KATHMANDU UNIVERSITY

SCHOOL OF ENGINEERING

DEPARTMENT OF GEOMATICS ENGINEERING

A PROJECT REPORT ON

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

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ABSTRACT

This report presents a comparative analysis of the Analytic Hierarchy Process (AHP) and the Fuzzy Analytic Hierarchy Process (FAHP) for flood susceptibility assessment in the Koshi Basin area. Both models are widely used in multi-criteria decision-making, but their effectiveness in handling complex environmental conditions varies. The study aims to evaluate and compare the performance of these models in predicting flood-prone areas using the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) as the performance metric.

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. 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.

Various criterion was utilized to develop both AHP and FAHP models. The AHP model yielded an AUC of 0.758, indicating good predictive capability. However, the FAHP model demonstrated superior performance with an AUC of 0.802, reflecting more accurate and reliable flood susceptibility predictions. The enhanced performance of the FAHP model can be attributed to its incorporation of fuzzy logic, which effectively handles the uncertainty and imprecision inherent in environmental data and expert judgments.

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

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LIST OF ABBREVATIONS

AHP	Analytical Hierarchical Process
AUC	Area Under Curve
CI	Consistency Index
COA	Center of Area
CR	Consistency Ratio
FAHP	Fuzzy Analytical Hierarchical Process
GIS	Geographic Information System
GM	Geometrical Mean
IDW	Inverse Distance Weightage
MCDA/MCDM	Multicriteria Decision 'Analysis or Making'
RI	Random Consistency Index
ROC	Receiver Operating Characterstics
RS	Remote Sensing
TFS	Triangular Fuzzy Scale
TWI	Topographical Wetness Index

LIST OF SYMBOLS

$\sum$	Summation
$\oplus$	Exclusive OR
λ	Lambda
μ	Mu
$^{\circ}$	Degree

CHAPTER 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., n.d.). 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., n.d.).

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., n.d.). 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.

1.2 PROBLEM STATEMENT

Flood is a significantly dangerous catastrophe, the occurrence of which affects various aspects of life, economy and the environment as well. Koshi River Basin is one of such area that triggers highly devastating floods. Due to various factors, more than 50 percent of the basin is projected to be in a zone of intermediate to high risk.

During the course of the project, we intended to delineate, analyze and understand flood prone areas and obtain different flood susceptibility maps around Koshi River Basin. We planned to use two different MCDA approach, AHP and Fuzzy AHP in the course of achieving the objectives and compare the result of both the methods.

1.3 OBJECTIVES

1.3.1 Primary Objectives

The primary objective of the project is to perform comparative analysis between AHP and Fuzzy AHP using a case study on Flood Susceptibility of Koshi Basin Area.

1.3.2 Secondary Objectives

The secondary objectives of the project were to:

- To identify various criterion based on literature review,
- To prepare and validate flood susceptible maps of the area,
- To prepare criteria maps, sub-criteria rating graphs.

1.4 SCOPE OF THE PROJECT

The scope of this project was to conduct a comparative analysis of the Analytical Hierarchy Process (AHP) and Fuzzy Analytical Hierarchy Process (Fuzzy AHP) methods for assessing flood susceptibility in the Koshi River Basin. Specifically, this project intended to:

- Identify the key factors influencing flood susceptibility in the Koshi Basin, such as topography, hydrology, land use, and precipitation patterns.
- Develop hierarchical decision models using both the traditional AHP and Fuzzy AHP approaches to evaluate the relative importance of the identified flood susceptibility factors.
- Apply the AHP and Fuzzy AHP models to the Koshi Basin and generate flood susceptibility maps using GIS.
- Compare the flood susceptibility results obtained from the AHP and Fuzzy AHP methods.
- Validate the flood susceptibility assessments by comparing the model outputs with historical flood event data in the Koshi Basin.

The outcome of this project will contribute to a better understanding of the applicability and performance of AHP and Fuzzy AHP techniques for flood susceptibility mapping, which can support more effective flood risk management and disaster preparedness efforts in the Koshi River Basin.

CHAPTER 2: LITERATURE REVIEW

In the developmental context, a lot of technology has been through major breakthrough phase with tremendous advancement. This technology includes GIS, RS & other survey techniques and also the approach of MCDA/MCDM as well as the integration of the both(Malczewski & Rinner, 2015). Decision makers require very precise understanding and analysis of the issue incorporated in order to achieve certain decisions or goals(Sivakumar et al., 2003). Flood susceptibility mapping is a crucial step in flood risk management, as it helps identify areas prone to flooding and informs mitigation strategies. The Analytical Hierarchy Process (AHP) and Fuzzy Analytical Hierarchy Process (Fuzzy AHP) are two widely used methods for assessing flood susceptibility.

There were various researches conducted in the field of dealing flood issues through the integration of GIS and MCDA. Similarly, various comparative studies were also undertaken between the AHP and Fuzzy AHP process to a standard scale. The major breakthrough obtained in the field of integration between GIS and MCDA techniques to solve the flood issues was delivered by delineating risk areas in and around the calamity source on the basis of the severity. With the risk areas being properly delineated, decision makers involved could design mitigation action plans in the various categorized zones as per the severity. The MCDA process in GIS allows any decision maker to incorporate various socioeconomic and demographic parameters that the issues are affected by and design a hierarchal approach in the form of AHP and Fuzzy AHP to deal with this multi-dimensional dynamic aspect of the flood issue. According to studies, the FAHP method is for dealing with linguistic scales whereas the AHP method deals with only the crisper scale values. The AHP method, as a mathematical model has higher degree of stability as the method is more mathematically justified but when evaluating the stability of a FAHP model, unambiguous results were shown when using different scales for triangular number(Vinogradova-Zinkevič et al., 2021).Bouamrane et al. conducted study in a semi-arid ungauged basin called the Biskra Basin in Algeria using both AHP and Fuzzy AHP method. According to their paper, both the methods are promising MCDA approach that can predict flood susceptibility in the study area with minimum subjectivity and vagueness in the process. Both AHP and FAHP have been widely used in flood susceptibility mapping due to their ability to handle multiple criteria and evaluate their relative impacts on flood risk. While AHP provides a robust framework for decision-making, FAHP offers a more nuanced approach by incorporating fuzzy set theory to handle uncertainty.(Noor et al., n.d.) The comparison of these methods in the context of the Koshi River Basin will provide a comprehensive understanding of their strengths and limitations, ultimately informing more effective flood risk management strategies.

The receiver operating characteristic (ROC) curve and the area under the ROC curve (AUC) are widely used to assess the accuracy and performance of flood susceptibility models. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1-specificity) at various classification thresholds, providing a comprehensive evaluation of model performance. The AUC value, which ranges from 0 to 1, represents the overall accuracy of the model, with a value of 1 indicating perfect discrimination between flood and non-flood areas. An AUC value greater than 0.7 is generally considered to indicate good model performance(Khosravi et al., 2019). The ROC curve and AUC value are essential tools for evaluating the accuracy and reliability of flood susceptibility models, allowing for a comprehensive and quantitative assessment of their performance. The use of these metrics provides a robust framework for evaluating and comparing the performance of different flood susceptibility models, ultimately enhancing the reliability of flood risk assessments and mitigation strategies(Chen et al., 2023).

2.1 FLOOD CONDITIONING FACTORS

a) Elevation

Elevation plays an important role in identifying high risk areas of flooding. This factor has a significant impact on flood propagation, especially controlling flow direction and flood depth. According to the classification process, the area with the lowest elevation was very heavily affected by flooding.

b) Slope

Slope plays an important role in determining flood risks because it regulates the rate of water flow and the infiltration of surface runoff. Slopes was determined from elevation curves and categorized. Therefore, according to the classification process, the area with the lowest slope will be very heavily affected by flooding.

c) Distance from the River Network

The factor "distance from the drainage network" plays a very important role in identifying flood risk areas and evaluating the flood risk index. There is a high risk of flooding in areas close to the river network, but the influence of this parameter gradually decreases as you move away from the river flow. The distance of the study area from the drainage network was determined by defining a buffer zone around the river/drainage network data.

d) Precipitation

Precipitation intensity is one of the key factors as it has a significant impact on spatio-temporal flood intensity. Precipitation intensity and meteorological data were collected from different weather stations within the study area. The precipitation intensity map was computed using ArcMap's IDW interpolation method.

e) Land Use/ Land Cover

Land use/land cover is an important factor in flood risk studies. This parameter affects components of hydrologic processes such as runoff, Infiltration, and evaporation. This includes urban land, water bodies, river bed, forest, grassland, crop land & other wooden land and snow.

f) Topographical Wetness Index

The Topographical Wetness Index (TWI) is a commonly used terrain analysis parameter in hydrology and geomorphology. It is particularly useful in flood susceptibility analysis because it helps to identify areas prone to water accumulation and saturation based on terrain characteristics.

g) Dominant Soil Type

In flood susceptibility analysis, considering soil types is crucial because different soils have varying infiltration rates, water retention capacities, and drainage properties, all of which influence flood vulnerability. When conducting flood susceptibility analysis, incorporating soil type data alongside terrain characteristics, hydrological parameters, and land use information helps to create a more comprehensive understanding of flood risk.

h) Flow Accumulation

Flow accumulation is a crucial factor in flood susceptibility analysis. It represents the amount of surface runoff that accumulates at any given point in a watershed, essentially indicating how much water flows into a particular area. Higher flow accumulation values typically correspond to areas where water collects, such as valleys and riverbeds, making these areas more susceptible to flooding.

i) Aspect

Aspect, the compass direction that a slope faces, is another important conditioning factor in flood susceptibility analysis. It influences several hydrological and environmental processes that affect flood risk, such as solar radiation, evapotranspiration, vegetation type, and soil moisture content.

j) Curvature

Curvature, which measures the rate of change of slope, is an important topographic attribute in flood susceptibility analysis. It provides insight into the surface flow dynamics, influencing water accumulation, soil erosion, and deposition processes.

k) NDVI

The Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing index that measures vegetation health and density by comparing the reflectance values of near-infrared (NIR) and red light. NDVI can be a significant conditioning factor in flood susceptibility analysis because it provides insights into land cover and vegetation, which influence infiltration, runoff, and soil stability.

CHAPTER 3: METHODOLOGY

3.1 STUDY AREA

The Koshi River is one of the major rivers in South Asia having snow fed characteristics. The Koshi basin is roughly located between 85˚ to 89˚ east longitude and 25˚ to 29˚ north latitude. The Koshi is a trans-boundary river, originating in Tibet, flowing through the Himalaya, through the eastern part of Nepal and the flat plain of Indian north territory(Kafle & Shakya, 2018). The Koshi River is the biggest in the catchment area of 87,311 square kilometers with regard to all Himalayas that pass into the Ganges basin. The transboundary Koshi River Basin is shared by China, India, and Nepal. Nepal accounts for almost 45% of the basin, with China at 32% and 23% in India.

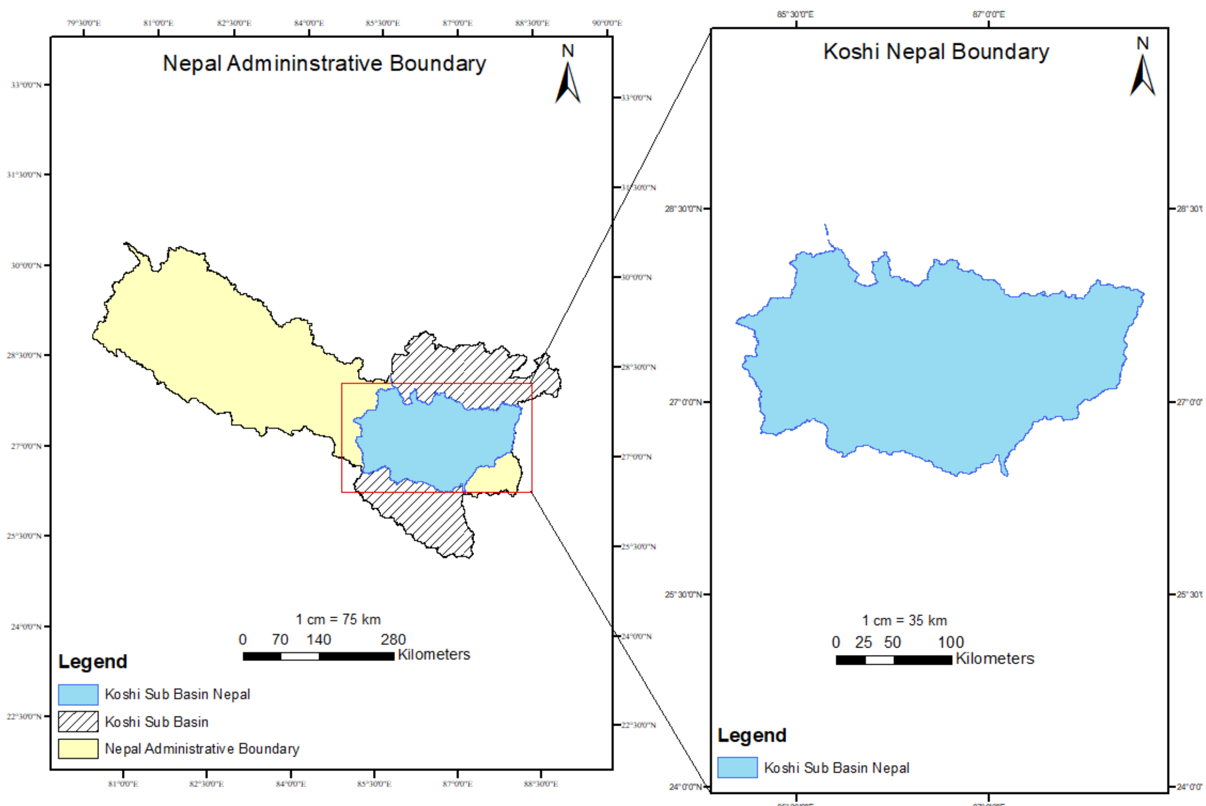

Figure 1: Study Area

3.2 DATA SOURCES USED

Table 1 shows the data sources that were used to extract the criteria data along with the type of Data and a short description.

Table 1:Data Sources

S.N.	Data	Description	Source
1	DEM Data	Elevation Data Nepal (ALOS PALSAR DEM 12.5m)	https://asf.alaska.edu/
2	Slope	Extracted from DEM	-
3	Hydrology	River Network of Nepal	https://rds.icimod.org/
4	Precipitation	Annual Precipitation	https://nepalindata.com/
5	LULC	Esri Land Cover 10m (Sentinel 2A)	https://livingatlas.arcgis.com/landcoverexplorer/
6.	Soil Type	Soil Type Data of World	https://data.isric.org/
7.	TWI	Extracted in GIS from Slope and Scaled Flow Accumulation	-
8.	Aspect	Extracted From DEM	-
9.	Curvature	Extracted From DEM	-
10.	Flow Accumulation	Extracted From DEM	-
11.	NDVI	Sentinel 2A Image extracted using GEE (10m)	https://earthengine.google.com/

3.3 SOFTWARES USED

Table 2 shows the software or extensions used in the course of the completion of our project along with a short description.

Table 2: Softwares Used

S.N.	Software/Websites	Description
1	GIS Environment	• Used primarily to view, edit, create, and analyze geospatial data. • ArcSDM toolbox to create the AUC Curve
2	Microsoft Office Package	• Excel was used to create PCMs, visualize exported weight tables, to create and store testing samples etc. • Word was used for report-writing.
3	Analytical Hierarchical Process	• Primarily used to perform FAHP using geometric mean to assign PCM & calculate weights.
4	BPMSG	• Primarily used to perform AHP to assign PCM and calculate weights

3.4 METHODOLOGICAL WORKFLOW

Figure 2 shows the methodological workflow from criteria identification process to validation and final output stage.

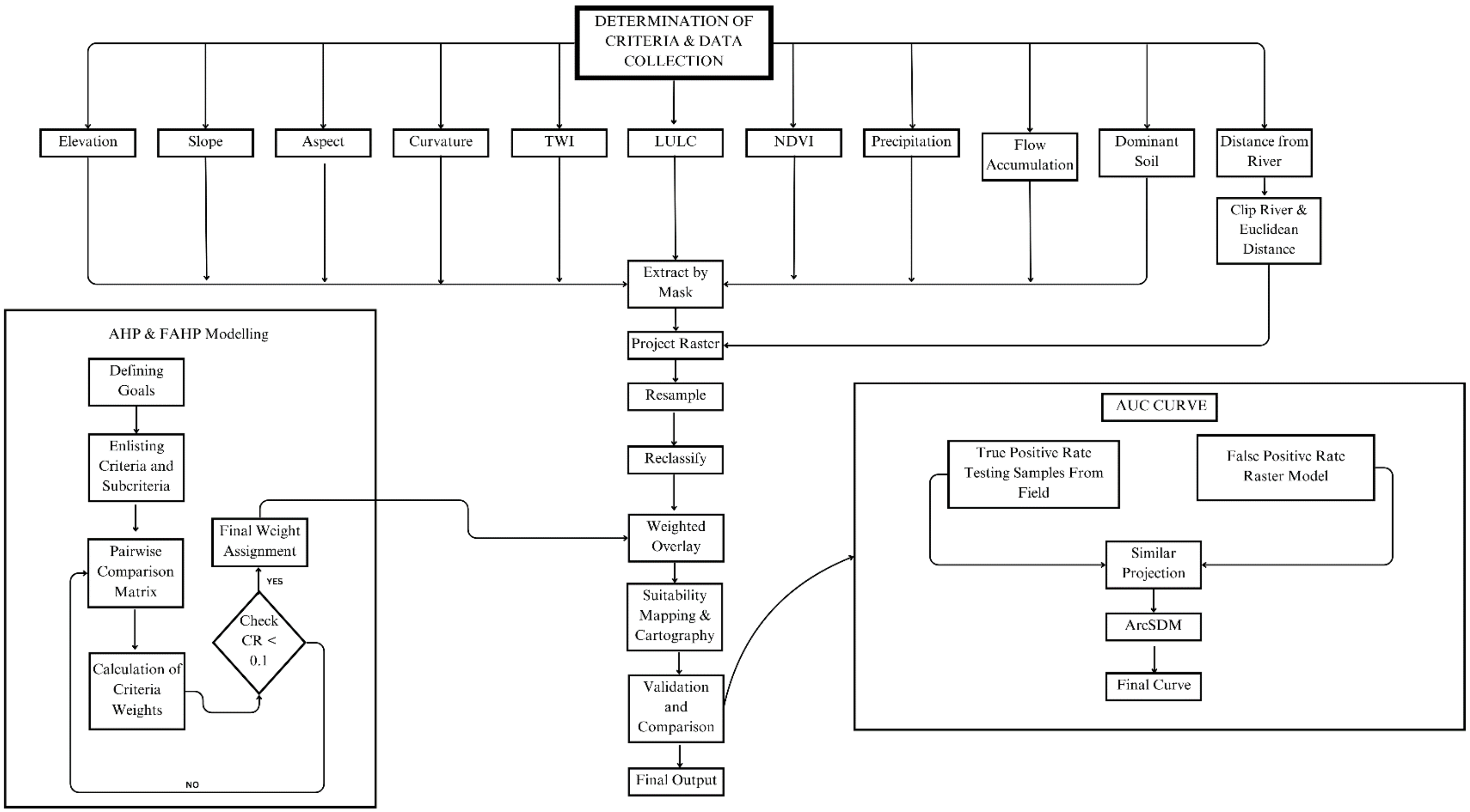

Figure 2: Methodological Workflow

3.4.1 GIS Workflow

a) Determination of Criteria and Data Collection

Flood is a natural calamity that is affected by multidimensional dynamic aspects or parameter. These parameters can be precipitation, soil type, land use dynamics for instance. We used suitable criterion as such that the data for it is easily accessible and up to date. The data related to the criteria will then be collected through secondary sources for the project.

b) Processing of Data

For some of the point data, they might have to be interpolated for further use. We employed the most suitable method of interpolation in order to interpolate such data. For instance, we used IDW interpolation technique to interpolate rainfall or precipitation data.

For generating a raster buffer around some line features like for a river layer, we will use Euclidean Distance and generate buffer.

c) Extract by Mask and Vector Clip & Project Raster

Extract by Mask and Vector Clip are very similar tools, function wise. We used the tools to extract the exact area of interest. Once the area of interest is acquired, we go for further projection processes.

The projection of raster is generally done to ensure all are in the same coordinate system and of the same cell size.

d) Resampling

Resampling was used to interpolate new cell values when transforming rasters to a new coordinate space or cell size.

e) Reclassify

Reclassifying is the process of assigning new classes with newer distribution values to an existing raster with predefined class values. It helped to delineate class values as per the sub-criteria we have assigned.

f) Weighted Overlay and Suitability Analysis

Once the weights were assigned from AHP and FAHP, we used those weights to perform weighted overlay of the criteria. The weighted overlay helped to delineate the severity zones in our susceptibility analysis according to the respective weights of the criteria.

Once the weighted overlay was done, we assigned flood susceptible zones with the linguistic terms and performed analysis on them.

g) Validation and Analysis

Once the susceptible zones had been obtained, proper validation and analysis were made. Analysis were be based on the severity of the zones obtained.

h) Final Map Preparation

Final maps were prepared accordingly for flood susceptibility. The maps included flood susceptible zones, criteria maps & other graphs.

3.4.2 Flood Susceptibility Criteria and Sub-Criteria Ranges

Figure 3 – 13 describes the rating of sub-criterion according to their effect on the susceptibility in a scale of one extending to five. **Table 3** provides an insight on how the criteria ratings and effect are related to each other

Table 3: Effect and Criteria Ratings

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

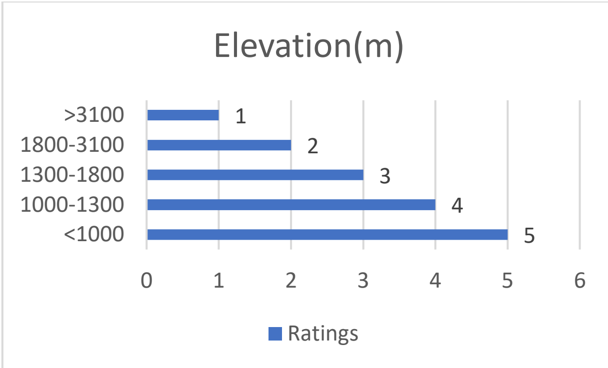

Figure 3: Elevation

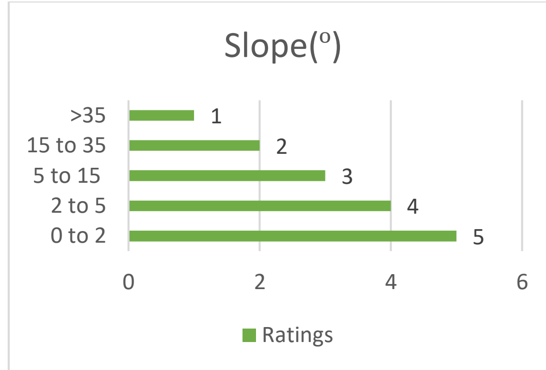

Figure 4: Slope

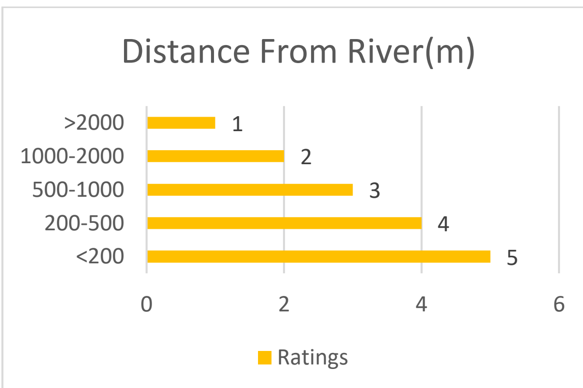

Figure 5: Distance From River

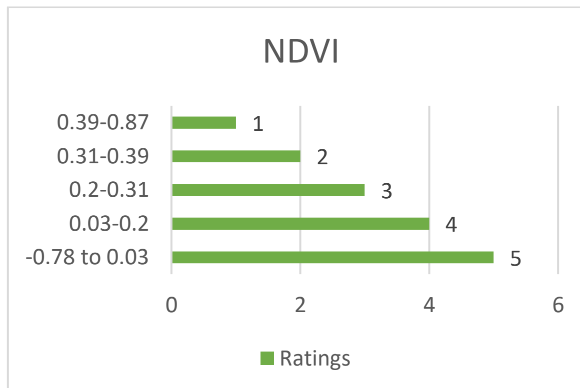

Figure 6: NDVI

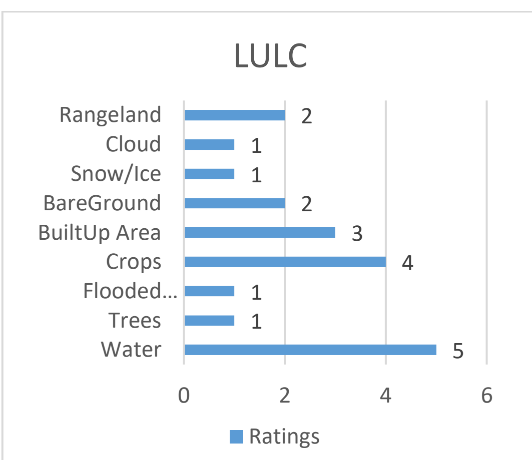

Figure 7: LULC

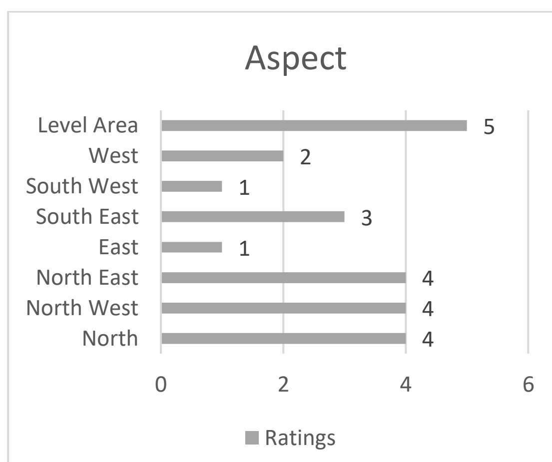

Figure 8: Aspect

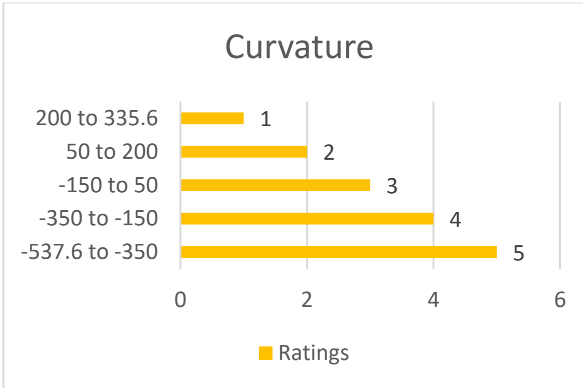

Figure 9: Curvature

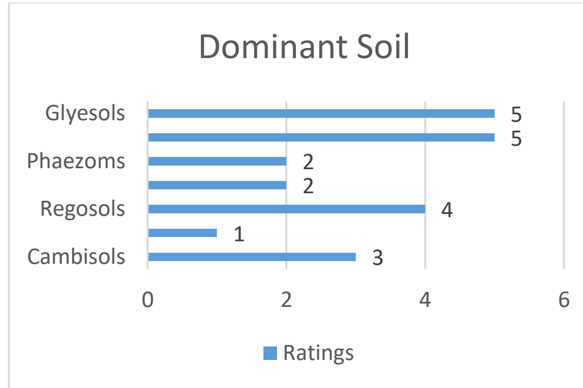

Figure 10: Dominant Soil

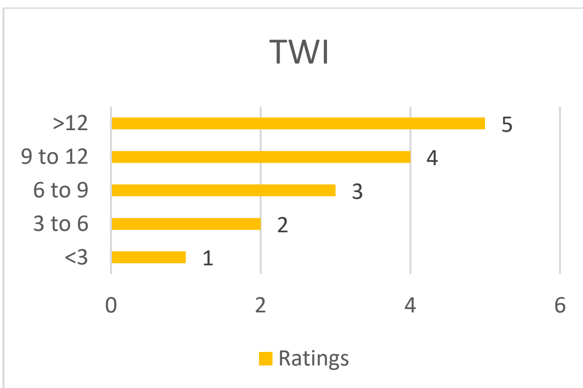

Figure 11: TWI

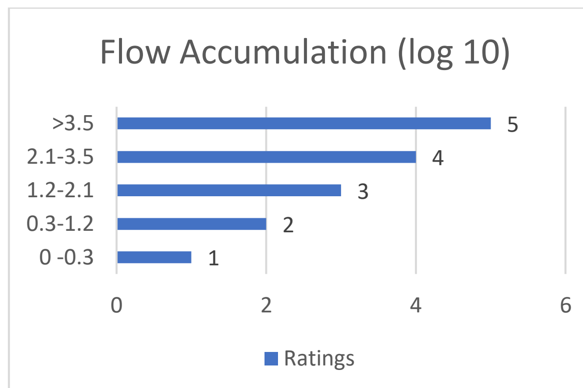

Figure 12: Flow Accumulation

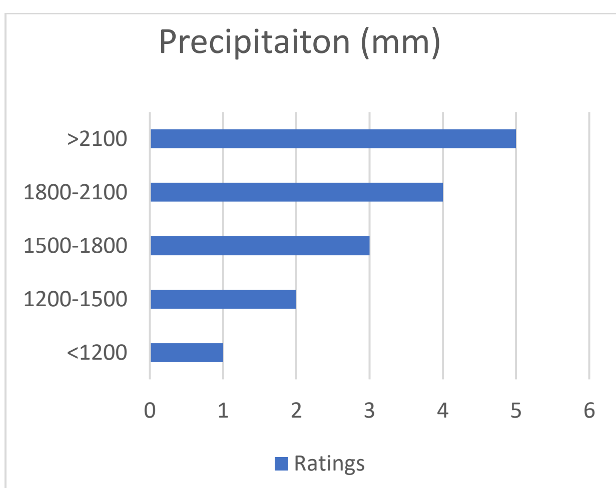

Figure 13: Precipitation

3.4.3 AHP Modelling Approach

After classifying the factors into different themes based on their relative importance to flooding in the study area and assigning appropriate weights to individual themes, the normalized weights of the factors and their different classes were determined using the pairwise comparison method (Sarty, 1990). PCM was developed by Saaty's in 1980 under the name "Analytic Hierarchy Process" (AHP) and is considered an effective way to deal with complex decision-making problems (Saaty & Vargas, 2013). The steps involved were:

Step 1: Defining Objective & Criterion

The major goal or the problem statement and criterion for assessment were identified in the first step. The sub-criteria to the criterion were also identified. **Figure 14** shows the hierarchical modelling in AHP between goals, criteria, sub-criteria and also alternatives.

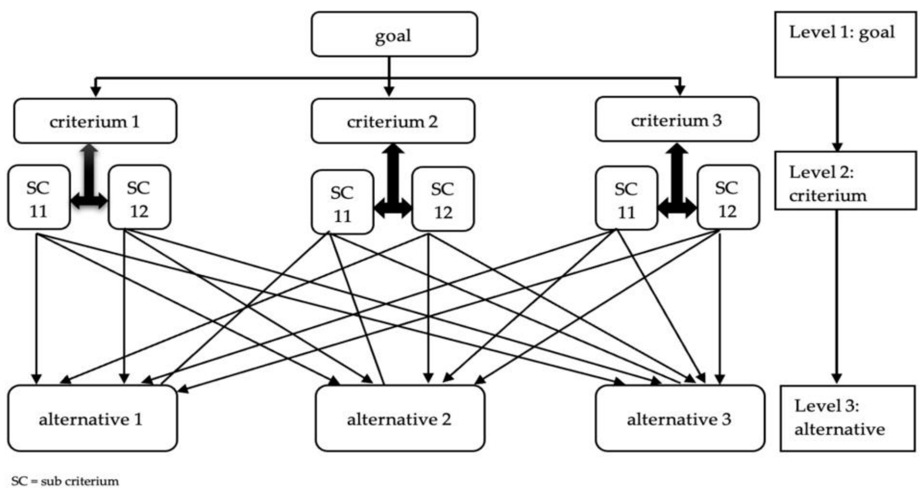

Figure 14: AHP Modelling (Source: (Stofkova et al., 2022))

Step 2: Creating Pairwise Comparison Matrix

Table 4 provides insight on how the pairwise comparison matrix is done and created

Table 4: Pairwise Comparison Matrix(Saaty & Vargas, 2013)

	Element 1	Element 2	....	Element n
Element 1	1	a_{12}	...	a_{1N}
Element 2	$1/a_{12}$	1		a_{2N}
....	...	...	....	...
Element N	$1/a_{1N}$	$1/a_{2N}$	...	1

Step 3: Individual Comparison of Criteria & Comparison Weight Assessment

Table 5 is an indication of the scale values that are used in AHP Modelling while creating a PCM.

Table 5: Scale Values(Saaty & Vargas, 2013)

Intensity of importance	**Definition**
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong or demonstrated importance
9	Extreme importance
2, 4, 6, 8	Intermediate values
1/1 to 1/9	Reciprocals values

The above-mentioned intensity of importance with their definition were used to assign respective weights during individual comparison of criteria v/s criteria.

Step 4: Normalized Weight Calculation

Firstly, from the available pairwise comparison matrix, the sum of each column was calculated. Then, each individual weights in the column were divided by the given column sum to calculate normalized weight. The final criteria weights were calculated by averaging. **Equation 1** shows the calculation of Normalized Weight while **Equation 2** shows the calculation of final criteria weights.

$$B_{ij=}a_{ij}/\sum_{i=1}^{n} a_{ij} \qquad \text{........1}$$

$$W_{ij=}\sum_{j=1}^{n} b_{ij}/\sum_{i=1}^{n} a_{ij}\sum_{j=1}^{n} b_{ij} \qquad \text{........2}$$

Step 5: Estimation of Consistency Ratio

CR should be less than 0.1 or else the weights assigned are inconsistent. 'λ' was calculated by dividing weighted sum with the corresponding entry. The λmax was obtained by averaging 'λ' from all the iterations. **Equation 3** shows the formula to calculate the Consistency Index and **Equation 4** shows the formula to find the Consistency Ratio.

$$\mu = CI = \frac{\lambda\text{max} - \text{n}}{n-1} \qquad \text{........3}$$

$$CR = \frac{CI}{RI} \qquad \text{........4}$$

The final weights obtained after this were used for 'Weighted Overlay'.

PAIRWISE COMPARISON MATRIX IN AHP & WEIGHT OF CRITERIAS

Table 6 shows the final assigned criteria weights from AHP modelling along with the normalized PCM.

Table 6: Weights and PCM for AHP

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

The CR ratio obtained was 7.5% (< 0.1), hence, we used the assigned weights. The PCM was created on the basis of literature reviews from various sources since all the criteria were not available in a single source.

3.4.4 FAHP Modelling Approach

Fuzzy AHP is a synthetic extension of classical AHP method when the fuzziness of the decision makers is considered. The steps of Fuzzy AHP only differs from AHP in the way how the scale is assigned and how the weights are calculated and normalized. We used Triangular Membership Function and Geometric Mean Method for calculations of weight in Fuzzy AHP.

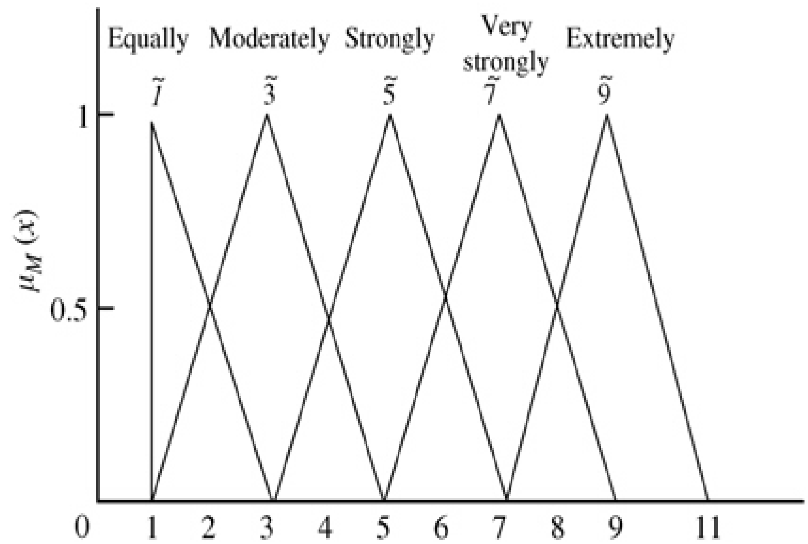

Figure 15: Triangular Membership Function(Kwong & Bai, 2002)

The steps involved in Fuzzy AHP can be enlisted as(Helmy et al., 2021):

Step 1: Define Problem and Planning

We performed similar process or works as in the step 1 of AHP method mentioned above.

Step 2: Fuzzification

In this step, we defined the membership function and the associated fuzzy scale. For our method, we had employed Triangular Membership function and Triangular fuzzy scale which can be visualized as below in **Table 7**.

Table 7: FAHP Scale

Intensity of importance	**Triangular Membership Function**	**Definition**
1	(1,1,1)	Equal importance
3	(2,3,4)	Moderate importance
5	(4,5,6)	Strong importance
7	(6,7,8)	Very strong or demonstrated importance
9	(9,9,9)	Extreme importance
2, 4, 6, 8	(1,2,3), (3,4,5), (5,6,7), (7,8,9)	Intermediate values
1/1 to 1/9	For ½: (1/3,1/2,1/1)	Reciprocals values

We then performed pairwise comparison computation of matrices. A decision matrix n*n was created as **Equation 5**.

$$A = \begin{pmatrix} a11\ a12 \ldots a1n \\ a21\ a22 \ldots a2n \\ \ldots \ldots \ldots \ldots \ldots \\ an1\ an2 \ldots ann \end{pmatrix} \quad \ldots\ldots..5$$

Then, we assigned the fuzzy scale numbers as (l, m, n) where l= m-1 and n=m+1 i.e. one lower value and one upper value from the mid-value as **Table 7.** Reciprocal was assigned likewise from the table.

We then calculated the weight using geometric mean method as:

Fuzzy geometric Mean value(r_i) is

$$A1 \oplus A2 \oplus \ldots \oplus An = (l1, m1, n1) \oplus (l2, m2, n2) \ldots \oplus (ln, mn, nn)$$

$$= (l1*l2*\ldots*ln, m1*m2*\ldots*mn, n1*n2*\ldots*nn) \wedge (1/n), \text{ where n=no. of criteria} \ldots\ldots\ldots 6$$

$$\text{Fuzzy Weight } (W_i) = r_i*(r1 \oplus r2 \oplus \ldots \oplus rn) \wedge -1 \quad \ldots\ldots\ldots 7$$

$$\text{Center of Area of Weights (COA)} = \frac{l+m+n}{3} \quad \ldots\ldots\ldots 8$$

$$\text{Normalized Weight} = \frac{Wi}{\sum_{n}^{i-1} Wi} \quad \ldots\ldots\ldots 9$$

In this way, normalized weight was obtained in the following. Once the weights were obtained, we followed the same process to calculate the Consistency Index and the ratio and use the final weights if the ratio is under the standard value.

Table 7 and **Figure 16** shows the Pairwise Comparative Matrix Distribution and final FAHP weights assigned to each criterion.

PAIRWISE COMPARISON MATRIX IN FAHP & WEIGHT OF CRITERIAS

Table 8: Pairwise Comparison FAHP

	Elevation			Slope			Curvature			Aspect			NDVI			LULC			Distance From River			Dominant Soil			Precipitation			Flow Accumulation			TWI		
	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U	L	M	U
Elevation	1	1	1	2	3	4	2	3	4	2	3	4	3	4	5	2	3	4	1	1	1	3	4	5	2	3	4	4	5	6	1	1	1
Slope	0	0	1	1	1	1	1	2	3	0	1	1	1	1	1	0	1	1	0	0	1	1	2	3	0	0	1	1	2	3	0	0	1
Curvature	0	0	1	0	1	1	1	1	1	1	1	1	1	2	3	0	1	1	0	1	1	0	1	1	0	0	1	1	1	1	0	0	1
Aspect	0	0	1	1	2	3	1	1	1	1	1	1	0	1	1	0	1	1	0	0	0	0	0	1	0	0	0	1	1	1	0	1	1
NDVI	0	0	0	1	1	1	0	1	1	1	2	3	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	0	1	1	0	0	1
LULC	0	0	1	1	2	3	1	2	3	1	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
Distance from Fiver	1	1	1	2	3	4	1	2	3	6	7	8	2	3	4	1	1	1	1	1	1	3	4	5	2	3	4	2	3	4	0	1	1
Dominant Soil	0	0	0	0	1	1	1	2	3	2	3	4	1	1	1	1	1	1	0	0	1	1	1	1	0	0	0	1	2	3	0	0	0
Precipitaiton	0	0	1	1	2	3	2	3	4	3	4	5	1	1	1	1	1	1	0	0	1	4	5	6	1	1	1	2	3	4	0	0	1
Flow Accumulation	0	0	0	0	1	1	1	1	1	1	1	1	1	2	3	1	1	1	0	0	1	0	1	1	0	0	1	1	1	1	0	0	1
TWI	1	1	1	2	3	4	2	3	4	1	2	3	2	3	4	4	5	6	1	2	3	4	5	6	2	3	4	2	3	4	1	1	1

L= Lower
M= Middle
U= Upper

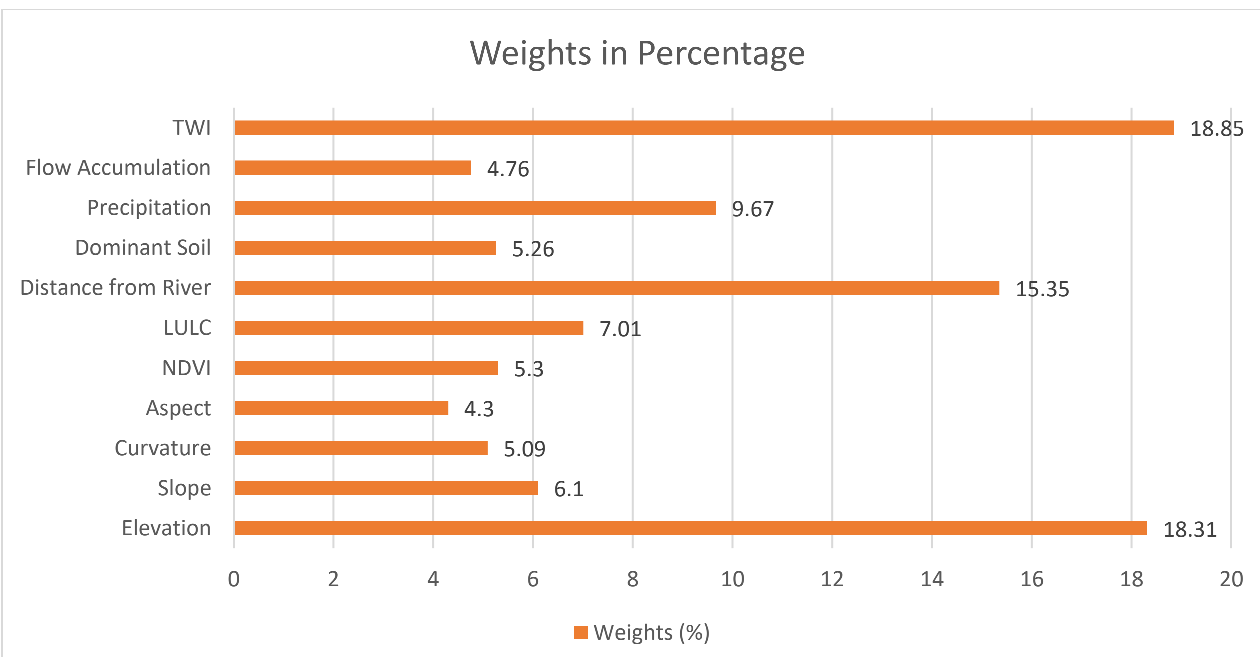

Figure 16: FAHP Weight

CHAPTER 4: RESULTS

The primary result of the project was mainly the AUC Curve or Graphs of the AHP and FAHP model. Using a set of 47 data points of Flood Data from BIPAD Portal, we validated the efficiency of the model and the results. We also constructed eleven criteria maps, flood zoning map, a simple validation map for both AHP and FAHP with four sample points and again with 47 sample points. The **Figures** from **17** to **27** shows the criteria maps. **Figure 28** and **29** shows the AHP and FAHP Models of Flood Susceptibility.

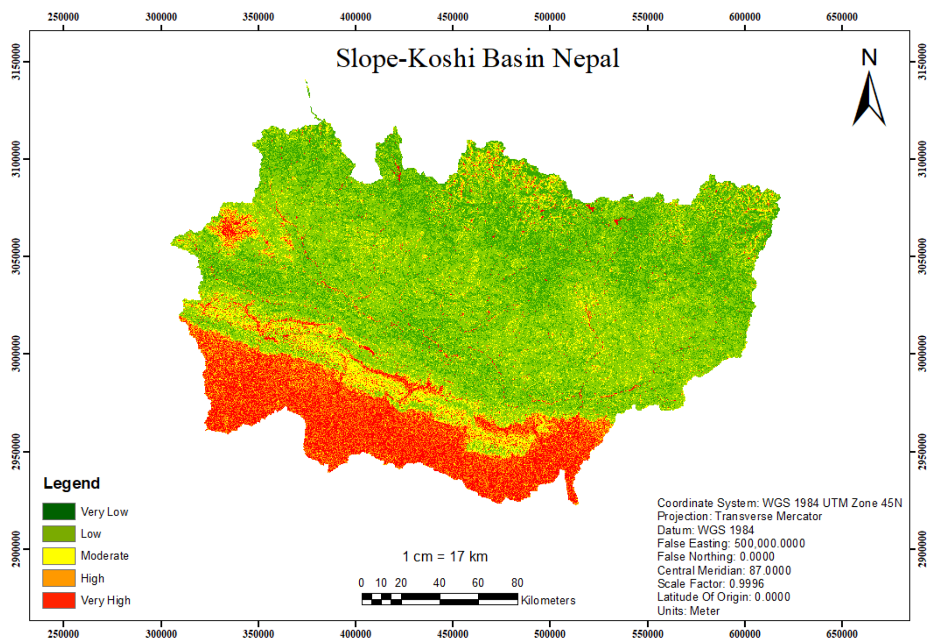

Figure 17: Slope

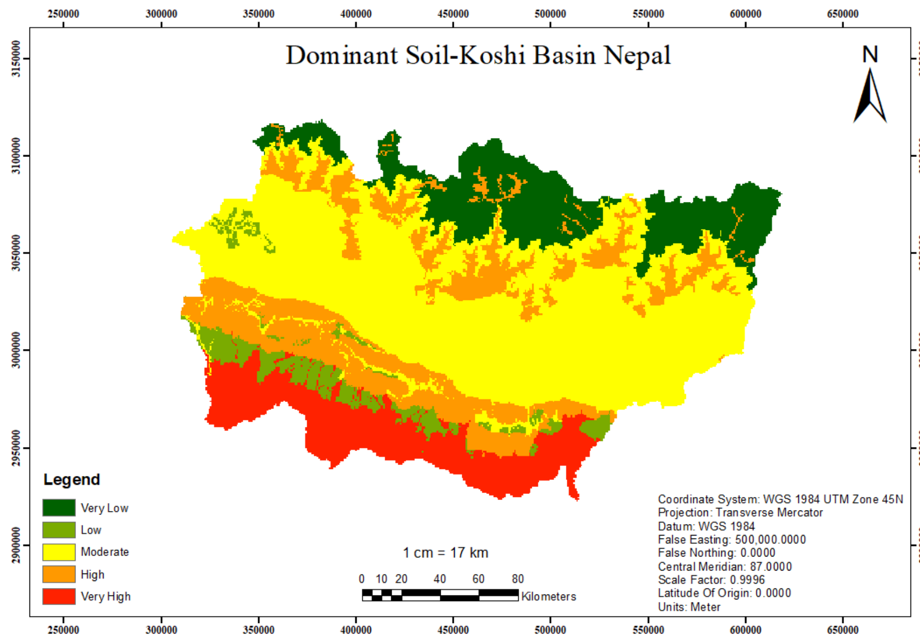

Figure 18: Dominant Soil

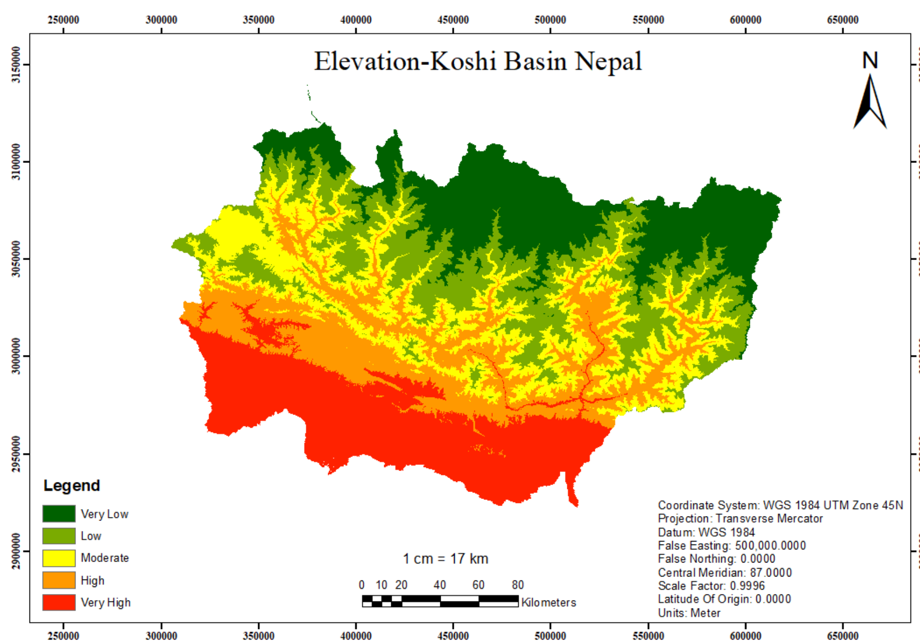

Figure 19: Elevation

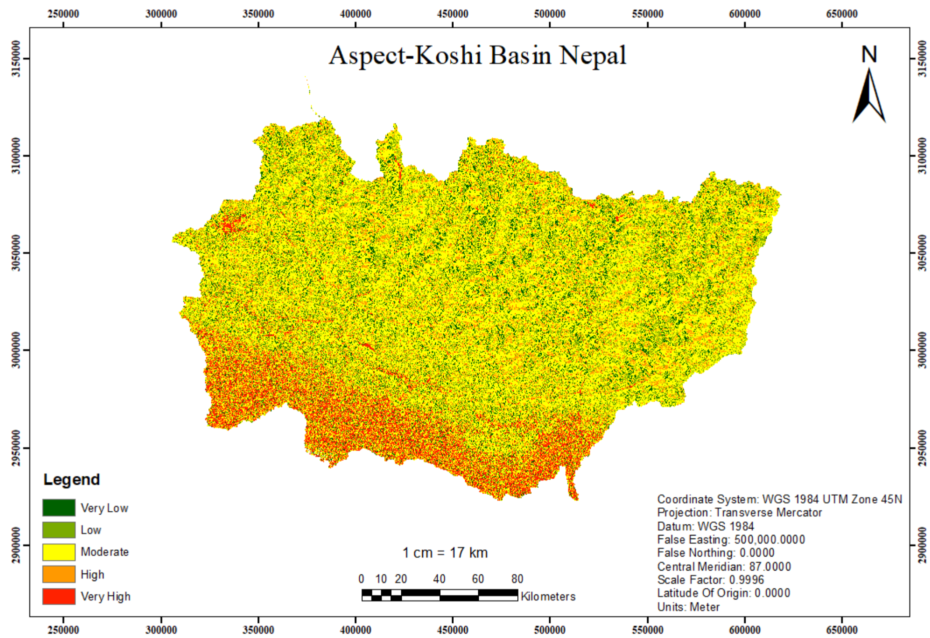

Figure 20: Aspect

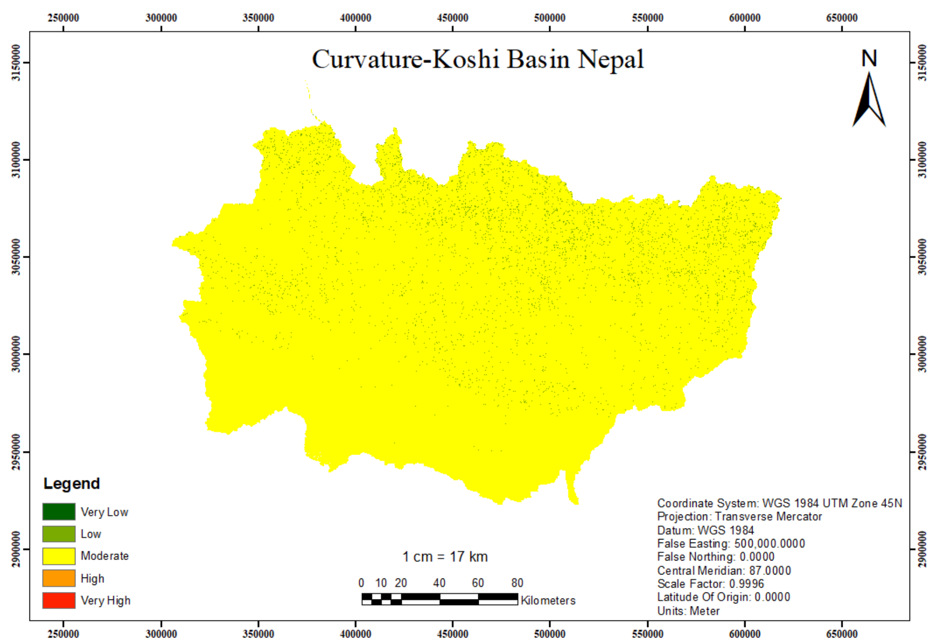

Figure 21: Curvature Map

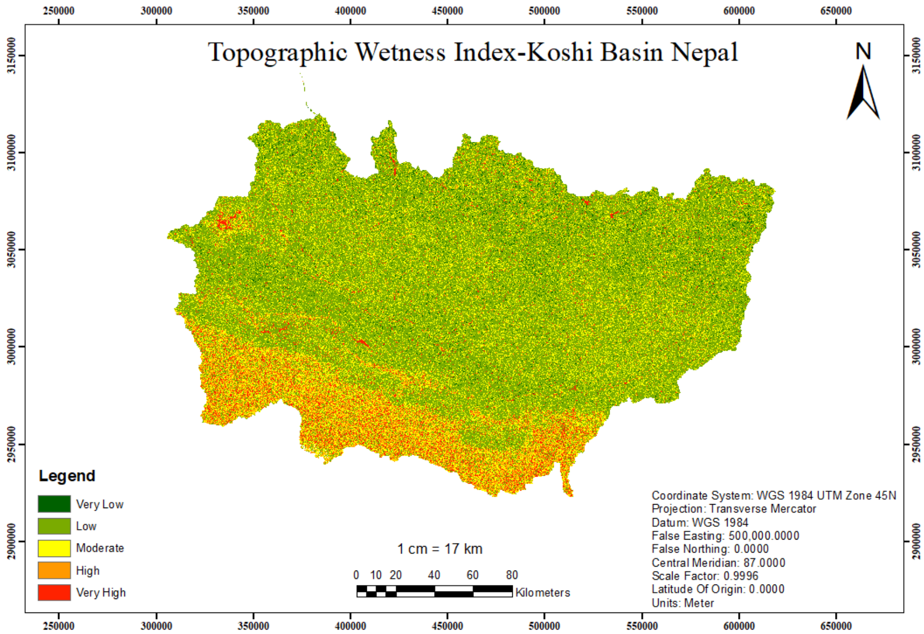

Figure 22: TWI

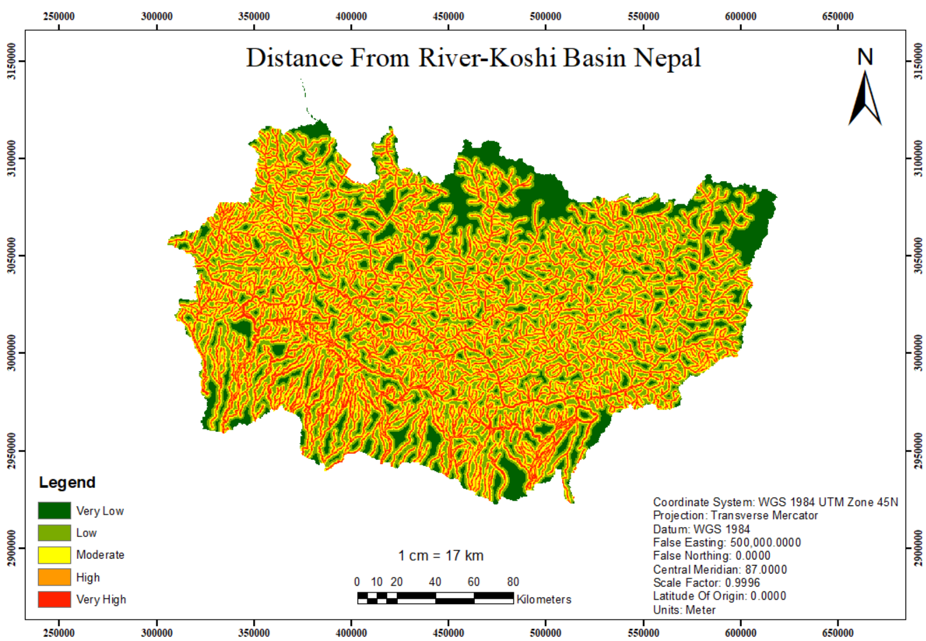

Figure 23: Distance From River

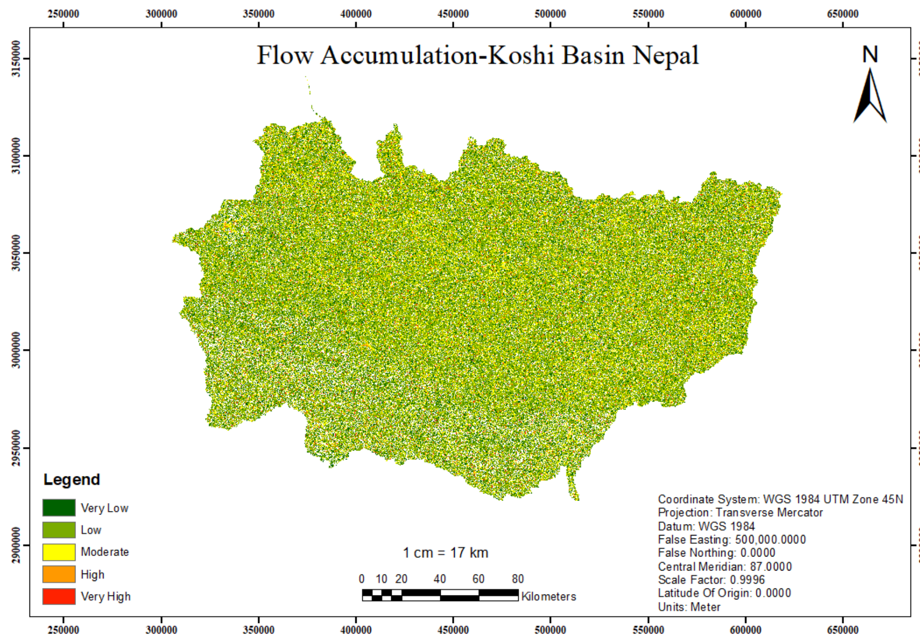

Figure 24: Flow Accumulation

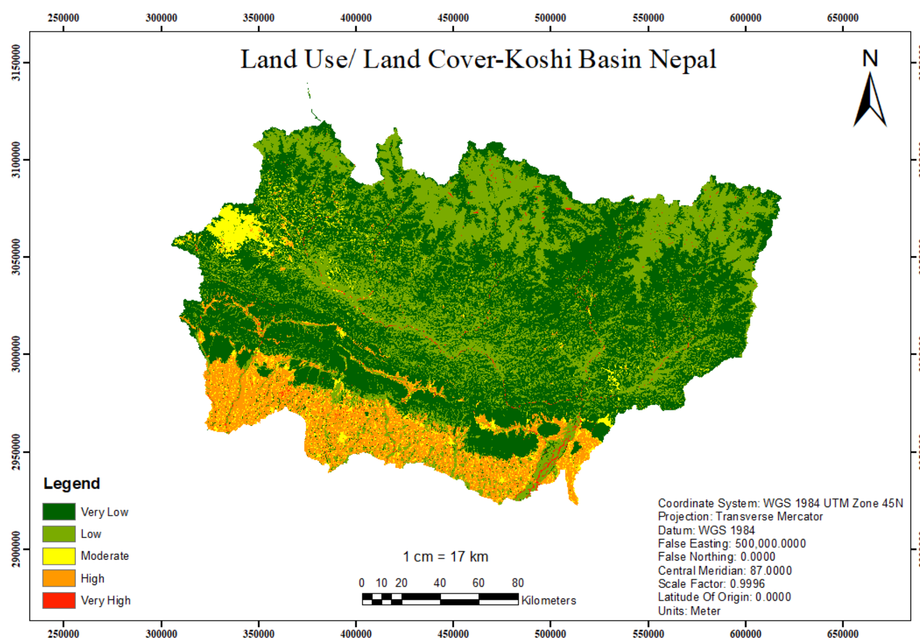

Figure 25: LULC

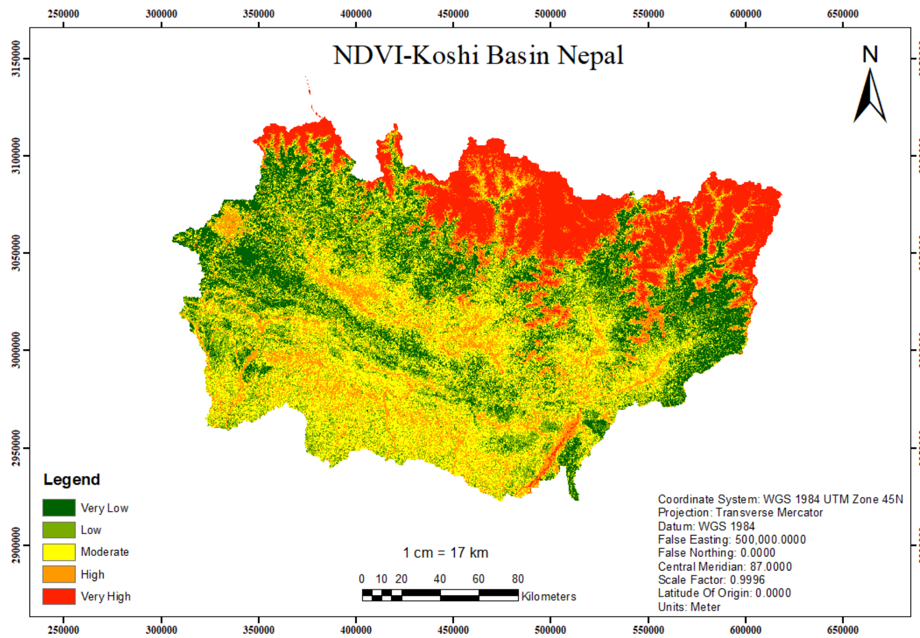

Figure 26: NDVI

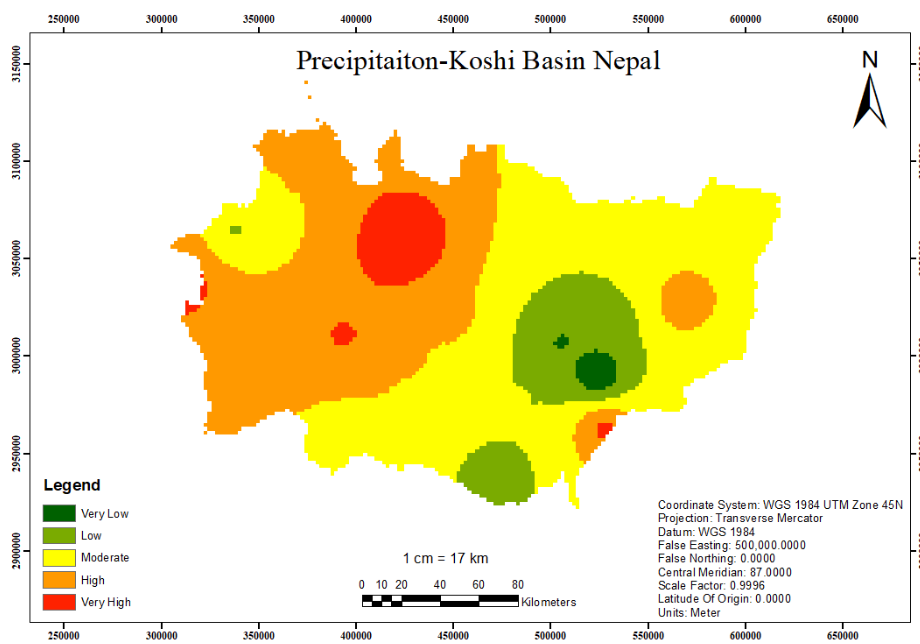

Figure 27: Precipitation

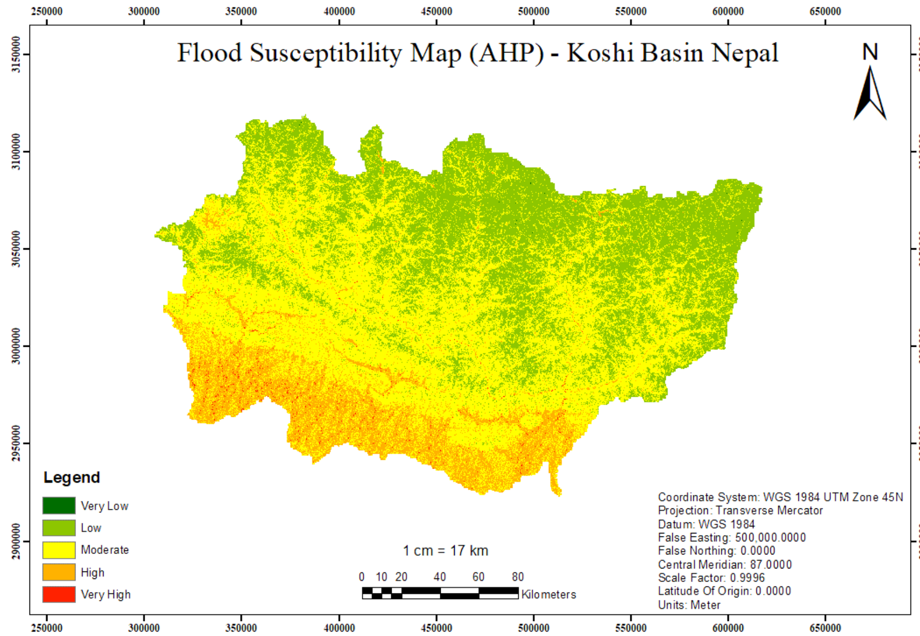

Figure 28: Flood Susceptibility Map (AHP)

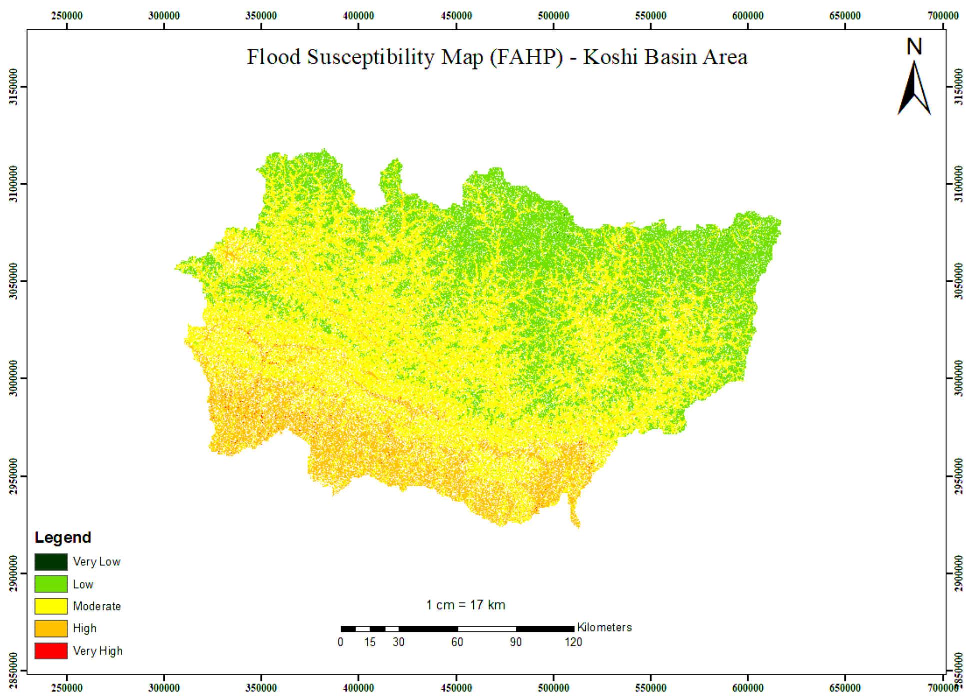

Figure 29: Flood Susceptible Map (FAHP)

The risk areas delineated in the above raster were:

Table 9:Area Coverage (Risk Area)

S.N.	Risk Zones	AHP (% Area Coverage)	FAHP(% Area Coverage)
1	Very Low	0.01	0.01
2	Low	35.04	31.41
3	Moderate	51.88	55.19
4	High	12.67	13.33
5	Very High	0.4	0.07

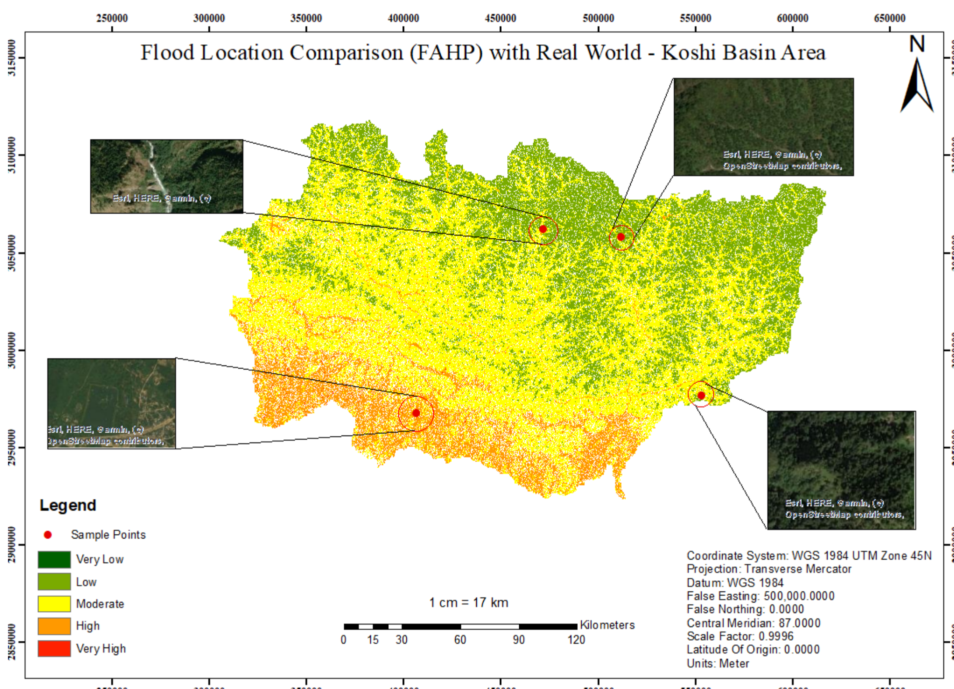

Figure 30: Validation of FAHP Model with real flood and non-flood points

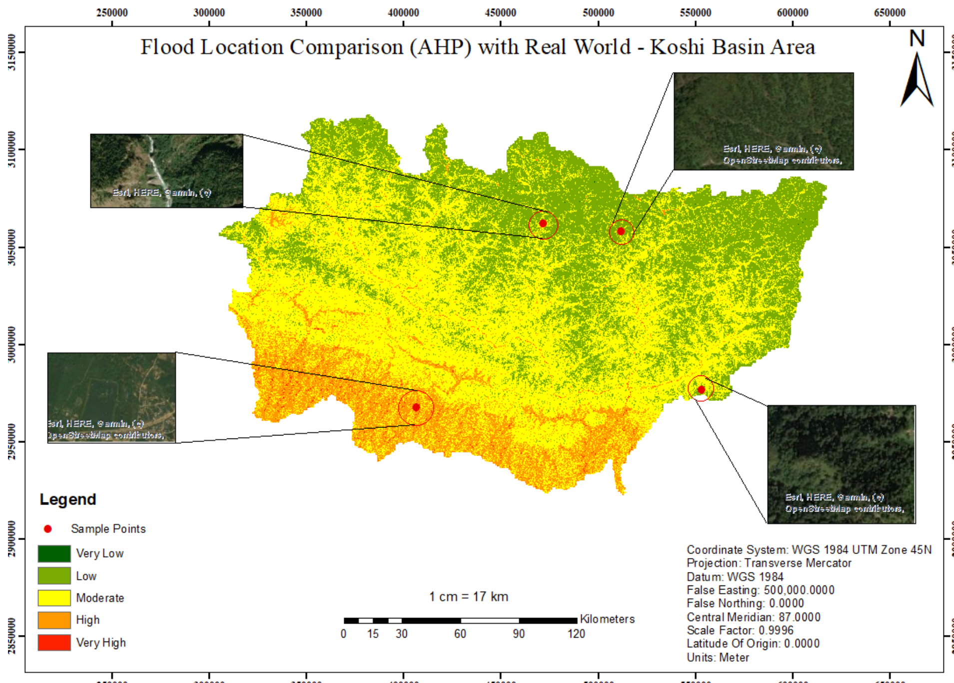

Figure 31 : Validation of FAHP Model with real flood and non-flood points

In the **Figure 30** and **31**, four sample points were placed in the model and the point location were connected to their real-world distribution to check the validity of the susceptible areas in the model.

In the **Figure 32** and **33**, forty-seven sample points were collected from BIPAD Portal complementing the study area. The sample points were point locations of past flooding activities. These sample points were used to create an AUC Curve for both the AHP and FAHP Models, depicted by **Figure 34** and **35.**

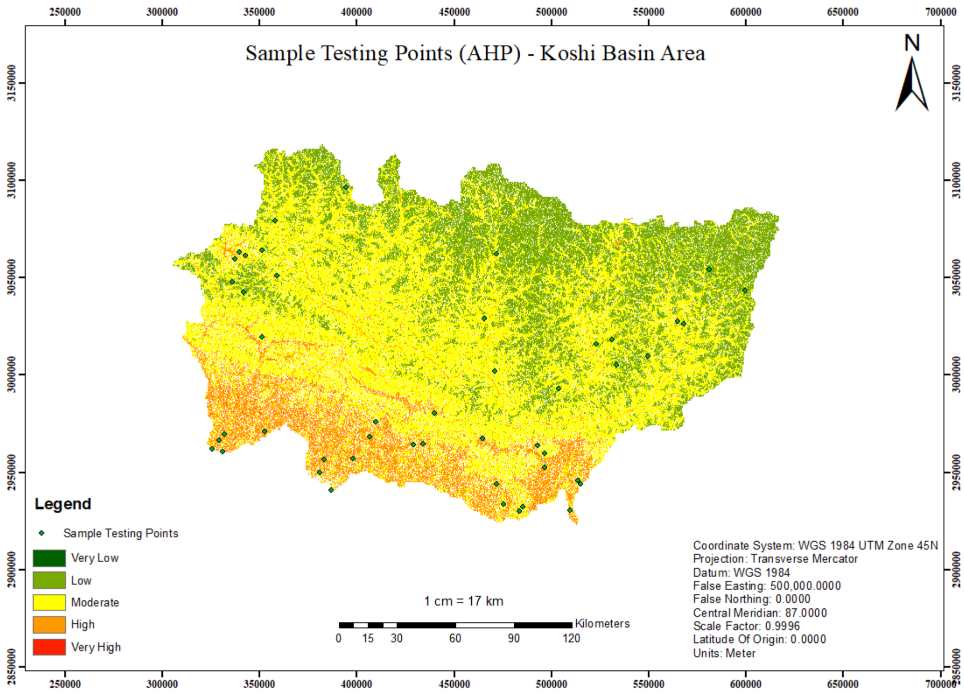

Figure 32: Sample Points in AHP Model

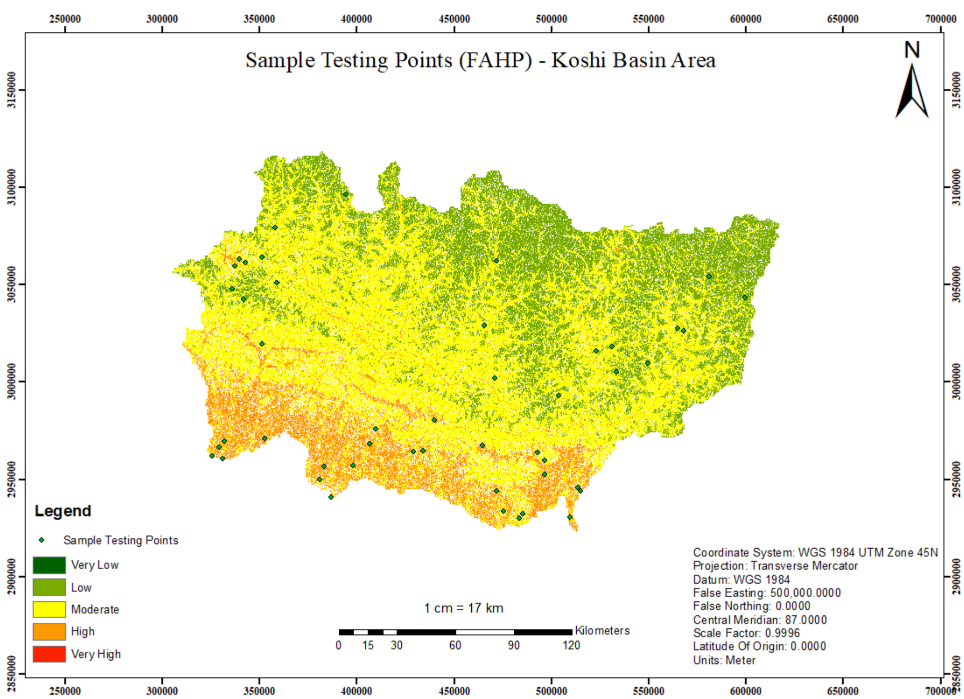

Figure 33: Sample Points in FAHP Model

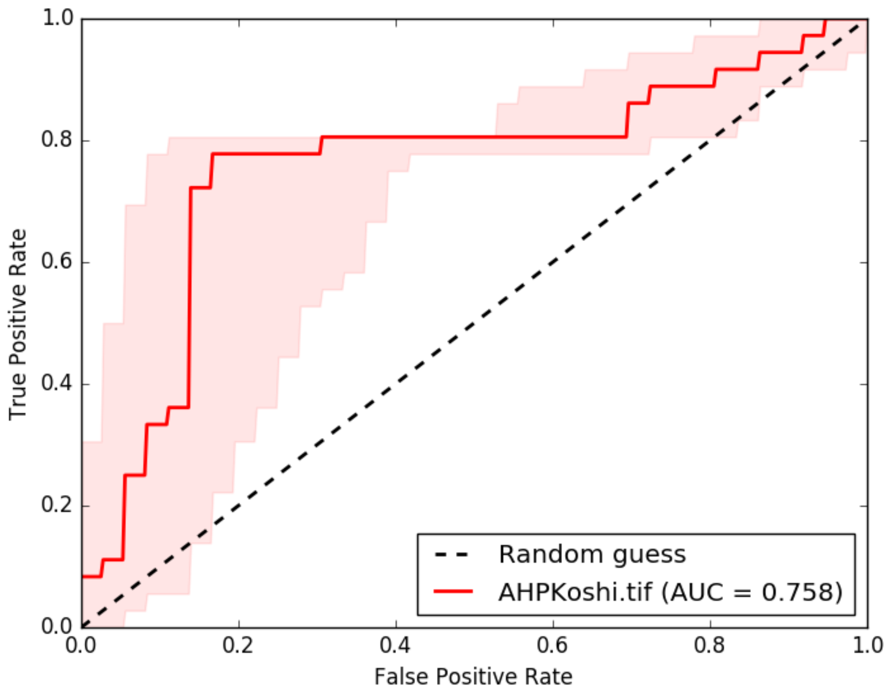

Figure 34: AHP Model (AUC)

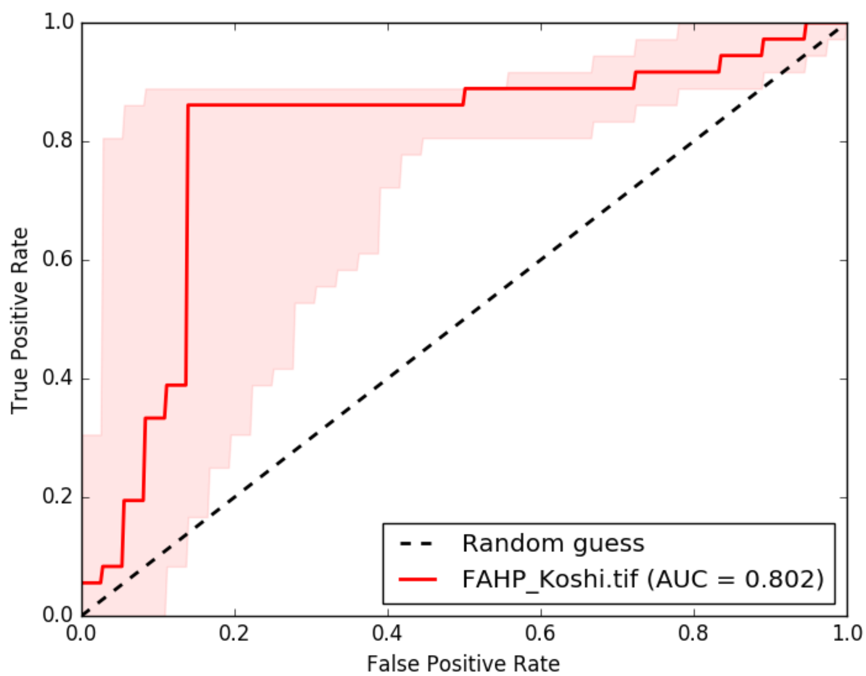

Figure 35: FAHP Model(AUC)

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.

CHAPTER 5: DISCUSSIONS AND 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. 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.

CHAPTER 6: REFERENCES

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CHAPTER 7: ANNEX

Figure 36: NDVI Extracted from GEE (Code Editor)

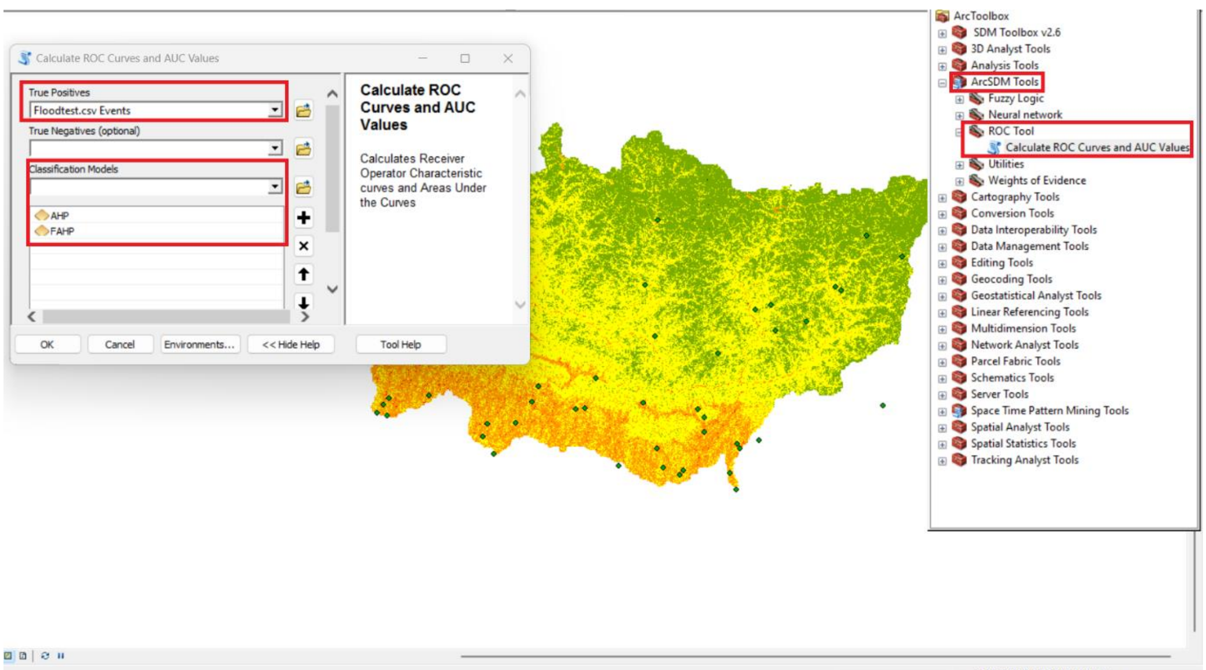

Figure 37:ArcSDM UI & Handling