FLOOD RISK ASSESSMENT IN NARAINAPUR RURAL MUNICIPALITY USING ANALYTICAL HIERARCHY PROCESS

Rubi chaulagain[1], Rekha Paudel[1], Bijaya Adhikari[2]

[1]Paschimanchal Campus

pas077bge034@wrc.edu.np, pas077bge034@wrc.edu.np

[3]Department Of Water Resources And Irrigation - bjayadk012@gmail.com

ABSTRACT

Natural disasters are catastrophic events resulting from natural phenomena that cause significant damage to the environment, property, and human life.Narainapur Rural Municipality, located in Banke District of Lumbini Province, Nepal, is situated at approximately 27.4° N latitude and 81.6° E longitude. This municipality is char- acterized by its flat terrain and proximity to the Rapti River, which significantly influences its hydrology and flood dynamics. For the flood risk assessment using the Analytic Hierarchy Process (AHP), nine key factors were selected: curvature, soil type, distance to road, distance to stream, slope, rainfall, Topographic Wetness Index (TWI), Normalized Difference Vegetation Index (NDVI), and aspect. Each factor plays a significant role in flood susceptibility. AHP is a multi-criteria decision-making approach. The AHP is a decision support tool. It is used to solve complex decision problems, uses a multi-level hierarchical structure of objectives, criteria, sub-criteria and alternatives. Hence, the Consistency Index (CI) for all parameters combined was found to be 0.063, indicating an acceptable level of consistency in the pairwise comparisons. The individual CI values for each parameter were as follows: slope (0.054), NDVI (0.038), soil type (0.070), distance to stream (0.030), rainfall (0.014), TWI (0.022), distance to road (0.015), aspect (0.029), and curvature (0.026). The approach proved effective in identifying areas vulnerable to flooding, providing valuable insights for targeted disaster preparedness and management efforts.

KEYWORDS: Catastrophic, Multi-criteria analysis, Normalized Difference Vegetation Index, Standardization, Infiltration

1. INTRODUCTION

Natural disasters are catastrophic events resulting from natural phenomena that cause significant damage to the environment, property, and human life. The frequency and severity of natural disaster events and their associated social and economic impacts have been increasing (Djalante, 2018). Floods are considered as one of the most dangerous natural disasters spreading worldwide. A flood is a natural phenomenon that results in the short-term submergence of land areas due to extreme rainfall events within a short period of time. A flood occurs when there is partial or complete inundation of normally dry areas due to the rapid accumulation of runoff (Khanday et al., 2022). Climate change may increase the frequency, magnitude, and seasonality of floods, which means that concurrent flood hazards important for flood risk management may occur more frequently in the future (Danumah et al., 2016). The occurrence of floods is a complex phenomenon that has long attracted researchers worldwide to better understand and explore mechanisms for better management and prevention. It is estimated that approximately 1.5 billion people have been affected by floods over the past decades in the 21st century (Khanday et al., 2022). Several factors on which the occurrence of floods depends include land use, geology, slope, rainfall, elevation, and more (Stefanidis & Stathis, 2013; Gacu et al., 2022). Flood hazard evaluation is the basis of flood risk assessment, which has significant implications for the natural environment, human life, and the social economy (Liu et al., 2016). Various methods have been used to evaluate flood-prone areas, including multi-criteria decision analysis (MCDA) methods like Analytical Hierarchy Process (AHP), which rely on expert judgment but may involve uncertainty, and statistical techniques like frequency ratio (FR) and logistic regression, which depend on dataset size and explanatory variables. Physically based models like HEC-RAS and MIKE11 require extensive data and processing power. Newer machine learning methods, such as random forest (RF), artificial neural networks (ANN), and support vector machines (SVM), efficiently identify flood-prone areas and produce susceptibility maps (Choubin et al., 2019). Le Cozannet et al. (2013) assessed the applicability and usefulness of a multi-criteria decision mapping method AHP to map physical coastal vulnerability to erosion and flooding in a structured way. One of the advantages of the AHP method is its extensibility and robustness. If the decision-maker wishes, they can modify the value of a criterion or add or eliminate criteria they deem relevant. The method allows them to readjust the evaluation previously carried out without repeating the entire hierarchy already established. GIS-based flood risk mapping integrated with multi-criteria analysis (MCA), particularly using the AHP, is an efficient, flexible, and low-cost approach for identifying flood prone areas by prioritizing criteria such as slope, distance to streams, soil type, and curve number. Studies have highlighted its adaptability in customizing risk maps based on social or economic vulnerabilities. Additionally, it has demonstrated that including effective precipitation improves accuracy, and its applicability is especially valuable in data-scarce regions, with potential for future enhancements, such as fuzzy logic integration (Rincón et al., 2018). In Nepal, floods frequently occur across various regions, causing significant impacts on lives and livelihoods. To better understand flood scenarios in Nepal, we conducted a thorough review of numerous research papers and studies highlighting the causes, impacts, and management strategies associated with flooding. Floods are among the most frequent natural disasters worldwide, causing substantial economic and social consequences, particularly in resource-constrained countries with limited disaster preparedness and response capacity. In Nepal, unique geographical and climatic conditions heighten vulnerability to multiple hazards such as floods, landslides, and earthquakes, with studies revealing that over 80% of the population is exposed to these risks. Historical events emphasize the severe impacts of multi-hazard scenarios, and the AHP serves as a crucial tool for multi-criteria decision-making in hazard assessments by systematically evaluating factors influencing vulnerability (Khatakho et al., 2021). Flood hazards in Nepal highlight the country's vulnerability due to a combination of geographical, climatic, and socio-economic factors. Nepal's steep mountain topography, high relief, and concentrated monsoon precipitation create an environment prone to severe flooding, leading to significant loss of life and property annually. These factors, along with communities' limited capacity to cope with disasters, contribute to the high vulnerability to floods (Khanal et al., 2007). Nepal faces a persistent struggle with flooding, intensified by its geological features, steep topography, and heavy monsoon rainfall. Floods have historically caused significant loss of life and property, with approximately 7,599 fatalities and economic losses of around 10.6 billion USD recorded between 1954 and 2018. Improper land use, unplanned settlements, and deforestation have further heightened community vulnerability, making effective flood control and prevention measures essential. Flood vulnerability assessments support early warning systems and emergency responses (Malla & Ohgushi, 2024). Similarly, flood assessment and vulnerability analysis highlight the increasing frequency and severity of disasters, emphasizing their profound impact on human lives and assets, particularly in vulnerable communities. The Sendai Framework for Disaster Risk Reduction emphasizes the importance of understanding vulnerability as the capacity of individuals or communities to cope with hazards for effective risk mitigation (Guragain & Doneys, 2022). Additionally, a community based flood damage assessment approach for the lower West Rapti River basin in Nepal, considering the impact of climate change, investigates the effects of climate change on flooding in the West Rapti River (WRR) basin, a vital agricultural region. Using community-based surveys and hydrological modeling, it estimates current and future flood damages, particularly referencing the significant 2007 flood event (Perera et al., 2015). The primary objective of this study is to develop a comprehensive flood risk assessment using the AHP. The secondary objectives include generating detailed thematic maps from high-resolution satellite imagery and Digital Elevation Models (DEMs), obtaining satellite imagery data for accurate ground truth collection, and evaluating the relationship between proximity to streams and slope gradients on flood susceptibility. Furthermore, the study seeks to analyze and classify the study area into high, medium, and low flood risk zones, and to assess the effectiveness of the AHP method in accurately identifying areas vulnerable to flooding.

2. MATERIALS AND METHODS

2.1 Study Area

Narainapur Rural Municipality, located in Banke District of Lumbini Province, Nepal, is situated at approximately 27.4° N latitude and 81.6° E longitude. This municipality is char- acterized by its flat terrain and proximity to the Rapti River, which significantly influences its hydrology and flood dynamics. The area experiences a subtropical monsoon climate, with the majority of its annual rainfall occurring from June to September, leading to substantial flood risks during the monsoon season. BIPAD (Building Information Platform Against Disaster) portal shows the average annual rainfall in Narainapur is around 1,500 mm, which is sufficient to trigger flooding, particularly in low-lying areas adjacent to the river. The demographic profile of Narainapur includes a predominantly agricultural community, with rice, wheat, and sugarcane as the primary crops. The population is dispersed across several settlements, with many households located near the riverbanks, making them particularly susceptible to flood impacts. Historical flood events have caused significant damage to infrastructure, agricultural lands, and housing, displacing any residents and disrupting livelihoods.

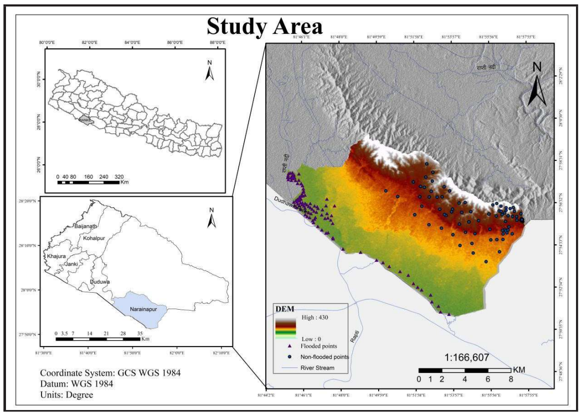

Figure 1. Study Area

2.2 Data Source

A high-resolution Landsat-08 satellite image acquired from March 2023 to October 2023, with a 30-meter spatial resolution, was utilized to generate a land use/ cover map of the study area. Additionally, a 30-meter Digital Elevation Model (DEM) was incorporated. This comprehensive geospatial dataset facilitated the production of detailed thematic maps, including slope, elevation, drainage density, distance to streams and aspect. These parameters are recognized as crucial factors in the generation of flood hazard maps.

Table 1. Data Source

Category	Type	Source	Resolution/ Scale
DEM	Raster	United States Survey(USGS)	30m
Landsat Images	Raster	United States Survey(USGS)	30m
Administrative boundary	Vector	National Geoportal	1 : 1000000
Rainfall	Raster	CHIRPS	5500m
Soil	Vector	National Soil Science Research Center NARC	1:10000

2.3 Flood Conditioning Factor

Slope

In the hydrological study, slope plays a vital role to regulate the flow of surface water, and slit is one of the most important topographic factors for such studies. Land surface slope is one of the effective factors in floods lower the slope higher is the intensity of flood and the higher the slope lower is the intensity of flood occurrence. The slope of a channel in a region is having a direct relationship with the flow velocity When the river slope increases then the flow velocity in the river also will increase. The slope has a direct relation to infiltration. An increase of the surface slope reduces the infiltration process but increases the surface runoff; as a result, in the regions having a lower surface slope, an enormous volume of water becomes stagnant and causes a flood situation. The slope map has been created from the Nasa Copernicus Digital elevation model (DEM) 30 m.

Normalized Difference vegetation index (NDVI)

The NDVI is another factor that is a valuable index in assessing vegetation coverage and its outcome on flooding in a study area. Normally NDVI value ranges from -1 to +1. NDVI map was prepared from satellite image of LANDSAT 8 OLI the NDVI values are calculated from below equation:

$NDVI = (NIR - RED) / (NIR + RED)$................................1

The NDVI values ranged from -0.24 to 0.68 in the study area. Stated that the negative values show water and the positive values show vegetation. So, NDVI has negative relationship with flooding: higher NDVI values indicate lower probability of flood and lower NDVI values indicates higher flood probability.

Soil

The water holding capacity and surface infiltration characteristics of an area are determined by two main factors, such as soil type and texture . In this study, the study area was divided into 3 soil classes : Fluvial Non-Calcareous, Fluvial Calcareous and Sandstone/ Greywacke/Arkose . The soil type map was obtained from the NARC. The produced map was classified on the bases of the infiltration capacity; the weightage has been assigned to each soil type. Then after normalizing the values of soil types and making their pairwise comparsion, we get value 0.07 which is less than 0.1.

Distance from Stream

Distance from the river is one of the most important factors in flood hazard mapping. As the distance increases, the elevation and slope becomes higher. Also, Stream is generally the lowest point of that particular region. As a result of this, areas far from the river are having lower vulnerability of flood occurrence. During floods, river banks get overflowed and submerge the dry land nearby the river. In this study we have classified distance from river in to five classes from very high (0 - 882 m), high (882 – 1,764 m), moderate (1,764 – 2647 m), low (2647 – 3529 m), and very low (3529 – 4,412). Lesser the distance from the river more is the flood vulnerability occurrence and more is the distance from the river lesser is the vulnerability.

Rainfall

It forms the most striking factor since the coastal area districts receive enough rainfall from both northeast and southwest monsoon, but northeast monsoon season (October to December is considered more rainy season than southwest monsoon. For the precipitation of the rainfall distribution map, the rainfall data of all the rain gauge stations have been calculated through the Inverse Distance Weighted (IDW) interpolation tool in ArcGIS 10.8.1 from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS).

Topographic Wetness Index (TWI) Topographic Wetness Index (TWI) indicates the effect of Topography on Runoff Generation and the amount of flow accumulation. The formula for calculating the TWI can be expressed as below:

$TWI = In\ (As/tan\ \beta)$ 2

Where, As represents the area and $\boldsymbol{\beta}$ indicates the local slope gradient in degree. Higher TWI regions have a higher potential of Vulnerability to flooding. Inversely, the lower TWI regions have a lower potential for Vulnerability.

Distance from Road

Distance from the road is also an important factor in quantifying flood vulnerability. During floods when water flows over banks of rivers incites as well as low lying areas flood water enters the roads and streams and damages the public properties and also damages the roads and houses as well.

Aspect

Aspect, or the direction a slope faces, is another vital factor in flood risk assessment, as it affects sun exposure, vegetation cover, and runoff patterns. For example, slopes facing away from direct sunlight tend to retain more moisture, leading to increased flood risk during heavy rainfall.

Curvature

Curvature is an important topographical parameter in flood risk assessment, as it determines the concavity or convexity of the land surface, which directly influences water flow and accumulation. Concave areas tend to collect water, increasing flood vulnerability, while convex areas facilitate water runoff, reducing flood risk.

2.4 Analytic Hierarchy Process

AHP is a multi-criteria decision-making approach and was introduced by Satty. The AHP is a decision support tool. It is used to solve complex decision problems, uses a multi-level hierarchical structure of objectives, criteria, sub criteria and alternatives. It determines the weights and ranks of different parameters for the flood vulnerable zones (FVZ). For preparing the all-thematic layers, the AHP model has been Grouping the prepared thematic maps into five vulnerable categories, an AHP-based pair-wise comparison matrix of different variables described above is constructed. The model is applied to assign varied weights for comparing the ten individual factors, and according to their relative importance, these nine parameters are rated from 1 to 9 as shown in table 2 on an absolute number scale. Pair-wise comparison scale weights on the bases of AHP scale. The selected factors considered for the analysis are as follows: Slope, Curvature, Distance to Stream, NDVI, Soil, Road, Aspect, Rainfall, and TWI. These factors were carefully chosen based on their significance and relevance to the study. The corresponding rating values assigned to each factor, which reflect their relative importance and contribution to the analysis, are presented below.

Table 2. Pair-wise comparison scale weights on the bases of AHP scale

Scale	Judgment of preference	Description
1	Equally Important	Two factors contribute equally to the objective
3	Moderate Important	Experience and judgment slightly favour one over the other
5	Important	Experience and judgment strongly important favour one over the other
7	Very strongly Important	Experience and judgment strongly important favour one over the other
9	Extremely Important	The evidence favoring one over the other is of the highest possible validity
2,4,6,8	Intermediate preference between adjacent scales	When compromised is needed

Consistency ratio

To rectify the constructed pair- wise matrix and its given weightage method is done by the following equation: evaluation through the consistency ratio (CR) was formulated where the acceptable CR must be blow 0.1. In the present study, the consistency of the derived Eigen vector- matrix following the index below found is 0.063 concludes that the set of decision considered is acceptable.

CR = CI/ RI 3

CI = $\lambda max - n/\ n - 1$ 4

Where CR represents the consistency ratio, CI stands for the consistency index, RI indicates the random index., λ max represents the principle Eigen value of the comparison matrix, and n is the number of components or factors in matrix. RI refers to the consistency of the randomly evolved pair-wise matrix depicted in normalized values. The values provided in the table 3 are subjected to various parameters involved in AHP.

Table 3. Random Index (RI) Value

Number of criteria	2	3	4	5	6	7	8	9	10	11
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

FVI = ∑ Wi∗Ri n i=1where WI is the individual weights for individual flood conditioning of each parameter, and RI is the rating class.

The normalized values and the corresponding weight values in the standardized pair-wise comparison matrix are important for ensuring consistency in the Analytical Hierarchy Process (AHP).It ensures that the sum of the values in each column equals one, allowing for the determination of the priority vector or weightage for each criterion. The weightage derived from the normalized pair-wise comparison matrix, calculated based on table-4, is presented below in table-5 which represent the relative importance of each criterion and serve as the foundation for further analysis.

3. RESULT AND ANALYSIS

3.1 Flood Conditioning Factor Map

To ensure consistency and comparability in flood risk assessment, all factor maps were first normalized. This standardization process allows for a uniform scale of analysis, enhancing the accuracy of spatial interpretations. The factor maps were then processed and presented in raster format using a stretched scale to effectively capture variations across the study area. Each factor plays a significant role in flood susceptibility. Curvature influences water flow accumulation by defining terrain shape, while soil type affects infiltration capacity and surface runoff behavior. Distance to roads impacts drainage patterns, and distance to streams determines proximity to potential flood sources. Slope governs water velocity and runoff distribution, whereas rainfall is a direct contributor to flood potential. Topographic Wetness Index (TWI) helps identify moisture retention zones, and Normalized Difference Vegetation Index (NDVI) provides insights into vegetation cover, which influences soil permeability and runoff regulation. The spatial distribution of these factors is essential for understanding flood prone areas and their contributing elements.

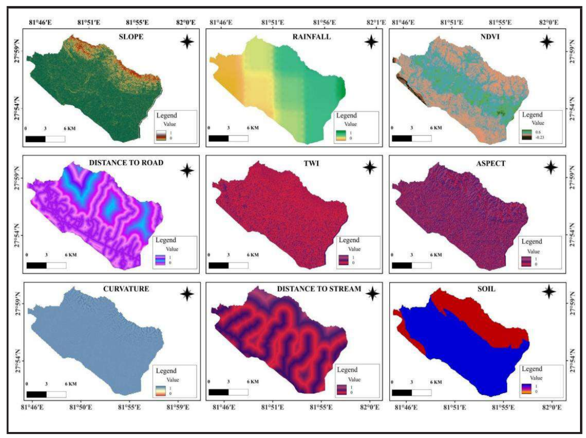

Figure 2. Parameters Map

3.2 Flood Susceptibility Map

The Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) was utilized to assess the significance of various flood conditioning factors. Firstly, the Consistency Ratio (CR) for all factors was calculated to ensure the reliability of the pairwise comparisons, as presented in the table 5. A CR value of less than 0.1 indicates acceptable consistency in the judgments. After verifying consistency, the Pairwise Comparison Matrix was constructed to evaluate the relative importance of each factor in the study area. Based on this matrix, weightages for each factor were determined, which are displayed in the corresponding table 6. Once the weightages were finalized, they were applied to the factor maps to generate a comprehensive flood susceptibility map. The final maps were then classified into five distinct flood risk categories: Very Low, Low, Moderate, High, and Very High as shown in figure 3, ensuring a clear representation of flood-prone areas for effective risk assessment and management.

Table 4. Parameters Criteria

Criteria	Class	Weightage	Remark	C.R
Slope	0.00 -0.05	0.5	Very High	0.054
	0.05 -0.12	0.26	High	
	0.12 -0.22	0.13	Moderate	
	0.22 -0.54	0.07	Low	
	0.54 -1.00	0.03	Very Low	
NDVI	0.00 -0.05	0.52	Very High	0.038
	0.05 -0.16	0.25	High	
	0.16 -0.27	0.13	Moderate	
	0.27 -0.36	0.06	Low	
	0.36 -0.66	0.03	Very Low	
Soil Type	Fluvial Non-Calcareous	0.63	High	
	Fluvial Calcareous	0.26	Moderate	
	Sandstone/Greywacke/Arkose	0.11	Low	0.07
Distance to Stream	0.00 -0.12	0.51	Very Low	0.03
	0.12 -0.25	0.25	Low	
	0.25 -0.41	0.12	Moderate	
	0.41 -0.62	0.07	High	
	0.62-1.00	0.05	Very High	
Rainfall	0.00 -0.17	0.05	Very Low	0.014
	0.17 -0.36	0.08	Low	
	0.36 -0.53	0.13	Moderate	
	0.53 -0.71	0.21	High	
	0.71-1.00	0.53	Very High	
TWI	0.00 -0.24	0.06	Very Low	0.022
	0.24 -0.33	0.09	Low	
	0.33 -0.44	0.14	Moderate	
	0.44 -0.60	0.23	High	
	0.60-1.02	0.48	Very High	
Distance to Road	0.00-0.10	0.43	Very High	0.015
	0.10-0.25	0.26	High	
	0.25-0.43	0.16	Moderate	
	0.43 -0.66	0.09	Low	
	0.66-1	0.06	Very Low	
Aspect	0.00 -0.23	0.53	Very High	0.029
	0.23 -0.41	0.23	High	
	0.41 -0.57	0.12	Moderate	
	0.57 -0.74	0.07	Low	
	0.74 -1.00	0.04	Very Low	
Curvature	0.00 -0.25	0.42	Very High	0.026
	0.25 -0.41	0.26	High	
	0.41 -0.54	0.17	Moderate	
	0.54 -0.68	0.09	Low	
	0.68-1.00	0.06	Very Low	

Table 5.Pair-wise comparison of 9*9 decision matrix

Factors	Slope	Curvature	Distance Stream	NDVI	Soil	Road	Aspect	Rainfall	TWI
Slope	1.00	7.00	3.00	4.00	5.00	9.00	8.00	2.00	6.00
Curvature	0.14	1.00	0.20	0.25	0.33	3.00	2.00	0.17	0.50
Distance to Stream	0.33	5.00	1.00	2.00	3.00	7.00	6.00	0.50	4.00
NDVI	0.25	4.00	0.50	1.00	2.00	6.00	5.00	0.33	3.00
Soil	0.20	3.00	0.33	0.50	1.00	5.00	4.00	0.25	2.00
Road	0.11	0.33	0.14	0.17	0.20	1.00	0.33	0.13	0.25
Aspect	0.13	0.50	0.17	0.20	0.25	3.00	1.00	0.14	0.33
Rainfall	0.50	6.00	2.00	3.00	4.00	8.00	7.00	1.00	5.00
TWI	0.17	2.00	0.25	0.33	0.50	4.00	3.00	0.20	1.00
Total	2.83	28.83	7.59	11.45	16.28	46.00	36.33	4.72	22.08

Table 6. Normalized and the weight values in the standardized pair-wise comparison matrix

Factors	Slope	Curvature	Distance to Stream	Rainfall	Soil	Road	Aspect	NDVI	TWI
Slope	0.35	0.24	0.4	0.35	0.31	0.2	0.22	0.42	0.27
Curvature	0.05	0.03	0.03	0.02	0.02	0.07	0.06	0.04	0.02
Distance to Stream	0.12	0.17	0.13	0.17	0.18	0.15	0.17	0.11	0.18
Rainfall	0.09	0.14	0.07	0.09	0.12	0.13	0.14	0.07	0.14
Soil	0.07	0.1	0.04	0.04	0.06	0.11	0.11	0.05	0.09
Road	0.04	0.01	0.02	0.01	0.01	0.02	0.01	0.03	0.01
Aspect	0.04	0.02	0.02	0.02	0.02	0.07	0.03	0.03	0.02
NDVI	0.18	0.21	0.26	0.26	0.25	0.17	0.19	0.21	0.23
TWI	0.06	0.07	0.03	0.03	0.03	0.09	0.08	0.04	0.05

Therefore, based on the nine variables, the derived RI obtained in the study is 1.49 and the obtained CR is 0.063

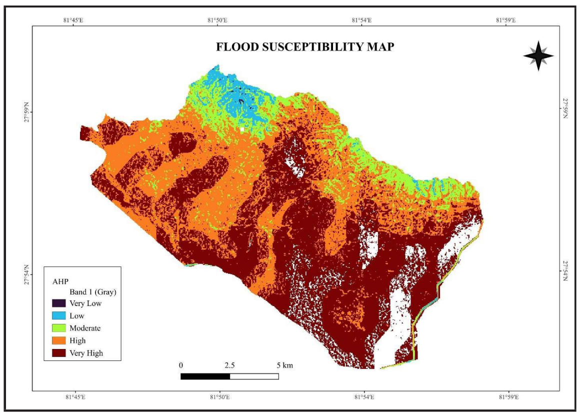

Figure 3. Flood Susceptibility Map

4.CONCLUSION

The flood risk assessment using the Analytic Hierarchy Process (AHP) was successfully conducted by integrating nine causative factors: curvature, soil, distance to road, distance to stream, slope, rainfall, Topographic Wetness Index (TWI), Normalized Difference Vegetation Index (NDVI), and aspect. By assigning appropriate weights through AHP based on the relative importance of each parameter, the study systematically classified the area into different flood risk zones. The approach proved effective in identifying areas vulnerable to flooding, providing valuable insights for targeted disaster preparedness and management efforts.

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AUTHOR INFORMATION

Name	:	Rubi Chaulagain
Academic Qualification	:	BE in Geomatics Engineering
Organization	:	Western Regional Campus
Current Designation	:	Geomatics Engineer
Work Experience	:	3 months
Published Article	:	1