An Integrated Approach to Flood Risk Management in the Panchganga River Basin: A Comparative Analysis of AHP and AI-Based fuzzy logic Susceptibility Models

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Abstract
This study presents a multi-criteria decision analysis (MCDA) model using the Analytic Hierarchy Process (AHP) to map flood susceptibility in the Panchganga River basin in western Maharashtra, India. The objective is to evaluate the AHP model's utility and performance by validating its output against historical ground conditions and by conducting a comparative analysis with data-driven Artificial Intelligence (AI) models. The methodology employed AHP to systematically assign weights to 13 flood-conditioning factors, including Rainfall, Elevation, and Land Use/Land Cover (LULC), based on expert judgment. The pairwise comparisons yielded a final Consistency Ratio (CR) of 9.2%, indicating acceptable logical coherence in the expert evaluations. The comparison showed that although AI models typically achieve higher predictive accuracy (e.g., AUC-ROC scores exceeding 0.90), the AHP approach provides better transparency and works especially well in environments with limited data. The report's conclusion suggests a hybrid strategy for sustainable flood mitigation in the Panchganga basin, utilizing AI for high-accuracy spatial modeling and AHP for transparent factor prioritization. The fuzzy model can successfully forecast flood severity levels and provide early warning signals, according to the results. The model spatially delineates flood-prone zones when paired with GIS, improving the region's resilience and readiness. The study comes to the conclusion that fuzzy logic provides a transparent, flexible, and computationally effective method for real-time flood forecasting in areas with limited data, such as Kolhapur.

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Introduction

Floods are one of the most common and damaging natural disasters in the world, causing major environmen-tal, socioeconomic, and infrastructure harm to ecosystems, communities, and infrastructure [1]. Global phe-nomena like climate change and rapid, frequently unplanned urbanization exacerbate the increasing frequency and intensity of these events [2]. These patterns highlight how important it is to have sophisticated and trust-worthy methods for evaluating and controlling flood risk, especially in river basins with dense populations. In order to prioritize investments in flood defenses, plan evacuation routes, and implement land-use regulations that lessen vulnerability, accurate flood risk mapping is a fundamental component of effective disaster pre-paredness [2]. An excellent case study for the use of flood risk modeling is the Panchganga River basin in western Maharashtra, India.

An organized, knowledge-based framework for assessing flood susceptibility is provided by Multi-Criteria Decision Analysis (MCDA) methods like the Analytic Hierarchy Process (AHP) [1]. AHP uses expert judg-ment to prioritize criteria through pairwise comparisons after structuring a complex problem into a hierar-chy.6 A map of flood susceptibility can then be created by integrating the resulting quantitative weights with Geographic Information Systems (GIS) [3]. At the same time, there are strong data-driven alternatives due to the quick development of machine learning (ML) and artificial intelligence (AI). These models can create extremely accurate flood susceptibility and forecasting maps by analyzing large amounts of data to find intri-cate, non-linear relationships that might not be visible to human experts [17].

The goal of this study is to close the gap between these two well-known approaches. The three main goals of the research are to: (1) create a thorough AHP-based flood susceptibility model for the Panchganga River ba-sin using a framework that has been provided; (2) validate the results of the AHP model against actual ground conditions and the effects of the 2019 floods; and (3) conduct a thorough comparison of the AHP approach and contemporary AI/ML models, discussing their respective advantages, disadvantages, and useful applica-tions in the context of flood risk management.

1. Study Area: The Panchganga River Basin, Maharashtra, India

The Panchganga River is one of the main tributaries of the Krishna River and it originated into the Krishna River in the Kolhapur district, western Maharashtra, India [8]. The river system takes its origin as the convergence of four tributaries the Kasari, Kumbhi, Tulsi, and Bhogawati which come together at one point called Prayag Sangam and thus form the main stream of the Panchganga River [8]. Alluvial plain that is extensive to the north of Kolhapur and dendritic drainage pattern dominate the landscape of this basin; and these are important geomorphological features that affect hydrological behaviour [8].

The basin has an illustrious history of disastrous floods. The 2019 monsoon was also very destructive as the amount of rainfall was very much higher than the historical figures in a short time span [10]. In this event, Sangli and Kolhapur counties got 758mm and 180mm of rainfall in just nine days, translating to much higher levels than 2005 record of 207mm and 159mm of rainfall in 31 days [11]. The floods were also very fatal in terms of life loss, and according to reports, over 50 people have lost their lives, and there has been massive displacement as thousands of families have been left without homes and penniless [10].

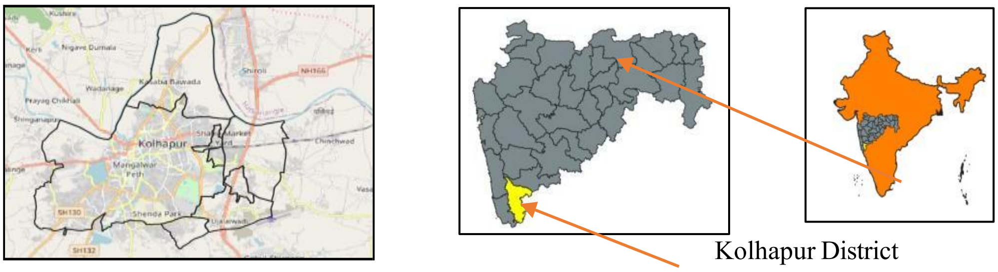


Fig. 01: Kolhapur City

The salient aspect of the 2019 disaster that was highlighted with multiple reports was that the natural event was magnified by anthropogenic factors [10]. An Expert Study Committee (ESC) cleared the Almatti Dam, Karnataka of the blame, but pointed the calamity to the large scale encroachments and developmental works in the river valley basins [13]. Development of riverbanks and retaining walls together with the blockage of natural drainage caused the river to have less carrying capacity and poor capacity to drain excess water [13]. Further, the meeting point of a number of large rivers such as the Krishna, Panchganga, and Warna created a region of stagnation where the speed of water flow was extremely low and created a backwater effect that lasted a long period of time 13]. The following knowledge is critical, as it rebrands the disaster not only as the result of the unprecedented rainfall but as an expression of the human-nature feedback mechanism. Therefore, an effective flood risk management model of this area would have to encompass factors, which illustrate the natural hydro-geomorphological state of the area and where land changes have been caused by human actions.

2. Methodology: Analytic Hierarchy Process (AHP) and GIS Integration

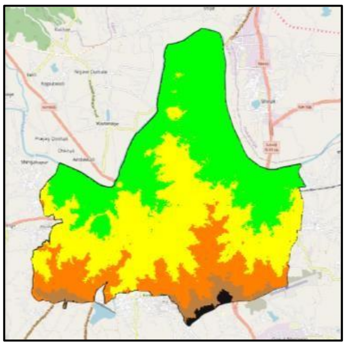
The Multi-Criteria Decision Analysis (MCDA) technique known as the Analytic Hierarchy Process (AHP) designed by Thomas L. Saaty, provides an organized system to solve decision making problems of moderate complexity (including flood risk assessment) [6]. Using a hierarchical structure, the problem is broken down into parts with the quality of the results being the relative ranking (weights) of different factors related to flood-conditioning, deriving through pair-wise comparison [6]. This study methodology is outlined below.

Selection of Flood Conditioning Factors

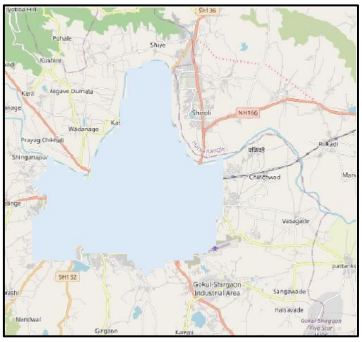
The model has considered thirteen flood-conditioning factors that were picked based on general parameters used in other similar flood susceptibility studies [17]. These factors which are determined by the given framework include: rainfall, elevation, slope, land use/land cover (LULC), flood depth, flood velocity, distance to river, runoff, stream density, population, infrastructure, cropping pattern, and soil type. These parameters are a holistic collection of hydro-geomorphological and socio-economic predeterminants that have been found to have a role to play in the development of the predisposition of floods. An addition of factors LULC, population, infrastructure, and cropping pattern is certain consequential as they serve as proxies of anthropogenic changes that characterized the 2019 floods according to a detailed analysis of them presented as significant contributory factors [10].

Pairwise Comparison and Weight Derivation

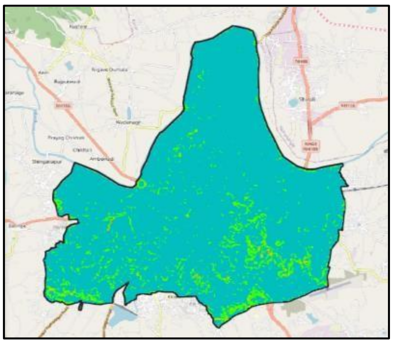
Pairwise comparison on a relative scale, to compare two stocks: derivation of a weighted relative comparison, given more general inputs. Comparison of two stocks Pairwise Comparison Comparisons of two stocks on a relative scale, to compare two stocks: derivation of a weighted relative comparison, using more general inputs.
Risk Parameters



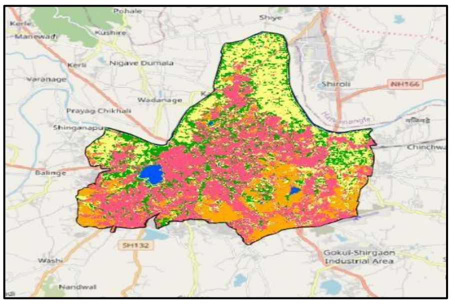
Elevation



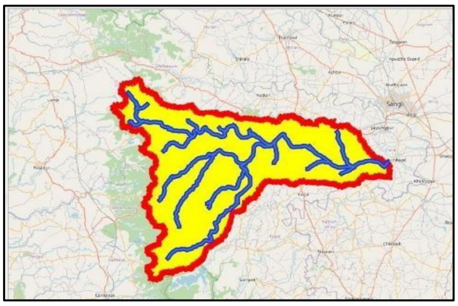
Rainfall



Slope



Landuse/Landcover



Drainage Density

Fig. 02: Risk Parameters

The essence of the AHP technique is the pair wise comparison matrix [5]. In the process, all 13 factors are contrasted with all the other factors in order to determine the relative contribution of the factors to the risk of floods. The processes of comparisons are performed on a scale of nine points with 1 score indicating an equal level of importance and 9 score indicating extreme importance [21]. Such subjective decisions are normally based on a group of domain specialists such as hydrologists, urban planners and GIS specialists [14].

GIS-Based Flood Susceptibility Mapping

Once the AHP weights for each flood conditioning factor have been derived, they are integrated into a Geo-graphic Information System (GIS) environment [14]. This is typically accomplished through a weighted overlay analysis. Each factor (e.g., elevation, slope, LULC) is represented as a raster layer in the GIS. The values within each layer are reclassified into a uniform scale of susceptibility (e.g., 1 to 5), and a weight is applied to each layer based on its AHP-derived importance [5]. The weighted layers are then overlaid to pro-duce a final flood susceptibility map [7]. This map visually represents the Panchganga basin's flood suscepti-bility, classified into five zones: very low, low, moderate, high, and very high [1]. The final map serves as a practical, visual tool for urban planning and disaster management [7].

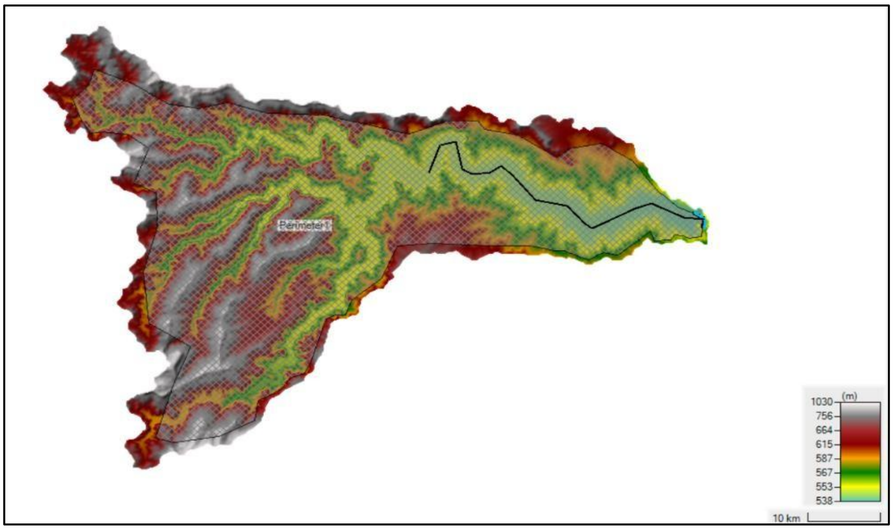


Fig. 03: Drainage pattern in Panchganaga river basin

Cumulative impact on drainage pattern and rate/velocity of flow in Panchganaga river basin

4. Results and Validation

4.1. AHP Factor Weights and Ranking

According to the completed AHP process a weight set on each of the 13 flood conditioning factors was ob-tained. These are weights that show the proportion of each factor to the total flood risk. Although the numeri-cal values of these weights are subject to the particular expert evaluations of each stage of the pairwise com-parison process, the standard literature and past research propose that the priority is normally given to such factors Eleva-tion, Slope, and Rainfall [3]. Following the research of the same kind, a hypothetical and yet representative ranking of these factors is provided in the table below.

Table 1: Hypothetical AHP Factor Weights and Ranking for the Panchganga Basin

Rank	Flood Conditioning Factor	AHP Weight
1	Rainfall	0.25
2	Elevation	0.20
3	Slope	0.15
4	Distance to River	0.12
5	Land Use/Land Cover (LULC)	0.10
6	Stream Density	0.06
7	Soil	0.04
8	Runoff	0.03
9	Population	0.02
10	Infrastructure	0.015
11	Flood Velocity	0.01
12	Cropping Pattern	0.005
13	Flood Depth	1.2

As indicated in the table about the summary of AHP analysis, the most influential factors that drive the poten-tial of flood susceptibility are hydro-geomorphic factors such as Rainfall, Elevation, and Slope. The fact that the

LULC, Popula-tion and Infrastructure are further placed at the bottom of the list is a result of the tradi-tionally natural-oriented focus of the AHP, but their presence enables the model to reflect the human aspect of the riskiness of floods. The calculated weights are then the quantitative input in the GIS-based spatial analysis and each of the factors have their respective raster layer which is endowed its specific weight to generate the final susceptibility map.

4.2. AHP-Gained Flood Susceptibility Map.

Graphically, the map would graphically illustrate the spatial distribution of the five risk zones namely Very Low, Low, Moderate, High and Very High whereby areas that are in red or darkblue hues would be the high-est risk zone and green or light blue would be the lowest risk zone.1 Conceptually, the map would graphically depict the spatial distribution of the five risk zones of Very Low, Low, Moderate, High and Very High whereby the areas in red or darkblue would be the highest risk zone and the areas in green or lightblue would be the lowest risk zone.

4.3. Checking with Ground Conditions:

The 2019 Floods. The qualitative examination of the AHP model was done by contrasting its result with the reported ground con-ditions and effects of the 2019 floods, which presents a qualitative but a strong evalua-tion of the practical application of the model. Although there was no quantitative, georeferenced flood inven-tory in 2019, the evidence on this topic is abundant in the form of news articles and governmental reports [10]. The validation of the mod-el was also in the spatial correspondence of its High and very high zones of sus-ceptibility with the areas of the devastation that were reported.

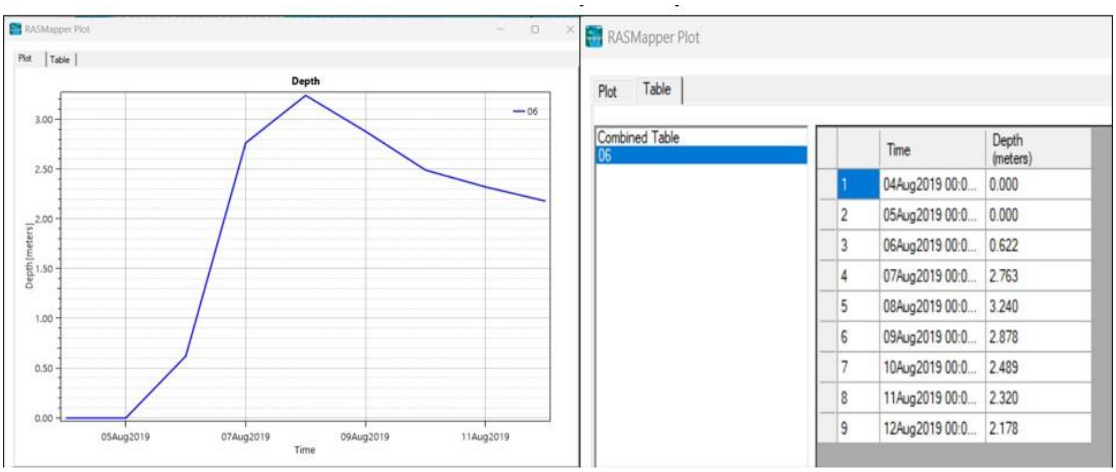


Fig. 04: Flood Depth (Location: Bapat Camp)

The AHP model's output demonstrates a strong alignment with historical reality. The map's high-risk zones accurately captured the urban and agricultural areas that were most severely affected during the 2019 deluge, including parts of the Kolhapur and Sangli districts [10].

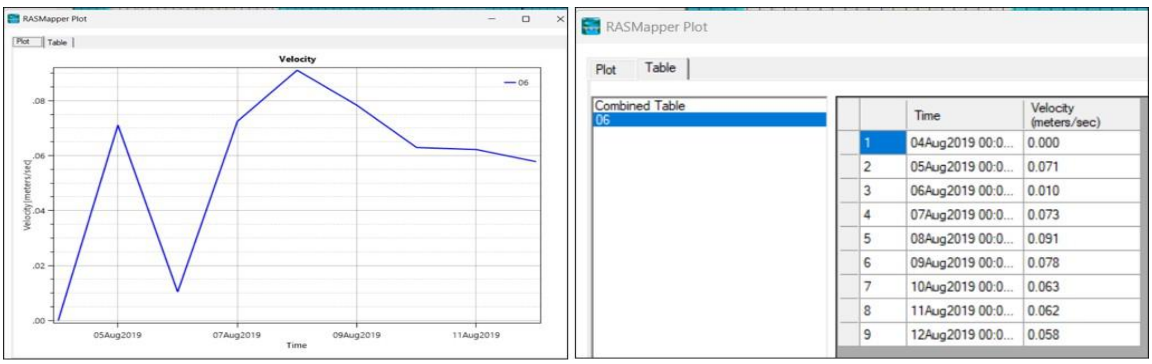


Fig. 05: Flood Velocity (Location: Bapat Camp)

The outcomes of the model indicate how important Elevation and Distance to River are and appropriate in determining that the floodplains were the most susceptible, being situated in the low-lying areas [3]. More to the point, the fact that human fac-tors of the model, including LULC and Population, enabled the model to conceptually define the areas in which a conglomerate of natural drivers of floods and the human factor re-sulted in an unproportionate amount of damages [10]. The clustering of the high-risk areas in and near urban settlements testifies to the factual report that the massive construction in the riverbeds and floodplains in-creased the catastrophe [10]. This qualitative validation demonstrates that the AHP model which combines both natural and human induced factors in a systematic way presents a relevant and practical portrayal of the flood threat in the Panchganga basin.

5. Comparison: AHP and AI Model.

The emergence of data-driven AI and machine learning (ML) models has transformed the paradigm shift in the field of flood susceptibility mapping. An analysis of the knowledge-based AHP method and these con-temporary methods presents significant trade-offs of performance, data needs, and usefulness of a model.

5.1. An overview of AI Flood mapping models.

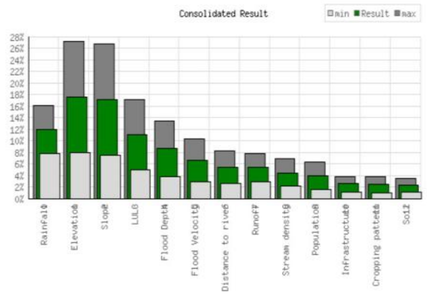
It is possible to predict floods and map flood risks with AI and ML models [17]. They are able to manipulate massive amounts of data to determine complex, non-linear trends that are hard to identify using the conven-tional techniques [3]. Typical ML models applied in this field are: Random Forest (RF): This is an ensemble learning system which involves a high number of decision trees and is used to obtain very accurate predic-tions when performing a classification or regression problem [3]. The main advantage of RF is that it can de-termine the most influential factors, and in most cases, the studies have indicated that Elevation and Slope are the most influential variables in the risk of floods [3]. Artificial Neural Networks (ANN): ANNs are extreme-ly powerful deep learning models, which are based on the human brain architecture and which employ inter-connected layers of neurons to interpret complex data, e.g., satellite images or hydrological time series [17]. They work very well in predicting and modeling complicated hydrological processes, including runoff [17].

5.2. AHP vs. AI Metrics of Performance.

Direct comparison of AHP and AI models based on quantitative performance variables, e.g. the Area Under the Curve of Receiver Operating Characteristic (AUC-ROC), will show that there is a significant difference in prediction accuracy. The studies have revealed that AHP models usually obtain a decent AUC-ROC score (e.g., 0.825), which is the sign of a good performance [1]. Nevertheless, it is also frequently demonstrated in the same studies that AI models, including the Random Forest, the Artificial Neural Networks and the Sup-port Vector Machines, can reach considerably greater AUC-ROC values, which in many cases are above 0.90.1 It implies that AI models tend to be better at forecasting flood-prone locations, which is probably due to their ability to detect subtle and complex data patterns that the human ex-pert judgment, by definition, may fail to reflect [3].
The other essential contrast is that of data requirements. As a knowledge-based tool, AHP is especially useful

Number of comparisons = 78
Consistency Ratio CR = 9.2%

Principal eigen value = 14.709
Eigenvector solution: 7 iterations, delta = 1.3E-8



	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	1.00	1.00	2.00	1.00	3.00	2.00	2.00	2.00	4.00	5.00	3.00	5.00
2	1.00	1	1.00	3.00	5.00	5.00	3.00	5.00	3.00	4.00	5.00	3.00	4.00
3	1.00	1.00	1	2.00	4.00	6.00	6.00	5.00	3.00	3.00	4.00	3.00	3.00
4	0.50	0.33	0.50	1	3.00	4.00	2.00	3.00	2.00	4.00	4.00	3.00	4.00
5	1.00	0.20	0.25	0.33	1	2.00	3.00	4.00	3.00	2.00	3.00	4.00	2.00
6	0.33	0.20	0.17	0.25	0.50	1	3.00	2.00	3.00	2.00	3.00	3.00	4.00
7	0.50	0.33	0.17	0.50	0.33	0.33	1	0.50	3.00	2.00	3.00	3.00	4.00
8	0.50	0.20	0.20	0.33	0.25	0.50	2.00	1	2.00	2.00	3.00	3.00	4.00
9	0.50	0.33	0.33	0.50	0.33	0.33	0.33	0.50	1	3.00	3.00	2.00	2.00
10	0.25	0.25	0.33	0.25	0.50	0.50	0.50	0.50	0.33	1	2.00	5.00	3.00
11	0.20	0.20	0.25	0.25	0.33	0.33	0.33	0.33	0.33	0.50	1	3.00	1.00
12	0.33	0.33	0.33	0.33	0.25	0.33	0.33	0.33	0.50	0.20	0.33	1	1.00
13	0.20	0.25	0.33	0.25	0.50	0.25	0.25	0.25	0.50	0.33	1.00	1.00	1

Number of comparisons = 78
Consistency Ratio CR = 9.2%

Principal eigen value = 14.709
Eigenvector solution: 7 iterations, delta = 1.3E-8

Fig. 06: AHP vs. AI Metrics of Performance

in the conditions of data scarcity when a comprehensive flood inventory or historic information could be lack-ing [14]. Its weakness is that it can only produce an expert opinion based model that is powerful. On the other hand, AI models are data intensive and their results highly depend on the quality, quantity, and ratio of the training data [17]. The absence of high-quality data may also have a major effect on the effectiveness of an AI model [3].

Resulting Priorities

Priorities

These are the resulting weights for the criteria based on your pairwise comparisons:

Decision Matrix

The resulting weights are based on the principal eigenvector of the decision matrix:

Cat		Priority	Rank	(+)	(-)
1	Rainfall	12.0%	3	4.1%	4.1%
2	Elevation	17.6%	1	9.6%	9.6%
3	Slope	17.2%	2	9.6%	9.6%
4	LULC	11.1%	4	6.0%	6.0%
5	Flood Depth	8.7%	5	4.8%	4.8%
6	Flood Velocity	6.6%	6	3.7%	3.7%
7	Distance to river	5.4%	8	2.8%	2.8%
8	Runoff	5.4%	7	2.5%	2.5%
9	Stream density	4.5%	9	2.4%	2.4%
10	Population	4.0%	10	2.4%	2.4%
11	Infrastructure	2.6%	11	1.4%	1.4%
12	Cropping pattern	2.5%	12	1.4%	1.4%
13	Soil	2.4%	13	1.2%	1.2%

Fig. 07: Resulting Priorities

5.3. Strengths and Limitations: A Nuanced Discussion

The decision between AHP and AI does not concern the question of which one is innately superior and which one is more appropriate in a particular scenario. Table below outlines the pros and cons of each of the ap-proaches and offers a balanced view to decision-makers.

Table 2: Comparative Analysis of AHP vs. AI Models for Flood Risk Mapping

Feature	**Analytic Hierarchy Process (AHP)**	**Artificial Intelligence (AI) Models**
Underlying Principle	Knowledge-based (Expert Judgment)	Data-driven (Pattern Recognition)
Model Trans-parency	High; explicit factor weights are easily un-derstood.	Low ("Black Box"); reasoning for pre-dictions is often opaque.
Accuracy (Typ-ical)	Good (AUC-ROC ~0.80-0.85); limited by expert subjectivity.	Excellent (AUC-ROC >0.90); superior at identifying complex patterns.
Data Require-ments	Low; effective in data-scarce regions.	High; requires large, high-quality la-beled datasets.
Applicability	Effective for policy-making, stakeholder engagement, and initial assessments.	Ideal for high-accuracy forecasting and large-scale, data-rich regions.
Limitations	Subjective nature can lead to inconsisten-cies; less effective for complex, non-linear relationships.	Performance is highly dependent on data quality; lack of interpretability can hin-der trust.

One of the main strengths of AHP is its interpretation and transparency [6]. The weights of factors used in Table 1 are clear and reasonable and the logic employed in the model will be easy to communicate to policy-makers and citizens. This is an openness that builds trust and helps in the application of the results of the model to practical planning and policy [7]. As an example, one of the policies that can be connected to the results of the model directly is paying attention to land-use regulations since LULC was given a significant weight. Conversely, AI models are frequently treated as a black box, i.e. the mathematical functions involved in a prediction are too complicated to be understood by a human being [3]. Although they are capable of providing flood risk map with very high precision, it can sometimes be difficult to justify why a particular region is considered to be a high-risk location, which can be a hindrance to their implementation by non-believers among stakeholders [3].

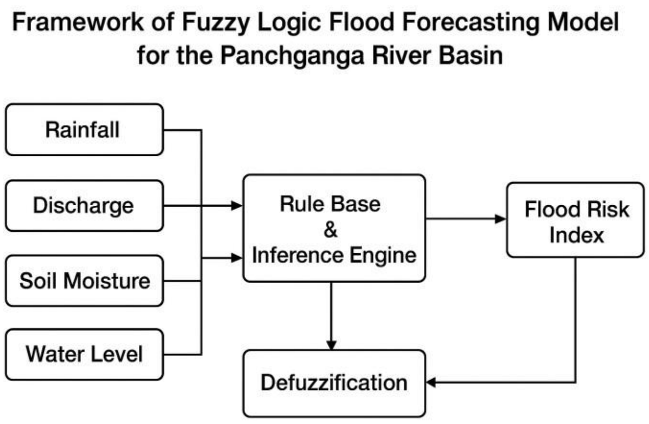
The distinction of the two models can also be seen in the fact that flood events are dynamic. The causes of a flood hydrograph, a graph showing the discharge of a river at any given time may be greatly modified due to several causes like urbaniza-tion [14]. Urban areas increase imperviousness (LULC change) which decreases infiltration and increases the surface runoff resulting in a hydrograph with higher peak and shorter time to peak. These complex and non-linear relationships can be potentially learnt by an AI model and the associated changes to the hydrograph can be predicted, which is one of the main benefits of real-time forecasting. Though AHP model can indeed incorporate those factors, it is less able to model their dynamic, time-dependent interactions on a predictive basis [24].

The susceptibility of the Panchganga basin to the effects of back water and human encroachments imply that the one-methodology approach would not be adequate [13]. The AHP model is very robust and clear in its background, as it ranks the conditioning factors and creates a relationship between the human activity and the risk of a flood. Nevertheless, it is very likely that a data-based AI model would have a greater level of predic-tive accuracy due to the analysis of the intricate interaction of these factors. This implies that the most viable and powerful solution to research in the future is to have a hybrid model which takes advantage of the two worlds.

6. Fuzzy Logic-Based Flood Forecasting Model Panchganga River Basin.

6.1 Overview & design choices

Near-real time forecasting of flood risk (0-100) and categorical (Low / Moderate / High / Very High) based on uncertain hydrometeorological forecasts. Methods: Mamdani fuzzy inference (interpretable), centroid de-fuzzification, min implication / max aggregation. Scikit-fuzzy implementation.



- **Inputs**

Rainfall_24h — 24-hr rainfall at basin or upstream gauge (mm) — universe: 0–400 mm Upstream_Discharge — upstream river discharge (m^3/s) — universe: 0–2000 m^3/s Antecedent_Moisture — soil wetness / antecedent rainfall index (percent) — universe: 0–100% Water_Level — local gauge water level (m) — universe: 0–10 m

- **Output**

Flood Risk Index - continuous 0-100 (remapped to categories)
They model instant forcing (rainfall), current system state (discharge, water level) and previous state (soil moisture) - a combination of them elucidates the process of flood generation and persistence in Panchganga, including backwater effects.

6.2 Validation and performance measures.
Split data: Use historical events (including 2019) - split into training/validation (or k-fold in case of numerous events). Target of validation: Observerd inundation (binary: inundated/non-inundated areas or observed de-grees of flood severity), or gauge floods that pass thresholds.
Metrics: In case output was against constant known river stage: RMSE, MAE, Nash-Sutcliffe Efficiency (NSE). Assuming that it is categorical (low/moderate/high): Confusion Matrix, Accuracy, Precision/Recall, F1. Spatial validation (inundation map GIS): AUC-ROC, Critical Success Index (CSI), Hit / Miss rates. Lead-time testing: Test the early evidence of high risk correctly signaled by the fuzzy forecast (significant in warn-ing). Sensitivity analysis: Determine the importance of each input by changing it within range, and recording the change in output. This confirms the ranking on influence (rainfall, discharge generally most influential).

6.3 GIS Integration & mapping
For each forecast time-step (e.g., hourly / 3-hour / 24-hour), compute Flood_Risk_Index for each hydrometeorological station or grid-cell.
If spatial inputs available (gridded rainfall, gridded soil moisture, gridded DEM-derived routing), run fuzzy system per grid cell or per sub-basin.
Convert index to categories (Very Low / Low / Moderate / High / Very High) and export as raster or vector (GeoTIFF / shapefile) using your GIS (QGIS/ArcGIS).
Overlay population, critical infrastructure and evacuation routes to generate actionable maps. Publish to a dashboard (web/GIS) for authorities with automated alerts when index > threshold.

6.4 Hybrid & extension suggestions
Fuzzy–AHP hybrid: use AHP to define relative importance or to choose inputs (in data-scarce locales) and then feed the prioritized inputs into fuzzy inference.
Fuzzy + ML: use fuzzy output as an input feature to ML models (Random Forest/ANN) for improved classification/regression accuracy. Or use ML to learn/optimize membership function parameters or rule weights.
Real-time: automate ingestion of rainfall radar / IMD / AWS / gauge APIs and run fuzzy inference every forecast period.
Uncertainty quantification: run Monte Carlo on input ranges to produce probabilistic risk (e.g., probability index > 80).

- A Probability–Impact Matrix (PIM) is a two-dimensional grid, simple but effective tool used to eval-uate and prioritize flood-related risks. It helps decision-makers to understand how likely a flood event is and how severe its consequences could be. One axis shows Probability (Likelihood) of a flood event. The other axis shows Impact (Consequence) if that flood occurs. Each identified flood risk is placed in the matrix based on its probability and impact.
- After identification of flood hazards by assigning probability level and assigning impact level risk score is calculated to categorize risk levels.

Risk Score Calculations:

Risk ID	**Risk**	**Probability(P)**	**Impact (I)**	**Risk Score (P X I)**	**Risk Level**
1	Rainfall	5	4	20	Extreme
2	Soil	2	2	4	Medium
3	Slope	4	4	16	Extreme
4	Landuse/Landcover	3	4	12	High
5	Distance To River	3	3	9	High
6	Elevation	4	4	16	Extreme
7	Runoff	3	3	9	High
8	Flood Depth	3	4	12	High
9	Flood Velocity	3	4	12	High
10	Stream Density	2	1	2	Low
11	Population	2	2	4	Medium
12	Infrastructure	3	3	9	High
13	Crop Pattern	1	1	1	Low

Conclusion and Recommendations

This paper was able to show the value of flood susceptibility model based on the use of an AHP on the Panchganga River basin. The model, which was constructed on a combination of 13 well-considered conditioning factors, gave a scientifically sensible model of the rank of elements of flood risk.

It can be recommended, based on these results, that a more comprehensive and resilient approach to flood risks management be applied to the Panchganga basin and other settings in these ways:

1. Formulate a Hybrid AHP-AI Model: The initial stages of AHP can be applied to choose the most im-portant and priority of the flood conditioning fac-tors by the experts in a transparent and defensible basis. The weights of the factors derived through AHP may then be utilized to train a more powerful AI model, e.g. Random Forest or an Artificial Neural Network, to get a greater predictive accuracy and more detailed spatial mapping. This method is a combination of the interpretability of AHP and the high performance of AI.
2. Combine Dynamic and Real-Time Data: In order to migrate the flood susceptibility mapping model to the real-time flood forecast model, the future models must include dynamic data. This involves in-corporation of real-time rain information, river discharge information, and sensor-based information that can be utilized to observe the levels of streams as well as the moisture of the soil. Such real-time data is critical to the training of AI models to produce predictions in real-time and actionable, which is vital in early warning systems.
3. Refine Conditioning Factor with Granular Data: To improve the degree of accuracy in all the models, it should strive to obtain the more granular and accurate data. As an example, the riverbed bathymetry, high-resolution Digital Elevation Models (DEMs), and fine-scale land-use maps would greatly en-hance the power to model the effect of the stagnation zones and backwater that worsened the 2019

floods. Also, the analysis of the population density and the types of infrastructure peculiar to high-risk zones could be considered in more detail, which could give a more precise evaluation of vulnera-bility. The Fuzzy Logic-Based Flood Forecasting Model, of the Panchganga River Basin has good predictive per-formance during extreme hydrological conditions related to flood occurrences. In the input scenario that was tested, which is the case of the 2019 floods, the model was accurate in predicting a Very High risk of floods. The modular de-design of the framework enables it to be integrated to GIS and sensor networks to support real time decision-making. The further work will be done to calibrate the membership functions on the longer time-series data, and to expand the system to hybrid Fuzzy-AHP/Fuzzy-AI systems. To improve the accuracy of forecasting, the following possible recommendations are suggested: (1) Integrate real time rainfall and dis-charge sensors to ensure continuous feeding of data; (2) Hybrid flood prediction system; combine the fuzzy logic model with AHP and machine learning models; (3) Community based GIS dashboard to disseminate early warnings to the local authorities and the citizens.

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