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SCHOOL OF ENGINEERING
DEPARTMENT OF GEOMATICS ENGINEERING

A PROJECT REPORT ON

LANDSLIDE SUSCEPTIBILITY MAPPING OF SINDHUPALCHOK USING GIS-BASED AHP APPROACH

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Submission Date: JULY 6, 2025

Acknowledgement

We would like to express our sincere gratitude to the Department of Geomatics Engineering for providing us with the opportunity and the necessary academic environment to carry out this project. The knowledge, guidance, and resources offered by the department were instrumental in the successful completion of our study on landslide susceptibility mapping.

We are especially thankful to our project supervisors, Prof. Dr. Reshma Shrestha and Er. Sujan Subedi, for their continuous support, encouragement, and constructive feedback throughout the course of this project. Their expertise and thoughtful insights greatly enriched the quality of our work. Their dedication to teaching and mentoring has been a constant source of motivation for us.

We also extend our appreciation to all faculty members, classmates, and anyone who directly or indirectly supported us during this project.

Abstract

Landslides are among the most frequent and damaging natural hazards in Nepal, particularly in mountainous regions like Sindhupalchok District. This study aimed to assess and map landslide susceptibility using Geographic Information Systems (GIS) integrated with the Analytic Hierarchy Process (AHP). Multiple conditioning factors including slope, curvature, rainfall, geology, fault lines, drainage density, land use/land cover, topographic wetness index (TWI), and proximity to rivers and roads were selected based on their relevance to landslide occurrence. The AHP method was used to assign relative weights to each factor based on expert judgment and literature review. These weighted layers were then integrated in a GIS environment to produce a landslide susceptibility map, which classified the study area into five susceptibility zones: low, low moderate, moderate, high, and extremely high. The map was validated using historical landslide inventory data and showed good correlation with past events. The results highlight high-risk areas that require priority attention for disaster risk reduction, land use planning, and infrastructure development. This study demonstrates the effectiveness of combining GIS and AHP for landslide hazard assessment and provides a valuable decision-support tool for local authorities and planners in Sindhupalchok District.

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$\sum$	Summation
□	Exclusive OR
λ	Lambda
μ	Mu
^{o}	Degree

List of Abbreviations

AHP	Analytical Hierarchical Process
MCDA/MCDM	Multi criteria Decision 'Analysis or Making'
GIS	Geographic Information System
RS	Remote Sensing
CR	Consistency Ratio
LULC	Land Use/ Land Cover
RI	Random Consistency Index
CI	Consistency Index

1 Introduction

1.1 Background

Landslides are among the most frequent and destructive natural hazards in mountainous regions worldwide, causing significant loss of life, damage to infrastructure, and disruption to local economies. Globally, landslides account for thousands of fatalities and the displacement of millions of people each year, particularly in tectonically active and high-relief regions (Froude & Petley, 2018). The intensity and frequency of landslides are influenced by a combination of geophysical, climatic, and anthropogenic factors such as steep slopes, weak lithology, intense rainfall, deforestation, and unplanned development (Dahal & Hasegawa, 2008).

In recent decades, climate change, land-use transformation, and increased human intervention in unstable mountainous terrains have heightened the frequency and impact of landslides. Mountain regions like Nepal are particularly vulnerable due to active tectonics, high monsoonal precipitation, and growing rural settlements. Effective landslide hazard management is crucial for minimizing disaster risks and improving community resilience in these sensitive environments.

Landslide susceptibility mapping (LSM) has become an essential approach to assess and manage landslide hazards. LSM helps in identifying areas likely to experience future landslides by analyzing terrain conditions and triggering factors. Advances in Geographic Information Systems (GIS) and Remote Sensing (RS) have significantly improved the accuracy and efficiency of susceptibility mapping by enabling the integration of spatial datasets, terrain modeling, and risk factor analysis (Guzzetti et al., 2005). In addition, Multi-Criteria Decision Analysis (MCDA) methods such as the Analytic Hierarchy Process (AHP) have been increasingly used in landslide studies to assign relative weights to various landslide-influencing factors (Saaty, 1980; Kanungo et al., 2009).

AHP, developed by Thomas Saaty, is particularly effective for landslide assessment because it combines expert knowledge with statistical reasoning to prioritize multiple contributing criteria—such as slope, geology, rainfall, land use, and distance to roads or rivers. The method supports the creation of a structured, hierarchical model that simplifies complex decision-making and enhances the reliability of landslide prediction models (Hammami et al., 2019). When combined with GIS-based spatial analysis, AHP can produce robust susceptibility maps for informed land-use planning and disaster mitigation strategies.

Nepal's topography, fragile geology, and intense monsoon precipitation make it highly susceptible to landslides. Between 1971 and 2020, more than 5,000 landslides were reported, resulting in over 6,000 deaths and widespread destruction (MoHA, 2020). The district of Sindhupalchok is particularly vulnerable, lying within the Main Central Thrust (MCT) zone of the Himalayas. The district has experienced numerous landslide disasters, especially during the monsoon season and post-earthquake periods. Notably, the 2015 Gorkha Earthquake triggered thousands of landslides in Sindhupalchok, with many becoming reactivated during subsequent rainy seasons (Kargel et al., 2016).

Sindhupalchok is characterized by steep slopes, weathered rocks, loose debris deposits, and rapidly expanding road networks. These factors, coupled with frequent intense rainfall and earthquake aftershocks, contribute to widespread slope instability. The 2014 Jure landslide and the 2020 Lidi landslide are prime examples of devastating events that led to mass casualties, blocked rivers, and destroyed communities (DWIDP, 2020; ICIMOD, 2016). In recent years, unplanned road construction, slope undercutting, and deforestation have further aggravated landslide risks in the region (Petley et al., 2007; Paudel & Omura, 2010).

Given these challenges, landslide susceptibility mapping using GIS and AHP in Sindhupalchok is essential for disaster risk reduction and sustainable land-use planning. By integrating terrain parameters such as slope angle, geology, land cover, drainage density, rainfall distribution, and proximity to roads and rivers, a spatially explicit susceptibility map can be produced. This tool can help local governments, planners, and disaster management authorities identify high-risk zones, establish early warning systems, and prioritize mitigation efforts.

The outcome of this project will contribute to enhancing community resilience, guiding infrastructure development, and reducing landslide-induced losses. As climate change continues to increase rainfall variability and as development pressures mount, the need for accurate and dynamic landslide susceptibility assessment in districts like Sindhupalchok has never been more urgent.

1.2 Problem Statement:

Sindhupalchok District has long been recognized as one of the most landslide-prone regions in Nepal. Over the years, frequent landslide events have resulted in significant loss of life, damage to infrastructure, displacement of communities, and disruption of local economies. The catastrophic Jure landslide in 2014 and the Lidi landslide in 2020 are stark examples of the devastating impact of such hazards. Additionally, the 2015 Gorkha Earthquake triggered thousands of landslides in the district, many of which reactivated during subsequent monsoon seasons, further worsening slope instability.

Despite the recurring nature of these disasters, the district lacked a comprehensive and up-to-date landslide susceptibility assessment. Many parts of the region continued to undergo unplanned road construction, slope modification, deforestation, and settlement expansion without adequate consideration of slope stability. These human activities, combined with natural factors such as steep terrain, fragile geology, and intense monsoonal rainfall, significantly increased the landslide risk.

Furthermore, the absence of detailed and scientifically validated susceptibility maps hindered the ability of local governments and stakeholders to implement risk-informed planning, early warning systems, or mitigation strategies. Therefore, a systematic and spatially accurate assessment of landslide susceptibility was required to identify high-risk zones and support disaster risk reduction in Sindhupalchok.

1.3 Objectives

1.3.1 Primary Objectives

The primary objective of this project was to prepare a landslide susceptibility map of Sindhupalchok District using GIS and a Multi-Criteria Decision-Making (MCDM) approach, the Analytic Hierarchy Process (AHP).

1.3.2 Secondary Objectives

Secondary objectives include:

- To identify the key factors influencing landslides in Sindhupalchok, including topographic, geological, hydrological, and land-use characteristics.
- To apply the Analytical Hierarchy Process (AHP) for systematic weighting and prioritization of landslide susceptibility factors.
- To integrate GIS-based spatial analysis for generating and visualizing landslide-prone zones.
- To validate the generated susceptibility map by comparing it with past landslide events and historical landslide inventory data available for the study area.

1.4 Scope of the Project

This project aims to provide a reliable and scientifically based landslide susceptibility map for Sindhupalchok District, which can support multiple real-world applications. The map can assist in the development of early warning systems, helping authorities to issue timely alerts in high-risk zones, especially during the monsoon season. It will also contribute to disaster preparedness and mitigation planning, offering a basis for identifying vulnerable areas and designing appropriate response strategies.

In addition, the project outcomes can guide policy and decision-making by helping planners and local governments prioritize slope stabilization, regulate land use, and plan infrastructure development more sustainably. The susceptibility map can also be used to raise community awareness about landslide hazards and promote safer land-use practices. Furthermore, this work provides a baseline for future research and monitoring, enabling updates and improvements as new data becomes available or environmental conditions change.

2 Literature Review

Landslides are among the most common and destructive natural hazards in mountainous regions of Nepal, posing serious risks to human lives, infrastructure, and the environment. Sindhupalchok District, located in central Nepal, is one of the most landslide-prone districts in the country due to its rugged terrain, weak geological formations, intense monsoon precipitation, and frequent seismic activity (Upreti & Dhital, 1996; Petley et al., 2007).

According to Keller and Blodgett (2004), landslides can be triggered by a variety of factors including geology, slope, climate, vegetation, and water. These factors interact in complex ways to create unstable slope conditions. Turner and Schuster (1996) classify landslides into five types fall, topple, slide, spread, and flow which are all observed in Nepal's hilly and mountainous landscapes. In Sindhupalchok, landslide types such as debris flows, rockfalls, and translational slides are particularly common due to steep topography and unconsolidated surface materials (Dahal & Hasegawa, 2008).

Geologically, Sindhupalchok lies within the Main Central Thrust (MCT) zone, a tectonically active region composed of weak, weathered metamorphic rocks such as schist, quartzite, and gneiss. These rocks are structurally deformed and often fractured, reducing slope stability and making them prone to failure, especially under heavy rainfall or earthquake conditions (Upreti & Dhital, 1996; Dahal et al., 2012). Colluvial deposits and alluvial fan materials along the river valleys also contribute to debris flows and shallow landslides (Hearn et al., 2008).

Climatically, the district receives heavy monsoonal rainfall over 2000 mm annually mainly between June and September. Intense rainfall increases pore-water pressure and reduces soil shear strength, making slopes more susceptible to failure (Gautam & Phaiju, 2013). Dahal and Hasegawa (2008) identified critical rainfall thresholds that can trigger landslides in central Nepal, emphasizing the role of both rainfall intensity and duration. In 2020, a deadly landslide in Lidi village of Sindhupalchok, triggered by heavy monsoon rains, buried homes and killed dozens, illustrating the continuing danger of rainfall-induced landslides (DWIDP, 2020).

Seismic activity is another key landslide-triggering factor in Sindhupalchok. The 2015 Gorkha Earthquake (Mw 7.8) caused over 20,000 landslides across central Nepal, with Sindhupalchok among the worst-affected districts (Kargel et al., 2016). The earthquake destabilized many slopes and left behind cracks and loosened materials, resulting in numerous secondary and delayed landslides in the following monsoon seasons (ICIMOD, 2016). Many of these earthquake-induced landslides were reactivations of pre-existing slide zones, suggesting the importance of historical landslide inventories in susceptibility assessment.

Human activities such as road construction, slope-cutting, deforestation, and haphazard urban expansion have further exacerbated landslide risks in the district. Roads are often constructed without proper drainage systems or slope stabilization measures, which undermines natural slope equilibrium (Petley et al., 2007; Paudel & Omura, 2010). The expansion of settlements onto steep and unstable slopes increases exposure to landslide hazards, particularly in rural areas. Agricultural practices such as terrace farming and overgrazing also contribute to slope degradation (Shrestha et al., 2005).

Vegetation plays a dual role in landslide susceptibility. While root systems can stabilize soil and reduce erosion, deforestation for agriculture, fuelwood, or infrastructure development weakens slope integrity (WECS, 2011). In Sindhupalchok, the removal of forest cover has made many slopes more vulnerable to shallow landslides and soil erosion.

Efforts have been made to assess and map landslide susceptibility using geospatial tools. Dahal et al. (2012) applied logistic regression and GIS-based methods to develop landslide susceptibility maps of Sindhupalchok, identifying high-risk areas along roads and river valleys. Institutions such as ICIMOD and the Department of Mines and Geology (DMG) have emphasized the importance of integrating remote sensing, field data, and community knowledge for effective landslide risk reduction (ICIMOD, 2017).

Landslides not only pose threats to life and property but also reshape the landscape over time. According to Korup (2009), large landslides modify stream networks, alter vegetation distribution, and create long-term geomorphological impacts. In the case of Sindhupalchok, landslides have damaged hydropower infrastructure, blocked rivers, and forced relocation of settlements, illustrating the far-reaching consequences of this hazard (MoHA, 2015).

3 Methodology

3.1 Theoretical/Conceptual Framework

In the developmental context, numerous technological domains have undergone significant breakthroughs and advancements. These include Geographic Information Systems (GIS), Remote Sensing (RS), and other surveying techniques, as well as Multi-Criteria Decision Analysis/Modeling (MCDA/MCDM) approaches and their integration. Effective decision-making in such complex scenarios necessitates a precise understanding and analysis of the multifaceted issues involved to achieve well-informed and sustainable outcomes.

Substantial research has been conducted on addressing landslide hazards through the integration of GIS and MCDA methodologies. Comparative analyses have also been carried out to evaluate the Analytical Hierarchy Process (AHP) against standard decision-making scales. One of the key advancements in the integration of GIS and MCDA techniques for landslide risk assessment has been the delineation of landslide-prone areas based on severity and susceptibility levels. This spatial differentiation enables decision-makers to formulate targeted mitigation strategies for various risk zones.

The integration of MCDA within a GIS environment provides a powerful platform to incorporate diverse socioeconomic, environmental, and topographical parameters influencing landslide susceptibility. Using hierarchical structuring through AHP, decision-makers can effectively address the multidimensional and dynamic nature of landslide phenomena. Studies have shown that while the AHP method typically operates on crisp value scales, it offers a high degree of methodological robustness and mathematical justification, making it a reliable tool for stability-focused hazard analysis and prioritization.

3.2 Study Area

Sindhupalchok District is in the Bagmati Province of central Nepal, approximately 85 km northeast of Kathmandu Valley (Fig. 1). It is bordered by Nuwakot, Kathmandu, Kavrepalanchok, Rasuwa, Dolakha districts, and China to the north. Covering an area of 2,542 km², Sindhupalchok lies between latitudes 27°42′ to 28°11′ N and longitudes 85°27′ to 86°06′ E. The terrain is predominantly hilly and mountainous, with elevations ranging from 593 to 6,959 meters above sea level, and several rivers flowing through the district. The climate varies from subtropical to temperate and alpine zones, with temperatures ranging between 4.0°C and 28.5°C. The district receives an average annual rainfall of approximately 3,604 mm, of which 80% falls during the monsoon season (Nepal Tourism Board, 2008). Intense monsoonal precipitation combined with extensive road construction and slope excavation are the main triggers of landslides in the area. The district had a population of 287,798 in 2011, with a density of about 110 persons per km² (CBS, 2012).

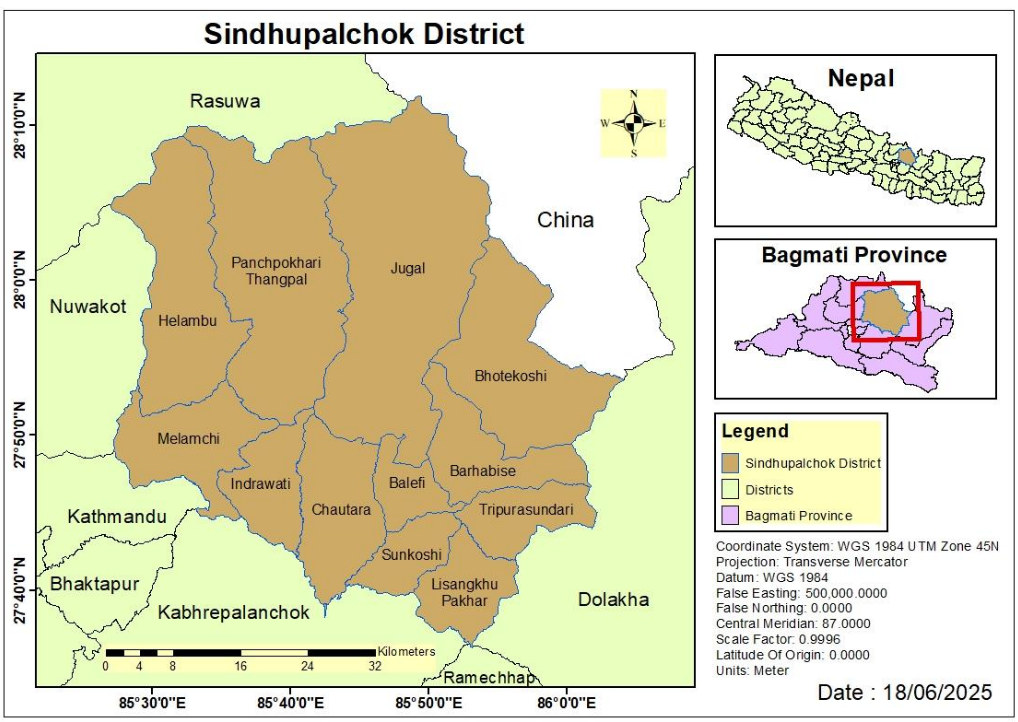


Figure 1: Study Area

3.3 Study Method/ Workflow

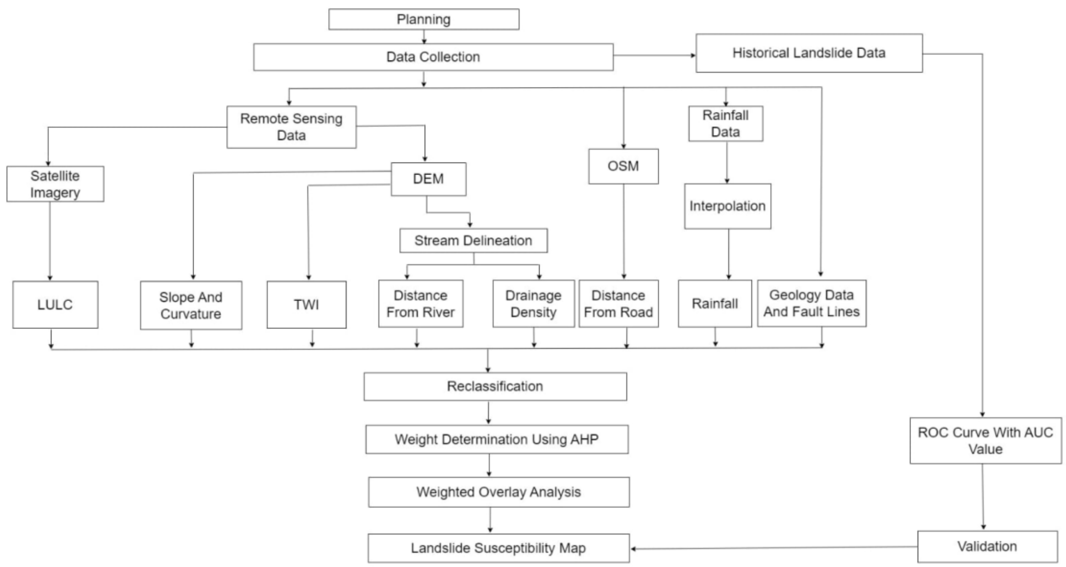


Figure 2: Methodological workflow

3.3.1 GIS Workflow

Determination of Criteria and Data Collection

Landslides are influenced by multiple factors such as slope, rainfall, geology, land use/land cover, TWI, drainage density, and proximity to rivers, roads, and fault lines. Suitable criteria were selected based on data availability, and the required spatial datasets were collected from secondary sources.

Processing of Data

Point data like rainfall were interpolated using the IDW technique to create continuous raster surfaces. Euclidean Distance was used to generate proximity buffers for features like rivers and roads.

Extract by Mask, Vector Clip & Projection

The study area (Sindhupalchok District) was extracted using Extract by Mask and Vector Clip tools. All raster layers were projected into the same coordinate system and cell size to maintain spatial consistency.

Resampling

Resampling was applied where necessary to ensure uniform resolution across all raster datasets.

Reclassification

All factor layers were reclassified into standardized classes based on their contribution to landslide susceptibility, enabling effective integration in the overlay analysis.

Weighted Overlay and Suitability Analysis

Using weights derived from AHP, a weighted overlay was performed to produce the landslide susceptibility map. The map categorized areas into zones like low, moderate, high, and very high susceptibility.

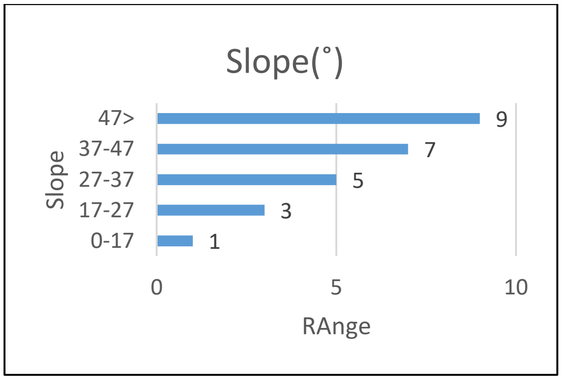
Validation and Analysis

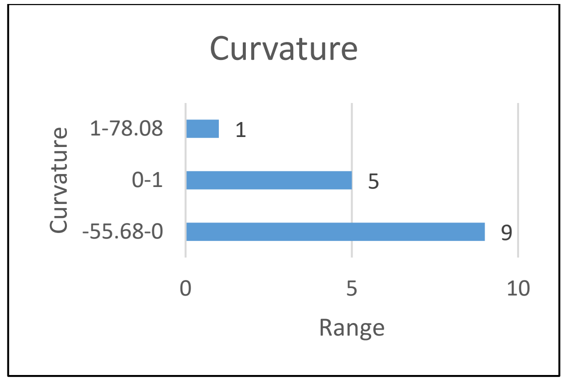
Validation was carried out using historical landslide points identified through Google Earth Pro. These points were overlaid on the susceptibility map to evaluate accuracy by observing their distribution across classified zones.

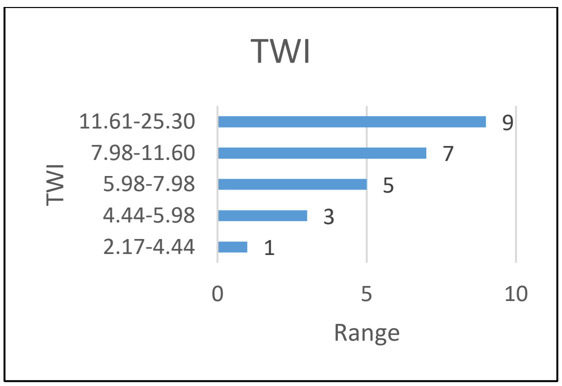
Final Map Preparation

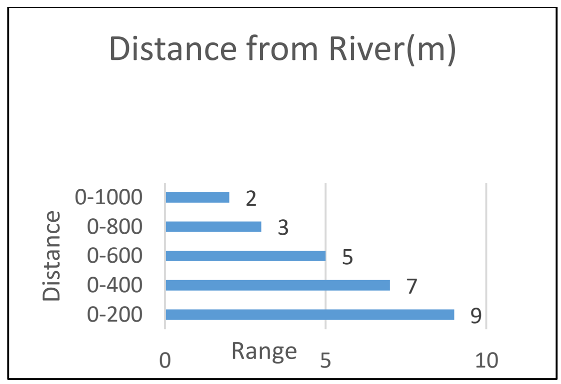
Final maps were prepared, showing landslide susceptibility zones and individual criterion maps. Graphs and supporting visuals were included for better interpretation.

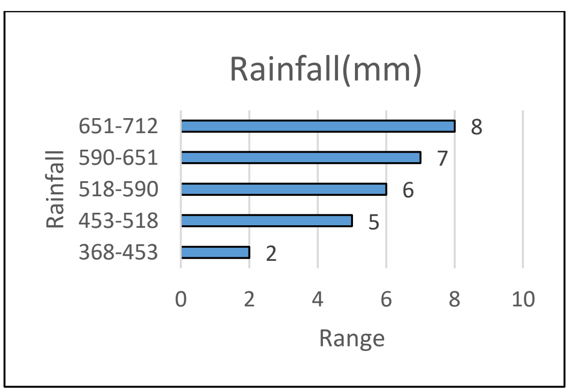
3.3.2. Landslide Susceptibility Criteria and Sub-criteria Ranges

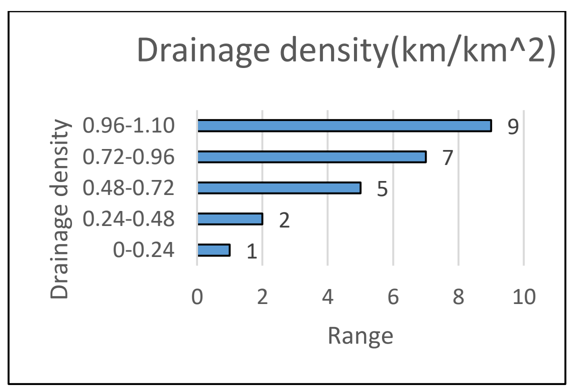












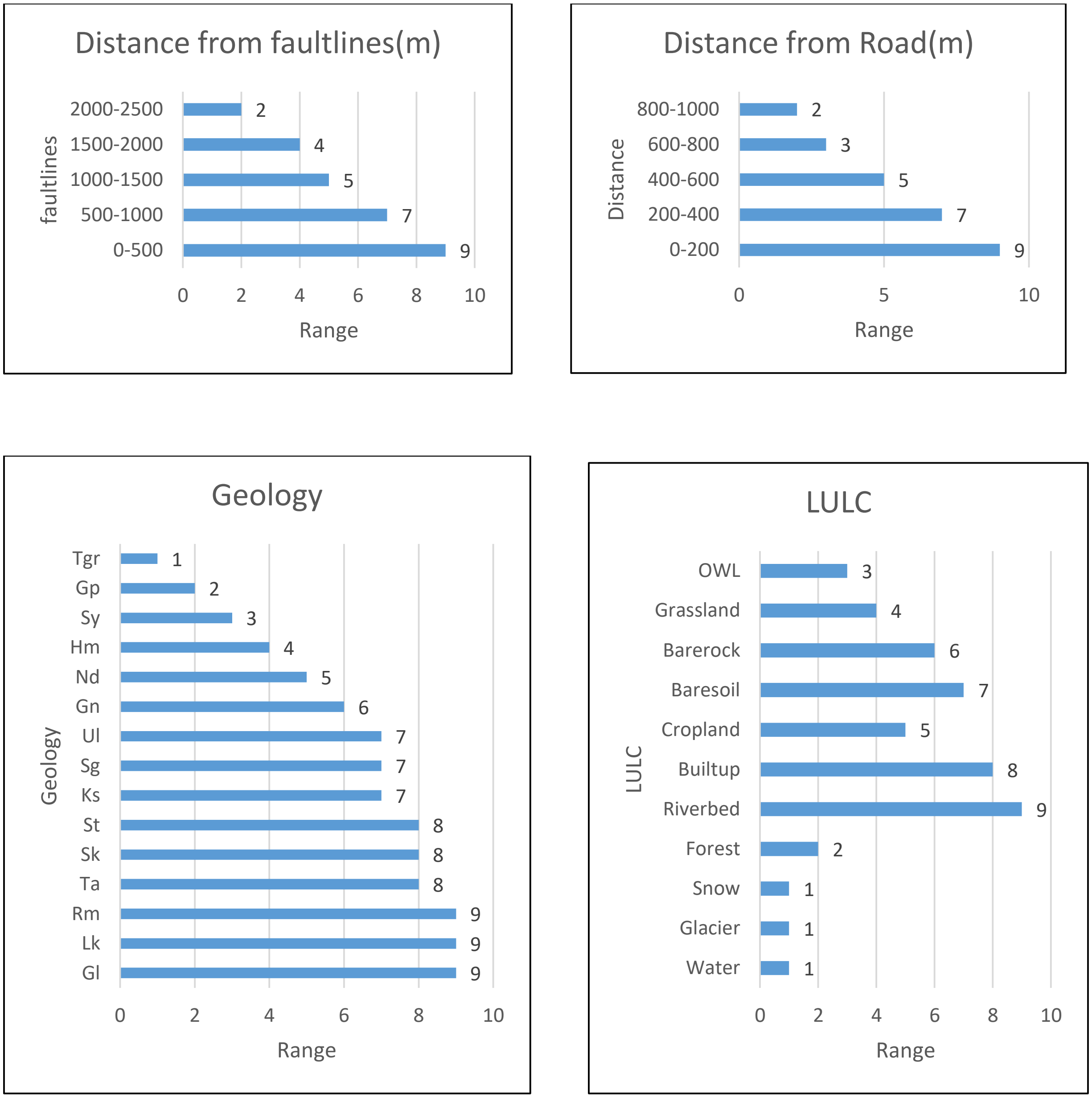


Figure 3: Landslide Susceptibility Criteria and Sub-criteria ranges

3.3.3 AHP Modelling Approach

After classifying the factors into different themes based on their relative importance to landslide 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)

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.

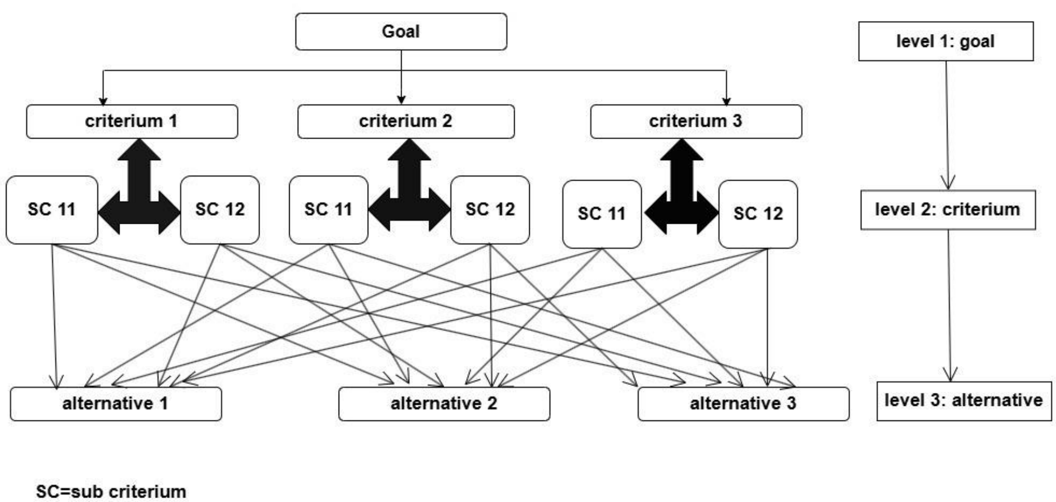


Figure 4: AHP Modelling

Step 2: Creating Pairwise Comparison Matrix

	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

Table 1: Pairwise Comparison Matrix

Step 3: Individual Comparison of Criteria & Comparison Weight Assessment

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

Table 2: Scale 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 then calculated by averaging

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

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

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 the weighted sum by the corresponding entry. The λmax was obtained by averaging λ’ from all the iterations.

$$\mu = CI = \frac{(\lambda max - n)}{n - 1}$$

$$CR = \frac{CI}{RI}$$

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

Pairwise Comparison Matrix in AHP & Weight of Criteria

Resulting Priorities

Priorities

These are the resulting weights for the criteria based on our pairwise comparison

Cat		Priority	Rank	(+)	(-)
1	Slope	24.1%	1	8.2%	8.2%
2	Rainfall	16.6%	2	5.9%	5.9%
3	Geology	14.7%	3	3.3%	3.3%
4	River	10.1%	4	3.7%	3.7%
5	Fault	9.4%	5	3.4%	3.4%
6	Road	8.8%	6	3.8%	3.8%
7	Drainage	5.2%	7	2.1%	2.1%
8	TWI	4.7%	8	1.6%	1.6%
9	Curvature	3.7%	9	2.3%	2.3%
10	LULC	2.6%	10	0.9%	0.9%

Number of comparisons=45

Consistency Ratio CR=5.1%

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
1	1	7	3	2	3	4	3	3	5	3
2		1	1	3	2	3	3	3	5	4
3			1	2	2	2	3	3	5	5
4				1	2	1	2	3	4	4
5					1	2	2	2	4	4
6						1	3	3	4	2
7							1	2	1/2	3
8								1	2	3
9									1	2
10										1

Principal eigen value = 10.685

Eigenvector solution: 5 iterations, delta=1.5E-8

Table 3: Weights and PCM for AHP

3.3.4 Landslide Conditioning Factors and Criteria Selected

The selection of landslide conditioning factors is critical for accurate susceptibility mapping. These factors influence the initiation and occurrence of landslides by affecting terrain stability, water infiltration, and stress distribution along slopes. In this study, the following factors were considered:

1. Slope

Slope is one of the most influential factors in landslide susceptibility. Steeper slopes are generally more prone to failure due to the higher gravitational force acting on the slope materials. Areas with high slope angles often experience more frequent and severe landslides, especially during intense rainfall events or seismic activity. The slope within the study area ranges from 0 degrees to 81.8 degrees.

2. Curvature

Curvature refers to the rate of change of slope and is categorized into plan curvature and profile curvature. It affects surface runoff, erosion, and material accumulation. Concave surfaces tend to accumulate water and sediments, increasing pore pressure and susceptibility to slope failure, whereas convex slopes may be more prone to erosion. The profile curvature of the study area ranges from -55 to 78.

3. Rainfall

Rainfall is a major triggering factor for landslides in Nepal, especially during the monsoon season. Prolonged or intense rainfall leads to increased pore water pressure in the soil, reducing shear strength and triggering slope failures. Rainfall data were interpolated using the IDW technique to reflect spatial variability across the study area. The annual average rainfall of the study area ranges from 367mm to above 712mm.

4. Geology

The geological structure and composition of the underlying rocks and soils significantly influence slope stability. Weak, weathered, or highly fractured rock formations are more susceptible to landslides. Lithological units with low shear strength and high permeability can further exacerbate instability. Altogether, there are 15 classes of geology in the study area.

5. Fault Lines

Proximity to active fault lines increases landslide susceptibility due to the frequent seismic activity and ground deformation in such zones. Fault zones often contain fractured and crushed materials, which reduce slope strength and make them vulnerable to failure, especially during earthquakes or heavy rains.

6. Topographic Wetness Index (TWI)

TWI indicates the potential of an area to accumulate moisture based on slope and upstream catchment area. Higher TWI values are associated with wetter zones where water infiltration and saturation are more likely, thus increasing landslide risk due to reduced soil cohesion. The TWI value of the study area varies from 2 to 25.

7. Drainage Density

Drainage density refers to the total length of streams and rivers per unit area. Areas with high drainage density tend to have increased surface runoff and greater potential for slope erosion and failure. This parameter also reflects the dissection level of the terrain, influencing water concentration and soil saturation. The drainage density within the study area ranges from 0 to 1.29 kilometers per square kilometer.

8. Land Use/Land Cover (LULC)

LULC greatly influences landslide susceptibility by affecting surface runoff, infiltration, and vegetation cover. Forested areas typically stabilize slopes through root reinforcement, while barren land, urban areas, and agricultural zones may contribute to instability due to vegetation removal and surface disturbance.

9. Distance from Rivers

Areas near rivers are more susceptible to landslides due to riverbank erosion, undercutting, and saturation of lower slope zones. The destabilization caused by flowing water weakens slope support, particularly in monsoon seasons when river discharge increases.

10. Distance from Roads

Road construction, particularly in hilly terrains like Sindhupalchok, often disturbs natural slopes and drainage patterns. Slopes near roads are vulnerable due to excavation, vibration, improper drainage, and slope loading. Therefore, proximity to roads is a critical human-induced factor in landslide studies.

3.4 Data Sources Used

The following data sources were used in the project:

S.N	Data Type	Description	Source
1	DEM Data	Elevation Data Nepal (ALSO PALSAR DEM 12.5)	https://search.asf.alaska.edu
2	Slope	Extracted from DEM	DEM 12.5
3	Curvature	Extracted from DEM	DEM 12.5
4	Hydrology	River Network of Nepal	https://rds.icimod.org
5	Precipitation	Annual Precipitation	https://chrsdata.eng.uci.edu/
6	LULC	Land Use Land Cover	https://rds.icimod.org/
7	Road	Extracted from OSM	https://extract.bbbike.org/
8	TWI	Extracted in GIS using slope tangent and flow accumulation scaled	DEM 12.5
9	Fault	Extracted distance from the fault line	Department of Geology and Mining
10	Geology	Types of soil and rocks	Department of Geology and Mining
11	Drainage	Extracted from DEM	DEM 12.5

Table 4: Data Sources

3.5 Software Used

The following software were used to achieve project goals:

- ArcMap:

ArcMap is the former main component of ESRI's ArcGIS suite of geospatial processing programs. Used primarily to view, edit, create, and analyze geospatial data. ArcMap allows the user to explore data within a data set, symbolize features accordingly, and create maps. It was used in our project to make and analyze all the landslide susceptibility maps by using its various analysis and decision-making tools.

- Microsoft Excel:

Excel is a spreadsheet program from Microsoft and a component of its Office product group for business applications. Microsoft Excel enables users to format, organize and calculate data in a spreadsheet. It was used in the project to manage the criteria and create pairwise comparison matrices and in turn calculate the final weights to use in GIS

4 Outcomes and Discussions

The primary result of the project was mainly the AUC Curve or Graphs of the AHP model. Using a set of landslide data points from Google Earth Pro, we validated the efficiency of the model and the results. We also constructed 10 criteria maps, a validation map, and a final landslide susceptibility map.

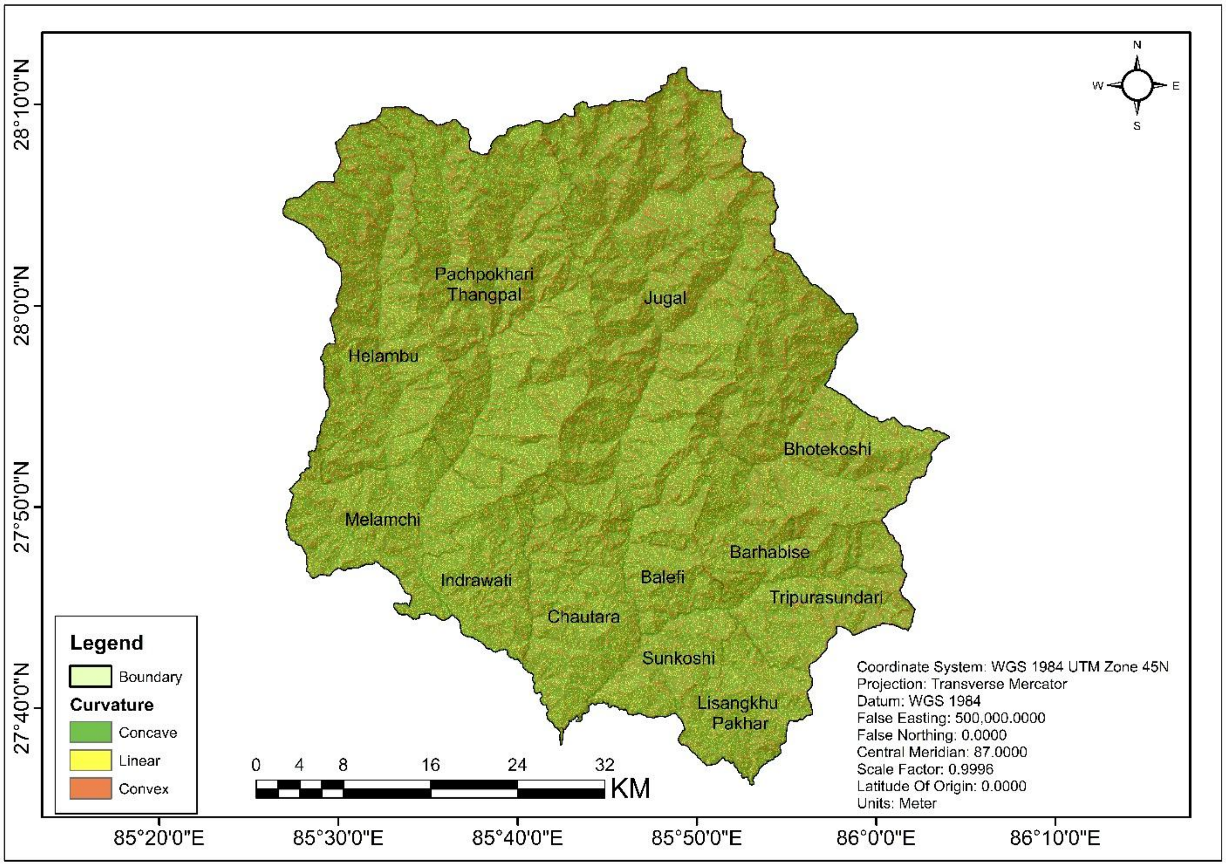


Figure 5: Curvature Map

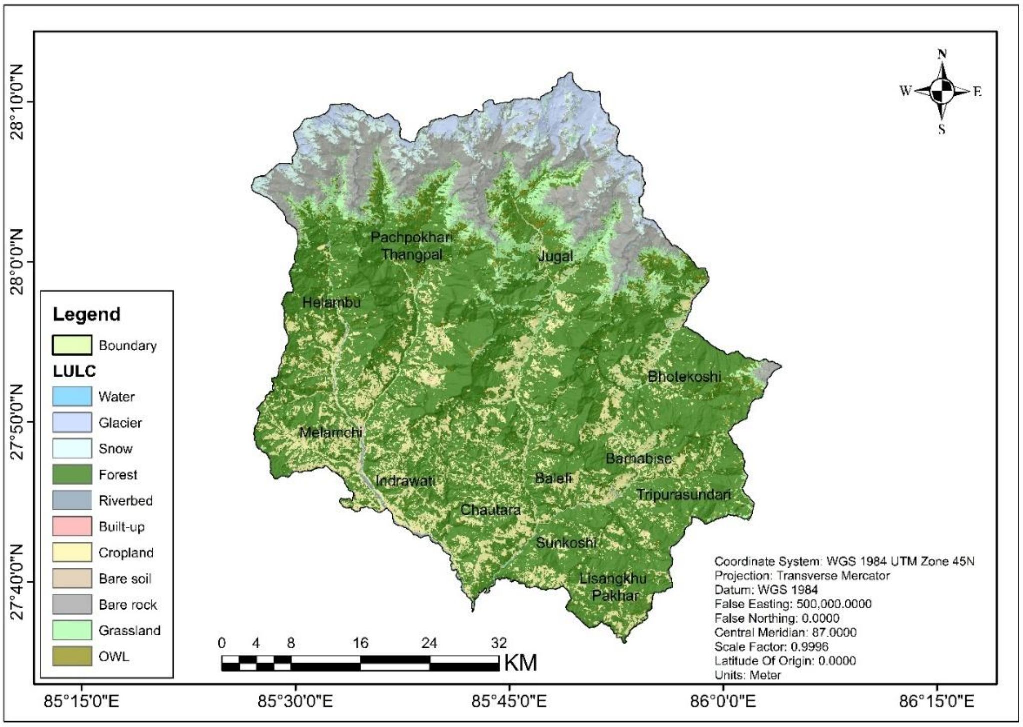


Figure 6: LULC Map

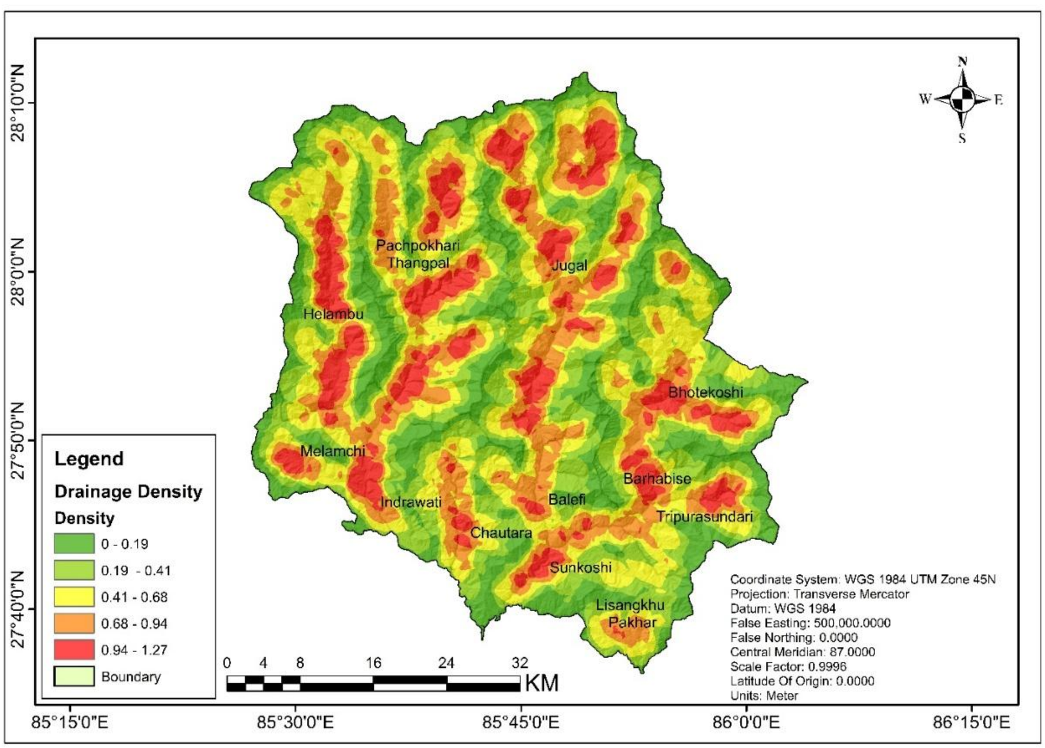


Figure 7: Drainage Density Map

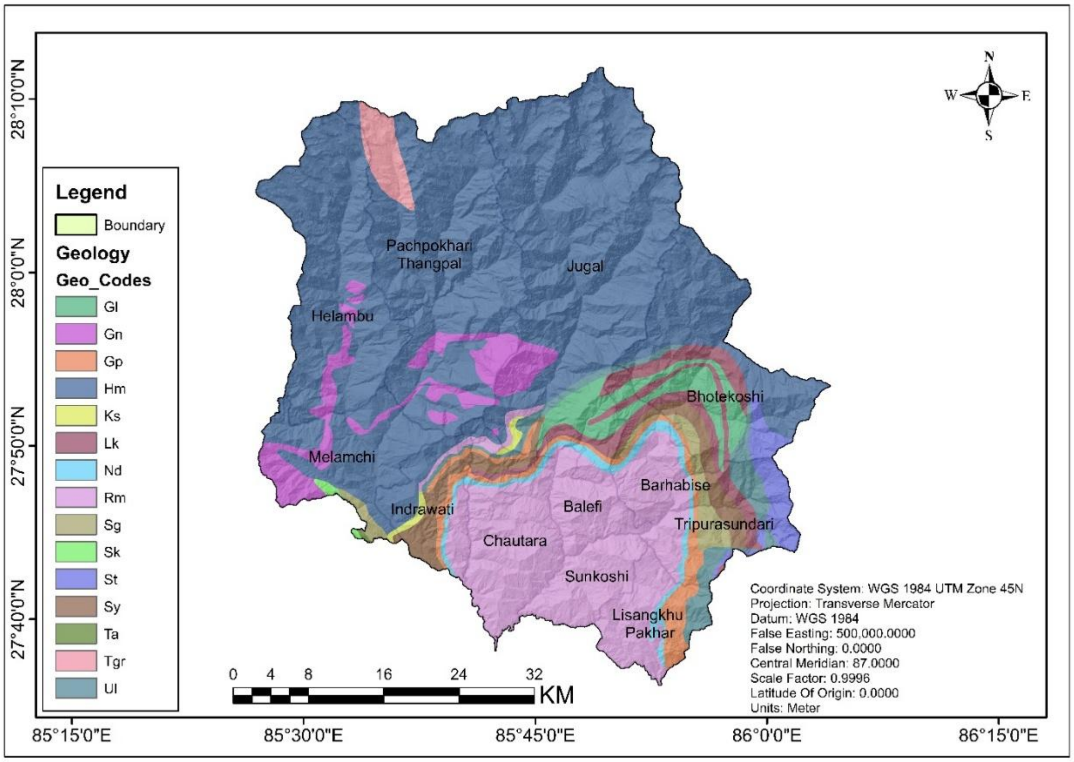


Figure 8: Geology Map

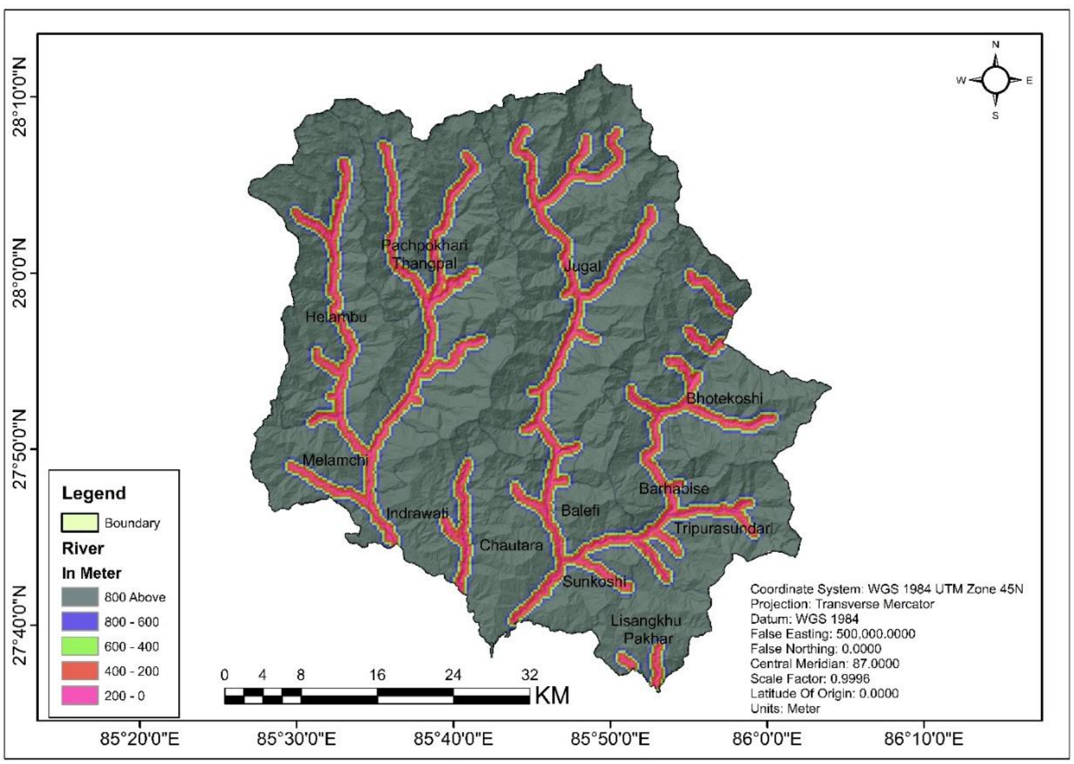


Figure 9: Distance from River Map

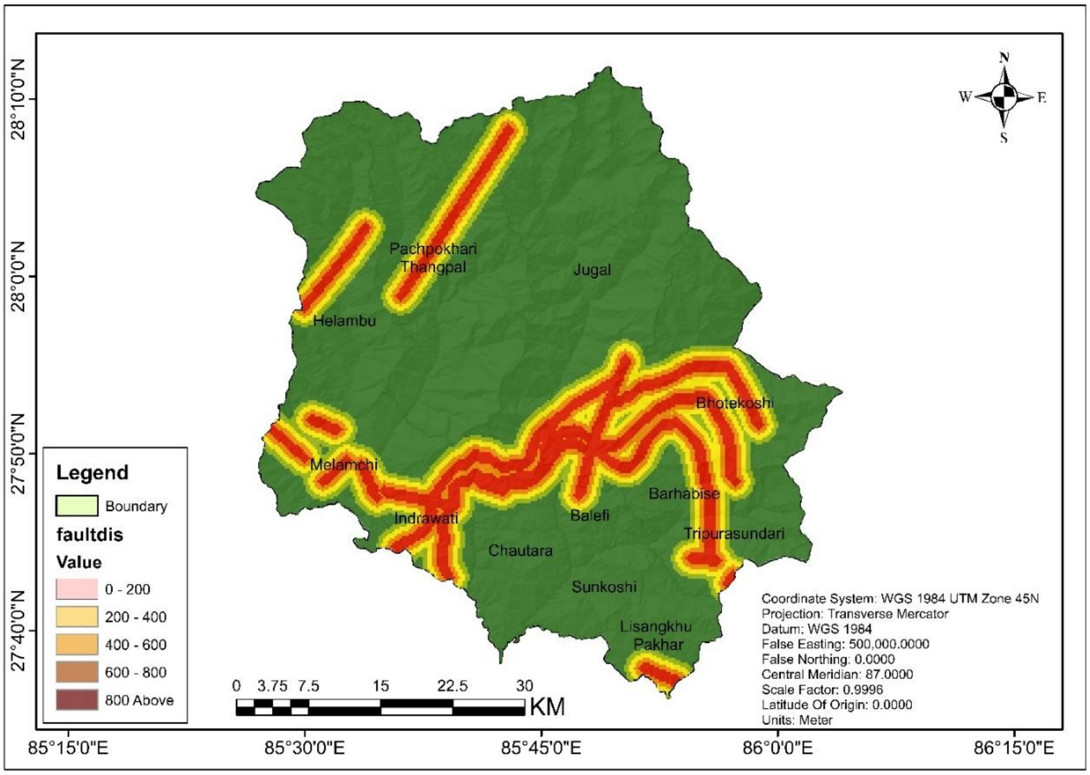


Figure 10: Distance from Faultline Map

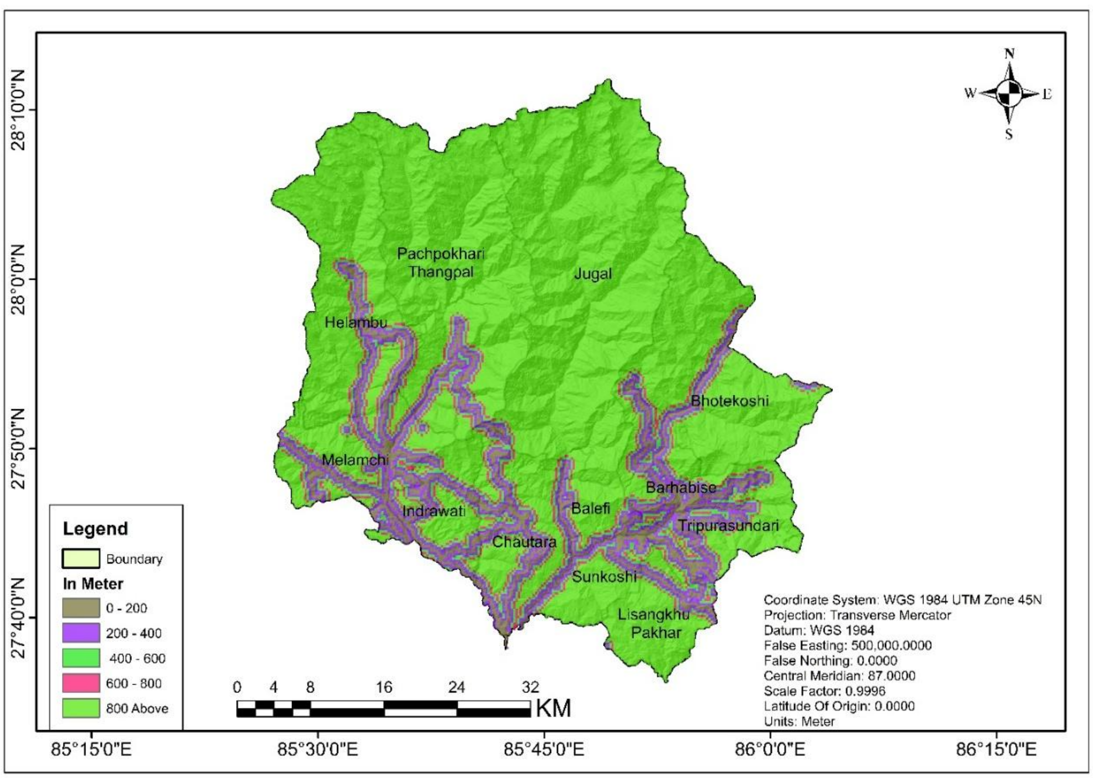


Figure 11: Distance from Road Map

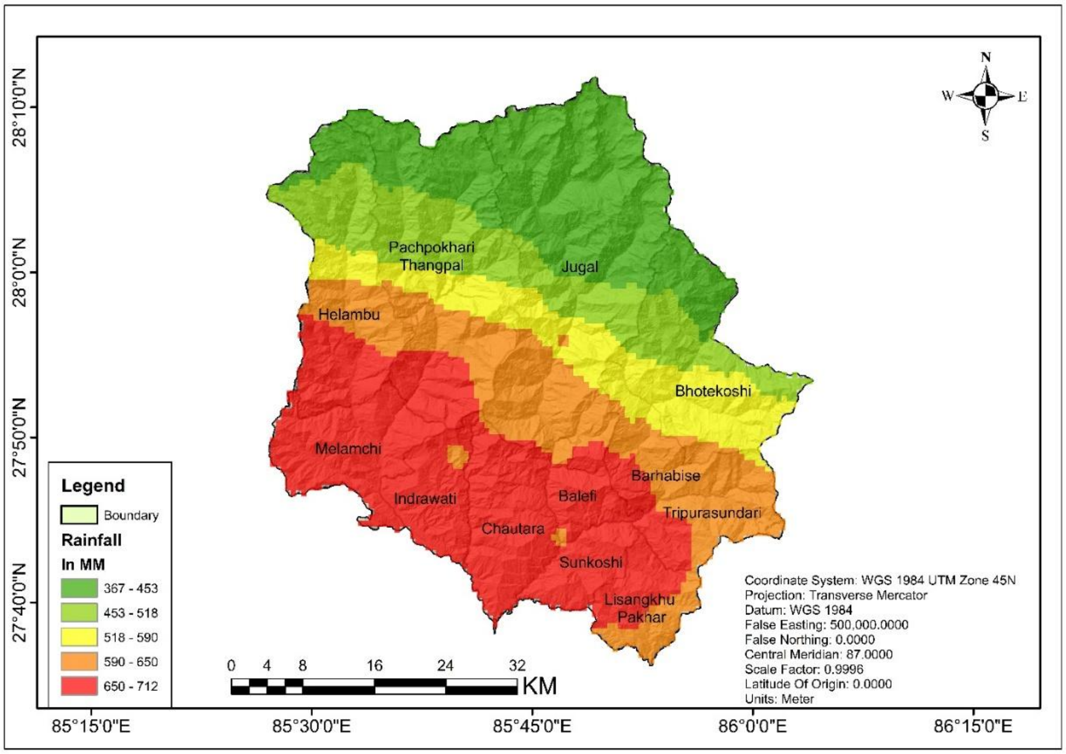


Figure 12: Rainfall Map

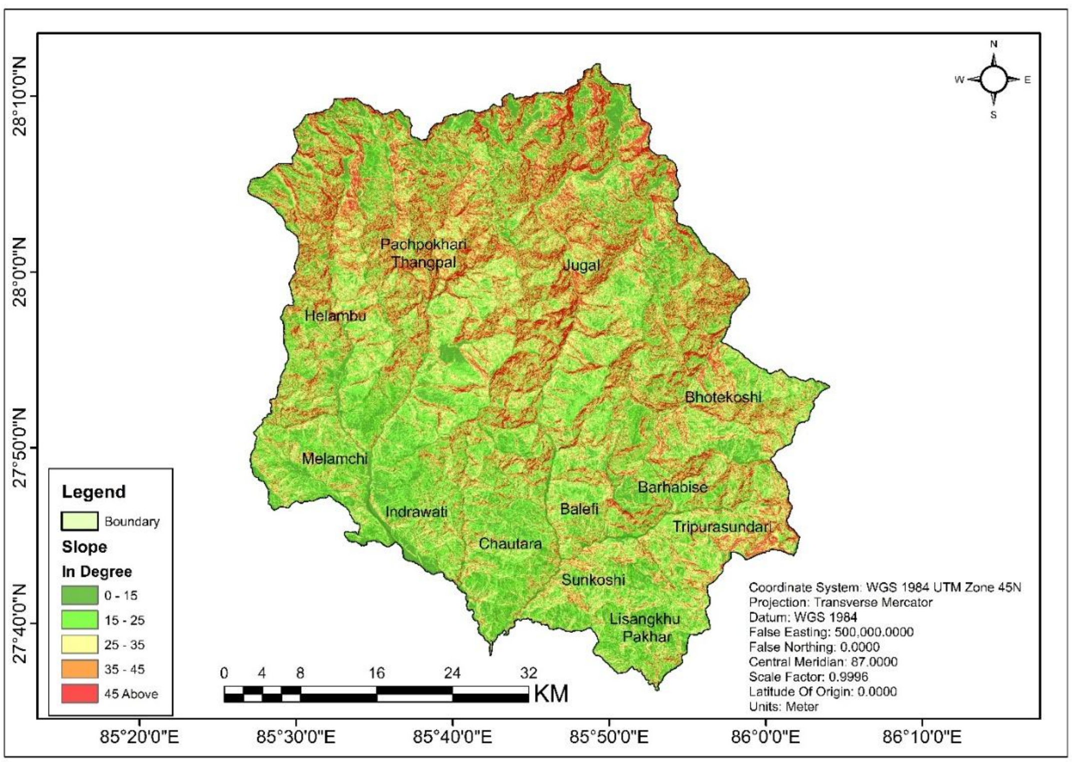


Figure 13: Slope Map

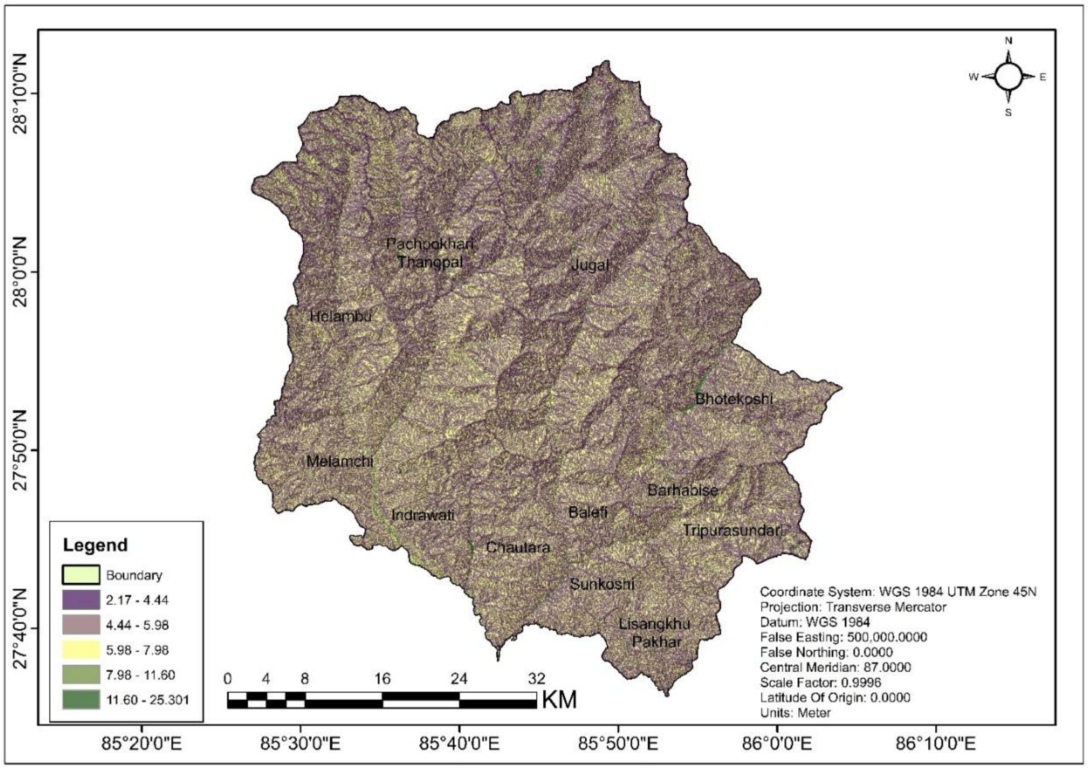


Figure 14: TWI Map

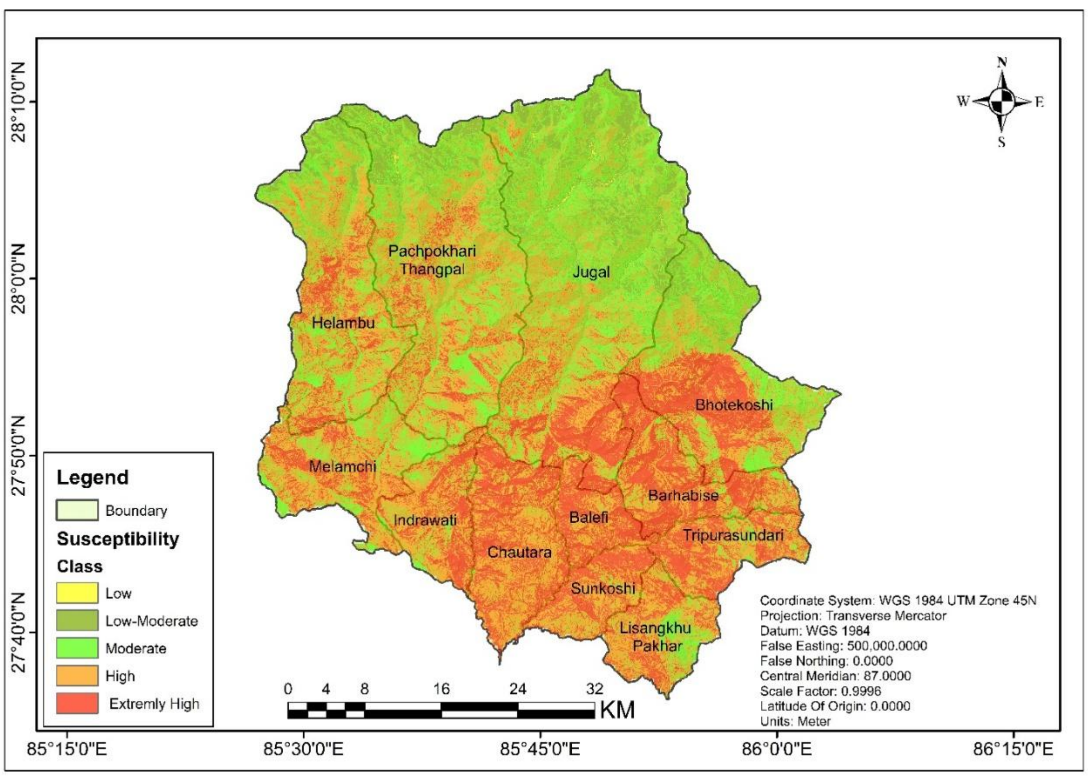


Figure 15: Landslide Susceptibility Map

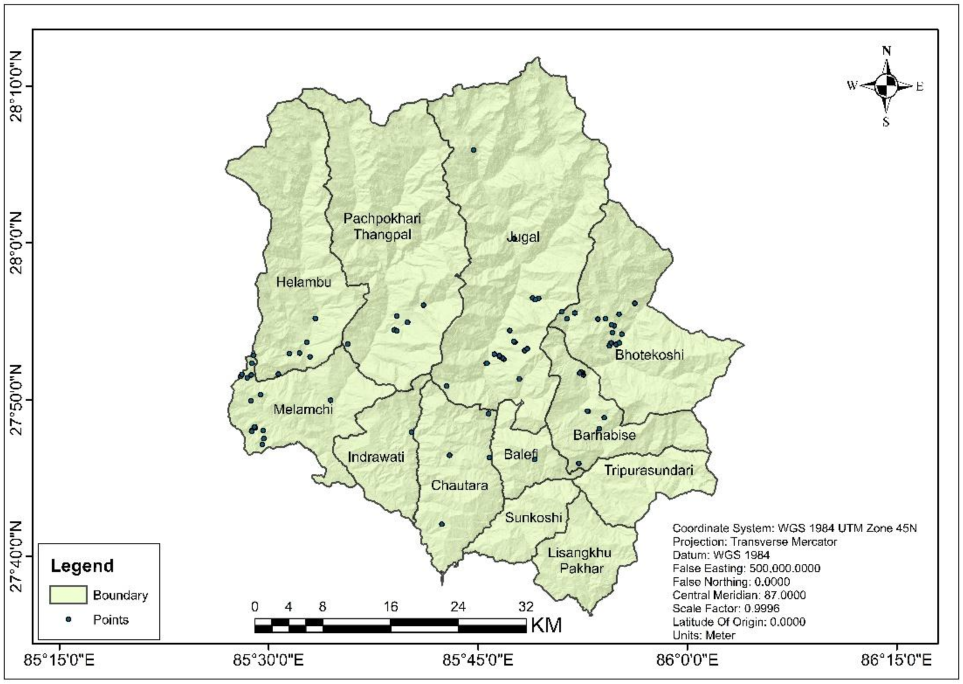


Figure 16: Landslide Inventory Map

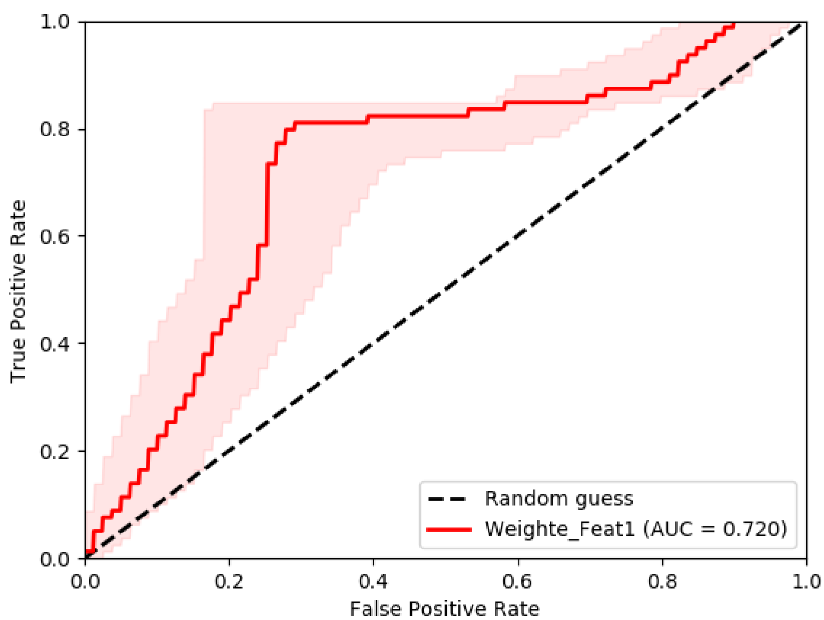


Figure 17 : ROC curve with AUC value

The AUC value of the AHP model is 0.720. An AUC of 0.720 indicates that the AHP model has a fair predictive performance for landslide susceptibility. This means the model is able to correctly distinguish between landslide-prone and non-landslide-prone areas 72.0% of the time.

5 Limitations and Solutions

Limitations:

- Limited Field Verification:
  Field visits were not conducted, so model outputs could not be ground-truthed.
- Data Availability and Resolution:
  Some datasets (e.g., rainfall, soil type, historical landslides) were insufficient or of low spatial resolution.
- Temporal Variability Not Considered:
  Seasonal changes (e.g., vegetation, rainfall intensity) were not dynamically incorporated in the model.
- Assumption of Static Conditions:
  The model assumes current slope and land use conditions, not accounting for future changes like road expansion or deforestation.

Solutions:

Future studies should include field validation and community-based mapping for more accurate assessments.

- Use of higher-resolution and real-time datasets, such as LiDAR, satellite imagery, or local weather stations.
- Incorporate expert consensus or combine AHP with data-driven models (e.g., machine learning) to reduce subjectivity.
- Apply multi-temporal analysis to consider dynamic environmental conditions.
- Regular updating of susceptibility maps to reflect ongoing land use changes and development activities.

6 Conclusion

This study successfully mapped the landslide susceptibility of Sindhupalchok District using the GIS-based AHP model. The analysis incorporated 10 key criteria: slope, curvature, rainfall, geology, fault lines, drainage density, land use/land cover, topographic wetness index, distance from rivers, and distance from roads. The resulting susceptibility map highlights high-risk areas critical for disaster management and planning.

Validation through historical landslide data and ROC curve analysis (AUC = 0.720) confirms the model's effectiveness, outperforming random guesses. This work provides a valuable tool for local authorities, guiding disaster mitigation and infrastructure development in landslide-prone zones.

7 References

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