COMPARITIVE ANALYSIS BETWEEN AHP & FUZZY AHP: A CASE STUDY ON FLOOD SUSCEPTIBILITY OF KOSHI RIVER BASIN

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ABSTRACT

The report compares the Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (FAHP) for flood susceptibility assessment in the Koshi Basin area. Both models are used in multi-criteria decision-making, but their effectiveness in handling complex environmental conditions varies. The study evaluates and compares the performance of these models in predicting flood-prone areas using the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) as a performance metric. The results show that the majority of the region falls under moderate flood risk, with low-risk zones accounting for 35.04% and 31.41%, and high-risk areas covering 12.67% and 13.33%. The topographical wetness index was the most weighted criteria in both models, while aspect was the least affecting criteria. The AHP model showed good predictive capability with an AUC of 0.758, while the FAHP model demonstrated superior performance with an AUC of 0.802, attributed to its incorporation of fuzzy logic..

KEYWORDS: Multi Criteria Decision Making/Analysis, AHP, FAHP, GIS, Flood, ROC & AUC Curve.

1. INTRODUCTION

1.1 Background

Flood is graded as one of the most calamitous disasters affecting 170 million people around the globe and is also accountable for more than 60 percent of deaths related to natural calamities (Bouamrane et al., 2022). The positive and negative effects of the catastrophe appear widely imbalanced as the negative effects weighs in more since the calamity is limited not only to affecting human and livestock's lives but also economy, food security, social insecurity etc. The impacts of flood are difficult to inspect on a larger area since it is highly influenced by various socioeconomic and demographic factors (Atiye Cikmaz et al., 2022). Due to the severity of the calamity, it is profoundly important to identify the areas under the flood risks and design various mitigation measures to address the catastrophe during its occurrence. With the advancement in the GIS and RS techniques and also with the development of statistical models such as AHP, we can precisely inspect the flood susceptible areas and in turn apply the various mitigation plans to minimize the effect of the catastrophe as much as possible (Atiye Cikmaz et al., 2022).

In the context of above topic, GIS can be defined as a decision support system involving the integration of spatially referenced data in a problem-solving environment (Sivakumar et al., 2003). With the help of varieties of tools in the working environment of GIS and RS, various qualitative and quantitative analysis can be created, understood, visualized and a meaningful result can be produced accordingly. The intent of dealing with a complex multi-dimensional dynamic issue such as flood is easily assisted by GIS along with the integration of some other disciplines as well.

Flood risk mapping is often a challenging task to provide a comprehensive risk assessment by covering social, economic, and geophysical processes as a whole (Noor et al., 2017). Conventionally, flood hazard assessment is conducted via hydrological and hydraulic modelling by estimating the flooding depth and extent for various return-periods but the application of these modelling techniques requires a range of observed data that

are not always available (Sivakumar et al., 2003). When the focus primarily shifted to developing feasible models which would help better understand the various criterion of different phenomenon and the relationship between such criterion, the concept of various MCDA/MCDM models such as Frequency Ratio, AHP, Logistic Regression etc. came into existence (Bouamrane et al., 2022).

AHP is one of such MCDA models commonly used. In the AHP, the decision-making process of complex problems is conducted by dividing the problem into issues, which may be divided further to form a simple and comprehensible hierarchical structure (Bouamrane et al., 2022). Developed by Saaty in 1980, it is considered a mathematical approach to MCDM (Hammami et al., 2019). This technique evaluates the importance of factors, according to weight values from human judgement and preferences.

Another method in MCDA is the Fuzzy AHP method. The fuzzy set theory is used to address the ambiguity and uncertainty issue occurring in AHP and incorporate human judgement and preference with least amount of error. The weights in AHP are either in Crisp Scale or in Linguistic Terms. Fuzzy AHP assigns a membership function (one that defines the relationship between an independent variable and a dependent variable, degree of membership) to each linguistic terms rather than assigning a single value.

2. MATERIALS AND METHODS

2.1 Study Area

The study area covers the Koshi River within Nepal, where it flows through the eastern region and accounts for 45% of the total 87,311 km² transboundary basin.

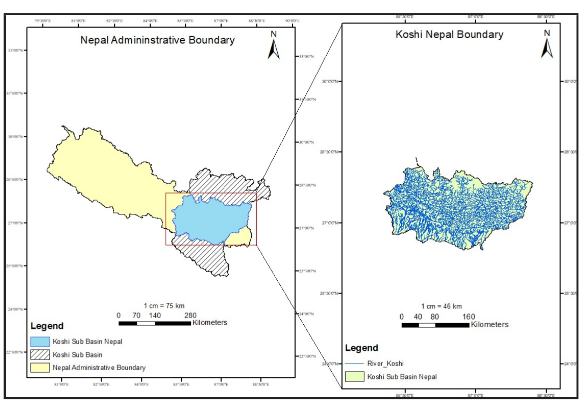


Figure 1: Koshi River Basin

2.2 Methodology

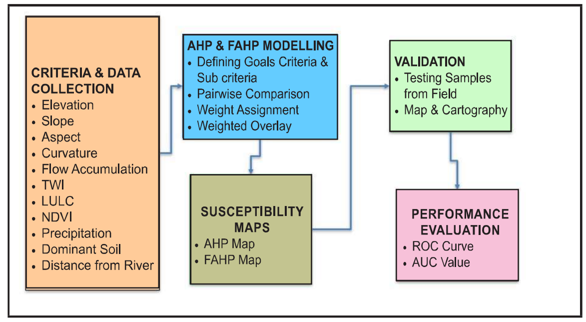


Figure 2. Methodological Workflow.

2.2.1 Data Collection

Various spatial and environmental datasets were collected from **Secondary Sources**, including Digital Elevation Model (DEM), land use/land cover (LULC), Normalized Difference Vegetation Index (NDVI), rainfall data, dominant soil type, and river shapefiles relevant to the study area.

2.2.2 Data Preprocessing and Analysis

i. DEM Processing: Mosaic, Extract by Mask, Slope/Aspect/Curvature.

ii. Hydrological Analysis: Fill, Flow Direction, Flow Accumulation, TWI.

iii. Thematic Layers: Rainfall Interpolation, NDVI (GEE), Soil, LULC, River Distance.

iv. Standardization: Clip, Project Raster, Resample, Reclassify.

v. Overlay & Analysis: Weighted Overlay, Susceptibility Mapping, Validation.

2.2.3 Data Re-Classification

Determining how different thematic layers, such as elevation, slope, land cover, and proximity to rivers, naturally affect flooding is the first stage in flood susceptibility mapping. The subsequent reclassification of these layers into standardized classes and their normalization for comparative analysis in a multi-criteria evaluation are informed by this crucial understanding, which is derived from established hydrological principles, expert knowledge, and frequently preliminary spatial analysis.

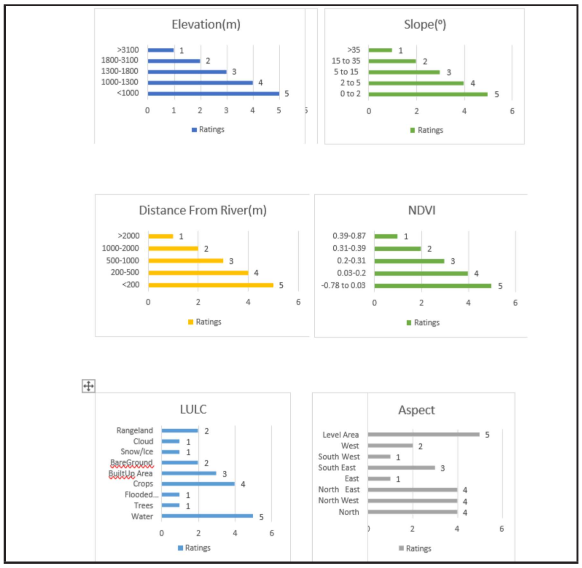


Figure 3. Criteria Reclassification (1)

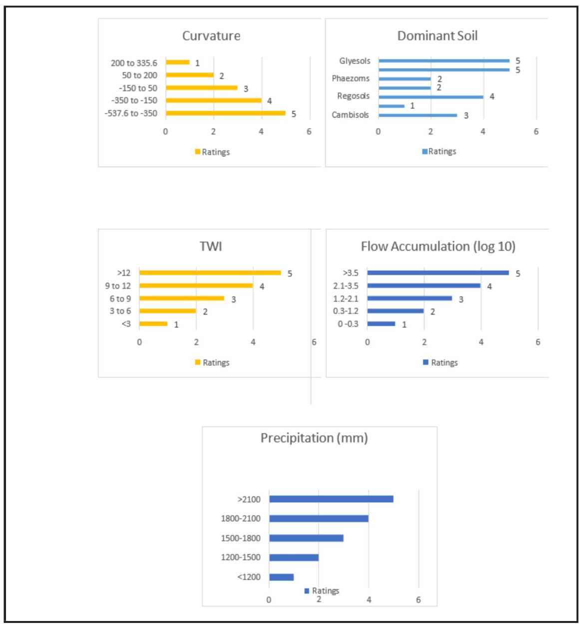


Figure 4. Criteria Reclassification (2)

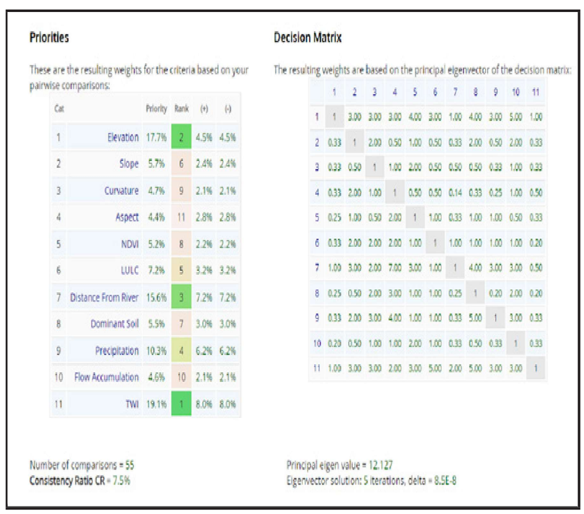
Table 1. Criteria Rating Description

S.N.	Effect	Criteria Ratings
1	Very Low	1
2	Low	2
3	Moderate	3
4	High	4
5	Very High	5

The provided figures consist of horizontal bar charts representing the rating scales assigned to various criteria used in flood susceptibility mapping. These ratings reflect how different ranges or categories within each factor contribute to flood risk, typically for use in AHP or FAHP-based MCDA models. For instance, lower elevations and gentler slopes are given higher ratings due to their greater tendency to accumulate water, increasing flood susceptibility. Proximity to rivers (e.g., within 0–200 meters) is also rated higher, as areas closer to water bodies are more prone to flooding. Vegetation cover, measured by NDVI, and land use types (e.g., built-up or rangeland) are considered for their ability to absorb or repel water. Aspect (slope orientation) is rated based on its influence on microclimate and runoff patterns. Other critical terrain attributes like curvature (shape of the land), TWI (Topographic Wetness Index), and flow accumulation highlight the landscape's capacity to store or direct water, with higher values indicating greater risk. Soil types, such as Gleyerats or Regosols, are evaluated for permeability and retention capacity, while higher precipitation levels are also assigned higher flood susceptibility ratings. These charts collectively support a structured and evidence-based approach to quantifying flood risks spatially.

2.2.4 AHP/FAHP Methodology

AHP and FAHP methods were used to assign weights to flood susceptibility factors. Expert judgment was collected to build pairwise comparison matrices, and consistency was checked. FAHP incorporated fuzzy logic to handle uncertainty in data and expert opinions, allowing for more flexible decision-making.



Priorities

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

Cat		Priority	Rank	(+)	(-)
1	Elevation	17.7%	2	4.5%	4.5%
2	Slope	5.7%	6	2.4%	2.4%
3	Curvature	4.7%	9	2.1%	2.1%
4	Aspect	4.4%	11	2.8%	2.8%
5	NDVI	5.2%	8	2.2%	2.2%
6	LULC	7.2%	5	3.2%	3.2%
7	Distance From River	15.6%	3	7.2%	7.2%
8	Dominant Soil	5.5%	7	3.0%	3.0%
9	Precipitation	10.3%	4	6.2%	6.2%
10	Flow Accumulation	4.6%	10	2.1%	2.1%
11	TWI	19.1%	1	8.0%	8.0%

Number of comparisons = 55
Consistency Ratio CR = 7.5%

Decision Matrix

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

	1	2	3	4	5	6	7	8	9	10	11
1	1	3.00	3.00	3.00	4.00	3.00	1.00	4.00	3.00	5.00	1.00
2	0.33	1	2.00	0.50	1.00	0.50	0.33	2.00	0.50	2.00	0.33
3	0.33	0.50	1	1.00	2.00	0.50	0.50	0.50	0.33	1.00	0.33
4	0.33	2.00	1.00	1	0.50	0.50	0.14	0.33	0.25	1.00	0.50
5	0.25	1.00	0.50	2.00	1	1.00	0.33	1.00	1.00	0.50	0.33
6	0.33	2.00	2.00	2.00	1.00	1	1.00	1.00	1.00	1.00	0.20
7	1.00	3.00	2.00	7.00	3.00	1.00	1	4.00	3.00	3.00	0.50
8	0.25	0.50	2.00	3.00	1.00	1.00	0.25	1	0.20	2.00	0.20
9	0.33	2.00	3.00	4.00	1.00	1.00	0.33	5.00	1	3.00	0.33
10	0.20	0.50	1.00	1.00	2.00	1.00	0.33	0.50	0.33	1	0.33
11	1.00	3.00	3.00	2.00	3.00	5.00	2.00	5.00	3.00	3.00	1

Principal eigen value = 12.127
Eigenvector solution: 5 iterations, delta = 8.5E-8

Figure 5. Criteria Weights in AHP

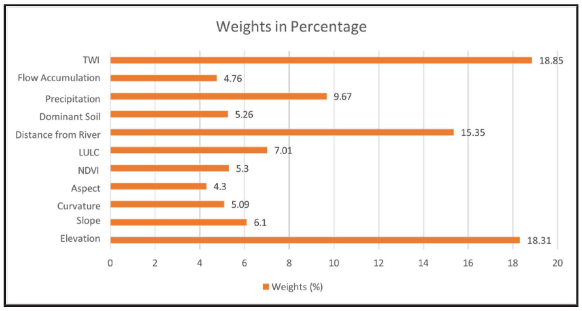


Figure 6. Criteria Weights in FAHP

2.2.5 Flood Susceptibility Mapping and Model Validation

The weighted criteria were used to generate a flood susceptibility map, classifying areas by risk. Model accuracy was validated with ROC curves, and adjustments were made to improve reliability.

3. RESULTS AND DISCUSSION

3.1 AHP and FAHP Results

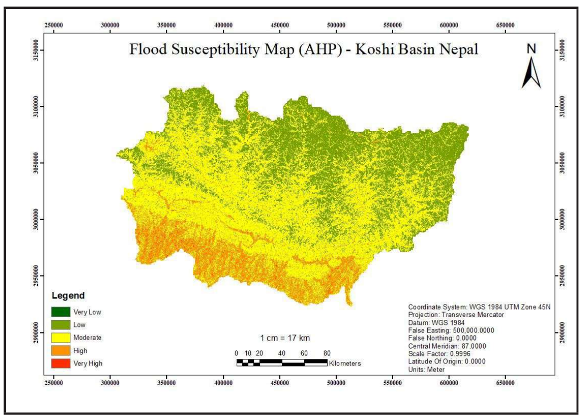


Figure 7. AHP Based Flood Susceptible Map

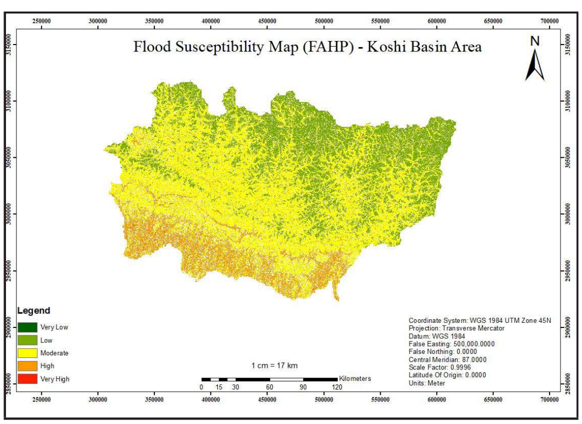


Figure 8. FAHP Based Flood Susceptible Map

ROC VALUE OF THE AUC CURVE FOR BOTH MODELS

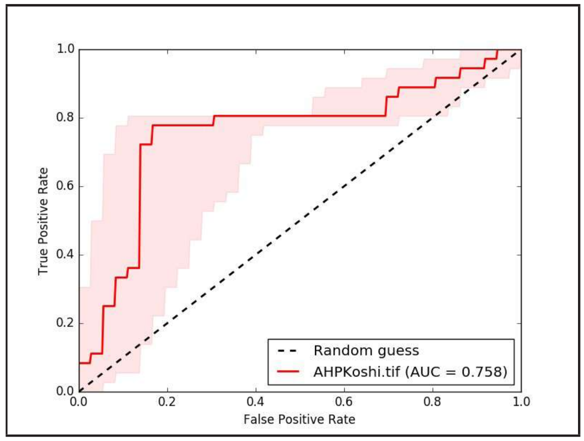


Figure 9. AHP Validation Curve

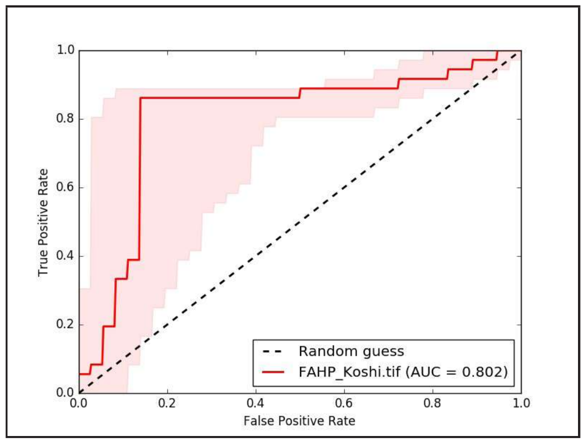


Figure 10. FAHP Validation Curve

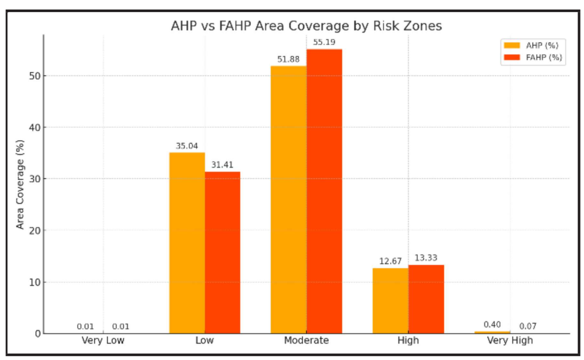


Figure 11. Area Coverage in the Models

In **Figure 7** and **8**, the AUC Value of the FAHP model is 0.802 while that of the AHP model is 0.758. An AUC of 0.758 indicates that the AHP model has good predictive performance for flood susceptibility. This means the model is able to correctly distinguish between flood-prone and non-flood-prone areas 75.8% of the time.

Similarly, an AUC of 0.802 indicates that the FAHP model has better predictive performance compared to the AHP model. This model correctly distinguishes between flood-prone and non-flood-prone areas 80.2% of the time. The predictive performance of these models is assessed using the Receiver Operating Characteristic (ROC) curve, which illustrates the trade-off between the true positive rate (sensitivity) and false positive rate (1 – specificity) at various threshold settings. The Area Under the Curve (AUC) provides a single quantitative measure of model accuracy. An AUC value of 0.5 corresponds to random guessing, indicating the model has no discriminatory power. Values closer to 1 signify better performance, meaning the model reliably differentiates between flooded and non-flooded areas. Thus, the higher the AUC, the more effective the model is at correctly predicting flood susceptibility beyond chance.

4. CONCLUSION

Our study compared the Analytic Hierarchy Process (AHP) and the Fuzzy Analytic Hierarchy Process (FAHP) to assess flood vulnerability in the Koshi Basin region with additional information about susceptible areas, highly affecting criteria etc. The flood susceptibility analysis of the Koshi Basin Area, using the Analytical Hierarchy Process (AHP) and the Fuzzy Analytical Hierarchy Process (FAHP), reveals that the majority of the region falls under moderate flood risk, covering 51.88% and 55.19% of the area respectively. Low-risk zones account for 35.04% (AHP) and 31.41% (FAHP), while high-risk areas cover 12.67% (AHP) and 13.33% (FAHP). Very low and very high-risk zones are minimal in both models. These findings highlight the necessity for targeted flood management in moderate and high-risk areas and the importance of multiple analytical approaches for effective flood prevention and resilience planning in the Koshi Basin. Topographical Wetness Index was the criteria with most weights in both the models, about nineteen percent. Aspect was the least affecting criteria with about only four percent weightage.

The AUC of the ROC was used to evaluate the performance of each model, resulting in an AUC of 0.758 for AHP and 0.802 for FAHP. The findings suggest that even though both models show strong predictive abilities, the FAHP model performs better than the AHP model. The FAHP model's AUC of 0.802 suggests a higher level of accuracy and dependability in forecasting flood-prone areas in comparison to the AHP model's AUC of 0.758. Bouamrane et al. conducted similar comparative assessment as "A comparison of the analytical hierarchy process and the fuzzy logic approach for flood susceptibility mapping in a semi-arid ungauged basin (Biskra basin: Algeria)" with similar conclusions as well. This enhancement is credited to the FAHP model's integration of fuzzy logic, enabling more effective management of uncertainty and imprecision in the input data and criteria weights. The superior capability of the FAHP model to capture the complex and uncertain flood susceptibility factors in the Koshi Basin area is emphasized by its enhanced performance. This enhances the FAHP model as a stronger tool for evaluating flood risk, offering important information for efficient flood control and reduction tactics.

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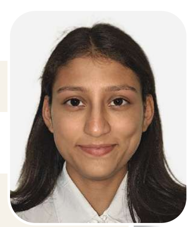

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