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Influence of Spatial Variability on Flood Prediction

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Abstract Accurate flood forecasting remains a significant challenge within hydrology, primarily due to the pronounced spatial heterogeneity of rainfall and catchment characteristics. This challenge is particularly evident in large river basins influenced by monsoons, where traditional lumped models frequently fail to capture localized hydrological responses effectively. This research examines the role of spatial variability in influencing flood prediction accuracy in the Kabini River Basin, India, by systematically evaluating the impact of sub-basin resolution in hydrological modeling. Four Hydrologic Engineering Center – Hydrologic Modeling System (HEC-HMS) models were developed using 4, 8, 16 and 32 sub-basin delineations derived from 30-meter resolution Digital Elevation Model (DEM) data. Rainfall observations were collected from NASA datasets, and Model parameter calibration was undertaken using observed streamflow data from the GEOGloWS Hydroviewer. The hydrological modeling framework included the SCS Curve Number method for estimating losses, the SCS Unit Hydrograph for generating runoff, and Muskingum routing for the propagation of flow. Model performance was assessed using Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The results indicated a clear enhancement in predictive accuracy with increasing spatial discretization. The configuration with 32 sub-basins yielded the best performance (NSE = 0.882, RMSE = 136.8, MAE = 91.1), while the model with 4 sub-basins demonstrated significantly lower accuracy (NSE = 0.563). These findings confirm that a finer sub-basin representation significantly improves the model's ability to capture spatial rainfall variability and the hydrological response of the basin. The study concludes that incorporating spatial heterogeneity through optimized sub-basin delineation markedly enhances the reliability of flood forecasting. This research contributes a practical methodological framework for balancing model precision and computational efficiency, thereby supporting improved flood risk assessment and water resources planning in data-limited river basins influenced by monsoons across the globe.

Keywords Spatial Rainfall Variability, Sub-Basin Discretization, Flood Prediction, HEC-HMS Distributed Hydrological Modelling, Monsoon Basin, Nash Sutcliffe Efficiency

1. Introduction

Rainfall is a crucial factor in flood prediction, as it directly influences the amount of water that drifts into rivers, streams, and drainage systems. However, the spatial variability of rainfall, which refers to the differences in rainfall intensity and distribution over a given area, presents a significant challenge in accurately predicting floods [1,2]. This inconsistency is influenced by various factors such as topography, land use, and atmospheric conditions. Evaluating how rainfall spatial variability affects flood prediction is essential for improving the accuracy of flood forecasts and mitigating their impacts on communities and infrastructure [3]. By enhancing model resolution and incorporating spatially distributed inputs, there is a significant improvement in the predictive capabilities of flood forecasting systems. Ultimately, the knowledge acquired from the research will enhance the comprehension of flood dynamics along with the creation of more resilient and precise flood prediction methods suited to various geographical contexts [4,5].

This research endeavour explored the efficacy of incorporating spatially explicit information into existing flood prediction models. By enhancing model resolution and incorporating spatially distributed inputs, a significant improvement in the predictive capabilities of flood forecasting systems was recognized [6]. The insights gained from the study advance the understanding of flood dynamics and inform the development of robust flood prediction methodologies. The findings emphasize the pivotal role of spatial heterogeneity in governing flood dynamics and the importance of integrating spatially explicit information into flood prediction frameworks [7]. Previous research highlights that effective flood forecasting relies on the integration of high-resolution Digital Elevation Models (DEMs) (30 m × 30 m), spatial rainfall distribution, and calibrated hydrological parameters within distributed modeling frameworks. Basin morphometric characteristics, including watershed area (~7,000 km^2), stream order (up to 5th order), total stream length (>1,800 km), and elevation range (>1,300 m relief), play a significant role in influencing runoff concentration and peak discharge response. The studies indicate that distributed models which incorporate spatial rainfall variability and calibrated loss transform routing parameters consistently demonstrate superior performance compared to lumped models, enhancing hydrograph shape, peak timing, and statistical reliability [8,9]. Recent research indicates that the integration of spatial rainfall variability along with distributed catchment characteristics significantly improves the accuracy of flood predictions when associated with lumped methods [10]. Distributed models show enhancements in NSE from 0.60–0.70 to 0.80–0.90, accompanied by reductions in RMSE of 15–30%, especially for basins exceeding 5,000 km^2. Ignoring spatial variability may lead to an underestimation of peak discharge by 20–40%, while the sensitivity of terrain and hydraulic parameters can modify simulated flood extents by 10–25% [11,12]. The discretization of sub-basins is essential, with research revealing NSE improvements of 0.10–0.20 and RMSE reductions of 12–25% when the number of subdivisions increases from coarse (≤8) to moderate–high (16–32). These results support the assessment of 4, 8, 16, and 32 sub-basin configurations within the Kabini basin to identify the optimal spatial resolution for dependable flood forecasting [13].

While previous studies show that the inclusion of spatial rainfall variability enhances the accuracy of hydrological models, most studies concentrate either on small experimental catchments or utilize fixed discretization levels without a thorough investigation of scale sensitivity. The reported enhancements in distributed models (NSE increases ranging from 0.10 to 0.20 and RMSE reductions between 15 and 30%) are frequently based on comparisons between lumped and distributed frameworks. The rare studies that clearly evaluate how the gradual refinement of sub-basins affects predictive robustness in extensive monsoon-influenced basins larger than 5,000 km^2 [14]. Many previous studies prioritize calibration performance without adequately evaluating parameter equifinality, computational tradeoffs, or uncertainties arising from discretization [15]. Unlike lumped methods that presume spatial uniformity and semi-distributed models with limited subdivisions, a well-structured multi-scale discretization framework facilitates the explicit quantification of the impacts of spatial heterogeneity on peak discharge and hydrograph timing. Consequently, a systematic comparison across hierarchical sub-basin configurations (4, 8, 16, and 32) is essential to determine the ideal equilibrium between model accuracy, stability, and computational efficiency in large tropical watersheds.

The primary objective of the study is to systematically assess the impact of spatial variability on the precision of flood predictions by analyzing the effects of different sub-basin discretization within the Kabini River basin, utilizing a distributed hydrological modeling framework. In particular, the study aims to quantify how varying scales of watershed delineation (4, 8, 16, and 32 sub-basins) influence the performance of rainfall runoff simulations regarding peak discharge estimation, hydrograph timing, and statistical efficiency metrics, including NSE, RMSE, and MAE. By incorporating spatially explicit terrain, land use, and rainfall data within HEC-HMS, this research aims to determine an optimal modeling resolution that strikes a balance between computational efficiency and predictive reliability, thereby enhancing flood forecasting in extensive river basins dominated by monsoon conditions. This study addresses the identified gap by systematically evaluating hierarchical sub-basin discretization levels (4–32) within a large monsoon-influenced basin.

2. Study Area and Fundamentals

The Kabini River begins its voyage close to Kavilumpara in the Kozhikode district of Kerala, created by the merging of the Panamaram and Mananthavady Rivers in India. It travels eastward through the Wayanad district and into the Mysore district of Karnataka, where it meets the Kaveri River, leading to the formation of the Kabini Reservoir near Sargur. The Kabini Dam, situated between the villages of Bichanahalli and Bidarahalli in Mysore district, Karnataka, stretches 696 meters and has an initial storage capacity of 19.52 tmcft.

The Kabini River basin, between latitudes 11°45’ to 12°30’ N and longitudes 75°45’ to 77°00’ E, features diverse topography with hills and valleys and includes sub-basins like Upper Kabini, Moyar River, and Nugu River. The basin has various soil types, predominantly forested (50-60) percentage and agricultural (30-40) percentage of land, and is influenced by a tropical monsoon system, resulting in significant rainfall during the Southwest Monsoon (June- September) and additional rainfall during the Northeast Monsoon (October-December). Temperatures range from over 30 ℃ in summer to 15-25 ℃ in winter. The region faces flood risks during monsoons, with soil erosion from agricultural practices, urbanization, and deforestation affecting hydrological processes [16,17]. For the present basin, Arc-GIS tools are used for basin parameters such as area of the basin, stream length, highest elevation, lowest elevation, and spatial reference, found with the stream length/longest flow path as 240 km, highest elevation as 2036 m, lowest elevation as 638 m, the area enclosed by watershed is 7039.65 km^2, the perimeter of watershed is 563.68 km, spatial reference taken as WGS_1984_UTM_ Zone_43N.

These constraints diverge for dissimilar basins according to their shape, size, slope, location, and topographic characteristics. Spatial reference is the system which is a structure used to precisely measure location on the Earth's surface. Thousands of coordinate systems have been quantified for use around the world or in specific regions and for various purposes, necessitating transformations between different spatial reference systems. Fig. 1 shows the location of Kabini Basin, and Fig. 2 shows the satellite image.

Spatial reference, also known as a coordinate reference system, serves as a framework for accurately determining locations on the Earth's surface. Many coordinate systems have been recognized for application globally or within particular areas and for diverse purposes, which require transformations between various spatial reference systems.

The Kabini River basin covers a total drainage area of 7039.65 km^2, which signifies a substantial monsoon-influenced watershed characterized by intricate geomorphological features. Analysis of the stream network reveals a fifth-order drainage system, indicative of a well-established hierarchical channel structure and considerable runoff convergence capacity. The basin has a total stream length of roughly 1828.2 km, implying a high drainage density and effective hydrological connectivity among sub-basins. From a topographical perspective, the basin ranges in elevation from 638 to 2036 m above mean sea level, resulting in a total relief of 1398 m. This notable elevation gradient facilitates rapid runoff generation, increased flow velocities, and a heightened sensitivity to variations in spatial rainfall. The combination of a large basin area, significant relief, and a clearly defined drainage hierarchy renders the Kabini basin particularly apt for assessing the impact of sub-basin discretization on the accuracy of rainfall runoff simulations and flood predictions.

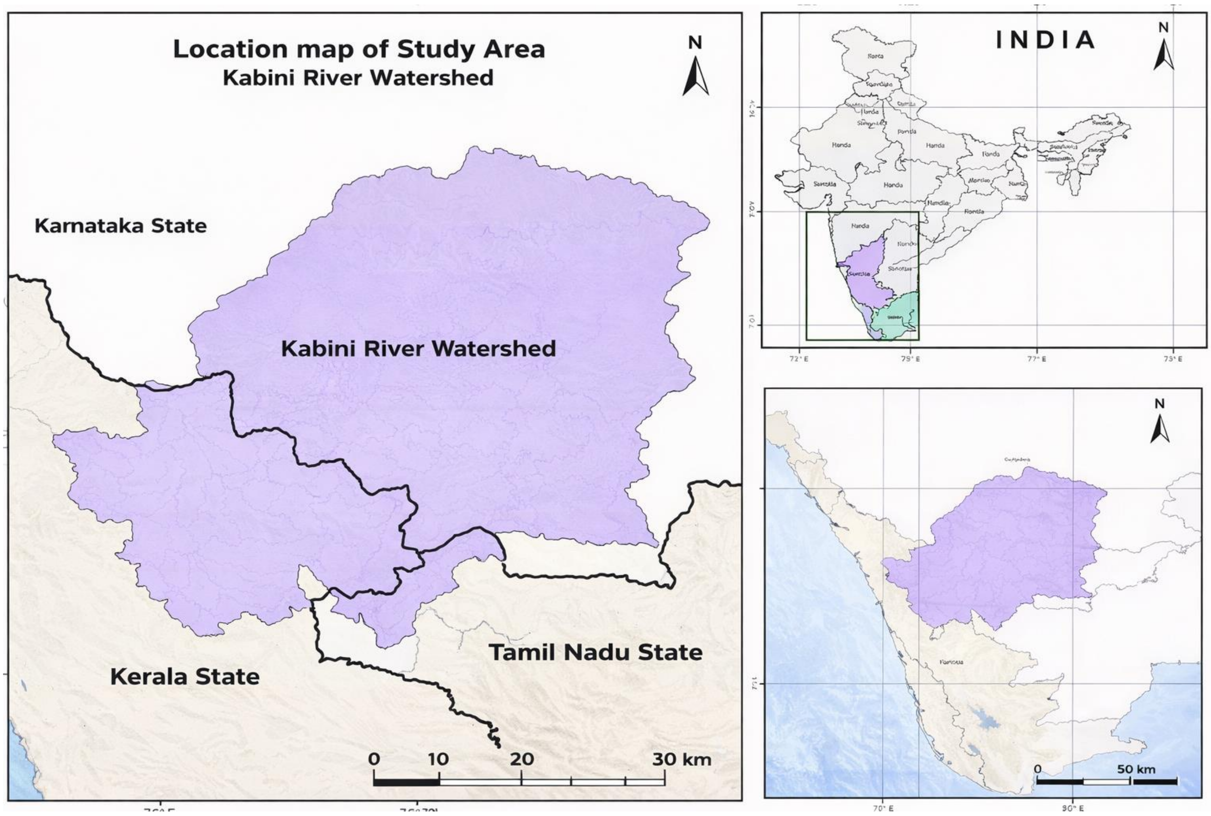


Figure 1. Location of Kabini Basin

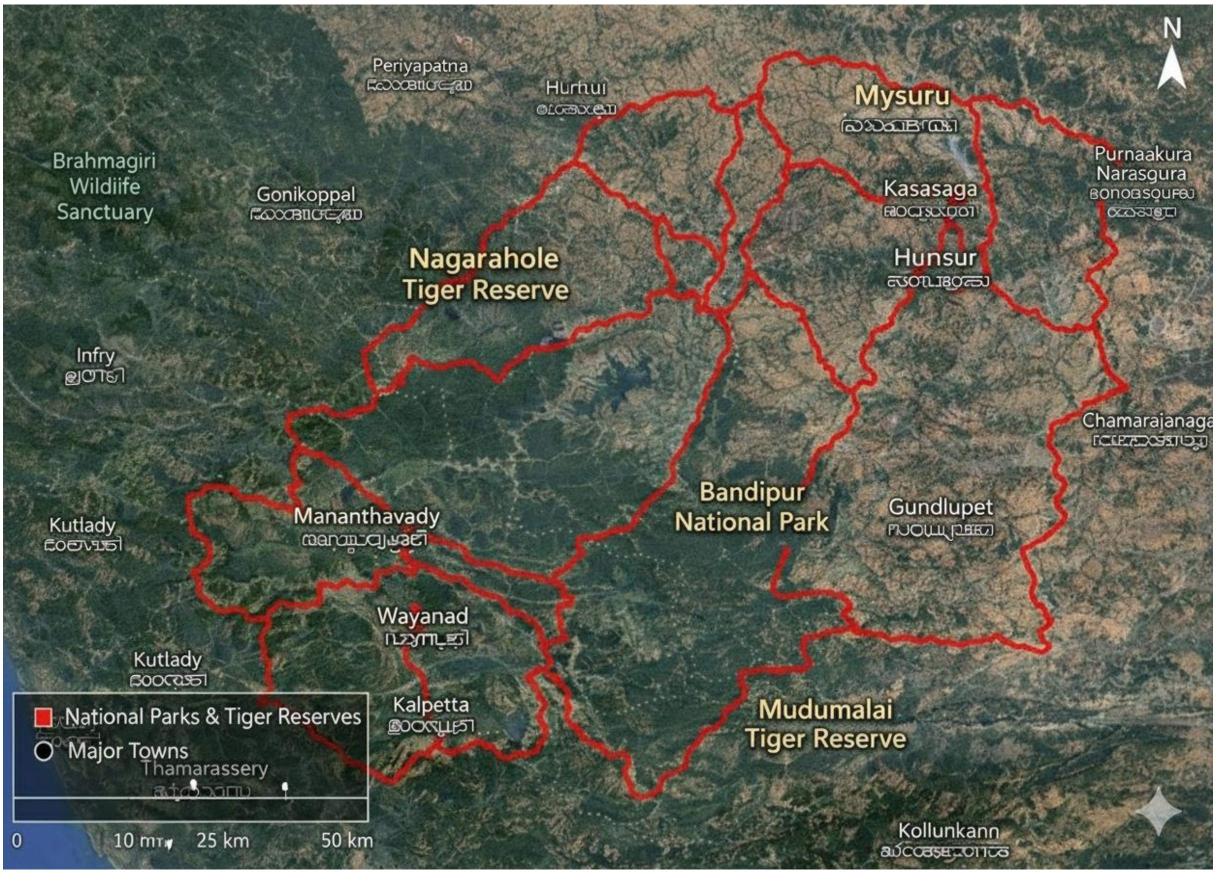


Figure 2. Kabin Sub-Basin – Satellite Imagery

3. Methodology

The methodology flow chart illustrates the sequence of steps involved in creating the two hydrological models, from data acquisition to model setup and analysis. Fig. 3 illustrates the overall methodological framework adopted in the study. HEC-HMS is a comprehensive software package developed by the U.S. Army Corps of Engineers to simulate the hydrologic processes occurring within dendritic watershed systems.

The procedure commences with data collection, which encompasses 30 m resolution DEM data, NASA rainfall datasets, and observed streamflow data sourced from GEOGloWS. The DEM undergoes processing for watershed delineation and sub-basin segmentation into configurations of 4, 8, 16, and 32. Hydrological modeling is conducted in HEC-HMS employing the SCS Curve Number loss technique, the SCS Unit Hydrograph transform technique, and the Muskingum routing technique. The models are standardized using practical streamflow data, followed by a statistical performance evaluation that employs NSE, RMSE, and MAE to examine the impact of spatial discretization on the accuracy of flood predictions.

This research employs a distributed hydrological modeling framework to assess the impact of spatial discretization on flood prediction efficacy in the Kabini River basin. The modeling strategy incorporates topographic, rainfall, and streamflow datasets within a physically coherent rainfall runoff simulation framework. A DEM with a determination of 30m was used to define watershed topography, drainage hierarchy and sub-basin morphometry. Utilizing the derived terrain characteristics, the basin was systematically discretized into four spatial configurations consisting of 4, 8, 16, and 32 sub-basins to evaluate scale sensitivity in a structured manner. The transformation of rainfall to runoff was modeled using the soil conservation service curve number (SCS-CN) method to calculate infiltration losses, in conjunction with the SCS Unit Hydrograph method for runoff transformation. Channel routing was simulated through the Muskingum method, which facilitates the representation of flow translation and attenuation within the drainage network. These modeling components were selected for their verified effectiveness in basins dominated by monsoon conditions and in environments with limited data availability.

Model calibration was conducted utilizing the available streamflow data, and the recital was evaluated through numerous numerical efficiency metrics, including NSE, RMSE, MAE, and PBIAS. A comparative analysis across different discretization levels facilitated the quantification of the effects of spatial variability on hydrograph shape, peak discharge estimation, and the robustness of the model.

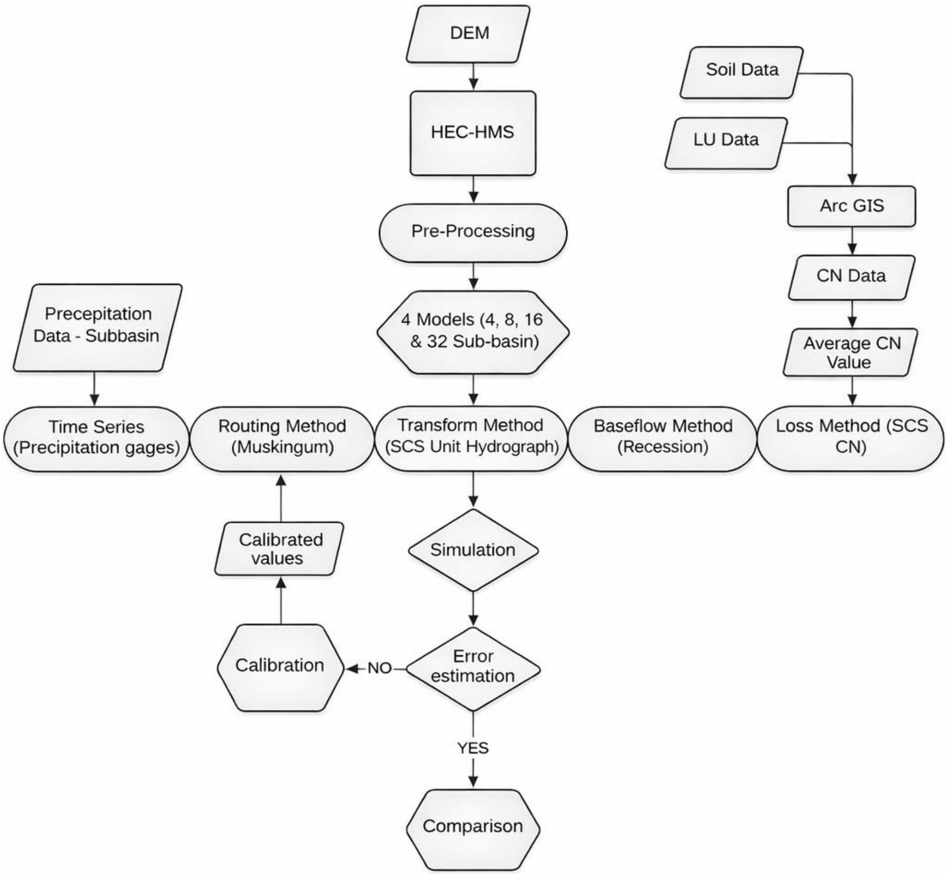


Figure 3. Design Methodology

4. Implementation of Project

4.1. Goals

Parametric evaluation of differential sub-basin in the performance of hydrological models for flood predictions. Assertive analysis on the performance of hydrological models with different sub-basin configurations using statistical metrics such as NSE, RMSE, and MAE. Refining the accuracy of flood predictions by determining the optimal sub-basin delineation that balances computational efficiency and model precision. Assessing the role of spatial variability in flood dynamics, evaluating the effectiveness of incorporating spatial data into flood prediction models. Proposing modifications to existing models to improve their predictive accuracy.

4.2. Model Setup Overview

A precipitation gauge was created and named in Gauge Manager. Historical rainfall data from NASA Data Access Viewer was imported into HEC-HMS. Time window set via Control Specifications menu, linking start and end dates to the basin model. The SCS Curve Number approach is utilized to evaluate the likelihood of runoff. Zonal Statistics tool in ArcGIS calculates the average CN for each sub-basin. Average CN values were imported into the loss method table in HEC-HMS. SCS unit hydrograph method converts rainfall excess into direct runoff, and lag time values are calculated using average CN data. Recession method simulates base flow, modeling the natural decline of water discharge over time. Muskingum routing method simulates channel routing. Storage, inflow and outflow are considered for flood wave propagation and flow dynamics.

4.3. Calibration of the Model Using Actual Data

Calibration is a critical step in hydrological modeling, ensuring that the model accurately represents the real-world behavior of the crisis. In this study, the calibration procedure was executed utilizing actual streamflow data sourced from the GEOGloWS Hydroviewer, a platform that grants access to worldwide streamflow data. The calibration process entailed modifying model parameters to reduce the differences between simulated and observed data, thus improving the model’s predictive precision. Following multiple iterations, a final set of parameters that yielded the optimal fit between simulated and observed streamflow was determined. These parameters comprised the recession constant (K), ratio to peak (R), Curve Numbers (CN), and Muskingum K and X values. Figure 4 illustrates the observed data gathered from the GEOGloWS Hydroviewer.

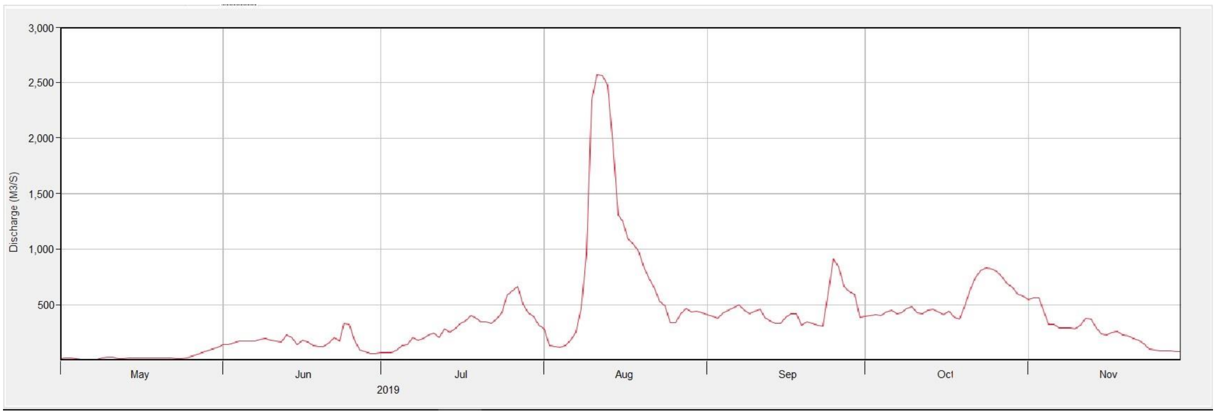


Figure 4. Observed Data from GEOGloWS

Each model was standardized utilizing observed flow data obtained from stream gauges located in the Kabini basin. The calibration process required the adjustment of model parameters to ensure that the simulated hydrograph closely aligned with the observed hydrograph. To achieve this, the calibration employed the HEC-HMS optimization tool, which aimed to reduce the inconsistencies amongst the observed and simulated flows, as illustrated in Fig. 4.

5. Results and Discussion

5.1. Characteristics of Sub-Basin

The key characteristics of 4, 8, 16 and 32 sub-basins are essential for hydrological modeling. These characteristics include the extended movement path length and slope, centroidal flow path length and slope, 10-85 flow path length and slope, basin slope, relief ratio, elongation ratio, and drainage density. These parameters provide a comprehensive understanding of each sub-basin's hydrological and geomorphological properties.

5.2. Results of Loss Method (SCS Curve Number)

The SCS Curve Number method was employed to estimate runoff. The average CN values for each sub-basin configuration (4, 8, 16, and 32) were obtained and utilized in the HEC-HMS model. Initial abstraction is a vital parameter in hydrological modeling, especially within the HEC-HMS (Hydrologic Engineering Centre - Hydrologic Modelling System) framework. It signifies the initial quantity of precipitation that is lost due to processes such as infiltration, surface storage, and evaporation prior to the onset of runoff. The initial abstraction value is determined using the formula provided below.

$$S = \frac{1000}{CN} - 10 \qquad (1)$$

$$IA = 0.2 \times S \qquad (2)$$

Where,

S = Runoff potential
CN = Curve number (Dimensionless)
IA = Initial Abstraction

5.3. Results of the Transform Method (SCS Unit Hydrograph)

The SCS Unit Hydrograph method was employed to transmute excess rainfall into direct runoff hydrographs for the Kabini River basin. This approach effectively simulates the watershed's runoff response to rainfall events, providing a detailed understanding of how rainfall is converted into runoff within the basin. Utilizing this approach allows us to create hydrographs that illustrate the water flow over time after a rainfall event, which is crucial for flood prediction and the management of water resources.

Additionally, lag time calculations were performed to better understand the temporal dynamics of runoff. Lag time, the interval between the peak of the rainfall event and the peak of the subsequent runoff, is a critical parameter in hydrology. It helps in assessing how quickly the basin responds to rainfall and the speed at which runoff travels through the watershed. Understanding lag time is vital for predicting the timing of flood peaks and for designing effective flood control measures. Through these calculations, a significant insight into the hydrological dynamics of the Kabini River basin is achieved, which facilitates more precise and dependable hydrological modeling and water management strategies.

5.4. Simulation Results

The simulation results after calibration are presented. Calibration was performed to minimize discrepancies between simulated and observed streamflow. Figs. 5, 7, 9 and 11 display the observed v/s simulated hydrograph and Figs. 6, 8, 10 and 12 display the statistical performance, respectively.

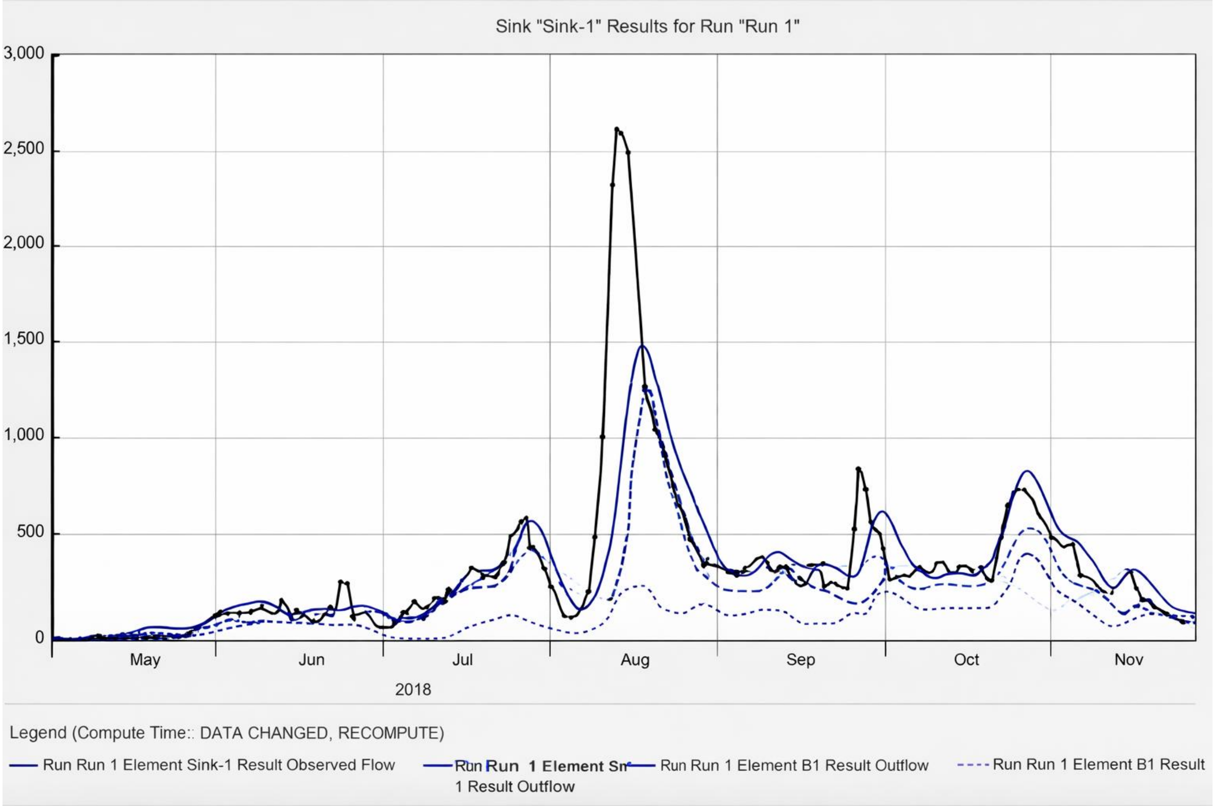
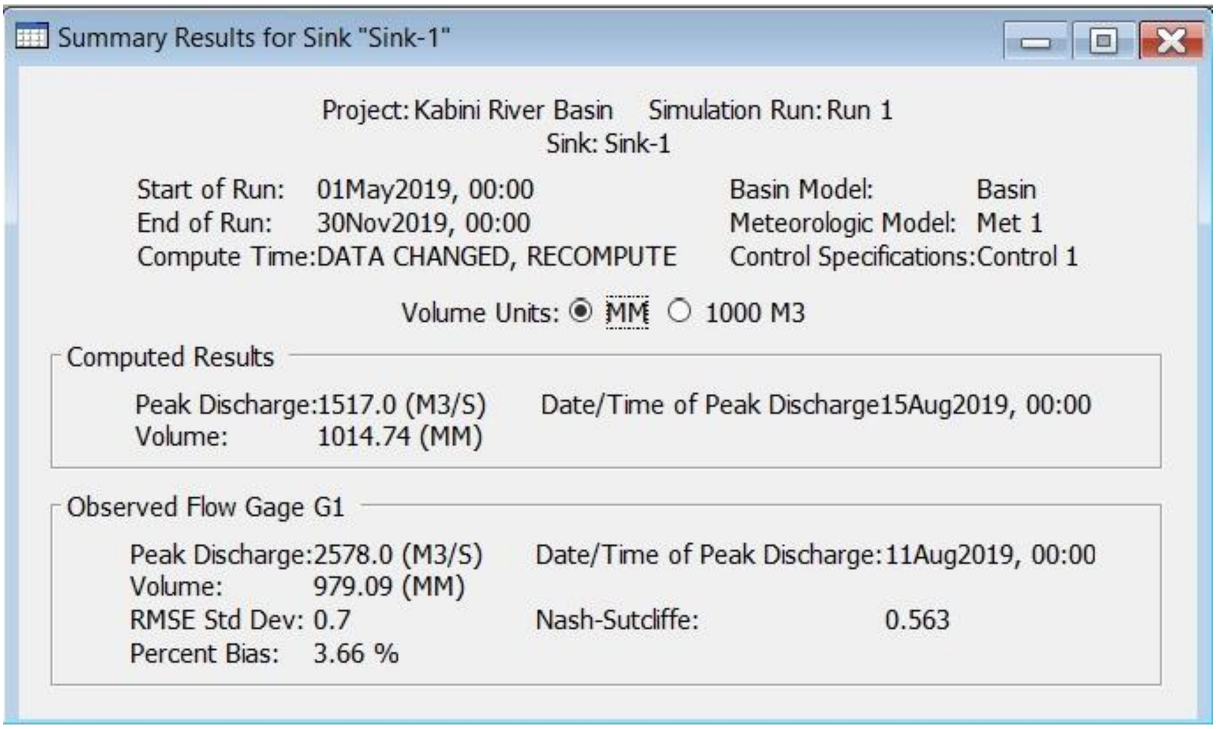


Figure 5. Comparison of observed and simulated hydrographs for 4 sub-basin


Summary Results for Sink "Sink-1"

Project: Kabini River Basin Simulation Run: Run 1
Sink: Sink-1

Start of Run: 01May2019, 00:00
End of Run: 30Nov2019, 00:00
Compute Time: DATA CHANGED, RECOMPUTE

Basin Model: Basin
Meteorologic Model: Met 1
Control Specifications: Control 1

Volume Units: ● MM ○ 1000 M3

Computed Results

Peak Discharge: 1517.0 (M3/S)
Volume: 1014.74 (MM)
Date/Time of Peak Discharge 15Aug2019, 00:00

Observed Flow Gage G1

Peak Discharge: 2578.0 (M3/S)
Volume: 979.09 (MM)
RMSE Std Dev: 0.7
Percent Bias: 3.66 %
Date/Time of Peak Discharge: 11Aug2019, 00:00
Nash-Sutcliffe: 0.563

Figure 6. Statistical performance metrics for 4 sub-basin model

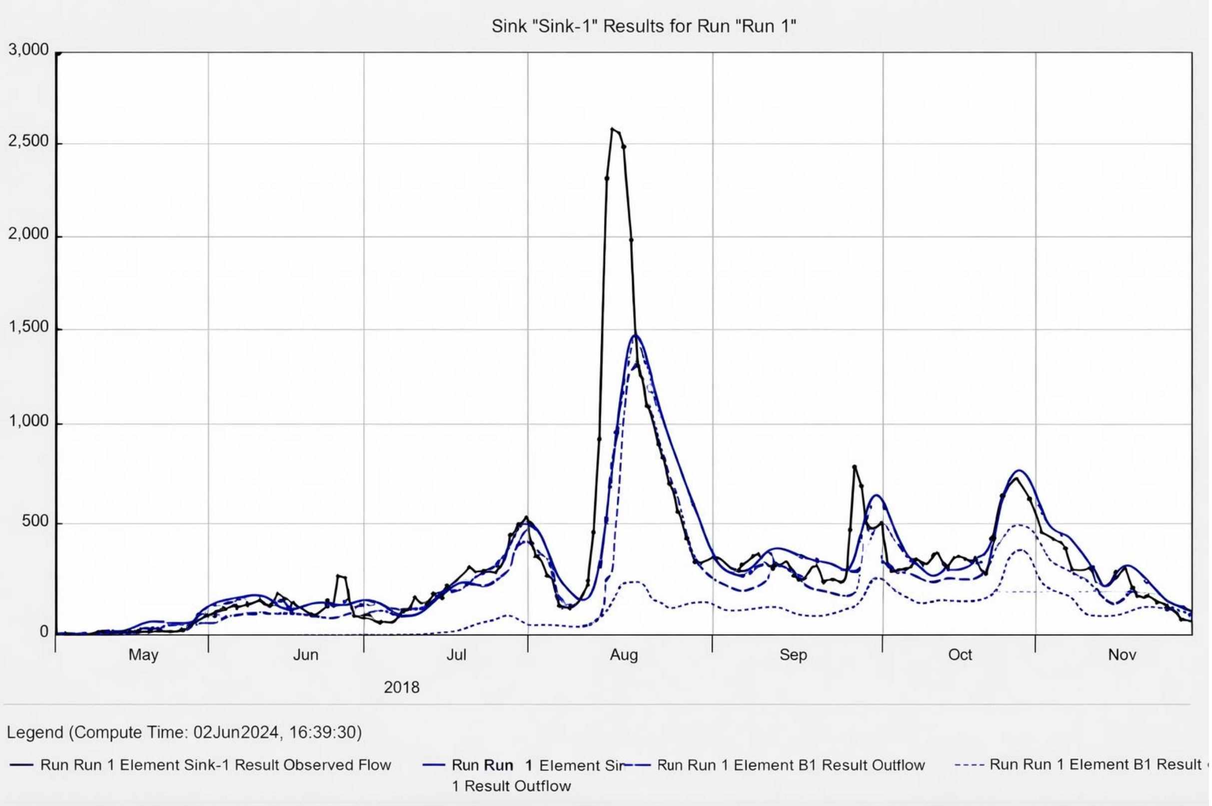
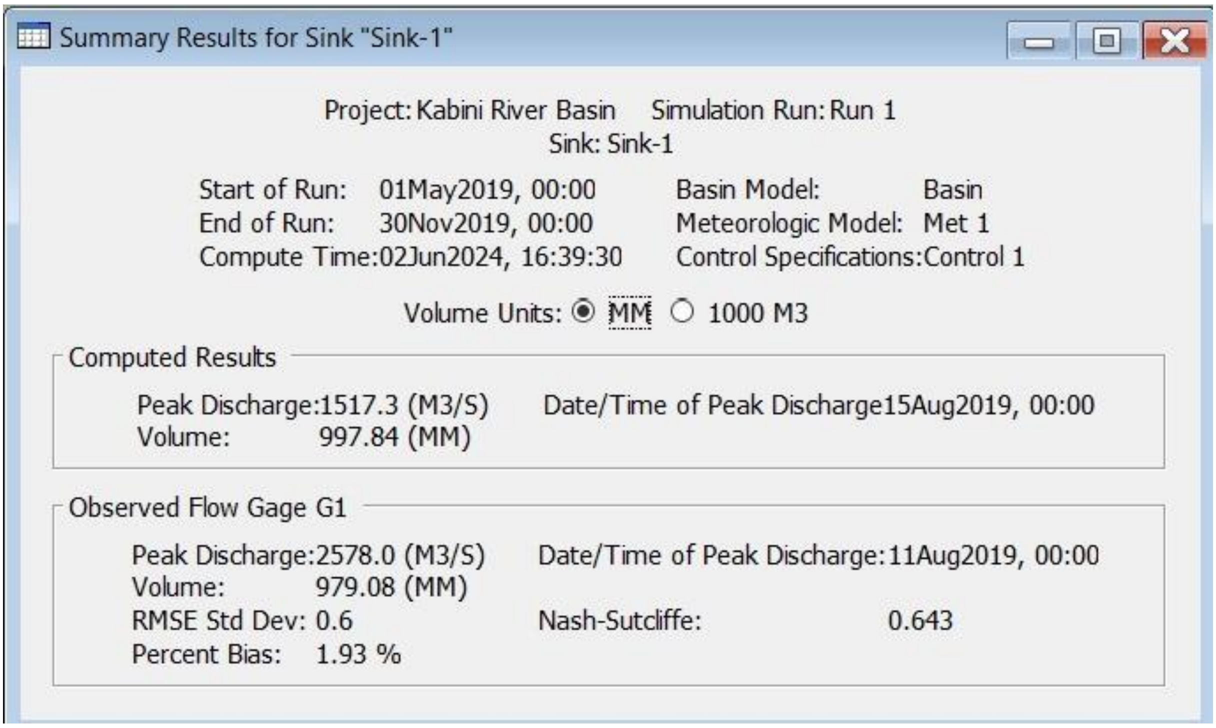


Figure 7. Comparison of observed and simulated hydrographs for 8 sub-basin



Project: Kabini River Basin Simulation Run: Run 1
Sink: Sink-1

Start of Run: 01May2019, 00:00 Basin Model: Basin
End of Run: 30Nov2019, 00:00 Meteorologic Model: Met 1
Compute Time: 02Jun2024, 16:39:30 Control Specifications: Control 1

Volume Units: ● MM ○ 1000 M3

Computed Results

Peak Discharge: 1517.3 (M3/S) Date/Time of Peak Discharge 15Aug2019, 00:00
Volume: 997.84 (MM)

Observed Flow Gage G1

Peak Discharge: 2578.0 (M3/S) Date/Time of Peak Discharge: 11Aug2019, 00:00
Volume: 979.08 (MM)
RMSE Std Dev: 0.6 Nash-Sutcliffe: 0.643
Percent Bias: 1.93 %

Figure 8. Statistical performance metrics for 8 sub-basin model

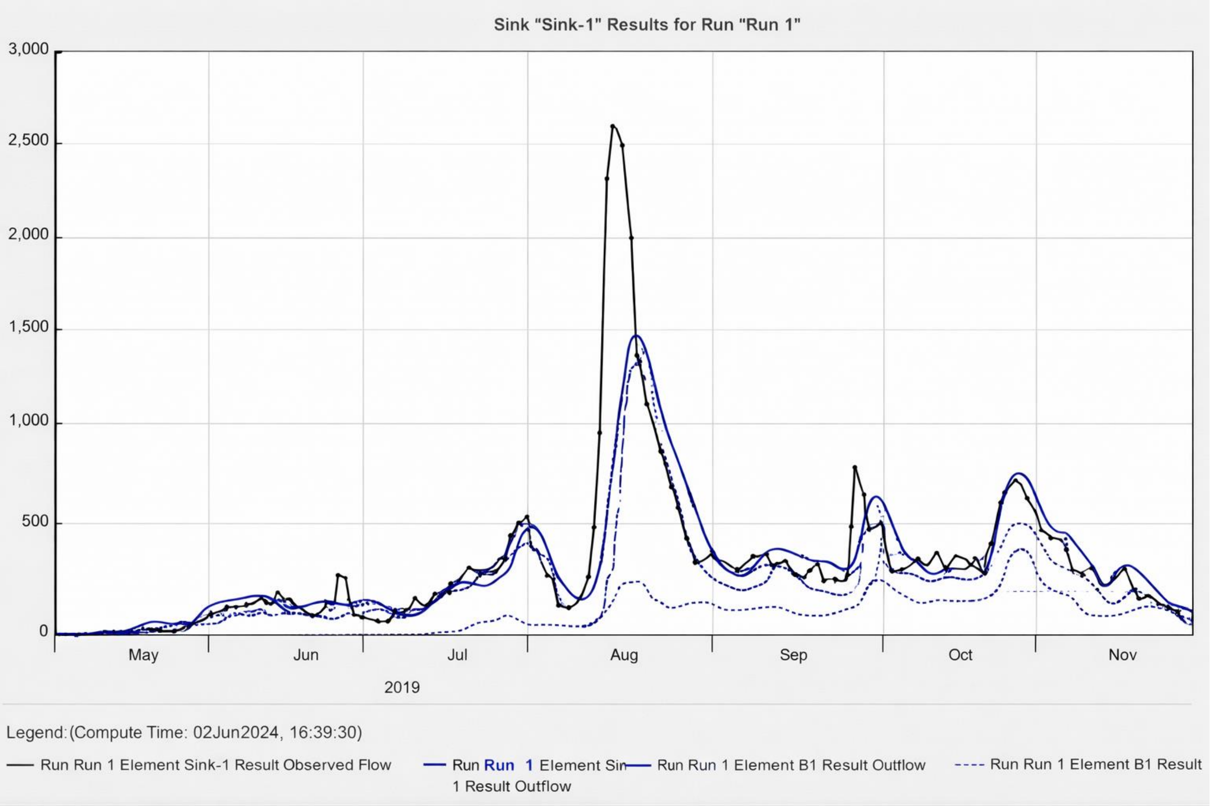
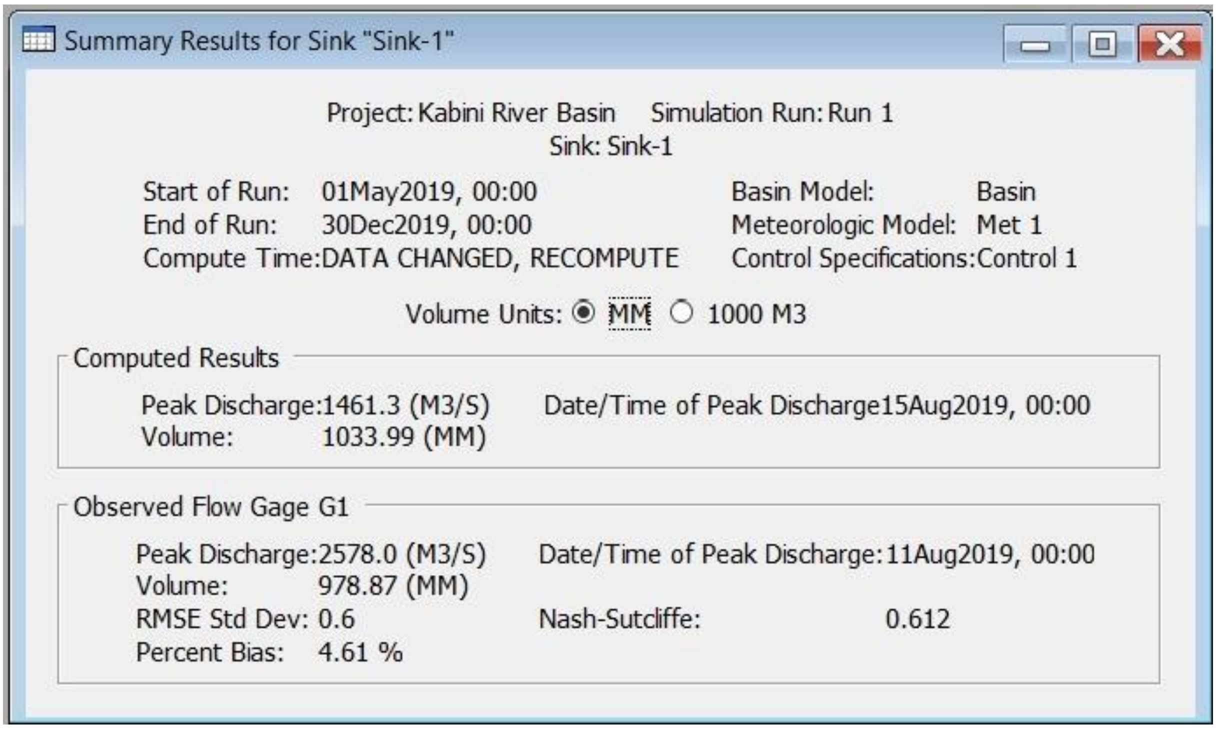


Figure 9. Comparison of observed and simulated hydrographs for 16 sub-basin



Summary Results for Sink "Sink-1"

Project: Kabini River Basin Simulation Run: Run 1
Sink: Sink-1

Start of Run: 01May2019, 00:00 Basin Model: Basin
End of Run: 30Dec2019, 00:00 Meteorologic Model: Met 1
Compute Time: DATA CHANGED, RECOMPUTE Control Specifications: Control 1

Volume Units: ● MM ○ 1000 M3

Computed Results

Peak Discharge: 1461.3 (M3/S) Date/Time of Peak Discharge 15Aug2019, 00:00
Volume: 1033.99 (MM)

Observed Flow Gage G1

Peak Discharge: 2578.0 (M3/S) Date/Time of Peak Discharge: 11Aug2019, 00:00
Volume: 978.87 (MM)
RMSE Std Dev: 0.6 Nash-Sutcliffe: 0.612
Percent Bias: 4.61 %

Figure 10. Statistical performance metrics for 16 sub-basin model

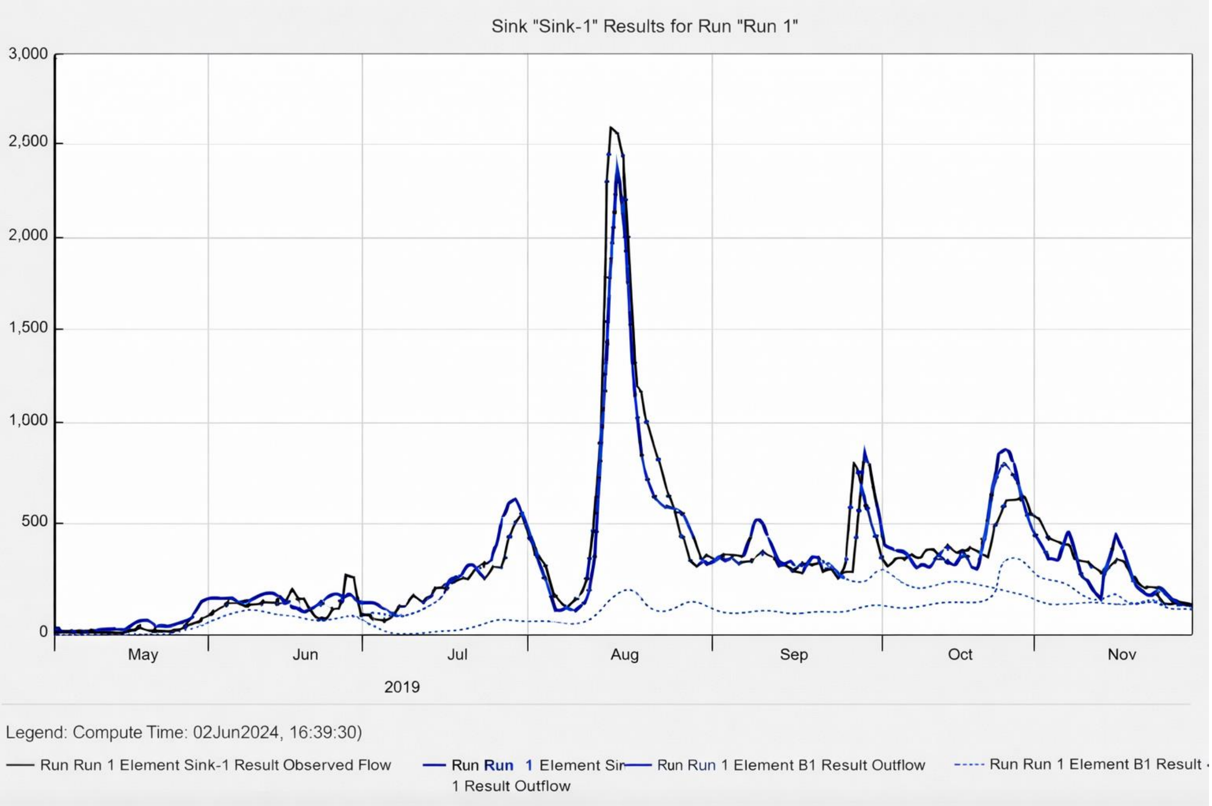
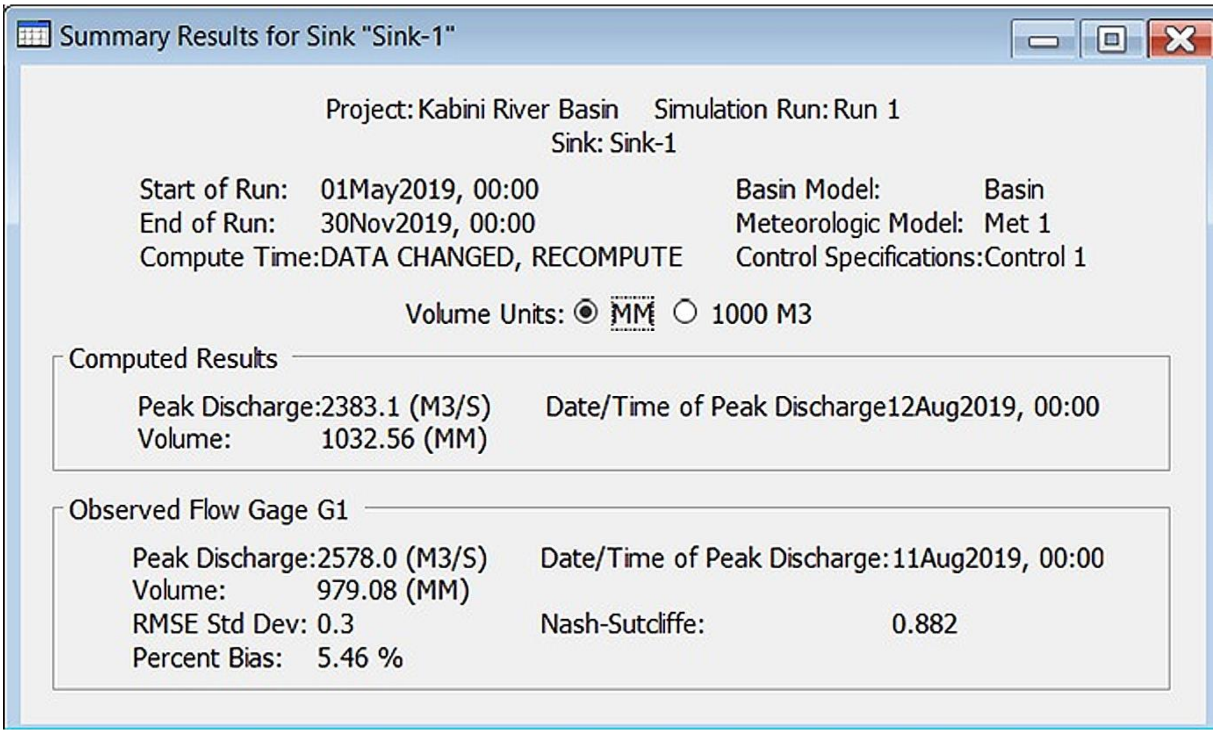


Figure 11. Comparison of observed and simulated hydrographs for 32 sub-basin


Summary Results for Sink "Sink-1"

Project: Kabini River Basin Simulation Run: Run 1
Sink: Sink-1

Start of Run: 01May2019, 00:00
End of Run: 30Nov2019, 00:00
Compute Time: DATA CHANGED, RECOMPUTE
Basin Model: Basin
Meteorologic Model: Met 1
Control Specifications: Control 1

Volume Units: ● MM ○ 1000 M3

Computed Results

Peak Discharge: 2383.1 (M3/S)
Date/Time of Peak Discharge 12Aug2019, 00:00
Volume: 1032.56 (MM)

Observed Flow Gage G1

Peak Discharge: 2578.0 (M3/S)
Date/Time of Peak Discharge: 11Aug2019, 00:00
Volume: 979.08 (MM)
RMSE Std Dev: 0.3
Nash-Sutcliffe: 0.882
Percent Bias: 5.46 %

Figure 12. Statistical performance metrics for 32 sub-basin model

5.5. Comparison of Statistical Metrics for Different Sub-Basin Configurations

5.5.1. Nash-Sutcliffe Efficiency (NSE)

The NSE evaluates the degree to which the simulated data aligns with the observed data. An NSE value of 1 signifies a flawless match, whereas an NSE value of 0 suggests that the model's predictions are as precise as the average of the observed data.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Oi - Pi)^2}{\sum_{i=1}^{n}(Oi - \bar{O})^2} \tag{3}$$

Where,
Oi = Observed value at the time step i
Pi = predicted (simulated) value at time step i
O = mean of observed values
n = number of observations

5.5.2. Root Mean Square Error (RMSE)

The RMSE represents the typical nonconformity of the residuals (prediction errors). It provides an understanding of the dispersal of the errors.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Oi - Pi)^2}{n}} \tag{4}$$

Where,
Oi = observed value at time step i
Pi = predicted (simulated) value at time step i
n = number of observations

5.5.3. Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) quantifies the average size of errors in a collection of predictions, disregarding their direction. It represents the average of the absolute differences between predicted values and actual observations across the test sample.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Oi - Pi\right| \tag{5}$$

Where,
Oi = observed value at time step i
Pi = predicted (simulated) value at time step i
n = number of observations

The recital of the hydrological model improved with an increasing number of sub-basins. The Nash-Sutcliffe Efficiency (NSE) values increase, indicating a better fit between observed and simulated data. The configuration with 32 sub-basins exhibits the highest NSE value of 0.881805, reflecting a high level of accuracy, while the 4 sub-basin configuration shows the lowest NSE value of 0.56271, indicating less accuracy.

In a similar manner, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values diminish as the number of sub-basins increases, with the configuration of 32 sub-basins exhibiting the lowest RMSE (136.8076) and MAE (91.06836), which indicates the smallest errors and the highest level of accuracy. On the other hand, the configuration with 4 sub-basins presents the highest RMSE (263.1453) and MAE (116.5661), reflecting larger errors. Overall, increasing the number of sub-basins enhances model performance across all metrics, demonstrating that finer sub-basin delineation strengthens the model's ability to accurately simulate hydrological processes in the Kabini River Basin. A comparison of statistical metrics for various sub-basin configurations is presented in Table 1 and Table 2.

Table 1. Comparison of Statistical Metrics for Different Sub-Basin Configurations

Sub-Basin Configuration	NSE	RMSE Std Dev	PBIAS
4-Sub-Basins	0.563	0.700	3.66%
8-Sub-Basins	0.643	0.600	1.93%
16-Sub-Basins	0.612	0.600	4.61%
32-Sub-Basins	0.882	0.300	5.46%

Table 2. Comparison of Statistical Metrics for Different Sub-Basin Configurations

Sub-Basin Configuration	NSE	RMSE	MAE
4-Sub-Basins	0.562	263.15	116.56
8-Sub-Basins	0.643	237.73	103.30
16-Sub-Basins	0.612	220.93	99.93
32-Sub-Basins	0.882	136.81	91.06

In Table 1, the PBIAS values below ±10% indicate good model performance, suggesting acceptable bias in volumetric estimation. Enhancing the sub-basin discretization from 4 to 32 led to a 56.9% enhancement in the NSE and a 48% decrease in the RMSE, thereby affirming the significant impact of spatial rainfall representation on predictive accuracy, which is publicized in Table 3.

Table 3. Percentage improvement analysis

Metric	4-Sub-basin	32-Sub-basin	% Improvement/ reduction
NSE	0.562	0.882	56.9 Improvement
RMSE	263.15	136.81	48 reduction
MAE	116.56	91.06	28.9 reduction

The significant rise in NSE from 0.562 (with 4 sub-basins) to 0.882 (with 32 sub-basins) suggested that a more detailed spatial discretization enhances the model's capacity to represent temporal variability in runoff generation. Hydrologically, this signifies an improved depiction of spatial rainfall diversity and localized runoff contributions within each sub-basin. Conversely, a coarser delineation tends to average out rainfall and watershed characteristics, leading to smoothed hydrographs and an underestimation of peak discharge variability. The 48% reduction in RMSE indicates a better simulation of high-flow events, especially regarding peak discharge levels during heavy monsoon rainfall. A lower RMSE signifies that flood peaks are represented with greater accuracy, which diminishes uncertainty in estimating flood magnitudes and enhances the reliability of risk assessments. The decrease in MAE from 116.56 to 91.06 signifies a better average deviation between the simulated and actual discharge values, indicating an increase in the reliability of daily flow estimations. This enhancement is vital for operational flood forecasting, as persistent under or over predictions can greatly affect warning thresholds.

5.6. Limitations and Uncertainty Analysis

Despite the enhanced performance noted with finer sub-basin discretization, various sources of uncertainty persist within the modeling framework. Rainfall inputs were sourced from NASA satellite datasets, which may introduce bias during high-intensity monsoon events due to constraints in spatial averaging and temporal resolution. Such uncertainties can influence peak expulsion assessment and the timing of hydrographs. The claim of a 30 m resolution DEM, while appropriate for basin-scale analysis (~7,039 km^2), may smooth out micro-topographic features that affect the accuracy of localized flow accumulation and drainage delineation. Model structural assumptions further contribute to uncertainty. The SCS Curve Number method presumes uniform antecedent moisture conditions across each sub-basin, which may oversimplify the variability in infiltration. Likewise, the Muskingum routing method employs a simplified linear storage–discharge relationship that may not adequately represent non-linear flood wave dynamics during extreme events. Increasing sub-basin discretization from 4 to 32 enhanced NSE by 56.9% and decreased RMSE by 48%, but also raised the number of calibrated parameters, introducing risks of parameter equifinality and over-parameterization. Additionally, calibration was based on the available GEOGloWS streamflow data for a limited simulation period, and long-term independent validation was not conducted. These findings demonstrate that spatial discretization significantly influences hydrological response representation in large tropical watersheds.

6. Conclusions

1. The performance of the models was assessed using NSE, RMSE, and MAE. Results showed that increasing sub-basin numbers generally improved performance, with the 32 sub-basin model achieving the highest NSE (0.881805) and lowest RMSE (136.8076) and MAE (91.06836), indicating greater accuracy.
2. The results indicate that spatial discretization has a substantial impact on the robustness of hydrological models in extensive monsoon-driven basins. The configuration of 32 sub-basins led to a 56.9% improvement in NSE and a 48% reduction in RMSE, which signifies a better representation of rainfall variability and runoff concentration dynamics. These findings imply that in basins with significant relief (1,398 m) and a fifth-order drainage hierarchy, spatial resolution is vital for accurately simulating peak discharge and the effectiveness of hydrographs. Nevertheless, refining the model requires a careful balance between statistical improvements, calibration stability, and computational efficiency.
3. This study offers a systematic approach for determining the most effective discretization levels in large tropical watersheds, thereby enhancing the reliability of flood forecasting and water resource management.
4. This study highlights the benefits of detailed sub-basin configurations in hydrological modeling while advocating for a balanced approach considering computational resources and data availability.

The methodological framework developed in this study can be extended to similar monsoon-driven river basins for improving flood forecasting robustness.

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