

SPATIAL MODELING OF LANDSLIDE SUSCEPTIBILITY USING RANDOM FOREST TECHNIQUE

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Abstract— This study aims to develop a comprehensive landslide susceptibility map to assess the vulnerability of regions to landslide occurrences. The map relies on the integration of various influential natural factors termed Landslide Causing Factors (LCFs). While some data, including road, river and DEM, were directly sourced from Google Earth Engine (GEE), other factors like slope aspect, convergence index, and relative slope position were derived from the Digital Elevation Model (DEM). We use Multicollinearity Assessment to check whether all the factors are independent and suitable. To optimize the quality of the susceptibility map, a quantitative factor selection process was executed. Recognizing that not all factors hold equal weight in landslide occurrences, we employed the Chi-square method to eliminate non-contributory variables. To elevate the performance of our model, we have used the Random Forest (RF) machine learning process. We divided our dataset into training and testing datasets using 80:20 ratio. Our results indicate that factors like elevation and TPI are highly significant, and these values were further utilized to create a Landslide Susceptibility Map (LSM). A performance analysis of the LSM was conducted using Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) as the performance metric. In addition to the ROC-AUC, we further assessed the Mean Squared Error (MSE) as a key evaluation measure. The results indicate that our model achieved an impressive ROC-AUC of 0.80, showcasing its ability to discriminate between positive and negative instances effectively. Furthermore, the model demonstrated strong predictive accuracy with a low MSE of 2, further underscoring their robust performance in this study. The resultant map serves as an important input for informing regional planning initiatives, effectively identifying areas of heightened risk and enabling the implementation of strategic projects in Hindu Kush Himalaya.

Keywords—Spatial modeling, Landslide Susceptibility, Machine Learning, Hindu Kush Himalaya.

I. INTRODUCTION

A landslide is a natural phenomenon characterized by the downward movement of a mass of soil, rock, debris along a slope or incline, influenced by gravity. Landslides are considered to be one of the major natural hazards, especially in hilly terrains, causing unprecedented loss of life and

property every year. Global economic expansion, unforeseen construction activities supplemented with effects of climate change has resulted in increased incidence of landslides, especially in the mountainous regions, highlighting these regions as hotspots for hazard mortality [1, 2]. From 2005 to 2014, over 70% of the disaster related deaths occurred in mountainous regions [3]. In 2020, 295 people died due to landslides across India [4]. The Hindu Kush Himalaya (HKH) region, which is the area of interest for the present study is known as a global hotspot for mortality risks associated with mountain disasters which are often inter-related [5]. The 2015 Gorkha earthquake which triggered ~24,000 landslides [6], the 2013 heavy rainfall event which caused catastrophic damage in Uttarakhand [7], and the 2021 flood in the Chamoli district of Uttarakhand due to rock-ice avalanche [8] are few notable examples. Although numerous methods have been previously employed to understand the distribution, frequency and mechanics of landslides, the availability of satellite datasets along with progress in remote sensing and GIS studies have opened up new avenues in research [1,9,10,11]. Therefore, Landslide Susceptibility Mapping (LSM) is one such important method implemented for disaster risk reduction. It involves a comprehensive analysis of various intrinsic and extrinsic factors in a specific area and categorizes them into different susceptible zones in order to predict future landslide risks [2,12]. LSM can be categorized into two methods: quantitative and qualitative. Qualitative methods mainly rely on expert knowledge introducing subjectivity such as Analytic Hierarch Process (AHP) [13,14,15]. In contrast, quantitative methods encompass deterministic methods based on physical models, data-driven statistical models [16,17], and machine learning techniques [18,19,20]. Recent advancement in ML algorithms, computing power, availability of high-resolution satellite data, and advanced geospatial techniques have drastically improved the LS methods. The key advantages of ML methods are their objective statistical foundation, repeatability, incorporation of a wide range of conditioning factors, usage at a regional scale, and the flexibility to update the models frequently [21]. Commonly employed machine learning techniques include logistic regression (LR) [22]; random forest (RF) [23]; support vector machine

(SVM) [24, 25], artificial neural network (ANN) [26, 27]. Even though LSM using machine learning has recently been conducted at a wide scale, there has been limited research specifically conducted for the entire HKH region except a study by Rusk et al. (2022) [28]. Here, they have tried to analyse and understand multi-hazard risks in the HKH using ML techniques, satellite data and previous hazard catalogues. Previous studies in HKH focused on specific zones or regions with mostly focusing on the best ML method for LS mapping. Implementing any ML method for the HKH region can be a challenging task due to variations in its topography, geology and climate. However, this study is an attempt to overcome the methodological challenges encountered while assessing large scale datasets by other statistical methods. Therefore, to create an effective LSM, it is imperative to use a technique that is both effective and generalized. A generalized technique is valuable as it can perform better with random samples and is more likely to be applicable to various geographical locations and conditions. Furthermore, previous studies show that most of the procedure of feature selection is qualitative with no specific explanation for the weightage assigned to each class. To address this issue, the present study utilizes statistical techniques such as chi-square test and multi-collinearity analysis to identify and prioritize the relevant classes and variables.

Overall, the primary goal of this paper is to produce an LSM for the HKH region which will help in limiting human and economic losses along critical corridors and major cities. It will also provide a regional framework for decision makers to avoid catastrophic damage in the future and provide strategic long-term solutions.

II. STUDY AREA

The study area for this project is defined in accordance with the boundaries considered by the ICIMOD as the Hindu Kush Himalaya. This choice was influenced by the high occurrence of landslides in the region and increasing amount of life and monetary loss. The diverse scope of factors present in the region provides a dynamic dataset to be worked on. The study region, known as the Hindu Kush Himalaya (HKH) study region, is depicted in Fig. 1 and spans approximately 608,100 square kilometers across South Asia. It encompasses the Indian states of Sikkim, Uttarakhand, and Arunachal Pradesh, as well as the Indian union territories of Ladakh and Jammu and Kashmir. Additionally, the study region includes the countries of Nepal, Bhutan and some regions of China, Pakistan and Afghanistan.

The HKH study region falls within the geographic coordinates of approximately 25° 57' 53" N to 35° 30' 5" N latitude and 73° 45' 47" E to 97° 24' 55" E longitude (refer Fig. 1). Throughout this study, references to the Hindu Kush Himalaya (HKH) are specifically directed to this designated study region. This entire area is characterized by significant seismic activity due to the interaction of the Indian Plate and the Eurasian Plate. The movement and slippage between these tectonic plates generate elastic strain that, upon release, can result in catastrophic high-magnitude earthquakes [29].

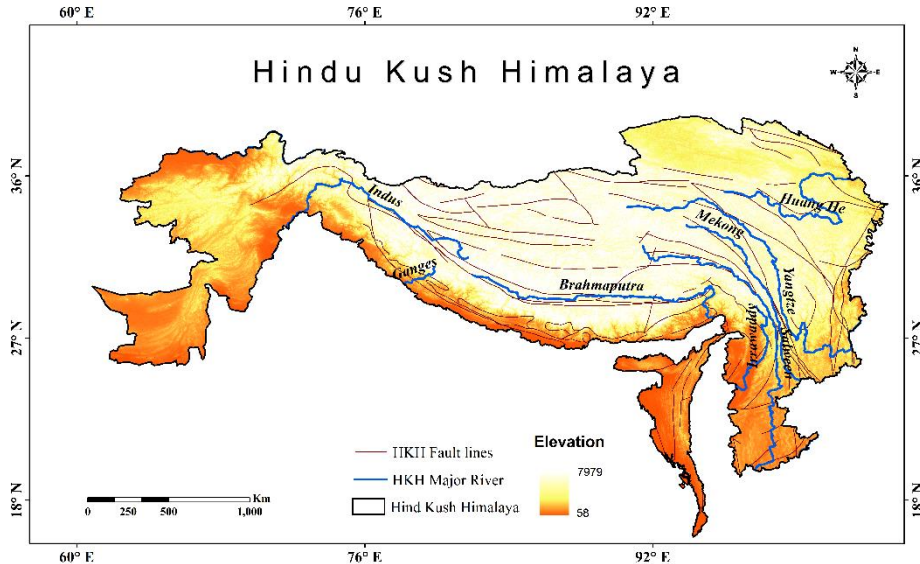


Figure 1: Study area map showing the region covered by Hindu Kush Himalaya (HKH)

III. DATA AND METHODOLOGY

A. Datasets

Table 1. depicts data sources utilized to develop the LSM. The dataset has been divided into primary and secondary datasets. We have acquired some of our datasets from Google Earth Engine (GEE) and have derived the rest. The GEE is a cloud-based computing platform which can process satellite and other Earth observation data. The HKH boundary has been procured from **International Centre for Integrated Mountain Development (ICIMOD)** (<https://www.icimod.org/>).

The list of datasets is provided below:

Table 1: Data Description

Data	Data Type	Resolution (Scale)	Data Source
Landslide Inventory	P	---	Link
SRTM DEM	P	30 m	Link
Slope (DEGREE)	S	30 m	
Aspect	S	30 m	Derived from DEM
Convergence Index,	S	30 m	Derived from DEM
Valley Depth	S	30 m	Derived from DEM
Topographic Position Index	S	30 m	Derived from DEM
Terrain Ruggedness Index	S	30 m	Derived from DEM
Relative Slope Position	S	30 m	Derived from DEM
River Network	P	---	Link
Road Network	P	---	Link

Here, ‘P’ indicates primary datasets and ‘S’ denotes secondary datasets.

Given below is a brief description of the primary datasets.

DEM: Digital Elevation Model provides the elevation of a given surface with respect to mean sea level. For the present study we have utilized Shuttle Radar Topography Mission (SRTM) DEM of 30 m spatial resolution.

Landslide Inventory:

NASA Global Landslide Catalogue, In vector format (656 Landslide points)

Derived Datasets are derived either only from primary datasets or may have been processed from GEE. Few datasets like fault line map, river network, road network, and soil map, were directly acquired from the ICIMOD (<https://www.icimod.org/>). These datasets were not directly applied for processing in its vector form and thus, were converted to raster for further processing.

Given below is a brief description of the secondary datasets.

1. **Road Network:** It was acquired as a line Vector Dataset and was further rasterized with a 13000-meter buffer.
2. **River Network:** It was acquired as a line Vector Dataset and was further rasterized with a 7500-meter buffer to convert it into Raster Dataset.
3. **Fault Line Map:** It was acquired as a line Vector Dataset and was further rasterized with a 150000-meter buffer to convert it into Raster Dataset.
4. **Slope degree:** It defines the steepness of any point on the surface. The lower the slope value, the flatter the terrain.
5. **Slope aspect:** Aspect values indicate the directions the physical slope faces. A slope that falls down to the valley on its western side and a shallower end on its eastern side has a west-facing slope or westerly aspect.
6. **Convergence Index (CI):** Convergence index is a terrain parameter which shows the structure of the relief as a set of convergent areas (channels) and divergent areas (ridges).
7. **Topographic position index (TPI):** It compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell.
8. **Terrain Ruggedness Index (TRI):** It is used to express the amount of elevation difference between adjacent cells of a DEM.
9. **Valley Depth:** This is the numerical difference between the elevation of the ridge and the base.
10. **Relative Slope Positions (RSP):** It defines the relative positioning of a slope in any region.

B. METHODOLOGY

The LSM was created using the methodology shown in Fig. 2. For accurate and reliable modeling, we need to evaluate our factors and select only the ones which contribute significantly to the occurrence of landslides [30, 31]. The causative factors are considered significant if they have a p-value <0.05 for which we utilized the Chi-Square test.

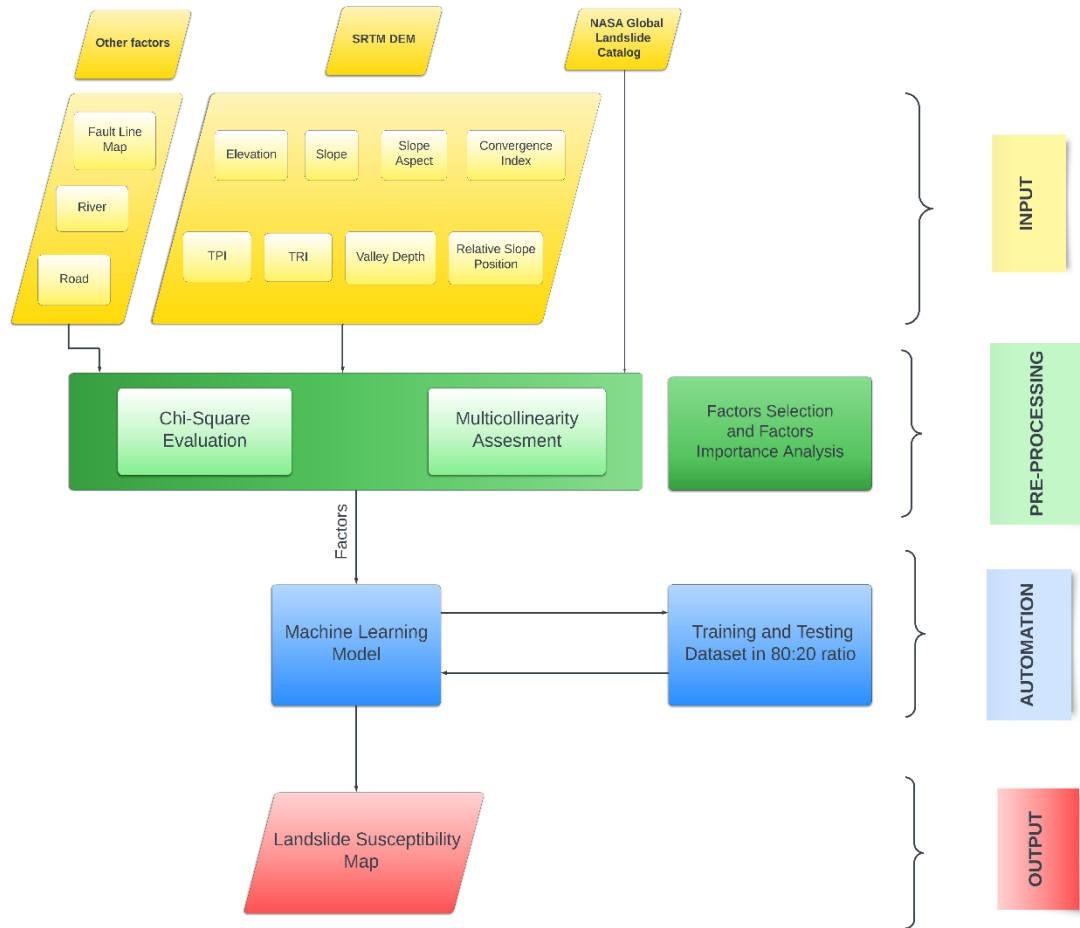


Figure 2: Flowchart representing the methodology of the present work

Subsequently, the entire dataset was divided into training and testing datasets in 80:20 ratio and RF was applied to provide the significance level of each factor. These significant level values will be finally utilized to create a map. The maps created are more generalized and can work for a broader set of values.

Steps:

- 1. Data Acquisition:** The initial process of data acquisition involves obtaining data from primary datasets and also using those primary datasets to derive secondary datasets. The process of data acquisition for secondary datasets involves mathematical operations and overlapping of raster images.
- 2. Pre-Processing:** Before applying any machine learning techniques, we need to process our obtained datasets, by scaling and normalizing. This process also involves feature selection. We cannot use all the features for computing the LSM, instead we only use the features that trigger or impact landslide occurrence.
 - Scaling and normalizing data:** Before directly using the dataset, we need to consider the fact that all these factors are present at different scales and cannot be placed together for computation. Furthermore, we have to limit the range of values for all the factors. Scaling and normalization have

been used for this purpose. This makes the data usable and operable for all the upcoming processes.

- Multicollinearity Assessment:** After preparing a dataset, a Multicollinearity assessment was performed to check the correlation between features. A correlation heatmap was generated to check the correlation between various factors. This assessment is used to find the correlation within various variables. We observe the importance of this technique in research papers like Garosi et al., (2023) [32]. Here, we compute the value of Variable Inflation Factor (VIF). If the value of VIF equals 1, then this shows that the features are independent and have no correlation. This is a very important condition within attributes before being utilized for further analysis.

$$VIF = \frac{1}{1 - R^2}$$

The value of VIF depends on R_j , High value of R_j means high correlation between features. R_j denotes the factor of determination of regression of explanator j on all the other explanators. Here, the explanator denotes various features that are used for making the Landslide Susceptibility Mapping.

- **Feature selection using Chi-square:** For this process we select the features and use them further for analysis and model applications. We use this method to evaluate if the feature is related with the landslide occurrence variable (target variable) or not. The basis of this is the p-value. We will use the hypothesis test:

H0 (Null hypothesis): There is no relationship between the target variable and the feature.

H1 (Alternate Hypothesis): There is a relationship between the target variable and the feature.

Here, if the p-value ≥ 0.05 , then cannot reject our null hypothesis. This will prove the fact that our selected feature is not related with the target variable. We will perform the same operation on all the features, resulting in filtering out of features which are not related.

But if the p-value < 0.05 , then we will reject the null hypothesis. This will approve the fact that the feature is related with the target variable and will be included in the features that are selected. So, for each feature we will compute the p-value and will reject the feature that has p-value greater than 0.05.

3. **Machine Learning:** In this study, we utilized an RF regression model to predict the 'weights' based on a set of input features. After loading and preprocessing the data, we split it into training and testing sets in 80:20 ratio, further subdividing the training data into validation sets. We employed a Random Forest Regressor with 100 decision trees, a robust ensemble learning technique known for its predictive power. Subsequently, we calculated and reported the importance of each input feature, providing insights into which features have the most significant impact on the target variable.

In the model training step, a Random Forest Regressor is used to learn the underlying patterns and relationships within the training data. The algorithm constructs an ensemble of decision trees, each trained on a subset of the data, and combines their predictions to make accurate and robust predictions. The model iteratively selects features and splits to minimize prediction errors. Training involves adjusting the decision tree parameters to optimize predictive performance, enabling the model to make predictions on new, unseen data with improved accuracy.

IV. RESULTS AND DISCUSSION

A. Quantitative Selection:

A.1 Multicollinearity Assessment:

As observed in the Fig. 3, we observe that all the factors have VIF value less than 5. All the VIF values lie in the suitable range of 1 to 5. This shows that all the features are nearly independent of each other and are suitable to be used in any model.

Factor	VIF
Slope	2.35188
Convergence Index	2.25575
Valley Depth	1.55816
TPI	1.23303
Relative Slope Position	1.10585
Elevation	1.08241
TRI	1.04055
Aspect	1.02482
Fault Line	1.0147
River	1.01004
Road	1.00673

Figure 3: VIF Values for different factors

A.2 Chi-square evaluation:

As shown in Fig. 4, factors like RSP and Valley Depth have a p-value of more than 0.05 which is significant for the 95% confidence interval. So, all these factors have low relation with the actual landslide occurrence data and hence they can be removed from the set of favorable factors.

As observed, factors like Elevation and TRI denote a value less than 0.05. Hence, they reject the null hypothesis and infer that they have a relation with the landslide occurrence data. This helps us in factor selection and all the favorable factors are selected.

Attribute	p-value
Valley Depth	0.994371
River	0.842393
Relative Slope Position	0.790405
Road	0.757728
Fault Line	0.282732
Convergence Index	0.0992364
Aspect	0.0119152
Slope	0.00178211
TRI	1.66448e-07
TPI	1.13451e-08
Elevation	3.35158e-93

Figure 4: p values for factors

B. Machine Learning - Random Forest Results

As observed in Fig.5, Elevation has the highest significance value among all the selected features. TRI and Aspect are also very significant factors with a high significance value.

Aspect	0.133155
Elevation	0.502113
Slope	0.100237
TPI	0.105248
TRI	0.159248

Figure 5: Significance value generated RF Model

After evaluating the results, we may conclude regarding the factors which have significant effect on landslides. The factors have been segregated into High, Moderate and Low based on significance values. Those segregations are depicted in Fig. 6. Using the significance values, a LSM has been created, as shown in the Fig. 7

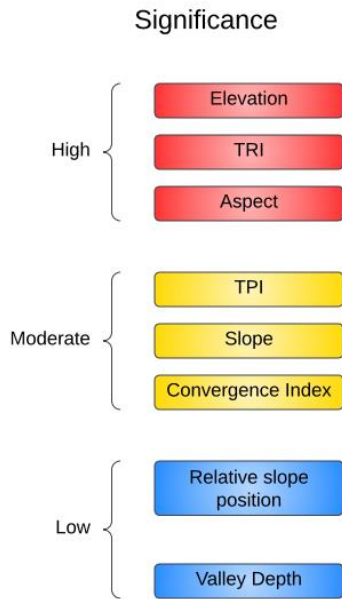


Figure 6: Factor segregation based on significance values

V. CONCLUSION AND FUTURE SCOPE

In conclusion, our paper represents a significant contribution to the field of landslide susceptibility assessment. Our study stands out in several key aspects, setting it apart from existing research in this domain.

First and foremost, our research covers the entire Hindu Kush Himalayan region, which spans multiple countries and encompasses diverse topographic and climatic conditions. This comprehensive scope allows us to provide a more holistic understanding of landslide susceptibility across this

critical region, facilitating better-informed decision-making and disaster management strategies.

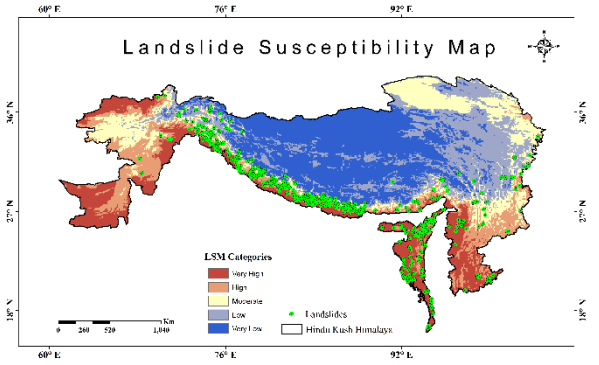


Figure 7: Landslide Susceptibility Map

One of the standout features of our paper is the utilization of the RF algorithm for LSM. This machine learning technique enhances the robustness and accuracy of our analysis. RF is well-suited for handling complex, non-linear relationships between landslide causative factors, and it excels at handling high-dimensional datasets. By leveraging the power of ensemble learning, it reduces the risk of overfitting and provides a more reliable prediction of landslide susceptibility. Moreover, in the Fig. 7, we can observe that less number of landslides occur in the Higher Himalayan regions.

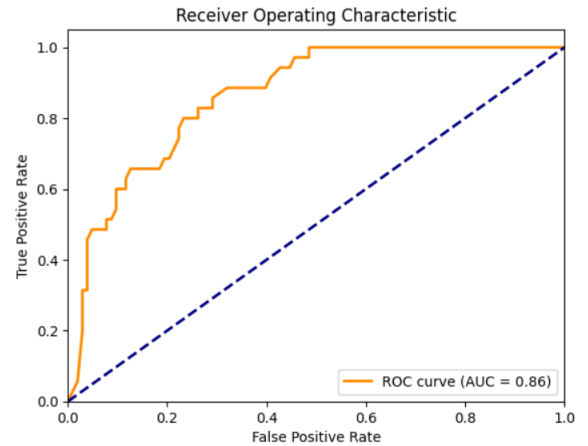


Figure 8: ROC-AUC Result

Furthermore, we would like to optimize our process in terms of algorithm complexity as well as increase the accuracy of our model. This would help us in predicting outputs that will not change values even in cases of drastic changes of geography and other LCFs.

Finally, an AUC value of 0.8 has been obtained for our model. We can see the ROC-AUC result for the model in Fig. 8. This is a good value but can be further improved using some more techniques.

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