Flood susceptibility zonation mapping: A critical review of GIS, remote sensing, and machine learning approaches

Ambika Thakur [a], Kanwarpreet Singh [b*]

[a] Department of Civil Engineering, Chandigarh University, Mohali, Punjab, India

[b*] Department of Civil Engineering, Bahra Research Innovation & Knowledge Cluster (BRIKC), Rayat Bahra University, Greater Mohali-140103, Punjab, India

[*]Corresponding author e-mail: singhkanwarpreetnit@gmail.com

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Abstract Floods are among the most frequent and destructive natural disasters, causing severe damage to infrastructure, property, and human lives worldwide. Flood susceptibility has become an essential tool for minimising flood impacts and supporting disaster management planning. This paper discusses the use of geographic information system (GIS) and remote sensing methods for flood susceptibility assessment, focusing on conditioning variables, modeling methodologies, and prediction performance. The review comprehensively examined published research, including spatial factors such as elevation, slope, rainfall, land use and land cover (LULC), soil properties, drainage density, proximity to rivers, and topographic and hydrological indices. The use of optical and radar satellite images for land-cover and temporal flood analysis and flood extent mapping was also evaluated. The review highlights the application of advanced approaches including the analytical hierarchy process (AHP), multi-criteria decision method (MCDM), logistic regression (LR), frequency ratio (FR), fuzzy logic, artificial neural network (ANN), and machine learning (ML), and convolutional neural network (CNN) methods for flood susceptibility zonation mapping. The finding indicates, when it comes to flood susceptibility mapping, CNN and advanced machine learning models typically achieve accuracy between 85%-97%. Logistic regression and frequency ratio have accuracies of 78%-92% and 75%-90%, respectively. AHP brings up the rear at 70%-85%. In addition, hydrological and hydraulic models such as Hydrologic Engineering Center – Hydrologic Modeling System (HEC-HMS) and Hydrologic Engineering Center – River Analysis System (HEC-RAS) provide a process-based understanding of rainfall-runoff transformation and flood propagation, with model performance commonly evaluated using the Nash–Sutcliffe Efficiency (NSE) and coefficient of determination (R^2). The results suggest that ML and deep-learning models are potent forecasting tools for flood susceptibility zonation, although physically based hydrological and hydraulic models provide a complementary understanding of flood dynamics. The study indicates that the combined use of GIS, remote sensing, data-driven models, and process-based hydrological modeling may increase the reliability of flood susceptibility assessment and facilitate effective flood mitigation, early warning, disaster preparation, and sustainable land-use planning.

Keywords: flood hazard, susceptibility, zonation mapping, remote sensing and GIS, machine learning model.

1. Introduction

Floods occur due to overflow or accumulation of water, resulting from excessive rainfall, snowmelt, ice dam failure, storm surges, or other events**.** Among all disasters, floods are the deadliest. The estimated total economic harm worldwide is $386 billion since the end of the 20th century (Rahman et al., 2023). Floods can vary in scale and duration, from localized and short-term flash floods to larger and longer-term river or coastal floods. The occurrence of flooding is often determined by certain water levels or flow thresholds relative to normal conditions in a given area. If the intensity of the flood remains within certain limits, it is beneficial to the ecosystem. It recharges groundwater and increases soil fertility (Ghosh et al., 2022). Most floods in India are associated with the annual monsoon season, which usually occurs in June, July, August, and September. During this period, heavy rains cause river floods, especially in regions such as West Bengal, Bihar, Uttar Pradesh, and Assam. According to India's national disaster management authority (NDMA), floods pose a serious hazard to the country. Approximately 40 million hectares of the 329 million hectares of total land area are at risk of flooding. In comparison to the average of the preceding 53 years, which was Rs. 1,805 million, the average yearly flood damage over the last ten years, from 1996 to 2005, was Rs. 4,745 crores. This could be caused by many factors, such as global warming, rapid urbanization and population rise, as well as uncontrolled construction and economic activity in floodplains. Every year, flood destruction reaches an average of 75 lakh hectares of land, claiming 1,600 lives, and causing 1,805 crores of damage to homes, businesses, and public spaces. The majority of the 11,316 were eradicated in 1977. More than one major flood happens every five years. Heavy rains in 2023 have resulted in widespread flooding in Delhi and North India, with damage estimated to be at least ₹10,000 crores. An estimated ₹3,000–4,000 crore was lost by Himachal Pradesh. During two weeks of heavy rain and flooding in Himachal Pradesh, UP, and Delhi in July 2023, at least 105 people died, and hundreds more were relocated to relief camps. In several parts of northern India, the floods resulted in the closure of schools as well as disruptions to train and road services. Flood threats are too much for many communities and nations to handle, with disastrous consequences (Xue et al., 2024). The main cause of these implications can be a deficiency of funding required for flood disaster management and improper design of the city or community (Leitold et al., 2021). It increases the risk of damage due to floods, and the situation becomes very difficult to handle during a

flood disaster. So, there should be proper management for flood risk analysis and preventive measures to control major losses at the national and state levels (Rubinato et al., 2019). The mitigation measures that can be included to avoid losses due to floods are early warning systems, planned land cover and land use, zoning, improved construction methods, and investment in disaster preparedness (Norizan et al., 2023). These all can help to deal with flood disaster management. For better management, understanding the basic causes of floods and developing technology that can help to recognize flood risks and provide preventive measures in advance to avoid losses. Flood modeling is essential for anticipating floods and identifying locations susceptible to flooding (Nikoo et al., 2016). Multiple approaches to the fundamental models can be used to model floods. When it comes to describing the behavior of an event and its consequences, an event-based approach is the most effective way (Filipova et al., 2022). Such approaches have one drawback: they can't be used for real-time events. Further development of these methods results in a continuous simulation approach that can deal with real-time events. Such forecasting can help in long-term and short-term decision-making processes. The model's efficiency and accuracy will depend upon the type of data available to the system (Saikh, 2023). Identifying the places inundated with floodwater is critical to lessen the effects of flooding. Using current flood data, disaster and relief organizations can expedite emergency and rescue efforts (Uddin et al., 2021). Several advanced techniques for calculating flood risk depend on time, resources, and data availability (Büchele et al., 2006). The goal is to determine the floods' hydraulic properties—that is, their extent and the areal distributions of water velocity and depth.

When it comes to such measures, three primary flood maps are utilized: flood susceptibility maps, which quantify the amount of flooding seen during or after an event and are used for emergency measures; vulnerability maps, which show the spatial distribution of variables describing the flood risk of a particular event; and flood inventory maps, which show the spatial distribution of variables describing the flood risk of a specific event. These serve as both preventative and emergency measures (Bentivoglio et al., 2022). RS and GIS analysis are typically utilized to create flood inundation maps. The multi-criteria decision process can be applied to create maps of flood susceptibility, and numerical analytic techniques can be used to create maps of hazards. When discussing remote sensing with GIS, manual or semi-automated processes are needed to enhance the results. It is unable to provide precise statistics on land cover and land use. However, although the maps of flood susceptibility created by multi-criteria decision analysis are easy to understand, their outcomes

are unreliable when it comes to intricate analysis. Therefore, the main objective of this research paper will be the evaluation of different techniques used for flood zonation mapping, along with an investigation of their limitations.

Flood susceptibility mapping (FSM) identifies flood-prone areas using environmental, physical, and hydrological parameters, including elevation, slope, rainfall, drainage density, and land cover (Büchele et al., 2006; Kumar et al., 2023). In contrast, flood hazard mapping (FHM), considers the frequency, magnitude, height, velocity, and extent of flooding under particular conditions (Wang et al., 2022; Kumar et al., 2023). On the contrary, flood vulnerability mapping (FVM) actually focuses on spotting how vulnerable people, infrastructure, ecosystems, and economic stuff are to flood damage (Nadal-Romero et al., 2022; Yu et al., 2017). Meanwhile, flood risk mapping (FRM) looks at figuring out what happens because of flooding, taking in count both hazard level and exposure level (Buchele et al., 2006; Wang et al., 2022). Although these terms are related but have different meanings. This paper mostly focused on flood susceptibility zonation mapping and how it is tied to flood hazard and risk assessments.

2. Literature Review

This review includes the bibliography analysis that has been performed using RStudio. This treemap is a quantitative analysis and shows the data in rectangles, as shown in Figure 1. The rectangles' dimensions and plot colours are determined by calculating the quantitative variables linked to each rectangle. The size of the rectangles starts decreasing from the left to the right side, and each rectangle has a particular value in it, which expresses the work done by different authors in different fields with numerous technologies. A smaller size shows that less research has been done on the particular parameter and that the technology is used very little. Here results can be seen that most works are done on susceptibility, zonation, and climate change, which is around 35%, and the rest of the studies include river basin studies, flash floods, hazard evaluation, rainfall studies, social vulnerability, and special prediction have very little research.

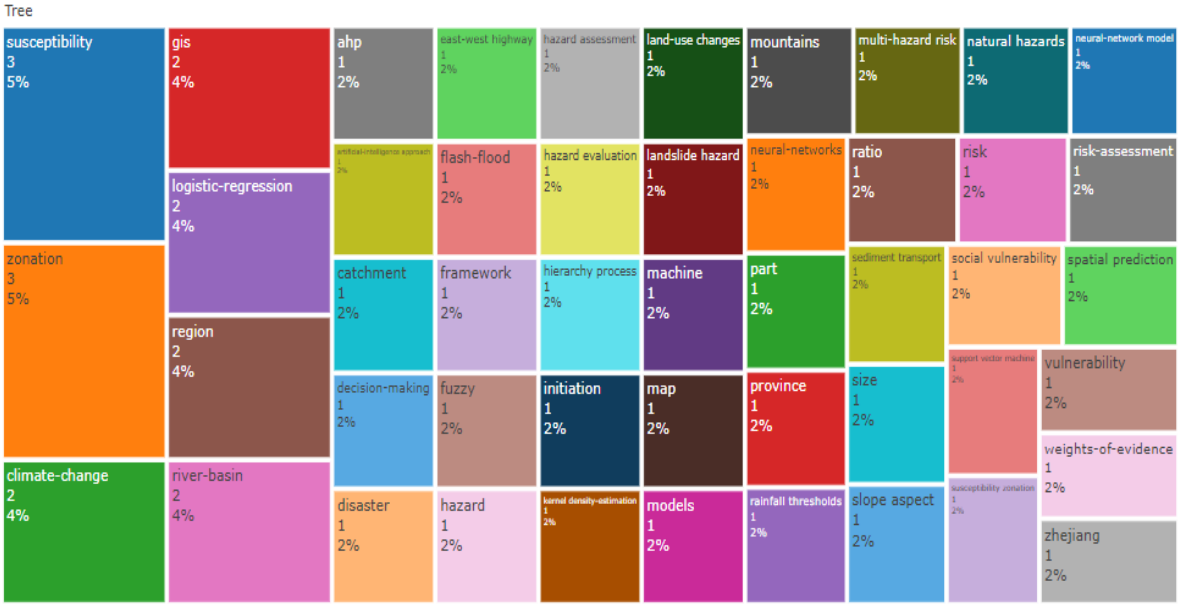


Figure 1: Flood susceptibility mapping technologies and methods used in earlier research work.

Most of the tools and technologies used for Susceptibility zonation mapping are ArcGIS, QGIS, and ERDAS. Logistic regression, the Analytical Hierarchy Process (AHP), artificial intelligence (AI), and multi-criteria decision-making (MCDM) are the approaches used for flood susceptibility zonation; other approaches, such as the fuzzy method, machine learning, mathematical models, artificial neural network (ANN), and frequency ratio (FR) approach, are used very infrequently. Landslide susceptibility, climate change, hazard assessment, river catch basin studies, social vulnerability, spatial prediction, and risk assessment are the main areas of research interest. There are extremely few authors who research flood susceptibility zonation mapping. Reviewing all currently available techniques for mapping flood susceptibility zonation and examining benefits and drawbacks is the goal of this study.

To ensure a systematic and comprehensive review, scientific literature was retrieved from the Web of Science and Scopus databases using a combination of keywords such as “flood susceptibility mapping”, “flood hazard”, “GIS”, “Remote sensing”, “machine learning”, “AHP”, “MCDM”, “logistic regression”, and “frequency ratio”. The retrieved records underwent filtering for duplicate removal, title and abstract screening, and relevance assessment. This study used only peer-reviewed articles, review papers, and conference paper here. This includes research papers from the last two decades. The selection of the time period was based on the basis of major advances in tech, like better geospatial tools, super high-resolution satellite images, GIS, cloud computing, and machine learning. These have made

flood susceptibility and risk assessments way more accurate. However, seminal studies published prior to this period were also considered where necessary to provide historical context and demonstrate the evolution of flood susceptibility mapping approaches. Bibliometric analysis was subsequently performed using the R software platform to identify major research trends, commonly used methodologies, and emerging directions in flood susceptibility zonation mapping research.

Recent advances in flood susceptibility mapping have increasingly focused on the integration of artificial intelligence, deep learning, cloud-based geospatial platforms, and multi-source remote sensing datasets. Recent studies have demonstrated that machine learning algorithms such as random forest (RF), Extreme Gradient Boosting (XGBoost), support vector machine (SVM), and Deep neural networks (DNN's)outperform several traditional statistical approaches in predicting flood-prone areas due to their ability to model complex nonlinear relationships among flood conditioning factors (Bentivoglio et al., 2022; Wang et al., 2022; Kumar et al., 2023; Rahman et al., 2023). Furthermore, the growing availability of Sentinel-1 Synthetic Aperture Radar (SAR), Sentinel-2 optical imagery, and high-resolution digital elevation models (DEM) has significantly enhanced the accuracy and reliability of flood susceptibility assessments (Bentivoglio et al., 2022; Xue et al., 2024). Recent research has also emphasised the use of explainable artificial intelligence (XAI) techniques and hybrid machine learning frameworks to improve model transparency, interpretability, and predictive performance, thereby supporting the decision-making process for disaster management authorities (Wang et al., 2022; Rahman et al., 2023; Saikh & Mondal, 2023). Additionally, hybrid frameworks combining GIS, remote sensing, multi-criteria decision making (MCDM), statistical approaches, and machine learning have emerged as promising solutions for achieving higher predictive accuracy and robustness in flood susceptibility mapping (Kumar et al., 2023; Saikh & Mondal, 2023; Merghadi et al.,2020). This development indicates a clear transition from conventional expert-based and statistical methods towards a data-driven and intelligent flood susceptibility assessment framework capable of supporting real-time flood risk management, climate adaptation strategies, and resilient infrastructure planning (Bentivoglio et al., 2022; Wang et al., 2022).

3. Methodology

A thorough investigation and desk study have been performed to identify various disaster phenomena, among which flooding is the one causing devastation worldwide, affecting life and property.

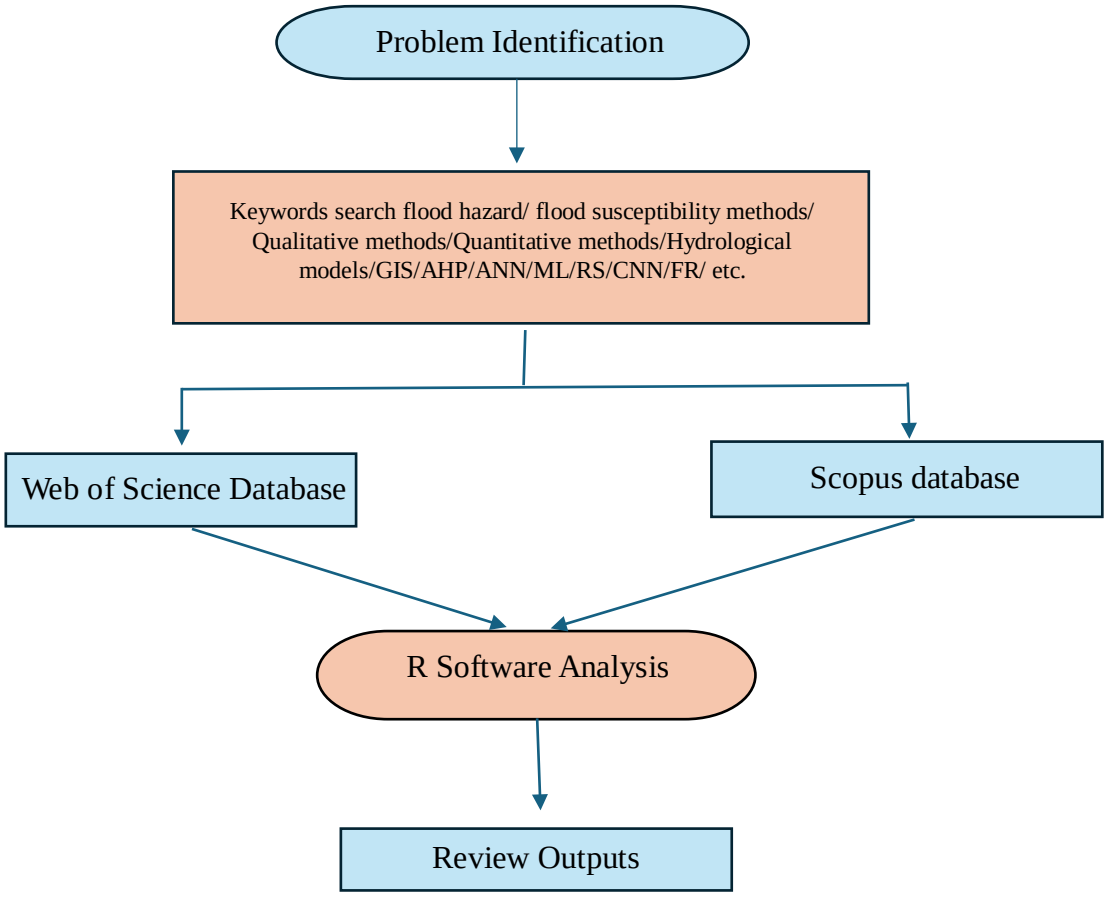


Figure 2: Workflow adopted for the systematic review of flood susceptibility mapping studies.

Identifying the red zone area in a given area and conducting a flood susceptibility mapping assessment are two of the primary mitigation strategies to prevent the destruction caused by flooding. To research flood susceptibility zonation mapping (FSZM), hydrological data, elevations, contours, ground slopes, and other characteristics of catchments are needed. The present study depicts an overview of flood FSZM considering publications available on the Web of Science and Scopus as shown in Figure 2. Bibliographic analysis has been carried out using the R software platform.

4. Flood Models and Data Requirements for Mapping

The following are some of the aspects associated with flood hazard analysis, and they include flood susceptibility mapping (FSM), flood hazard mapping (FHM), flood vulnerability mapping (FVM), and flood risk mapping (FRM). Flood susceptibility mapping involves mapping locations that are prone to flooding due to factors such as topography, geology, rainfall amount, and drainage density, among others. The above process plays an integral role in ensuring sustainable urban planning, disaster preparedness, and prevention. Flood hazard

mapping encompasses more than just the identification of vulnerability in terms of taking into account the likelihood, intensity, depth, velocity, and extent of floods under certain conditions. While flood vulnerability mapping is concerned with measuring the sensitivity of those at risk from flood effects, the flood risk map incorporates hazard, exposure, and vulnerability data to provide an estimation of flood consequences (Wang et al., 2022). Any good flood risk assessment framework will consist of two fundamental elements, namely: (i) hazard assessment, involving modeling using hydrological and hydrodynamic models to produce flood maps, and (ii) vulnerability and exposure assessment (Wang et al., 2022). Due to the fact that susceptibility assessment is the basis of flood hazard and risk assessment, several scientists have adopted FSM techniques based on geographic information systems and remote sensing software like ArcGIS, ArcGIS Pro, and QGIS. Some of the FSM methods used include statistical techniques, artificial neural network (ANN), machine learning (ML), logistic regression (LR), frequency ratio (FR), fuzzy logic, analytical hierarchy process (AHP), multi-criteria decision making (MCDM), and other artificial intelligence-based techniques (Kumar et al., 2023).

4.1 Hydrological Models

The two key elements for evaluating flood susceptibility assessment and mapping are hydrological and hydraulic modeling. Hydrological models continue to be indispensable in determining the susceptibility of floods as they can predict rainfall-runoff and water flow dynamics based on various hydrometeorological scenarios (Kumar et al., 2023; Pradhan & Youssef, 2011; Tam, 2019).

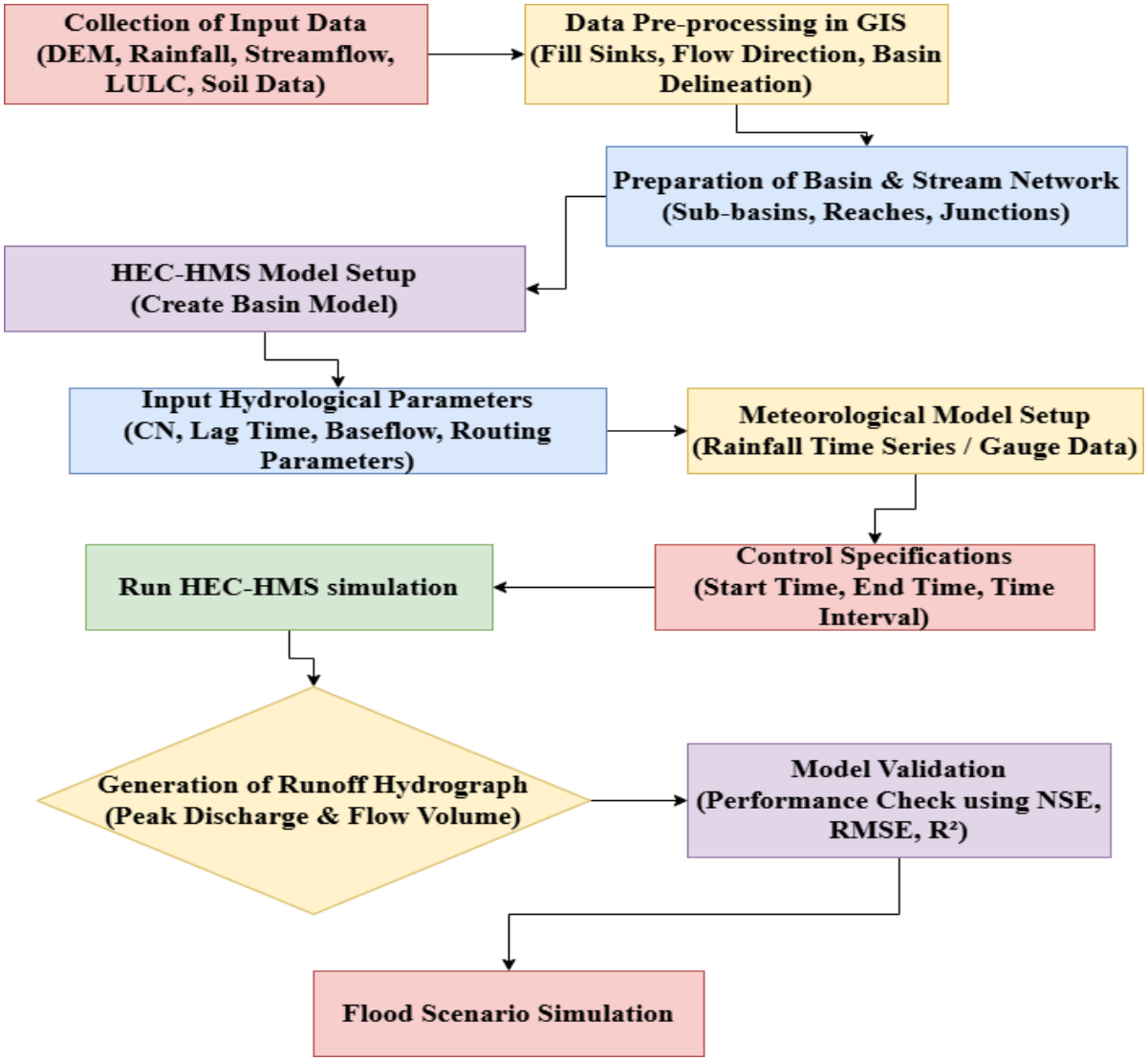


Figure 3: Flood Modeling Workflow for Hydrological Models

According to the literature examined here, hydrological models are highly predictive and based on physically realistic assumptions when there is availability of reliable and accurate information regarding topography, hydrology, and meteorology (Kumar et al., 2023; Pradhan & Youssef, 2011). Their limitations may be attributed to complex data requirements, calibration, and computation involved in their application (Wang et al., 2022; Kumar et al., 2023). Hence, hydrological modeling is best suited for smaller scales, while geographic information systems (GIS)-based statistical and machine learning methods work well at larger scales (Kumar et al., 2023). The general hydrological model methodology flow chart is shown in Figure 3.

4.2 Geospatial Tools and Techniques

Information that can be mapped or expressed about point locations on the Earth is called geospatial data. These qualities are linked to specific locations and are typically acquired using satellite images, GPS, aerial photography, or other mapping methods. Thomas L. Saaty invented the multi-criteria analytical hierarchy process (AHP). This approach weighs the importance of each criterion and compares the outcomes pairwise to establish priorities in difficult decision-making circumstances (Tam, 2019). It is structured and mathematical. In a spatial setting, more advanced decision-making is possible when geospatial data and the AHP methodology are combined. Setting up the Hierarchy, Pairwise Comparisons, Spatial Analysis, and decision-making are the steps in integrating AHP with geographical data. Urban planning, environmental management, site selection, natural resource management, transportation planning, mapping flood susceptibility, and other domains are among the many areas where AHP with geospatial data is applied. Remote sensing allows for geographical observations of the Earth's surface (Rahman et al., 2021). In remote sensing, different sensors are used to record different types of data (Jensen, 2007). The Earth is monitored twice a day for about twenty days at a time. As a result, coverage of the region flooded by floods can be obtained for flood inundation mapping and monitoring before, during, and after the flood occurrence (Schumann et al., 2009). Floodplain zoning, planning for flood control, flood management, and other applications can all benefit from the information produced through mapping (Zephania et al., 2016). Demarcating the flooded territory using conventional methods is difficult, costly, and time-consuming. Because of the difficulty in accessing the inundated area and the length of time required for a typical survey, it might not be possible to map the entire impacted area. Currently, remote sensing and GIS technologies address this problem. A geographic information system (GIS) uses computers to map and assess events on Earth. This tech blends traditional map functions with database tasks like Queries and statistical analysis. GIS makes managing location data easier and provides tools for deep analysis and presentation, covering things like population traits, economic growth potential, and plant diversity. It joins databases with maps for interactive visuals and lets users explore these connections in ways spreadsheets can’t. Plus, GIS allows for advanced visualization, questioning, and layering of data. These features make GIS stand out and super helpful for planning, predicting, and explaining things to both business and public groups. One study demonstrates that GIS and remote sensing can reduce flood impact a lot, even if it can’t eliminate the risk entirely. This specific research looks at past flood areas and how different land types in India’s Prayagraj have been hit. They do this by merging the geographic

information system with the analytical hierarchy process, a way to make decisions based on multiple criteria. Several elements lead to flooding, such as drainage density, elevation, flow accumulation, land use/land cover, surface roughness, slope, and topography wetness index (Kumar et al.,2020). AHP technique was used for overlay and to identify flood-susceptible places, and validation was performed using the ROC and AUC curves. According to the flood risk map, the study region's 1273.0 km^2 (23.22.8%) and 701.71 km^2 (12.80%) are at high risk and moderate risk, respectively. Many researchers have used this technique for research purposes in different fields like water management, urban Planning, and flood susceptibility zonation mapping assessment. Broadly, these approaches are divided into qualitative and quantitative approaches. The main motive of these methods is to evaluate the main reasons for flood havoc and to provide suitable measures to control them.

4.2.1 Qualitative Approaches For FSZM

Qualitative methods such as Analytical Hierarchy Process (AHP) and MCDM have continued to enjoy popularity in the application of susceptibility mapping due to the ease with which expert knowledge and various factors responsible for floods can be combined using such methods (Kumar et al., 2023; Malczewski, 2006; Yalcin & Akyurek, 2004; Das, 2020; Lin et al., 2019). As observed from the discussed literature, qualitative methods are easy to apply, do not require extensive data, and work well under conditions of data scarcity (Kumar et al., 2020; Das, 2020; Fatah et al., 2022). However, being dependent on experts' judgement, there is always the possibility of subjective factors weighing in addition to susceptibility assessment (Malczewski, 2006). While such methods are useful for conducting initial assessment and are applicable at the local scale, current literature indicates that prediction power can be further enhanced through the incorporation of statistical and machine learning approaches into hybrid models (Kumar et al., 2023).

4.2.1.1 Analytical Hierarchy Process (AHP) Method

Das (2020) investigated flood susceptibility mapping in the Western Ghat Coastal belt using the analytical hierarchy process (AHP) and multi-source geospatial data (Das, 2020). This study creates maps of flood risk, sensitivity, and susceptibility throughout India's Western Ghat coastal region using a wide range of multi-sourced environmental flood conditioning factors, including elevation, slope, distance from drainage, drainage density, flow accumulation, rainfall, land use, soil texture, geology, geographical roughness index, and

socioeconomic factors like population density and literacy rate. The entire steps of the analytical hierarchy process are shown in Figure 4.

Using AHP methodologies, eleven criteria are taken into consideration, along with four socio-economic aspects. The results indicate that 28% of the entire land falls into high susceptibility zones, and 22% into very high susceptibility zones. To prevent the disruptions that flood threats may cause, quick mitigation measures are required (Das, 2020). In the Akre District, Kurdistan Region, Iraq, AHP techniques were used for mapping flood susceptibility zonation (Fatah et al., 2022). Altitude, slope, distance to streams, flow accumulation, drainage density, rainfall, soil type, lithology, curvature, topographic wetness index (TWI), topographic roughness index, stream power index, stream transport index, land use/cover, and normalized difference vegetation index were the fifteen ideal causative factors for flooding that were used to assess flood susceptibility.

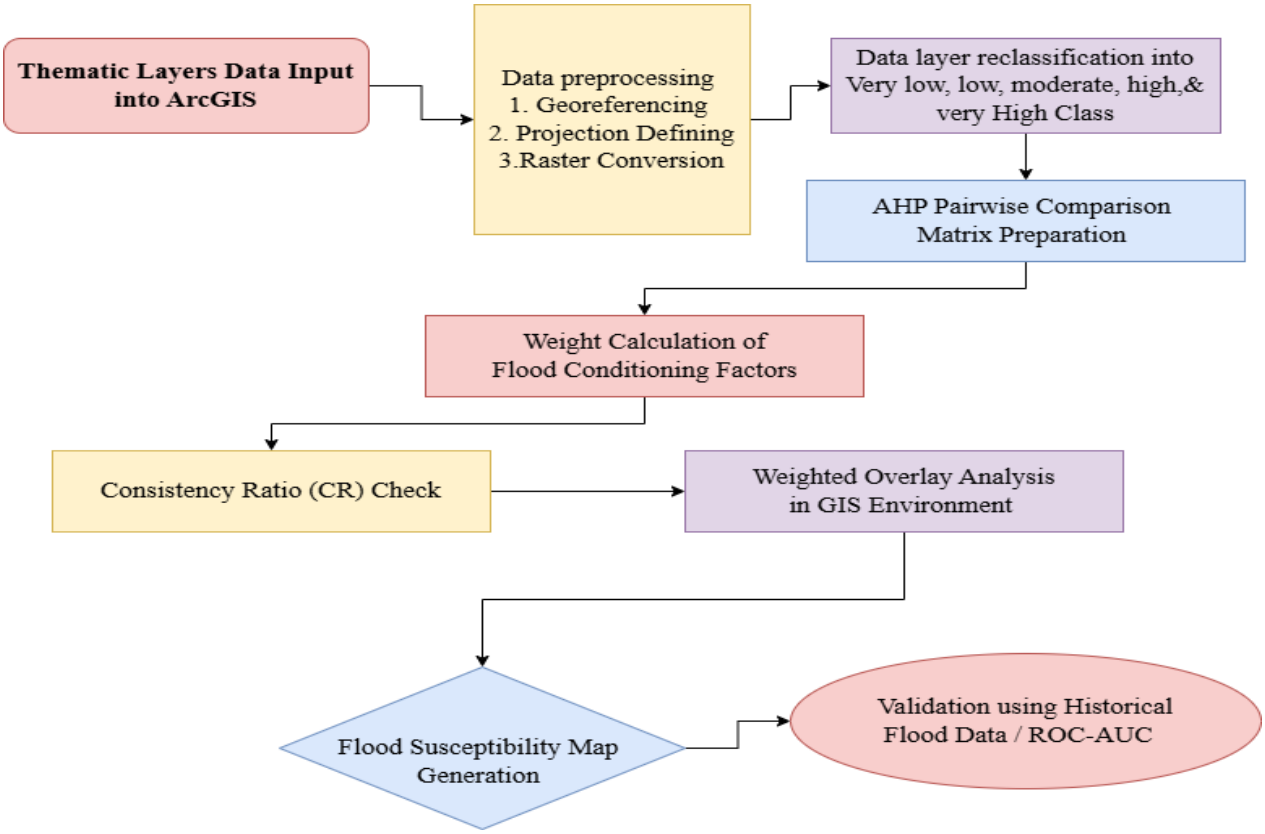


Figure 4: Analytical Hierarchy Process (AHP) framework for flood susceptibility mapping.

The appropriate weighting of the elements that contribute to flooding was ascertained using the proposed model. A flood susceptibility zonation map showed the following risk levels: very low (16.64% of the study region), low (19.53%), moderate (38.92%), high (17.83%), and

very high (7.08%). The predicted accuracy of the model is between 95% and 97%. This indicates how much more accurate the AHP method is. This illustrates how the AHP method is more reliable and successful in forecasting floods and creating maps of flood zones.

4.2.1.2 Multi-criteria Decision Analysis (MCDA) Method

In a study by Kumar et al. (2020a/2020b), multi-criteria decision-making was used to construct the flood risk map. AHP has been a tool used in MCDM. Considerations such as elevation, ground slope, flow accumulation, TWI, drainage density maps, roughness maps, and LULC maps have all been taken into consideration while performing flood susceptibility zonation mapping. These are the main considerations that are made. The AHP technique begins with a pairwise comparison for every conceivable criterion. Each parameter is assigned a weight based on how it has been reclassified. After each data collection, layering is performed through GIS, which simulates the results and gives the mapping results in the form of maps. The consistency ratio is calculated by dividing the consistency index by the random index, as stated in equation (1), after the comparison and normalized matrix have been prepared.

$$\mathrm{CR} = \frac{CI}{RI} \qquad \text{eq. (1)}$$

Here CR stands for consistency ratio, CI for consistency index, and RI for random consistency index. CI is calculated by equation (2).

$$\mathrm{CI} = (\gamma_{\max}\text{-n})/(\text{n-1}) \qquad \text{eq. (2)}$$

where λ is the average of the priority vector, and n is the number of factors. A flood risk map is generated with the help of Weighted overlay analysis. FHI (Flood Hazard Index) is generated through eq. (3)

$$\text{FHI} = \sum_{i=1}^{n} \text{Pi} * \text{Wi} \qquad \text{eq. (3)}$$

Note: Here Wi is the weight of each parameter, Pi is the rating of an individual parameter, and n is the number of criteria.

A graph for the receiver operating characteristic (ROC) and area under the curve (AUC) is created to do the quantitative validation of the flood risk map. While the receiver operating characteristic (ROC) curve is a probability curve, the area under the curve (AUC) indicates the separability of many classes. According to Malczewski (2006) and Malczewski et al.

(1999), the ROC curve's ordinate (y-axis) reflects the true positive rate (TPR) or sensitivity, while the abscissa (x-axis) represents the false positive rate (FPR) or 1-specificity. If AUC values approach unity, the results will have a high degree of accuracy.

TPR or Sensitivity = {True Positive/ (True Positive + False Negative)}

Specificity = {True Negative/ (True Negative + False Positive)}

FPR = 1 – Specificity

The performance of qualitative techniques like AHP and MCDM highly depends on geographical and environmental settings of the study area. Qualitative analysis works best in locations where past flood events have not been recorded adequately, but where expert opinion and thematic spatial data exist (Kumar et al., 2020; Malczewski, 2006; Das, 2020; Fatah et al., 2022). It proves to be quite efficient in smaller to moderate-sized catchments, where flood vulnerability is controlled by a number of easily recognizable parameters (Kumar et al., 2023). But in the case of very dynamic systems that have undergone fast urbanization or changed their land use patterns or complex hydrological interactions, the predictive power of such techniques might be reduced since they depend significantly on the weightages provided subjectively and assumptions made about the factors influencing them (Lee, 2005; Mosavi et al., 2018). For this reason, qualitative analysis is generally better suited for initial analyses, while data-based approaches perform well in complex flood-prone areas (Kumar et al., 2023).

4.2.2 Quantitative Methods for FSM

Quantitative techniques that have been reviewed above possess distinct merits and weaknesses, depending on availability of information, computational needs, and research goals. Statistical techniques like Logistic Regression (LR) and Frequency Ratio (FR) offer straightforward, computationally inexpensive, and understandable outcomes, thus applicable for susceptibility mapping at a regional level (Ghosh et al., 2022; Merz et al., 2007; Pradhan et al., 2010; Juaidi, 2018; Bui et al., 2018; Lee et al., 2007). On the other hand, statistical techniques have some drawbacks in terms of their inability to represent nonlinear associations between factors affecting floods (Merz et al., 2007; Lee et al., 2007). ML and CNN models usually offer better accuracy due to their capacity to capture complex spatial relations within large geospatial data, yet they need considerable amounts of data and computing power for

training (Bentivoglio et al., 2022; Mosavi et al., 2018; Krizhevsky et al., 2017; LeCun et al., 2015; Wang et al., 2019; Tehrany et al., 2014). Conversely, Fuzzy logic-based models provide solutions for dealing with uncertainties and ambiguities related to environmental parameters; however, they can be affected by bias in selecting membership functions and decision rules (Pradhan, 2010; Nampak et al., 2014; Nefeslioglu et al., 2013). In summary, it is clear from literature reviews that there is a shift towards adopting more hybrid/ensemble modeling approaches incorporating GIS, RS, statistics, and machine learning for flood susceptibility analysis (Kumar et al., 2023; Rahman et al., 2023; Xue et al., 2024; Saikh & Mondal, 2023). The standard workflow for quantitative methods is shown in Figure 5.

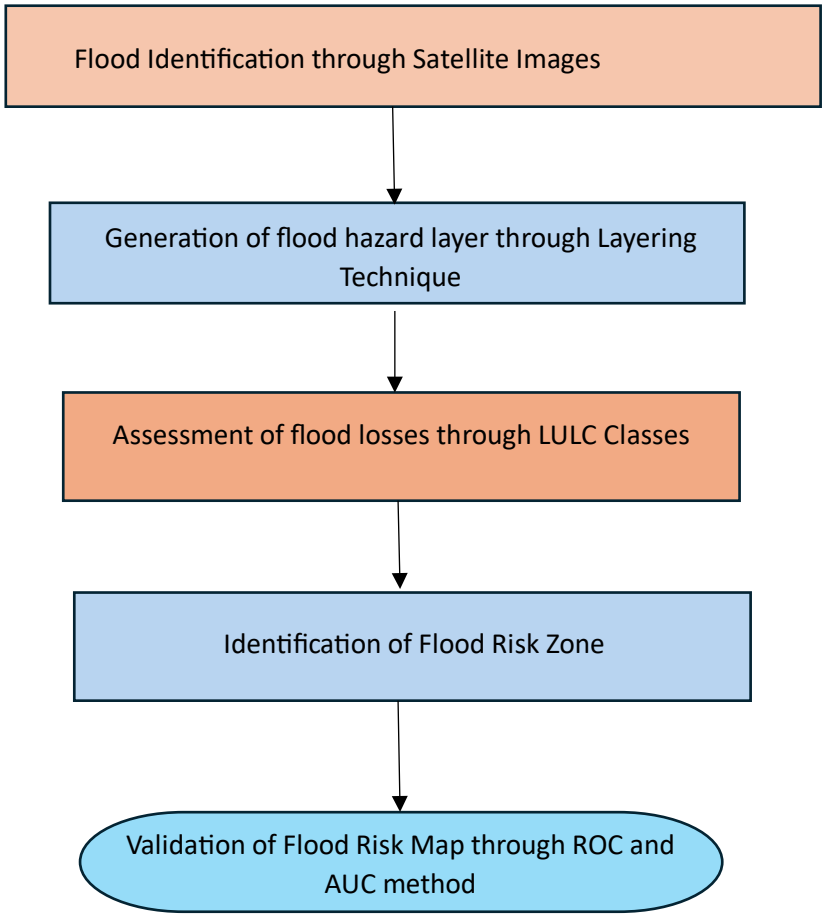


Figure 5: Quantitative methodology framework for flood susceptibility mapping and validation.

4.2.2.1 Conventional Neural Network (CNN)

One type of artificial neural network that is specifically intended to assess structured grid data, like photos, is called a convolutional neural network (CNN). It performs very well in image recognition and classification (Krizhevsky et al., 2017). They have got convolutional, pooling,

and fully connected layers that each play key roles. Convolutional layers start by creating feature maps that spot local image features using a bunch of learnable filters. Then, pooling layers come in, trimming down the size of these maps to save on computation and avoid overfitting. After this, fully connected layers step in to merge everything and make the final map. These stages help CNNs learn complex patterns, making them well-suited for tasks like object detection, image segmentation, and face recognition. CNNs have transformed the field of computer vision and are now the foundation of many modern AI applications, propelling progress in areas such as autonomous driving, medical image analysis, and robotics (LeCun et al., 2015).

A study used convolutional neural network frameworks to map flood susceptibility (Wang et al., 2019). In this study, in Shangyou County, China's flood susceptibility, the CNN framework is presented. Different convolutional procedures can be applied by CNNs to extract different types of information from different data modalities. The following summarizes the three primary contributions of this study: First, the use of CNNs in FSM is still extremely uncommon. In this work, the authors have investigated CNNs' viability in FSM. Second, two CNN models are introduced for FSM. In particular, the CNN model is employed directly as a classifier to determine flood susceptibility for the first framework. In contrast, the second framework uses a hybrid integration of CNN and the support vector machine (SVM) classifier; the CNN model is utilized to extract relevant and potent representations of flood-triggering elements, and the SVM classifier is used for classification using the features that are extracted. Third, to accommodate feature extraction and classification during the FSM process, three different data presentation techniques are built into the CNN architecture. To validate and compare the prediction ability of the suggested CNN-based methods to SVM was evaluated using several objective measures were used, such as receiver operating characteristic (ROC), area under the ROC curve (AUC), kappa coefficient (k), and overall accuracy (OA) (Wang et al., 2019). Altitude, aspect, curvature, slope, stream power index (SPI), sediment transport index (STI), topographic wetness index (TWI), lithology, land use, normalized difference vegetation index (NDVI), soil, distance to rivers, and rainfall are among the thirteen trigger factors that have been chosen for this study. Numerous factors—discussed below—are based on formulas. In this case, SPI stands for Stream Power Index, a novel factor that is determined using the subsequent equation (4) (Pamučar et al., 2017).

$$SPI = A_S * \operatorname{Tan} \beta \qquad \text{eq. (4)}$$

(Note: whereas is the area of the basin and β is the slope gradient in degrees)

Another parameter, the sediment transport index (STI), is considered for the formation of FSM, which is calculated based on eq. (5) (Moore et al., 1991).

$$STI= (A_S/22.13)^{0.6} *(\text{Sin } \beta/0.0896)^{1.3} \quad \text{eq. (5)}$$

Topography Wetness Index (TWI) is calculated by the following eq. (6) (Chapi et al., 2017).

$$TWI= \ln(\frac{\alpha}{tan\beta}) \quad \text{eq. (6)s}$$

(Note: Here α and β represent the upslope area per unit contour length and the slope angle, respectively).

Normalized difference vegetation index (NDVI), is calculated by following eq. (7) (Liang et al., 2017).

$$NDVI= (R_{NIR}-R_R)/ (R_{NIR}+R_R) \quad \text{eq. (7)}$$

(Note: where RNIR and RR represent the spectral reflectance acquired in the near-infrared region and the red region, respectively).

The following summarizes the primary conclusions of this study that the suggested 1D-CNN, 2D-CNN, and 3D-CNN classifiers outperformed SVM in terms of AUC prediction performance, demonstrating the superiority of CNN frameworks. Secondly, SVM's prediction power was significantly increased by employing CNN for feature extraction. The 2D-CNN-SVM approach, in particular, produced the best results in terms of OA, α, and AUC. Thirdly, it is anticipated that the suggested CNN-based techniques will be applied to the assessment and management of flooding disasters. In the interim, more potent FSM methods may be inspired by CNN's application prospects.

4.2.2.2 Logistic Regression Method

The logistic regression method's interpretability and capacity to handle binary dependent variables make it a prominent statistical tool in flood susceptibility mapping. In this instance, a range of contributing elements, including geography, hydrology, land use, and soil qualities, are taken into account when modeling the chance of flood occurrence using logistic regression (Merz et al., 2007). By combining historical flood data with several environmental variables, logistic regression forecasts future floods (Pradhan et al., 2010).

Flood susceptibility modeling was done using the logistic regression method. Using historical observations of a data set, logistic regression is a statistical analytic technique that predicts a

binary result, such as yes or no. By examining the correlation between one or more extant independent variables, a logistic regression model forecasts a dependent variable in the data (Hosmer et al., 2013; Menard, 2002). Here, the probability and correlation with other factors and their dependency are calculated by Eq. (8) and Eq. (9)

$$P=\{\frac{1}{1+e^{-Z}}\} \quad \text{Eq. (8)}$$

$$Z = \beta o + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots + \beta_n X_n \quad \text{Eq. (9)}$$

In this case, Z is the linear combination of the flood factors Xi (i = 1, 2,..., n), P is the probability of a flood occurring, βo is the model's intercept, and βi is the logistic regression model's parameters. The logistic regression parameters were utilized by the GIS to generate a map of flood susceptibility (Lee, 2005; Tehrany et al., 2014).

The resulting algorithm creates a map that categorizes locations into risk tiers by estimating flood susceptibility over a landscape. Urban planners, legislators, and emergency management organizations may identify high-risk locations, develop infrastructure, and successfully carry out mitigation measures with the help of this map. Quantifying complex interactions between many elements with the logistic regression method improves the comprehension and management of flood threats. Juaidi (2018) has done work on FSM by using Logistic Regression and the GIS method. This study explores the use of a logistic regression (LR) model to assess the flood risk map in areas of the southern Gaza Strip (Juaidi, 2018). This research was developed in five stages for Flood susceptibility mapping, as mentioned below-

- Creating basic flood inventory maps from a spatial database,
- Conducting statistical analysis,
- Conducting logistic regression data comparison,
- Creating the flood susceptibility map, and
- Validating the results by using the receiver operating characteristic (ROC) under the curve (AUC) method.

This study aims to define the mapping of flood susceptibility. The study uses statistical software to analyze the data, specifically ArcGIS 10.2 and EViews 10. The logistic regression analysis's main premise is the likelihood that a flood will return in the future or not. This study will produce a flood susceptibility (probability) map, which will be compared to maps of past floods. Initially, maps of rainfall, soil classification, land use and land cover (LULC), digital

elevation model (DEM), and other flood-causing elements were collected from the Palestinian Water Authority database (Hosmer et al., 2013; Tehrany et al., 2015). Using ArcGIS, the flow direction and terrain grade were determined. The flow accumulation map was made using spatial analysis tools, flow direction, and DEM maps. The flow direction and DEM maps were used to create the flow accumulation map using the tools for spatial analysis. After that, validation will be done using the AUC-ROC method. The validity and accuracy of the logistic regression parameters will be ascertained by employing an array of statistical approaches. Tests for multicollinearity, heteroscedasticity, and Pearson correlation are some of these methods. The correlation between the two was then determined using logistic regression. Similar GIS-based flood susceptibility studies have recently been conducted by Kader et al. (2024), Bokhari et al. (2024), and Singh et al. (2024).

4.2.2.3 Machine Learning Method

The integration and analysis of several datasets to accurately predict flood-prone areas has been made possible by machine learning (ML), which has completely changed the mapping of flood susceptibility. ML models can examine intricate, non-linear relationships between different flood-influencing agents, such as rainfall, soil classification, land uses land cover, elevation, and proximity to water bodies, by utilizing supervised learning algorithms like Random Forests, Support Vector Machines, and Artificial Neural Networks (Tehrany et al., 2014). The flood susceptibility index is calculated by Eq. (10).

$$\text{Yi} = f \sum_{i=1}^{n} \text{Wij} * \text{Xi} + bj \qquad \text{Eq. (10)}$$

Here, Yi is the output neuron which represents flood susceptibility, Xi is the input flood conditioning factor, Wij is the weight assigned to the factor, bj is the bias term, and f is the activation function. These algorithms handle big, high-dimensional datasets, since they are trained on historical floods events data and remote sensing pictures. GIS Techniques help us to visualise the findings and create maps that show the risk of flooding in different areas. These maps divide the world into risk categories. Urban planning, disaster relief, and early warning systems can benefit a lot from these maps. Researchers like Pham et al. (2018) have shown that these maps are really helpful. New machine learning techniques are being integrated with real-time monitoring systems. These advantages are helping us to predict floods and manage flood hazards better. We are getting better at predicting floods when we

face problems, like data quality and understanding the model. The use of GIS and machine learning is improving our ability to manage flood risks.

One of the case studies has been done on Iran's Greatest River, the Ajichay River. The Ajichay River empties into Lake Urmia in the northwest of the nation. The Ajichay River basin, which has been chosen for the case study, is situated east of the Lake Urmia basin and covers an area of 7567 km^2 (Sutradhar & Mondal, 2023). According to De Martonn's climate index, the area is categorized as semi-arid. East mountains to the plains in the west, the Ajichay River travels roughly 220 km before emptying into Lake Urmia. It passes through the Vanier valley and the Tabriz plain. Flood susceptibility maps were produced using a variety of techniques and ten distinct influencing elements. After ANN was chosen as the approach, they assessed all ten of the contributing elements' potential effects on the likelihood of flooding. They used MLP, SOM, and FART, the three types of supervised ANN, to classify networks in FSM. Using a flood inventory and publicly accessible records on normalization variables, flood impact factors, and destruction, the influencing dataset was collected and produced as part of the first step. Soft classification utilizing activation functions. In the last stage, the model outputs were classified into (very low, low, moderate, high, and very high) using the results of the hard and soft classifications. Outcome classes will be verified with past data events, and accuracy will be checked.

4.2.2.4 Fuzzy Method

Fuzzy logic is a go-to tool for mapping flood susceptibility because it deals with the uncertainty of natural disasters. It helps by considering multiple factors when finding areas prone to flooding. Studies show that using fuzzy logic in a geographic information system makes those flood susceptibility maps more accurate. It has good handling of continuous spatial data and various susceptibility levels. The excessive making of flood susceptibility map can be generated by setting up a fuzzy membership function as discussed in Eq. (11) for factors such as elevation, slope, aspect, soil type, land use/land cover, rainfall, and drainage density.

$$u(X) = \begin{cases} 0 & x \geq a \\ (x - a/b - a) & a < x < b \\ 1 & x \geq b \end{cases} \quad \text{Eq. (11)}$$

$u(X)$= membership value

a= lower threshold

b= upper threshold

These variables are integrated with fuzzy operators to formulate more efficient flood mitigation strategies and enhance resource management (Tehrany et al., 2010; Tehrany et al.,2013). Many case studies demonstrate how fuzzy logic works well for difficult environments and technical problems. A good example is the hazard watershed of Iran. There, the researcher used fuzzy logic to determine flood susceptibility and was surprised by its performance as compared to traditional method. They have also produced a detailed landslide susceptibility map in Malaysia, which was very helpful in reducing disaster risk. In Istanbul, Turkey, a study also successfully mixed various hydrological and environmental factors to perform a detailed risk assessment. Using fuzzy logic, they modeled the risk or ground water contamination and demonstrated the usefulness of this approach to handle complex data (Nampak et al.,2014).

The case highlights how fuzzy logic enhances risk management and decision-making in complex systems, showing its effectiveness in various settings. Though it excels at managing uncertainty in FSM, there are drawbacks, as pointed out by Nefeslioglu et al. (2013). One big problem is that creating fuzzy rules and membership functions is highly subjective. Because of this, bias and inconsistency can creep in based on the expert's knowledge. This can result into differ results if experts work with the same data. Fuzzy required lots of computing power, particularly with big datasets. Though it offers some awesome advantages, we must consider these physical challenges. Another drawback is that fuzzy logic results can be challenging to integrate and comprehend with typical deterministic models, which can make the process of assessing flood risk more complex overall.

4.2.2.5 Frequency Ratio Method

Since the Frequency Ratio (FR) method is a simple statistical method that effectively quantifies the relationship between flood occurrences and influencing factors, it has been widely used in flood susceptibility mapping. The framework for the FR method is shown in Figure 6. The FR technique determines the ratio for each conditioning element, including elevation, slope, land use, and soil type, between the likelihood of a flood occurring and the absence of one, as discussed in Eq. (12).

$$FR = \frac{\left(\frac{N_f}{N_t}\right)}{\left(\frac{A_f}{A_t}\right)} \quad \text{Eq. (12)}$$

Note: Here N_f represents the number of flooded pixels in a given class, N_t is the total number of flooded pixels in the study area, A_f denotes the number of pixels in that class, and A_t is the total number of pixels in the entire study area.

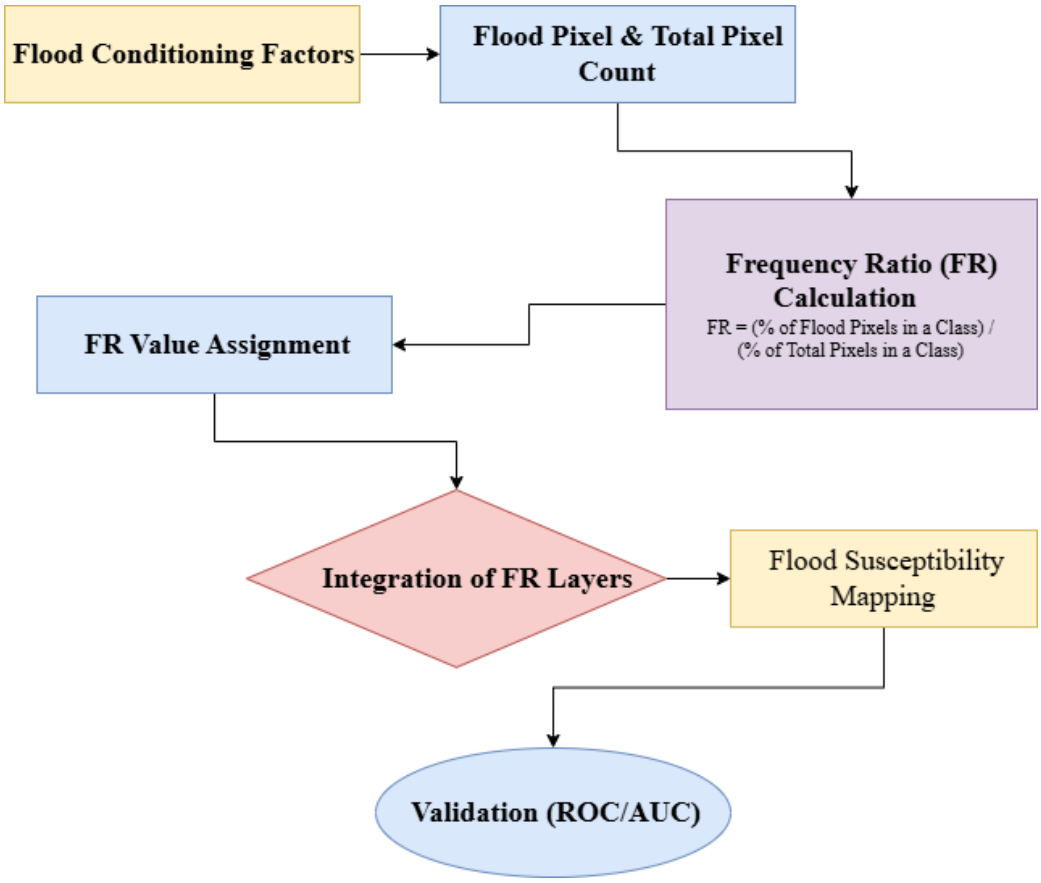


Figure 6: Frequency Ratio framework for flood susceptibility mapping and validation.

In the Malaysian Kelantan River Basin, researchers successfully pinpointed areas at risk of flooding using a specific approach, with a high rate of accuracy according to Tehrany et al. (2013). Another study in the Yom River Basin, Thailand, employed the FR approach and GIS combined with remote sensing to make detailed flood susceptibility maps. This map will help with disaster management and mitigation measures to avoid losses (Bui et al., 2018).

The frequency ratio method (FR) used in flood susceptibility mapping (FSM) works in many situations, but it has some serious problems. It relies heavily on historical flood data, which

can be unreliable. Sometimes data is outdated and incomplete, and fails to reflect recent climate changes and alterations in land use. Because of this, the results can get variations. Also, in complex natural systems, the interaction between different elements is not always straightforward; they can be non-linear and interconnected. The FR method's accuracy declines in dynamic environments too, as it struggles with the unpredictable changes in factors like LULC and rainfall patterns over time. The quality and resolution of input data really matter for the FR approach's performance too. Poor data leads to less reliable susceptibility maps. These drawbacks imply that, although the FR approach is a helpful tool, it should be used in conjunction with other methods and up-to-date datasets to enhance the precision and consistency of flood susceptibility assessments (Lee et al., 2007).

It is evident that the applicability and efficiency of quantitative methods used for flood susceptibility mapping depend on many factors associated with geography, environment, and hydrology of an area of interest. LR and FR models are effective in areas where there is a predictable relationship between flood occurrence and conditioning factors, and there is enough historical information about floods in the area (Merghadi et al., 2020; Costache et al., 2022). On the other hand, machine learning and deep learning approaches, including ANNs and CNNs, are superior in environments where topography, rainfall, land cover, and hydrological features interact nonlinearly (Mosavi et al., 2018; Nhu et al., 2020; Ahmadlou et al., 2024).

The above methods tend to perform better in cases of big river basins and highly urbanized areas where assumptions used in traditional statistics might not be able to represent the flood-generation process properly. Likewise, in situations characterized by uncertainty in environmental factors, the use of the fuzzy logic method performs well as it can easily capture any fuzziness in environmental data (Mosavi et al., 2018; Costache et al., 2022; Khosravi et al., 2024). Their success depends on the right choice of membership function and rules. The cited research work as a whole implies that hybrid approaches using GIS, Remote Sensing, statistics, and machine learning often provide better results, combining the advantages of all approaches under various environmental and hydrological circumstances (Tehrany et al., 2015; Costache et al., 2022; Ahmadlou et al., 2024; Khosravi et al., 2024).

5. Result Analysis

Flood susceptibility mapping is crucial for being ready for disasters and managing risks. Several methods exist for figuring out flood-prone zones. AHP taps into expert opinions to figure out what matters most in flooding, and it uses qualitative methods for predicting flood susceptibility in areas. On the other hand, CNNs rock at supporting patterns in huge datasets, like satellite images. They use deep learning to tackle complicated links, but they require huge data and computing power. The FR method chugs through numbers, comparing flood events to non-flood events against specific triggers. Simple as it is, it often struggles with non-linear relationships.

LR predicts flooding probabilities using several predictor variables, making the outcome very easy to grasp. But it assumes a linear relationship between variables. Meanwhile, MCDM methods like Fuzzy and AHP are really flexible and can integrate both quantitative and qualitative information. They do rely heavily on expert opinions, which might introduce bias while assigning weights to the criteria factors. The AHP accuracy is about 75-80%, while the Fuzzy methods score 75-90% since its uses statistical relationships between flood events and their cause. LR is a widely used probabilistic model that usually hits 78-92% accuracy, but that depends upon which variable is picked and what dataset is used. Lately, machine learning techniques have been making waves because they perform better. They score between 85-95% accuracy. Apart from this, CNN performed better by finding complex patterns and achieved accuracy around 90-97%.

In the end, while advanced machine learning methods usually win on prediction accuracy, hydrological models excel at depicting the actual physics of how floods happen and water runs off. Each method comes with its own set of pros and cons – it really depends on what data you have, how complex the area is, and the scale of your project. They list the strengths and limitations of each method in Table Number 1.

Table No. 1: Strengths, Limitations, and Applications of Methods for Flood Susceptibility Modelling

Parameter	**MCDM**	**LR**	**FR**	**CNN**	**AHP**
Type	Multicriteria	Statistical	Statistical	Machine Learning	Multicriteria
Strength	Flexible; handles quantitative & qualitative criteria; incorporates expert preferences; accuracy 75–85%	Simple and interpretable; handles continuous & categorical variables; probability outputs; accuracy 78–92%	Simple; uses historical flood data to quantify factor contribution; suitable for limited data; accuracy 78–92%	Handles large/high-dimensional datasets; learns complex non-linear relationships; no manual feature extraction; accuracy 85–97%	Simple, transparent and interpretable; incorporates expert knowledge; accuracy 70–85%
Limitation	Subjective weighting; time-consuming with many criteria; results depend on method selection	Assumes linear relationships; limited for non-linear relationships; multicollinearity issues	Limited handling of factor interactions and complex spatial relationships	Requires large training datasets; complex interpretation; overfitting risk	Subjective weighting; time-consuming with many criteria; limited handling of large datasets
Application	Decision-support and flood susceptibility mapping involving environmental & socio-economic criteria	Flood susceptibility mapping with moderate data availability	Flood mapping using historical flood data and relatively simple models	High-resolution flood mapping using remote sensing and historical flood data	Regional-scale flood mapping where expert knowledge and limited data are important

Conclusions

Flood susceptibility zonation mapping is crucial for reducing flood risks and creating wise planning for land uses. This review examines main flood methods, technical tools, and data used to assess flood susceptibility. It finds that there is no single best approach because what works depends on stuff like available data, study area characteristics, scale, computing capacity, and user skills and accuracy. So, each case calls for its own customised solutions. The review highlights that geographic information systems and remote sensing are the core technologies for today's flood susceptibility maps. These integrate various spatial datasets, including Slope, TWI, Aspect, precipitation, drainage density, soil properties, and other parameters, and are used for flood susceptibility mapping.

Qualitative methods like AHP and MCDM are used for finding the flood-prone areas. They are simple to use and integrate expert knowledge to get the outputs. Because of this, these methods work perfectly for small-scale projects. Sometimes, it introduces bias because it depends on experts and can create creep in weight assignment for conditioning factors. For a bigger task, quantitative methods like Logistic Regression (LR), Frequency Ratio (FR) will be used, as they have higher accuracy for larger-scale projects. These methods have good performance because of their clear outputs and fast processing for large datasets. Still, they might overlook intricate nonlinear links in flood-related studies. Compared to that, Machine Learning (ML) models such as ANN and CNN have good capacity for handling complex datasets and provide highly accurate results.

The finding indicates that, when it comes to Flood susceptibility mapping, CNN and advanced machine learning models typically achieve accuracy between 85-97%. Logistic regression and Frequency ratio have accuracies of 78-92% and 75-90%, respectively. AHP brings up the rear at 70-85%. Although ML and deep learning are top prediction model and Hydrological model Like HEC-HMS/RAS gives better understanding of flood processes through their physical representations, which we evaluate using NSE and R^2 metrics. These methods need serious computational resources, big training datasets, and expert knowledge for both implementation and validation. A comparative look shows that hybrid approaches combining GIS, remote sensing, statistical models, and machine learning usually do better than standalone techniques. They bring together the strengths of different methods and cut down on their individual weaknesses. With recent progress in cloud computing, big data, AI, and high-res satellite images, we can expect even more accurate and practically useful flood susceptibility

assessments. Future research needs to focus on creating more explainable hybrid models and integrating real-time hydrogeological data. Using multi-source remote sensing data and evaluating how climate change affects flood susceptibility are other key areas. Standardizing validation procedures and benchmarking can also make Flood Susceptibility studies more reliable and comparable between different places. When choosing flood susceptibility mapping techniques, researchers need to consider their goals, available data, spatial complexity, and required prediction accuracy. That way, we can better tailor our approaches for each specific situation. The insight presented in this study can support researchers, planners, and decision-makers in selecting suitable methodologies for effective flood risk assessment and management, thereby contributing to the development of more resilient and sustainable communities.

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Statements and Declarations

We hereby declare that the work presented in this paper, titled "Flood Susceptibility Zonation Mapping: A Critical Review of GIS, Remote Sensing, and Machine Learning Approaches," is our original creation and has not been submitted, wholly or partly, for any other degree or academic award. All sources of information used in this work have been duly acknowledged.

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