Identifying the high-risk slope locations in Phewa Lake Catchment

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Abstract

Landslides in Phewa Lake Catchment, triggered by slope failure, poses risks to life, infrastructure, and degradation of soil quality while contributing to shrinkage of Phewa Lake. This study identifies potentially unstable slope within the catchment using landslide susceptibility mapping and then assesses slope stability of a selected unstable slope. A landslide susceptibility map (LSM) is developed using Geographic Information Systems (GIS) considering key factors such as slope, aspect, curvature, stream proximity, proximity to faults, proximity to thrust, rock/soil types and rainfall patterns applying the Frequency Ratio (FR) method. The prediction ratio obtained from FR shows the slope as the principal influencing factor for landslide occurrence followed by rainfall pattern and then rock/soil types. The LSM with 73.49% accuracy evaluated from Area under curve, indicates good performance of the model considered, classifies the catchment area into five susceptibility classes: very low (18.05%), low (29.92%), moderate (27.50%), high (13.19%) and very high (11.33%). The areas with high and very high susceptibility indicates higher possibility of slope failure emphasizing the priority for slope stability analysis during land-use planning and preparation of disaster mitigation strategy. Slope stability analysis will be conducted on selected unstable slope. Samples were collected from the selected slope, and direct shear tests were conducted to determine shear strength parameters. The next phase of the research involves a detailed slope stability analysis using Finite Element Analysis (FEA) in Plaxis 2D, applying the Shear Strength Reduction (SSR) method to estimate the Factor of Safety (FoS).
Keywords: *Landslide, Phewa Lake, Slope stability, Susceptibility*

1. Introduction

Nepal, being a mountainous region, encompasses rapid variation of elevation from 60 meters to 8848 meters in less than 200 kilometers of with relatively young mountains. In just a span of 6 years, from 2018 and 2024, a total of 2743 landslide incident has occurred in Nepal killing 859 people as per Ministry of Home Affairs, (2024). The death toll from landslide has been the highest in Gandaki province.

Phewa Lake Catchment within Gandaki Province has been facing recurring landslide incidents. The recurring landslide has not only led to a significant loss of lives and properties but also degrading the soil quality. According to C. Scott Watson et al., (2019), the sediment deposit from landslide is resulting in the shrinkage of Phewa Lake, a natural asset of Pokhara valley. Hence, there is a pressing need for detailed research in understanding the causes of landslides and stability of slope within the area for developing long-term solutions to mitigate risks, protect lives, and ensure environmental sustainability. There have been several approaches and efforts in mitigating landslide but the mitigation measures still remain inadequate. The study of causes of landslides and stability of slope helps better understand the landslide occurrence and in turn serve in effective mitigation.

Landslide Susceptibility Mapping (LSM) is one such study which gives us the likelihood of a landslide occurring in a particular area. It is a technique which is used to identify and classify landslide-prone regions by analyzing terrain characteristics, geological conditions, hydrological influences, and human activities which contributes to slope instability. The core principle of LSM is that, the conditions that caused past landslide are likely to result in future landslide when they reoccur (Guzzetti et al., 1999). Collection of landslide inventory and selection of condition factors are the important aspect of LSM. This information is then analyzed using various tools such as Geographic Information Systems (GIS), Remote Sensing, Machine Learning, etc.(Fell et al., 2008). Analytical Hierarchy Process (AHP), Frequency Ratio (FR), Weights of Evidence (WoE), Logistic Regression (LR), etc. are some of the methods used for LSM. LSM is generally done on a larger area which gives us a spatial representation of landslide prone areas. It is more generic and helps identify potential areas for slope failure leading to landslides.

Slope stability analysis on the other hand, is site specific and a detailed assessment of slope stability. It is usually assessed using numeric values for safety and potential failure zones with factor of safety (FoS) being a key factor to quantify slope stability. Slope fails when the driving force exceeds the resisting strength of the slope. Limit Equilibrium Methods (LEM), Finite Element Methods (FEM), Probabilistic Methods, etc. are some of the methods used for Slope stability analysis. GeoStudio (SLOPE/W), Slide2, STABL, PLAXIS, RS2, RocFall, GSlope, etc. are some of the software available for Slope stability analysis.

For a larger area, carrying out slope stability analysis alone can be quite time consuming as well as expensive for a developing country like Nepal. Hence, the multi-scale approach where LSM is developed first for a regional scale to identify potential slope failure area and then carrying out slope stability analysis on identified slope can be a better and efficient option. The objective of this research is to utilize LSM and slope stability analysis for mitigation measure. In this paper, the 1st phase of the research i.e. preparation of LSM to identify the possible failure locations is discussed.

2. Literature review

There have been several studies in the past regarding LSM enhancing the understanding of the process. S.M. Sikrikar et al. (1998) classified the hazard zone based on landslide frequency (LF) values by utilizing geological, soil, slope and land use data establishing a foundation for future land management and landslide mitigation strategies in the rapidly urbanizing region. P. Basnet et al., (2012) utilized GIS and Analytical Hierarcy Process (AHP) to assess landslide hazards by considering lithology, slope, land use, rainfall and proximity to faults and roads. Ananta Man Singh Pradhan & Yun-Tae Kim, (2016) employed the Artificial Neural Network (MLP-ANN) model within GIS to evaluate landslide susceptibility utilizing topographic, hydrological and geological factors. This model achieved high predictive accuracy, reinforcing the effectiveness of machine learning in LSM. Bimal Bahadur Kunwar et al., (2024) applied Frequency Ratio (FR) to analyze eight causal factors to classify five susceptibility classes.

Based on these studies, 7 causative factors (slope, aspect, curvature, distance to stream, proximity to fault, proximity to thrust, rock/soil types) and 1 triggering factor (rainfall pattern) is used and Frequency Ratio (FR) method is applied for LSM.

2.1 Causative Factors

Causative Factors are the predisposing factors that are the inherent characteristics of the terrain. The causative factors considered in this study are as follows:

i. Slope: Slope is the inclination of the existing terrain. The steeper the slopes, the higher is the susceptibility to failure and landslide occurrence.
ii. Aspect: Aspect is the direction of the slope which is generally represented in degrees from 0° to 360°. Aspect affects moisture content and solar exposure, influencing stability of the slope. South-facing slopes are more often found to be more susceptible.
iii. Curvature: Curvature is the concavity or convexity of the terrain. This affects the water flow and accumulation of water influencing the soil saturation and stability. Concave areas tend to collect water affecting the moisture and pore pressure, hence increasing the susceptibility.
iv. Distance to stream: The areas near the stream influences the water content in the adjacent slopes increasing the susceptibility for slope failure and leading to landslide.
v. Distance to fault and thrusts: The presence of weak zones due to the presence of faults and thrusts increases the susceptibility of areas near them.
vi. Rock/soil types: The rock/soil types with higher strength are more stable compared to soft or

weathered rock/soils.

2.2 Triggering Factors

Triggering factors are the external events that initiate a landslide when the terrain is already susceptible to failure due to pre-existing characteristics. Rainfall pattern is considered in this study. Heavy and prolonged rainfall saturates soil, increases pore water pressure, and reduces shear strength, making it a major trigger, especially during monsoon seasons (Shano et al., 2020).

2.3 Landslide Susceptibility Mapping

Landslide susceptibility mapping (LSM) is a crucial tool for predicting areas prone to landslide risks. It aims to determine the probability of landslides occurring in a specific location by evaluating the relationship between previous landslide occurrences and various causative factors. LSM divides the land surface into zones based on different levels of susceptibility. This information is valuable for land use planning and mitigating the impacts of landslides.

2.4 The Frequency Ratio (FR) Method

The frequency ratio (FR) model is a dependable and popular statistical approach for determining LSMs. It is a statistical method that can be used to generate precise maps of landslide susceptibility and to analyze the relationship between landslide incidences and causative factors.

The FR model has a significant advantage that, it can determine the rank of the causative factors concerning a landslide occurrence It can also identify whether or not a specific range of causative factor values will be dangerous in the event of landslides. Evaluations of several statistical approaches have revealed that the FR model often outperforms others. For example, studies comparing FR with methods like Weights of Evidence (WoE), Analytical Hierarchy Process (AHP), Weighting Factor (WF), and Logistic Regression (LR) have concluded that FR can have a higher prediction rate (Bimal Bahadur Kunwar et al., 2024) .

The calculations involved in FR method is as follow:

$$FR_{i,j} = \frac{Npix(S_{i,j})/\sum_j NPix(S_{i,j})}{Npix(N_{i,j})/\sum_j NPix(N_{i,j})} \tag{1}$$

Where;

FRi,j = Frequency ratio of a class

Npix(Si, j) = the number of pixels containing landslide within class j in factor i;

Npix(Ni, j) = the number of pixels of class j in factor i;

ΣjNPix(Si, j) is the number of total pixels containing landslide in the study area;

ΣjNPix(Ni, j) is the number of total pixels in the study area.

$$Relative\ Frequency\ ratio\ of\ a\ class\ (RF) = \frac{FR\ of\ a\ class}{Sum\ of\ FR\ of\ all\ class} \tag{2}$$

$$Predictive\ ratio\ (PR) = \frac{(Max\ RF - Min\ RF)}{MIN\ of\ (Max\ RF - Min\ RF)} \tag{3}$$

3. Methodology

The methodology of the study is as shown below in Fig. 1. Both thematic and spatial data were collected from different national agencies. The landslide data (number and location) were collected from field visit and landslide of inaccessible areas were collected from Google Earth Data. A total of 320 landslide data were collected and were then processed and susceptibility of the catchment area was evaluated. Samia et al., (2014) found that landslide causes higher susceptibility for a flow-up landslides over a period of about 10 years. Hence, in this study landslide of 10 years (2016-2025) is taken. The landslide collected is presented below in Fig. 2 along with site photograph in Fig. 3

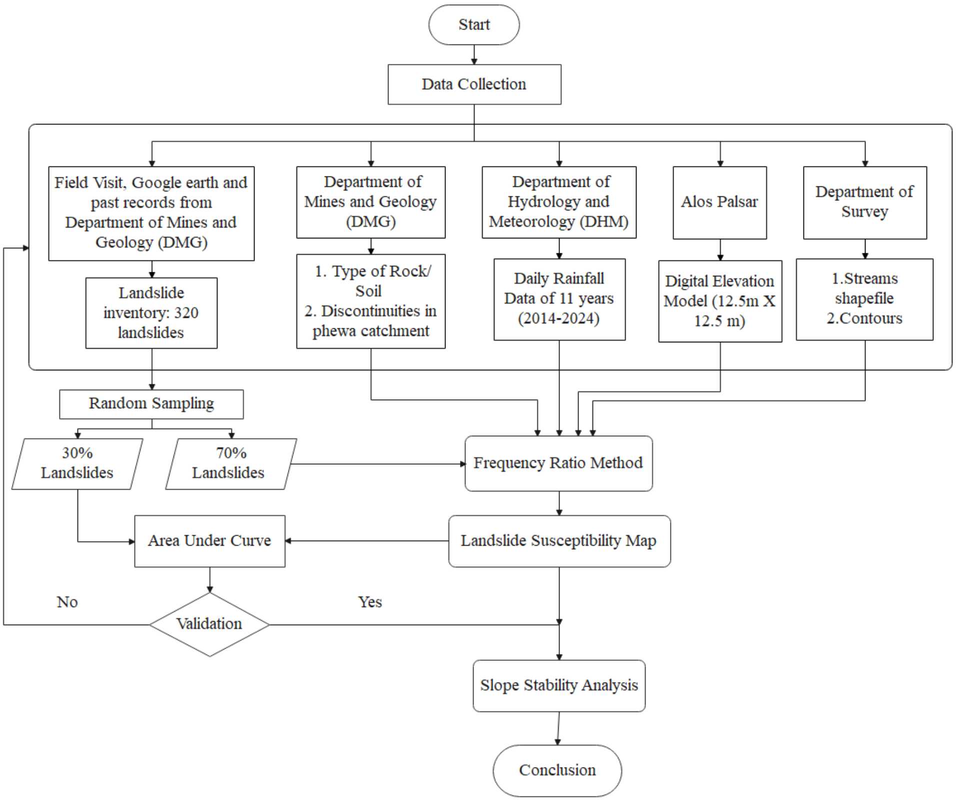

Fig. 1: Methodology of the study

The landslide data collected were randomly split into 70% (224) for training the model and 30% (102) for validating the model by keeping their spatial distribution into account. The split balances the need for sufficient training data while retaining enough independent samples for validation.

The rainfall station influencing the catchment area were identified using Theissen polygon and co-ordinate of rainfall station available in Department of Hydrology and Meteorology (DHM) website. The 24 hr daily rainfall data for 11 years (2014 to 2024) collected from DHM were interpolated into thematic map of 12.5m x 12.5m resolution applying IDW interpolation.

The high-resolution terrain corrected DEM of resolution 12.5m x 12.5m from ALOS PALSAR (L-band synthetic aperture radar (SAR) is used for the analysis. The Thematic maps including Slope, Aspect, Curvature, Distance to stream, Distance to Fault, Distance to Thrust, Rock/Soil Types and Rainfall are shown Fig. 4 to Fig. 11.

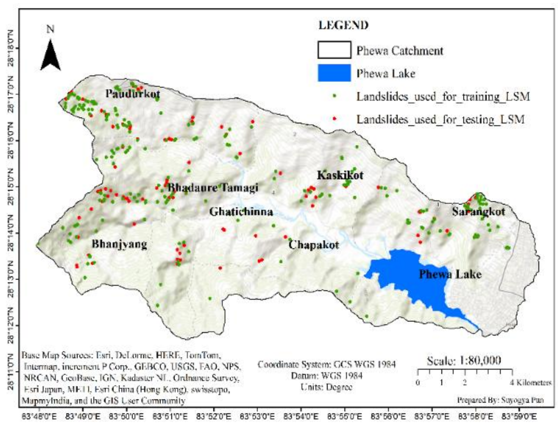

Fig. 2: Landslide Location in Phewa Lake Catchment

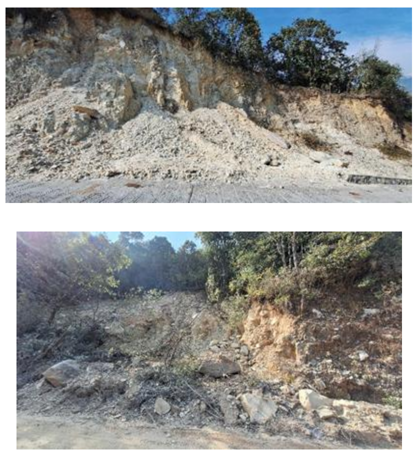

Fig. 3: Landslides in Phewa Catchment

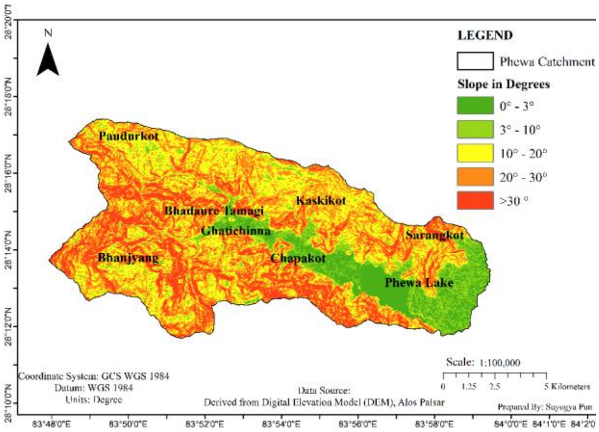

Fig. 4: Slope

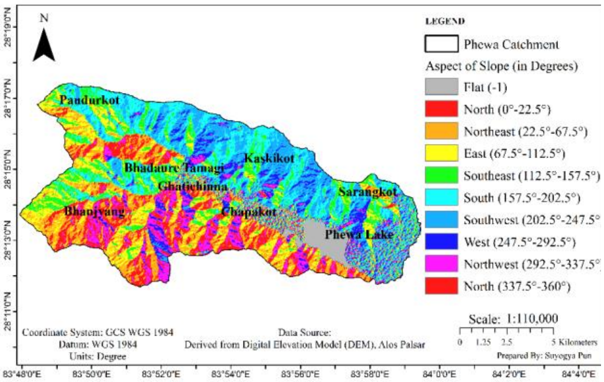

Fig. 5: Aspect of Slope

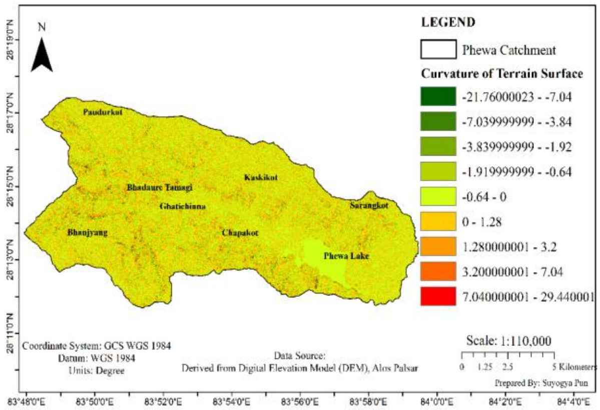

Fig. 6: Curvature of terrain

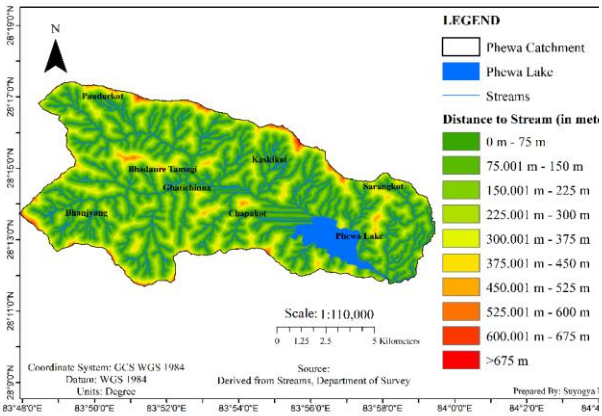

Fig. 7: Distance to stream

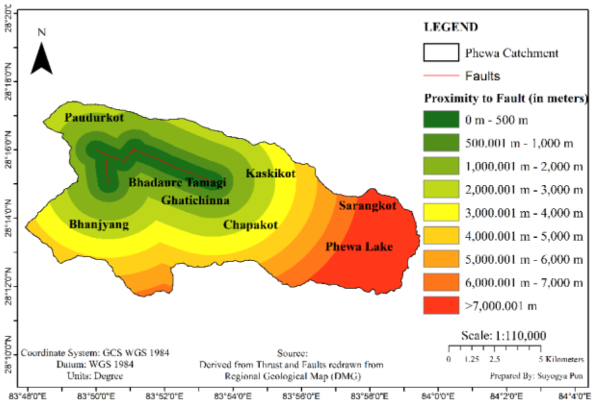

Fig. 8: Proximity to fault

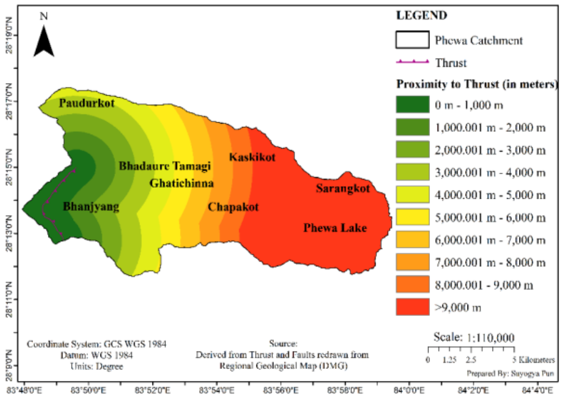

Fig. 9: Proximity to thrust

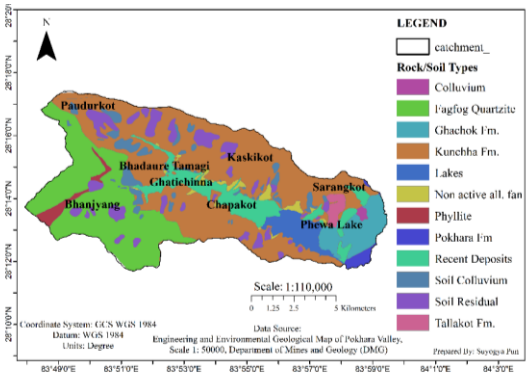

Fig. 10:Rock/Soil Types

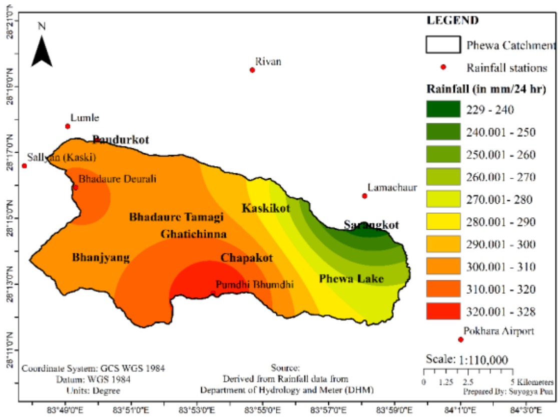

Fig. 11: Rainfall Pattern

S.N	Factor	Study Area		Landslide	FR	RF	Max RF - Min RF	MIN (Max RF - Min RF)	PR
		Class	%Class Pixel	%Landslide Pixel					
1	Slope (in degrees)	0° -3°	10.648	0.048	0.005	0.001	0.633	0.210	3.009
		3° -10°	10.829	1.512	0.140	0.030			
		10° - 20°	29.645	15.235	0.514	0.111			
		20° - 30°	31.489	32.366	1.028	0.223			
		>30°	17.389	50.840	2.924	0.634			
2	Aspect (in degrees)	Flat (-1)	4.784	0.120	0.025	0.003	0.260		1.237
		North (0°-22.5°)	5.792	3.695	0.638	0.078			
		Northeast (22.5°-67.5°)	13.220	15.403	1.165	0.142			
		East (67.5°-112.5°)	12.060	16.771	1.391	0.169			
		Southeast (112.5°-157.5°)	12.845	27.807	2.165	0.263			
		South (157.5°-202.5°)	15.554	17.826	1.146	0.139			
		Southwest (202.5°-247.5°	15.387	13.124	0.853	0.104			
		West (247.5°-292.5°)	6.933	1.008	0.145	0.018			
		Northwest (292.5°-337.5°	8.278	1.823	0.220	0.027			
		North (337.5°-360°)	5.145	2.423	0.471	0.057			
3	Curvature	-21.76 - -7.04	0.071	0.144	2.037	0.116	0.218		1.034
		-7.04 - -3.84	0.695	2.087	3.002	0.171			
		-3.84 - -1.92	8.239	13.840	1.680	0.096			
		-1.92- -0.64	29.202	28.256	0.968	0.055			
		-0.64 - 0	23.657	15.927	0.673	0.038			
		0 - 1.28	29.068	25.210	0.867	0.049			
		1.28 - 3.2	8.314	11.250	1.353	0.077			
		3.2 - 7.04	0.705	3.166	4.490	0.256			
		7.04 - 29.440001	0.049	0.120	2.467	0.141			
4	Distance to stream (m)	0m -75m	35.606	36.987	1.039	0.189	0.210		1.000
		75m - 150m	23.710	26.193	1.105	0.201			
		150m -225m	17.280	19.045	1.102	0.201			
		225m -300m	11.376	13.145	1.155	0.210			
		300m - 375m	6.626	3.766	0.568	0.104			
		375m - 450m	3.284	0.552	0.168	0.031			
		450m - 525m	1.371	0.192	0.140	0.025			
		525m - 600m	0.563	0.120	0.213	0.039			
		600m - 675m	0.157	0.000	0.000	0.000			
		>675 m	0.027	0.000	0.000	0.000			
5	Distance to Fault (m)	0m - 500m	7.123	9.019	1.266	0.140	0.244		1.159
		500m -1000m	7.942	19.813	2.495	0.276			
		1000m -2000m	17.747	18.877	1.064	0.118			
		2000m -3000m	16.121	27.609	1.713	0.189			
		3000m -4000m	13.846	9.259	0.669	0.074			
		4000m -5000m	11.021	3.166	0.287	0.032			
		5000m -6000m	6.577	3.910	0.594	0.066			
		6000m -7000m	5.279	3.166	0.600	0.066			
		>7000m	14.343	5.181	0.361	0.040			
6	Distance to Thurst (m)	0m -1000m	7.501	12.641	1.685	0.186	0.255		1.212
		1000m -2000m	6.382	12.161	1.906	0.211			
		2000m -3000m	8.408	17.390	2.068	0.229			
		3000m -4000m	10.940	27.177	2.484	0.275			
		4000m -5000m	9.726	4.725	0.486	0.054			
		5000m -6000m	6.959	1.223	0.176	0.019			
		6000m- 7000m	6.460	3.790	0.587	0.065			
		7000m- 8000m	5.765	2.351	0.408	0.045			
		8000m -9000m	5.361	3.238	0.604	0.067			
		>9000m	32.497	15.303	0.471	0.052			
7	Rock/ Soil types	Kunchha Fm.	42.063	39.002	0.927	0.145	0.349		1.659
		Fagfog Quartzite	23.755	52.890	2.227	0.349			
		Soil Colluvium	4.447	3.718	0.836	0.131			
		Soil Residual	7.031	1.271	0.181	0.028			
		Pokhara Fm	0.950	0.000	0.000	0.000			
		Recent Deposits	8.332	1.919	0.230	0.036			
		Non active all. fan	1.603	0.000	0.000	0.000			
		Phyllite	1.516	0.384	0.253	0.040			
		Ghachok Fm.	5.265	0.000	0.000	0.000			
		Tallakot Fm.	1.085	0.456	0.420	0.066			
		Colluvium	0.276	0.360	1.305	0.205			
		Lakes	3.677	0.000	0.000	0.000			
8	Rainfall (mm/24 hr)	229-240	0.789	2.327	2.950	0.365	0.365		1.736
		240- 250	2.015	2.039	1.012	0.125			
		250- 260	3.752	1.847	0.492	0.061			
		260 - 270	5.367	3.598	0.670	0.083			
		270- 280	0.001	0.000	0.000	0.000			
		280 - 290	15.010	4.893	0.326	0.040			
		290-300	8.405	1.895	0.225	0.028			
		300 - 310	40.863	62.941	1.540	0.191			
		310-320	0.001	0.000	0.000	0.000			
		320-328	23.798	20.461	0.860	0.106			

Fig. 12: Frequency Ratio Calculation

Fig. 12 presents the tabulated calculation of the FR. The FR of each class of factors considered is calculated using Equation 1. This FR value represents the degree of correlation between landslide and a certain class of factor. Then, the RF of each class is calculated using Equation 2. The PR of a Factor is then calculated using Equation 3. The PR gives the degree of influence of a factor in LSM.

4. Results and Discussion

The preparation of the Landslide Susceptibility Map applying Frequency Ratio (FR) method, showed that the principal influencing factor for landslide occurrence in Phewa Lake Catchment is the slope (causative factor) of the terrain followed by the rainfall pattern (triggering factor) in the area and then rock/soil types. These factors are also the governing factors in slope stability analysis. Fig. presents the predictive ratio of each causative factors considered.

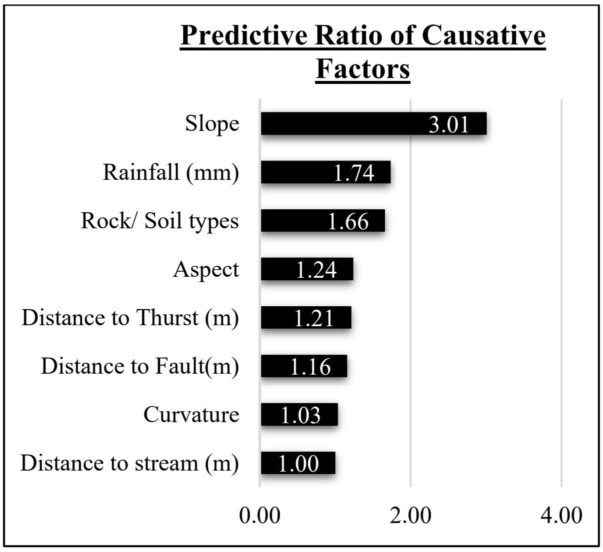

Fig. 13: Predictive Ratio

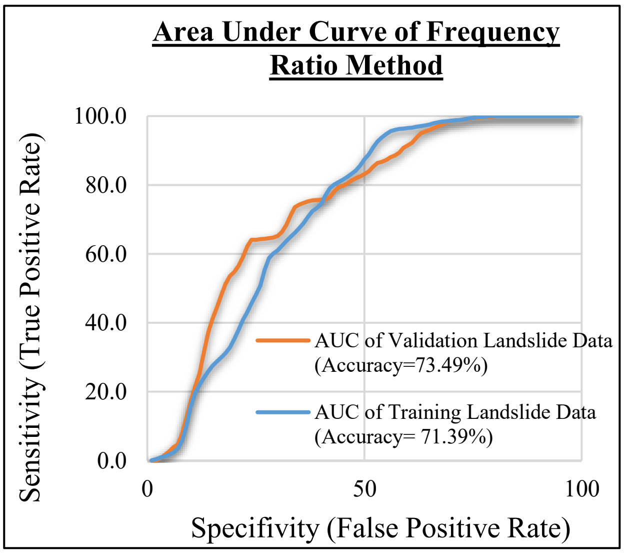

Fig. 14: Area Under Curve

Fig. 14 shows Area Under the Curve of the LSM prepared. The evaluated accuracy is 73.49% for landslide data used for testing the model and 71.39% for landslide data used for training the model which shows a good performance of the model. Although, the advancement in technology has developed incorporation of machine learning to build model with better accuracy of more than 80% as presented in various studies by (Singh et al., 2024), FR method is simpler, easy to understand and follow as it relies on a straightforward statistical approach to calculate the relationship between landslide occurrences and conditioning factors. As this model is used for preliminary identification of high-risk slope for slope stability analysis. The LSM thus prepared with acquired 73.49% can be used for further analysis.

The LSM was then categorized into 5 different classes. The final LSM is presented in Fig. . LSM classified into five classes shows 18.05% area of catchment has very low susceptibility, 29.92% area has low susceptibility, 27.50% area has moderate susceptibility, 13.19% area has high susceptibility and 11.33% has very high susceptibility to Landslide occurrence as shown in Fig. .

The region with high and very high susceptibility are the areas with the high possibility of slope failure. Hence, further detail study of the slope stability analysis will be done within these high and very high susceptible regions.

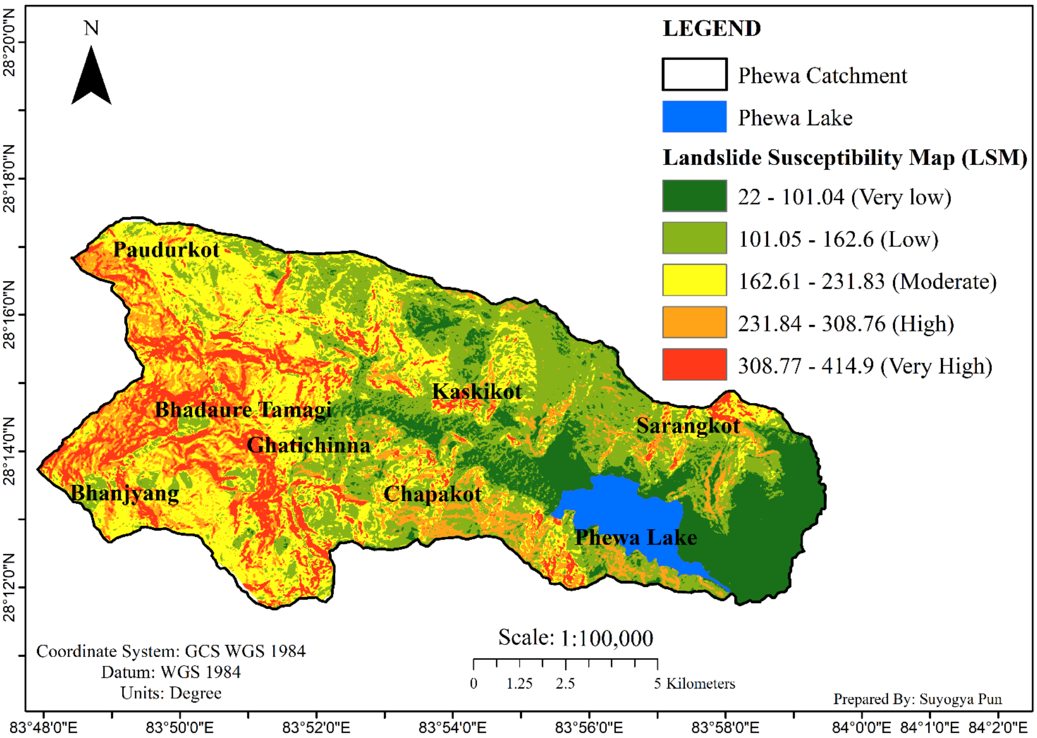

Fig. 15: Landslide Susceptibility Map of Phewa Lake Catchment

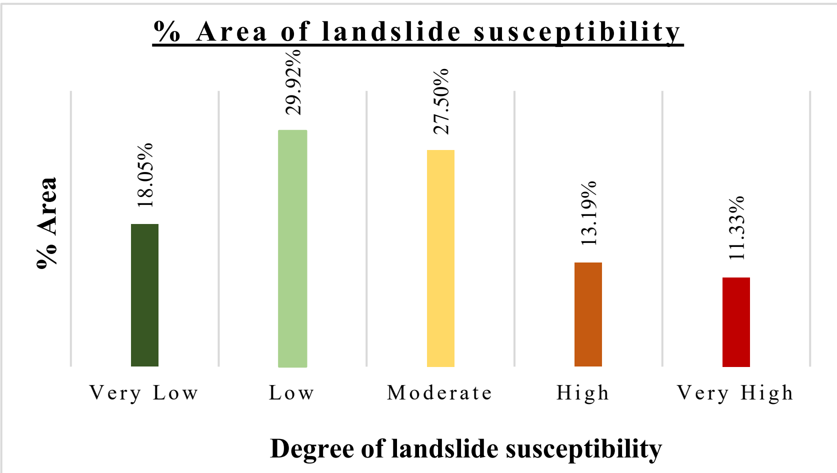

Fig. 16: Degree of Landslide Susceptibility

5. Conclusion and Recommendations

The Landslide Susceptibility Map prepared using the Frequency Ratio (FR) method effectively identifies the key factors influencing landslide occurrence in Phewa Lake Catchment. The results indicate that terrain slope is the primary causative factor, followed by rainfall patterns and rock/soil types, which are crucial in slope stability analysis. The model demonstrated good accuracy, with an Area Under the Curve (AUC) of 73.49% for testing data and 71.39% for training data, confirming its reliability for further analysis.

The LSM categorization into five susceptibility classes highlights that 24.52% of the catchment area falls under high and very high susceptibility zones, indicating a significant risk of slope failure. These regions require detailed slope stability assessments and targeted mitigation measures to minimize potential landslide hazards. The prepared Landslide Susceptibility Map serves as a valuable tool for land-use planning and disaster risk management in Phewa Lake Catchment.

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