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LANDSLIDE SUSCEPTIBILITY ANALYSIS USING ANALYTICAL HIERARCHY PROCESS AND FREQUENCY RATIO METHOD: A CASE STUDY OF BHOTEKOSHI RURAL MUNICIPALITY, NEPAL

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ABSTRACT

Landslides are a recurring natural threat in Nepal, often causing significant harm to human life and infrastructure. This damage can be mitigated if the cause-and-effect relationships of the events are known. This study focuses on analyzing landslide susceptibility in Bhotekoshi Rural Municipality, an area acknowledged for its vulnerability to landslides. A landslide inventory map of the area was prepared using temporal information from Google Earth Pro over the past ten years. Approximately 56 landslides were identified and mapped, with 80% of them being randomly selected for model training, and the remaining 20% were used for validation purposes. To comprehend the factors contributing to landslides and predict future occurrences, landslide susceptibility mapping of this region was carried out using frequency ratio (FR) and Analytical Hierarchy Process (AHP) models. The data of slope, aspect, curvature, rivers, roads, geology, and landslides are used as causative factors for landslides. After the complete analysis, two different maps of susceptible areas for landslide based on the AHP and FR method are obtained. Finally, the results are compared and validated with the training data using the approach of Receiver Operating Characteristics (ROC) and Area Under the Curve (AUC). From the analysis, it is seen that both the models were equally capable of predicting the region's landslide susceptibility (AHP model (prediction rate = 0.610); FR model (prediction rate = 0.710)). The obtained landslide susceptibility map can serve as a major tool for engineers and planners to carry out development works in the study area.

Keywords: Landslide Susceptibility, Analytical Hierarchy Process, Frequency Ratio, Receiver Operating Characteristic Curve, Area Under Curve.

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INTRODUCTION

Nepal is among the world's most disaster-prone nations due to its varied physiographic and meteorological characteristics. Nepal is situated on the Asian, Indo-Australian, and continental-sized plates. Situated in an area that is tectonically active, a significant portion of Nepal's hilly terrain is intricately formed by geological processes. The movement of rock, soil, or particles down a sloped area of land is called a landslide (Rutledge, 2022). In Nepal, landslides are naturally caused by earthquakes, extremely heavy rainfall events (on hills), and rapid snow and ice melt (on mountains) (Petley et al. 2007). However, human activities like inappropriate land use, encroachment into areas of vulnerable land, and unplanned development projects like building roads and irrigation canals in areas of vulnerable mountain ranges without appropriate safety precautions increase the risk of landslides. As one of the biggest geological risks in the world, landslides cause thousands of victims and deaths, hundreds of billions of dollars of damage, and environmental losses every year (Gutiérrez et al. 2015). So, proper visualization of susceptible areas is very important.

A landslide susceptibility map is a useful tool for visualizing the spatial likelihood of an event occurring inside a specific territory. A spatial multicriteria decision analysis method based on GIS is used. Information such as land cover, lithology, roads, rivers, elevation, aspect, and slope gradient, among other things, are used. Recent studies have improved many approaches for determining a region's susceptibility to landslides and have demonstrated an increase in natural process-related damage over the past few decades, which can be broadly divided into three categories. The qualitative approach (heuristic methods) weighs the relative influence of causative factors on slope instability in an immediate or semi-direct way based on the logical judgment of experts. The heuristic approaches can be applied once the connection between the importance of intrinsic variables and the risk of landslides is recognized (Anbalagan, 1992). The deterministic method demonstrates susceptibility or chance diploma through the safety element and is an indirect estimation of slope instability analysis based on engineering standards. Deterministic methods, also known as physical-based models or geotechnical models, can be applied in situations where the ground conditions are largely constant across a research area (Mavrouli et al., 2009).

Based on its capacity to lessen the inherent subjectivity in choosing the enter statistics and their applicability in both small- and large-scale settings, statistical (quantitative approach) methods have become increasingly important (Soeters et al., 2006). Several statistical techniques (generally categorized into three types: multivariate, bivariate, and probabilistic prediction models) have been used and evaluated to determine which model is most effective in assessing the susceptibility of landslides (Pradhan et al., 2010). It's a great effort that the landslide methodology framework has recently recommended applying the quantitative method of landslide hazard, vulnerability, and risk analysis at various spatial scales (Corominas et al., 2014). Utilizing the quantitative method of landslide risk, vulnerability, and hazard analysis at different spatial scales is a recent, superb endeavor that is suggested for the landslide methodology framework. However, the quantity and quality of the input data, as well as the size of the study area, are crucial to applying the appropriate quantitative technique for landslide susceptibility or hazard mapping. To increase the prediction capacity for landslide susceptibility or hazard mapping, a lot of work is also put into combining empirical and physically based models (Strauch et al., 2019).

Bhotekoshi Rural Municipality, nestled within the rugged landscapes of Nepal, represents a region of significant geographical and socio-economic importance. However, like many mountainous areas, it faces the pervasive threat of landslides, which pose considerable risks to human lives, infrastructure, and livelihoods. Understanding and mitigating these risks are imperative for ensuring the safety and sustainable development of the region. Although very prone to landslides, the number of studies in this area is unsatisfactory. Hence, we have conducted our study in this area. Landslides, triggered by various geological, topographical, and climatic factors, are recurrent regional hazards, often exacerbated by anthropogenic activities and rapid urbanization (Subodh Dhakal, 2019). Although the monsoon-dominated climate, with intense rainfall events occurring during the summer months, exacerbates the risk of landslides greatly, due to the unavailability of sufficient metrological data on the area, we focused our study only on DEM, LULC, lithology, roads, and rivers data. The findings of this study are expected to have practical implications for disaster risk reduction efforts, urban planning, and sustainable development initiatives in the region.

This project's objectives are divided into two groups. The project primarily focuses on preparing a landslide susceptibility map using the Analytical Hierarchy Process (AHP) and Frequency Ratio (FR) methods. Complementing these primary goals, the secondary objectives aim to address and support the core project objectives. These include facilitating the development of infrastructures and urban expansion through proper zonation of landslide-susceptible areas. Additionally, the project seeks to contribute to the meticulous planning of safety measures for landslides, whether it involves the construction of embankments or the implementation of diversions. This work presents a novel method in the context of Bhotekoshi Rural Municipality, where no prior research has used both AHP and FR models for landslide susceptibility mapping. The use of these methodologies in this specific location provides a distinctive perspective on localized hazard assessment and planning, as well as novel insights into Nepal's geohazard analysis sector.

1. METHODOLOGY

Our research employs a two-fold methodology, consisting of a comprehensive desk study and an in-depth case study, to analyze the susceptibility of landslides in Bhotekoshi Rural Municipality. The desk study included a literature review, data collection, and data analysis. In contrast, the case study included a selection of the study area, the collection of respective data, and their analysis. We then integrated our desk study and case study.

1.1. Study Area

The Bhotekoshi rural municipality is located in the Sindhupalchowk district of the Bagmati Zone in Nepal's Province No. 3, roughly between the latitudes of 27°48'30'N and 28°3'30'N and the longitudes of 85°50'20'E and 86°04'30'E. It is situated on the Himalayan range close to the Chinese border with Tibet. Jugal is to the west, Bahrabise to the south, and Dolakha District to The east encircles it. Tibet is situated in the northern section of the rural municipality. The rural municipality spans 273.62 square kilometers or 105.65 square miles.

The study area was chosen for its remoteness and difficulty of access, which presents a unique set of challenges and vulnerabilities to natural hazards such as landslides. This combination of factors makes Bhotekoshi rural municipality an ideal case study for understanding landslide susceptibility and developing effective mitigation strategies. Additionally, the municipality's location in the Himalayan range, close to the Chinese border with Tibet, adds geopolitical significance, further underscoring the importance of assessing and managing landslide risk in this region.

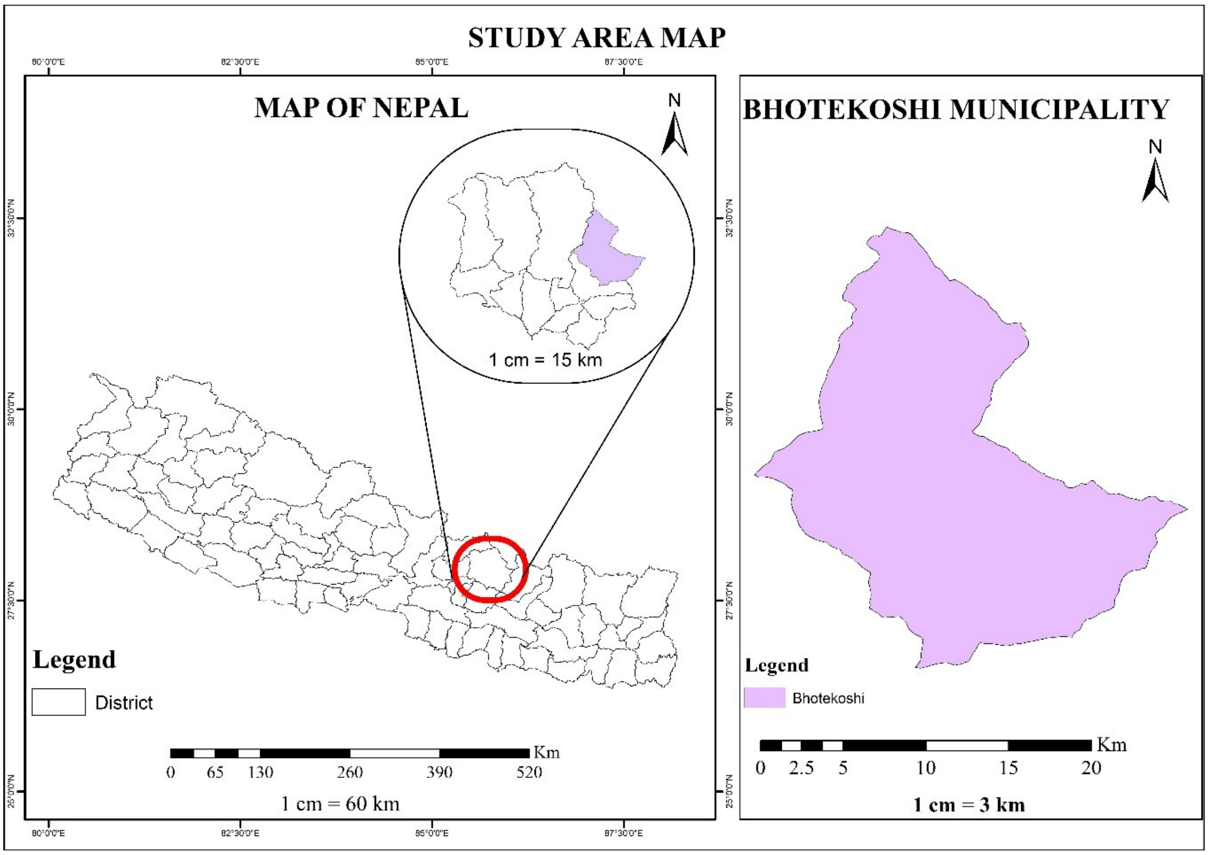

Figure 1. Study area map.

1.2. Data acquisition

Topographic information needed to understand the landslide mechanism was obtained from the United States Geological Survey (USGS) global datasets. The analysis utilized a 30 m resolution DEM from USGS. This data set was chosen for its coverage of the study area as well as its consistency with prior large scale landslide studies in Nepal (Devkota et al., 2013). While higher resolution datasets (10 m for instance) may aid in micro scale accuracy, no high-resolution datasets were discovered for the Bhotekoshi region considered in this study. The model validation (AUC = 0.71 and 0.611) indicates that usable 30 m resolution DEMs can be employed for village scale susceptibility mapping. The Regional Database System of the International Center for Integrated Mountain Development (ICIMOD) provided a readily available land use map derived from Landsat8 image processing. In addition, it also provided a database of geological data for Nepal through which road, river, and lithological information of 30m resolution were derived. The landslide inventory information was derived from 30m resolution Landsat images, which were extracted from the temporal information from Google Earth Pro over the past ten years.

Table 1. Data Sources.

S.N	Data	Source	Date of access
1	DEM and its derivatives	USGS (www.usgs.com)	22nd December, 2022
2	Landcover and Land use	ICIMOD (www.icimod.com)	22nd December, 2022
3	Geology, Road, River	ICIMOD (www.icimod.com)	23rd December, 2022
4	Landslide inventory	Google Earth Pro	15th November, 2022

1.3. Data analysis

Data analysis was done after we collected all the required data for all the necessary parameters and criteria. For this purpose, ArcGIS 10.8 was used. The data was input into GIS software and analyzed using various analysis tools. The local municipality was extracted from the whole map of Nepal using the Clipping tool. Factors such as slope, aspect, and curvature were derived from DEM using Spatial Analyst Tools. Buffers of each causative factor were created using the Euclidean Distance tool. Then, the factors were reclassified using the Reclassify tool. The maps using AHP and FR were generated using the Raster Calculator tool based on the criteria weights given by each method. Finally, these two methods were compared using the ArcSDM tool.

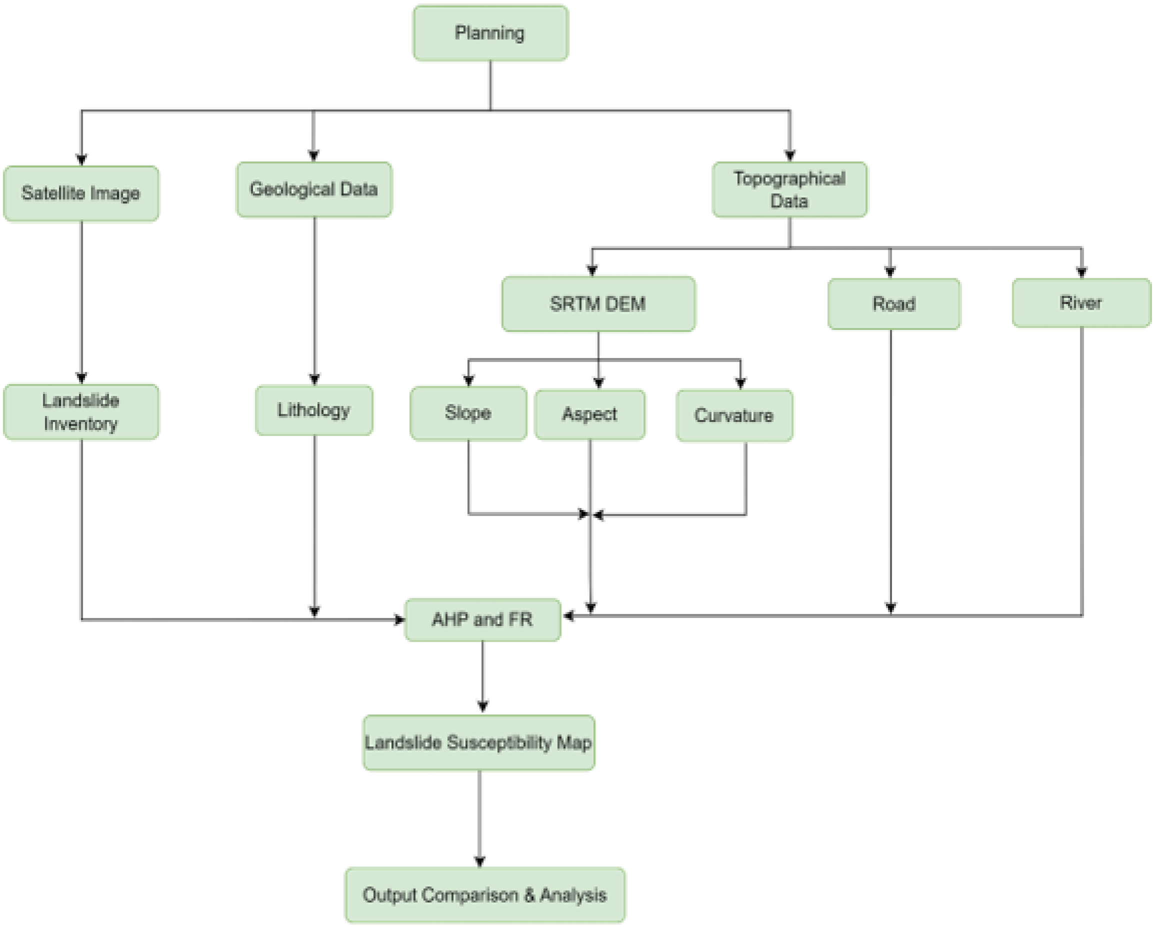

Figure 2. Methodological Flowchart.

1.3.1. FR Method

Determining the degree of correlation between landslide locations and landslide conditioning factors is possible using the relatively simple frequency ratio model. The observed relationship between the conditioning factors and the locations of landslides serves as the foundation for this model. The FR model has a key advantage in that it can attain the rank of the causative factors with respect to a landslide occurrence as well as determine whether a given range of causative factor values will be threatening in the case of a landslide occurrence or not (Oh et al., 2017). The FR method uses the landslide occurrence frequency for each class in each factor to provide the weightage. It is calculated as below:

$$FR_{i,j} = \frac{N_{i,j}/A_{i,j}}{N_T/A_T} \tag{1}$$

Where Ni, j is the total landslides in the class j in factor i, Ai, j is the class area, NT is the total landslides, and AT is the total study area.

1.3.2. AHP method

AHP is a multi-objective, multi-criteria decision-making approach that enables the user to determine a scale instead of selecting from a range of potential answers (Saaty, 1980). A pairwise comparison matrix is created by ranking each factor in relation to other factors, and this method solves the problem.

The consistency index in this model also referred to as the ratio of consistency (CR), is used to show the likelihood that the matrix judgments were produced at random (Saaty, 1977, 1980, 1994 in Mandal, 2018). If the consistency ratio is 10% or less, it is considered valid.

1.4. Validation and Comparison

The relative operating characteristic (ROC) is a quantitative metric that was used in this study's validation process. The ROC curve is a helpful technique for illustrating the caliber of both probabilistic and deterministic detection and forecasting systems (Swets 1988).

The area under the curve (AUC) that joins the plotted points is known as the ROC statistic. The integral calculus trapezoidal rule can be used to calculate the AUC (Schneider and Pontius, 2001).

$$Y=\sum_{i=1}^{n}(x_{i+1}-x_i)\left(y_{i+1}-y_i-\frac{y_i}{2}\right) \tag{2}$$

Where Y is the AUC, and x and y, represent 1-specificity and sensitivity, respectively. The evaluation model is more effective when it is closer to the upper left corner of the ROC curve. The size of the AUC allows us to assess how well the models' overall explanation works.

2. RESULTS

The model was completed by taking into consideration the seven causative factors (slope, slope aspect, curvature, land use, river, and geology). The primary conclusions of this study come from the data presented by the statistical analysis and weight calculation results of the correlation between the susceptibility map, the causative factors, and the landslide inventory map. The results of reclassified maps are shown below:

2.1. Reclassified Data

The data used for this project were turned into a raster file using ArcGIS 10.8 and then reclassified into several classes. Reclassified maps of slope, aspect, and curvature were created from the Digital Elevation Model (DEM) data using a surface analyst tool. Similarly, spatial analyst tools also reclassified other data like road, stream, geology, and land use.

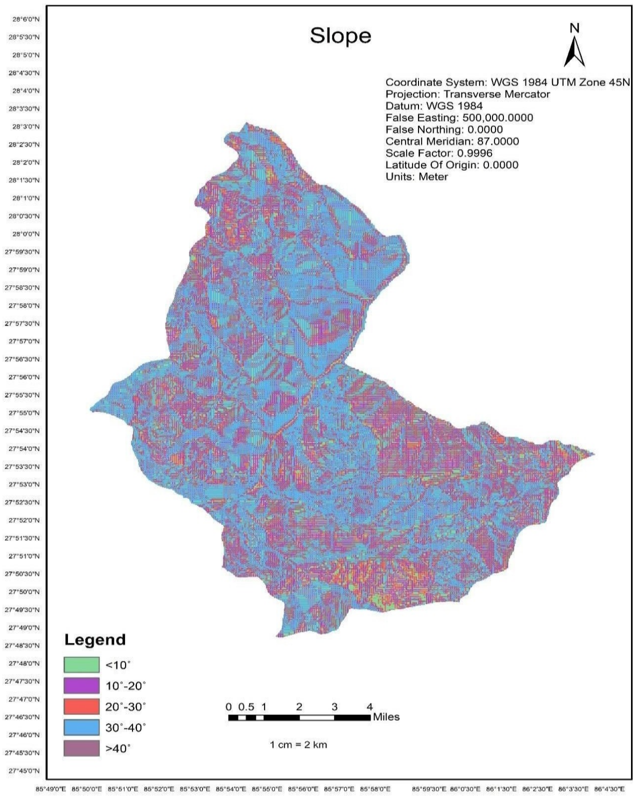

Figure 3. Slope.

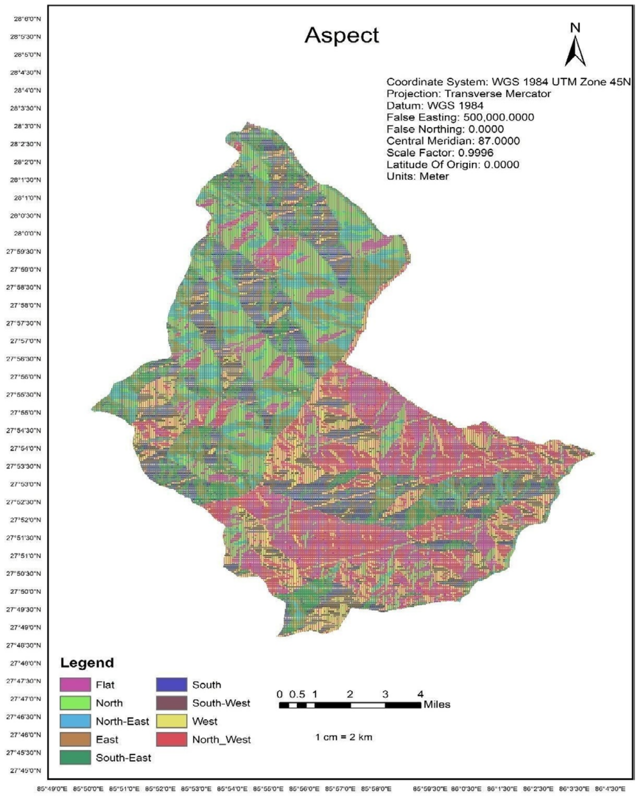

Figure 4. Aspect.

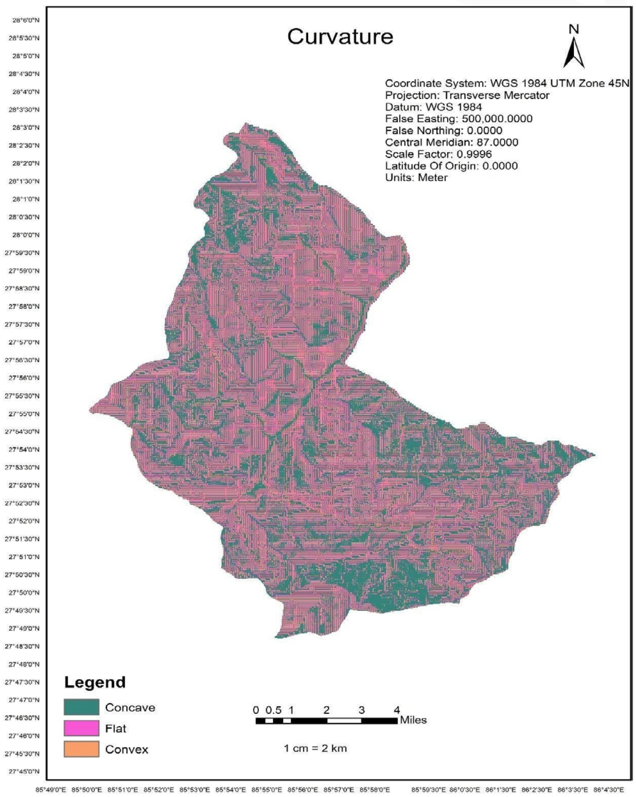

Figure 5. Curvature.

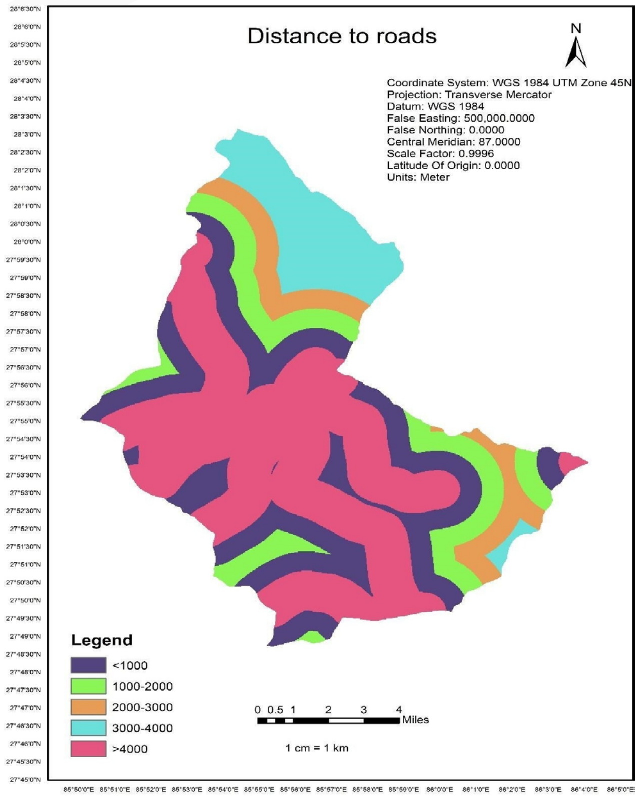

Figure 6. Distance to road.

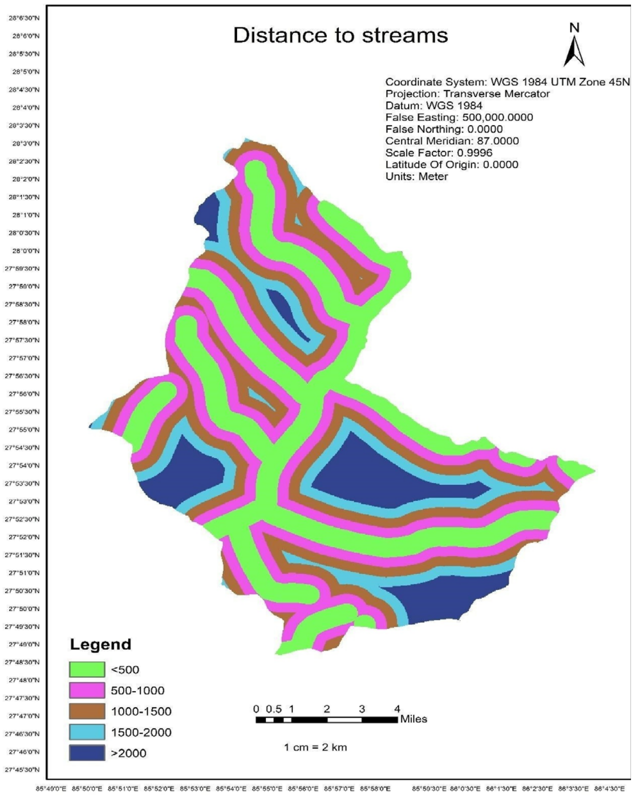

Figure 7. Distance to streams.

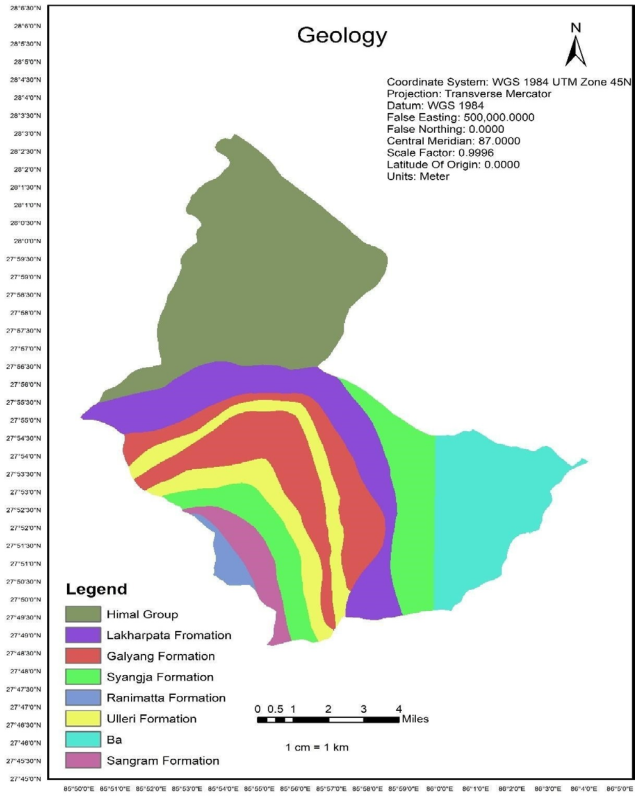

Figure 8. Geology.

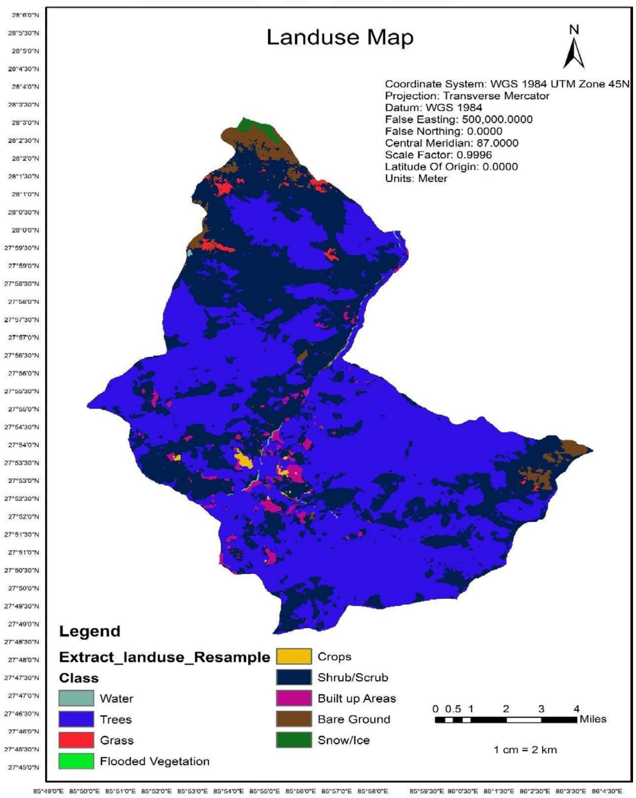

Figure 9. Landuse.

2.2. Calculation

2.2.1. Frequency Ratio Method

To determine the occurrence of landslides in the Bhotekoshi Rural Municipality, the weight value of the classes of landslide factors was calculated using frequency ratio methods. The frequency coefficient was nominal for all classes of factors, where the influence of each class of landslide factors on slope instability was established.

The results of the FR model for each of the classes of effective factors are shown in Table 2. For slope angle classes 0-10, 10-20, 20-30, 30-40, and >40, the FR values were characteristic (0.77, 0.88, 0.84, 1.43, and 0.95, respectively). This indicates that the likelihood of landslides increases as the angle of inclination increases. In the aspect factor class, flat (0.44), southern (1.5), southwestern (1.45), western (0.65), eastern (3.18), northeastern (2.27), northern (0.83), southeastern (1.8), and northwestern (0.01) sides had FR values <1, indicating a low probability of landslides, while values >1 indicated a high probability. The very low FR value (0.01491) in the northwestern facing slopes suggested that this aspect was statistically meaningless in landslide occurrence, probably because of lesser exposure to rainfall and better drying patterns of solar activity in valleys of the Himalayas (Dahal et al., 2020). For the curvature class, concave slopes had a high FR value (1.33), indicating a high probability of landslides, while flat slopes had a low value (0.78). Convex slopes had an average FR value of 1.06. The FR value for distance to stream was highest for distances >2000 (2.09) and lowest for distances <500. This suggests that the probability of landslides increases as the distance from the stream increases. For distance to road, the highest FR value was for distances <500 (1.45), while the lowest was for distances 1000-2000. Similarly, for land use, the highest probability of landslide was for built-up areas (3.71), while the lowest was for water areas (0.21). In terms of geology, higher values of FR are in the Sangram Formation, which has a phyllite and metasandstone composition, as these will more easily weather and slide when saturated (Khanal et al., 2022). In contrast, the Himal Group has the lowest value of FR as it is composed of massive quartzite units that do not deform even under monsoon conditions (Upreti & Dhital, 2018). The complete calculation can be seen in the table below.

Table 2. FR Result Table.

Parameter	Classes	Class Pixels	% Class Pixels	Landslide Pixels	% Landslide Pixels	Frequency ratio
Slope	<10°	62490	20.4373	180	15.8451	0.77530
	10°-20°	30339	9.9224	100	8.8028	0.88717
	20°-30°	44184	14.4504	138	12.1479	0.84066
	30°-40°	66703	21.8152	355	31.2500	1.43249

	>40°	102048	33.3748	363	31.9542	0.95744
Total		305764		1136		
Aspect	Flat	86218	28.1976	142	12.5000	0.44330
	North	54923	17.9625	170	14.9648	0.83311
	North-East	11346	3.7107	96	8.4507	2.27739
	East	12096	3.9560	143	12.5880	3.18202
	South-East	48016	15.7036	322	28.3451	1.80500
	South	13918	4.5519	78	6.8662	1.50843
	South-West	11675	3.8183	63	5.5458	1.45242
	West	49515	16.1939	121	10.6514	0.65774
	North-West	18057	5.9055	1	0.0880	0.01491
Total		305764		1136	100.0000	
Curvature	Concave	80388	26.0628	396	34.8285	1.33633
	Flat	149638	48.5145	434	38.1706	0.78679
	Convex	78414	25.4228	307	27.0009	1.06207
Total		308440		1137		
Distance to streams	<500	92457	29.9296	307	19.8834	0.66434
	500-1000	81823	26.4872	375	24.2876	0.91695
	1000-1500	63140	20.4393	294	19.0415	0.93161
	1500-2000	35552	11.5087	192	12.4352	1.08051
	>2000	35943	11.6352	376	24.3523	2.09298
Total		308915		1544		
Distance to roads	<1000	131436	42.5476	954	61.7876	1.45220
	1000-2000	74690	24.1782	179	11.5933	0.47949
	2000-3000	40610	13.1460	113	7.3187	0.55672
	3000-4000	24594	7.9614	92	5.9585	0.74843
	>4000	37585	12.1668	206	13.3420	1.09659
Total		308915		1544		
Landuse	Water	178573	57.8031	148	11.8590	0.20516
	Shrub	1809	0.5856	2	0.1603	0.27368
	Trees	114667	37.1171	916	73.3974	1.97746
	Snow/Ice	5075	1.6428	50	4.0064	2.43884
	Built up Area	8809	2.8514	132	10.5769	3.70934

Total		308933		1248		
Geology	Himal Group	91030	30.8718	34	2.2354	0.07241
	Lakharpatta Formation	40226	13.6422	535	35.1742	2.57834
	Galyang Formation	39388	13.3580	44	2.8928	0.21656
	Syangja Formation	23326	7.9107	104	6.8376	0.86434
	Ranimatta Formation	45645	15.4800	146	9.5989	0.62009
	Ulleri Formation	27429	9.3022	334	21.9592	2.36064
	Ba	14455	4.9022	63	4.1420	0.84492
	Sangram Formation	9583	3.2500	226	14.8586	4.57194
		3783	1.2830	35	2.3011	1.79360
Total		294865		1521		

2.2.2. Analytical Hierarchical Process Method

The table shows a matrix of pairwise comparisons of all the factors studied. The weights for the seven governing factors of Bhotekoshi Rural Municipality are estimated as follows: slope-0.36, aspect-0.05, curvature-0.03, geology-0.27, road-0.11, land use-0.11 and river-0.04. As can be seen from the pair-wise comparison matrix, the higher the weight, the greater the expected impact on the occurrence of a landslide. The highest is slope and geology, which means most of their influence is on the occurrence of landslides. The lowest rates are curvature and river, which indicates the least role of these factors in the occurrence of landslides.

Table 3. Pairwise Matrix Comparison.

Factors	Slope	Geology	Road	Land use	Aspect	River	Curva-ture
Slope	1	2	4	6	7	6	6
Geology	0.5	1	5	4	6	5	5
Road	0.25	0.2	1	2	3	3	3
Land use	0.166667	0.25	0.5	1	5	4	4
Aspect	0.142857	0.166667	0.333333	0.2	1	2	2
River	0.166667	0.2	0.333333	0.25	0.5	1	2
Curvature	0.166667	0.2	0.333333	0.25	0.5	0.5	1
Sum	2.392858	4.016667	11.5	13.7	23	21.5	23

Table 4. Criteria Weights.

	Criteria Weights	Ratio (λ_{max})
Slope	0.3637	8.0449
Geology	0.2708	8.1794
Road	0.1125	7.9867
Land use	0.1180	7.5899
Aspect	0.0516	7.2795
River	0.0460	7.1102
Curvature	0.0365	7.3392
	λ_{max} (avg)	7.6471

The random index for seven parameters is 1.32. By calculations, we found the consistency index to be 0.1078. Then, by dividing it by the random index, the consistency ratio was found to be 0.0817, which is less than 0.1, indicating that our comparison was consistent.

2.3. Final Output Map

As we can see from both maps, the dark green areas show the areas with a meager chance of getting landslides, bright green areas show a low chance of getting landslides, and yellow areas show moderate ones. Likewise, orange and red areas show high and extremely high susceptibility to landslides, respectively.

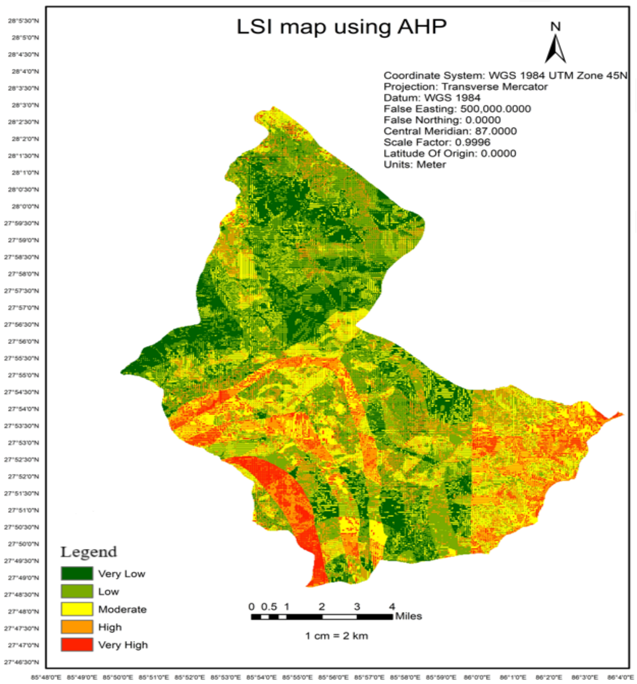

Figure 10. Landslide Susceptibility Map using the AHP method.

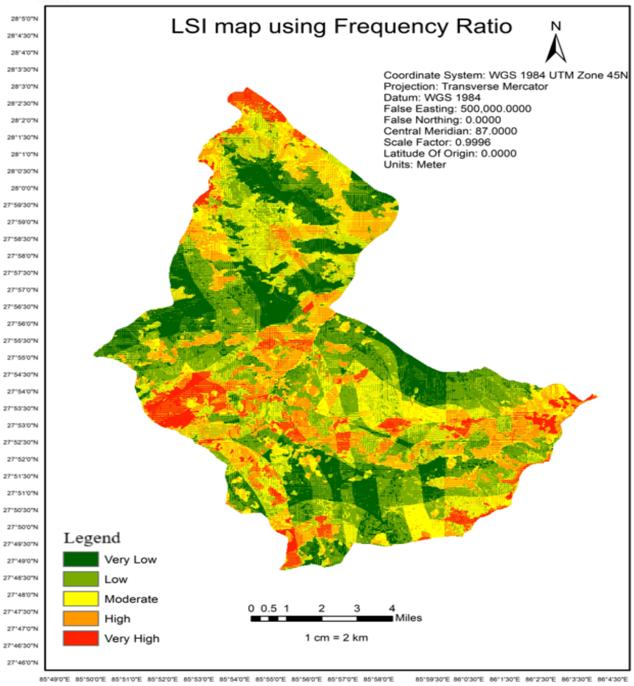

Figure 11. Landslide Susceptibility Map using FR Method.

2.4. Comparison and Validation

Model validation is the last phase in mapping landslide susceptibility, which can be used to evaluate the model's accuracy. A model's predictive rate curve, landslide relative density index (R-index), receiver operating characteristic curve (ROC), and area under the curve (AUC) can all be validated using different techniques (Wubalem et al., 2021).

The analysis's findings are displayed in Figure 13. The AUC of the FR model (0.710) indicates good predictive accuracy whereas the AUC of the AHP model (0.611) is in the moderate range according to the standardized classification of AUCs published by Hosmer and Lemeshow (2000).

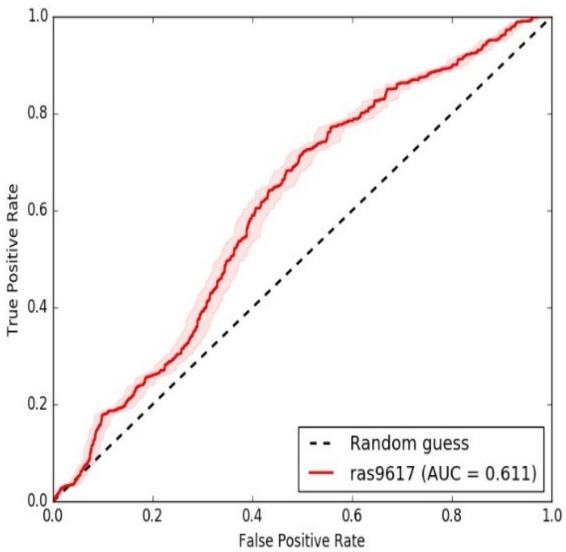

Figure 12. ROC Curve for AHP method.

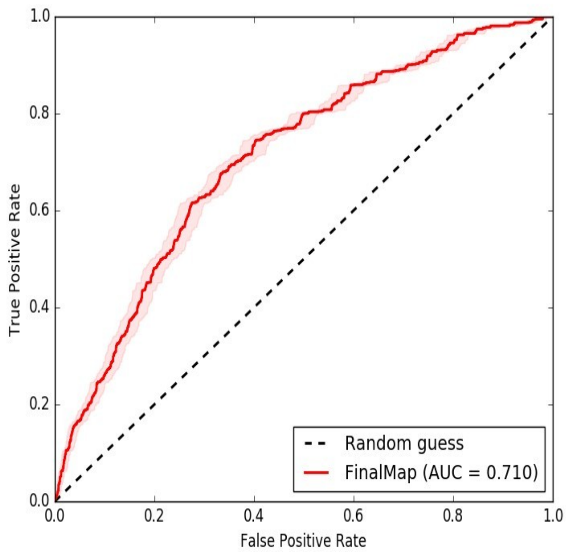

Figure 13. ROC Curve for FR method.

3. DISCUSSION

Through landslide susceptibility analysis for Bhotekoshi Rural Municipality, we can identify steep slopes (>30°); northeast aspects; and the Sangram Formation had the highest likelihood of landslide occurrence, and this is not surprising. Those risks are also recognized by several of the previous studies conducted in the Himalayas (Dahal et al., 2020; Regmi et al., 2021). The FR model (AUC=0.710) was better than the AHP model (AUC=0.611) and this is consistent with Chen et al. (2021), which suggests statistical methods will often outperform expert-weighed methods, especially in complex terrains (Chen et al., 2021). Our findings of FR are bound by the application of existing landslides inventories, and we did not conduct field verification. Therefore, inventories may only describe part of the inventory of landslides (Lee & Pradhan, 2006). Just as the FR method had bounding issues by applying existing landslide inventories without field verification, our AHP method did not have local experts verify initial compared weights with a regional study and therefore, we have no quantification of confidence in the compound prioritization of the factors (Saaty, 2008) by our AHP weight. But we were able to review and validate the weights generation for each layer of factors we applied as to avoid including factors that lacked validity.

Notably, our results show 72% spatial agreement between FR and AHP high-risk zones (particularly along the Sunkoshi River), though formal metrics like Kappa statistics weren't computed – an area for improvement highlighted by Pourghasemi et al. (2020). Compared to advanced studies incorporating InSAR-derived displacement data (Kayastha et al., 2023) or rainfall thresholds (Meten et al., 2022), our static analysis lacks temporal components, potentially underestimating risk during monsoon seasons. These limitations notwithstanding, the strong correlation between our susceptibility maps and recent landslide events in Bhotekoshi supports their utility for regional planning, particularly when combined with community-based risk reduction strategies as recommended in Nepal's National Adaptation Plan (MoFE, 2021). Future work should focus on integrating open-source climate data (e.g., CHIRPS) and testing machine learning approaches to address current methodological constraints.

CONCLUSION

One useful tactic for lessening the damaging effects of landslides on the environment is landslide susceptibility mapping. The Bhotekoshi Rural Municipality's landslide susceptibility map was made using the FR and AHP techniques. Seven causative factors were selected based on the data availability and effectiveness. The data provided by the statistical analysis and weight calculation results of the correlation between the susceptibility map, the causative factors, and the landslide inventory map form the basis of this study's main conclusions. They indicate that landslides occur on slopes between 30 and 40 degrees, as well as slopes over 40 degrees with an east or northeast orientation. Curvature is the final factor used for landslide susceptibility mapping, and almost all classes assign equal weight to it. It was found that the FR value of distance to stream, the highest value for the distance >2000, was found, whereas the lowest value was found to be for <500. Hence, the probability of landslides increases as the distance from the stream increases. Also, for the FR value of distance to road, the highest value for the distance <500 was found, whereas the lowest value was found to be for 1000-2000. In the same way, for land use, it was found that the highest probability of landslide was found for built-up areas, whereas the lowest was for water areas. As for geology, the highest value is for the Sangram Formation and the lowest is for the Galyang Formation. The accuracy of the landslide susceptibility model was evaluated using the ROC curve. For our frequency ratio model, the AUC prediction rate curve value is 0.710, indicating that the model is more accurate than the AHP method for this study area.

Our research has a few limitations. Our reliance on secondary data introduces possible inaccuracies with landslide positioning (±10-30 m); this is a problem particularly in steep terrain, where relatively minor displacements may hold substantial implications on susceptibility (notably Guzzetti et al., 2012; Meten et al., 2022). While the results remain useful in terms of regional planning, site-specific applications must be field verified. Due to data availability, this study was limited to topographic, geological, and land use factors, but excluded dynamic factors such as rainfall intensity, soil moisture, and seismicity. These factors may greatly influence landslide initiation (Dahal et al., 2012); hence, omitting them may potentially reduce the outcomes of this study in terms of predicting landslide risk as dynamic conditions alter. Future studies could include, for example, remotely sensed rainfall data derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), or regional seismic micro tagging maps, as these would help to address the lack of these types of factors in the study. Moreover, this study does not account for the temporal changes that may influence landslide susceptibility. Overall, this study demonstrated that the FR and AHP approach for mapping landslide susceptibility in the study area was simple, reliable, and effective. Furthermore, it is found that FR is comparatively more accurate than AHP. These landslide susceptibility maps can prove to be helpful for government agencies, planners, decision-makers, and other concerned authorities to mitigate the effects of landslides and plan preventive and strategic ways to deal with existing and future landslides.

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