of the flood peak, which is correlated with the shape of the rainfall graph.

Similarly, we performed simulations of a total of $2^5 = 32$ parameter set combinations when considering both the travel time K and initial loss Ia parameters. The analysis results revealed that the Muskingum K of the river sections affected the time of occurrence of the flood peak, the shape, and the magnitude of the flood. However, the range of K values in the reach is quite small (see Figure 6), so it is not sensitive and has less influence on the simulation results. The initial loss Ia value is low and does not affect much the entire flood hydrograph but only slightly on the flood foot of the rising limb. This is because, during the main flood season, the soil is almost saturated due to previous consecutive rains. In fact, 90% of the value range of Ia is quite small, at only approximately 0.05 to 1.00 mm (Figure 6). Therefore, parameter Ia also becomes less significant. This is completely different from the continuous simulation of multiyear flow, where Ia plays an important role.

4.3. Auto-calibration and uncertainty analysis

Based on the parameter sensitivity analysis, the authors chose to vary only the values of three sensitive parameter types: Tp , CN , and Tc . This reduces the number of dimensions of the parameter space from 50 to 18 dimensions. This finding is crucial as it helps to significantly speed up the search speed, especially in the context of real-time simulation for the Krong H'nang basin. In addition to the three dominant parameter types, the initial flow parameter Q_0 is based on the actual measured values at the beginning of the simulation. The remaining 5 parameter types (Ia , Rp , Rc , K , and X) are simulated in the model using their median values.

Figure 8 shows the automatic search results of the last evolution when optimizing the model parameters for flood event #22 for both Phase 1 and Phase 2. Their optimal solutions (opt1 and opt2) are also displayed on the same graph, respectively. It can be

easily seen from the graph that by using two phases of search, the search space is improved. Most of the points in Phase 2 fall close to the optimal solution compared to those of Phase 1, which leads to an improvement in the search result. The KGE value of the optimal solution increases from 0.922 in Phase 1 to 0.976 in Phase 2.

In addition, we can also see that using multiple objective functions (here is the minimization of both $(1-KGE)$ and $|VE|$ functions) on the Pareto fronts led to a better choice of the optimal solution compared to that of only a single objective function. For example, if we only use the $(1-KGE)$ function, then there exist several optimal solutions with almost similar $(1-KGE)$ values at the end of Phase 1 but the $|VE|$ can vary between 0 and 6%.

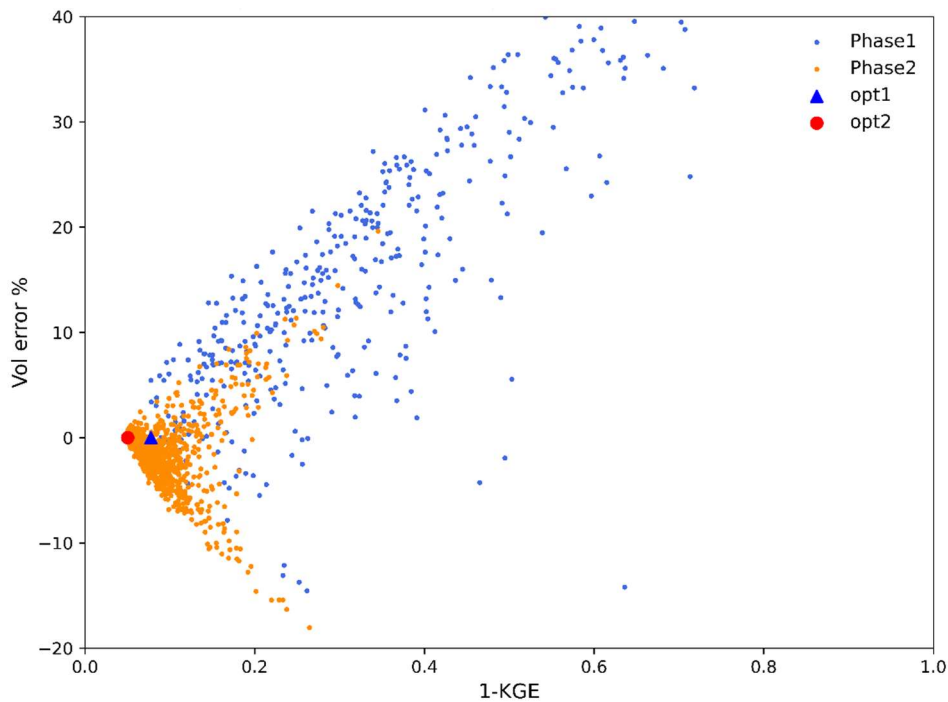


Figure 8. Optimal solutions of Phase 1 and Phase 2 are selected based on the Pareto fronts with two objective functions: (i) minimization of $1-KGE$ and (ii) minimization of $|VE|$ (%) of flood event #22.

Figure 9 shows the entire observed hydrograph of flood event #22 and the simulated result corresponding to the optimal parameter sets of Phase 1 and Phase 2. The confidence intervals corresponding to $Q_{5\%}$ - $Q_{95\%}$, and $Q_{25\%}$ - $Q_{75\%}$ based on the ‘accepted’

solutions according to the GLUE analysis are also added to the graph. Visually, it can be seen that not only has the optimal solution improved from Phase 1 to Phase 2, but also the confidence intervals have been narrowed. The uncertainty range has decreased and closely follows the observed data.

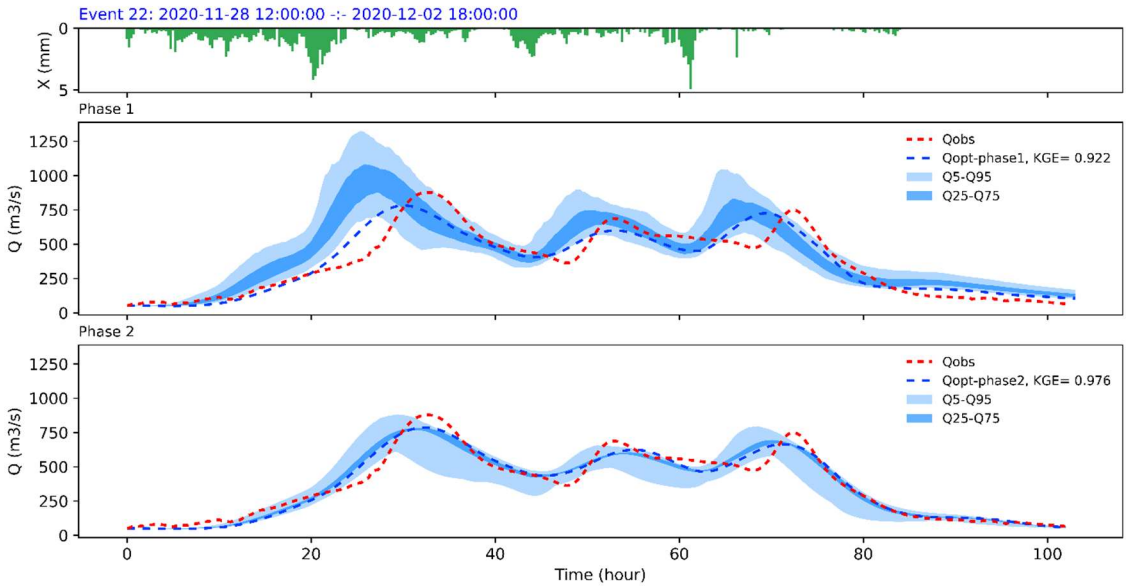


Figure 9. Optimal solution and model prediction uncertainty of the flood event #22.

The same procedure is applied to other flood events (from #19 to #23). Table 4 summarizes the simulation results based on the different indices to assess the Krong H'ngang-RTFF program's performance in the automatic detection of the optimal parameter sets.

Table 3. Summary of the auto-calibration results for flood events from #19 to #23.

No.	KGE		RRMSE		PE %		VE%	
	Phase1	Phase2	Phase1	Phase2	Phase1	Phase2	Phase1	Phase2
19	0.918	0.987	0.141	0.089	5.48	1.17	7.12	-0.23
20	0.537	0.783	0.245	0.210	-19.53	-4.37	-13.36	-6.65
21	0.935	0.985	0.200	0.172	17.49	9.29	-3.89	-0.15
22	0.922	0.976	0.202	0.199	8.81	7.61	0.05	-0.03
23	0.886	0.882	0.246	0.237	8.73	13.46	-0.68	0.67

4.4. Real-time flood forecasting

Based on the results of the auto-calibration above, the program was then applied for the real-time flood forecast of ten flood events from #24 to #33. Figure 10 shows the forecast

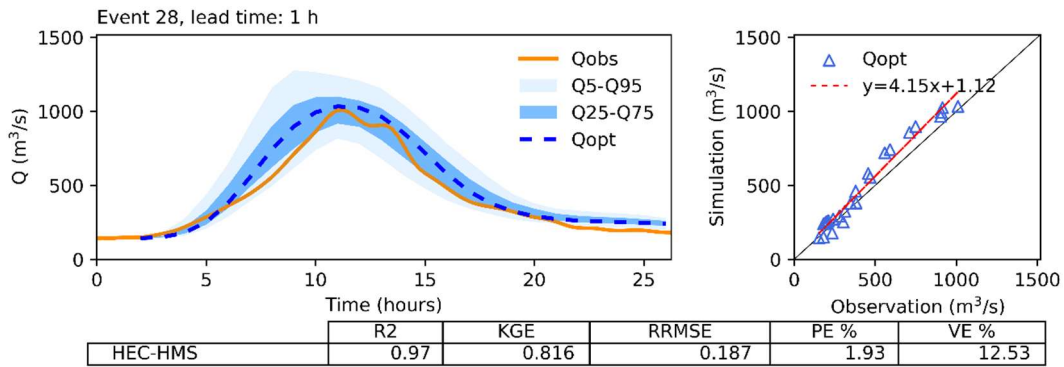
results for flood #28 at different lead times (1, 3, 4, and 6 hours). The scatter plots between the observed and simulated data are also presented next to the forecasted time series plots. The results show that for this event, the model forecasts the flood hydrograph very well within 6 hours in advance, with R^2 decreasing from 0.97 for the 1-hour lead time to 0.85 for the 6-hour lead time. In addition, the forecasted results are well captured within the uncertainty range between $Q_{5\%}$ and $Q_{95\%}$.

Table 4 summarizes the results of evaluating the reliability of the forecasting model at different lead times from 1 to 6 hours for ten flood events from #24 to #33. The results based on different criteria show that the model generally performs well up to $t + 4$ hours, with $KGE > 0.8$ and $|VE| < 10\%$. The comparison of evaluation criteria at different lead times is shown in Figure 11 (depicted in orange).

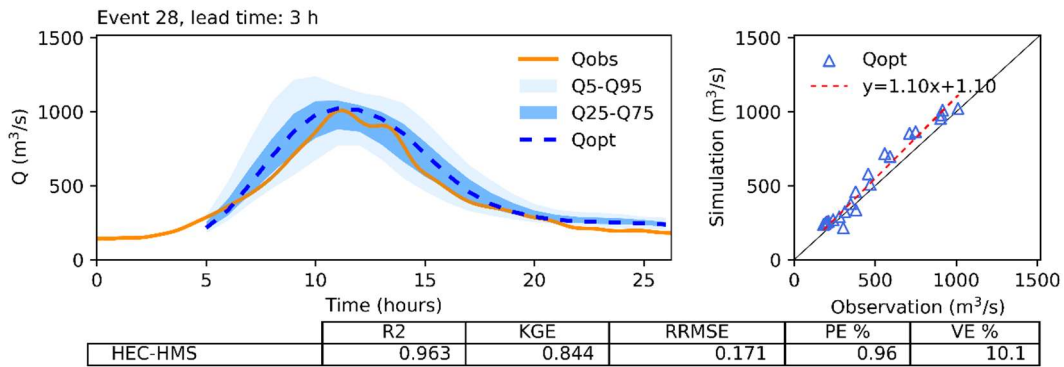
Table 4. Summarizes the model error evaluation criteria for flood events from #24 to #33.

No.	Lead time (h)	t+1	t+2	t+3	t+4	t+5	t+6
24	KGE	0.929	0.766	0.847	0.822	0.682	0.453
	VE %	-5.56	-7.32	-6.66	-7.48	-9.65	-14.60
25	KGE	0.919	0.895	0.835	0.823	0.715	0.582
	VE %	-2.16	-6.31	-9.47	-10.06	-22.17	-25.37
26	KGE	0.954	0.845	0.837	0.841	0.620	0.550
	VE %	2.33	-5.53	-8.94	-9.14	-12.37	-23.57
27	KGE	0.881	0.898	0.804	0.724	0.603	0.533
	VE %	4.96	-3.71	-7.88	-8.58	-12.75	-15.07
28	KGE	0.816	0.83	0.844	0.933	0.870	0.860
	VE %	12.53	10.80	10.10	3.45	-4.25	-6.76
29	KGE	0.949	0.838	0.762	0.724	0.672	0.645
	VE %	0.38	-7.94	-9.03	-9.86	-21.11	-26.85
30	KGE	0.919	0.914	0.905	0.856	0.741	0.756
	VE %	-0.49	-1.90	-5.93	-8.47	-14.92	-19.93
31	KGE	0.868	0.857	0.848	0.654	0.525	0.506
	VE %	-6.05	-7.96	-8.35	-9.81	-13.80	-20.04
32	KGE	0.849	0.852	0.763	0.693	0.649	0.570
	VE %	-0.84	1.15	-2.30	-4.06	-7.08	-11.65
33	KGE	0.831	0.854	0.895	0.917	0.843	0.710
	VE %	2.65	4.65	6.64	7.85	-6.42	-14.80

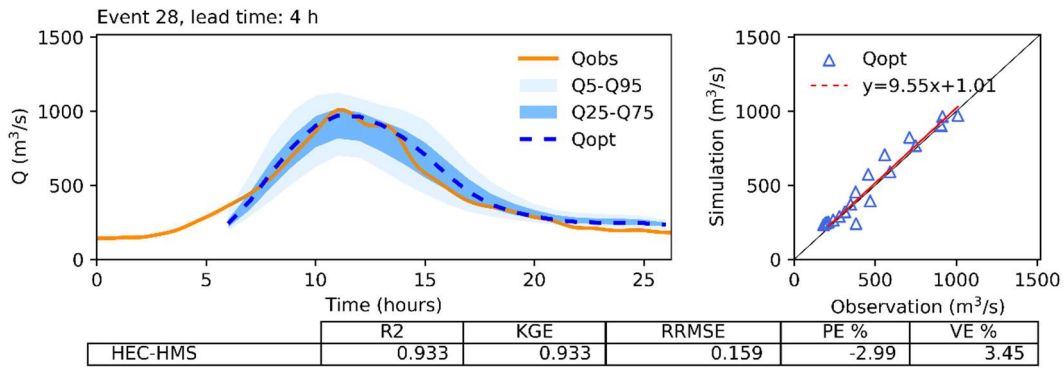
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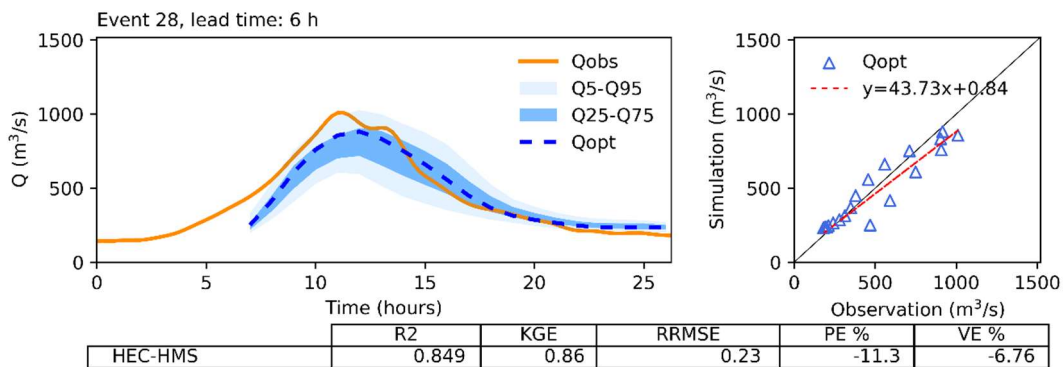
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470 Figure 10. Flood forecasting results for event #28 for different lead times. In the left
 471 figure, the solid orange line is the actual measured flow Q_{obs} , and the blue dashed line is
 472 the Q_{opt} optimal solution. The shaded area represents the confidence intervals $Q_{5\%}$ - $Q_{95\%}$
 473 and $Q_{25\%}$ - $Q_{75\%}$ of the forecast results.

4.5. Discussion

The HEC-HMS model shows a high forecast reliability for the results of less than 6 hours lead time, which is pretty similar to the behaviour of natural lag time from the upper catchment to the outlet of the Krong H’ngang River basin based on the analysis of the rainfall-runoff correlation. Beyond this period, the accuracy and uncertainty of the forecasted results decrease significantly.

To increase the lead time forecast (i.e., an earlier prediction), the authors suggest the use of additional forecasted rainfall data from different sources, such as radar or global/regional numerical model predictions. For example, Azam et al. (2017) applied the HEC-HMS model to create an early flood warning system for the Mushim Stream watershed in Korea. They used short-range weather forecasts from the Korea Meteorological Administration at three-hour intervals to provide early warning flood information for floods with a lead time of up to 3 hours. Grek and Zhuravlev (2020b) predicted floods in the Polomet River basin of Russia using radar rainfall data, which combined radar and ground measurements with the Soil and Water Assessment Tool. They reported that using radar data greatly increases the efficacy of rainfall-runoff modelling.

Another strategy involves enhancing the performance of physically based hydrology models by integrating them with data-driven models (Barbetta et al., 2018; Saber et al., 2023). In a recent study, we combined the HEC-HMS model with an artificial neural network (ANN), and the findings revealed a significant improvement in flood forecasting accuracy for the Krong H’ngang River basin (Nguyen et al., 2024). The results revealed that the HEC-HMS-ANN hybrid model significantly improved the forecast quality, especially for results at a longer forecasting time. In detail, the KGE efficiency

index, for example, increased from $\Delta_{KGE} = 16\%$ at time $t + 1$ hour to $\Delta_{KGE} = 69\%$ at time $t + 6$ hours.

Talking about the value of the parameter set, we also compared the results of the new auto-calibration method (automatically detects the optimal parameters for each flood event) to those of the traditional method (which uses a fixed parameter set, often the average values, and remain unchanged post-calibration). The comparison results are plotted in Figure 11. From these violin plots, it can be easily seen that the new approach is superior to the conventional one. This is because the new method allows the hydrology model to dynamically self-correct errors, and to adapt well to the dynamic and variable nature of rainfall patterns and characteristics.

Table 5 shows the numerical comparison between the two methods based on the average KGE and VE values of the ten flood events for different lead times. Overall, model performance was enhanced, between $t+1$ and $t+6$ (hours), with increases in the model goodness indicators (on average, the relative differences $\Delta_{KGE} = 51.99\%$ and $\Delta_{VE} = 60.1\%$, equations for computing the Δ_{KGE} and Δ_{VE} are provided in *Appendix A3*) as the results of automatic detection utilizing the SCE-UA approach. The prediction accuracy significantly decreased when a fixed set of parameters was used; KGE ($t+6$) dropped to 0.17, almost four times lower than KGE ($t+1$) = 0.78.

Table 5. Comparison of the KGE and VE results of the new method (using SCE-UA) and the traditional one (fixed parameters)

Criteria	Lead time (h)	$t + 1$	$t + 2$	$t + 3$	$t + 4$	$t + 5$	$t + 6$	Average
KGE	Ideal	1	1	1	1	1	1	
	Fixed parameter	0.78	0.71	0.63	0.57	0.42	0.17	0.55
	Using SCE-UA	0.90	0.85	0.84	0.82	0.68	0.58	0.78
	Δ_{KGE} (%)	54.55	48.28	56.76	58.14	44.83	49.40	51.99
VE (%)	Ideal	0	0	0	0	0	0	
	Fixed parameter	-6.77	-7.95	-14.12	-21.25	-30.27	-37.7	-19.68
	Using SCE-UA	-0.05	-4.62	-7.27	-8.86	-12.56	-17.5	-8.48
	Δ_{VE} (%)	99.26	41.89	48.51	58.31	58.51	53.58	60.01

From Figure 11, it is noticed that the forecasted flood volume tends to be underestimated for a lead time longer than two hours (i.e. VE tends to be negative). A similar thing can be observed with the forecasted flood peak for lead time beyond three hours. This underestimation of the forecast can have a significant impact on the early release of flow to mitigate flood risks for the safety of dam and reservoir operations. Hence, an adjustment in the flood volume (based on the forecasted volume) of early release might help to compromise downstream flood reduction efforts and dam operation safety. Therefore, conducting uncertainty analysis on flood forecast information becomes crucial for practical operations. Depending on the rainfall measurement within the basin, coupled with total rainfall forecasts and correlation analysis, operational decisions can be adjusted towards the upper or lower uncertainty bound.

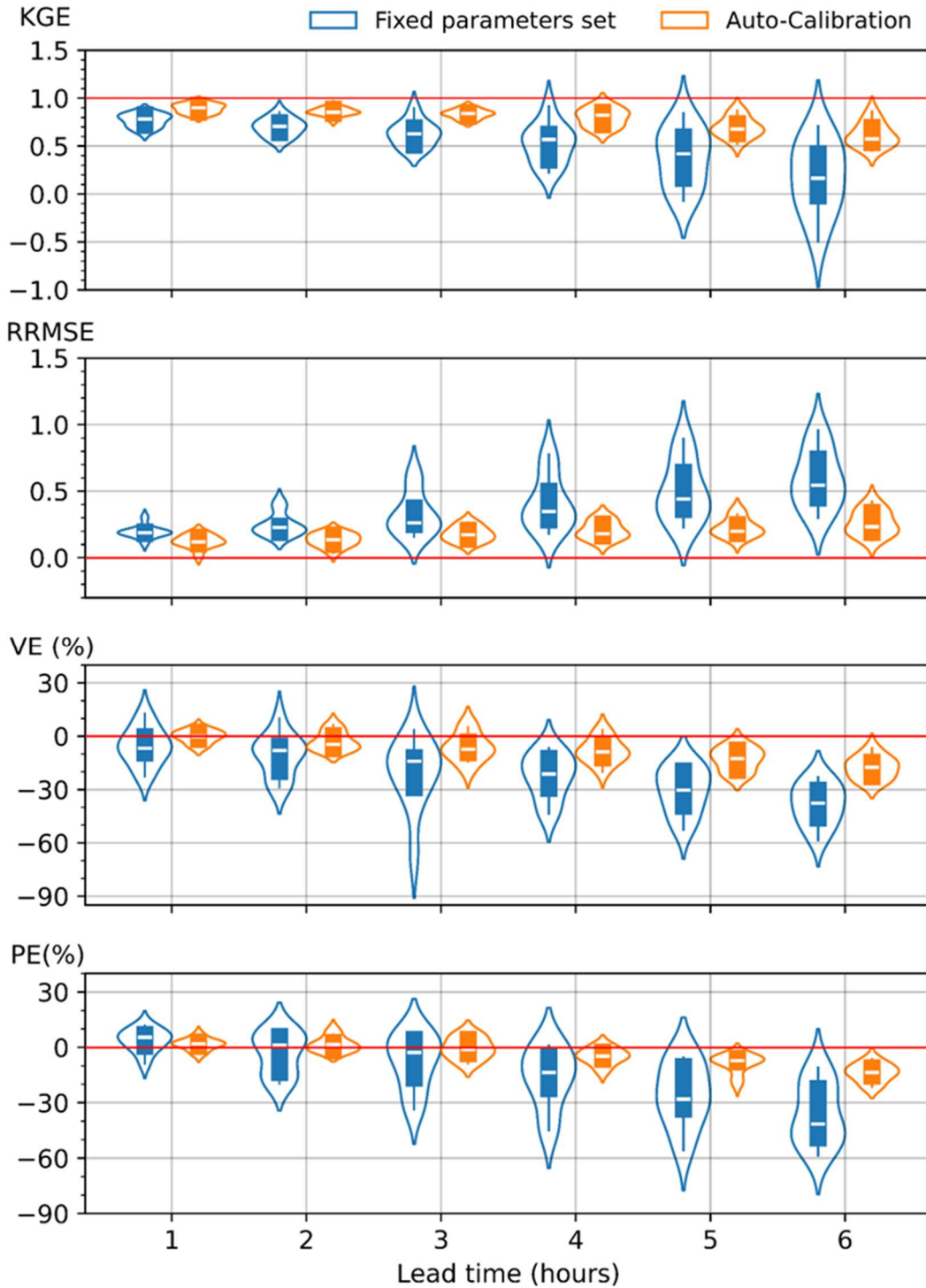


Figure 11. Compare and synthesize the model error evaluation criteria for ten flood events from #24 to #33, at lead-time steps $t+1$ to $t+6$ hours. The HEC-HMS model uses the fixed median parameters set (blue color), and the HEC-HMS model uses the auto-calibration SCE-UA methodology (orange color). The red line represents the ideal value of the metric.

5. Conclusions

This paper presents the development of a real-time flood forecasting program for the Krong H’ngang River basin in the Central Region of Vietnam by exploiting highly advanced automatic calibration approaches and uncertainty analysis. The program is based on Python scripting to automatically drive and update thousands of the HEC-HMS simulations of the rainfall-runoff process. The Latin Hypercube Sampling procedure was employed to efficiently sample parameter values across the feasible domain and the Shuffled Complex Evolution (SCE-UA) algorithm was used to search for the global optimum parameter value by complex shuffling and evolving. The optimal solution was selected based on the Pareto front of two different objective functions, including (i) minimization of the (1-KGE) function and (ii) minimization of absolute relative flood volume error $|VE|$. The uncertainty of the model prediction was analysed and computed using the Generalised Likelihood Uncertainty Estimation (GLUE) method.

Using the observed data from 18 out of 33 flood events, we established the parameter ranges or feasible search domains of different parameters for the Krong H’ngang HEC-HMS model. These parameter ranges are significantly narrower than those suggested in the HEC-HMS manual, which is designed to be used for a wide range of different kinds of watershed characteristics. Additionally, we conducted a sensitivity analysis of different parameter combinations and found that three types of parameters - time of concentration Tp , curve number CN , and adjustment coefficient Tc – were more sensitive than others. As a result, the dimensions of parameter space were reduced from 50 to 18, and the feasible solution domain became much smaller. This finding was crucial for enabling the search for an optimal solution with thousands of repetitions in real-time flood forecasting, with data and results updated every 15 minutes.

Our results indicated that the model forecasts the flood flow very well for lead time up to $t + 4$ hours, with the $KGE > 0.8$ and the absolute relative volume error $|VE| < 10\%$. The forecast results, determined by the optimal SCE-UA solution value Q_{opt} , agreed well with the observed data. In addition, the confidence interval was also computed for the uncertainty ranges. The results showed that observed values were well-captured within the uncertainty ranges. We also compared this approach to the traditional method which uses fixed parameter set values. Results revealed that the new method is superior to the conventional one.

As the forecast results beyond 6 hours are much less accurate, we recommend integrating additional forecasted rainfall data sources as well as combining the physically based hydrologic models with data-driven models to enhance lead time prediction and flood forecasting accuracy. By integrating advanced modelling techniques, leveraging additional data sources, implementing dynamic parameter optimization approaches, and uncertainty analysis, we can significantly enhance the accuracy and reliability of flood forecasts, ultimately contributing to more effective flood risk management in the Krong H'rang River basin.

Data availability statement

The datasets used in the current study are available from the Song Ba Joint Stock Company on reasonable request.

Acknowledgment

Phuoc Sinh Nguyen was supported by the Master Scholarship Program of Vingroup Innovation Foundation (VINIF), Institute of Big Data, code VINIF.2021.ThS.97 (Vietnam), and the Ph.D. Scholarship Program of Amano Institute of Technology (Japan). The authors acknowledge Song Ba Joint Stock Company (Da Nang, Vietnam) to provide the database. We thank the anonymous reviewers for their many insightful comments and suggestions, and we appreciate the support from the HEC-Support Team (USACE, USA) during this study.

References

- Abbaspour, K. C. (2015). SWAT-Calibration and uncertainty programs (CUP). *Neprashtechology*.Ca. <https://doi.org/10.1007/s00402-009-1032-4>
- Albo-Salih, H., & Mays, L. (2021). Testing of an optimization-simulation model for real-time flood operation of river-reservoir systems. *Water*, 13(9), 1207. <https://doi.org/10.3390/w13091207>
- Azam, M., Kim, H. S., & Maeng, S. J. (2017). Development of flood alert application in Mushim stream watershed Korea. *International Journal of Disaster Risk Reduction*, 21. <https://doi.org/10.1016/j.ijdr.2016.11.008>
- Barbetta, S., Coccia, G., Moramarco, T., & Todini, E. (2018). Real-time flood forecasting downstream river confluences using a Bayesian approach. *Journal of Hydrology*, 565. <https://doi.org/10.1016/j.jhydrol.2018.08.043>
- Beven, K. (2010). Rainfall-runoff modelling: The Primer, 2nd Edition. In *John Wiley & Sons, Ltd* (pp. 18–20).
- Beven, K., & Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of Hydrology*, 249(1–4), 11–29. [https://doi.org/10.1016/S0022-1694\(01\)00421-8](https://doi.org/10.1016/S0022-1694(01)00421-8)
- Chu, X., & Steinman, A. (2009). Event and Continuous Hydrologic Modelling with HEC-HMS. *Journal of Irrigation and Drainage Engineering*, 135(1), 119. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2009\)135:1\(119\)](https://doi.org/10.1061/(ASCE)0733-9437(2009)135:1(119))
- Cooper, V. A., Nguyen, V. T. V., & Nicell, J. A. (1997). Evaluation of global optimization methods for conceptual rainfall-runoff model calibration. *Water Science and Technology*, 36(5), 53–60. [https://doi.org/10.1016/S0273-1223\(97\)00461-7](https://doi.org/10.1016/S0273-1223(97)00461-7)
- Cooper, V. A., Nguyen, V. T. V., & Nicell, J. A. (2007). Calibration of conceptual rainfall-runoff models using global optimisation methods with hydrologic process-based parameter constraints. *Journal of Hydrology*, 334(3–4). <https://doi.org/10.1016/j.jhydrol.2006.10.036>
- Decision No. 878 Vietnam Gov. (2018). Process of the cascading reservoirs operation in Ba River basin.
- DHI. (2020). MIKE Powered by DHI. <https://www.mikepoweredbydhi.com/>

619 Duan, Q., Sorooshian, S., & Gupta, V. (1992). Effective and efficient global optimization
620 for conceptual rainfall-runoff models. *Water Resources Research*, 28(4), 1015–
621 1031. <https://doi.org/10.1029/91WR02985>

622 ECHO. (2021, December 3). Vietnam - Floods, update (Vietnam Disaster Management
623 Authority, Government of Vietnam, NCHMF, FloodList) (ECHO Daily Flash of
624 03 December 2021) - Viet Nam | ReliefWeb. [https://reliefweb.int/report/viet-](https://reliefweb.int/report/viet-nam/vietnam-floods-update-vietnam-disaster-management-authority-government-vietnam-nchmf)
625 [nam/vietnam-floods-update-vietnam-disaster-management-authority-](https://reliefweb.int/report/viet-nam/vietnam-floods-update-vietnam-disaster-management-authority-government-vietnam-nchmf)
626 [government-vietnam-nchmf](https://reliefweb.int/report/viet-nam/vietnam-floods-update-vietnam-disaster-management-authority-government-vietnam-nchmf)

627 Eckhardt, K., & Arnold, J. G. (2001). Automatic calibration of a distributed catchment
628 model. *Journal of Hydrology*, 251(1–2). [https://doi.org/10.1016/S0022-](https://doi.org/10.1016/S0022-1694(01)00429-2)
629 [1694\(01\)00429-2](https://doi.org/10.1016/S0022-1694(01)00429-2)

630 EPA. (2017). An Overview of Rainfall-Runoff Model Types (iEMSs 2018).
631 September,30.
632 <https://scholarsarchive.byu.edu/iemssconference>[https://scholarsarchive.byu.edu/i](https://scholarsarchive.byu.edu/iemssconference/2018/Stream-C/41Thisoralpresentation)
633 [emssconference/2018/Stream-C/41Thisoralpresentation](https://scholarsarchive.byu.edu/iemssconference/2018/Stream-C/41Thisoralpresentation)

634 EVN Vietnam. (2019). Solutions to improve the efficiency of hydropower reservoir
635 operation. [https://en.evn.com.vn/d6/news/Solutions-to-improve-the-efficiency-](https://en.evn.com.vn/d6/news/Solutions-to-improve-the-efficiency-of-hydropower-reservoir-operation-66-163-1627.aspx)
636 [of-hydropower-reservoir-operation-66-163-1627.aspx](https://en.evn.com.vn/d6/news/Solutions-to-improve-the-efficiency-of-hydropower-reservoir-operation-66-163-1627.aspx)

637 EVN-PECC4. (2007). Krong Hnang - Technical design documents (phase 2).

638 Filianoti, P., Gurnari, L., Zema, D. A., Bombino, G., Sinagra, M., & Tucciarelli, T.
639 (2020). An evaluation matrix to compare computer hydrological models for flood
640 predictions. *Hydrology*, 7(3). <https://doi.org/10.3390/hydrology7030042>

641 Grek, E., & Zhuravlev, S. (2020). Simulation of rainfall-induced floods in small
642 catchments (The Polomet' River, North-West Russia) using rain gauge and radar
643 data. *Hydrology*, 7(4). <https://doi.org/10.3390/hydrology7040092>

644 Houska, T., Kraft, P., Chamorro-Chavez, A., & Breuer, L. (2015). SPOTting model
645 parameters using a ready-made Python package. *PLoS ONE*, 10(12).
646 <https://doi.org/10.1371/journal.pone.0145180>

647 IFRC. (2020, December 1). Vietnam: Floods - Emergency appeal n° MDRVN020
648 Operation update n°1 (1 December 2020) - Viet Nam | ReliefWeb.
649 [https://reliefweb.int/report/viet-nam/vietnam-floods-emergency-appeal-n-](https://reliefweb.int/report/viet-nam/vietnam-floods-emergency-appeal-n-mdrvn020-operation-update-n-1-1-december-2020)
650 [mdrvn020-operation-update-n-1-1-december-2020](https://reliefweb.int/report/viet-nam/vietnam-floods-emergency-appeal-n-mdrvn020-operation-update-n-1-1-december-2020)

651 Joo, J., Kjeldsen, T., Kim, H. J., & Lee, H. (2014). A comparison of two event-based
652 flood models (ReFH-rainfall runoff model and HEC-HMS) at two Korean

- catchments, Bukil and Jeungpyeong. *KSCE Journal of Civil Engineering*, 18(1).
<https://doi.org/10.1007/s12205-013-0348-3>
- Lee, S., & Kang, T. (2016). Analysis of Constrained Optimization Problems by the SCE-
 UA with an Adaptive Penalty Function. *Journal of Computing in Civil
 Engineering*, 30(3). [https://doi.org/10.1061/\(ASCE\)cp.1943-5487.0000493](https://doi.org/10.1061/(ASCE)cp.1943-5487.0000493)
- Mays, L. W., and Tung, Y.-K. (2002). Hydrosystems engineering and management,
Water Resources Publications, LLC, Englewood, CO.
- McKay, M. D., Beckman, R. J., & Conover, W. J. (1979). A Comparison of Three
 Methods for Selecting Values of Input Variables in the Analysis of Output from
 a Computer Code. *Technometrics*, 21(2), 239–245.
<https://doi.org/10.2307/1268522>
- Nguyen, B. Q., Kantoush, S., Binh, D. Van, Saber, M., Vo, D. N., & Sumi, T. (2023).
 Understanding the anthropogenic development impacts on long-term flow
 regimes in a tropical river basin, Central Vietnam. *In Hydrological Sciences
 Journal* (Vol. 68, Issue 2). <https://doi.org/10.1080/02626667.2022.2153298>
- Nguyen, P. S., Nguyen, T. H., & Nguyen, T. H. (2022). Automatic calibration of HEC–
 HMS model using Shuffled Complex Evolution (SCE–UA) algorithm. *Vietnam
 Journal of Hydrometeorology*, 9(741), 1–18.
[https://doi.org/10.36335/vnjhm.2022\(741\).1-18](https://doi.org/10.36335/vnjhm.2022(741).1-18)
- Nguyen, P. S., Nguyen, T. H., & Nguyen, T. H. (2024). A real-time flood forecasting
 hybrid machine learning hydrological model for Krong H’rang hydropower
 reservoir. *River*, 3(1). <https://doi.org/10.1002/rvr2.72>
- Nguyen, T. T., Pittock, J., & Nguyen, B. H. (2017). Integration of ecosystem-based
 adaptation to climate change policies in Viet Nam. *Climatic Change*, 142(1–2).
<https://doi.org/10.1007/s10584-017-1936-x>
- NOAA. (2021). U.S. Climate Extremes Index (CEI). *In Climate Services and Monitoring
 Division* (Vol. 2021). <https://www.ncdc.noaa.gov/extremes/cei/definition>
- Reig, E., Boucher, M. A., & Tremblay, É. (2020). Ensemble hydrological forecasts for
 reservoir management of the Shipshaw River catchment using limited data.
Canadian Water Resources Journal, 45(4), 372–390.
<https://doi.org/10.1080/07011784.2020.1834880>
- Saber, M., Boulmaiz, T., Guermoui, M., Abdrabo, K. I., Kantoush, S. A., Sumi, T.,
 Boutaghane, H., Hori, T., Binh, D. Van, Nguyen, B. Q., Bui, T. T. P., Vo, N. D.,
 Habib, E., & Mabrouk, E. (2023). Enhancing flood risk assessment through

integration of ensemble learning approaches and physical-based hydrological modelling. *Geomatics, Natural Hazards and Risk*, 14(1).
<https://doi.org/10.1080/19475705.2023.2203798>

Şensoy, A., Uysal, G., & Şorman, A. A. (2018). Developing a decision support framework for real-time flood management using integrated models. *Journal of Flood Risk Management*, 11, 866–883. <https://doi.org/10.1111/jfr3.12280>

Skahill, B. E. (2006). ERDC/CHL TR-06-13, Potential Improvements for HEC-HMS Automated Parameter Estimation.

To, T. N., Vu, H. C., & Le, H. (2022). Impacts of reservoir operation and urbanization on flood inundation in the Vu Gia Thu Bon Basin, Vietnam. *Water Supply*, 22(4).
<https://doi.org/10.2166/ws.2022.124>

Tong, R., & Komma, J. (2017). Calibration of HEC-Ras hydrodynamic model using gauged discharge data and flood inundation maps. *EGU General Assembly 2017 (p. 1)*. Copernicus Publications. <http://hdl.handle.net/20.500.12708/62327>

USACE. (2000). Hydrologic Modeling System HEC-HMS Technical Reference Manual. US Army Corps of Engineers, March. <https://doi.org/CDP-74B>

USACE. (2009). HEC-DSSVue Data Storage System Visual Utility Engine User's Manual. U.S. Army Corps of Engineers, July.

USACE. (2024, May 8). HEC-HMS- User's Manual Release Notes Version 4.12.0. USACE. <https://www.hec.usace.army.mil/confluence/hmsdocs/hmsum/latest/release-notes/v-4-12-0-release-notes>

Vrugt, J. A., Gupta, H. V., Bouten, W., & Sorooshian, S. (2003). A Shuffled Complex Evolution Metropolis algorithm for optimization and uncertainty assessment of hydrologic model parameters. *Water Resources Research*, 39(8).
<https://doi.org/10.1029/2002WR001642>

WB and ADB. (2020). Climate Risk Country Profile: Vietnam (2020): The World Bank Group and the Asian Development Bank.

Yapo, P. O., Gupta, H. V., & Sorooshian, S. (1998). Multi-objective global optimization for hydrologic models. *Journal of Hydrology*, 204(1–4).
[https://doi.org/10.1016/S0022-1694\(97\)00107-8](https://doi.org/10.1016/S0022-1694(97)00107-8)

Yu, X., & Zhang, J. (2023). The Application and Applicability of HEC-HMS Model in Flood Simulation under the Condition of River Basin Urbanization. *Water (Switzerland)*, 15(12). <https://doi.org/10.3390/w15122249>

- 720 Zakermoshfegh, M., Ghodsian, M., Salehi Neishabouri, S. A. A., & Shakiba, M. (2008).
721 River flow forecasting using neural networks and auto-calibrated NAM model
722 with shuffled complex evolution. *Journal of Applied Sciences*, 8(8).
723 <https://doi.org/10.3923/jas.2008.1487.1494>
- 724 Zelelew, D. G., & Melesse, A. M. (2018). Applicability of a spatially semi-distributed
725 hydrological model for watershed scale runoff estimation in Northwest Ethiopia.
726 *Water* (Switzerland), 10(7). <https://doi.org/10.3390/w10070923>