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Integration of Artificial Intelligence and HEC-RAS for Rapid Flood Inundation Prediction and Risk Assessment

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Abstract: Flooding is one of the most frequent and destructive natural hazards, causing significant damage to human life, infrastructure, agricultural land, and the environment. Accurate and rapid prediction of flood inundation is therefore essential for effective disaster preparedness and risk management. HEC-RAS is widely used for one-dimensional and two-dimensional hydraulic modelling and flood inundation mapping; however, detailed simulations may require considerable computational effort, particularly for large study areas, high-resolution terrain data, and multiple flood scenarios. The integration of Artificial Intelligence (AI) with HEC-RAS provides a promising approach to overcome these limitations by combining physically based hydraulic modelling with the rapid predictive capability of data-driven techniques. This review examines the application of machine learning, artificial neural networks, deep learning, and surrogate modelling techniques in combination with HEC-RAS for rapid prediction of flood depth, flow velocity, inundation extent, and flood hazard. It further discusses the supporting role of Geographic Information Systems (GIS), remote sensing, Digital Elevation Models (DEMs), hydrological observations, and satellite-derived flood information in developing reliable AI-assisted flood assessment frameworks. Particular attention is given to model development, training data generation from HEC-RAS simulations, performance evaluation, validation, computational efficiency, and practical applications in flood risk management. The review indicates that AI–HEC-RAS integration can substantially reduce prediction time while maintaining acceptable accuracy, making it particularly valuable for rapid scenario analysis and near-real-time flood assessment. However, challenges associated with data availability, model generalization, uncertainty, interpretability, and transferability remain important. Overall, an integrated AI–HEC-RAS framework has strong potential to support faster flood forecasting, improved inundation mapping, and more effective risk-informed decision-making for resilient and sustainable flood management.

Keywords: *Artificial Intelligence, HEC-RAS; Flood Inundation, Machine Learning, Deep Learning, Flood Risk Assessment, Hydraulic Modelling.*

1. Introduction

Flooding is one of the most widespread and damaging natural hazards, affecting human settlements, transportation networks, agricultural land, critical infrastructure, and economic activities across the world. Rapid urbanization, changes in land use and land cover, increasing impervious surfaces, and changing rainfall characteristics have further increased the exposure of communities to flood hazards. Consequently, reliable prediction of flood extent, water depth, and flow characteristics has become an important component of disaster preparedness, infrastructure planning, emergency response, and sustainable flood-risk management. Recent advances in remote sensing, Geographic Information Systems (GIS), hydraulic modelling, and data-driven techniques have significantly improved the ability to identify flood-prone areas and assess their associated risks (Amiri et al., 2024; Islam et al., 2025; Silwal et al., 2026).

Hydraulic and hydrodynamic models play an important role in understanding the movement of floodwater through river channels and floodplains. Among the available modelling tools, the Hydrologic Engineering Center's River Analysis System (HEC-RAS) has become one of the most widely applied platforms for river hydraulics and flood inundation analysis. Its one-dimensional (1D) and two-dimensional (2D) modelling capabilities enable the simulation of water-surface elevation, flood depth, flow velocity, inundation extent, and other hydraulic characteristics under different flow conditions. HEC-RAS 2D is particularly valuable for representing complex floodplain flow and spatial variations in hydraulic conditions. However, the reliability of model results is influenced by several factors, including terrain resolution, computational mesh, Manning's roughness coefficients, boundary conditions, model configuration, and availability of calibration and validation data (Pathan et al., 2022).

Despite its strong physical basis and widespread application, high-resolution two-dimensional hydraulic modelling can become computationally demanding when simulations are performed over large areas, at fine spatial resolution, or for a large number of rainfall, discharge, and flood scenarios. Sensitivity analysis of HEC-RAS 2D has also demonstrated that model configuration, boundary conditions, parameterization, and other modelling choices can introduce uncertainty into simulated flood characteristics. These limitations may restrict the direct application of computationally intensive hydraulic simulations for rapid or near-real-time flood forecasting and emergency decision-making.

Artificial Intelligence (AI) has emerged as a promising approach for overcoming some of these computational limitations. Machine Learning (ML) and Deep Learning (DL) algorithms can identify complex nonlinear relationships between hydrological, topographical, meteorological, and hydraulic variables and produce predictions with considerably lower computational requirements after successful model training. Techniques such as Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and other deep-learning architectures are increasingly being investigated for flood forecasting, flood susceptibility analysis, inundation prediction, and risk assessment (Silwal et al., 2026).

An important development in this field is the use of AI as a surrogate or emulator of computationally intensive hydrodynamic models. In such an approach, a physically based model is first used to simulate numerous representative flood scenarios. The resulting flood depths, velocities, water levels, and inundation patterns can subsequently serve as training and validation data for an AI model. Once appropriately trained, the surrogate model can reproduce the relationship between flood-driving variables and hydraulic responses considerably faster than repeatedly performing complete hydrodynamic simulations. Zahura et al. (2020), for example, demonstrated that machine-learning surrogate models trained using high-resolution physics-based flood simulations could substantially reduce computational runtime while retaining the potential to support real-time flood-management decisions.

The combination of AI and HEC-RAS therefore provides a promising hybrid framework in which the physical reliability of hydraulic modelling can be complemented by the computational efficiency of data-driven prediction. Instead of completely replacing HEC-RAS, AI can learn from HEC-RAS-generated hydraulic outputs and rapidly estimate flood characteristics for new hydrological conditions. Recent investigations using deep neural networks with HEC-RAS-generated simulations have demonstrated the feasibility of predicting spatial flood conditions substantially faster than conventional hydrodynamic simulations. Haces-Garcia et al. (2025), for instance, evaluated deep neural network architectures as surrogate models for two-dimensional HEC-RAS simulations and reported substantial improvements in computational speed while maintaining useful predictive capability.

Similarly, deep-learning frameworks combining temporal prediction and spatial inundation modelling are increasingly being explored to emulate HEC-RAS 1D/2D simulations. Such frameworks can use sequential models such as LSTM to estimate changing river conditions and spatial deep-learning techniques such as CNNs to generate inundation information. These developments indicate considerable potential for transforming computationally demanding hydraulic simulations into faster predictive systems suitable for operational flood forecasting.

Machine-learning surrogate modelling has also shown considerable potential beyond purely riverine flooding. Zahura et al. (2022) demonstrated that an ML surrogate approach could predict flood extent and depth under combined tidal and pluvial flooding conditions. This is important because flood risk in urban and coastal regions frequently results from interacting processes rather than a single hydrological driver. Similarly, Dang et al. (2024) investigated machine-learning surrogate models for rapid prediction of multi-driver flooding in coastal urban environments, further demonstrating the potential of data-driven models for computationally efficient flood assessment (Dang et al., 2024; Zahura et al., 2022).

The effectiveness of an integrated AI–HEC-RAS framework also depends considerably on the quality of spatial and hydrological input information. Digital Elevation Models (DEMs), river geometry, rainfall, discharge, land-use/land-cover characteristics, soil information, drainage networks, hydraulic structures, and surface roughness can influence flood propagation and inundation patterns. GIS provides an effective platform for managing, processing, integrating, and visualizing these spatial datasets, while remote sensing can provide valuable information regarding land-cover conditions and observed flood extent. The integration of remote sensing information and ensemble machine learning with an independently developed HEC-RAS 2D model has recently been demonstrated as an approach for enhanced flood prediction and risk assessment (Oluwadare et al., 2026).

AI-based flood modelling is therefore progressing from conventional flood-susceptibility classification toward more advanced spatial and temporal prediction of actual flood characteristics. Modern surrogate models are increasingly designed to estimate variables such as inundation extent, maximum water depth, spatially distributed water levels, and flood evolution. Comparative research on flood-inundation surrogate modelling has demonstrated that appropriately developed surrogate approaches can achieve high computational efficiency while maintaining useful accuracy for flood extent and water-depth prediction, including under conditions beyond some of the training scenarios (Fraehr et al., 2024).

However, the integration of AI and hydraulic modelling also presents several important challenges. AI performance strongly depends on the quantity, quality, and representativeness of training datasets. Models developed for a particular catchment or flood regime may not automatically provide equivalent accuracy when transferred to areas with different terrain, drainage characteristics, land use, or hydrological conditions. Furthermore, extreme events outside the training range may create additional prediction uncertainty. Issues related to model interpretability, uncertainty quantification, spatial generalization, computational requirements during training, and integration with operational forecasting systems therefore require careful consideration. Current literature increasingly emphasizes the need to develop hybrid and physics-informed approaches that retain hydraulic consistency while exploiting the computational advantages of machine learning and deep learning (Silwal et al., 2026).

From a flood-risk-management perspective, rapid inundation prediction can provide significant practical benefits. Near-real-time information on probable flood extent, depth, velocity, and affected locations can assist authorities in identifying vulnerable communities, critical roads, hospitals, bridges, utilities, and other infrastructure before or during an emergency. It can also support evacuation planning, flood-warning systems, emergency resource allocation, floodplain management, and long-term mitigation strategies. Therefore, integrating HEC-RAS with AI, GIS, remote sensing, and real-time hydrometeorological information represents an important direction toward developing more responsive and intelligent flood-risk-management systems.

The emerging literature demonstrates considerable progress in both physically based flood simulation and AI-driven prediction. Nevertheless, studies still vary considerably in their selection of AI algorithms, HEC-RAS configurations, input variables, spatial resolutions, training strategies, validation procedures, and performance indicators. A systematic understanding of how these technologies can complement each other is therefore necessary. This review focuses on the integration of Artificial Intelligence and HEC-RAS for rapid flood inundation prediction and risk assessment, with particular attention to the transition from computationally intensive hydraulic simulations toward reliable, efficient, and operationally applicable hybrid modelling frameworks.

1.1 Objectives of the Review

The present review has the following three major objectives:

1. To review the use of Artificial Intelligence (AI) with HEC-RAS for flood prediction and inundation mapping.
2. To study how AI can improve the accuracy and speed of HEC-RAS for flood depth, water level, and inundation prediction.
3. To identify the current research gaps and future possibilities of AI–HEC-RAS models for rapid flood prediction and risk assessment.

2. Review of Literature

S. No.	Author(s) & Year	Method / Model Used	Major Findings / Contribution	Research Gap
1	Zahura et al. (2020)	Physics-based flood modelling + ML surrogate	ML surrogate modelling provided very rapid flood predictions compared with computationally intensive physics-based simulations, demonstrating its suitability for real-time applications.	Further testing is needed for different catchments, extreme events, and unfamiliar hydrological conditions.
2	Zhang et al. (2020)	Artificial Neural Network-based surrogate modelling	Demonstrated the ability of neural networks to reproduce complex simulation-model behaviour with reduced computational requirements.	Generalization and reliability under conditions outside the training dataset require further investigation.
3	Integrated ML–HEC-RAS study (2021)	ANN + HEC-RAS	Demonstrated the potential of combining ANN-based prediction with HEC-RAS for flood inundation mapping using hydro-meteorological and terrain information.	Limited investigation of alternative ML/DL algorithms and real-time operational implementation.
4	Zahura et al. (2022)	Random Forest surrogate + physics-based flood model	Successfully predicted flood extent and depth under combined tidal and pluvial flooding conditions.	Transferability to other geographic regions and different combinations of flood drivers remains limited.
5	Pathan et al. (2022)	HEC-RAS 2D + mesh/grid	Demonstrated that computational-grid	AI-based optimization of mesh size and

		analysis	configuration significantly affects the stability and reliability of 2D flood simulations.	hydraulic-model parameters was not investigated.
6	Silva-Cancino et al. (2022)	ML-based surrogate flood model	Showed that ML surrogate models can reproduce spatial flood information while significantly reducing computational effort.	Further validation for extreme flood events and diverse catchment characteristics is required.
7	HEC-RAS sensitivity study (2022)	HEC-RAS 2D + global sensitivity analysis	Identified the influence of model configuration, boundary conditions, and hydraulic parameters on simulated flood characteristics.	Did not fully integrate AI techniques for automatic calibration, uncertainty reduction, or rapid prediction.
8	Vu et al. (2023)	ML + Remote Sensing	Demonstrated the importance of land-use changes and remotely sensed information for flood-susceptibility assessment.	Focused mainly on susceptibility rather than dynamic prediction of flood depth, velocity, and inundation extent.
9	Haces-Garcia et al. (2023/2025)	HEC-RAS 2D + Deep Neural Networks	Demonstrated that DNN surrogate models trained using HEC-RAS outputs can rapidly predict spatial flood characteristics.	More validation is required across different rivers, terrain conditions, and extreme flood scenarios.
10	Shi et al. (2023)	Deep Learning surrogate models	DL models demonstrated the ability to rapidly estimate river-stage behaviour compared with computationally intensive hydraulic modelling.	Prediction focused primarily on water stages rather than complete spatial flood-inundation and risk mapping.
11	Dang et al. (2024)	ML surrogate + numerical flood modelling	Demonstrated rapid multi-driver flood prediction in coastal urban areas and captured nonlinear relationships between flood drivers and responses.	Application to inland river flooding and direct integration with HEC-RAS requires further investigation.
12	Fraehr et al. (2024)	Surrogate flood-inundation modelling	Surrogate approaches efficiently predicted flood extent and water depth with high computational efficiency.	Additional testing is required for highly complex terrain and extreme events outside the training range.
13	Amiri et al. (2024)	ML + GIS + Remote Sensing	Demonstrated effective flood-susceptibility mapping by combining ML with geospatial and remotely sensed information.	Hydraulic parameters such as water depth and velocity were not directly simulated through HEC-RAS integration.
14	Kazemi et al. (2024)	ML + Remote Sensing	Identified flood-prone areas using environmental, topographical, and spatial factors through machine-learning models.	Mainly susceptibility-based; dynamic hydraulic processes and real-time flood propagation were not considered.
15	Riche et al. (2024)	Hybrid Deep	Hybrid DL improved flood-	Requires large and

		Learning	susceptibility assessment and demonstrated the capability of advanced AI algorithms for spatial flood analysis.	representative training datasets, which may not be available in data-scarce regions.
16	Al-Sheriadeh et al. (2024)	Machine Learning	Demonstrated the robustness of ML algorithms for flood-susceptibility mapping and classification of flood-prone areas.	Limited consideration of physically based hydraulic modelling and temporal flood evolution.
17	Mirhoseini (2024)	Deep Learning surrogate + hydrodynamic simulations	Developed a rainfall-driven DL surrogate capable of rapidly estimating flood inundation and water depth.	Transferability to different catchments and performance under unseen extreme rainfall events need further validation.
18	Haces-Garcia et al. (2025)	Multiple DNN architectures + HEC-RAS 2D	Demonstrated substantial computational acceleration of HEC-RAS 2D outputs using DNN surrogate architectures.	Broader evaluation with real-time observational data and different hydrological environments remains necessary.
19	Islam et al. (2025)	Review of ML + Remote Sensing approaches	Highlighted the increasing use of AI, ML, and remote sensing for urban flood-susceptibility assessment.	Limited standardization exists for integrating AI predictions with physically based hydraulic models.
20	Chowdhury et al. (2025)	ML + extreme rainfall variables	Demonstrated that incorporating extreme rainfall characteristics can improve flash-flood susceptibility assessment.	Detailed hydraulic characteristics such as flood depth, velocity, and time-varying inundation were not fully considered.
21	Rugină et al. (2025)	RNN, LSTM, GRU, Bi-LSTM and Bi-GRU	Recurrent DL models demonstrated strong potential for rapid flood-wave prediction and propagation analysis.	Full spatial flood-inundation mapping and direct HEC-RAS coupling require further research.
22	Wang et al. (2025)	ML + Remote Sensing	Developed a rapid and interpretable ML framework for flood-susceptibility assessment using remotely sensed data.	Focused on susceptibility classification rather than dynamic flood depth and inundation prediction.
23	Shirzadi et al. (2025)	ML and Deep Learning	Compared ML and DL models for urban flood susceptibility and demonstrated their usefulness in identifying flood-prone locations.	Physical hydraulic processes and HEC-RAS-generated flood characteristics were not fully incorporated.
24	Holmberg et al. (2025)	HEC-RAS + GRU + Fourier Neural Operator	Used HEC-RAS as a simulation-data generator and developed a DL surrogate for faster prediction of spatial and temporal river dynamics.	Further field-scale validation and testing of model transferability between river systems are required.
25	HEC-RAS–AI hydraulic	HEC-RAS +	Demonstrated the potential of	Comparison with

	study (2025)	Extreme Learning Machine	integrating ELM with HEC-RAS to improve computational efficiency in flood prediction.	advanced algorithms such as CNN, LSTM, transformers, and physics-informed models remains limited.
26	Oluwadare et al. (2026)	Remote Sensing + Ensemble ML + HEC-RAS 2D	Developed an integrated framework combining remote-sensing indices, ensemble ML and HEC-RAS 2D for improved flood prediction and risk assessment.	Operational real-time implementation and transferability to other watersheds require additional evaluation.
27	Silwal et al. (2026)	Review of ML and DL in flood management	Highlighted the growing importance of ML/DL in flood forecasting, inundation prediction, risk assessment, and integrated hydraulic modelling.	Identified the need for better interpretability, generalization, uncertainty analysis, and physically consistent AI models.
28	Soma et al. (2026)	HEC-RAS 2D Rain-on-Grid + ML	Demonstrated the potential of using physically based 2D simulation information to support ML-based flood prediction.	Requires additional testing for different rainfall patterns, terrain conditions, and real-time forecasting environments.
29	Rahimi et al. (2026)	Geospatial Intelligence + ML	Demonstrated the value of combining geospatial datasets and ML for improved flood assessment and spatial decision-making.	Greater integration and benchmarking with physically based models such as HEC-RAS are required.
30	Al-Hussein et al. (2026)	HEC-RAS 2D + DEM analysis	Demonstrated the importance of terrain representation and DEM characteristics for reliable HEC-RAS-based flood-hazard assessment.	AI-based correction, optimization, or uncertainty handling of terrain-related effects remains insufficiently explored.

2.1 Research gap

Existing studies mainly apply HEC-RAS and AI techniques separately for flood modelling and prediction. Limited research integrates AI with HEC-RAS for rapid, accurate, and real-time flood inundation assessment. Further research is needed to improve model transferability, computational efficiency, uncertainty handling, and reliable prediction of flood depth, velocity, extent, and risk.

3. Materials and Methods

This study adopted a systematic review approach to examine the integration of Artificial Intelligence (AI) with HEC-RAS for rapid flood inundation prediction and risk assessment. Relevant research studies related to HEC-RAS, Artificial Intelligence, Machine Learning, Deep Learning, flood inundation modelling, flood forecasting, GIS, remote sensing, and flood-risk assessment were identified and critically reviewed.

3.1 Literature Search and Data Collection

Published research articles related to the selected topic were identified from major scientific databases, including Scopus, Web of Science, ScienceDirect, SpringerLink, Google Scholar, and IEEE Xplore. Different combinations of keywords were used to obtain relevant literature, such as HEC-RAS, Artificial Intelligence, Machine Learning, Deep Learning," flood inundation prediction, flood modelling, surrogate modelling, flood risk assessment, "GIS, and remote sensing.

3.2 Selection of Research Articles

The collected literature was screened based on its relevance to the objectives of the review. Studies dealing with HEC-RAS-based hydraulic modelling, AI/ML-based flood prediction, deep-learning applications, surrogate flood models, GIS and remote-sensing-based flood analysis, and integrated AI–hydraulic modelling were considered. Duplicate studies and articles that were not directly related to flood prediction or risk assessment were excluded.

3.3 Classification of Selected Studies

The selected studies were classified into five major groups:

1. HEC-RAS-based flood inundation and hydraulic modelling
2. Artificial Intelligence and Machine Learning-based flood prediction
3. Deep Learning-based flood forecasting and inundation modelling
4. AI-based surrogate models for rapid hydrodynamic simulation
5. GIS and Remote Sensing-supported flood prediction and risk assessment

This classification helped to systematically understand the development of conventional hydraulic modelling and its transition toward AI-assisted rapid flood prediction.

3.4 Review and Comparative Analysis

The selected research articles were critically reviewed based on the model or technique used, input data, flood parameters predicted, major findings, computational performance, and limitations. Particular attention was given to studies in which AI or Machine Learning models were trained using outputs generated from physically based hydraulic or hydrodynamic simulations.

The reviewed studies were compared to determine the advantages and limitations of different approaches for predicting important flood characteristics such as:

- Flood inundation extent
- Flood depth
- Water level
- Flow velocity
- Flood propagation
- Flood hazard and risk levels

3.5 Conceptual Integration of AI and HEC-RAS

Based on the reviewed literature, a conceptual AI–HEC-RAS framework was considered for rapid flood inundation prediction. In this approach, hydrological, topographical, and spatial datasets are initially prepared and supplied to HEC-RAS. Different flood scenarios are then simulated using HEC-RAS 1D/2D to generate flood depth, water level, velocity, and inundation maps.

The HEC-RAS simulation outputs can subsequently be organized into a structured dataset for training suitable AI/ML models. Algorithms such as Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and other Deep Learning models can be evaluated.

The trained AI model can then be validated against HEC-RAS simulations or observed flood information. Once satisfactory performance is obtained, the AI model can provide rapid flood predictions for new hydrological conditions without requiring a complete HEC-RAS simulation for every new event.

3.6 Performance Evaluation

The performance of AI-assisted flood prediction models reported in the selected literature was evaluated using commonly adopted statistical measures such as:

- Coefficient of Determination (R^2)
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Nash–Sutcliffe Efficiency (NSE)
- Accuracy and F1-score, where applicable

In addition to prediction accuracy, computational time, model reliability, transferability, and suitability for rapid or near-real-time flood assessment were considered important factors in evaluating AI–HEC-RAS integration.

3.7 Flood Risk Assessment

The final stage considered the use of predicted flood characteristics for risk assessment. Flood depth, velocity, inundation extent, and spatial exposure information can be integrated in a GIS environment to identify low-, moderate-, high-, and very-high-risk zones. Such information can support flood-warning systems, emergency planning, evacuation management, infrastructure protection, and long-term flood-risk-reduction strategies.

3.8 Flowchart of the Adopted Methodology

Research Topic Identification

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Selection of Relevant Keywords

HEC-RAS, AI, ML, DL, Flood Inundation, GIS, Remote Sensing, Flood Risk

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Literature Search

Scopus, Web of Science, ScienceDirect, SpringerLink, Google Scholar & IEEE Xplore

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Collection of Relevant Research Articles

↓

Screening and Removal of Duplicate/Irrelevant Studies

↓

Selection of Relevant Studies

↓

Classification of Literature

HEC-RAS | AI/ML | Deep Learning | Surrogate Models | GIS & Remote Sensing

↓
Critical Review and Comparative Analysis
↓
Identification of Major Findings and Research Gaps
↓
Assessment of AI–HEC-RAS Integration
↓
Evaluation of Rapid Flood Inundation Prediction Approaches
Flood Depth | Water Level | Velocity | Inundation Extent
↓
Flood Hazard and Risk Assessment
↓
Conclusions and Future Research Directions

Conceptual AI–HEC-RAS Integration Framework

The technical integration identified from the reviewed studies can be represented in a simple form as:

Rainfall + Discharge + DEM + Land Use + River Geometry
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Data Preparation using GIS/Remote Sensing
↓
HEC-RAS 1D/2D Hydraulic Modelling
↓
Generation of Multiple Flood Scenarios
↓
Flood Depth + Water Level + Velocity + Inundation Extent
↓
Preparation of AI Training Dataset
↓
AI/ML/DL Model Training
ANN | RF | SVM | LSTM | CNN
↓
Model Testing and Validation
↓
Rapid Prediction of New Flood Events
↓
Flood Inundation and Hazard Mapping
↓
Flood Risk Assessment and Decision Support

Figure 1: Proposed methodological framework

5. Conclusion

The integration of Artificial Intelligence with HEC-RAS offers an effective approach for rapid and reliable flood inundation prediction and risk assessment. AI models can reduce the computational time of conventional hydraulic simulations while predicting flood depth, velocity, water level, and inundation extent. Combining HEC-RAS with AI, GIS, and remote sensing can improve flood forecasting and decision-making. However, further research is required to enhance model accuracy, transferability, and real-time application

6. **Future Scope**

1. **Real-Time Flood Prediction:** Future research should integrate AI with HEC-RAS and real-time rainfall and discharge data to develop faster and more reliable flood forecasting and early-warning systems.
2. **Improved AI Models:** Advanced Machine Learning and Deep Learning techniques can be developed to improve the accuracy of flood depth, velocity, water level, and inundation extent predictions.
3. **Model Transferability and Risk Management:** AI–HEC-RAS models should be tested across different river basins and flood conditions to develop transferable systems for reliable flood-risk mapping, emergency planning, and decision-making.

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