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Landslide Susceptibility Mapping Thorough GIS-Based Heterogeneous Ensemble Techniques: A Case Study In Parts Of Darjeeling Himalayas

Sannidhi Das
Department of CS and IT JAIN UNIVERSITY Bengaluru,India

Manjushri Shetty
Department of CS and IT JAIN UNIVERSITY Bengaluru,India

Prerana Agrawal
Department of CS and IT JAIN UNIVERSITY Bengaluru,India

***Abstract* -** Annually, the hilly areas experience significant loss of human lives, properties and an extensive damage to infrastructure caused by one of the worst and recurring internal catastrophes, landslides. Darjeeling Himalayan area is non-exceptionally very susceptible to the most perilous geo-hazards caused by the non-coherent geo-environmental planning and intense tropical precipitation. The present assessment is focused to delineate the landslide hazard vulnerable zones in Kali Khola river basin in Darjeeling district using knowledge-based Frequency Ratio model incorporating Support Vector Machine ensemble. Total 107 landslide sites have been selected through field survey and satellite imagery obtained from Google earth imagery. Out of the locations identified, 75% of the landslide locations are randomly chosen as the training data and the remaining as validation dataset. The classification methods have given that the lower basin region has been dominated by the landslide susceptible zones compared to other regions in the catchment. Five classes; namely, very high, high, moderate, low, and very low vulnerability, have been introduced for the susceptibility area. Lastly, the results have been rigorously analyzed through the AUC-ROC curves, indicating the rate of prediction, from 72 to 75% accuracy-wise.

Index Terms - Landslide susceptibility zonation, frequency ratio, support vector machine, AUC-ROC curve.

INTRODUCTION

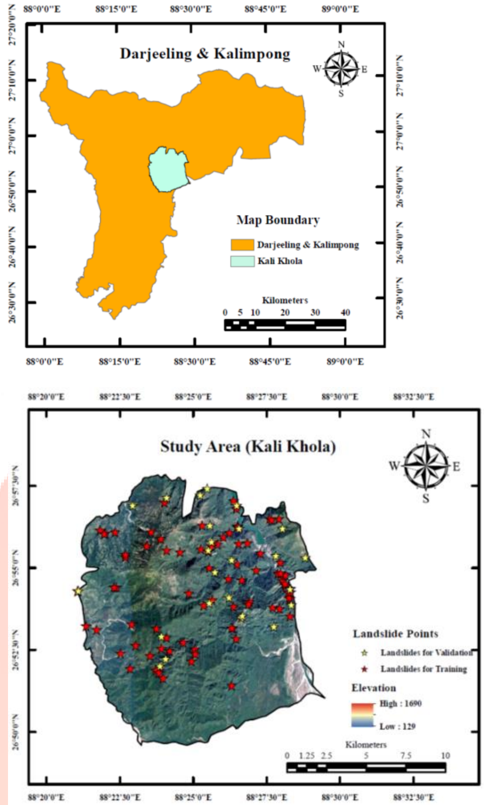
A landslide is the downward movement of rock, soil, or debris along a slope under the influence of gravity. It is a type of mass wasting that can be triggered by natural factors such as heavy rainfall, earthquakes, volcanic activity, or human activities like deforestation and construction. Landslides vary in scale and speed, posing significant risks to life, infrastructure, and the environment. Every year, especially the mountainous regions face a considerable amount of economic and infrastructural loss along with endangered human lives. It is estimated that 9% of the natural calamities worldwide, constitute landslides or mudslides during the year 1990. In India, according to the International Disaster Analysis report (2000-2021), 321 various natural disasters were notified with approximately 75000 human deaths along with 1,95,000 human injuries. In 2021, more than 1400 people died due to natural cataclysm and among them landslide is one of the most recurrent factors. Landslides are found to be the most perilous cataclysms of the Darjeeling Himalayan region due to the topology of rug cliffs, which has an unwarranted landuse-landcover purpose and ruinous rainy seasons (Solaimani et al., 2012; Pattanaik et al., 2018). The Darjeeling-Himalayan region faced several types of disastrous natural calamities, and landslides are prominently one of them, due to which human lives, property, agricultural lands were damaged to a greater extent as compared to the other geo-hazards such as flood, earthquake etc. Kali Khola river basin, the chosen area for the evaluation of landslide vulnerability, too has suffered a considerable amount of destruction due to landslides occurrence; henceforth the said area was thought to be an acceptable one to assess the prevalence and dissemination of landslides. Consequently, landslide hazard mitigation and vulnerability studies are undoubtedly the most indispensable fields of study in this area.

In view of reducing the landslide repercussions, a lot of collaborative efforts are essential, but landslide vulnerability and zonation mapping is the most convincing tool for the same (Arabameri et al., 2019; Pecoraro & Calvello, 2019). In a study region, based on geo-environmental components like elevation, aspect, slope gradient, curvature, soil type, drainage density, geology, distance to roads, STI, SPI, TWI, landuse-landcover, NDVI, geology and geomorphology etc., the distribution of the spatial probabilities of the phenomenon of landslide can be disclosed notably by the landslide susceptibility maps (Pecoraro & Calvello, 2019).

In recent times, ensemble techniques are widely used due to the comprehensiveness and novelty they possess for the assessment of landslide related parameters for discrete classification. For the present investigation, a knowledge based Frequency Ratio model along with support vector machine ensembles has been used for slope instability analysis. The present study map is prepared with a view to help the governmental policy makers in order to mitigate the terrestrial landslide occurrences.

AREA OF STUDY

Kali Khola river catchment or Kali Khola is a tiny tributary of West Bengal state that flows through the Darjeeling district. The catchment lies between 26^{0}49' N to 26^{0}58' N and 88^{0}20' E to 88^{0}30' E, of about 151.91 sq. km. The research region is located in the Himalayan Region and is distinguished by heavy rainfall, rendering it vulnerable to natural calamities. The study area faces intensive rainfall, which is, in quantification, approximately 175-235 cm/annually. The moderate-type temperature is another familiar characteristic of Kali Khola river basin. The study region is composed of Precambrian rocks (Crystalline Gneiss, Lingtse Gneiss), Miocene (Crude Immature Conglomerate, Siwalik group), Permian rocks (Lower Gondwana group, Damuda formation), Daling group (Reyang formation, Gorubathan formation) and Undifferentiated Fluvial lithologies (Pawde & Saha, 1982). Being surrounded by forest, the area has suffered many landslides. The Kali Khola basin is found to be a habitat place, and frequent landslides make the lives of the people much more challenging; as a consequence of landslide occurrence, the area faces a considerable amount of property loss along with human lives. Fig-1 Study area demarcation for the Kali Khola Catchment.



METHODOLOGIES

The study employed the following methodology (i) the pre-existing landslide attributes were acquired through the use of the Google Earth Imagery and verified using field measurements; (ii) preparation of the data layers for conditioning factors of landslides; (iii) examination of the relationship between the past landslides and landslide conditioning components has been conducted; (iv) application of the frequency ratio technique and support vector machine ensemble learning technique; (v) application of AUC-ROC to identify the accuracy of the framework.

DATA PREPARATION

I. Landslide Inventory Construction

For current study fulfillment, many significant data were acquired from heterogeneous sources. For the landslide susceptibility mapping, fifteen landslide conditioning factors are selected using frequency ratio, frequency ratio-Support Vector Machine ensemble assessing current studies. The GIS environment has extensively been used to perform raster data processing in order to predict the potential susceptible areas. Along with the raster data processing, the mathematical computations have been accomplished with SPSS and PyCharm IDE (Community Edition).

II. Inventory Map Preparation for Landslides

It is necessary to recognize the accumulation of the historical landslides to construct a landslide assessment model (Chen et al., 2017). Several field investigations were conducted to confirm the collected landslide data from Google Earth imagery. In addition, from NDMA (Govt. of India) and Office of the District Magistrate, the past landslide and disaster records were also collected. In total, 107 landslide locations are identified for the composition of the landslide catalogue and the places represent the location of landslide incidents in the past in Kali Khola. The inventory maps prepared were partitioned into two segments, namely training dataset and testing dataset. 75% of the identified places were used as learning data for the simulation of the proposed models and the rest of the 25% data to validate the simulated models

III. Occurrence Factors for Landslides

For the landslide susceptibility study in Kali Khola basin, elevation, slope, curvature, aspect, SPI, TWI, STI, distance to roads, soil type, lineament density, drainage density, normalized differential vegetation index, landuse-landcover, geomorphology, and geology were selected for the recognition and production of the landslide susceptibility model of the catchment,

ANALYSING MULTICOLLINEARITY OF LCFS

In the present study, multicollinearity of the LCFs was estimated through the tolerance and VIF values. Conventionally, tolerance values and VIF values of under 0.1 and 10 and above respectively, specify multicollinearity issues.

Since the tolerance value for each LCF is greater than 0.1 and the values of the Variable Inflation Factor (VIF) are within the range of 0.1 and 10, the exhibits of the multicollinearity analysis indicate that there are no collinearity issues among the LCFs. Consequently, 15 factors were found to be suitable for the susceptibility modelling. Table-1 displays the multicollinearity analysis of the selected factors influencing landslide occurrence.

Table 1. Multicollinearity analysis of LCFs

LCFs	Collinearity Statistics	
	Tolerance	VIF
TWI	0.35	2.85
Elevation	0.49	2.02
Aspect	0.53	1.86
NDVI	0.55	1.79
Curvature	0.56	1.76
Soil Map	0.61	1.63
Geomorphology	0.62	1.61
SPI	0.66	1.51
STI	0.68	1.45
Geology	0.68	1.45
Distance to River	0.81	1.23
Drainage Density	0.86	1.15
Landuse / Landcover	0.92	1.08
Lineament Density	0.95	1.05
Slope	0.96	1.03

APPLIED MODELS

I. Frequency Ratio Analysis

One of the most widely used bi-variate statistical techniques or the likelihood ratio approach, the FR analysis is based on interdependence among the landslides spatial locations and the reasons for landslide occurrence (Pal & Chowdhuri, 2019). The ratio of landslides in a factor class to that factor class's area divided by the total area of landslides was used to calculate the FR value, which then was normalized to '1' since it is the mean value,

Between the occurred landslides and the potential attributed factors, a frequency ratio value greater than 1 indicates a higher correlation and less than 1 indicates a lower correlation. The FR values collected were totaled into the study area, as the values were applied to acquire LSI. The FR value for a data layer group was calculated through the equation provided below:

$$FR =$$

$$\frac{Proportion\ of\ Landslide\ in\ a\ Feature\ Class}{Area\ of\ Feature\ Class\ as\ a\ Proportion\ of\ the\ Total\ Area} = \frac{\frac{Total\_Pixel_{(S_i)}}{Total\_Pixel_{(N_i)}}}{\frac{\sum_i Total\_Pixel_{(S_i)}}{\sum_i Total\_Pixel_{(N_i)}}} \quad (1)$$

Using the following expression, the raster components of the estimated frequency ratio have been aggregated to provide the LSI value after creating the frequency ratio for each conditioning component for landslide occurrence.

$$LSI = \sum_{j=1}^{n} FR_j \quad (2)$$

Lower value of the LSI stipulates low landslide susceptibility, whereas higher value of the LSI stipulates higher landslide susceptibility (W. Chen et al., 2018).

II. SVM

SVM generates a decision hyperplane by analyzing and separating the given training data. It is a supervised Machine Learning technique. The subspace is constructed in the vector containing n co-ordinates between the data-points of two perceptible groups (Yao et al., 2008). The general algorithm for the implementation of SVM is: Provided a linearly distinct problem specification, a vector $V = \{A_j B_j\}$, has n points of $A_j \in \mathbb{R}^n$, with $B_j \in \{-1, +1\}$, where $j = 1,2, \ldots\ldots, n$. SVM aims to detect the optimal decision boundary which splits $a_i$belonging to $b = +1$ from the a_i belonging to $b = -1$with optimal margin (Pradhan et al., 2019). If a point is found on the construction, then it is categorized as $+1$ or else -1. In present study, to characterise the landslide vulnerability zones, A denotes the vector space including the landslide occurring factors: slope, aspect, distance to roads, elevation, SPI, soil type, TWI, lineament density, normalized differential vegetation index, geology/lithology, curvature, drainage density, landuse-landcover, geomorphology, STI. The pixels are represented by +1 for landslide whereas the non-landslide pixels are represented by -1. The partitioning hyperplane that segregates the data has the function shown in the equation given:

$$B_i = (W.A_i + x) \geq 1 - \xi_i \quad (3)$$

where, W is a multiplier vector defining hyperplane direction, x is the displacement from the origin, ξ_i designates the weak positive entities (Tien Bui et al., 2012).

With exploitation of Lagrangian Multiplier, cost function will be resolved and the optimal hyperplane will be determined (Cortes & Vapnik, 1995).

$$Minimize \sum_{j=1}^{n} \beta_j - \sum_{j=1}^{n}\sum_{k=1}^{n} \beta_j \beta_k B_j B_k (A_j A_k) \quad (4)$$

subject to,

$$\sum_{j=1}^{n} \beta_j B_j = 0, \qquad 0 \leq \beta_j \leq C \quad (5)$$

where,$\beta_j$signifies the Lagrangian Multiplier, C signifies the penalty term.

The cost function can be constituted by the following mathematical formula:

$$g(A) = sign\left(\sum_{j=1}^{n} B_j \beta_j A_j + x\right) \quad (6)$$

In some occasion, if there is no existence of linear hyperplane which segregates the input vectors, then the actual input dataset may be projected into a higher dimensional feature space; the penalty function then be represented as the following mathematical expression:

$$g(A) = sign\left(\sum_{j=1}^{n} B_j \beta_j K(A_j A_k) + x\right) \quad (7)$$

where, $K(A_j, A_k)$ represents the Kernel function.

Linear, Polynomial, Sigmoid, and Radial Basis Function are the four currently used kernels in SVM Analysis. The latter is considered to be the most promising in terms of classification(Hong et al., 2016; Yao et al., 2008).Consequently, the RBF has been ensembled with the FR model, as the following Table-2 shows the mathematical formulations which are extensively used for the calculation using different SVM kernels.

Table-2: Kernel types of Support Vector Machine ensemble

Types of Kernels	Kernel Arguments	Mathematical Equations
Linear	-	$K(X_j, X_k) = X_j^t X_k$
Polynomial	γ, d	$K(X_j, X_k) = (-\gamma X_j^T X_k + r)^d$
Sigmoid	γ	$K(X_j, X_k) = tanh(-\gamma X_j^T X_k + r)$
Radial Basis Function	γ	$K(X_j, X_k) = e^{-(\gamma \lVert X_j - X_k \rVert^2)}$

RESULTS

I.Frequency Ratio Analysis

The susceptibility map of the region developed using the FR model is depicted in the following Fig-2. The thematic map of each landslide conditioning factors was developed with the ArcGIS IDE followed by the calculation of the FR values. The corresponding susceptibility to landslides is shown by the FR values calculated for each data point in the LSI. Increased LSI pixel values indicate greater landslide vulnerability, whilst lower pixel values signal reduced susceptibility. The frequency ratio values found after the training phase, which may be entered into an ArcGIS raster calculator as follows, were uitlized to create the LSI.

$$LSI = FR_{(sl)} + FR_{(as)} + FR_{(cu)} + FR_{(el)} + FR_{(spi)} + FR_{(twi)} + FR_{(sti)} + FR_{(dr)} + FR_{(st)} + FR_{(ld)} + FR_{(dd)} + FR_{(ndvi)} + FR_{(lulc)} + FR_{(geo)} + FR_{(geom)} \quad (7)$$

where, $FR_{(sl)}$ = FR of slope, $FR_{(as)}$ = FR of aspect, $FR_{(cu)}$ = FR of curvature, $FR_{(el)}$ = FR of elevation, $FR_{(spi)}$ = FR of stream power index, $FR_{(twi)}$ = FR of topographic wetness index, $FR_{(sti)}$ = FR of the sediment transportation index, $FR_{(dr)}$ = FR of distance to roads, $FR_{(st)}$ = FR of the soil type, $FR_{(ld)}$ = FR of lineament density, $FR_{(dd)}$ = FR of drainage density, $FR_{(ndvi)}$ = FR of normalized differential vegetation index, $FR_{(lulc)}$ = FR of the landuse-landcover, $FR_{(geo)}$ = FR of geology, $FR_{(geom)}$ = FR of geomorphology.

The FR methodology illustrates that 77.29 sq. km. (50.88%) and 23.31 sq. km. (15.34%) areas are covered under very high and highly vulnerable areas in terms of landslide occurrence.

II. Results from SVM

The SVM ensemble was coupled with FR analysis in this study. The LCFs utilized were elevation, slope gradient, aspect, curvature, SPI, TWI, STI, distance to roads, soil types, lineament density, drainage density, normalized differential vegetation index, landuse-landcover, geomorphology and geology. These parameters were considered inputs of the SVM classifier. The probability values of SVM classification range between 0 and 1. The landslide susceptibility or vulnerability index shows two values, ranging from 0 to 1, as 0 represents safe conditions and 1 represents a greater chance of landslide event. SVM classifier employs four types of kernels: linear kernel, polynomial kernel, sigmoid kernel, and radial basis function. The SVM classification in the current research employed Radial basis function (RBF) as the kernel type since it indicates higher potential compared to the other remaining kernel types. To map the landslide vulnerability (LSMs) by using GIS approach, the resulting images generated by the SVM classifier were combined and utilized. The map produced for landslide susceptibility by using the SVM ensemble has been depicted in Fig-3.

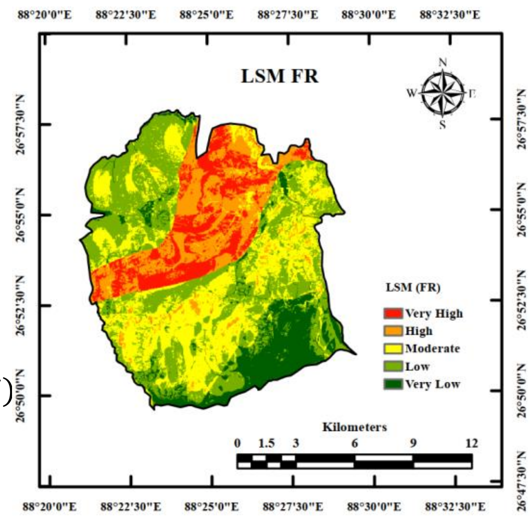


Figure-2:- Landslide Susceptibility Map developed by Knowledge Driven Frequency Ratio(FR) Analysis

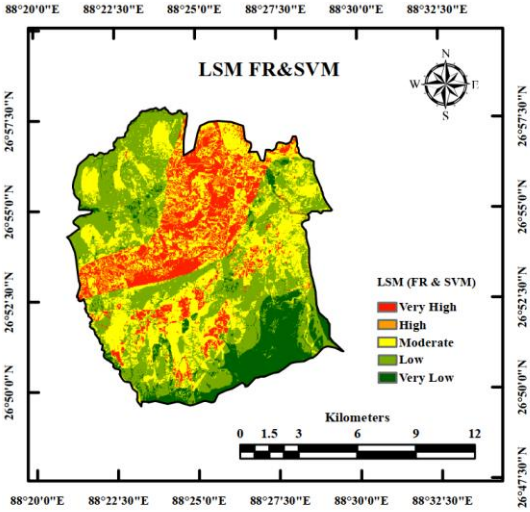


Figure-3:- Landslide Susceptibility Map developed

The areal distribution of the LSMs generated by FR and FR&SVM ensemble models are shown and depicted in Table-3 and Fig-4 respectively as follows.

Table-3:-Areal distribution of LSMs

Classes of Susceptibility	FR&SVM	Area (Percentage)	Total Area	FR	Area (Percentage)	Total Area
Very High	279	16.92	25.70	253	15.34	23.31
High	852	51.67	78.49	839	50.88	77.29
Moderate	430	26.08	39.61	470	28.50	43.30
Low	65	3.94	5.99	57	3.46	5.25
Very Low	23	1.39	2.12	30	1.82	2.76

III. Accuracy assessment

The ROC curve has been used for the validation of the used models. The curve has been drawn on an XY axis, with the Y and X axes representing sensitivity and specificity respectively. Out of a total of 107 slides, 75% of them were utilized as training datasets, while 25% of them were employed to verify the accuracy of the frameworks utilized. The AUC derived using FR and the FR-SVM joint models were around 72% and 75% respectively. The FR-SVM model is considered to be more precise as per the results of the ROC curve. The below Figure-4 expounds on the FR versus FR-SVM ensemble performance comparison based on ROC curves showing the AUC for the generated LSMs.

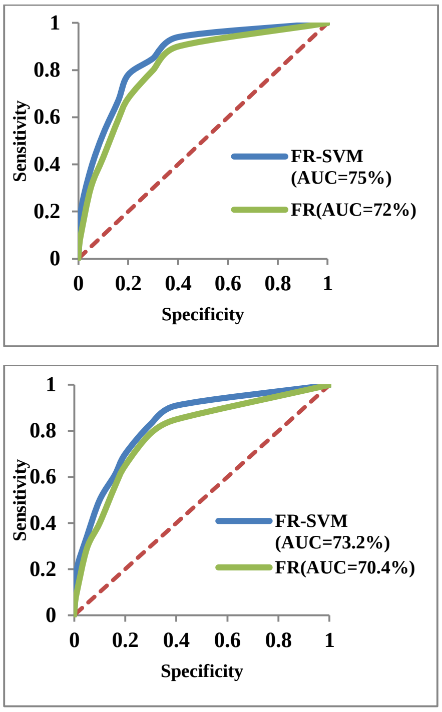


Figure-4:- Performance Evaluation

Discussion and Conclusion

Landslide hazard maps are critical in assisting decision-makers in making appropriate resolutions in landslide-prone areas. Landslides not only kill people, but they also destroy homes, roads, and agricultural areas. The application of LSMs in assessing landslides hazards in this research is an essential mitigation tool in reducing landslide events and hazard, maintaining the eco-system, and helping residents in potentially hazardous landslide susceptibility areas. To identify areas at high risk of landslide occurrence, various statistical, knowledge based, stochastic, and ML models were used. Several previous studies used various methodological approaches to create landslide hazard maps, including the LNRF, fuzzy AHP, conditional probability (CP), logistic regression (LR), expert system (ES), MCDM methodologies, bivariate and multivariate statistical models. The current research, nonetheless, utilizes, the ensembled techniques of Frequency Ratio and Support Vector Machine, which has improved performance compared to the previous models utilized for the same. Following the chronology in terms of susceptibility, the FR approach covers the areas of 23.31 sq. km.(15.34%), 77.29 sq. km.(50.88%), 43.3 sq. km.(28.5%), 5.25 sq. km.(3.46%) and 2.76 sq. km.(1.82%) respectively, whereas, ensembled FR-SVM approach covers area of 25.7 sq. km.(16.92%), 78.49 sq. km. (51.67%), 39.61 sq. km.(26.08%), 5.99 sq. km.(3.94%) and 2.12 sq. km.(1.39%) respectively. Susceptibility maps of landslide hazard were substantiated using the ROC validation method. The ensembled model is rated as being of very high quality based on these validation techniques. The current analysis shows that the places that are most vulnerable to landslides are located near the Teesta River, which is a key tributary in the Darjeeling district. Principal factors influencing the happening of landslide in the region are elevation, topographic wetness index, soil type, geomorphology, geology, distance to roads and landuse-landcover. The main issue facing the researchers in this study is the lack of a cost-free high-resolution DEM for this region. These techniques could be utilized to increase the substantiability of the model for landslide vulnerability at micro level if high resolution images were used instead of a 30m DEM for the extraction of LCFs (Haneberg et al., 2009; Nichol et al., 2006). Landslide susceptibility maps (LSMs) for the Kali Khola river basin were prepared in this research based on an integration of FR and SVM models. Compared with the use of one model, the ensemble method is discovered to be a more suitable method for landslide mapping. In the current research, a historical list of landslides was employed for the formation of training (75%) and validation (25%) sets. Fifteen variables were selected as inputs for LSM models to develop landslide susceptibility maps. A GIS platform was applied to detail all data. The research area had been demarcated into five distinct susceptibility zones: i.e., very high, high, moderate, low and very low in terms of susceptibility based on the learned final LS maps. Through the provision of sufficient measures and mitigation techniques against hazards, the study purports to minimize the impact of landslides on the government and public. In a few of the vulnerable regions of the area, a few significant steps and practices are significant.

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