hydrology

Review

Comprehensive Overview of Flood Modeling Approaches: A Review of Recent Advances

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Abstract: As one of nature's most destructive calamities, floods cause fatalities, property destruction, and infrastructure damage, affecting millions of people worldwide. Due to its ability to accurately anticipate and successfully mitigate the effects of floods, flood modeling is an important approach in flood control. This study provides a thorough summary of flood modeling's current condition, problems, and probable future directions. The study of flood modeling includes models based on hydrologic, hydraulic, numerical, rainfall–runoff, remote sensing and GIS, artificial intelligence and machine learning, and multiple-criteria decision analysis. Additionally, it covers the heuristic and metaheuristic techniques employed in flood control. The evaluation examines the advantages and disadvantages of various models, and evaluates how well they are able to predict the course and impacts of floods. The constraints of the data, the unpredictable nature of the model, and the complexity of the model are some of the difficulties that flood modeling must overcome. In the study's conclusion, prospects for development and advancement in the field of flood modeling are discussed, including the use of advanced technologies and integrated models. To improve flood risk management and lessen the effects of floods on society, the report emphasizes the necessity for ongoing research in flood modeling.

Keywords: flood modeling; rainfall–runoff; hydrologic; hydraulic; metaheuristic

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1. Introduction

Flooding is a serious global issue that has an impact on several towns and countries. It is caused by a combination of factors including hurricanes, storm surges, excessive rainfall, and rapid snowmelt [1]. Floods can kill people and seriously harm buildings, infrastructure, and crops [2]. Floods may have disastrous effects on the economy and society, and rehabilitation and reconstruction can be expensive [3]. The consequences of sea level rise and the increased frequency of extreme weather events make flooding worse in some locations, such as low-lying coastal areas [4]. The frequency and intensity of flooding in certain locations can significantly shift in response to even small changes in sea level. The health and welfare of populations can potentially suffer long-term effects from floods [5]. Public health might be endangered by toxic chemicals and microbes found in floodwaters. Increased poverty and social unrest may be caused by population displacement, as well as the loss of houses, jobs, and other assets. Flooding can also have indirect impacts that might be equally as damaging as the direct ones. For instance, it messes with supply chains and transportation networks, which drives up the cost of goods and services and slows down economic activity [6]. Additionally, it leads to soil erosion, which can reduce agricultural productivity and lead to the loss of fertile land [7].

Many communities and countries are unprepared to handle the hazards associated with floods despite the catastrophic implications they can have [8]. This results from a combination of factors, including a lack of funding for flood protection infrastructure as well as ignorance of the underlying causes and effects of floods [9]. Because of this, many communities are still at risk of flood damage and are unable to effectively lessen its consequences. Communities and nations must create an all-encompassing and integrated flood risk management plan to face the difficulties of flooding [10]. The development of early warning systems, better land use planning and zoning, increased investment in flood protection infrastructure, and the adoption of resilient construction standards are a few examples of actions that could be included [11]. In order to increase our understanding of flood causes and effects, as well as to develop better tools for anticipating and managing this danger, communities and nations must invest in research and technology.

To comprehend and forecast flood behavior and effects, flood modeling is an important tool [12]. To anticipate the geographical and temporal distribution of flood waters, as well as the damage and hazards related to them, necessitates the development of mathematical models that replicate the hydrologic and hydraulic processes that lead to floods [13]. Flood forecasting [14], risk assessment [15], flood mitigation [16], and response planning and management are just a few of the uses for flood models. For example, 1D hydraulic models [17], 2D hydraulic models [18], and hydrologic models [19] are among the several types of flood models. Based on hydraulic engineering principles, 1D hydraulic models mimic water movement in rivers and canals. They are frequently used to simulate the impacts of flood control devices like dams and levees, and to anticipate floods. The intricate interactions between flood waters and the surrounding environment may not be sufficiently captured by 1D hydraulic models, despite their relative simplicity and ease of use [20]. On the other hand, 2D hydraulic models replicate both longitudinal and cross-sectional water flow, and offer more thorough data on flood water distribution and the impacts of floods on neighboring regions. In addition to showing the geography and land use of the region, these models may also show how flood waters interact with their surroundings, such as the effects of urbanization and vegetation [21]. Despite being more complex and computationally intensive than 1D hydraulic models, 2D hydraulic models can provide more accurate and realistic flood depictions. To calculate the quantity and timing of catchment runoff, hydrologic models are used to simulate the precipitation–runoff processes that result in floods. These models might be based on physically based methods [22], like the distributed hydrologic model [23], or empirical techniques [24], such the rainfall–runoff relationship. The volume and timing of catchment runoff may be estimated using hydrologic models, which can also be used to help in the creation of flood predictions and warnings [25].

Flood modeling can use a number of approaches in addition to these fundamental types of models. One of the most common techniques is the event-based approach, which entails creating a flood model for a given event, and using the model to anticipate the behavior and effects of that event [26]. This approach can offer thorough flood information, but it takes a lot of time and might not be suitable for extensive or real-time applications. Developing a model that can replicate flood behavior throughout time is another technique, and it is known as the continuous simulation approach [27]. The possibility of various flood situations is forecasted using this technique, which also helps with long-term planning and decision-making. Regardless of the model or technique employed, the accuracy and dependability of flood models depend on the caliber and accessibility of data, including hydrologic, hydraulic, meteorological, and land use data [28]. For the purpose of creating realistic flood models, it is crucial that hydrologic data, such as data on precipitation and stream flow, be available and reliable. The models themselves may also be intricate and computationally demanding, requiring the deployment of substantial computer resources [29]. Different techniques for data assimilation and model optimization have been employed to solve these problems, including Bayesian inference [30], genetic algorithms, and particle swarm optimization [31].

Another crucial element in flood modeling is the estimation of uncertainty. Flood models are prone to a great deal of uncertainty because of the complexity of the underlying physical processes and the constraints of the data and models. To address these problems, a number of methods for measuring uncertainty have been created, such as Bayesian inference [30], Monte Carlo simulation [32], and probabilistic sensitivity analysis [33]. These approaches can help with more effective flood risk management and decision-making by estimating the probability of various flood conditions. Mathematical modeling, statistical techniques, and hydrologic and hydraulic concepts are all included in the interdisciplinary field of flood modeling. Despite its challenges, flood modeling has lately made substantial advancements and is still essential for reducing flood risk and making judgments. To make flood models more accurate and reliable is desirable, in order to better understand and forecast flood behavior and consequences, and to support flood risk management and mitigation techniques that are consequentially more effective.

This study conducts an in-depth assessment of flood models in order to assess the current degree of understanding and expertise of these models [34]. The review aims to synthesize the body of information available on several flood model types, and identify the benefits, drawbacks, and challenges of each. At present, there are many systematic reviews on traditional flood modeling [35]. State-of-the-art benchmarking reviews are also available for many flood modeling packages. Significant amounts of literature are available on flood mitigation and management strategies, such as structural flood protection, sustainable urban drainage systems (SUDS), sponge cities, and blue-green infrastructure [36]. This review article offers a distinct contribution by comprehensively addressing various methods used in flood models, including hydrologic, hydraulic, numerical, rainfall–runoff, remote sensing and GIS-based, artificial intelligence and machine learning-based, multiple-criteria decision analysis-based models, as well as heuristic and metaheuristic approaches. While existing reviews often focus on specific areas such as hydrology, hydraulics, or remote sensing, or the use of artificial intelligence and machine learning-based approaches, this review takes a broader perspective to encompass multiple modeling techniques employed in flood studies. Rather than focusing on a specific aspect of flood modeling, this review bridges the gap between different methodologies and provides readers with a holistic overview. It allows readers to explore and grasp the benefits and challenges associated with each model type. By consolidating this diverse information, the review supports a deeper understanding of flood modeling practices, facilitating informed decision-making and the development of effective flood management strategies. One of the notable advantages of this review is its ability to present a comprehensive picture of flood modeling by considering multiple methodologies in a single article. This allows readers to compare and contrast different approaches, gaining insights into their respective strengths and weaknesses. Such a broad perspective is particularly valuable for researchers and practitioners who seek to explore a wide range of flood modeling techniques, or require a comprehensive understanding of the field.

2. Research Methodology

Numerous techniques may be used for flood risk assessments and management. Any method for estimating flood risk must begin by determining and assessing potential dangers and vulnerabilities [37]. This comprises predicting the risk of flooding in a specific region, figuring out the probable severity of a flood event, and assessing any potential vulnerabilities or weaknesses in the neighborhood or community [38]. The next step is to assess any potential consequences of a flood occurrence, including any potential property damage, impacts on crucial infrastructure like roads and bridges, and any potential fatalities [39]. After assessing the hazards and vulnerabilities and weighing the potential consequences, the next step is to create a risk management plan [40]. This may include building levees or flood walls, relocating critical infrastructure out of flood-prone areas [41], or developing early warning systems to reduce the risk of flooding [42]. In the event of a flood, the risk management plan should also include provisions for emergency response and recovery. Evacuating affected areas, providing emergency shelter and supplies, and launching a recovery effort to restore critical infrastructure and services are all examples of possible actions. Finally, provisions for ongoing monitoring and evaluation should be included in the risk analysis methodology to ensure that the risk management plan is effective and up to date [43]. This may include monitoring weather conditions and river levels, assessing the effectiveness of flood control measures, and updating the risk management plan as conditions change or new information becomes available. Figure 1 depicts a graphical representation of the research methodology as a flowchart diagram that provides a high-level view of the research procedure, and clearly and comprehensively presents the methodology's essential components.

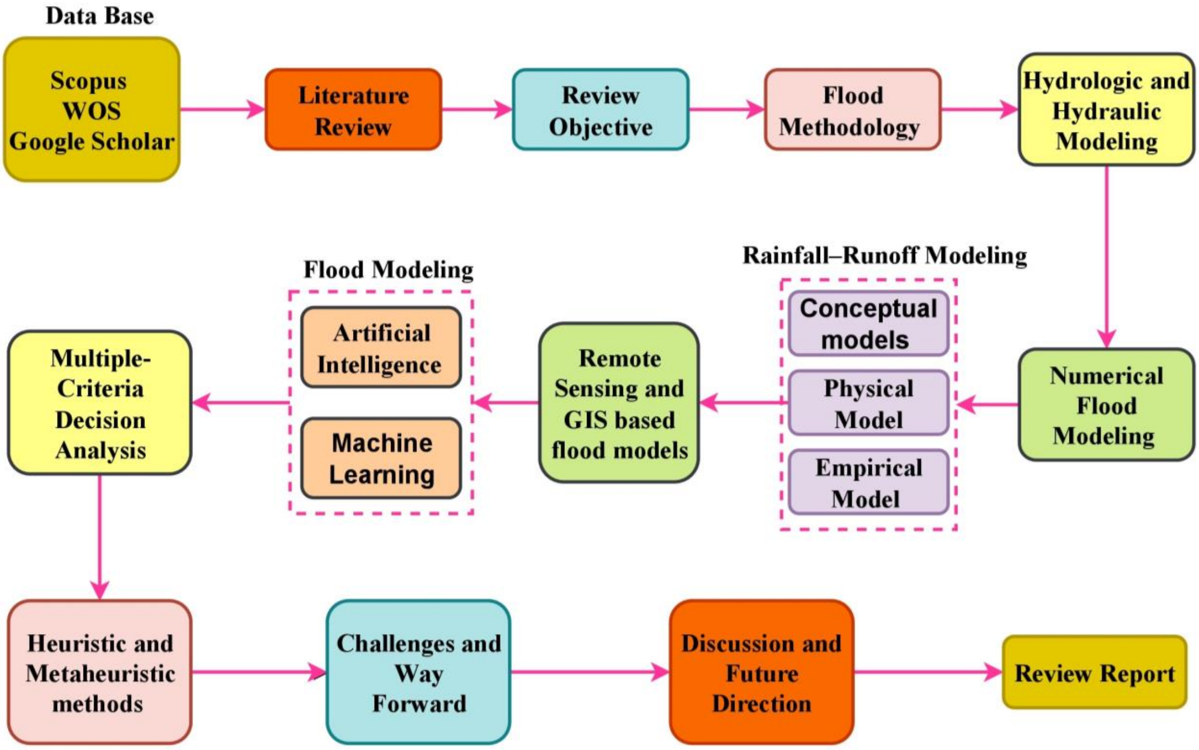

Figure 1. Graphical representation of the research methodology.

The basic flowchart for a flood model is shown in Figure 2. The stages for developing the flood model are as follows.

(a) Define the study area—Determine the geographical area that will be investigated for flood risk;
(b) Data collection—Gather data about topography, hydrology, meteorology, land use, and other pertinent variables;
(c) Hydrologic analysis—Analyze the data to identify the flow characteristics of the study area's rivers and streams;
(d) Hydraulic analysis—Use the hydrologic analysis findings to simulate water movement during a flood occurrence;
(e) Floodplain mapping—Using the hydraulic analysis results, make maps that depict the extent of potential floodplain inundation;
(f) Risk assessment—Take into account the potential consequences of a flood occurrence, such as damage to buildings and infrastructure, casualties, and financial impact;
(g) Flood mitigation planning—Construct levees and floodwalls, non-structural measures including zoning and land use regulations, and emergency preparation and response to lessen the danger of flooding disasters;
(h) Implementation and monitoring—Put the mitigation strategies into action and monitor how well they work over time.

This is only a broad overview; depending on the approach and subject topic, the details of each stage may vary. The secret is to approach flood risk management methodically and exhaustively, taking into account all relevant aspects and a range of viable solutions.

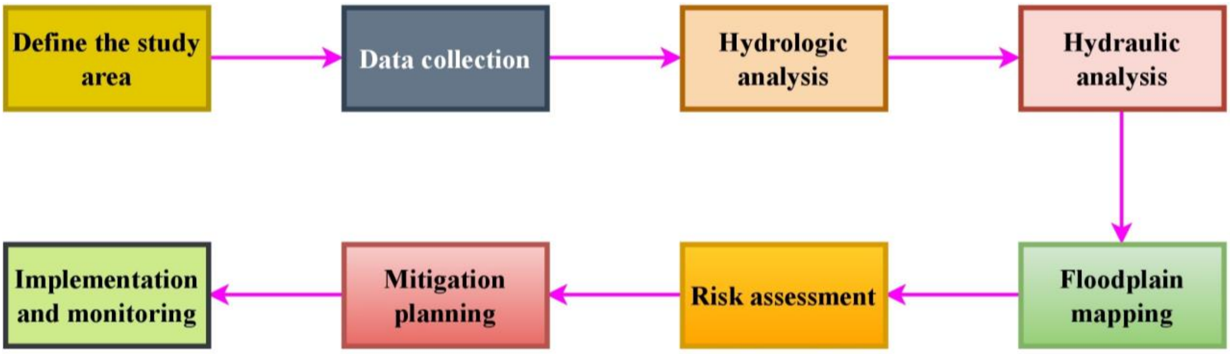

Figure 2. Flowchart for a comprehensive flood model.

3. Hydrologic and Hydraulic Modeling

Hydrologic modeling and hydraulic modeling are two crucial components of the evaluation and management of flood risk [13]. Hydrologic modeling is the act of analyzing the water flow in a river or stream system using mathematical and computer tools [44]. Gathering data on topographical elements like elevation and land usage, as well as elements like precipitation, evaporation, and soil moisture, is required. The data are then used to simulate the flow rate, volume, and timing of water at different sites along the river or stream system [45,46]. Hydrologic modeling produces data that are used in hydraulic modeling, which simulates how water would behave during a flood event [47]. This involves examining how water will flow through a river or stream system and surrounding terrain, while taking factors like channel shape, roughness, and water velocity into consideration. The depth and extent of flooding in each area, as well as the location and timing of peak flows, may all be better understood using hydraulic modeling [48].

Understanding flood risk and creating efficient mitigation plans both require hydraulic and hydrologic modeling [49]. By examining the water flow during a flood event, it is feasible to pinpoint locations that are at a high risk of flooding, as well as the potential effects of flooding, such as harm to buildings and infrastructure, and fatalities [15,50]. Using this information, structural and non-structural flood risk reduction strategies are developed, and emergency response planning is also informed [51]. It is crucial to keep in mind that the assumptions and constraints of the models employed, as well as the quality and availability of the data, all affect how accurate hydrologic and hydraulic modeling is [52–54]. As a result, before being employed as one of many instruments in the entire process of flood risk assessment and management, the outcomes of these models must be thoroughly examined and understood [55]. The steps to take while considering hydrologic and hydraulic modeling are shown in Figure 3:

1. Describe the study area—Determine the research area's borders, taking special note of the river or watershed of interest;
2. Data collection—Compile details regarding the terrain, land use, soil composition, and hydrologic parameters of the research area. For the construction and calibration of models, these data are crucial [56];
3. Decide on a modeling strategy—Depending on the research issue, the information at hand, and the modeling goals, select a model. Common modeling techniques include hydraulic models [57], integrated hydrologic–hydraulic models [58], and hydrologic models (rainfall–runoff models) [59];
4. Build the model—Build the hydrologic and/or hydraulic model using the data gathered. The model should be calibrated to make sure that predictions of flow behavior are accurate;

5. Verify the model—By contrasting the predicted outcomes with the actual data, you can determine how accurate the model is. This stage is essential to making sure the model is acceptable for the research domain, and that it can be used in decision-making;
6. Run simulations—After calibrating and validating the model, run simulations to predict water flow behavior under various conditions, such as land use changes or climate scenarios;
7. Analyze the results to identify potential flood risks and assess flood mitigation measures [60]. This step is critical to ensuring that the modeling results are effectively communicated to stakeholders and decision-makers;
8. Communicate results—Share the findings with stakeholders and decision-makers in order to inform flood management strategies and decision-making. This step is critical to ensuring that the modeling results are used to make informed flood risk management decisions.

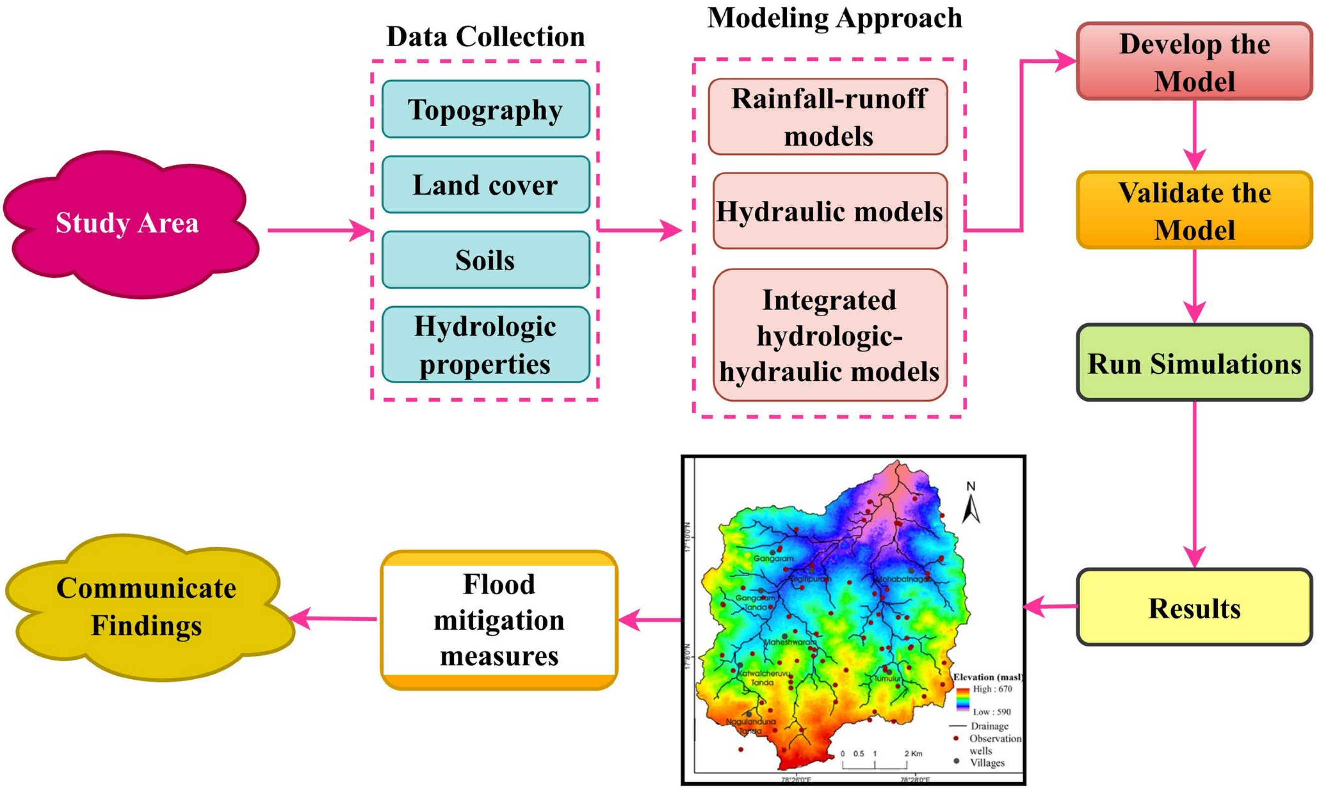

Figure 3. Steps when undertaking the hydrologic and hydraulic modeling.

Applications of hydrologic and hydraulic models in floods are described in [61–64]. Some of the limitations of these models that should be considered when choosing a model include the following: The quality and availability of data, as hydrologic and hydraulic models are complex and require specialized knowledge and skills to develop and interpret [65]. This may limit non-specialists' ability to use the models effectively. The models are highly uncertain, which may result in incorrect results [66]. Real-world conditions are typically simplified in hydrologic and hydraulic models to make them more manageable and computationally feasible. This can result in incorrect results and a loss of detail in the analysis [29]. Cea and Costabile [67], Cosco et al. [68] and Palla et al. [69] examined the difficulties in calculating and controlling flood risk in urban areas, highlighting the effects of climate change and the demand for adaptation measures. In order to comprehend urban flood processes and modeling, encompassing flow dynamics, human–object stability, computational advancements, and crowd-sourced data for validation, Mignot and Dewals [70], Martins et al. [71] and Rubinato et al. [72] offered a review of hydraulic modeling in inland urban flooding.

4. Numerical Flood Modeling

Numerical flood models are computer-based models that use mathematical and computational techniques to simulate the behavior of water during a flood event [73]. These models typically employ numerical algorithms to solve equations that describe the flow of water in a river or stream, while taking into consideration factors such as rainfall, runoff, channel geometry, and riverbed roughness. Numerical flood models can be used to simulate the effects of various flood scenarios, as well as to assess the efficiency of the proposed flood mitigation measures [74]. They are also used to simulate how flood behavior will alter in response to changes in climate, land use, and other factors. Numerical flood models can take several forms, such as one-dimensional models that mimic water flow in a river channel [75] or two-dimensional models that simulate water flow over a floodplain [76]. The vertical distribution of water is also depicted in greater detail in three-dimensional models of the floodplain [77]. The capacities to include more data and information, simulate intricate hydrologic and hydraulic processes [78], and run large-scale simulations are only a few of the benefits that numerical flood models offer over physical flood models [79]. However, they do have certain drawbacks, including the requirement for specific knowledge and abilities to create and evaluate the models, as well as the potential for mistakes and the unpredictability of the outcomes [80]. For numerical flood modeling, a number of software packages are available, including:

(a) HEC-RAS—This software, created by the US Army Corps of Engineers, is used to simulate the hydraulics of river systems in both one and two dimensions [81];
(b) MIKE FLOOD—This software, which was created by DHI, is utilized for the two- and three-dimensional hydraulic modeling of floodplain and river systems [82];
(c) TUFLOW—This software is used for the two-dimensional and three-dimensional hydraulic modeling of floodplain and river systems [83];
(d) Flood Estimation Handbook (FEH) models—Developed by the United Kingdom Environment Agency, used for rainfall–runoff modeling and flood frequency analysis [84];
(e) Environmental Protection Agency's Environmental Fluid Dynamics Code (EFDC)—This software, developed by the United States Environmental Protection Agency, is used for three-dimensional hydraulic and water quality modeling of surface water systems [85].

Table 1 summarizes some of the advantages and disadvantages of these models. It is important to note that the software chosen will be determined by the specific needs of the flood study, as well as the availability of data and resources. Shustikova et al. [86], Schubert et al. [87] and Chang et al. [88] compared two 2D numerical models (LISFLOOD-FP and HEC-RAS) used for assessing floodplain flooding, and discovered that although coarser grids perform comparably, higher-resolution grids produce superior outcomes. However, in other places, the geographical distribution of flood characteristics may differ. David and Schmalz [89] and Garcia-Alen et al. [90] contrasted the traditional "decoupled" technique with an "integrated" strategy for assessing flood hazards in small, rural catchments, highlighting the benefits, drawbacks, and restrictions of each approach. Costabile et al. [91] and Fernandez-Pato et al. [92] offered a benchmarking analysis of the HEC-RAS 2D (HR2D) program for Rain-on-Grid (RoG) simulations, assessing their appropriateness and limits for storm hazard assessment in various situations. Zeiger and Hubbart [93] and Cea and Blade [94] evaluated the efficacy of an integrated modeling strategy for estimating environmental fluxes using SWAT and HEC-RAS. The results demonstrate realistic simulations and potential uses of 2D Rain-on-Grid HEC-RAS simulations.

Table 1. Advantages and disadvantages of (a) HEC-RAS, (b) MIKE FLOOD, (c) TUFLOW, (d) FloodMOD, (e) Flood Estimation Handbook (FEH) models, (f) FloodSense and (g) EFDC etc.

Model	Advantages	Disadvantages	Application in Floods
HEC-RAS	1. A user-friendly graphical interface for creating and visualizing models. 2. Widely used and recognized throughout the engineering community. 3. Capability to simulate both steady-state and unsteady flows.	1. Its ability to depict complex geometries and boundary constraints is limited. 2. Large models or complicated simulations can be computationally intensive. 3. Its ability to manage interactions between water and the environment, such as sediment transport, is limited.	1. Riverine floodplain modeling and study are possible. 2. Used to assess the effects of various floodplain management methods. 3. It is used to assess the effects of planned developments on floodplain conditions.
MIKE FLOOD	1. A comprehensive and versatile flood study and prediction tool. 2. Capable of dealing with a broad range of hydraulic and hydrological processes. 3. Integrates with other MIKE software tools to provide a more comprehensive solution.	1. Steep learning curve for new users. 2. Can be computationally intensive for large models or complex simulations. 3. Requires a high level of technical expertise to use effectively.	1. Can be used for riverine and coastal floodplain modeling and analysis. 2. Can be used to evaluate the impacts of different floodplain management strategies. 3. Can be used to evaluate the impacts of proposed developments on floodplain conditions.
TUFLOW	1. User-friendly interface with a graphical interface for building and visualizing models. 2. Ability to handle a wide range of hydraulic and hydrological processes. 3. Flexible and adaptable to unique modeling requirements.	1. Limited in its ability to handle large-scale models or complex simulations. 2. Steep learning curve for new users. 3. Requires a high level of technical expertise to use effectively.	1. Can be used for riverine and coastal floodplain modeling and analysis. 2. Can be used to evaluate the impacts of different floodplain management strategies. 3. Can be used to evaluate the impacts of proposed developments on floodplain conditions.
Flood Estimation Handbook (FEH)	1. Widely accepted and used in the UK. 2. Provides a consistent and standardized approach to flood estimation. 3. Easy to use and set up.	1. Limited in its ability to handle complex models or simulations. 2. May not be suitable for use in other countries or regions with different climatic and hydrological conditions. 3. Can be limited in its ability to account for changes in land use and land cover over time.	1. Can be used for flood hazard assessments and floodplain mapping in the UK. 2. Can be used to support floodplain management and planning decisions in the UK.
EFDC	1. Comprehensive tool for simulating a wide range of environmental processes, including floods. 2. Ability to handle complex models and simulations. 3. User-friendly interface with a graphical interface for building and visualizing models.	1. Steep learning curve for new users. 2. Can be computationally intensive for large models or complex simulations. 3. Requires a high level of technical expertise to use effectively.	1. Can be used for riverine and coastal floodplain modeling and analysis. 2. Can be used to evaluate the impacts of different floodplain management strategies. 3. Can be used to evaluate the impacts of proposed developments on floodplain conditions.

5. Rainfall–Runoff Modeling Approaches

Rainfall–runoff models are hydrological models used to simulate the transformation of rainfall into runoff in a catchment. These models are important for predicting the amount and timing of runoff in a catchment, which is crucial for managing water resources and for flood forecasting [95]. Rainfall–runoff models can be classified into three categories: empirical, conceptual, and physical process-based models [96]. Details on rainfall runoff models, including their advantages and disadvantages, are shown in Table 2. Conceptual models, which mimic runoff generation, are based on a simplification of the hydrological cycle, and employ ideas such as the water balance equation and the soil water balance. These models may be used to anticipate the behavior of catchments with a limited amount of input data when a thorough understanding of the hydrological processes is desired. Conceptual models include, but are not limited to, the Nash cascade model [97], Bayesian networks (BNs) [98], and the HBV model [99].

A full knowledge of the physical processes involved in runoff production is the foundation for physical process-based models of infiltration, evapotranspiration, and runoff routing. Although these models need a lot of computation and precise input data, they can accurately reproduce catchment behavior in a wide range of hydrological conditions, and are useful for simulating complex hydrological processes [100]. The Soil and Water Assessment Tool (SWAT) [101] is an illustration of a physical process-based model. It simulates the hydrological processes in a watershed, including surface runoff, groundwater recharge, and sediment transport [102,103]. The MIKE SHE model [104] simulates surface water–groundwater interactions, considers land use, soil properties, and topography, and evaluates climate and land use impacts. WATFLOOD [105] simulates catchment hydrological processes including floods, runoff, infiltration, recharge, and routing. It evaluates management strategies and assesses flood risk.

Empirical models are based on statistical relationships between rainfall inputs and observed runoff outputs. These models do not necessarily reflect the underlying physical processes, but they are simple to use and require minimal input data. Empirical models are commonly used for flood forecasting, urban drainage design, and water resources planning. Some examples of empirical models include data-driven methods such as regression models [106], artificial neural networks [107], various machine learning algorithms, and the Soil Conservation Service Curve Number (SCS-CN) method [108]. Teng et al. [109] and Buttinger-Kreuzhuber et al. [110] provided an in-depth review of empirical, hydrodynamic, and conceptual flood inundation models, highlighting their benefits, drawbacks, and potential applications. Maranzoni et al. [111] compares several methodologies, factors at risk, and applications when looking at quantitative methods for evaluating flood hazard. This provides guidance on how to choose appropriate evaluation techniques.

Figure 4 shows the rainfall–runoff model flow diagram. The models involve collecting data about a river basin, determining model parameters, and calculating runoff based on rainfall input. The model is then evaluated and adjusted if necessary, and used to predict future water flow in the river or stream. This information is useful for managing water resources and planning for floods [36]. The choice of rainfall–runoff model depends on the specific objectives of the study, the available data, and the level of complexity required to accurately simulate the hydrological processes involved [112]. The selection of model structures and related factors affects how well distributed hydrological models function. Model parameter uncertainty is a serious restriction, and computation time can be rather long. However, with improvements in computer resources, autonomous optimization, calibration-free models, and parallel methods can show enhanced performance [113]. For probabilistic flood forecasting utilizing deterministic models, Bayesian systems provide a theoretical foundation [114].

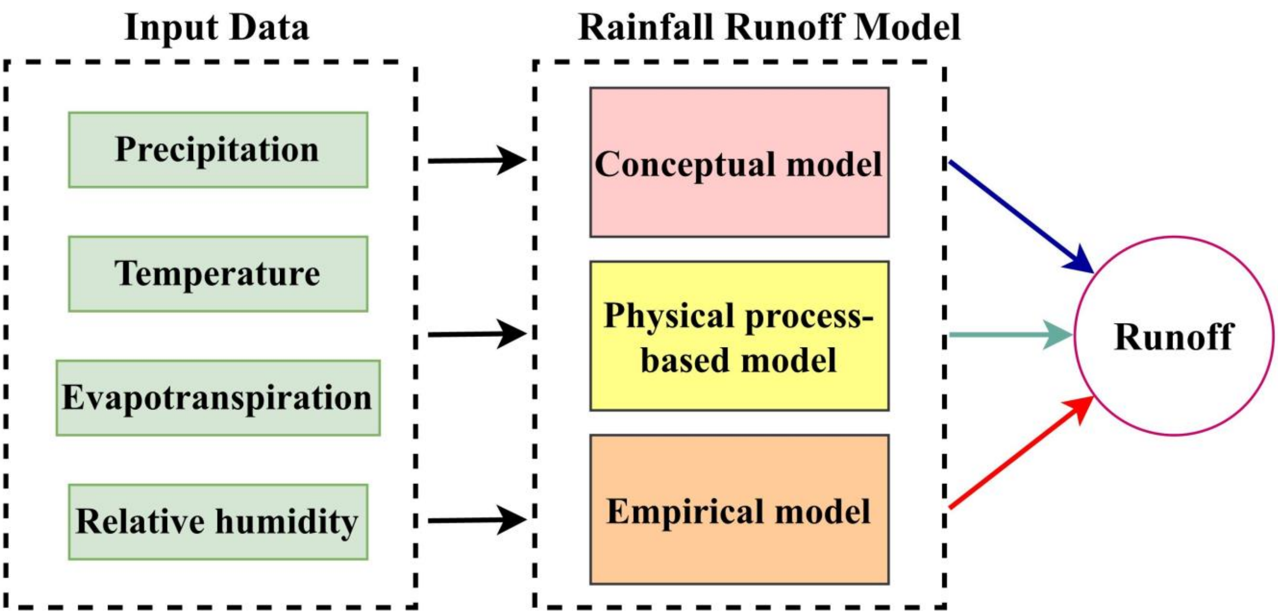

Figure 4. Rainfall–runoff modeling approaches.

Table 2. Information on the rainfall runoff models, including its advantages and disadvantages.

Model Type	Description	Strengths	Weaknesses	Related Research
Conceptual Models	Based on a simplified representation of the hydrological cycle	Easy to use, require only a few input parameters, useful for predicting the behavior of small to medium-sized catchments where there is a good understanding of the hydrological processes involved	May not accurately represent the physical processes involved in runoff generation, limited ability to simulate the effects of land use change and climate change	[115,116]
Physical Process-Based Models	Based on a detailed understanding of the physics of hydrological processes	Accurately represent the physical processes involved in runoff generation, useful for predicting runoff from large catchments and for simulating complex hydrological processes	Require a large amount of detailed data and computational resources, can be complex and time-consuming to set up and run, may be sensitive to errors in input data	[117,118]
Empirical Models	Based on statistical relationships between rainfall inputs and observed runoff outputs	Simple and efficient, require only historical data on rainfall and runoff, useful for flood forecasting, urban drainage design, and water resources planning	May not accurately represent the physical processes involved in runoff generation, limited ability to simulate the effects of land use change and climate change, may not perform well outside the range of historical data used to develop the model	[119]

6. Remote Sensing and GIS-Based Flood Models

Flood models are developed using remote sensing and Geographic Information Systems (GIS) technologies to help in storm prediction and management [120]. Remote sensing gathers data about the surface of the Earth from a distance using sensors such as satellites or aircraft. To handle, analyze, and visualize geographic data, the GIS software system is used [121]. Using remotely sensed data and GIS, flood models can simulate how water would behave during a flood event [122]. These models analyze and assess the topography, hydrology, meteorology, and land use of the study region using data from a variety of sources, including satellite images, aerial photography, and ground-based [123]. The models may be used to evaluate the effectiveness of recommended flood mitigation measures, as well as to simulate the consequences of various flood scenarios [124,125]. For example, satellite imagery is used to map flood extents and locate flood-prone areas [126]. Digital elevation models (DEMs) generated from remote sensing data are used to create flood inundation maps that forecast the areas that are likely to flood during a given flood event [127]. GIS is used to examine the spatial relationships between various variables that contribute to flooding, such as land use, soil type, and topography [128]. It is also used to generate flood hazard maps that represent the extent and depth of possible flood inundation, as well as to aid in flood risk assessment and decision-making [129,130].

The following methodology is usually used in remote sensing and GIS-based flood models, as shown in Figure 5.

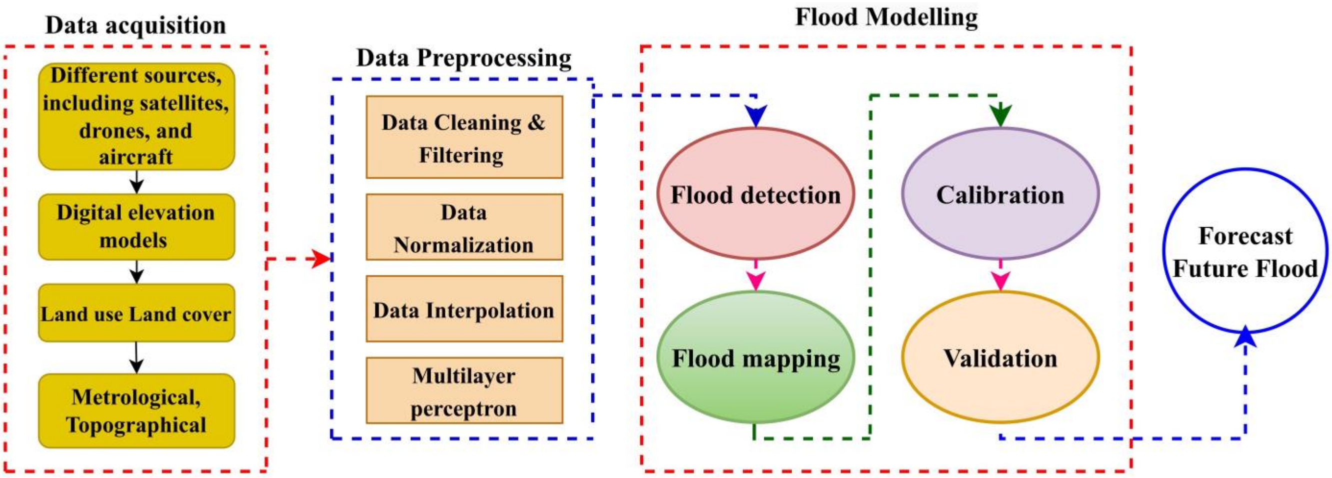

Figure 5. Remote sensing and GIS-based flood forecasting model.

The models' function by gathering data from various sources, including satellite imagery, aerial photography, and ground-based measurements. The data acquired include digital elevation models, land use/land cover maps, soil data, and meteorological data [131]. Preprocessing is necessary for the acquired data to increase in accuracy and eliminate distortions, such as radiometric calibration, atmospheric correction, and geometric correction. Similar processing operations for GIS data include geo-referencing, data conversion, and data integration. Flood detection: The preprocessed data are applied to image analysis methods such as thresholding and image segmentation to identify areas affected by floods. Using the flood maps as raw data, flood models can simulate the flood process and forecast flood levels and flows [132]. There are many different kinds of flood models that can be used, including hydrological, hydraulic and coupled models. Hydrologic modeling is used to simulate water movement in a watershed, such as infiltration, runoff, and evapotranspiration [133]. Hydrologic models of various kinds, such as distributed [134], lumped [135], and semi-distributed models [136], are used. The movement of water in river channels and floodplains is simulated using hydraulic modeling [137]. The hydraulic models can be one-dimensional (1D), two-dimensional (2D), or three-dimensional (3D) depending on the complexity of the river channel and floodplain [138].

Flood mapping: Flood maps are created that depict the extent and severity of the flood. The flood maps are then used to identify flood-prone areas and to create flood-mitigation strategies, such as land use planning, infrastructure design, and emergency response planning [139,140]. GIS-based flood models have several advantages over traditional flood models, including the ability to integrate various kinds of data and visualize the results spatially. However, there are disadvantages to them, such as the difficulty of the modeling process and the need for specialist software and knowledge [141].

The next technique that is widely employed in the validation of flood models is flood calibration. A better match between forecasts and actual flood levels and flows can be achieved by changing the model's input parameters [142]. Flood map validation is a vital step in locating flaws, correcting them, and raising the accuracy of flood maps. It is necessary to use field observations or other unbiased data sources to confirm the accuracy of the flood maps. This process is essential because it guarantees that flood models are reliable and that they can be applied to develop effective mitigation methods [143]. Now, it is possible to utilize flood models to predict future floods and provide vulnerable people early warnings. Real-time information from far-off sensors and other sources can be used for forecasting.

Remote sensing and GIS-based flood models have a number of benefits over other types of flood models, including the ability to use a wide range of data and information, the ability to combine different types of data into a single framework, and the ability to support spatial analysis and visualization [144]. They do have certain disadvantages, though, including the need for precise and high-quality data, the potential for errors and ambiguity in the outcomes, and the need for specific knowledge and abilities to build and comprehend the models [145]. Table 3 displays the characteristics of various remote sensing data types and their uses in flood and water resources. Some of the applications of remote sensing and GIS in floods include in the context of flash floods [146], flood-affected urban areas [147], flood risk assessment [148], flood risk index [149], flood vulnerability mapping [150], and flood hazards [151].

Table 3. Shows the features of remote sensing data types with their applications.

Remote Sensing Data Type	Features	Applications
Optical Imagery	Captures visible and near-infrared light High-resolution images	Land cover classification, vegetation monitoring, urban planning, flood mapping Coastal management, flood risk assessment, disaster response, flood damage assessment
Thermal Imagery	Captures heat radiation Provides information on temperature distribution	Flood detection and monitoring, flood mapping Water resource monitoring, flood extent mapping
Radar Imagery	Uses radar waves to detect and measure objects and terrain Provides information on elevation, surface roughness, and moisture content	Mapping terrain, monitoring coastal erosion, detecting oil spills, flood mapping Agriculture, forestry, urban planning, flood risk assessment, flood damage assessment
LiDAR	Uses laser pulses to measure distance and create 3D models Provides information on topography, vegetation height, and building structure	Urban planning, floodplain mapping, flood extent mapping Flood risk assessment, flood damage assessment
Hyperspectral Imagery	Captures data across a wide range of wavelengths Provides detailed information on material composition and vegetation health	Environmental monitoring, flood mapping Flood risk assessment, water quality monitoring, flood damage assessment
Infrared Imagery	Captures thermal radiation Provides information on temperature distribution	Fire detection and monitoring, crop health, water resource monitoring, flood mapping Building inspection, energy efficiency, flood extent mapping, flood damage assessment
Satellite Imagery	Captures remote sensing data using sensors on board Earth-orbiting satellites Provides global coverage and frequent revisits to areas of interest	Monitoring weather, land use changes, natural disasters, flood mapping Climate monitoring, oceanography, flood risk assessment

Examples of flood models based on remote sensing and GIS include:

(1) SRTM Flood—This model simulates the behavior of water during a flood event by using Shuttle Radar Topography Mission (SRTM) data to map the topography of a study area [152];
(2) Inundation Mapping System (IMS)—The IMS is a flood risk management and emergency response software tool. It was developed by the US Army Corps of Engineers and is used to forecast the extent and depth of flooding in a specific region [153];
(3) ArcGIS Flood Analysis Tool—Part of the ESRI ArcGIS software suite, this tool is used to map and evaluate flood risk, including the extent and depth of possible flood inundation, as well as to support flood risk assessment and decision-making [154].

Future flood models built on remote sensing and GIS technology are very promising, and have the ability to completely change the way we perceive and handle flood risk. What follows are a few possible future developments. Increasing the integration of ML and AI—by autonomously identifying patterns and trends in large amounts of data, ML and AI algorithms can be used to improve the precision and reliability of remote sensing- and GIS-based flood models. Real-time monitoring and prediction—flood events can be monitored in real time, and early warnings and forecasts of their effects can be provided using remote sensing and GIS-based flood models. This aids in lowering the possibility of property and life loss and to support effective emergency response. Improved data access and quality—data from remote sensing and GIS are becoming more and more readily available, and their quality is also rising. This will enable the development of more accurate and comprehensive flood models. Greater collaboration and data sharing can be supported by remote sensing and GIS-based flood models, which will be used by a variety of stakeholders, including government agencies, academic institutions, and the commercial sector. Better understanding the effects of floods on communities and the environment will aid in decision-making and risk management methods.

7. Flood Modeling Using Artificial Intelligence and Machine Learning

Flood modeling using artificial intelligence (AI) and machine learning (ML) is a relatively new field that has the potential to revolutionize the way floods are predicted and managed [155,156]. AI and ML algorithms are used to analyze large amounts of data, including meteorological, hydrological, and topographical data, to improve the accuracy and reliability of flood models. ML technology enables systems to improve themselves through experience without the need for explicit programming [157,158]. ML methodologies involve a learning process that seeks to accomplish a given task by learning from past experiences [159]. To evaluate the performance of an ML model for a particular task, a performance metric is utilized to enhance the learning experience [160,161]. There are four categories of ML technology based on learning methods, namely, supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning [162].

Figure 6 depicts the typical machine learning algorithms utilized in flood prediction and forecasting frameworks.

The entire process involves three primary stages, which are data collection, the selection of appropriate machine learning models, flood forecasting, prediction, and risk mapping. Data of all kinds are gathered in the first step, including time series of water levels, data from remote sensing, and tabular data. ML models are chosen in the second step depending on the features of the data and the prediction issue. Regression techniques may be used to estimate flood levels using historical data, such as linear regression [163] and support vector regression [164]. The output variable and the input variables, such as the weather and the soil moisture levels, are mathematically related by these algorithms [14]. Based on input characteristics including topography, soil type, and previous flood history, classification algorithms, such as decision trees and random forests, can categorize locations into high, medium, or low risk of flooding [165]. It is possible to identify flood-prone locations and prioritize them for flood prevention and mitigation activities by using clustering algorithms such as hierarchical clustering and k-means to group together areas with comparable flood risk factors [166].

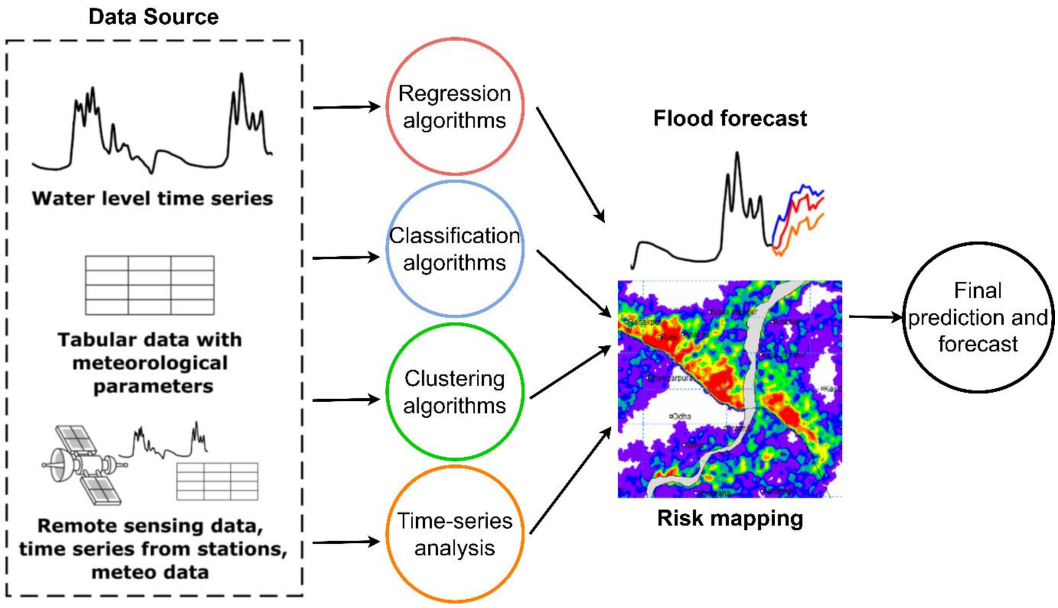

Figure 6. Models for flood prediction and forecasting using ML methods.

Time series analysis techniques, such as Long Short-Term Memory (LSTM) [167] and Autoregressive Integrated Moving Average (ARIMA) [168], are utilized to analyze time-dependent data and make short-term flood forecasts. These techniques can capture patterns and trends in the data to make more accurate predictions [169]. In the third stage, the selected machine learning models are used to generate flood predictions and forecasts, and risk maps are generated to help emergency response teams and policymakers make informed decisions regarding flood preparedness and mitigation measures. The use of machine learning methods in flood prediction and forecasting models can enhance the accuracy and timeliness of flood forecasts, which is crucial in mitigating the impact of flooding events and protecting lives and property. The main machine learning algorithms used in flood prediction and forecasting include k-nearest neighbor [170], deep convolutional neural network models [171], decision trees [172], support vector regression models [173], random forest [174], clusters [175], and artificial neural networks (ANN) [176]. Bentivoglio et al. [177] published a paper on deep learning in flood control, emphasizing its merits in flood mapping. The assessment highlights knowledge gaps and makes recommendations for future research areas in real-time flood warning and probabilistic forecasts. A study by Seleem et al. [178] evaluated the efficacy of CNN and RF models for predicting flood water depth. In comparison to RF models, CNN models exhibit a larger potential for generalization and enhanced performance using transfer learning approaches.

Karim et al. [179] discusses the application of ML and deep learning algorithms for flood inundation modeling. Deep learning models are more accurate, yet there are problems due to a lack of expert knowledge and benchmark data. In order to anticipate the effects of a fluvial flood in real-time, Bomers and Hulscher [180] compared conceptual models with data-driven models, especially neural networks, pointing out both their advantages and disadvantages. Table 4 summarizes different flood modeling techniques as well as their associated AI/ML methods. Hydrological modeling has been achieved using supervised learning algorithms such as Support Vector Machines (SVM) [181] and ANN [182], whereas flood inundation mapping is modeled using deep learning (DL) algorithms such as Convolutional Neural Networks (CNN) and other DL methods [179]. Decision trees (DT), Random Forest (RF), and other ML algorithms are used to evaluate flood risk, early warning systems, and flood damage [183,184].

Table 4. Various AI and ML techniques are applied in flood modeling.

Flood Modeling	AI/ML Method
Hydrological Modeling	ANN, SVM, and other supervised learning algorithms are used to simulate intricate hydrological processes and forecast flooding events.
Flood Inundation Mapping	Using CNN and other deep learning algorithms, locations that have been inundated by floods are mapped using high-resolution remote sensing data, such as satellite photography or aerial photographs.
Flood Risk Assessment	Using decision trees, Random Forest, and other machine learning algorithms, flood risk is evaluated in relation to a variety of criteria, including land use, elevation, and rainfall.
Early Warning Systems	ANN and other machine learning algorithms are used to create early warning systems that deliver real-time alerts based on forecasts of flood occurrences and their possible repercussions.
Flood Damage Assessment	The probable harm brought on by flood disasters has been assessed using DT, RF, and other machine learning techniques.

Some examples of how AI and ML can be used in flood modeling are described in the following:

(a) Predictive modeling—AI and ML algorithms can be used to build predictive models that can provide flood warnings and forecasts. These models can be developed using historical data and updated in real time as new data become available [185];
(b) Data analysis—AI and ML algorithms can be used to analyze large amounts of data, such as remote sensing and GIS data, to identify patterns and trends that can provide insights into flood causes and effects [186];
(c) Risk assessment—AI and ML algorithms can be used to assess the potential consequences of a flood event, such as damage to buildings and infrastructure, loss of life, and economic impact. This knowledge can be used to support risk management and decision-making [187];
(d) Mitigation planning—AI and ML algorithms can be used to create flood mitigation strategies, such as levees and floodwalls, non-structural measures such as zoning and land use laws, and emergency planning and response [188].

Incorporating AI and ML into flood modeling has the potential to increase the accuracy and dependability of flood models, facilitate more efficient decision-making, and lower the danger of property and human casualties during flood occurrences [189]. However, it is essential to note that these technologies are still in their early stages of development, and more studies are required to fully understand their potential and limitations. There are several limitations, for example, flood models frequently require data from multiple sources, including meteorological, hydrological, and topographical data. Integrating data from various sources can be difficult, especially when the data formats and units are different. Table 5 explains the advantages and disadvantages of each algorithm, enabling customers to select the one that will best meet their particular needs. Table 6 shows a summary of the different ML methods compared in terms of accuracy, speed of learning, speed of classification, tolerance to missing data, dealing with discrete data, dealing with binary data, tolerance to noise, over fitting, model parameter handling, and linear/nonlinear.

Table 5. Different ML method advantages and disadvantages.

Method	Advantages	Disadvantages
Decision Trees	Simple to understand and analyze; handle categorical and continuous variables; handle missing values; handle variable interactions.	Prone to over fitting; sensitive to small variations in data; produce biased trees if some classes prevail.
Random Forests	High accuracy; robust to over fitting; handle missing values and multidimensional data; handle variable interactions; provides feature significance measures.	The underlying decision process is difficult to analyze and comprehend; longer training periods and more storage space are required.
Support Vector Machines	High accuracy; capable of handling high-dimensional data; capable of handling missing values; capable of handling nonlinear connections; provides feature importance measures.	Sensitive to kernel function and parameter selection; large datasets can be computationally intensive; direct handling of categorical factors is not possible.
Naive Bayes	Quick and simple to use; capable of handling high-dimensional data; missing values; categorical and continuous variables,; and able to provide probabilities and interpretability	Assumes independence between variables; performs poorly if independence assumption is violated; cannot capture complex relationships between variables.
k-Nearest Neighbors	Simple and intuitive; handle both categorical and continuous variables; handle missing values; handle nonlinear relationships	Can be sensitive to the choice of k; computationally intensive for large datasets; can be biased towards variables with high variance
Neural Networks	High accuracy in complex tasks; handles high-dimensional data; handles missing values; handles both categorical and continuous variables; handles nonlinear relationships	Prone to over fitting; difficult to interpret and understand the underlying decision process; Can require longer training times and larger storage space; Can be sensitive to the choice of architecture and hyper parameters
Deep Learning	State-of-the-art performance in many tasks; handles high-dimensional data; handles missing values; handles both categorical and continuous variables; handles nonlinear relationships	Requires large amounts of data and computing resources; can be prone to over fitting and require regularization; difficult to interpret and understand the underlying decision process; can be sensitive to the choice of architecture and hyper parameters

Table 6. Different ML methods comparison.

Method	Accuracy	Speed of Learning	Speed of Classification	Tolerance to Missing Data	Dealing with Discrete Data	Dealing with Binary Data	Tolerance to Noise	Over Fitting	Model Parameter Handling	Linear/Nonlinear
Decision Trees	Moderate to High	Fast	Fast	Can handle missing data	Can handle discrete data	Can handle binary data	Sensitive to noise	Prone to over fitting	Easy to handle	Both
Random Forests	High	Moderate	Fast	Can handle missing data	Can handle discrete data	Can handle binary data	Tolerant to noise	Less prone to over fitting	Easy to handle	Both
Support Vector Machines	High	Moderate	Moderate	Can handle missing data	Cannot handle discrete data directly	Can handle binary data	Sensitive to noise	Prone to over fitting	Model complexity	Non linear
Naive Bayes	Moderate to High	Fast	Fast	Can handle missing data	Can handle discrete data	Can handle binary data	Sensitive to noise	Less prone to over fitting	Easy to handle	Both
k-Nearest Neighbors	Moderate to High	Slow	Moderate	Cannot handle missing data directly	Can handle discrete data	Can handle binary data	Tolerant to noise	Prone to over fitting	Model complexity	Non linear
Neural Networks	High	Slow	Moderate to slow	Can handle missing data	Cannot handle discrete data directly	Can handle binary data	Tolerant to noise	Prone to over fitting	Model complexity	Non linear
Deep Learning	High	Slow	Moderate to slow	Can handle missing data	Cannot handle discrete data directly	Can handle binary data	Tolerant to noise	Prone to over fitting	Model complexity	Non linear

It can be difficult to validate AI and ML algorithms, especially when there is a lack of historical data. Because of this, judging these models' accuracy and suitability for various uses can be challenging. It is essential to remember that the decision regarding which AI/ML method to use will rely on the particular needs and specifications of the flood modeling project, and that various methods might be better suited for various kinds of predictions and data. In order to ensure accuracy and reliability, AI/ML-based flood modeling methods should also be validated and calibrated using accurate and reliable data and their results should be interpreted cautiously.

8. Multiple-Criteria Decision Analysis-Based Flood Management

Multiple-criteria decision analysis (MCDA) is a technique used to assist decision-makers in making well-informed decisions when confronted with complex and conflicting decisions, such as those involved in flood management [190]. As part of its multi-criteria decision-making process, MCDA takes into account both quantitative and qualitative factors [191]. In terms of flood management, MCDA is used to evaluate and compare various flood management alternatives, including structural measures, non-structural measures, and land use planning, based on a variety of criteria, such as to minimize the risk of flood damage or to reduce the effects of a flood event [192]. The two broad categories of MCDM techniques are MADM (multi-attribute decision-making) and MODM (multiple-objective decision-making) [193]. There are various types of MADM methods that can be used to evaluate and compare different options based on multiple criteria. MADM is suitable for choosing a small number of alternatives and preference ranking. Figure 7 shows the different classifications of MCDM methods. Here are a few typical examples:

(a) Value/utility function methods—These techniques involve developing a function that rates each option's value or utility in accordance with how well it fulfills each criterion. Multi-attribute value theory (MAVT) [194] and multi-attribute utility theory (MAUT) [195] are two examples of value/utility function methods. It serves to assess and compare various flood mitigation options based on a variety of criteria including cost, effectiveness, environmental impact, and social acceptance;

(b) Pairwise comparison methods—In these approaches, the options are ranked by making pairwise comparisons of the way each option compares to other in terms of the way well it fulfills each criterion [196]. Analytic hierarchy process (AHP) [197] and the analytic network process (ANP) [198] are two examples of pairwise comparison techniques. These techniques are used to prioritize emergency response actions, such as evacuation, rescue, and relief efforts, during a flood event [199]. They compare the efficacy of various response actions based on factors such as speed of response, responder safety, and affected population;

(c) Outranking techniques—These techniques evaluate each alternative to every other option in terms of how well they fulfill each criterion in order to identify which possibilities "outrank" others [200]. Outranking techniques include, for example, the elimination and choice expressing reality (ELECTRE) approach and the preference ranking organization method for enrichment evaluation (PROMETHEE) [201]. Based on a range of criteria, such as accuracy, computational complexity, and data accessibility, these strategies are used to choose the optimal flood forecasting model [16,202];

(d) Distance-based methods—These methods involve calculating the distance between each option and an ideal solution, and then ranking the options based on these distances. The technique for order of preference by similarity to ideal solution (TOPSIS) [203] and the weighted aggregated sum product assessment (WASPAS) methods [204] are two examples of distance-based methods. The methods are used to assess the risk of flooding in various areas and determine the best flood management strategies [205];

(e) Fuzzy decision-making methods—These approaches involve incorporating uncertainty or imprecision into decision-making [206]. To deal with uncertainty in criteria weights, preference values, and rankings, fuzzy logic and fuzzy set theory can be used [207]. The MADM method chosen will be determined by the nature of the decision problem, the number and types of criteria, and the decision-makers' preferences [208].

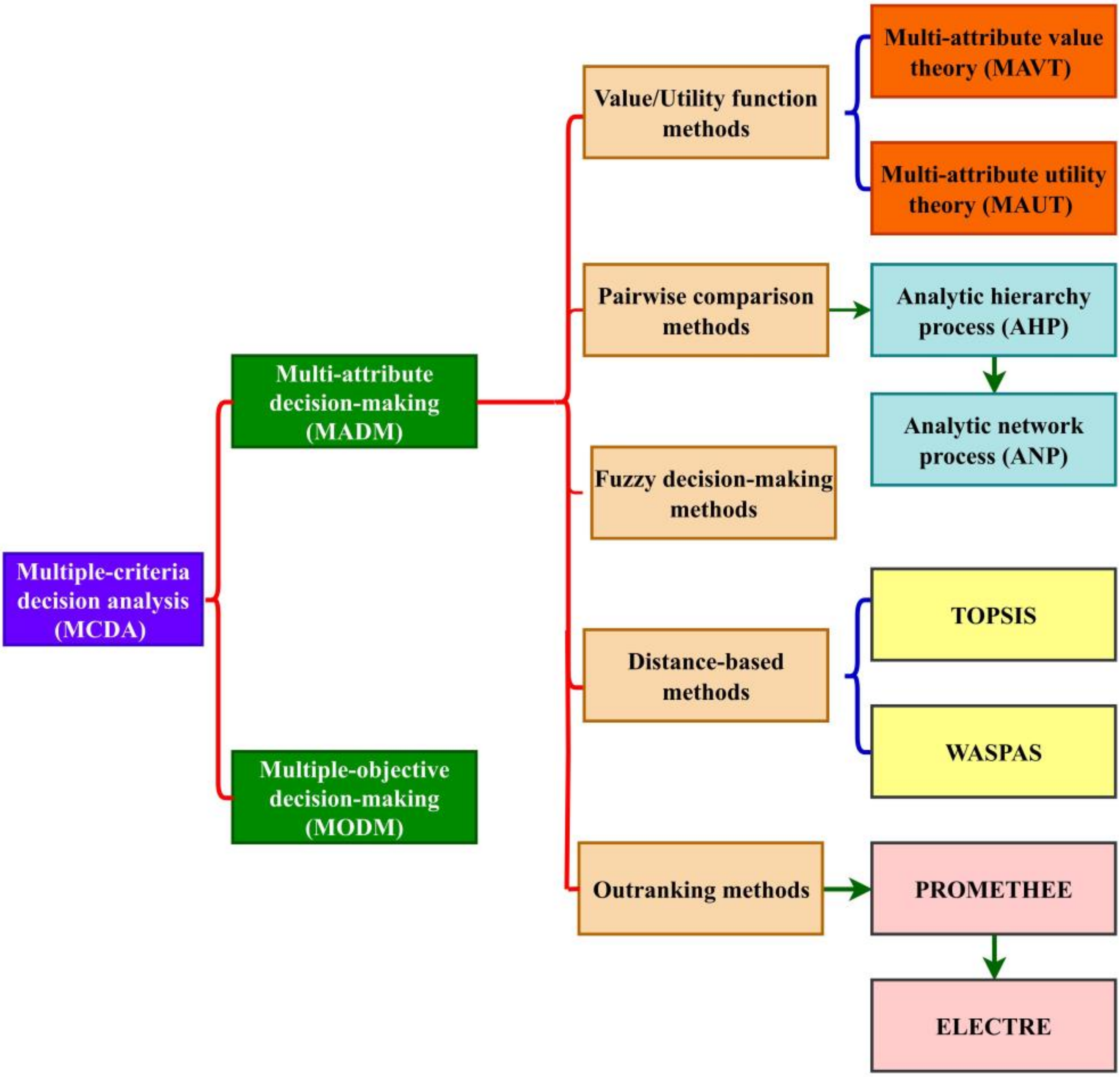

Figure 7. Different classifications of MCDM.

Figure 8 depicts the steps taken to solve the problem. MCDA involves the following steps: defining the problem and identifying objectives, identifying relevant criteria, assigning weights to criteria, identifying alternatives, evaluating alternatives against each criterion, aggregating results, conducting sensitivity analysis, making a decision based on objectives and preferences, and monitoring and evaluating the decision over time. Table 7 illustrates the various MCDM techniques and their applications in flood management. It is essential to note that the MCDM method chosen will be determined by the specific needs and requirements of the flood management project, and that various methods may be more appropriate for different types of decisions and situations.

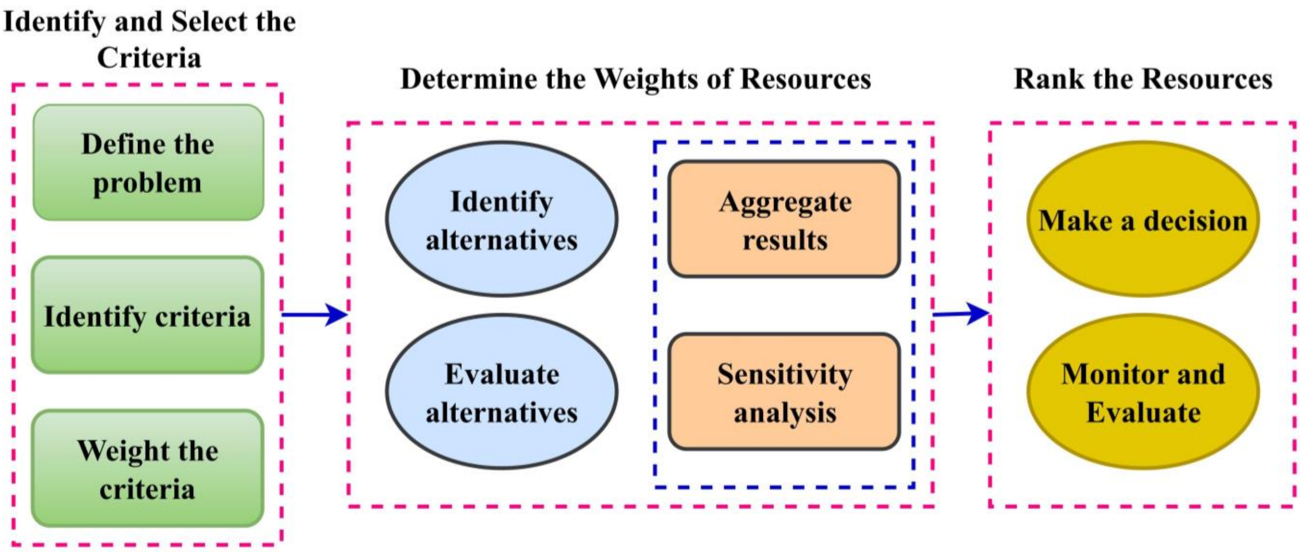

Figure 8. Steps of MCDM.

Table 7. Different MCDM methods and their applications in flood management.

Method	Application in Flood
Multi-attribute value theory (MAVT)	Used to compare various flood mitigation strategies in terms of cost, effectiveness, and impact on the environment.
Multi-attribute utility theory (MAUT)	Used to compare various flood mitigation methods based on factors such as cost, efficacy, and environmental impact, while keeping decision-makers' preferences in mind.
Analytic hierarchy process (AHP) and the analytic network process (ANP)	Used to assess flood mitigation plans using a variety of factors, including effects on the environment, society, and the economy.
The elimination and choice expressing reality (ELECTRE) method and the preference ranking organization method for enrichment evaluation (PROMETHEE)	It ranks various flood mitigation methods according to the extent to which they work in comparison to ideal and undesirable solutions.
The technique for order of preference by similarity to ideal solution (TOPSIS)	Ranks various flood mitigation methods according to their proximity to an ideal response.
Weighted aggregated sum product assessment (WASPAS)	Used to assess flood mitigation based on attributes such as cost, efficacy, and environmental impact while taking into account decision-makers' weights.
Fuzzy decision-making methods	It is used when there is uncertainty or imprecision in the available data or decision-makers' preferences.

MODM is preferred for continuous optimization problems with an infinite number of alternatives [209]. Based on computational time and solution, MODM methods are further classified as mathematical programming models and heuristic algorithms. Linear programming (LP), non-linear programming (NLP), mixed integer linear programming (MILP), goal programming (GP) and dynamic programming are all mathematical methods [210]. Genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA), particle swarm optimization (PSO), etc., are all heuristic methods [211]. To ensure that stakeholders' perspectives and concerns are considered, MCDM methods necessitate their participation in the decision-making process. More details are given in Section 9.

9. Heuristic and Metaheuristic Methods Used in Flood Management

Optimization techniques can be used in flood management in a variety of ways, including flood control, flood warning, flood forecasting/predication and flood risk management. Optimization techniques can be used in flood control to identify the most effective flood control measures to reduce flood damage [212]. To make sure they can resist flooding, flood control facilities like levees and dams can be improved by design. Based on variables including flood frequency, possible damage, and cost, optimization techniques may also be used to choose the optimal locations for flood protection structures [213]. It is used in flood warning to enhance the setup and functionality of flood warning systems. This entails placing sensors and gauges optimally to deliver precise and fast flood warnings. The best algorithms for predicting flood levels and sending flood alerts are also found using this method [34]. In order to enhance flood risk assessments, which involve detecting flood-prone locations and determining the most effective flood risk management procedures, optimization techniques can be applied [208]. In order to ensure that resources are allocated efficiently during a flood event, optimization is also used to improve emergency response plans and evacuation strategies [214].

Traditional optimization methods include dynamic programming (DP), non-linear programming (NLP), and linear programming (LP) [215]. In order to address complex issues related to flood control, flood warning, and flood risk management, heuristic and metaheuristic optimization techniques have been shown to be helpful in flood management. These methods were created to address the drawbacks of earlier optimization methods such as linear programming (LP) [216], nonlinear programming (NLP), and dynamic programming (DP). When traditional approaches are too slow, problem-solving techniques called heuristic methods are used to find a solution quickly. Metaheuristic techniques are more advanced methods for choosing or creating heuristics that can effectively address optimization problems [35,217]. These methods are divided into neighborhood-based and population-based algorithms [218]. Population-based algorithms, such as swarm intelligence and evolutionary algorithm, are adaptable and can easily offer a global solution. Genetic algorithms (GA), differential evolution (DE), genetic programming (GP), evolutionary programming (EP), and evolutionary strategies (ES) are a few examples of evolutionary algorithms. Ant colony optimization (ACO), harmony search (HS), particle swarm optimization (PSO), cuckoo search (CS), artificial bee colony (ABC), firefly algorithm (FA), bat algorithm (BA), honey bee mating optimization (HBMO), and shuffled frog leaping algorithm are examples of swarm intelligence-based algorithms (SFLA). Tabu search (TS) and simulated annealing (SA) are two neighborhood-based algorithms [219].

These algorithms can be used to locate areas that are vulnerable to flooding, design flood protection measures, and order flood response measures [220]. Overall, heuristic and metaheuristic optimization techniques are useful tools for managing floods because they offer a quicker and more adaptable method of locating the best answers to challenging issues relating to flood control, flood warning, flood forecasting, flood predication and flood risk management [221]. Figure 9 depicts the methodology for creating a hybrid flood forecasting/predicting model. It involves collecting relevant data, such as rainfall and water levels, choosing the most relevant features, selecting suitable models, combining them into a hybrid model, training and validating the model, fine-tuning the model by optimization, adjusting its parameters to improve its performance, deploying the model, and continuously monitoring and evaluating its performance. This process assists in the creation of a model that can make use of the strengths of several models and compensate for their weaknesses, leading to accurate and reliable flood forecasting and prediction.

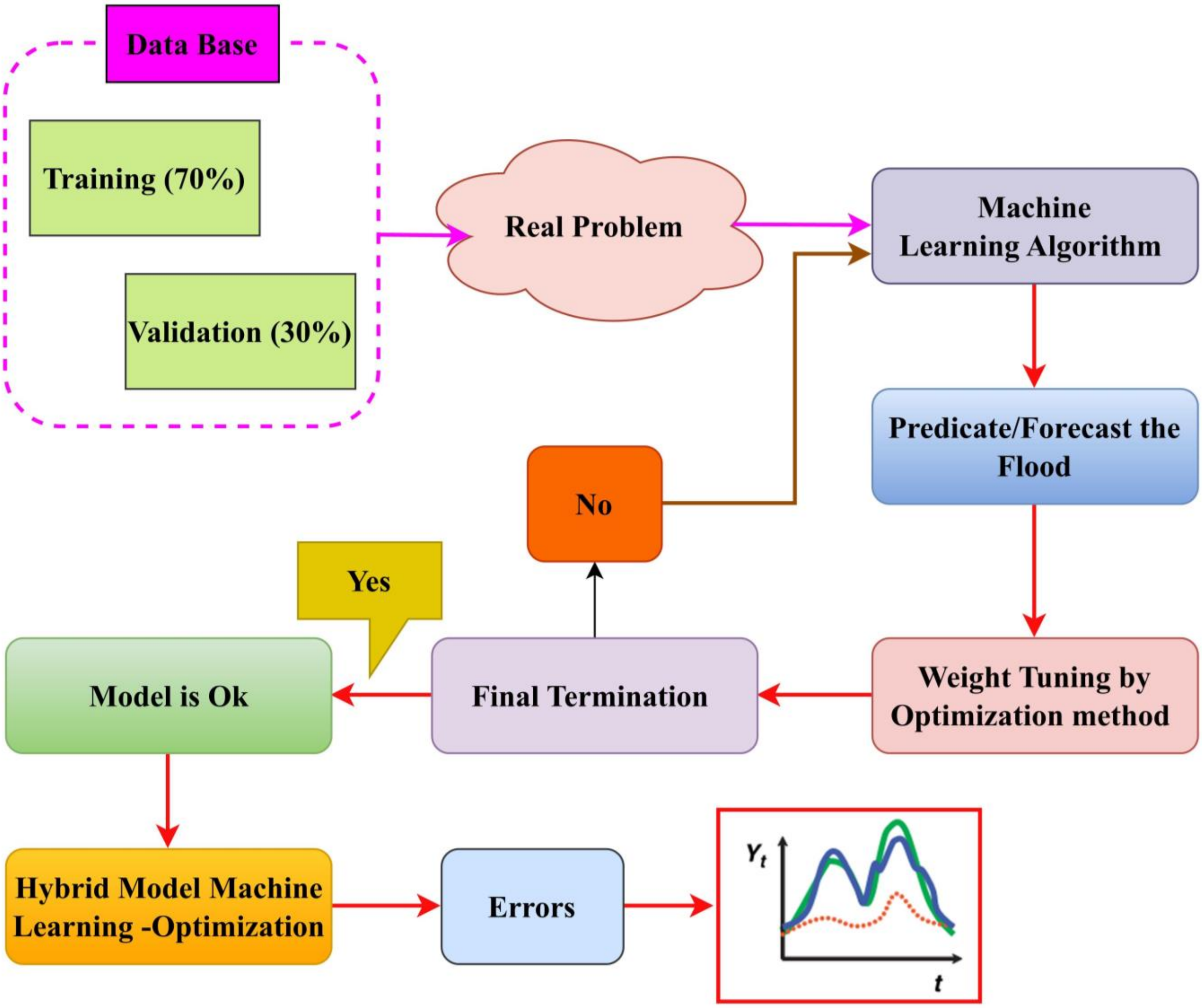

Figure 9. Flowchart of developing a hybrid flood forecasting/predicting model.

10. Challenges and Way Forward

Flood modeling is the process of predicting and analyzing how floods will affect a certain area using numerical models, data, and simulations. Understanding the physical mechanisms that cause floods and forecasting their behavior and effects, such as water levels, flow patterns, inundation extent, and damage assessment, are the main objectives of flood modeling. The creation of mitigation and adaptation methods, as well as the evaluation of flood risk, can all be aided by the data produced by flood models. However, considering that flood modeling is a difficult and complex process, a number of factors may have an impact on the accuracy and dependability of the models. The following are a few difficulties encountered with flood modeling:

(1) The availability and quality of data provide one of the major difficulties in flood simulation. Many data are required for flood models, including topographic information, data on land use, hydrological information, and data on prior floods. The quality and completeness of the data utilized determine the models' accuracy and dependability. The information utilized for flood modeling is obsolete, contradictory, or nonexistent. For instance, topological information can be obsolete and not exactly reflect the local environment right now. In places with poor monitoring networks, hydrological data, such as precipitation and stream flow data, may also be erroneous. The quality of the data used for flood modeling must be updated and improved in order to meet

these requirements. By creating new monitoring networks, enhancing data gathering and processing procedures, and utilizing satellite data and other remote sensing technologies, this may be accomplished;

(2) Flood models can range in complexity from straightforward empirical models based on a few factors to intricate hydraulic models that replicate the underlying physical processes. The models' complexity may have an impact on their precision, dependability, and computational effectiveness. In order to construct and operate complex models, more information, processing power, and skill are needed. Complex models are more accurate in simulating the physical processes involved in floods. On the other hand, simple models are simpler to create and maintain, but they cannot adequately capture the intricate processes involved in floods. The availability of data and computing resources must be balanced with the complexity of the models in order to overcome this difficulty. To get the greatest results, a combination of basic and complicated models may be utilized often;

(3) Validation and calibration of the models—The calibration and validation of the models are essential procedures in flood modeling to make sure that the models appropriately reflect the behavior of floods. While validation entails contrasting model outputs with independent observations to judge the models' correctness, calibration entails changing model parameters to fit the observed data. However, because to the scarcity of observed data, the difficulty in gathering precise flood data, and the complexity of the physical processes involved in floods, calibrating and validating flood models may be difficult. It is essential to calibrate and test the models using a range of observational data, such as historical flood data, satellite data, and in-situ observations, in order to solve these concerns. Additionally, it is crucial to combine data from many sources and use statistical techniques such as sensitivity analysis to determine the degree of uncertainty in the models;

(4) Model uncertainty—Another issue in flood modeling that may have an impact on the models' accuracy and dependability is model uncertainty. The unpredictability of the data utilized, the complexity of the physical processes involved in floods, and the constraints of the models themselves are only a few of the factors that contribute to model uncertainty. Sensitivity analysis and other statistical techniques should be used to assess and communicate model uncertainty using flood models in order to overcome these difficulties. Sensitivity analysis is a popular statistical technique used for understanding how model parameters affect the outcomes of flood simulation. Sensitivity analysis seeks to comprehend the uncertainty of the models as a result of the uncertainty in the parameter values by identifying the variables that have the greatest impact on the model outputs. The sensitivity analysis techniques include One-at-a-Time (OAT), Global, and Probabilistic Sensitivity Analysis (PSA). In contrast to OAT sensitivity analysis, which includes altering one parameter at a time and examining its impact on the model outputs, global sensitivity analysis requires changing a number of factors at once to record the interactions between them. PSA use probability distributions to compute parameter uncertainty and evaluate the likelihood of various model outcomes. In addition to sensitivity analysis, Bayesian inference and Monte Carlo simulation are other statistical methods that are crucial for flood modeling. In order to update model parameters and determine model uncertainty, Bayesian inference uses prior information and observational data. Monte Carlo simulation creates a number of simulated model runs with different parameter settings in order to compute the likelihood of various model outputs and assess the level of model uncertainty.

11. Discussion and Future Direction

A key tool for understanding and predicting flood behavior as well as choosing the best course of action for managing the risk of flooding is flood modeling. There are several flood models available, each with their own benefits and drawbacks. When choosing a flood model, it is vital to consider factors including the simulation's complexity, data accessibility, and the user's precise requirements and specifications. One of the most important aspects of flood modeling is the choice of model inputs, such as data on precipitation, geography, land use and land cover, and hydrological conditions. Because it could be challenging or expensive to acquire high-quality data, the flood model's accuracy and reliability may be limited in many situations. Forecasting future flood conditions is typically fraught with uncertainty, particularly in regions where climate change is expected to have an impact on the frequency and intensity of catastrophic floods.

The choice of model, which may include hydrodynamic models, statistical models, and physically based models, is a crucial component in flood modeling. While statistical models utilize statistical approaches to evaluate flood risk based on historical data, hydrodynamic models mimic the movement of water in a river or floodplain. Hydrodynamic and statistical methods are combined in physically based models, such as those that use the Flood Estimation Handbook (FEH) technique, to produce more precise forecasts of flood conditions. The choice of model output, such as forecasts of flood size, flood depths, and flood velocity, is another crucial element of flood modeling. These results can be used to guide flood risk management choices, such as creating evacuation plans, designing flood protection systems, and putting floodplain zoning and land use regulations into practice. Additionally, the effectiveness of various management techniques, such as the development of levees and other flood protection structures, on flood risk and floodplain conditions may be evaluated using flood models. It is crucial for both practitioners and decision-makers to carefully assess the strengths and limits of various models and techniques when making judgments on flood risk management since, in general, flood modeling is a complicated and quickly-evolving area.

In order to enhance flood modeling in the future, several critical areas must be addressed. The following are some methods that could be applied to flood studies in the future:

(a) The incorporation of modern technology to increase the precision and effectiveness of flood models—emerging technologies such as remote sensing, cloud computing, and artificial intelligence will be essential;
(b) Data management and processing—improving flood modeling will require the efficient administration and processing of huge and varied data sources;
(c) Development of user-friendly interfaces and visualization tools—these improvements will make it simpler for practitioners and decision-makers to utilize flood models in practical applications;
(d) Multidisciplinary collaboration—researchers, practitioners, and decision-makers from a variety of disciplines must work together to advance flood modeling and enhance flood risk management;
(e) Addressing uncertainty—improving the accuracy of probabilistic flood models and addressing the difficulties of uncertainty quantification will be crucial for enhancing the dependability of flood forecasts;
(f) Integrated models—for the accuracy of flood predictions to increase, it will be essential to create more thorough and integrated models that take into account interactions between various flood system components;
(g) Adaptation to climate change—as the climate changes, it will be crucial for flood models to take these effects into account and to help decision-making in terms of adaptation and resilience.

In general, the future of flood modeling entails a mix of technical developments, collaboration, and addressing the problems of uncertainty and data management. In order to undertake efficient flood risk management and decision-making, it is important to create models that are more precise, trustworthy, and user-friendly.

12. Conclusions

In conclusion, flood modeling has evolved into a crucial instrument in the management of flood risk, assisting academics and professionals in comprehending and predicting the behavior of floods, as well as making defensible choices to lessen their effects. Although there has been a lot of work in creating new and better models, issues like uncertainty and data constraints still need to be resolved. However, improvements in computing capability, data accessibility, and fresh models provide hope for the future of flood modeling. This thorough examination of flood models has produced a useful synthesis of the body of knowledge, showing the advantages and disadvantages of various models and suggesting areas for further research and development. The study also emphasizes the necessity of continuing research in this area to guarantee that flood risk management measures continue to be successful in the face of rising flood danger. The review can help decision-makers reduce the danger of flooding by enhancing their understanding of flood models, which will eventually improve community safety and well-being throughout the world. For the purpose of creating more precise and trustworthy flood models and management plans, this evaluation will serve as a reference for academics, professionals, and decision-makers.

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