eISSN: 2976-1190

Journal of Engineering and Sciences

Vol. 2 Issue 1 November 30, 2023

Journal homepage: **Journal of Engineering and Sciences (nepjol.info)**

Publisher: Research Management Cell, Pashchimanchal Campus, Lamachour, Pokhara

Landslide Susceptibility Mapping Using Analytical Hierarchy Process in Gandaki Province, Nepal

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(Manuscript Received:12/092023; Revised:22/11/2023; Accepted: 23/11/2023)

Abstract

Nepal has a diverse geography ranging from the majestic Himalayas to the fertile plains in the Terai and this varied topography makes it susceptible to different hazards. This study analyzed the most recurring destructive natural hazard, i.e., a landslide in Gandaki Province. The result has been presented using Geographic Information System (GIS) based susceptibility mapping employing Analytical Hierarchy Process (AHP). The susceptibility mapping was performed based on 11 conditioning parameters under four groups, mainly topographic factors (Elevation, Slope, Land Use Land Cover and Profile curvature), hydrological factors (Proximity to stream, Precipitation, Drainage Density and Topographic Wetness Index), geological factors (Geology and Fault lines) and infrastructure factor (Proximity to the road). The final result was classified into five classes: shallow, low, moderate, high, and high susceptibility. The validity and accuracy were tested by calculating the areas under the curve (AUC) value of the receiver operating characteristic (ROC) curve. The AUC value of the landslide was found to be 0.793, indicating the model's good performance. The final map can be used for disaster risk reduction, land use planning and early warning systems.

Keywords: AHP; GIS; Hazard; Susceptibility

1. Introduction

Landslides seriously threaten human life, property, built infrastructure and the environment in most mountainous and hilly locations of the world. Landslides result from a combination of different causative factors, including elevated slopes, uneven terrain, absence of vegetation or forest depletion, geologically weak formations, structurally fractured rocks and common earthquakes, and heavy and prolonged rainfall [1]. The increasing frequency and magnitude of landslides have become a major concern for many countries, particularly those with rugged landscapes. Understanding the due loss experienced by the built environment as a result of landslides requires conducting a susceptibility assessment beforehand so that preventive measures can be adopted before the occurrence of such a disaster [2].

Being a mountainous country, Nepal experiences many landslides every year. Around 3000 landslides occurred in different parts of Nepal in the last decade, per the BIPAD Portal record, which the Ministry of Home Affairs initiated for disaster risk reduction. Global Climate Risk Index ranks Nepal fourth in climate risks [3], emphasizing the need to identify landslide-prone areas for proper disaster planning, preparation, and mitigation.

Gandaki Province, one of the seven provinces of Nepal, is located in the central part of the country. Most of the province's area is characterized by hilly and mountainous terrain, which is highly susceptible to landslides. So, this research aims to map the susceptible areas, considering various factors that can be valuable for understanding and managing landslide risks in the province.

Landslides susceptibility mapping is drawing more attention globally for two reasons: first, with the increasing population density and urbanization, more people are living in areas prone to landslides and second, changes in climate patterns such as increased rainfall or temperature fluctuations contribute to an elevated risk of landslides [4]. Despite the numerous methods and techniques proposed and applied, there is currently no consensus on the most effective method and technique for mapping landslide susceptibility [5].

In this study, AHP, one of the widely used methods for landslide susceptibility mapping, is employed. It involves prioritizing the factors triggering landslides based on their potential impact and relative importance.

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The final map can be very helpful for planning and designing mitigation strategies and locating regions that need more attention.

2. Materials and Method

2.1 Data Collection

The study incorporates datasets from several sources. First, a 30-meter resolution Aster GDEM, which was freely accessible, was downloaded from the NASA webpage. Then, Meteorological data (Rainfall) was acquired from the Department of Hydrology and Meteorology (DHM), Nepal. Historical data (past incidents of landslides) was acquired from the BIPAD Portal. Similarly, the data related to geology, including fault lines, was obtained from the Department of Mines and Geology (DMG), whereas infrastructure data (road) was extracted from the OpenStreetMap (OSM) platform.

2.2 Study Area

This study focuses on Gandaki Province, which has a latitude ranging from 27° 26' 15" N to 29° 19' 15" N and a longitude ranging from 82° 52' 45" E to 85° 12' 01" E. It is one of the seven provinces situated in the western part of Nepal, covering 11 districts, namely Kaski, Syangja, Parbat, Tanahun, Gorkha, Lamjung, Nawalpur, Baglung, Myagdi, Manang and Mustang. There are 85 local governing bodies in Gandaki Province: 1 Metropolitan City, 26 Municipalities and 58 Rural Municipalities. The total area of this province is approximately 22,000 sq. km, which is nearly 15% of the total area of Nepal and has a total population of 2,479,745.

The altitude in this province ranges from 91 meters above sea level at Nawalpur to the highest elevation at Mt. Dhaulagiri at 8,167 meters.

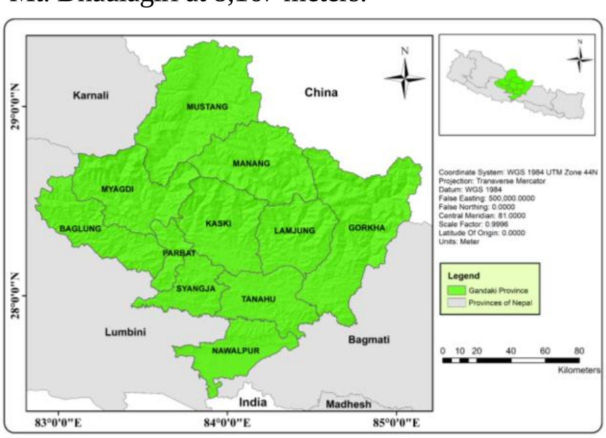


Figure 1: Study Area

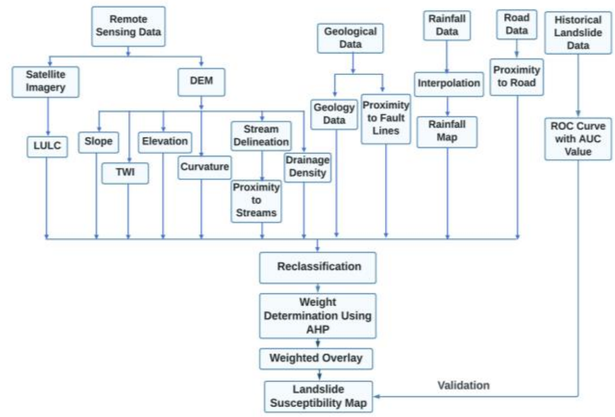


Figure 2: Methodology adopted for landslide susceptibility mapping

2.3 Landslide Inventory

Satellite images from Google Earth, historical records and the database prepared by BIPAD Portal, as well as data from the field survey, were integrated to prepare landslide inventory, which was used to generate the Receiver Operating Characteristic (ROC) curve for the verification of the model. Altogether, 436 landslides were mapped in the study area.

2.4 Landslide Conditioning Factors

Altogether, eleven conditioning factors were selected for landslide susceptibility mapping based on the literature review and their relevance to susceptibility.

Elevation

Elevation is a very important and most used factor for analyzing landslide susceptibility as different elevation values act differently with a landslide. Generally, high-elevated areas usually exhibit more landslides compared to low-elevated areas. The elevation of the study area ranges from 91 to 8167 meters.

Slope

The slope is another crucial factor that exerts a more significant influence when compared to other conditioning factors. Identifying susceptible areas of landslides involves recognizing that steep slopes are particularly vulnerable due to their increased likelihood of experiencing soil erosion, soil saturation and slope instability [6]. The slope within the study area ranges from 0 degrees to 83.8 degrees.

Profile Curvature

The curvature is defined as the rate of slope change in a specific direction. It is taken as a useful indicator of the potential for landslides to occur. High curvature

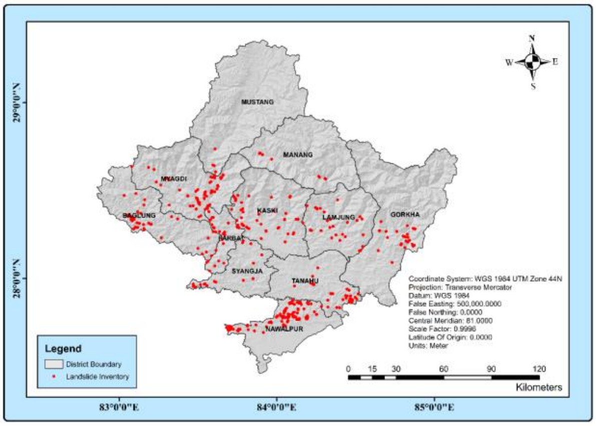


Figure 3: Landslide Inventory Map

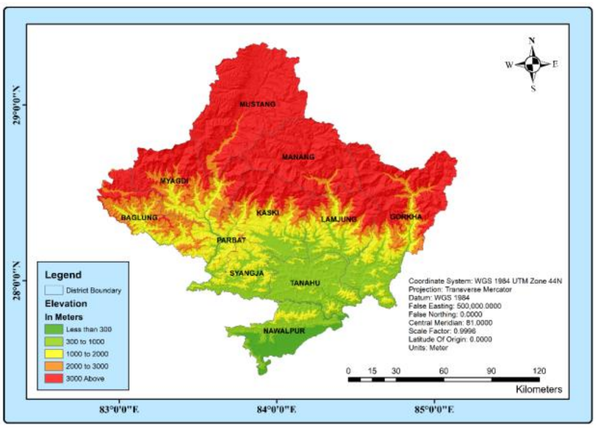


Figure 4: Elevation Map

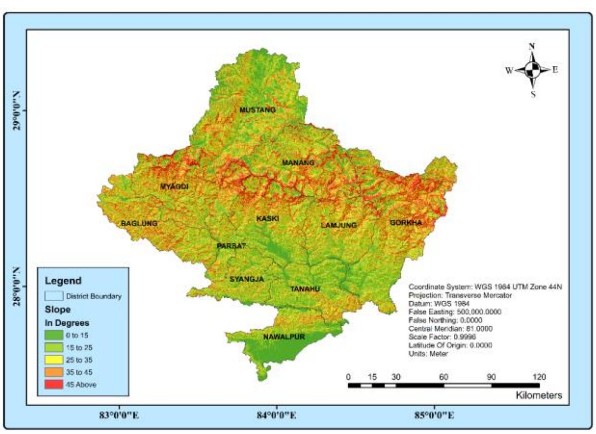


Figure 5: Slope Map

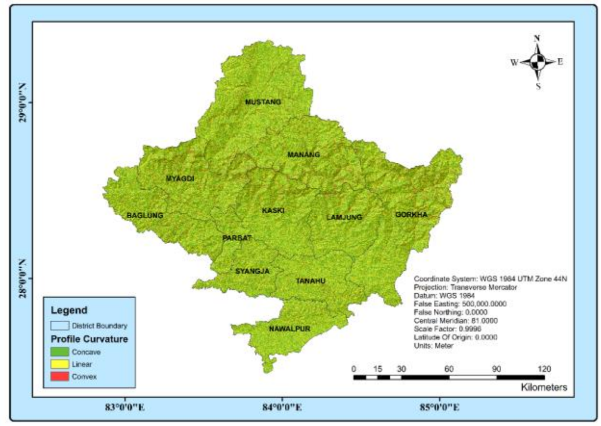


Figure 6: Profile Curvature Map

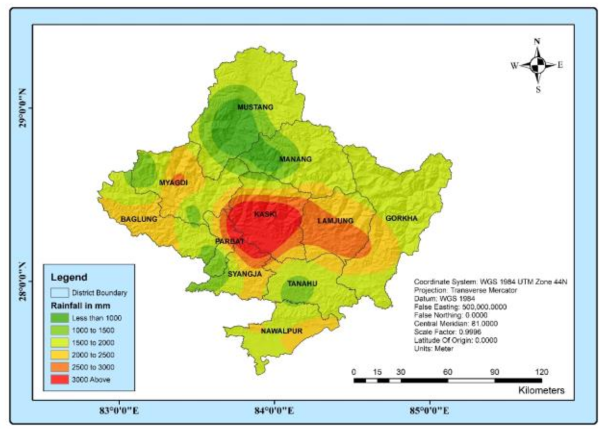


Figure 7: Rainfall Map

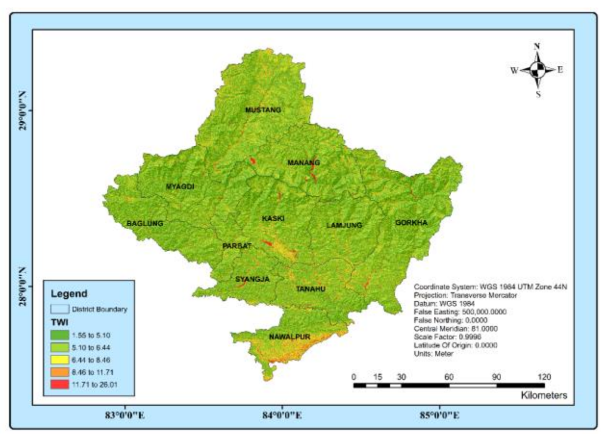


Figure 8: TWI Map

values indicate areas where the slope changes rapidly, indicating areas where landslides are more likely to occur [7]. Profile curvature exhibits the surface that aligns with the direction of the maximum slope. The profile curvature of the study area ranges from -21.56 to 23.31.

Precipitation

Precipitation is widely considered as the main triggering factor for a landslide initiation. Altogether, 38 rainfall gauge stations inside the Gandaki Province and 9 rainfall gauge stations of the surrounding districts of the province were taken into account and the annual average rainfall from 2005 A.D. to 2022 A.D. of these stations was interpolated using the kriging interpolation technique. The annual average rainfall of the study area ranges from 121.89 mm at Samar Gaun, Mustang, to 5288.7 mm at Lumle, Kaski.

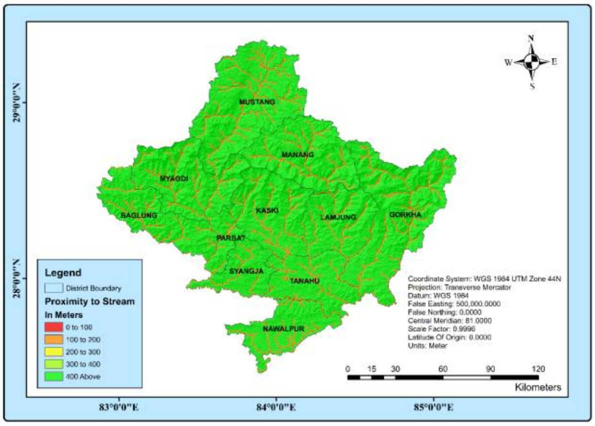


Figure 9: Proximity to Stream Map

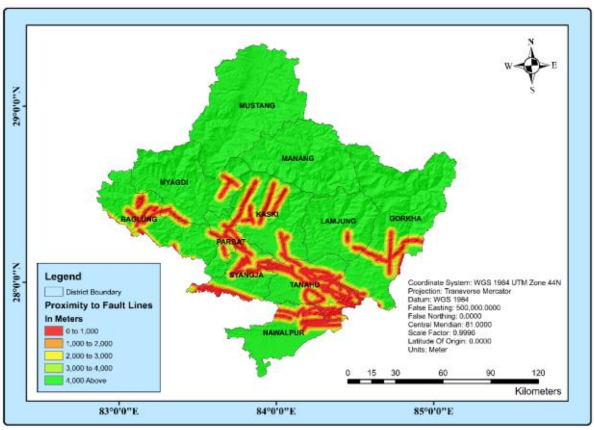


Figure 10: Proximity to fault lines Map

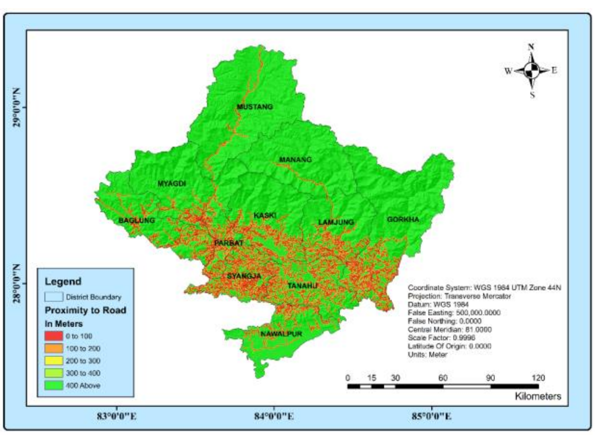


Figure 11: Proximity to Road Map

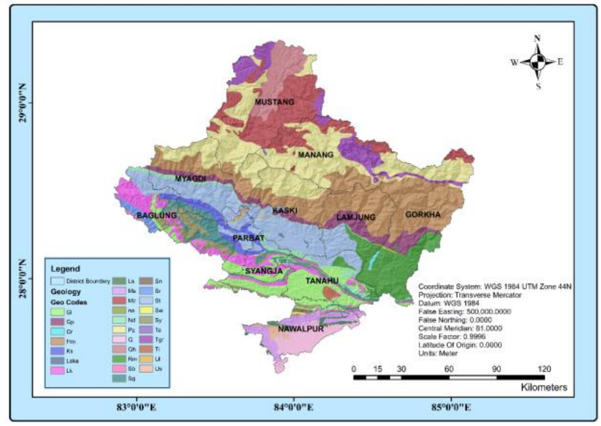


Figure 12: Geology Map

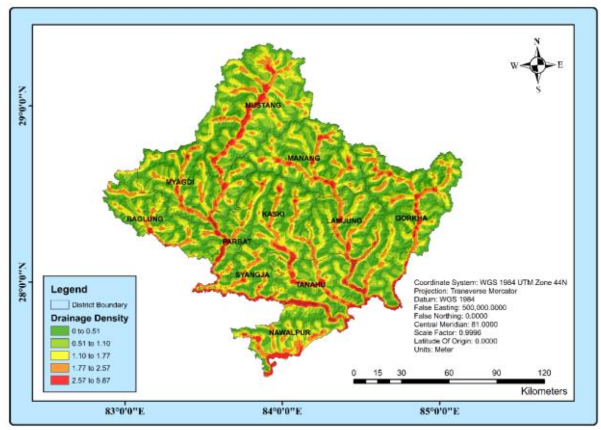


Figure 13: Drainage Density Map

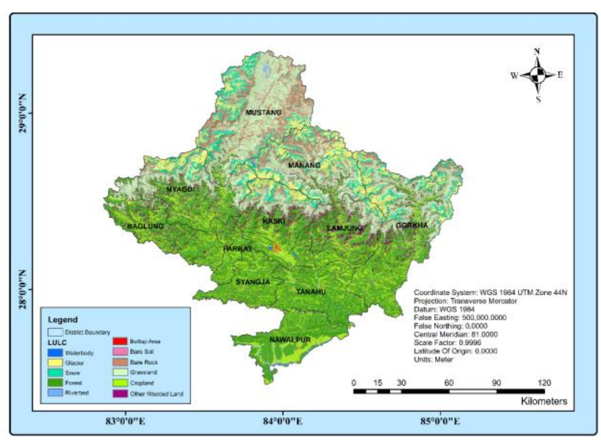


Figure 14: LULC Map

TWI

The topographic wetness index (TWI) is another crucial factor considered for landslide susceptibility mapping. It is the secondary outcome from DEM incorporating slope and flow accumulation factors. The formula is expressed as:

$$\text{TWI} = \ln(\alpha/tan\beta)$$

Where α represents the upslope value derived from flow accumulation, signifying the contributing area above, while β denotes the slope angle. The topographic wetness index (TWI) typically indicates both the soil moisture content and the propensity of an area to accumulate water. Areas with high TWI values can be more prone to landslides as soil saturation reduces its stability and increases the risk of slope failure [8]. The TWI value of the study area varies from 1.27 to

25.6.

Proximity to Stream

Another crucial factor for landslide occurrence is proximity to streams since these areas are more likely to have landslides and soil erosion due to the scouring action of the water [2]. Steep terrain near streams can be more prone, especially during heavy rainfall, because soil saturation increases mass movement.

Proximity to Fault Lines

Fault lines are another key geological factor for landslide susceptibility mapping. The earth's surface generally breaks along these lines, and earthquakes influence these surfaces more than other normal surfaces [9]. So, areas near fault lines are more likely to experience mass movement.

Proximity to Road

Proximity to the road is another significant factor that directly contributes to the occurrence of landslides. Newly constructed roads can potentially increase the chance of landslides by destabilizing slopes, altering drainage patterns and exerting pressure on the upper slope of the road[10].

In this study, roads on the plain land are not taken into account as they don't have any influence in landslide occurrences.

Geology

The underlying geological conditions can greatly influence the likelihood of landslides occurring in a particular area. Geology affects the stability of slopes and the risk of landslides, as different types of rocks and soils have different levels of strength and resistance to erosion [11]. Altogether, there are 28 classes of geology in the study area.

Drainage Density

Drainage density refers to the frequency and spacing of drainage networks such as streams and rivers in a landscape. Areas with high drainage density can have increased erosion potential as runoff from such areas can destabilize slopes and increase the possibility of landslides [12]. The drainage density within the study area ranges from 0 to 5.87 kilometers per square kilometer.

Land Use Land Cover

LULC plays an indirect role in contributing to landslide occurrences. Forests and other dense vegetation serve as a protective barrier for landslide initiation. Plant roots bind soil particles together, reducing erosion and enhancing slope stability. Whereas areas with minimal or no vegetation, such as bare soil, rocky surfaces or locations with recent deforestation, are more susceptible to landslides [2]. The LULC data was obtained from the ICIMOD of the year 2019 A.D. and there are 11 classes in the study area.

2.5 Analytical Hierarchy Process

The AHP (Analytic Hierarchy Process) framework, introduced by Saaty in the early 1970s, is a versatile approach for analyzing complex matters in multiple disciplines using a multi-criteria decision-making approach. Over time, this method has been proven an effective algorithm in creating landslide susceptibility maps [14].

In this study, experts compared the importance of criteria, two at a time, through pair-wise comparisons. The pairwise comparison was done with relative importance using Saaty's scale from 1 to 9 and a decision matrix was prepared. From the decision matrix, the normalized pairwise matrix was constructed. After that, the weightage of each factor was calculated and the consistency ratio was used to assess the quality of the pairwise comparisons made.

AHP calculates the consistency ratio as:

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

Where CI is the consistency index and is calculated as:

$$\boldsymbol{CI} = \frac{\boldsymbol{\lambda max - n}}{\boldsymbol{n-1}}$$

$\lambda_{\max}$ is the largest eigenvalue of the matrix of order n and RI is the random consistency index of A. It's value is taken from table 1 where the first row (n) indicates the number of rows i.e., matrix size. Whereas the second row is a random consistency index.

Table 1: Number of criteria and their random index

n	1	2	3	…..	11	12
RI	0.00	0.00	0.58	…..	1.51	1.54

If $CR \leq 0.1$, the level of consistency is acceptable; otherwise, the decision maker may need to re-estimate the pairwise comparison to realize better consistency.

The table 2 shows the pairwise comparison matrix and weights for each conditioning factor for landslide susceptibility mapping by AHP and it is seen that slope angle and LULC factor have the most and less influence on landslide occurrence with values of 25.5% and 2.1%, respectively. Finally, we checked the consistency of a matrix using the CR and it was found to be 0.031, indicating a reasonable level of consistency in the pair-wise comparison. The weight obtained from the pairwise comparison of the factors was used to perform a weighted overlay on reclassified layers of the triggering factors in the Arc-GIS platform. The final landslide susceptibility map was obtained, shown in Figure 15.

Table 2: Pairwise Comparison of the Matrix for Landslide Susceptibility Mapping

S.N.	1	2	3	4	5	6	7	8	9	10	11
1	1	1/7	1/2	1/3	1/5	1/3	1/4	1/4	1/3	1/6	1/5
2		1	7	6	5	5	4	4	5	1	3
3			1	1/3	1/3	1/3	1/4	1/4	1/3	1/6	1/5
4				1	1	1	1/2	1/2	1	1/4	1/3
5					1	2	1	1	2	1/4	1/3
6						1	1/3	1/3	1/2	1/4	1/3
7							1	1	2	1/3	1/2
8								1	1	1/3	1/2
9									1	1/4	1/3
10										1	2
11											1

Table 3: Conditioning factors and their weights

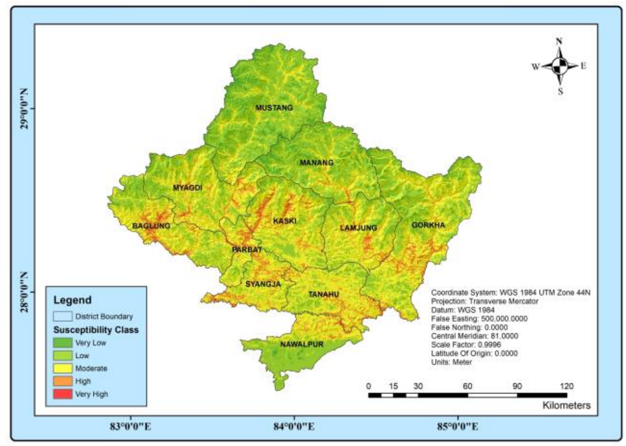
S.N.	**Conditioning Factors**	**Weights (%)**
1.	LULC	2.1
2.	Slope	25.5
3.	Elevation	2.3
4.	Drainage Density	4.5
5.	TWI	8.0
6.	Profile Curvature	4.2
7.	Proximity to Stream	8.0
8.	Proximity to Road	7.2
9.	Proximity to fault Lines	5.3
10.	Geology	19.0
11.	Rainfall	13.9
Total		**100.00**

3. Results and Discussion

3.1 Landslide Susceptibility Map

The landslide susceptibility map was generated through a weighted overlay tool in the Arc-GIS platform. The susceptibility map underwent reclassification into five categories using the natural breaks method, where the moderate risk class has the largest area (46.18%) followed by low (41.24%), high (7.96%), deficient (4.42%) and very high (0.20%) classes.

In the figure, we can see that the Kaski district is found to be more prone to landslides. The Kaski district is followed by Baglung, Myagdi, Lamjung, Gorkha, Parbat, and Syangja districts in terms of susceptibility to landslides. Dominant rocks of sedimen-



15: Landslide Susceptibility Map

tary facies i.e., limestone, sandstone and mudstone, are found in two districts across the Himalayas – Manang and Mustang. These rocks are not very strong, although these districts are less susceptible as they receive less yearly rainfall.

3.2 Model Validation

Field verification is one of the most accurate methods for validating the result obtained, but it is a time-consuming and tedious process. However, a sufficient number of samples were taken into account.

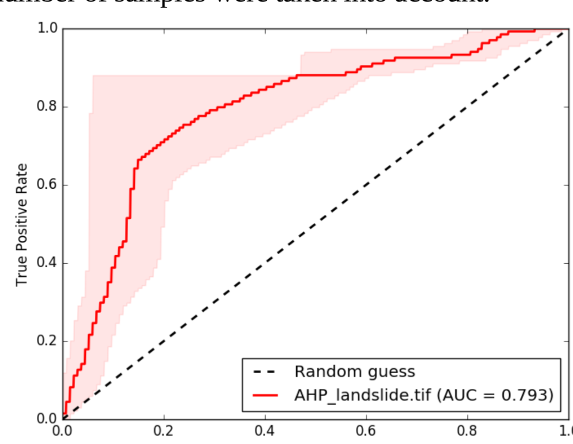


Figure 16: ROC Curve with AUC Value

Figure 16 shows the ROC curve for landslide susceptibility of Gandaki Province. The AUC was found to be 0.793, which indicates the model's good performance.

3.3 Discussion

The investigation of slope instability and the creation of susceptibility maps are vital elements in the management of hazards, decreasing the risk of living with landslides. So, the landslide susceptibility map of Gandaki Province was prepared following AHP. Although the AHP is a subjective judgment of the experts, it can have some bias. However, the findings indicated a strong correlation between active landslide zones and the map's high and very high susceptibility classes. Through this study, it is found that Gandaki Province is highly prone to landslides. Central and western hills of the Kaski district are found to be highly susceptible to landslides due to weak geology, heavy rainfall and steep slopes, which are the most influencing factors and gained more weightage in AHP calculation.
Similarly, the southern part of Baglung and the eastern side of Myagdi are determined to be highly susceptible to landslides, the main causes are found as steep slopes and haphazardly constructed earthen roads without any engineering practice and considerations. Likewise, the areas around the Beni-Jomsom Road, the newly constructed Kali Gandaki Corridor and the Mid-Hill Highway are also found as more susceptible to landslides through the susceptibility map and field survey. Ultimately, the outcome of this study indicates that when field conditions are accurately assessed with expertise, the AHP method can yield more accurate results.

4. Conclusion

This study offers a landslide susceptibility analysis of Gandaki Province. The analysis was conducted considering eleven conditioning factors employing the AHP procedure. Through this procedure, the slope is found to be the most important conditioning factor, having a 25.5% influence, followed by geology, having 19% influence. Kaski, Baglung, and Myagdi districts are seen as most susceptible to landslides, while two districts across the Himalayas, Manang and Mustang, are found to be less susceptible in comparison to other districts. The results were validated with the help of historical records of hazards recorded by the BIPAD Portal, satellite imagery, and field surveys. The accuracy was shown using the ROC curve with AUC value which is found to be 0.793.

The susceptibility map is very useful for the province's overall planning, including infrastructures, settlements, land use, etc. Further improvements in this study can be made with more qualitative, up-to-date, and exact historical events and by considering other variables that could provide a better alternative to risk assessment in the area.

Acknowledgment

The authors would like to acknowledge the Department of Hydrology and Meteorology (DHM), Department of Geology and BIPAD Portal by providing meteorological, geological and historical landslide, respectively. Also, we would like to acknowledge ICIMOD for the LULC data employed here in the study.

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