Landslide susceptibility mapping of Chaliyar river basin by multivariate statistical model

ABSTRACT

Landslides were frequently observed in nature that can result in significant property damage and fatalities. Land management in landslide-prone areas can be aided by preparing a landslide susceptibility map. The landslide susceptibility of Chaliyar river basinwas evaluated using the logistic regression (LR) technique. For this, an inventory map of 592 prior landslides was created using Landsat 8 OLI satellite imagery. The inventory of landslides was then randomly split into 30% and 70% for model training and validation respectively.Fifteen landslidecausative factors *viz.*, Slope, Aspect, Curvature, Relative Relief, TWI, Distance to Road, Distance to Streams, Distance to Lineaments, Land Use Land Cover, Drainage Density, Road Density, Lineament Density, Geomorphology, Soil Texture, NDVI were considered for landslide susceptibility modelling. Utilising a Receiver Operating Characteristics Curve (ROC) and Area Under Curve (AUC) value, the resulting susceptibility maps were validated. Analysis reveals that the validation stage of the LR model had a ROC-AUC value of 0.815. The study also demonstrates that slope, soil texture and LULC play a substantial role on theoccurrence of landslides in the study area. The proposed landslide susceptibility model is appropriate, taking into account the ROC-AUC (0.815), and can be applied to future land use planning and landslide mitigation in the Chaliyar basin.

Keyword: *Landslide susceptibility, Logistic regression, Causative parameters, ROC-AUC, Chaliyar river basin*

1. INTRODUCTION

Landslides were a disastrous natural hazard that frequently result in fatalities and significant property damage in hilly Western Ghats regions (Vijith et al., 2014; Froude et al., 2018; Karim et al., 2019; Su et al., 2022). To reduce the damage and fatalities caused by landslides, accurate forecasting and susceptibility mapping were recognised as crucial and necessary (Chang et al., 2023). However, due to the complexity of landslides, which were influenced by an amalgamation of some or all of the causative factors such as bedrock, climate, hydrology, soil condition, and even human activities, producing reliable spatial prediction and assessment of landslides susceptibility is a difficult task (Wu and Sidle, 2010). The quality of Landslide Susceptibility Maps (LSM) is also significantly impacted by the modelling techniques used (Trigila et al., 2015). Due to the complexity and accessibility of the data, many researchers have developed methods for creating maps of landslide susceptibility (Corominas and Moya, 2008; Van Westen et al., 2008). Based on regional geo-environmental parameters, LSM define the spatial distribution of the likelihood of a landslide in a given area. There is a Landslide Susceptibility Index (LSI) value assigned to each pixel of the LSM (Goyes-Peñafiel et al.,2021).

Numerous quantitative techniques were used to evaluate landslide susceptibility (Guzzetti et al., 2006a). The majority of them have as their primary objective as the identification of the factors that contribute to the occurrence of landslides, the evaluation of the significance of controlling factors and the classification of the study area according to landslide susceptibility. With the presumption that slope collapses in the future will be more likely to occur under conditions that contributed to historical and present instability, statistical analysis is still the most popular technique for largerareas. In the last few decades, a number of statistical methods have been applied to landslide susceptibility assessment, such as the Logistic Regression (LR) method (Hadji et al., 2013), discriminant analysis (Guzzetti et al., 2006b), Weights of Evidence (WoE) Model (Mahdadi et al., 2018), Artificial Neural Network (ANN) method (Chen and Zeng, 2013; Chen et al., 2013), fractal method (Li et al., 2012), fuzzy logic (Kayastha et al., 2013), Support Vector Machines (SVM)(Pourghasemi et al., 2013), etc. No consensus has been achieved on the optimal strategy or method, despite the fact that numerous techniques have been shown to be beneficial (Huabin et al., 2005). The LR model has been widely used in landslide susceptibility mapping by many studies because it is particularly efficient and reliable for expressing problems with binary variables (such as the existence or absence of landslides) (Zhao et al., 2019).

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By identifying and mapping the slide locations and the related topography parameters, the current work shows how Logistic Regression (LR) may be applied to build a landslide susceptibility zonation map for the Chaliyar river basin in Kerala at a scale of 1:50,000 for the study area. The objective of this study is to generate the landslide susceptibility map and validate the applicability of the LR model in the Chaliyar basin.

2. MATERIALS AND METHODS

2.1 Study area

Chaliyar river basin in Kerala, India, situated between 11°06´–11°36´N and longitude 75°48´–76°33´E falls in Survey of India (SOI) toposheets 58A and 49M (Fig.1) The river originates from the Western Ghats mountain range and flows through the districts of Wayanad, Malappuram, and Kozhikode before emptying into the Arabian Sea.The basin is characterized by a diverse landscape, ranging from the hilly terrain of the Western Ghats to the coastal plains near the Arabian Sea. The region experiences a tropical monsoon climate, with heavy rainfall during the southwest monsoon season (June to September) and a relatively drier period from October to December.

The Chaliyar river basin, like many other hilly regions, is susceptible to landslides due to its topography, geological characteristics, and monsoon rainfall patterns. Landslides can occur in various forms, including rockfalls, debris slides, and slope failures, posing risks to human lives, infrastructure, and the environment. Ongoing monitoring and periodic reassessment of landslide susceptibility in the Chaliyar river basin were also essential to adapt to changing conditions and minimize the potential impacts of landslides.

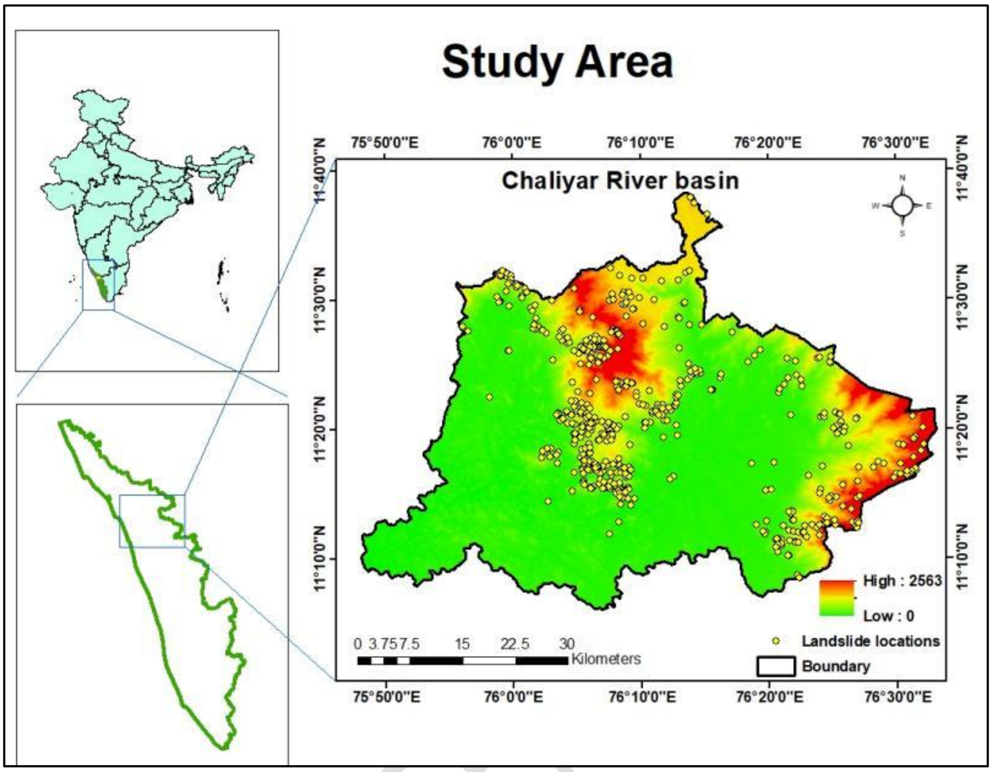

Fig.1 Location map of the study area showing the elevation and landslide inventory

2.2. Identification of the causative factors of landslide.

There were no fixed guidelines for selecting the parameters that influence landslides insusceptibility mapping (Sato et al., 2008). The causative factors were selected based on previouslandslide studies (Martha et al., 2018; Banerjee et al., 2018; Maheshwari et al., 2019), the scale of analysis, and data availability, in the basin. At first, we reviewed the literature and government reports relatedto landslide susceptibility mapping in Kerala (Wadhawan et al., 2020;Gururajan et al., 2021; Vishnu et al., 2022). After that,the most significant landslide-related spatial and attribute data, namely geomorphology,soil type, Land Use Land Cover (LULC), slope angle, aspect,curvature, relative relief,Topographic Wetness Index (TWI), distance to lineaments, distance to streams, distance to roads, drainage density, lineament density, drainage frequency, road frequency, lineament frequency and Normalized Difference Vegetation Index (NDVI) , were selected based on the previous research conducted in Kerala. Multi-collinearity among the selected landslide causative factors were analyzed and thereafter the factors critical for the study area were selected

The geomorphology map of the study areawas gathered from Kerala State Remote Sensing and Environment Centre (scale 1:50,000). Land use/land cover data of the study areawere collected from the Kerala State Land Use Board (scale 1:50,000). Terrain parameters, such as slope angle, aspect, curvature, relative relief, streams, lineaments and TWI were calculated from the ASTER

GDEM (30m resolution). Soil texture data of the study areawere collected from the Department of Soil Survey & Soil Conservation. Roads data were collected from KSDMA, Trivandrum. NDVI map was prepared using Landsat 8 Operational Land Imager (OLI) satellite data obtained from the United StatesGeological Survey (USGC). All causative factor maps were converted into raster maps with the same coordinate system (WGS 1984 UTM zone 43N) and the same pixel size (30mx30m) (Mersha et al., 2020). Figure 2 shows the various thematic layers of the causative factors used in this study. The rasterized training (70%) landslide map and all the causative factor maps have been added to the LR model in SPSS software to calculate the ratings or weights of all factor classes. The summation of these ratings or weights of each landslide factor will help to evaluate the spatial relationship between them and the probability of landslide occurrence in the study area.

2.2.1Multi-collinearity in logistic regression

The impact of correlation among independent variables is a crucial factor in regression. When two independent variables were very closely associated, there is a problem. The issue is referred to as multi-collinearity. Two crucial indices for multi-collinearity diagnosis were tolerance and the Variance Inflation Factor (VIF). Actually, tolerance is 1-R2 when a variable is regressed against all other independent variables without the dependent variable. VIF, on the other hand, is merely the inverse of tolerance. VIF assesses how much the variance of the estimated regression coefficient for the variable is inflated by the interdependence of the variable with other predictor variables. As a result, the amount that collinearity has raised the variable's standard error is represented by the squwere root of the VIF. A tolerance of less than 0.20 or 0.10 and/or a VIF of 5 or 10 and above indicates a multi-collinearity problem (Pourgasemi et al.2013; Chen et al., 2018; Chen et al., 2019).

2.3 Landslide susceptibility mapping

Landslide Susceptibility Mapping (LSM) in the Chaliyar river basin can be a valuable tool for assessing the vulnerability of the region to landslides and facilitating effective land use planning and disaster risk management.The steps involved in the LSM involves:

- Data Collection: Gather various types of data, including topographic data, geological maps, land cover information, rainfall patterns, soil characteristics, and existing landslide records. Remote sensing data from satellite imagery can also be used to assess land cover changes and terrain features.
- Landslide Inventory: A landslide inventory map is prepared with the aid of multiple sources ; (1) National Remote Sensing Center (NRSC), of the Indian Space Research Organization (ISRO), (2) Geological Survey of India (GSI) in collaboration with the Kerala State Disaster Management Authority (KSDMA), (3) BHUVAN (Indian earth observation visualization), a web-based geospatial platform developed by the Indian Space Research Organization (ISRO) (bhukosh.gsi.gov.in). A total of 592 landslides were identified and divided into 70%–30% proportion for training and testing the models (Vineetha et al., 2019; Yuvaraj et al., 2021).
- Geospatial Analysis: Utilize Geographic Information Systems (GIS) software to integrate and analyze the collected data layers. Analytical techniques such as statistical analysis, multi-criteria

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evaluation, and weighted overlay can be applied to identify the factors contributing to landslides and their relative importance.

- Landslide Susceptibility Modeling: Develop a landslide susceptibility model using the analyzed data. This can involve different methods, including statistical approaches (e.g., logistic regression, frequency ratio, or Bayesian techniques) or physically based models (e.g., slope stability analysis using geotechnical parameters). The model should assign susceptibility values to different areas within the Chaliyar river basin, indicating the likelihood of landslide occurrence. Here in this study, a multivariate statistical model called Logistic Regression (LR)model was used.

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- Validation: Validate the landslide susceptibility model by comparing the predicted landslide susceptibility areas with the known landslide locations from the inventory. This step helps assess the accuracy and reliability of the model and can be refined iteratively. The validation of the landslide susceptibility map was evaluated by calculating the relative operative characteristic (ROC) method and the percentage of the observed landslide in various susceptibility categories. The area under the curve (AUC) of the ROC represents the quality of the probabilistic model (its ability to predict the occurrence or non-occurrence of an event (Polykretis et al., 2015) . An AUC value close to 1 indicates high accuracy, and an AUC value close to 0.5 indicates inaccuracy (Ram et al., 2021).

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- Mapping and Zonation: Based on the validated model, generate landslide susceptibility maps for the Chaliyar River basin. These maps categorize different areas into zones representing different levels of landslide susceptibility, typically using a color-coded scheme (Pascale et al. 2013). In this study, final LS map is again segmented in to five classes using the expert opinion from KSDMA to yield five susceptibility levels such as very low, low, moderate, high and very high.

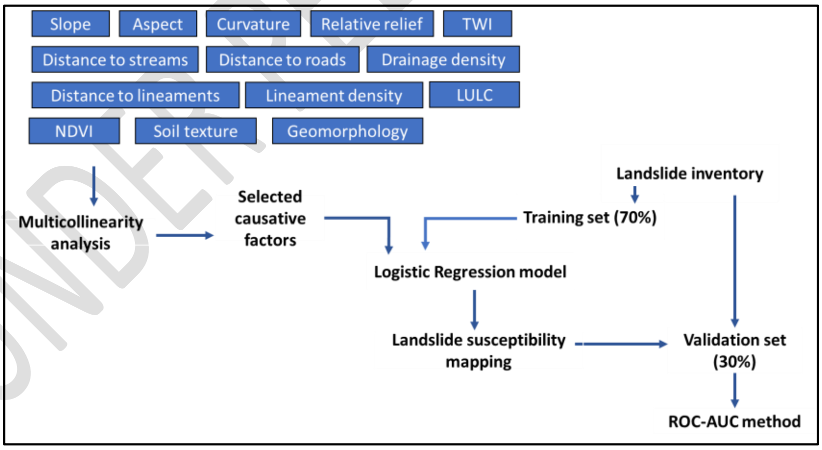

Fig.2 Flowchart of the LSM preparation

2.3.1 Logistic Regression (LR) model

LR analysis is considered as one of the most popular multivariate regression analysis used to investigate a binary response from a set of measurements using forward method (Lee and Pradhan, 2006). In the case of landslide susceptibility mapping, the set of measurements will be landslidecausative factors (either discrete or continuous) and binary response is the presence and absence of landslide occurrence (Althuwaynee et al., 2014). Finding the ideal model to explain the association between a dependent variable and a number of independent factors is the aim of logistic regression (Ozdemir 2011). The benefit of logistic regression is that, unlike traditional linear regression, where the variables must all have normal distributions, it allows for the inclusion of both continuous and discrete variables as well as any mix of the two. After converting the dependent variable into a logic variable that represents the natural logarithm of the probability of the dependent (landslide) occurring or not, the logistic regression technique performs maximum likelihood estimation (Bai et al. 2010).

The mathematical expression of the LR model is as follows (Chang et al., 2007; Achu et al., 2020)

$$P = \frac{1}{1+e^{-z}}$$

where p is the probability of occurrence of landslides or non-landslides, e is the exponent and z is the linear combination. The probability value ranges from 0 to 1 on an S-shaped curve. The linear combination “z ” has been shown in the following equation:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots.\beta_n X_n$$

where β_0 represent the intercept of the curve and n is the number of independent variable, β_i (i = 1, 2, 3, …, n) is the slope coefficient, and X_i (i = 1, 2, 3, …, n) is the independent variable.

3. RESULTS AND DISCUSSION

3.1 Multicollinearity analysis

In the present study, the multi-collinearity between each landslide causative factor were estimated and presented in Table 1. As shown in Table 1, the tolerance value of drainage frequency, lineament frequency and road frequency were found to be 0.13, 0.156 and 0.147 respectively. So, factors whose tolerance value <0.2 should be eliminated for the smooth data analysis.

Table 1. Multi-collinearity among the selected factors

Sl. No	Landslide causative factors	Collinearity Statistics	
		Tolerance	VIF
1	Slope	0.374	2.671
2	Aspect	0.990	1.010
3	Curvature	0.925	1.082
4	Relative Relief	0.272	3.674
5	TWI	0.748	1.336
6	Distance to streams	0.767	1.304
7	Drainage density	0.845	1.183
8	Drainage frequency	0.13	7.690

9	Distance to roads	0.715	1.398
10	Road density	0.951	1.051
11	Road frequency	0.147	6.802
12	Distance to lineaments	0.896	1.117
13	Lineament density	0.948	1.055
14	Lineament Frequency	0.156	6.582
15	Soil Texture	0.894	1.119
16	Geomorphology	0.478	2.092
17	LULC	0.842	1.189
18	NDVI	0.918	1.090

3.2 Selected causative factors

Out of 18 causative factors, three factors were eliminated. The thematic layers of the selected causative factors were shown in figure 3.

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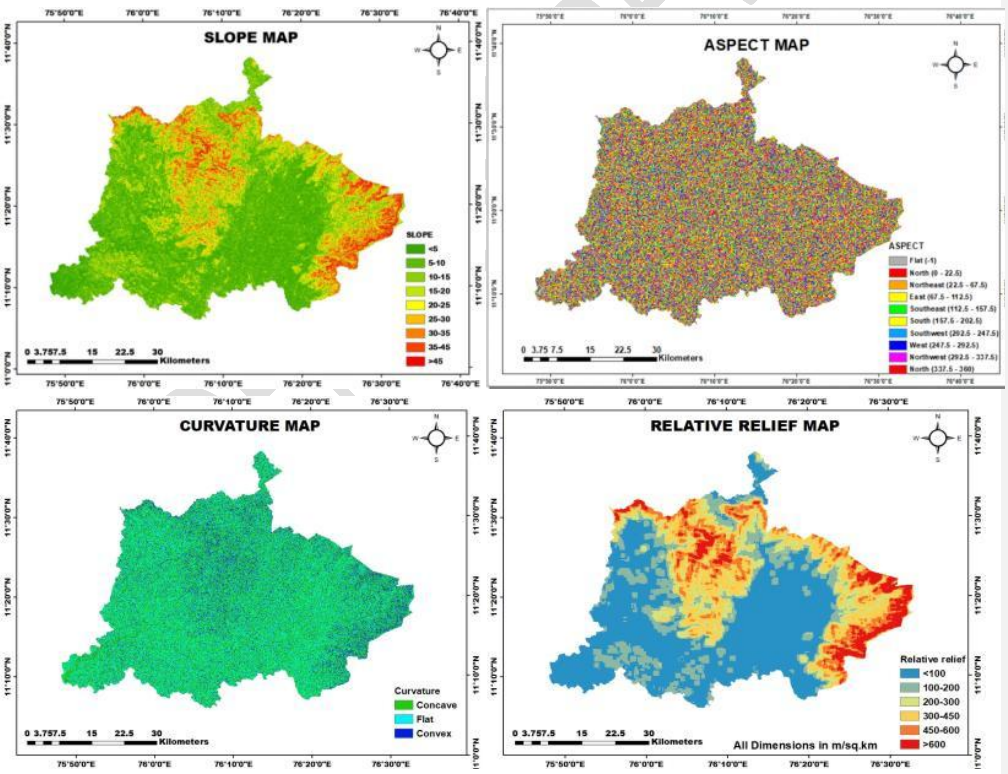

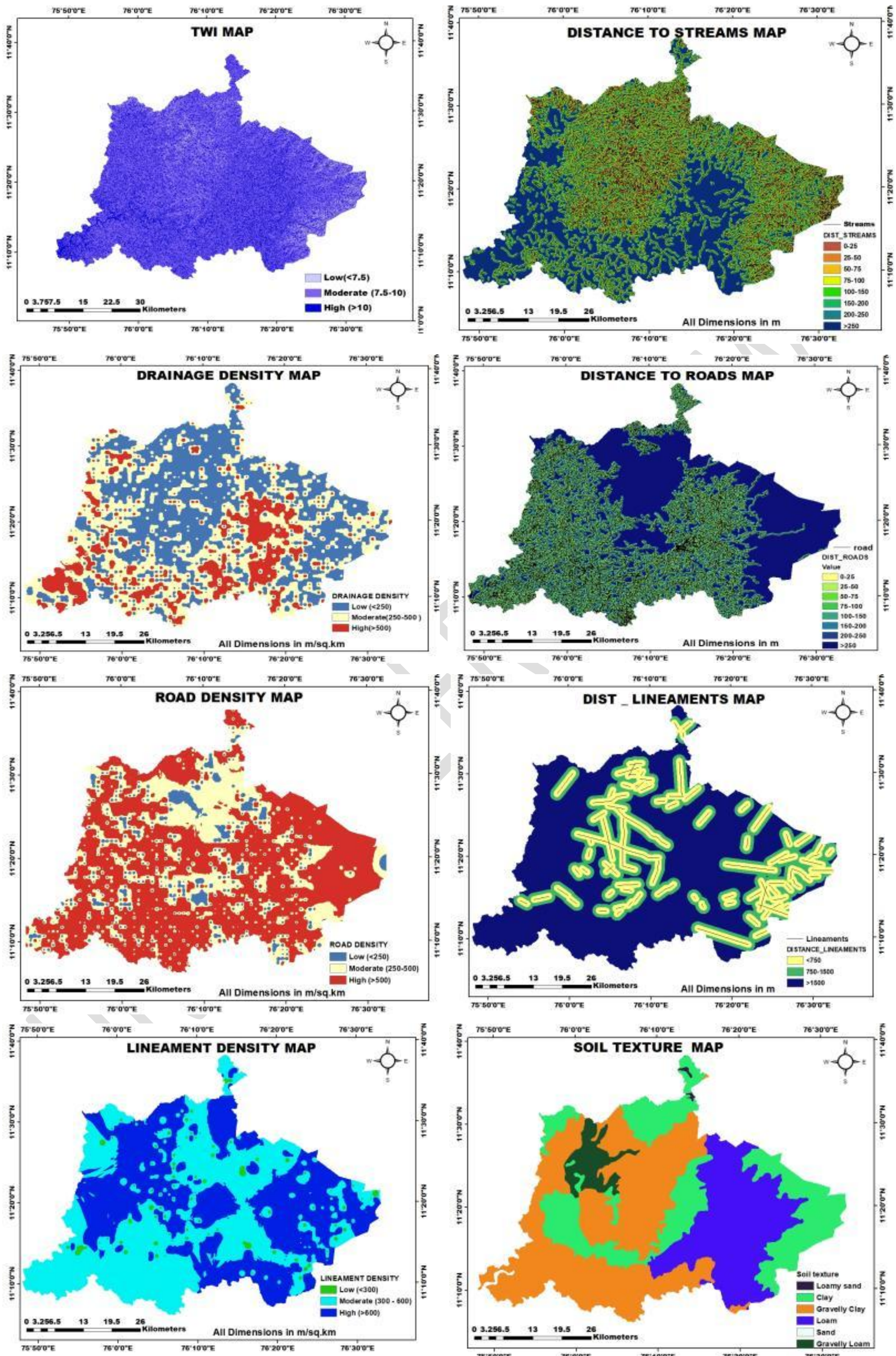
TWI MAP
Low(<7.5)
Moderate (7.5-10)
High (>10)
0 3.757.5 15 22.5 30
Kilometers
DISTANCE TO STREAMS MAP
Streams
DIST_STREAMS
0-25
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DRAINAGE DENSITY
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All Dimensions in m/sq.km
DISTANCE TO ROADS MAP
road
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Value
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Kilometers
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LINEAMENT DENSITY
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All Dimensions in m/sq.km
SOIL TEXTURE MAP
Soil texture
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Sand
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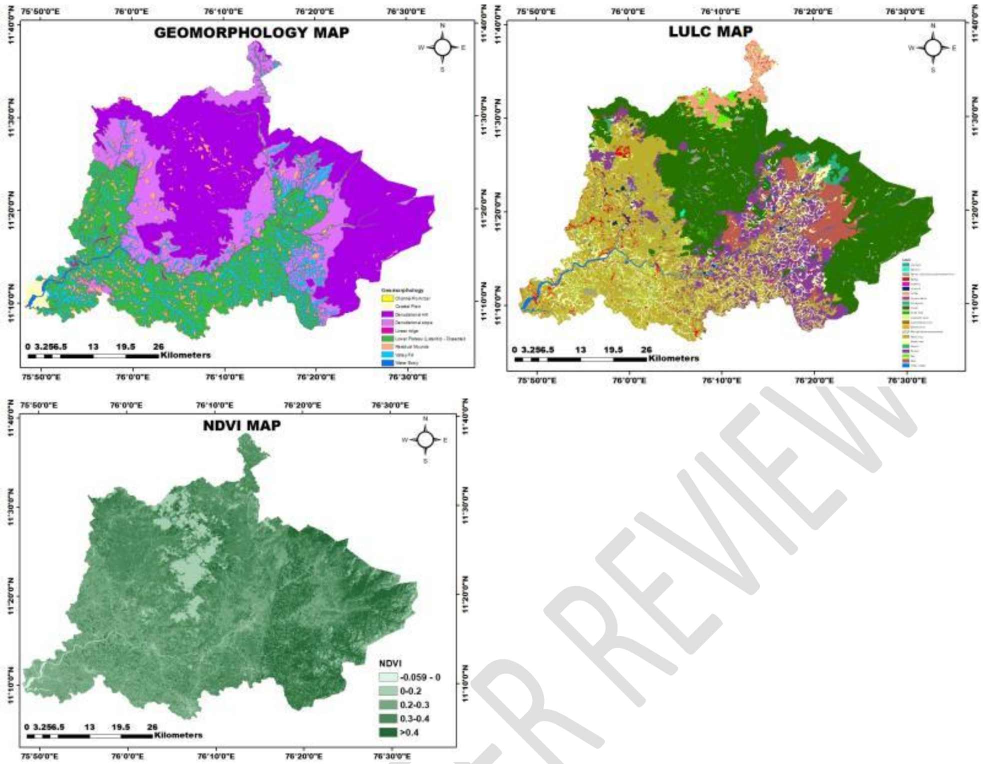

Fig 3. Fifteen landslide causative factors used in the study

3.3 Logistic regression model

The statistical package for the social sciences (SPSS) was used to carry out the binary logistic regression analysis. All the causative factors and landslides were transformed into grid format and subsequently into ACSII data format in order to process the input data layers (Devkota et al. 2013). The binary logistic regression model was performed in SPSS using the ASCII data of each map to get the coefficients of the landslidecausative factors for both numerical and categorical data. The Hosmer and Lemeshow test revealed that since the significance of chi-squwere is more than 0.05 (1.00), the equation's goodness of fit can be accepted. Cox and Snell R2 (0.380) and Nagelkerke R2 (0.507) values demonstrated that independent variables can partially explain dependent variables.

Table 2. Model summary

Step	-2 Log likelihood	Cox & Snell R Squwere	Nagelkerke R Squwere
1	751.609[a]	.380	.507

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Table 3. Hosmer and Lemshow test

Hosmer and Lemeshow Test			
Step	Chi-squwere	df	Sig.

1	13.661	8	.091

The β coefficient of each causative factor is shown in Table 4. According to Table 4, it is observed that normalized different vegetation index (NDVI), Geomorphology, distance from lineaments, lineament density, TWI, relative relief and curvature have negative effect in the landslide susceptibility mapping of study area, because of negativeβ value. The β values of these causative factors were-0.62, -0.02,0, -0.01, -0.09, -0.13 and -0.19, respectively. On the other hand, slope, distance to streams, drainage density, distance to roads, road density, soil texture and LULC have an important role in landslide occurrence with β values of 0.04, 0.10, 0.02, 0.20, 0.14, 0.13, 0.41 and 0.05 respectively.

In the case of slope angle, the higher β value was obtained for >45° (β = 3.51). For land use factor, results showed that only forest type has an effect on landslide susceptibility with value of 12.39, while the remaining land use types does not have any role in landslide occurrence. In the study area, the major portion of the landslides occurred in the forest area due to the following reasons:

- High rainfall intensity resulting in soil disintegration
- Shallow soil depth resulted in water seeping into the cavities or soil piping.
- Unsustainable land use practices like intensive agriculture on steep slopes, illegal mining and quarrying, construction of roads and buildings on unfavorable slopes, drastic reduction in forest cover and human interventions have resulted in massive and frequent landslides (Mandal et al., 2018)
- Trees decreases the slope stability on steep slopes, as the weight of trees may increase the sliding force in the parallel direction.
- Wind loading and bedrock fracturing by roots

Based on results of logistic regression for soil texture factor, we seen that sandy soil hashigher positive βvalue (β = 35.25) when compared to other texture classes.

Table 4. Variables in the equation

Factors	β	Std. Error	Wald	df	Sig.	Exp (β)	95% CI for Exp(β)	
							Lower	Upper
(Constant)	0.27	0.06	22.02	1	0	1.31	1.17	1.46
Slope	-0.04	0.03	1.62	1	0.203	0.96	0.89	1.02
Aspect	-0.10	0.11	0.92	1	0.336	0.90	0.73	1.11
Curvature	0.19	0.09	4.53	1	0.033	1.22	1.02	1.45
Relative relief	0.13	0.17	0.60	1	0.440	1.14	0.82	1.60
TWI	0.09	0.04	4.71	1	0.030	1.09	1.01	1.18
Distance to streams	-0.02	0.13	0.03	1	0.874	0.98	0.76	1.27
Drainage density	-0.20	0.04	30.59	1	0.0	0.81	0.76	0.88

Distance to roads	-0.14	0.12	1.28	1	0.258	0.87	0.69	1.11
Road density	-0.13	0.09	2.19	1	0.139	0.88	0.73	1.04
Distance to lineaments	0.0	0.16	0.0	1	0.987	1.00	0.73	1.36
Lineament density	0.01	0.08	0.01	1	0.928	1.01	0.86	1.17
Soil texture	-0.41	0.07	30.67	1	0.0	0.66	0.57	0.77
Geomorphology	0.02	0.02	1.21	1	0.272	1.02	0.99	1.05
LULC	-0.05	0.10	0.22	1	0.640	0.96	0.79	1.16
NDVI	0.62	0.95	0.42	1	0.515	1.85		

3.4 Landslide Susceptibility Map

In the study, LSI map of the area was generated by combining each parameter using the raster calculator by adding the themes one by one to assess the influence of each evidential theme in the final LSI map with values ranging from -5.1712to 3.1748.If the LSI value is high, it means a higher susceptibility to landslide, a lower value means a lower susceptibility to landslides (Vijith et al., 2014). This final LSI map is again segmented in to five classes based on expert opinion to yield five susceptibility levels. Then this reclassified susceptibility zone map was merged with the area classified as very low, low, moderate, high and very high. The resulting classes were named with the associated degree of susceptibility (Table 5) namely very low (61.08%), low (10.07%), moderate (11.21%), high (10.48%) and very high (7.16%). The validation of the landslide susceptibility map was checked against randomly selected landslides. TheROC (AUC) curve of model performance is shown in Figure 4. The AUC value indicates that the LR method gave a high success rate (AUC = 0.815). The resulting map of areas susceptible to landslides has a prediction accuracy of 81.5%.

Table 5. Area covered in each susceptibility class

Susceptibility zones	No. of landslides	% of landslides	Area(sq.km)	Area(%)
Very Low	17	9.55	1536.71	61.08
Low	20	11.24	253.37	10.07
Moderate	32	17.98	282.07	11.21
High	54	30.34	263.72	10.48
Very High	55	30.90	180.15	7.16

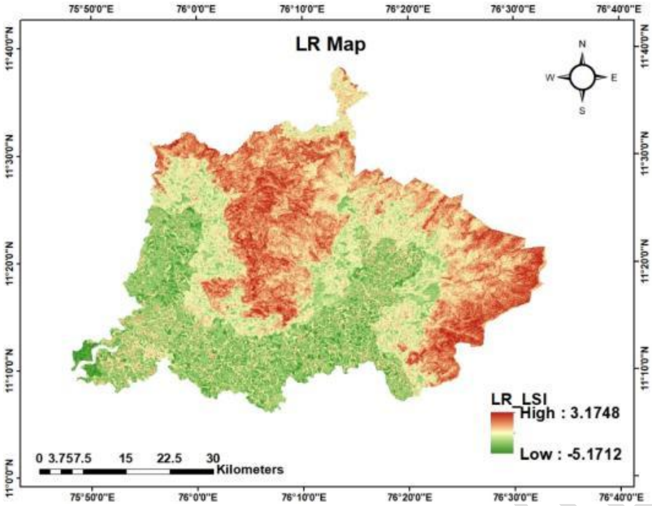

Fig.4 Landslide Susceptibility Index mapby LR Model

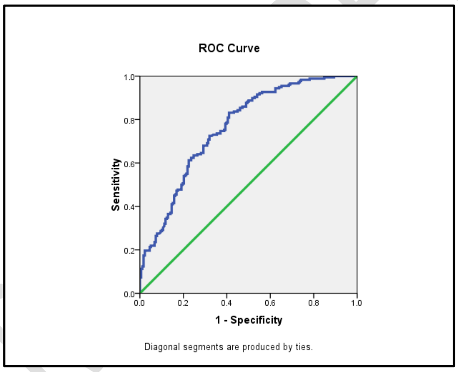

Fig.5 ROC-AUC of the LR model

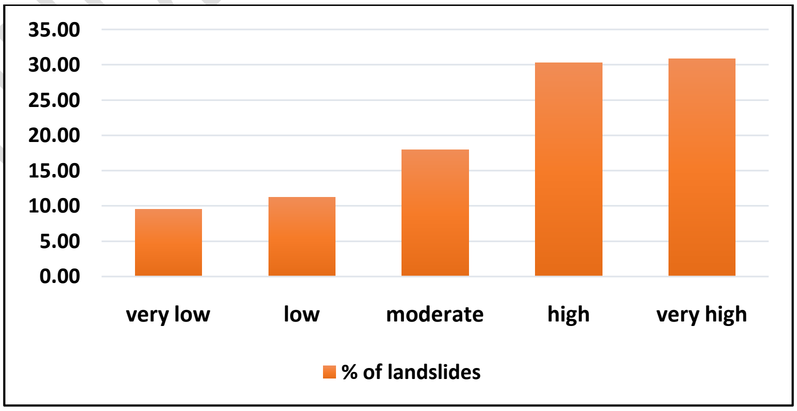

Fig.6 Percentage of landslides in each susceptibility class

4. CONCLUSION

To take action to protect life and property from a future landslide disaster, trustworthy and accurate landslide susceptibility maps were crucial. These maps were becoming increasingly possible because of cutting-edge hybrid data mining algorithms. In this study, the LR model was utilised to forecast the mapping of landslide susceptibility. This was accomplished by compiling and analysing landslide inventory of 592 past landslides using fifteen landslide causative factors, including slope, aspect, curvature, relative relief, TWI, distance to road, distance to stream, distance to lineaments, land use and land cover, drainage density, road density, lineament density, geomorphology, soil texture, and NDVI.

The LR approach does a good job of simulating the site's sensitivity to landslides. The high and very high landslide susceptibility groups occur within the 92% of the validation data. The approach used in this study shows potential for simulating comparable landslide-prone regions of the state.

REFERENCES

Achu, A.L., Aju, C.D. and Reghunath, R., 2020. Spatial modelling of shallow landslide susceptibility: a study from the southern Western Ghats region of Kerala, India. Annals of GIS, 26(2), pp.113-131.

Althuwaynee, O.F., Pradhan, B., Park, H.J. and Lee, J.H., 2014. A novel ensemble bivariate statistical evidential belief function with knowledge-based analytical hierarchy process and multivariate statistical logistic regression for landslide susceptibility mapping. Catena, 114, pp.21-36.

Bai, S.B., Wang, J., Lü, G.N., Zhou, P.G., Hou, S.S. and Xu, S.N., 2010. GIS-based logistic regression for landslide susceptibility mapping of the Zhongxian segment in the Three Gorges area, China. Geomorphology, 115(1-2), pp.23-31.

Banerjee, P., Ghose, M.K. and Pradhan, R., 2018. Analytic hierarchy process and information value method-based landslide susceptibility mapping and vehicle vulnerability assessment along a highway in Sikkim Himalaya. Arabian Journal of Geosciences, 11, pp.1-18.

Chang, K.T., Chiang, S.H. and Hsu, M.L., 2007. Modeling typhoon-and earthquake-induced landslides in a mountainous watershed using logistic regression. Geomorphology, 89(3-4), pp.335-347.

Chang, Z., Catani, F., Huang, F., Liu, G., Meena, S.R., Huang, J. and Zhou, C., 2023. Landslide susceptibility prediction using slope unit-based machine learning models considering the heterogeneity of conditioning factors. Journal of Rock Mechanics and Geotechnical Engineering, 15(5), pp.1127-1143.

Chen, H. and Zeng, Z., 2013. Deformation prediction of landslide based on improved back-propagation neural network. Cognitive computation, 5, pp.56-62.

Chen, J.W., Chue, Y.S. and Chen, Y.R., 2013. The application of the genetic adaptive neural network in landslide disaster assessment. Journal of Marine Science and Technology, 21(4), p.9.

Chen, W., Shahabi, H., Shirzadi, A., Li, T., Guo, C., Hong, H., Li, W., Pan, D., Hui, J., Ma, M. and Xi, M., 2018. A novel ensemble approach of bivariate statistical-based logistic model tree classifier for landslide susceptibility assessment. Geocarto International, 33(12), pp.1398-1420.

Chen, W., Sun, Z. and Han, J., 2019. Landslide susceptibility modeling using integrated ensemble weights of evidence with logistic regression and random forest models. Applied sciences, 9(1), p.171.

Corominas, J. and Moya, J., 2008. A review of assessing landslide frequency for hazard zoning purposes. Engineering geology, 102(3-4), pp.193-213.

Devkota, K.C., Regmi, A.D., Pourghasemi, H.R., Yoshida, K., Pradhan, B., Ryu, I.C., Dhital, M.R. and Althuwaynee, O.F., 2013. Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling–Narayanghat road section in Nepal Himalaya. Natural hazards, 65, pp.135-165.

Froude, M.J. and Petley, D.N., 2018. Global fatal landslide occurrence from 2004 to 2016. Natural Hazards and Earth System Sciences, 18(8), pp.2161-2181.

Goyes-Peñafiel, P. and Hernandez-Rojas, A., 2021. Landslide susceptibility index based on the integration of logistic regression and weights of evidence: A case study in Popayan, Colombia. Engineering Geology, 280, p.105958.

Gururajan, B. and nehru Jawaharlal, A., 2021. Landslide Vulnerability Assessment in Devikulam Taluk, Idukki District, Kerala Using Gis and Machine Learning Algorithms.

Guzzetti, F., Galli, M., Reichenbach, P., Ardizzone, F. and Cardinali, M.J.N.H., 2006b. Landslide hazard assessment in the Collazzone area, Umbria, Central Italy. Natural hazards and earth system sciences, 6(1), pp.115-131.

Guzzetti, F., Reichenbach, P., Ardizzone, F., Cardinali, M. and Galli, M., 2006a. Estimating the quality of landslide susceptibility models. Geomorphology, 81(1-2), pp.166-184.

Hadji, R., Limani, Y., Baghem, M. and Demdoum, A., 2013. Geologic, topographic and climatic controls in landslide hazard assessment using GIS modeling: a case study of Souk Ahras region, NE Algeria. Quaternary International, 302, pp.224-237.

Huabin, W., Gangjun, L., Weiya, X. and Gonghui, W., 2005. GIS-based landslide hazard assessment: an overview. Progress in Physical geography, 29(4), pp.548-567.

Karim, Z., Hadji, R. and Hamed, Y., 2019. GIS-based approaches for the landslide susceptibility prediction in Setif Region (NE Algeria). Geotechnical and Geological Engineering, 37(1), pp.359-374.

Kayastha, P., Bijukchhen, S.M., Dhital, M.R. and De Smedt, F., 2013. GIS based landslide susceptibility mapping using a fuzzy logic approach: A case study from Ghurmi-Dhad Khola area, Eastern Nepal. Journal of the Geological Society of India, 82, pp.249-261.

Lee, S. and Pradhan, B., 2006. Probabilistic landslide hazards and risk mapping on Penang Island, Malaysia. Journal of Earth System Science, 115, pp.661-672.

Li, C., Ma, T., Sun, L., Li, W. and Zheng, A., 2012. Application and verification of fractal approach to landslide susceptibility mapping. Terrigenous Mass Movements: Detection, Modelling, Early Warning and Mitigation Using Geoinformation Technology, pp.91-107.

Mahdadi, F., Boumezbeur, A., Hadji, R., Kanungo, D.P. and Zahri, F., 2018. GIS-based landslide susceptibility assessment using statistical models: a case study from Souk Ahras province, NE Algeria. Arabian Journal of Geosciences, 11, pp.1-21.

Maheshwari, B.K., 2019. Earthquake-induced landslide hazard assessment of chamoli district, uttarakhand using relative frequency ratio method. Indian Geotechnical Journal, 49, pp.108-123.

Martha, T.R., Roy, P., Govindharaj, K.B., Kumar, K.V., Diwakar, P.G. and Dadhwal, V.K., 2015. Landslides triggered by the June 2013 extreme rainfall event in parts of Uttarakhand state, India. Landslides, 12, pp.135-146.

Mandal, B. and Mandal, S., 2018. Analytical hierarchy process (AHP) based landslide susceptibility mapping of Lish river basin of eastern Darjeeling Himalaya, India. Advances in Space Res., 62(11), pp.3114-3132.

Mersha, T. and Meten, M., 2020. GIS-based landslide susceptibility mapping and assessment using bivariate statistical methods in Simada area, northwestern Ethiopia. Geoenvironmental disasters, 7(1), pp.1-22.

Ozdemir, A., 2011. Using a binary logistic regression method and GIS for evaluating and mapping the groundwater spring potential in the Sultan Mountains (Aksehir, Turkey). Journal of Hydrology, 405(1-2), pp.123-136.

Pascale, Stefania, Serena Parisi, Annagrazia Mancini, Marcello Schiattwerella, Massimo Conforti, Aurelia Sole, Beniamino Murgante, and Francesco Sdao. "Landslide susceptibility mapping using artificial neural network in the urban area of Senise and San Costantino Albanese (Basilicata, Southern Italy)." In Computational Science and Its Applications–ICCSA 2013: 13th International Conference, Ho Chi Minh City, Vietnam, June 24-27, 2013, Proceedings, Part IV 13, pp. 473-488. Springer Berlin Heidelberg, 2013.

Polykretis, C., Ferentinou, M. and Chalkias, C., 2015. A comparative study of landslide susceptibility mapping using landslide susceptibility index and artificial neural networks in the Krios River and Krathis River catchments (northern Peloponnesus, Greece). Bulletin of Engineering Geology and the Environment, 74, pp.27-45.

Pourghasemi, H.R., Moradi, H.R. and Fatemi Aghda, S.M., 2013. Landslide susceptibility mapping by binary logistic regression, analytical hierarchy process, and statistical index models and assessment of their performances. Natural hazards, 69, pp.749-779.

Ram, P. and Gupta, V., 2021. Landslide hazard, vulnerability, and risk assessment (HVRA), Mussoorie township, lesser himalaya, India. Environment, Development and Sustainability, pp.1-29.

Sato, H.P. and Harp, E.L., 2009. Interpretation of earthquake-induced landslides triggered by the 12 May 2008, M7. 9 Wenchuan earthquake in the Beichuan area, Sichuan Province, China using satellite imagery and Google Earth. Landslides, 6, pp.153-159.

Su, A., Feng, M., Dong, S., Zou, Z. and Wang, J., 2022. Improved statically solvable slice method for slope stability analysis. Journal of Earth Science, 33(5), pp.1190-1203.

Trigila, A., Iadanza, C., Esposito, C. and Scarascia-Mugnozza, G., 2015. Comparison of Logistic Regression and Random Forests techniques for shallow landslide susceptibility assessment in Giampilieri (NE Sicily, Italy). Geomorphology, 249, pp.119-136.

Van Westen, C.J., Castellanos, E. and Kuriakose, S.L., 2008. Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. Engineering geology, 102(3-4), pp.112-131.

Vijith, H., Krishnakumar, K.N., Pradeep, G.S., Ninu Krishnan, M.V. and Madhu, G., 2014. Shallow landslide initiation susceptibility mapping by GIS-based weights-of-evidence analysis of multi-class spatial data-sets: a case study from the natural sloping terrain of Western Ghats, India. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 8(1), pp.48-62.

Vineetha, P., Sarun, S. and Sheela, A.M., 2019. Landslide susceptibility analysis using frequency ratio model in a tropical region, South East Asia. Journal of Geography, Environment and Earth Science International, 22(2), pp.1-13.

Vishnu, C.L., Oommen, T., Chatterjee, S. and Sajinkumar, K.S., 2022. Challenges of modeling rainfall triggered landslides in a data-sparse region: A case study from the Western Ghats, India. Geosystems and Geoenvironment, 1(3), p.100060.

Wadhawan, S.K., Singh, B. and Ramesh, M.V., 2020. Causative factors of landslides 2019: case study in Malappuram and Wayanad districts of Kerala, India. Landslides, 17, pp.2689-2697.

Wu, W. and Sidle, R.C., 1995. A distributed slope stability model for steep forested basins. Water resources research, 31(8), pp.2097-2110.

Yuvaraj, R.M. and Dolui, B., 2021. Statistical and machine intelligence based model for landslide susceptibility mapping of Nilgiri district in India. Environmental Challenges, 5, p.100211.

Zhao, Y., Wang, R., Jiang, Y., Liu, H. and Wei, Z., 2019. GIS-based logistic regression for rainfall-induced landslide susceptibility mapping under different grid sizes in Yueqing, Southeastern China. Engineering geology, 259, p.105147.