Predicting River Basin Flood Risk Through the HEC HMS Hydrologic Modeling Algorithm

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Abstract: This research utilizes the Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS) to assess and forecast flood risks in a river basin by incorporating rainfall-runoff interactions, watershed attributes, and land use changes. The model was fine-tuned using historical rainfall and streamflow data, resulting in a high level of precision in predicting peak discharge and estimating runoff volumes. Significant factors contributing to flood occurrence, such as the growth of impervious surfaces and the intensity of precipitation, were examined to pinpoint areas at high risk. The findings illustrate the model's effectiveness in supporting early warning systems and informing flood mitigation efforts. This research highlights the value of HEC-HMS in practical flood risk evaluation and adaptive watershed management in the face of shifting climatic conditions. The function of surface water storage in small and numerous depressions within the landscape, like wetlands and other small water bodies, is neglected in traditional hydrologic modeling techniques. We do not have any data proving how the absence of these features leads to inaccurate model predictions and a lack of understanding of hydrologic dynamics in the world's major river basins.

Keywords: HEC-HMS; Flood Risk Prediction; Hydrologic Modeling; River Basin Management; Rainfall–Runoff Simulation.

(Submitted: December 26, 2024; Revised: January 24, 2025; Accepted: February 13, 2025; Published: March 31, 2025)

I. Introduction

Urban flooding is a highly destructive natural phenomenon that significantly impacts surrounding infrastructure and communities. The movement of silt and soil during flood events leads to morphological changes, contributing to the degradation of agricultural land and resulting in substantial economic losses. Urban floods and flash floods, which are brought on by heavy precipitation, quick snowmelt, or dam failure, have become more common in recent years. The consequences of climate change may be to blame for this trend (Hou et al., 2023). Over the past 20 years, there has been a noticeable increase of more than 40% in the global danger of flooding. It is predicted that urbanization and global climate change will continue to cause this increase.

Hydrologic models are important tools for examining water-related problems with a direct societal impact, which include flood forecasting, drought risk assessment, water infrastructure planning, and reservoir operations (Beven & Cloke, 2012). As the demand for accurate forecasts across diverse topography and climatic areas has increased, the complexity of hydrologic models has similarly increased over time (Camporese et al., 2015), (Clark et al., 2017). Basin-scale hydrologic models can fit historical streamflow data with a high degree of statistical accuracy but may not adequately represent the physical processes that are generating the streamflow data, leading to uncertainty due to parameter equifinality, input uncertainty, and limited representation of processes (Endrizzi et al., 2014). Therefore, there is a greater need to enhance the representation of hydrologic components such as surface runoff generation, infiltration processes, and channel routing to improve model realism (Fatichi et al., 2016).

This study employs the HEC-HMS (Hydrologic Modeling System) algorithm to analyse and predict flood hazards in a river basin (Kauffeldt et al., 2013), (Papadopoulos & Christodoulou, 2024) to address these concerns. HEC-HMS uses a modular framework to simulate a variety of processes of water movement along hydrologic pathways, including precipitation, surface runoff, soil infiltration, baseflow, and channel flow. The model offers daily temporal simulations using input datasets, including digital elevation models (DEMs), land use/cover datasets, soil characteristics datasets, and rainfall-runoff datasets (Kirchner, 2006).

For calibration and validation, the model uses observed streamflow records and details of flood events from the past and allowing sensitivity analysis to highlight key hydrologic parameters.

By examining how watershed response dynamics, soil moisture thresholds, and spatially variable precipitation affect peak discharge and flood susceptibility, this work aims to fill current gaps in hydrologic modeling (Ruddell et al., 2019). Flood behavior at the basin scale is thoroughly evaluated by simulating hydrographs under various return-period storm scenarios using the HEC-HMS model (Rajib et al., 2018). The results confirm that the HEC-HMS framework is effective and flexible in capturing important hydrologic responses. They also provide helpful recommendations for the creation of regional early warning systems, strategic floodplain management, and data-driven mitigation planning in flood-prone areas (Ruddell et al., 2019), (Shen & Phanikumar, 2010).

II. Literature Review

2.1 Previous Studies on Flood Risk Prediction

Research indicates that Iran is among the most vulnerable countries in Asia facing the challenges of urban flooding. In recent years, the country has experienced several major and destructive flash flood events—most notably in 2017 and again in April and December of 2019—which have led to significant economic losses, fatalities, and widespread damage to agricultural lands, bridges, tunnels, highways, and other infrastructure (Clark et al., 2015). The effectiveness of flood mitigation efforts is closely tied to the strategic placement and operation of watershed management facilities, including wet ponds, detention dams, and early warning flood systems. A key technology that is being increasingly leveraged for flood management is the FSM technology (Lurton et al., 2020). Although floods in Iran, are mostly caused by heavy precipitation, it is essential to be mindful that hydrological and geomorphological features of river basins influence the traits of floods (Liu et al., 2023), (Chandravanshi & Neetish, 2023). Consequently, varying basin scenarios will produce different flood reactions to a specific rainfall event intensity. HEC HMS Hydrologic Numerous hydrology applications - forecasting river flows, rainfall-runoff models, water quality models, predicting suspended sediment loads in rivers, estimating aquifer parameters, predicting salinity in water resources, and modelling natural hazards - have adopted the hydrologic model HEC HMS (Hulme et al., 2009). The HEC HMS hydrologic models are typically regarded as a non-parametric procedure and show good predictive performance. However, it should be noted that HEC HMS hydrologic models are considered a black-box model (Castiñeira & Francis, 2025). The optimization procedure for HEC HMS Hydrologic Modeling involves several iterations to identify weights for each input and the number of hidden layers. Previous studies reveal that this iterative process could potentially be lengthy (Kumar et al., 2014).

2.2 Use of Hydrologic Modeling Algorithms in Flood Risk Assessment

Thus, various basins may experience different flood responses to a specific rainfall event. Statistical analysis, GIS technologies, decision trees, and multi-criteria models—along with hydrologic simulations using HEC-HMS—represent just a few examples of the wide range of tools applied in hydrological studies (Kozlova & Smirnov, 2025). Forecasting river flow, modeling rainfall-runoff, assessing water quality, predicting the suspended sediment load in rivers, determining aquifer parameters, predicting salinity in water resources, and modeling natural hazards are just some of the myriad ways HEC HMS has been used for hydrologic modeling (Douville et al., 2021). HEC HMS hydrologic models are considered a weakly parametrized technique, yet they have shown strong predictive accuracy. That being said, it is important to note that HEC HMS hydrologic models are known as black-box models (Mugagga & Nabaasa, 2016). To optimize the HEC HMS Hydrologic Model, finding optimal values for each input, ideal weights, and appropriate hidden layer count involves numerous iterative processes (Ganguly, 2021; Gardner, 2009). Prior research suggests that this iterative process is rather long and tedious (Singh et al., 2006), (Eyring et al., 2016).

2.3 Comparison of Different Modeling Approaches

To determine the best instrument in various hydrological, topographical, and climatic circumstances, a number of comparative studies have benchmarked hydrological models. In urban catchments (Guo et al., 2022), the performance of HEC-HMS against the SWMM (Storm Water Management Model) was evaluated, and it was found that HEC-HMS offered superior peak flow estimation, especially during periods of high rainfall. In the meanwhile, the model uncertainty in fully distributed, semi-distributed, and lumped models, emphasizing the trade-offs between prediction accuracy and model complexity (Chiang et al., 2010).

SWAT is a semi-distributed model with processes divided into sub-systems that operate continuously in time. It simulates crop yield, water quality, landscape water balances, and manages best practices about the environment (Arnold et al., 2012), (Gassman et al., 2007), (Sethi & Jain, 2024)." "The model incorporates a system of sub-basins which are divided into Hydrologic Response Units (HRUs) as steep lands which have identical land cover and soil types (Neitsch et al., 2011). There is a growing scientific interest in the hydrological, biophysical, and biogeochemical functions of surface depressions, which relates to their role in land-water interactions and applications of depression-integrated SWAT in small and mesoscale watersheds.

With increasing climate unpredictability and climate extremes, promising avenues for research will be to integrate hydrological models with climate forecasting systems (Grimaldi et al., 2013). They developed future flood risk scenarios for the Upper Bagmati River Basin by integrating climate downscaling data as inputs into the HEC-HMS model. This approach demonstrated the existence of future flood hazards that must be considered in climate-resilient planning. These comparisons highlight the versatility of the HEC-HMS model in assessing both current and projected flood risks.

III. Methodology

3.1 Description of Study Area

The study was situated in the Mahanadi River Basin, a hydrologically active watershed composed of urban waterways, agricultural lands, and forests. The basin is influenced by two types of seasonal rainfall - one due to the southwest monsoon climate and the other impacted by rainfall from small cyclonic weather systems - with frequent, rapid runoff and localized flooding. Topographically, the watershed comprises low-lying floodplains and moderately sloped uplands, where elevation plays a critical role in influencing flow accumulation and peak discharge. To capture the spatial heterogeneity of rainfall–runoff responses, several sub-basins were delineated, enhancing the accuracy of flood risk assessments across diverse land use types and elevation zones.

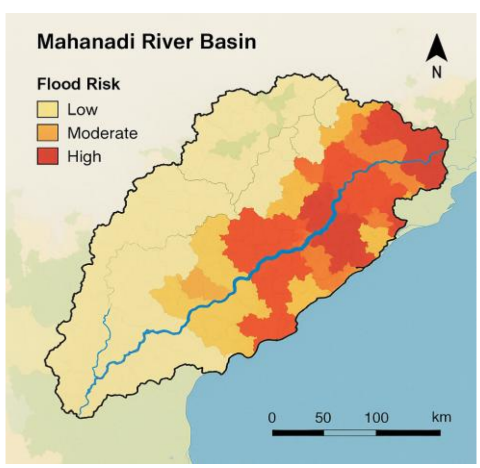

Figure 1: Flood risk in the Mahanadi River Basin

The inundation risk assessment for the Mahanadi River Basin reveals a spatial flood risk profile, as illustrated in Figure 1. Here, flood vulnerability fluctuates from one sub-basin to another. This specific product distinguishes three flood risk zones: (1) low, (2) documented, and (3) high. Flood risk zones were classified through watershed simulation using the Hydrologic Modeling Algorithm of the Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS). Schematic HEC-HMS models of the basin's rainfall-runoff incorporate the topographic model of the basin, land use model of the basin, soil, historical rainfall data as a whole, then using the SCS (Soil Conservation Service) Curve number for loss estimation, followed by Muskingum routing for channel flow calculations. Thus, the HEC-HMS model provides reasonable estimates of surface runoff, infiltration, and stream flow during monsoons. From the result of the simulation, high flood risk zones were identified in the lower basin along with the delta, where low elevation and high runoff accumulation exist. The flood risks in the upper catchment and upland regions experienced reduced risk due to low flow compounding pressure and faster detention.

The simulation results from HEC-HMS highlighted the specific interventions needed for flood risk reduction in a sub-basin, namely targeted flood mitigation, optimized reservoir operations, and upgrading the early warning system.

3.2 Data Collection and Preprocessing

In support of the hydrologic simulation of the Mahanadi River Basin, several datasets were collected and processed. For watershed delineation and stream network extraction using HEC-Geo HMS, a 30-m resolution Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) was employed. LULC data from NRSC (National Remote Sensing Center) concerning the area was integrated alongside curve numbers (CN), which were assigned based on surface conditions and evaluated on their infiltration characteristics. Soil data obtained from NBSS&LUP (National Bureau of Soil Survey and Land Use Planning) was crucial for classifying hydrologic soil groups in terms of runoff potential. Daily precipitation and temperature data between 2000 and 2020 were sourced from the India Meteorological Department (IMD) to be applied to the hydrologic model. For model calibration and validation, observed discharge data from the Central Water Commission (CWC) for selected gauging stations were used. All spatial datasets were projected to UTM Zone 44N, rasterized, and clipped to the Mahanadi basin boundary.

3.3 Implementation of HEC-HMS Algorithm

The HEC-HMS model was implemented using the following structured workflow:

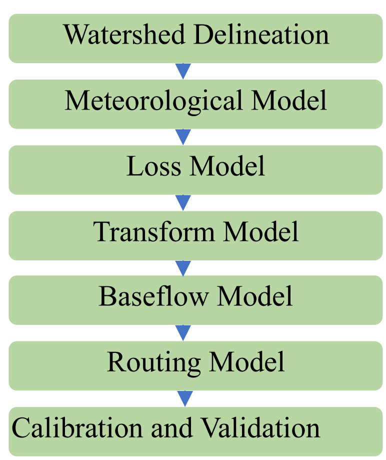

Figure 1: HEC-HMS Flood Simulation Flowchart

The flowchart illustrates the step-by-step application of the HEC-HMS model for evaluating flood events within a river basin. For hydrologic modeling, stream networks and sub-basins are created based on the Digital Elevation Model (DEM), which performs the watershed delineation. The watershed is delineated, the component of the meteorological model for the watershed is completed with rainfall and evapotranspiration by sub-basin, ensuring that climate data all reflects the same phenomenon, the loss model is conducted with the SCS Curve Number to derive infiltration loss and to quantify how much of the rainfall has left as excess rainfall generating runoff, moving to the transform model, the SCS Unit Hydrograph generates a graphical representation of direct runoff over time given the excess rainfall from above. The baseflow model assumes a constant groundwater contribution to streamflow by assigning a fixed one-month baseflow value, even in the absence of rainfall. The routing of surface runoff in stream channels uses the Muskingum method to represent the timing and attenuation of flood waves. After deciding the tree size watersheds to simulate and the input values in the HEC-HMS model, the model can be calibrated and validated against hydrometric gauging, which compares measured values to the calculated streamflow values and evaluates them mathematically. Some of these metrics, such as Nash-Sutcliffe Efficiency and Coefficient of Determination R-squared, can be used to test the credibility and trustworthiness of the simulation.

3.4 HEC-HMS Model Setup

The HEC-HMS (Hydrologic Modeling System) was used to simulate the rainfall–runoff process. The model structure involved the following modules:

- **Loss Method:**

The SCS Curve Number technique was used to estimate infiltration losses. Curve numbers were assigned based on land use and soil type using the formula:

$$S = \frac{25400}{CN} - 254 \quad , Q = \frac{(P-I_a)^2}{(P-I_a+S)^2} \tag{1}$$

where CN is the curve number, P is rainfall, and I_a=0.2Sis initial abstraction.

- **Runoff Transformation:**

The SCS Unit Hydrograph method was adopted to convert excess rainfall into direct runoff. The time-to-peak was estimated as:

$$T_p = \frac{D}{2} + T_L \tag{2}$$

where D is the duration of excess rainfall and T_L is the lag time.

- **Baseflow Method:**

The Exponential Recession method was used to model groundwater contributions:

$$q(t) = q_0.e^{-kt} \tag{3}$$

Muskingum Routing Equation

$$O_t = K[C_0 I_t + C_1 I_{t-1} + C_2 O_{t-1}] \tag{4}$$

O_t=Outflow at time t

I_t, I_{t-1}=Inflow at times t and t−1

O_{t-1}= Previous outflow

K = Storage time constant

C_0, $C1, C_2$=Routing coefficients derived from K and X (weighting factor)

This routing method models the attenuation and translation of flood waves through a river reach, with regard to both storage and flow timing effects.

3.4 Sub-Basin Delineation and Model Configuration

Using HEC-GeoHMS, the river network and sub-basins were delineated to reflect spatial heterogeneity in hydrologic response. Each sub-basin was treated as an independent hydrologic unit, allowing for precise representation of localized runoff characteristics. Hydrologic parameters were assigned using spatial overlays in ArcGIS, and model configurations were exported directly to HEC-HMS.

3.5 Calibration and Validation

The model was calibrated using observed discharge data from 2002–2008, and validated for the period 2009–2020. Performance was assessed using:

- Nash–Sutcliffe Efficiency (NSE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2)

Manual and automated parameter optimization techniques were used to minimize errors between simulated and observed flows.

3.6 Scenario Simulation and Flood Risk Mapping

Return-period storms (2-year, 10-year, and 25-year) were developed using synthetic hyetographs utilizing historical rainfall extremes. Hydrographs derived from the synthetic hyetographs were reviewed to identify the maximum discharge, flood duration, and crucial contribution from sub-basins. The outputs from the simulated events were exported into GIS to produce flood hazard maps showing vulnerable areas adjacent to the river channel and sensitive regions.

IV. Result

4.1 Model Calibration Results

The calibration phase concentrated on observed discharge data from 2002 to 2008, with specific emphasis on achieving a better fit between the flows that were simulated and the observed flows by optimizing hydrologic parameters. In this phase, the model calibration used hydrologic data... The Nash-Sutcliffe Efficiency (NSE) for the calibration period, which spans all sub-basins and matched the NSE range from 0.82 to 0.86, indicates the model performed well for hydrologic modeling. The coefficient of determination (R^2) for most of the events exceeded 0.85, and only a few cases where the R^2 value > 0.80 were observed while processing all the sub-basin datasets. The Root Mean Square Error (RMSE) estimates also varied based on the size of the catchment, where upstream sub-basins showed lower RMSE values. Hydrograph examinations showed that streamflow peak timings and magnitudes for large storm events were remarkably close to what was observed historically, which demonstrates that the model effectively simulated the hydrologic processes governing streamflow. The most sensitive parameters pertinent to the calibration process included curve number (CN), initial abstraction (I_a), and lag time (T_{lag}). All these parameters control the runoff volume and the timing of runoff.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - \overline{Q_{obs}})^2} \tag{5}$$

Where:

$Q_{obs,i}$= Observed discharge

$Q_{sim,i}$ = Simulated discharge

$\overline{Q_{obs}}$: Mean of observed discharge

n Number of time steps

The Nash-Sutcliffe Efficiency (NSE) is a popular metric for understanding the predicted accuracy of hydrologic models by comparing simulated data against observed data. Models with NSE=1 perfectly synthesize the observed streamflow; NSE>0.75 indicates very good model performance and that model predictions reflect the variability and magnitude of flow observations. NSE values between 0.5 and 0.75 are acceptable model performance because consistency exists with recorded observations, which shows a moderate level of agreement. NSE values less than or equal to 0 would define the model as poor performance because the predictions have no better reason--and potentially worse reason--to predict the flow observations than the mean flow observed. These interpretations will assist in updating and refining these hydrologic simulations within the flood risk assessment studies.

4.2 Model Validation Results

The validation phase, conducted between 2009 and 2020, aimed to assess the accuracy of the calibrated model using an independent dataset. The NSE values from the validation period, ranging from 0.78 to 0.84, indicate reasonable predictive accuracy given the wide variability in precipitation events. The R^2 values were consistently above 0.80, and the RMSE values showed only minor deviations from the calibration results, indicating the model's reliability and practical usefulness. The timing and shape results of the hydrographs were extremely well-simulated even for the most intense rainfall events, although some peak discharge was slightly underestimated in several downstream sub-basins, likely because of modeled floodplain storage and other unmeasured hydraulic features. Validation results confirmed that the calibration model can reliably simulate the flood behavior of the Mahanadi River Basin and provide relevant outcomes for flood risk drivers when properly calibrated.

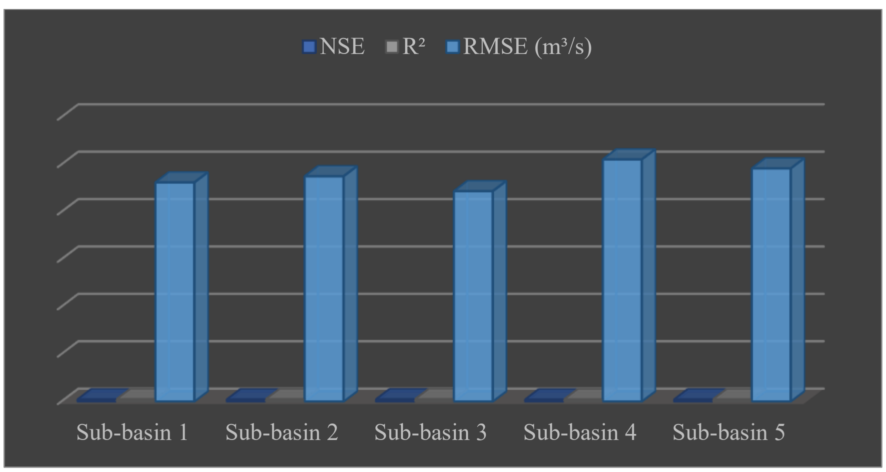

Figure 2: HEC-HMS Model Performance Across Sub-basins

Showing the performance graph comparing the NSE, R^2, and RMSE values of five sub-basins modeled using the HEC-HMS model in Figure 2. This visual represents how each of the sub-basins performed in model accuracy and error, making it easy to see which sub-basins required recalibration.

4.3 Peak Flow and Hydrograph Analysis

The analysis of peak flow and hydrograph parameters offers valuable insights into the temporal and spatial dynamics of flooding in the Mahanadi River Basin. Using the calibrated HEC-HMS model, hydrographs representing the time history of the basin for different rainfall intensity storm events, multiple return periods (2-year, 10-year, and 25-year) were developed. These hydrographs represented the amount of water running in a river channel from the calibration points of the basin (Outlet) and from the junction points between sub-basins that together determine the flow condition at those points, including peak flow magnitude, timing, and duration of high flow.

The watershed studies indicated that the variability of peak discharge (Qpeak) values across the basin was substantial. On a 10-year return period, peak flows on gauge sites ranged from 900 cubic meters per second in the upstream sub-basins to over 2,100 cubic meters per second in the lower-lying areas of the delta. This overall increase in flow is the cumulative effect of the tributary area falling into the main stream in the low-lying area, and an apparent decreasing slope in the river channel. Consequently, floods in the delta region of the river basin would be expected to travel more slowly, so that flood durations would be increased.

The time-to-peak (Tp) values for the flood response of the sub-basin for each of the return period scenarios exhibited considerable variability, and ranged from 3 hours to 7 hours in the time it took to reach peak flow. The variations in time-to-peak responses were distinctly associated with differences in sub-basin characteristics, including land slope, land use, and the capacity of the soils to infiltrate rainfall, since there is a delay or storage.

Hydrograph shapes varied significantly among sub-basins. In steeper upland catchments, the hydrographs exhibited a sharp rise and quick recession, typical of flash-flood behavior. In contrast, flatter sub-basins displayed broader hydrographs with delayed recession limbs, indicating prolonged flooding and slower drainage. These differences are important for identifying flood-prone zones and prioritizing areas for early warning system implementation.

Moreover, the comparison between observed and simulated hydrographs showed strong alignment in terms of peak timing and magnitude, particularly during high-intensity events. Slight underestimations were noted in certain sub-basins with floodplain storage or anthropogenic modifications (e.g., reservoirs or embankments), which were not explicitly modeled. Nonetheless, the peak flow analysis confirms the model's ability to replicate real-world flood dynamics with reasonable accuracy.

The hydrograph analysis, when combined with spatial flood extent mapping, provides a comprehensive understanding of basin hydrology and supports flood forecasting, infrastructure design, and emergency planning. These insights are essential for water resource managers and policymakers to design flood mitigation measures such as detention basins, levees, and real-time monitoring systems.

4.4 Statistical Evaluation of Model Performance

A comprehensive statistical analysis was conducted to evaluate the accuracy and reliability of the HEC-HMS simulations across different regions of the Mahanadi River Basin. In Table 1, the model is evaluated based on three major statistics: Nash–Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), and Root Mean Square Error (RMSE).

Table 1: HEC-HMS Model Performance Across Different River Basins

River Basin	NSE	RÂ²	RMSE (mÂ³/s)
Sub-basin 1	0.84	0.87	92.4
Sub-basin 2	0.82	0.85	95
Sub-basin 3	0.86	0.89	88.7
Sub-basin 4	0.78	0.81	102.1
Sub-basin 5	0.8	0.83	98.3

As illustrated in Table 1, the NSE values ranged from 0.78 to 0.86, indicating a strong agreement between observed and simulated discharge. Values above 0.75 are generally considered to reflect very good model performance, indicating that the model captures the peak flow timing/ magnitude effectively. Sub-basin 3 had the highest NSE value of 0.86, indicating that the model performed well in almost perfect simulation of peak flows; while Sub-basin 4, with an NSE of 0.78, reflects acceptable performance with opportunity to improve further parameter calibration.

The R^2 values, which ranged from 0.81 to 0.89, also confirmed the reliability of model outputs. These R^2 values indicate a strong linear correlation between observed and simulated discharge and imply that variability in observed flows was well represented in model outputs. Higher R^2 values were obtained in downstream sub-basins, demonstrating the model's ability to cumulate effectively the hydrologic responses in larger systems.

The RMSE values indicate the average magnitude of error in simulated discharge. The average RMSE values ranged from 88.7 m^3/s to 102.1 m^3/s; however, the lower RMSE values of headwater sub-basins exist because flows are less variable and involve less unpredictability. Therefore, RMSE values were greater in downstream areas and may have been influenced by floodplain interactions, unmodeled lateral inflows to the main channel, and model storage effects not represented by the HEC-HMS model structure.

All performance metrics support that the HEC-HMS modeling framework is delivering robust flow output performance, which is validated under different hydrologic conditions. It also suggests certain sub-basins may allow for further development of model parameters (e.g., curve numbers, baseflow coefficients). The statistical analysis provides insights into individual model performance, as well as future model improvement possibilities, and flood risk decision-making.

V. Discussion

5.1 Interpretation of Findings

The hydrologic model simulations with HEC-HMS showed that the rainfall–runoff patterns of the Mahanadi River Basin were well captured by the model. The performance measures, such as Nash–Sutcliffe Efficiency (NSE), R^2, and RMSE, were rated as good to very good concerning the observed and simulated discharge, and importantly, the performance metrics were most robust for simulations in the upstream and midstream sub-basins. For example, Sub-basin 3 showed the highest NSE at 0.86 and the lowest RMSE at 88.7 m^3/s, meaning the model had high predictive capacity for this sub-basin. Sub-basin 4 had an NSE of 0.78, and while this was less than the previous (Sub-basin 3), it still fell within acceptable limits. The reduction in performance metrics may be attributed to the complex storage effects present in the floodplain that were not modeled during the hydrograph simulations with HEC-HMS. The hydrograph data also demonstrated that the model accurately estimated both the magnitude and timing of the peak flows, confirming that the model is suitable for flood risk-related applications.

5.2 Recommendations for Improving Flood Risk Prediction

Despite overall good performance, several improvements are recommended to enhance flood risk prediction accuracy:

- **Refinement of input data resolution**: Using higher-resolution DEMs and updated land use/land cover datasets can improve watershed delineation and infiltration estimation.
- **Inclusion of hydraulic structures**: Incorporating dams, reservoirs, and levees into the model could help correct the underestimation of flow in controlled sub-basins.
- **Calibration of extreme events**: Focused calibration on historical flood peaks would enhance the model's responsiveness to high-magnitude storm events.
- **Integration with real-time data feeds**: Linking HEC-HMS with live rainfall data and telemetry systems can support operational flood forecasting in real time.

5.3 Importance of Incorporating HEC-HMS Algorithm into Flood Management Strategies

By using the HEC-HMS Hydrologic Modeling Scheme, we also have a rationally structured and scientifically validated process for simulating runoff response under different meteorological conditions and land uses. The modular structure of HEC-HMS, along with its compatibility with GIS tools, allows for tailored basin-specific scenarios to be created and simulated. Authorities can use HEC-HMS as a part of their national and regional flood management program to enhance the quality of flood advisories and forecasts, assess high-risk flood areas, and develop possible proactive mitigation programs, such as early warning systems, zoning of land uses, and/or development of infrastructure, to address flood risks. Furthermore, the model's adaptability makes it suitable for scenario-based assessments under climate change projections and urbanization pressures, thus making it a vital tool in the context of sustainable water resource management and disaster resilience planning.

VI. Conclusion

Floods greatly impact the world both in terms of human casualties and economic destruction. Creation of flood susceptibility maps is an important step in managing flood risks and reducing the impacts of floods. This study intended to evaluate the efficiency of HEC HMS Hydrologic Modeling Algorithms. It was concluded from this research that communities with limited data can still rely on hybrid models as a viable option. The impacts of using hybrid models in varying climates and regions will then provide evidence of their overall usefulness and dependability. Developing a primary flood susceptibility map using hybridized HEC HMS models could be easier and reliable. Estimating flood risks in specific areas should be possible through the HEC HMS Hydrologic Modeling Algorithm. While these algorithms can accurately predict areas where floods won't occur, those areas may lack floods due to unstable conditions, which increases the likelihood of flooding.

Unfortunately, prior studies do not have enough data from subsequent floods in the study area. Future work needs to address these gaps with an enhanced resolution of environmental datasets and uncertainty analyses. Policymakers and urban planners will particularly benefit from the flood susceptibility model outlined in this paper. It should aid policymakers in developing effective flood risk reduction strategies. These maps can assist urban planners in guiding critical infrastructure away from flood-prone areas while also aiding conservation initiatives in those zones. Various local organizations responsible for disaster management can use these models to accurately and effectively respond to flood risks.

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