RESERVOIR INFLOW FLOOD FORECASTING USING NEAR REALTIME SATELLITE PRECIPITATION AND RAINFALL-RUNOFF MODEL FOR TA TRACH RESERVOIR

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Abstract - Reliable precipitation data are critical for rainfall–runoff modeling and flood forecasting, yet rain gauge networks remain sparse in many developing regions. This study evaluates the suitability of three near-real-time satellite precipitation products—GSMaP-NRT, GPM-IMERG Early Run, and PERSIANN PDIR-Now—for forecasting reservoir inflow to the Ta Trach watershed in central Vietnam. A linear scaling bias-correction method was applied to reduce systematic errors before using the datasets as inputs to the HEC-HMS hydrological model. Performance was assessed using the Nash–Sutcliffe efficiency (NSE), coefficient of determination (R^2), and relative volume error (RVE). Bias correction significantly improved rainfall estimates and streamflow simulations for all products. Among them, GPM-IMERG Early Run achieved the highest accuracy, with NSE = 0.85, R^2 = 0.84, and RVE = 4.95%. These findings demonstrate that bias-corrected GPM-IMERG Early Run provides reliable rainfall forcing for operational reservoir inflow forecasting and supports flood management in data-scarce basins.

Key words - Satellite precipitation product; reservoir inflow forecasting; hydrological model; HEC-HMS; Ta Trach Reservoir

1. Introduction

Water is a vital natural resource essential for sustaining ecosystems and human societies. Growing water demand, combined with irregular and increasingly variable precipitation patterns, poses significant challenges for water resource management [1, 2]. Floods are among the most damaging natural hazards, causing substantial infrastructure damage and loss of life [3]. Their frequency and severity have increased in many regions due to climate change, urbanization, and land-use change. Without effective mitigation and planning measures, flood impacts can escalate, leading to significant human, ecological, and economic losses [4]. Reservoirs play a critical role in flood risk management by regulating river flows and attenuating flood peaks through temporary storage during high-flow events. Accurate flood forecasting and reservoir inflow prediction are therefore essential for effective flood management, requiring reliable hydrological models that realistically represent basin processes with adjusted parameters and rainfall inputs [5].

Hydrological models are widely used for streamflow forecasting and have demonstrated strong practical applicability [6]. Distributed models require extensive input data, including dense hydro-meteorological observations and detailed information on soils, geology, and land use, making them more suitable for well-instrumented basins. In contrast, lumped models require fewer inputs and are computationally efficient, making them appropriate for operational applications in data-scarce regions [7]. The HEC-HMS rainfall–runoff model, which applies lumped parameter formulations to transform rainfall into runoff, is freely available and has been widely used for flood forecasting in Central Vietnam and the Central Highlands, where it has shown satisfactory performance.

The reliability of hydrological forecasts depends largely on the performance of calibrated and validated models and the accuracy of rainfall inputs [8]. In data-scarce regions, however, models are often calibrated with limited observations and assume time-invariant parameters, which can introduce substantial forecasting uncertainties [4]. Precipitation forecasts from meteorological models remain highly uncertain, particularly in mountainous regions with sparse rain-gauge networks. Flood forecasting in large and complex catchments is further challenged by the limited spatial coverage of conventional gauges, leading to uncertainties in rainfall estimation and consequently reduced accuracy in runoff simulations [5].

Recent advances in remote sensing have significantly improved precipitation monitoring. Satellite-based rainfall products now provide higher spatial resolution, increased temporal frequency, and improved estimation accuracy, with several datasets available in near-real time [9]. These products offer promising alternatives to conventional rainfall forecasts for operational flood prediction, particularly in data-scarce basins.

Ta Trach Reservoir is the largest hydraulic structure in Thua Thien Hue Province, Central Vietnam, with a catchment area of 717 km² and a flood-control storage capacity of 556.25 million m³. The reservoir serves multiple functions, including early- and main-season flood regulation in the Huong River system and water supply for domestic and industrial uses. During the rainy season, it plays a key role in reducing flood peaks in Hue City and downstream areas [10]. Accurate inflow forecasting combined with proactive reservoir operation can significantly enhance downstream flood mitigation and reduce flood-related damages.

This study develops a reservoir inflow flood forecasting framework for Ta Trach Reservoir by integrating the HEC-HMS model with near-real-time satellite precipitation products (GSMaP-NRT, GPM-IMERG Early Run, and

PERSIANN PDIR-Now). Observed rainfall and discharge data for 1981–2020 were used to calibrate and validate the model. The validated model with time-variant parameters was then forced with the selected satellite rainfall products to forecast reservoir inflows and assess the feasibility of using near-real-time satellite precipitation for operational flood forecasting in a data-limited mountainous basin.

2. Datasets and Methodology

2.1. Study Area

The Ta Trach Reservoir basin is located in Nam Dong and Huong Thuy districts, Thua Thien Hue Province, Vietnam (16°13′–16°19′ N, 107°19′–107°38′ E). The Ta Trach dam is situated in Duong Hoa Commune, Huong Thuy District (16°19′ N, 107°38′ E) (Figure 1). The basin originates in the eastern Truong Son Mountains at elevations of approximately 900–1,000 m, forming the watershed divide between the Ta Trach and Huu Trach basins. These rivers converge at the Tuan confluence about 14 km upstream of Hue City to form the Huong River. The Ta Trach River is mainly fed by the Thuong Nhat and Thuong Lo tributaries, which flow through Khe Tre Town and merge near Huong Son Commune. The western basin boundary is characterized by high mountain ranges (900–1,000 m) with slopes of 20–40°, separating it from the Bo River basin, while the eastern boundary adjoining the Nong River basin, consists of lower hills (50–100 m) and low mountain passes [10].

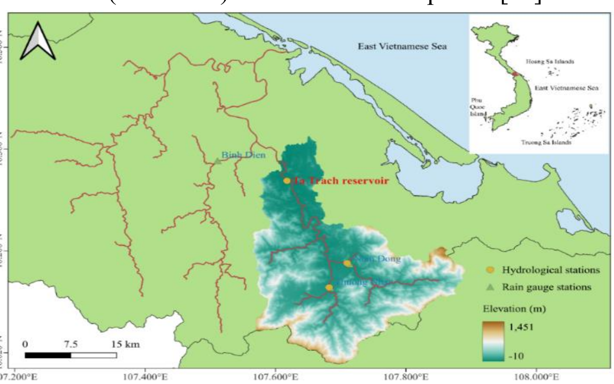

Figure 1. The Ta Trach River basin

Geologically, the Ta Trach basin is dominated by Ordovician–Silurian formations composed of greenish- to dark-gray quartz–sericite schists arranged in southeast–northwest trending belts and locally intruded by granitic bodies. The youngest units are unconsolidated Quaternary (QIV) deposits, consisting mainly of alluvial sand, gravel, and pebbles distributed along riverbanks.

The flood regime comprises two periods: early-season floods in May–June and the main flood season from September to December, with major events typically occurring between mid-October and mid-November. Flood hydrographs often display multiple peaks due to prolonged rainfall over consecutive days and are characterized by rapid rising and recession limbs, reflecting the basin's short river network and steep topography. Within the study basin, discharge observations are available only at Thuong Nhat station, where records from 1981–2020 indicate 17 major floods, 13 moderate floods, and 10 minor floods.

The methodological framework comprised five steps. First, the NASA DEM was processed in HEC-GeoHMS to delineate subbasins and the river network. Second, near-real-time precipitation datasets were bias-corrected. Third, the HEC-HMS hydrological model was calibrated and validated to simulate annual peak discharge at Thuong Nhat station using continuous records from 1981–2000 and 2001–2020, respectively. Fourth, the calibrated parameters were applied to simulate inflow floods to the Ta Trach Reservoir, using the 2020 flood event hydrograph for calibration and the 2017 flood event hydrograph for validation. Finally, parameters derived from rain-gauge data were transferred to bias-corrected satellite precipitation datasets, and time-variant parameter settings were used to forecast reservoir inflows with a 3-day lead time. The complete workflow is illustrated in Figure 2.

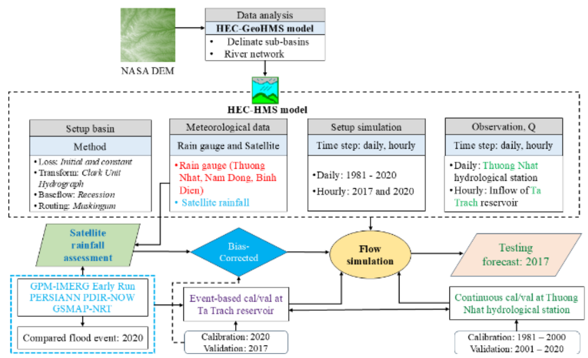

Figure 2. The flowchart of the study

2.2. Datasets

2.2.1. Model input data

A 30 m Digital Elevation Model (DEM) from the NASA DEM dataset [11] was used in HEC-GeoHMS to delineate subbasins. Soil hydrologic group and land use/land cover (LULC) layers from the FAO dataset [12] were combined to generate the Curve Number (CN) map used in the HEC-HMS model.

Table 1. Summary of the model input data

Data	Spatial/ Temporal resolution	Available period	Source
DEM	30 m x 30 m	2011	NASA DEM
Soil	1 km x 1 km	2013	FAO
LULC	1 km x 1 km	2013	FAO
Climate data	Station/Daily	1981-2020	HHS
Discharge	Station/Daily	1981-2020	HHS
Reservoir inflow	Station/Hourly	2017, 2020	HHS

Daily observed discharge at Thuong Nhat station and daily climate data (rainfall and temperature) from three meteorological stations (Thuong Nhat, Nam Dong, and Binh Dien) were obtained from the Hue Hydrometeorological Station (HHS). Hourly reservoir inflow data for the Ta Trach Reservoir were also collected. The reservoir inflow used in this study was reconstructed from reservoir water level, storage change, and operational release data rather than directly measured natural inflow observations. This approach was adopted due to the limited availability of continuous observed inflow data for the study period.

2.2.2. Near real-time satellite precipitation

Satellite rainfall products (SRPs) were obtained from three near-real-time precipitation products with daily and 3-hourly temporal resolution, including GPM-IMERG Early Run, PERSIANN PDIR-Now, and GSMaP-NRT. Key characteristics of these datasets are summarized in Table 2.

GPM-IMERG Early Run

The Global Precipitation Measurement (GPM) mission improves upon the Tropical Rainfall Measuring Mission (TRMM) and retrieves precipitation using the Integrated Multi-satellitE Retrievals for GPM (IMERG) algorithm [13]. IMERG provides three products: Early, Late, and Final. This study used the near–real-time IMERG-Early product, which is generated from multi-sensor satellite observations and is typically available within approximately 4 hours after observation.

PERSIANN-PDIR Now

The PERSIANN-Dynamic Infrared Rain Rate (PDIR) product [14], developed as an extension of the PERSIANN-CCS system, provides near-real-time precipitation estimates at 0.04° × 0.04° spatial resolution and hourly temporal resolution. Owing to its low latency (15–60 min), PDIR is well-suited for time-sensitive hydrological applications such as flood forecasting and real-time flood mapping.

GSMAP-NRT

The Global Satellite Mapping of Precipitation (GSMaP) dataset, developed by the Japan Aerospace Exploration Agency (JAXA), estimates precipitation using brightness temperatures from passive microwave radiometers combined with infrared cloud imagery [15]. GSMaP provides several products, including near-real-time estimates (GSMaP_NRT), the microwave–IR combined product (GSMaP_MVK), reanalysis products (GSMaP_RNL), and gauge-calibrated rainfall (GSMaP_Gauge). In this study, the GSMaP_NRT product with 0.1° spatial resolution and hourly temporal resolution was used.

All three satellite rainfall products used in this study are near-real-time, satellite-only datasets that have not been bias-corrected with rain gauge observations. While these products provide valuable information for capturing runoff dynamics and supporting early flood warning for reservoir inflow, rainfall estimates derived from satellite retrieval algorithms may contain systematic biases. This limitation remains a key constraint in the use of real-time satellite-based precipitation products.

Table 2. *Summary of the three near-real-time satellite rainfall products*

Dataset	Spatiotemporal resolution	Availability period	Latency	Source
GPM-IMERG Early Run	0.1°/ 30 minutes	1998 – present	4 hours	NASA (National Aeronautics and Space Administration)
PERSIANN PDIR Now	0.04° /Hourly	2003 – present	15–60 minutes	Center for Hydrometeorology and Remote Sensing (CHRS) of the University of California, Irvine
GSMAP-NRT	0.1° / Hourly	2000 – present	4 hours	The Japan Aerospace Exploration Agency (JAXA)

2.3. Bias correction of satellite rainfall

Bias correction was applied to reduce discrepancies between rain gauge observations and near-real-time satellite-based rainfall products (SRPs) for individual events. The corrected SRPs were then used as inputs to the HEC-HMS model and evaluated based on streamflow simulation performance. A linear scaling method was employed to adjust near-real-time SRP estimates using rain gauge observations, as expressed in the following equations.

$$X_{corrected,i} = X_{SRP,i} + MAE \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(X_{RG,i} - X_{SRP,i}) \quad (2)$$

where

$X_{corrected}$ is bias-corrected SRPs, I is near real-time SRPs, X_{RG} is rain gauge data, and MAE represents the error correction coefficient derived from Mean Absolute Error between time series of SRPs data and rain gauge data.

The linear scaling bias-correction method adjusted satellite precipitation using correction factors derived from the calibration event based on observed rain gauge data. These correction factors were independently applied to the validation event without recalibration to assess the robustness and transferability of the approach.

A simple linear scaling bias-correction approach was adopted because it is computationally efficient, requires limited calibration data, and is suitable for operational near-real-time flood forecasting in data-scarce basins, while still providing substantial improvements in satellite precipitation performance for hydrological applications [16].

2.4. Hydrological model HEC-HMS

The HEC-HMS (Hydrologic Engineering Center – Hydrologic Modeling System), developed by the U.S. Army Corps of Engineers, is a deterministic lumped-parameter rainfall–runoff model that represents a watershed as interconnected subbasins, river reaches, reservoirs, and hydraulic structures [17, 18]. HEC-GeoHMS was used to process topographic data, delineate subbasins, and derive the drainage network from the Digital Elevation Model (DEM), generating GIS-based input files for HEC-HMS (Figure 3). In this study, the Initial and Constant method was used for loss estimation, the Clark Unit Hydrograph method was applied for runoff transformation, the recession method was adopted for baseflow simulation, and the Muskingum method was used for channel routing.

The upstream reservoir catchment was subdivided into sub-basins based on land use, soil type, hydrological station locations, and DEM-derived topography. The HEC-HMS model configuration comprised four components: (i) basin model, (ii) meteorological model, (iii) control specifications, and (iv) time-series data management. Key model parameters, methods for estimating areal rainfall, simulation time step, calibration and validation periods, and rainfall–discharge datasets are summarized in Figure 1.

2.5. Models Setup

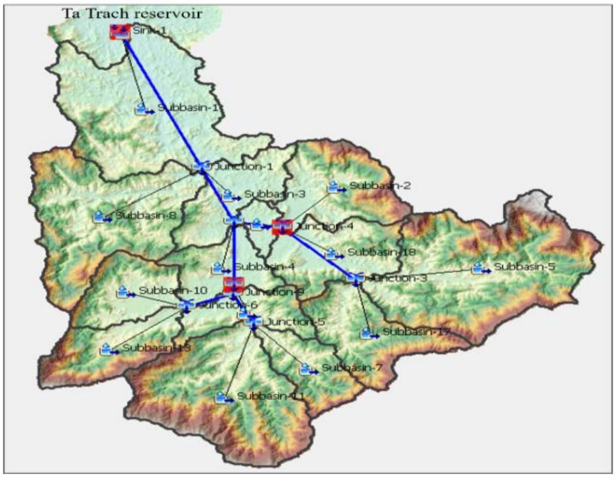

Figure 3. *HEC-HMS model representation of the Ta Trach Reservoir Watershed with 14 subbasins*

HEC-GeoHMS, a GIS-based preprocessing tool for the HEC-HMS hydrological model, was used to derive watershed characteristics from the basin digital elevation model (DEM). The tool was applied to delineate the river network, subbasins, and drainage features of the Ta Trach Reservoir watershed. As shown in Figure 3, the watershed was divided into 14 subbasins with areas ranging from 8.2 to 107.2 km², forming the basis for the HEC-HMS model configuration.

The HEC-HMS model comprises four main components: the basin model, meteorological model, control specifications, and input data (Figure 2). The basin model describes the physical characteristics of the watershed, including subbasin areas and river network connectivity, while the meteorological model defines precipitation inputs. Rainfall from three rain gauges and corresponding satellite precipitation grid cells was averaged using the Thiessen polygons method to generate a representative rainfall input for the basin. Control specifications determine the simulation period and computational time step. Input data include time-series, paired, and gridded datasets that provide parameters and boundary conditions for the model. In this study, key inputs consisted of near-real-time satellite and in situ precipitation, observed streamflow, and basin characteristics (e.g., curve number, soil type, and land use/land cover) derived from the HEC-GeoHMS preprocessing workflow.

2.6. Model calibration and validation

Because the Ta Trach Reservoir watershed is nested within the Thuong Nhat basin, the HEC-HMS model was first calibrated at Thuong Nhat station using continuous streamflow records to derive initial parameter estimates. Calibration and validation at Thuong Nhat were performed for the periods 1982–2000 and 2001–2020, respectively, with 1979–1980 used as the model warm-up period. The calibrated parameters were then transferred to the Ta Trach watershed and further refined using event-based simulations. Flood discharge was calibrated using the 10–13 November 2020 event and validated against the 3–7 November 2017 event before application to reservoir inflow forecasting.

Satellite rainfall products were evaluated against rain gauge observations to quantify errors and identify the product with the highest performance for use in the HEC-HMS model. Flood discharge forecasts generated with the selected SRPs and the calibrated–validated parameter set were subsequently validated against the flood events of 10–13 November 2020 and 3–7 November 2017 to assess forecasting performance.

The flood event of 3–7 November 2017 was used to validate the forecasting performance of the HEC-HMS model following an evaluation of the GSMaP-NRT, GPM-IMERG Early Run, and PERSIANN PDIR-Now satellite rainfall products. Hindcast simulations were conducted from 01:00 on 3 November to 24:00 on 4 November 2017, while the forecast period spanned 01:00 on 5 November to 22:00 on 7 November 2017.

2.7. Evaluation metrics

Four continuous statistical metrics were used to quantitatively compare SRPs with rain gauge observations and simulated streamflow with observed streamflow. These performance indicators include the correlation coefficient (R), root mean square error (RMSE), Nash–Sutcliffe efficiency (NSE), and percent bias (PBIAS). In addition to peak discharge, total flood volume is a key metric for reservoir operation. Therefore, the Relative Volume Error (RVE) index was used to evaluate model performance in simulating total flood volume.

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \bar{O}) \times (S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 \times \sum_{i=1}^{n}(S_i - \bar{S})^2}} \quad (3)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{n}} \quad (5)$$

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - S_i)}{\sum_{i=1}^{n}(O_i)}\% \quad (6)$$

$$RVE = \frac{\sum_{i=1}^{n}(S_i - O_i)}{\sum_{i=1}^{n} O_i}\% \quad (7)$$

In which O_i is the rainfall gauge or observed streamflow; S_i is the satellite-based rainfall or simulated streamflow.

Table 3. *Contingency table used for categorical verification*

		Observation	
		Yes	**No**
Forecasted	**Yes**	a (Hits)	b (False alarms)
	No	c (Misses)	d (Non-Events)

Model forecasting performance was evaluated using categorical verification metrics, including the Probability of Detection (POD), False Alarm Ratio (FAR), and Critical Success Index (CSI), calculated from the contingency table (Table 3). POD measures the fraction of observed flood events correctly predicted by the model, FAR represents the proportion of forecasted events that did not occur, and CSI quantifies the ratio of correctly predicted events relative to the total number of observed and/or forecasted events. These indices range from 0 to 1, with optimal performance indicated by POD = 1, FAR = 0, and CSI = 1. In this study, the predefined threshold discharge value is 300 (m^3/s).

$$POD = \frac{a}{a+c} \quad (8)$$

$$FAR = \frac{b}{a+b} \quad (9)$$

$$CSI = \frac{a}{a+b+c} \quad (10)$$

where: a is the number of time steps when both the forecasted discharge and the observed discharge exceed a predefined threshold discharge value.

b is the number of time steps when the forecasted discharge exceeds the threshold value, but the observed discharge is lower than the threshold.

c is the number of time steps when the forecasted discharge is lower than the threshold value, but the observed discharge exceeds the threshold.

d is the number of time steps when both the forecasted discharge and the observed discharge are lower than the threshold value.

3. Results and Discussion

3.1. Evaluate real-time satellite rainfall products

Table 4 shows substantial discrepancies between satellite-derived and gauge-measured rainfall at the daily scale during the 2020 rainy season. Among the evaluated products, GPM IMERG Early Run performs best, with NSE values ranging from 0.26 to 0.28 across the Thuong Nhat, Nam Dong, and Binh Dien stations. GSMaP-NRT shows weaker agreement (NSE = 0.08–0.16), while PERSIANN PDIR-Now exhibits the poorest performance, with negative NSE values (−1.77 to −0.88), indicating very poor correspondence with observations.

Table 4. *Comparison of daily statistical metrics between three satellite rainfall products and rain gauge observations during the 2020 flood season*

Satellite product	Indicator	Rain gauge station		
		Thuong Nhat	Nam Dong	Binh Dien
GPM-IMERG Early Run	R^2	0.58	0.60	0.59
	NSE	0.26	0.25	0.28
	RMSE	104.49	109.15	40.76
	PBIAS	51.07	54.31	82.57
PERSIANN PDIR Now	R^2	0.46	0.48	0.44
	NSE	-1.13	-0.88	-1.77
	RMSE	177.12	172.67	162.66
	PBIAS	-23.47	-13.35	-31.12
GSMAP-NRT	R^2	0.52	0.44	0.43
	NSE	0.16	0.08	0.12
	RMSE	111.14	120.6	91.61
	PBIAS	48.78	53.73	41.85

Evaluation of the 10–13 November 2020 flood event at a 3-hour time step still indicates that the GPM-IMERG Early Run product outperforms the other satellite rainfall datasets. The model achieved an NSE of 0.58 at the Thuong Nhat hydrological station (Table 5). Accordingly, the 3-hour GPM-IMERG Early Run dataset was selected as the rainfall input for flood inflow forecasting to the Ta Trach Reservoir.

Table 5. *Simulated streamflow performance of three satellite rainfall products with the rain gauge at a 3-hour time step during the flood event of November 10–13, 2020*

Satellite product	Indicator	Rain gauge station		
		Thuong Nhat	Nam Dong	Binh Dien
GPM-IMERG Early Run	R^2	0.92	0.72	0.80
	NSE	0.58	0.26	0.45
	RMSE	12.53	19.09	7.25
	PBIAS	60.30	67.74	50.87
PERSIANN PDIR Now	R^2	0.30	0.12	0.01
	NSE	-0.12	-0.34	-0.55
	RMSE	20.41	25.75	13.44
	PBIAS	76.49	88.19	83.33
GSMAP-NRT	R^2	0.22	0.107	0.35
	NSE	-0.25	-0.39	-0.48
	RMSE	21.54	26.28	13.12
	PBIAS	89.85	91.30	96.12

Among the evaluated datasets, GPM IMERG Early Run shows the best performance. This relatively better performance is likely related to the multi-sensor retrieval framework. In contrast, GSMaP-NRT exhibits weaker agreement with observations, possibly due to differences in retrieval algorithms and reduced capability to represent localized convective rainfall typical of the region. PERSIANN PDIR-Now performs poorest, with negative NSE values indicating that model estimates are less accurate than using the observed mean rainfall. Near-real-time satellite-only precipitation products are subject to substantial uncertainty due to retrieval errors, latency constraints, and the absence of gauge correction in real time. Such discrepancies are consistent with previous studies showing that satellite precipitation products often struggle to capture intense, short-lived convective storms and complex orographic precipitation patterns common in mountainous tropical regions. These limitations suggest that while satellite rainfall products provide near-real-time and valuable spatial coverage, caution is required when applying them at hourly or daily temporal scales for hydrological modeling or flood analysis without bias correction or gauge merging.

3.2. Bias-Correction of GPM-IMERG Early Run

Evaluation of three satellite rainfall products at the daily scale during the 2020 flood season and at the 3-hour scale for the 10–13 November 2020 flood event indicates that GPM-IMERG Early Run outperforms the other products (Tables 4 – 5). Consequently, this dataset was selected for bias correction and subsequent analysis. The MAE-based correction coefficients derived for the three rain-gauge stations show smaller errors at Thuong Nhat (6.97 mm) and Binh Dien (4.04 mm), while Nam Dong (10.03 mm) exhibits the largest bias, indicating greater discrepancies between satellite-derived and observed rainfall at this location.

After applying linear scaling bias correction to the GPM-IMERG Early Run product, the corrected rainfall data were re-evaluated against gauge observations (Table 7). All statistical indicators at the three stations improved relative to the pre-correction results (Table 6). NSE increased by 22.4%, 80.8%, and 37.8% at Thuong Nhat, Nam Dong, and Binh Dien stations, respectively, while RMSE decreased by 16.9%, 14.9%, and 17.0%.

After bias correction, the percent bias (PBIAS) was reduced to near zero, indicating that systematic differences between satellite-derived and observed rainfall were effectively removed (Table 6, Figure 4). These improvements demonstrate the effectiveness of the bias-correction approach in enhancing the reliability of satellite precipitation for hydrological modeling, particularly for improving flood inflow forecasting to the Ta Trach Reservoir and supporting more proactive reservoir operation and downstream flood mitigation.

Table 6. *Comparison of statistical indicators between bias-corrected GPM-IMERG Early Run rainfall and observed rainfall at the 3-hour time scale for the flood event of 10–13 November 2020*

Satellite product	Indicator	Rain gauge station		
		Thuong Nhat	Nam Dong	Binh Dien
GPM-IMERG Early Run	R^2	0.92	0.72	0.80
	NSE	0.71	0.47	0.62
	RMSE	10.41	16.24	6.02
	PBIAS	0.00	0.00	0.00

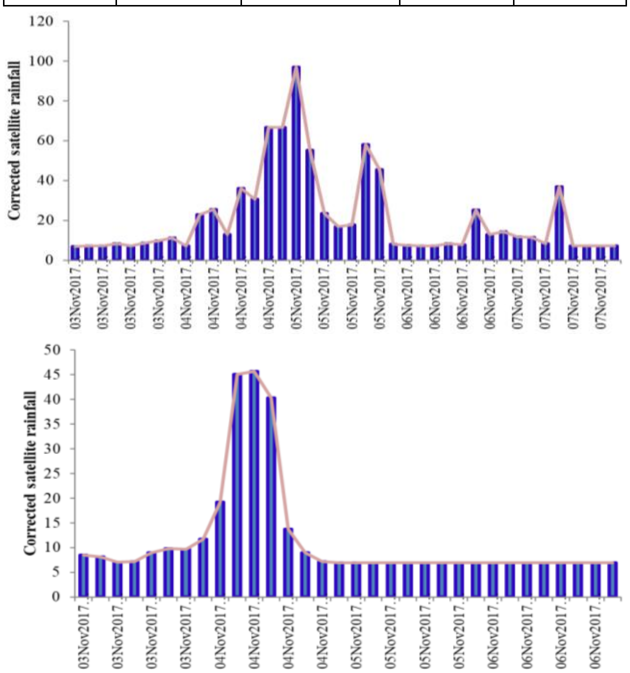

Figure 4. *Satellite rainfall from GPM-IMERG Early Run at Thuong Nhat station for the flood events of 3–7 November 2017 (a) and 10–13 November 2020 (b)*

3.3. HEC-HMS model calibration and validation performance

3.3.1. Countinuous simulation at Thuong Nhat station

Calibration (1981–2000) and validation (2001–2020) at the Thuong Nhat hydrological station indicate that the model satisfactorily reproduces observed streamflow dynamics, capturing peak magnitude, timing, and overall hydrograph shape. Model performance was acceptable, with R^2 and NSE values of 0.76 and 0.65 during calibration and 0.69 and 0.65 during validation, respectively (Figure 5). These statistics suggest that the calibrated parameter set provides stable and reliable simulations for long-term streamflow representation.

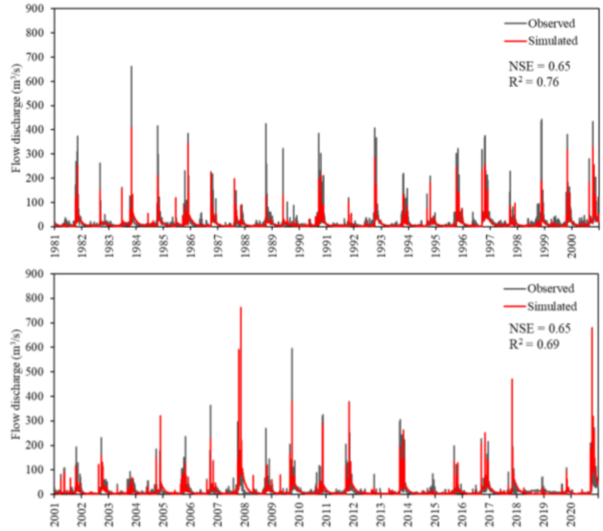

Figure 5. *Calibration and validation results at the Thuong Nhat hydrological station based on rain gauge for the periods (a) 1981–2000 (calibration) and (b) 2001–2020 (validation)*

3.3.2. Event-based simulation at Ta Trach Reservoir

For the selected flood events at Ta Trach Reservoir, the model reproduces the peak discharge and overall hydrograph shape, including the rising and recession limbs, with good accuracy. The Nash–Sutcliffe Efficiency (NSE) values are 0.95 and 0.86 for the 2020 and 2017 events, respectively, indicating very good performance (Figure 6). Minor differences in peak magnitude and timing likely reflect uncertainties in rainfall inputs and watershed parameterization, but overall model performance is satisfactory for flood simulation applications.

Bias correction of the satellite-based rainfall substantially improved the simulated flood hydrographs, particularly the peak discharge and total flood volume. The NSE values obtained using the corrected GPM-IMERG Early Run product were comparable to those achieved with rain-gauge observations for both the 2017 and 2020 flood events (Figures. 6–7), indicating the effectiveness of the bias-correction method and its potential suitability for operational flood forecasting.

HEC-HMS simulations are influenced by uncertainties in both calibrated hydrological parameters and satellite rainfall inputs, especially during high-intensity storm events. Nevertheless, model calibration and bias correction helped reduce these uncertainties and improved the reliability of reservoir inflow forecasting.

A limitation of this study is that the model calibration and validation were conducted using only two flood events, which may not fully capture the variability of hydrological responses under different climatic and flood conditions. Additional flood events would improve the robustness of parameter estimation and the reliability of model performance assessment.

Accurate simulation and forecasting of total flood inflow to reservoirs are essential for enabling operators to pre-release water and create flood control storage prior to flood arrival. Model evaluation shows that the relative volume error (RVE) of simulated inflow was 0.52% for the 2020 calibration flood and 4.93% for the 2017 validation event, both below 5%. These results demonstrate that the GPM IMERG Early Run satellite rainfall product, combined with calibrated HEC-HMS parameters, can reliably reproduce total flood inflow to the reservoir.

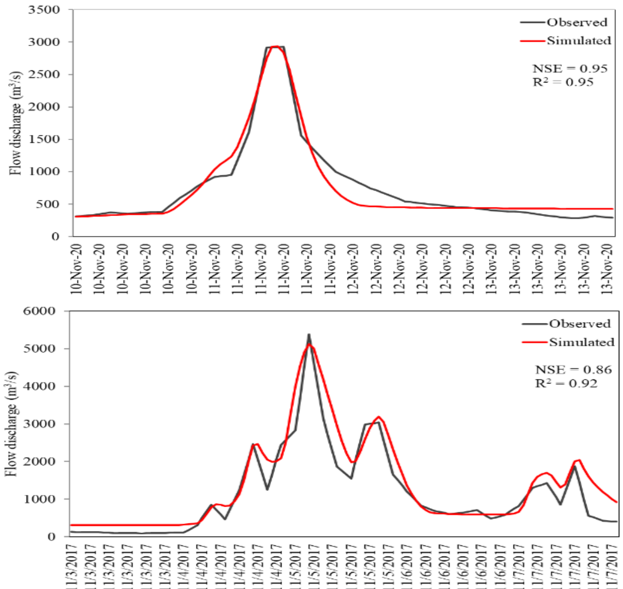

Figure 6. *Calibration and validation results of flood inflow to Ta Trach Reservoir using rain gauge for the flood events of 10–13 November 2020 (a) and 3–7 November 2017 (b)*

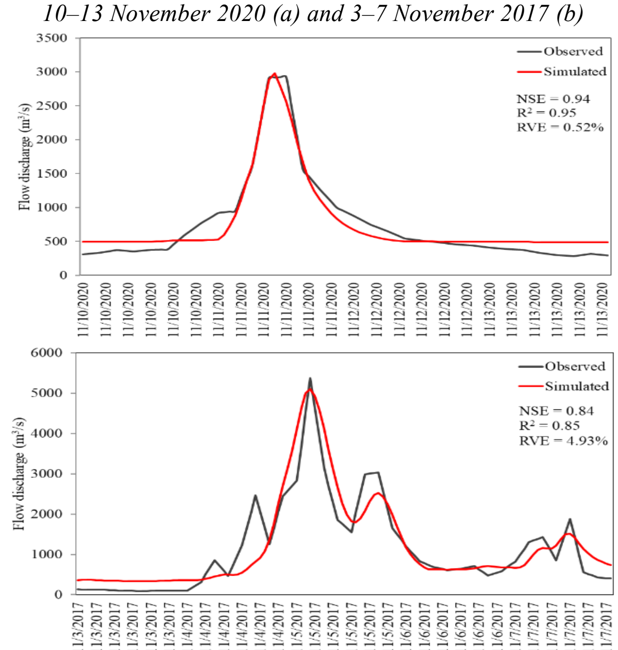

Figure 7. *Calibration and validation results of inflow to Ta Trach Reservoir using the 3-hour GPM-IMERG Early Run product for the flood events of 10–13 November 2020 (a) and 3–7 November 2017 (b)*

3.4. Testing forecast for the 2017 flood event

Forecasted discharge was evaluated against observations for the 3–7 November 2017 flood event (Figure 8), yielding POD = 0.67, FAR = 0.80, and CSI = 0.33. The obtained POD, FAR, and CSI values indicate moderate event detection capability with substantial false alarm uncertainty. These results suggest that although the proposed framework has potential for operational flood forecasting, uncertainties in detecting extreme inflow events remain significant when relying solely on near-real-time satellite precipitation products.

The model reliably predicts reservoir inflow up to a lead time of approximately 5 hours, defined as the interval between the end of the hindcast simulation and the forecasted flood onset. Forecast skill decreases beyond this lead time, which is consistent with the watershed concentration time at the basin outlet and the flood routing time within the Ta Trach reservoir basin.

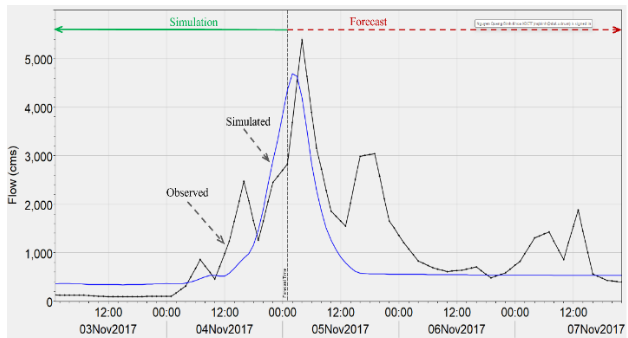

Figure 8. *Hindcast simulation from 01:00 on 3 November 2017 to 24:00 on 4 November 2017 and forecast from 01:00 on 5 November 2017 to 22:00 on 7 November 2017*

The approximately 5-hour forecasting lead time is consistent with the ~4-hour latency of GPM IMERG Early Run and the hydrological concentration time of the Thuong Nhat basin, supporting near-real-time forecasting applicability. This lead time is operationally relevant for Ta Trach Reservoir management by providing advance information for flood regulation and downstream warning activities. It should be noted that the decrease in forecast skill beyond the 5-hour lead time is mainly attributed to increasing uncertainties in GPM IMERG Early Run rainfall estimates, especially for the timing and magnitude of intense precipitation events. These precipitation errors propagate through the HEC-HMS model and accumulate over longer forecasting horizons, leading to reduced inflow prediction accuracy.

The 5-hour forecasting capability provides practical lead time for reservoir operators to optimize flood release operations and mitigate downstream flood impacts. This is especially important for Hue City, located approximately 25 km downstream of Ta Trach Reservoir, where timely inflow forecasts can support early warning and emergency response activities

The findings are consistent with previous studies in tropical mountainous basins, where underestimation of flood peaks and timing uncertainty have also been reported in Vietnam [19] and China [20]. These studies demonstrated that near-real-time satellite precipitation products can still provide acceptable flood forecasting performance, particularly in regions with limited rain gauge observations.

Although the proposed framework shows potential for application to Ta Trach Reservoir and sparsely gauged Thuong Nhat basins, its transferability may be affected by regional differences in climate, topography, hydrological response, and reservoir operation conditions. In particular, uncertainties in satellite precipitation estimates and limited calibration data in ungauged basins remain critical challenges for reliable flood forecasting across different climatic regions.

Incorporating forecast rainfall products may help extend forecasting lead time and enhance operational reservoir management capability. Nevertheless, uncertainties in numerical weather prediction rainfall forecasts, especially for extreme events in tropical mountainous regions, remain an important challenge requiring further investigation.

4. Conclusion

This study developed a comprehensive database for the lumped-parameter HEC-HMS model applied to the Ta Trach reservoir basin to support flood inflow forecasting. The calibrated and validated parameter set, based on gauge-derived rainfall data, provides a reference for reservoir management and flood-season operations in accordance with established operating rules.

The study evaluated the applicability of real-time satellite rainfall products - PERSIANN PDIR-Now, GSMaP NRT, and GPM IMERG Early Run - combined with the validated HEC-HMS parameter set for forecasting flood inflow to the Ta Trach reservoir. Comparison with gauge observations shows that GPM IMERG Early Run provides higher correlation than PERSIANN PDIR-Now and GSMaP NRT over the study basin.

Simulated inflows to Ta Trach Reservoir driven by bias-corrected GPM-IMERG Early Run rainfall achieved Nash–Sutcliffe Efficiency (NSE) values of 0.94 for the 10–13 November 2020 flood and 0.84 for the 3–7 November 2017 event. The model accurately reproduced hydrograph shape, peak timing, and flood volume, with total volume errors below 5%

Real-time flood forecasting using GPM-IMERG Early Run rainfall data (4-hour latency) and the state-updating module in HEC-HMS (Forecast Alternative) demonstrates that the model can reliably predict reservoir inflows up to 5 hours in advance. These results highlight the potential of integrating near-real-time satellite precipitation products into operational flood forecasting for the Ta Trach Reservoir.

Because only two flood events were available for calibration and validation, the operational verification of the proposed framework remains limited. Therefore, the conclusions should be considered preliminary, and additional flood events are needed to further assess model robustness and forecast reliability.

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