SSRG International Journal of Recent Engineering Science
ISSN: 2349–7157 / https://doi.org/10.14445/23497157/IJRES-V11I6P116

Volume 11 Issue 6, 187-197, Nov-Dec 2024

Original Article

Geospatial and Machine Learning Techniques for Landslide Risk Mapping in Sikkim, India

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Received: 20 October 2024 Revised: 24 November 2024 Accepted: 13 December 2024 Published: 28 December 2024

Abstract - *Identifying landslides and producing landslide susceptibility maps are essential components in supporting planners, local administrators, and decision-makers in effective disaster management strategies. The accuracy of these susceptibility maps plays a pivotal role in mitigating potential loss of life and property. Effective models for landslide susceptibility mapping require the integration of multiple factors that characterize both terrain features and meteorological conditions. Numerous algorithms have been developed and implemented in the literature to enhance the accuracy of these maps. This study employs a hybrid approach combining four machine learning techniques: Logistic Regression (LR), Random Forest (RF), Support Vector Classifier (SVC), and CatBoost, supplemented by a grid search to determine optimal hyperparameter settings. This methodological framework aims to achieve precise and reliable predictions for generating landslide susceptibility maps for Sikkim, India. In this study, eleven conditioning factors were considered, including aspect, slope, Land Use and Land Cover (LULC), elevation, distance to roads, distance to streams, the Normalized Difference Vegetation Index (NDVI), plan curvature, soil type, rainfall, and seismic activity. The performance of the models was assessed using several metrics, including training score, testing score, kappa, sensitivity, specificity, and Area Under the Curve (AUC). The results indicated that the random forest model outperformed the other models, achieving kappa and AUC values of 0.519 and 0.756, respectively, in developing susceptibility maps. Consequently, the random forest model emerges as the most reliable and effective tool for landslide susceptibility mapping within this study, making it an optimal choice for such predictive analyses.*

Keywords - *Landslide susceptibility mapping, Machine learning, CatBoost, Hybrid techniques, Random Forest.*

1. Introduction

A natural disaster is characterized by an unexpected alteration in environmental conditions, such as earthquakes, tsunamis, and floods, which can result in significant financial, environmental, and human losses. Among these phenomena, landslides rank among the most devastating, leading to dramatic transformations in landscape morphology and causing damage to both natural and built structures. Landslides are mass movements of soil or rock that involve shear displacement along one or multiple slip surfaces, which may be easily identifiable or inferred from surrounding conditions. Identifying landslide-prone areas is crucial for ensuring human safety and mitigating adverse effects on regional and national economies. Assessing landslide susceptibility zones and developing accurate and current landslide susceptibility maps have emerged as a prominent area of research in hazard management. Such maps provide essential information for government agencies, urban planners, decision-makers, and local landowners, enabling them to formulate emergency plans to minimize detrimental impacts on infrastructure, superstructure, and human life [1–3]. Implementing landslide assessments can significantly reduce associated hazards; nonetheless, it is vital to catalogue historical landslide events to identify trends effectively. Producing hazard zonation maps is integral to this process, allowing decision-makers to pinpoint sensitive areas for enhanced land-use management. The primary objective of landslide assessment is the preparation of landslide susceptibility maps, which incorporate both spatial and temporal predictions of landslides at a regional scale. This task presents considerable challenges to the global research community focused on climate change. The outcomes are influenced by the data utilized and the modelling methodologies applied, which is a central emphasis of ongoing research. In the case of Sikkim, the region's physical characteristics—including tectonic activity, geological structure, topography, and meteorological factors—frequently contribute to natural hazards resulting in significant socio-economic impacts and loss of life. Sikkim has encountered numerous natural disasters, resulting in substantial human casualties, injuries, and property damage. When natural disasters are ranked according to their frequency of occurrence, landslides occupy the second position following earthquakes [4–7].

Numerous techniques have been developed and successfully utilized in the literature to create landslide susceptibility maps. These modelling approaches can be categorized into key groups, including geomorphological hazard mapping, analysis of landslide inventories, heuristic methods, and statistical or geotechnical models. Several statistical methods were utilized for landslide zonation. Arabameri et al. [8] conducted a comparative study on various methodologies for landslide susceptibility mapping (LSM) in Semnan, Iran.

The study examined four different approaches: Index of Entropy (IOE), Frequency Ratio (FR), Weights-of-Evidence (WofE) and Analytical Hierarchy Process (AHP), incorporating thirteen conditioning factors into the analysis. Considering several conditioning factors, Bopche et al. [9] applied the weights-of-evidence technique for landslide zonation in Pune, India. Tang et al. [10] performed a comparative analysis between logistic regression and the Analytical Hierarchy Process Information Value (AHP-IV) in Zhushan County, China, utilizing eight conditioning factors in their study. Cervi et al. [11] conducted a comparative study of the weight of evidence, the fuzzy logic, and SHALSTAB for landslide zonation in Reggio Emilia Province, Italy. In addition to the aforementioned statistical methods, machine learning techniques have emerged as more advanced tools for landslide susceptibility mapping.

Kavzoglu et al. [12] conducted a comparative study among Random Forest, Extreme Gradient Boosting (XGBoost) and Natural Gradient Boosting (NGBoost) for landslide zonation of Macka County of Trabzon province, Turkey. Karakas et al. [13] evaluated the efficacy of multilayer perceptron neural networks compared to Random Forest for landslide susceptibility mapping in Elazig, Turkey. Colkesen et al. [14] conducted a comparative analysis of Support Vector Machine and logistic regression techniques for landslide zonation in Trabzon, Turkey. Aditian et al. [15] assessed the performance of artificial neural networks, frequency ratio, and logistic regression in the context of landslide susceptibility in Ambon, Indonesia. In addition to the standalone algorithms previously mentioned, hybrid algorithms have also been employed for landslide susceptibility mapping.

These advanced methods combine multiple algorithms in parallel, enhancing the evaluation process and resulting in more reliable and accurate performance. Wu et al. [16] conducted a comparative study on the effectiveness of bagging and AdaBoost techniques for landslide zonation in Shaanxi Province, China. Matougui et al. [17] performed a thorough comparative analysis of heterogeneous ensemble models—including stacking (ST), voting (VO), weighting (WE), and meta-dynamic ensemble selection (DES)—in contrast to homogeneous ensemble models such as AdaBoost (ADA), bagging (BG), random forest (RF), and random subspace (RSS) for the Djebahia region of Algeria. Numerous studies have been undertaken in various locations worldwide to enhance the accuracy and reliability of these methods [18–21]. The study employs random forest (RF), logistic regression (LR), support vector classifier (SVC), and CatBoost to develop a landslide susceptibility map for Sikkim, India. These machine learning classifiers have been selected due to their growing prominence and effectiveness in engineering applications. Performance evaluations were conducted using standard accuracy metrics, including user and overall accuracies, receiver operating characteristics (ROC) and success rate curves, to facilitate objective and comprehensive comparisons among the methods.

2. Study Area

Sikkim, a small yet significant state in the North-Eastern Himalayas of India, encompasses 7096 square kilometers of diverse landscapes (Figure 1). Characterized by younger mountain systems, the region is rich in geological features but susceptible to landslides and seismic activity. Gangtok, the vibrant capital, serves as a gateway to explore elevations that range from 300 to 8000 meters above sea level, with 66% of the area being mountainous and often adorned with snow.

The climate in Sikkim is varied, transitioning from tropical to alpine, which fosters a unique ecosystem. Rainfall patterns indicate substantial precipitation in Gangtok (3494 mm), contrasting sharply with the minimal rainfall in Thangu (82 mm). Culturally, Sikkim boasts a multi-ethnic population, contributing to the state's rich heritage. As of 2011, it comprised less than 0.05% of India's total population, with a population density of 86 people per square kilometer. This diversity and the region's natural beauty position Sikkim as an important ecological and cultural study area.

The uneven distribution of inhabitants in Gangtok has significantly strained urban services due to rapid population growth in a limited area. This strain manifests as traffic and transportation issues, a lack of modern commercial development, housing shortages, and the rise of informal settlements. Gangtok struggles to meet the demands of its increasing population, with unregulated development harming the natural environment. The geological landscape of the Sikkim Himalaya, particularly along the Teesta valley, is shaped by the Main Central Thrust (MCT) and Main Boundary Thrust (MBT) zones, which separate various grades of Himalayan rocks. The central crystalline area in North Sikkim exhibits high-grade gneisses, migmatites, and granitic intrusions. According to India's seismic zone zoning map, Sikkim is located in Zone IV for seismic risk.

3. Landslide Conditioning Factors (LCFs)

The study identified eleven key conditioning factors essential for accurate landslide susceptibility mapping and an analysis of their spatial distribution (Figure 2).

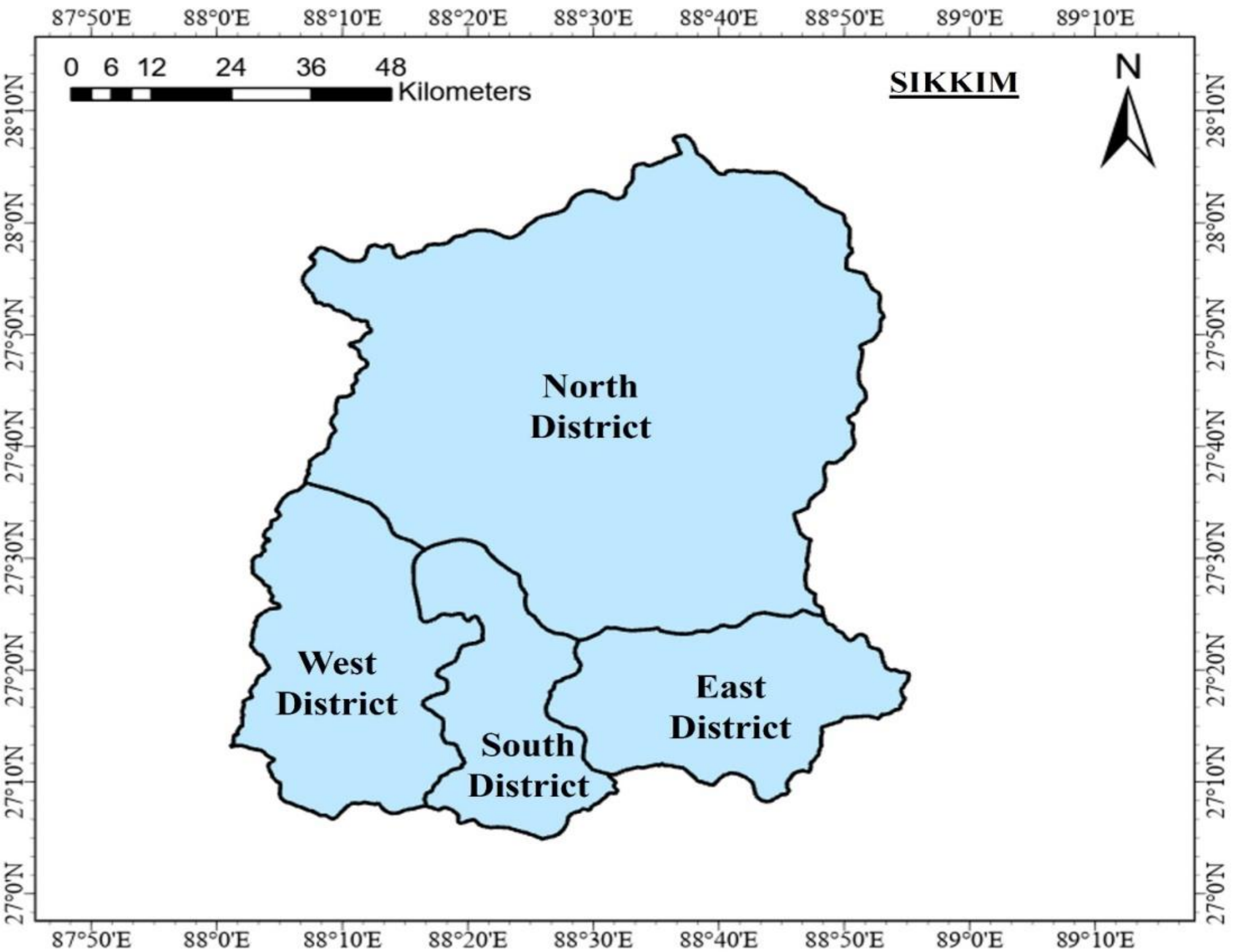


Fig. 1 Study area map

The slope map of the study area has been categorized into five distinct classes: 0-15° (very low), 15-25° (low), 25-35° (moderate), 35-45° (high), and 45-90° (very high).

The aspect map has been classified into nine categories: flat, north, northeast, east, southeast, south, southwest, west, and northwest. The elevation map is divided into three classes: (i) 222 – 2460 m, (ii) 2460 – 4227 m, and (iii) 4227 – 7899 m. The distance to the streams map is classified into five ranges: (i) 111.32 – 556.6 m, (ii) 556.6 – 1335.84 m, (iii) 1335.84 – 2115.08 m, (iv) 2115.08 – 2894.32 m, and (v) 2894.32 – 6233.92 m.

The distance to roads map is also categorized into five classes: (i) 111.32 – 2449.04 m, (ii) 2449.04 – 5343.36 m, (iii) 5343.36 – 9016.92 m, (iv) 9016.92 - 14026.32 m, and (v) 14026.32 – 22264 m. The land use/land cover (LULC) map is classified into nine categories: (i) Water, (ii) Trees, (iii) Flooded vegetation, (iv) Crops, (v) Built area, (vi) Bare ground, (vii) Snow/ice, (viii) Clouds, and (ix) Rangeland. The normalized difference vegetation index (NDVI) map is classified into five classes: (i) (-) 0.603 – 0.025, (ii) 0.026 – 0.125, (iii) 0.126 – 0.232, (iv) 0.233 – 0.465, and (v) 0.466 – 1. The plan curvature map has also been classified into five categories: (i) (-) 1.92 to (-) 0.034, (ii) (-) 0.034 to (-) 0.011, (iii) (-) 0.011 to 0.0003, (iv) 0.0003 to 0.023, and (v) 0.023 to 1.016. The rainfall map is divided into five categories: (i) 1000 - 1647 mm, (ii) 1648 - 2235 mm, (iii) 2236 - 2729 mm, (iv) 2730 - 3353 mm, and (v) 3354 - 4000 mm.

The soil type map has been classified into five categories: (i) Humid Acrisols, (ii) Dystric Cambisols, (iii) Gleysols luvi Soils, (iv) Lithosols, and (v) Dystric Regosols. Lastly, the earthquake map is categorized into three magnitude classes: (i) 0.011 - 3.291, (ii) 3.292 - 6.018, and (iii) 6.019 - 11.794.

These thematic maps were meticulously prepared to enhance landslide susceptibility analysis by integrating them with landslide occurrence data, enabling a more precise and comprehensive assessment.

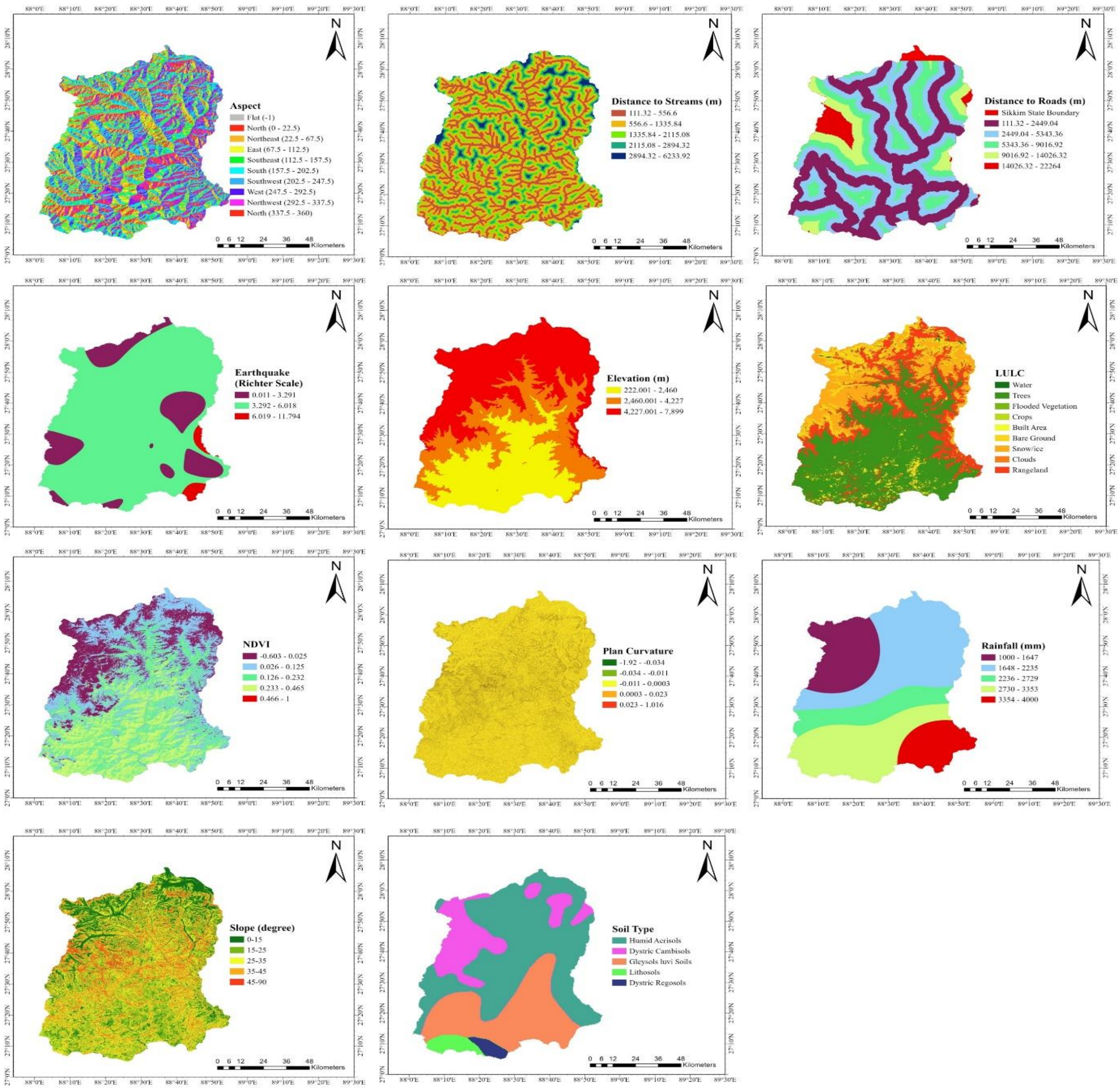


Fig. 2 Landslide conditioning factors (LCFs)

4. Landslide Inventory and Methodology

4.1. Landslide Inventory

The landslide data utilized for this analysis has been sourced from Bhukosh, Geological Survey of India, comprising 693 data points, as illustrated in Figure 3. These data points were imported into ArcGIS, where polygons were generated to create a comprehensive dataset for further analysis. An additional 695 non-landslide data points were randomly generated within ArcGIS to ensure a balanced dataset and corresponding polygons were constructed. By integrating the LCFs, landslide and non-landslide data, a consolidated dataset consisting of 12165 data points was developed. This dataset was subsequently divided into a 70:30 ratio, allocating 70% for training and 30% for testing to facilitate thorough analysis. The distribution and variability of each input variable on landslide are shown in Figure 4 . Figure 4 illustrates notable correlations among various features, indicating significant relationships between them. For example, the correlation coefficient of 0.61 between Land Use and Land Cover (LULC) and Elevation emphasizes how vegetation patterns and human activities fluctuate with altitude.

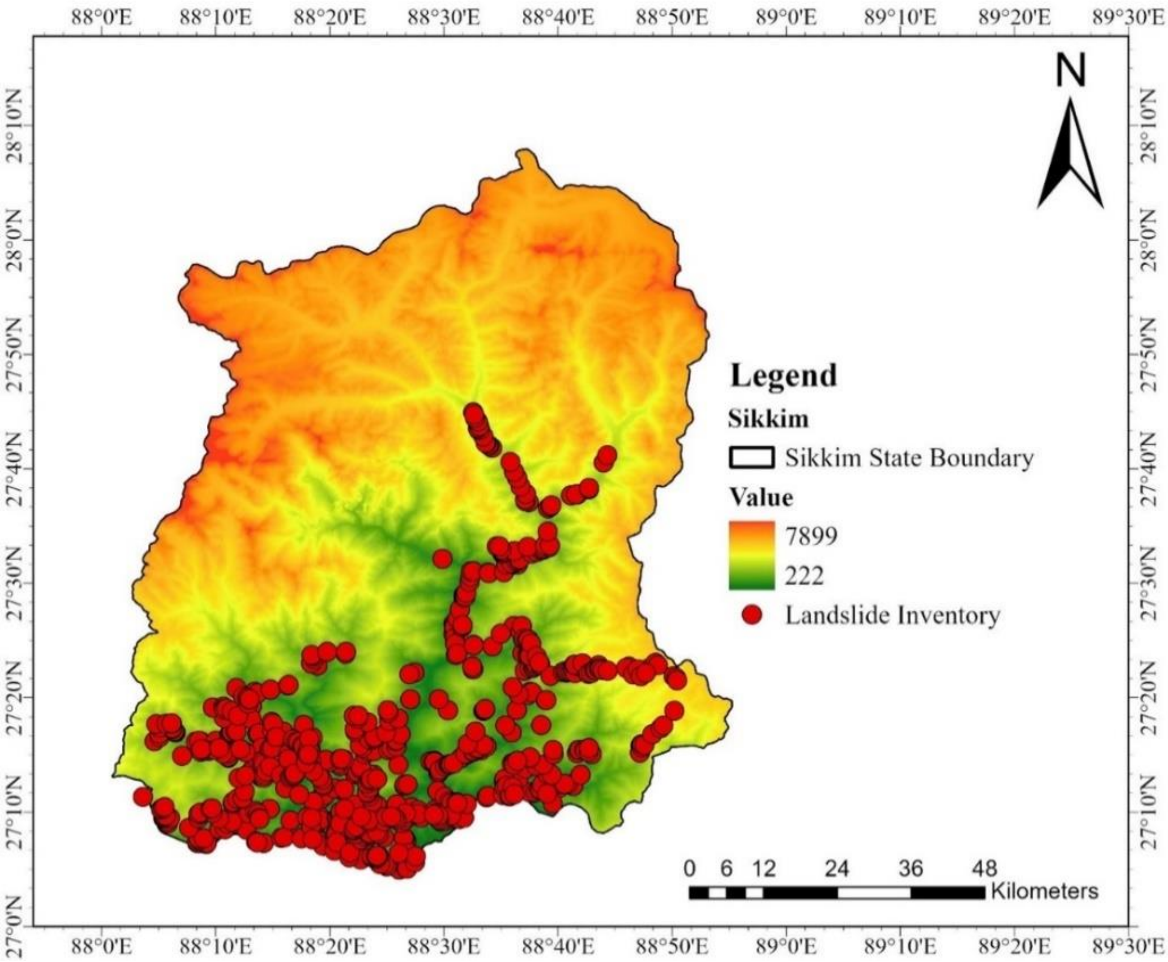


Fig. 3 Landslide data points of the study area

Additionally, a moderate correlation of 0.53 between the Normalized Difference Vegetation Index (NDVI) and Rainfall highlights the influence of precipitation on vegetation health and density. Furthermore, a correlation of 0.58 between Rainfall and Soil Type suggests that soil characteristics are shaped by rainfall distribution, impacting factors such as soil moisture and composition. Conversely, some features display minimal correlation, indicating weaker interdependence.

For instance, the weak correlation between Elevation and Soil Type implies that soil properties are predominantly independent of altitude. Similarly, Rainfall and Elevation exhibit a low correlation, indicating that rainfall patterns are not strongly associated with elevation variations within the region. The correlation between NDVI and Elevation is also low, suggesting that altitude in this study area does not significantly influence vegetation density. These insights into feature correlations are crucial for understanding the interplay of factors contributing to landslide susceptibility. Identifying highly correlated features aids in reducing redundancy within models while including weakly correlated features ensures the diversity and independence of factors considered in the analysis.

4.2. Methodology

The study's methodology is shown in Figure 5, illustrating the step-by-step process undertaken to achieve reliable landslide susceptibility mapping. Prior to conducting the analysis, the optimal hyperparameters for all models—Random Forest (RF), Logistic Regression (LR), Support Vector Classifier (SVC) and CatBoost—were established through the application of Grid Search.

This method is a systematic approach for hyperparameter tuning, thoroughly exploring a defined range of hyperparameter values to identify the combination that produces the best performance for each model. The specific ranges of hyperparameters evaluated in this study are detailed in Table 1.

For example, we carefully examined parameters such as the number of estimators and maximum depth for the Random Forest model, the kernel type and regularization parameter for SVM, and the learning rate and number of iterations for CatBoost. This rigorous optimization ensured that each model was finely tuned to its most effective configuration for landslide susceptibility mapping.

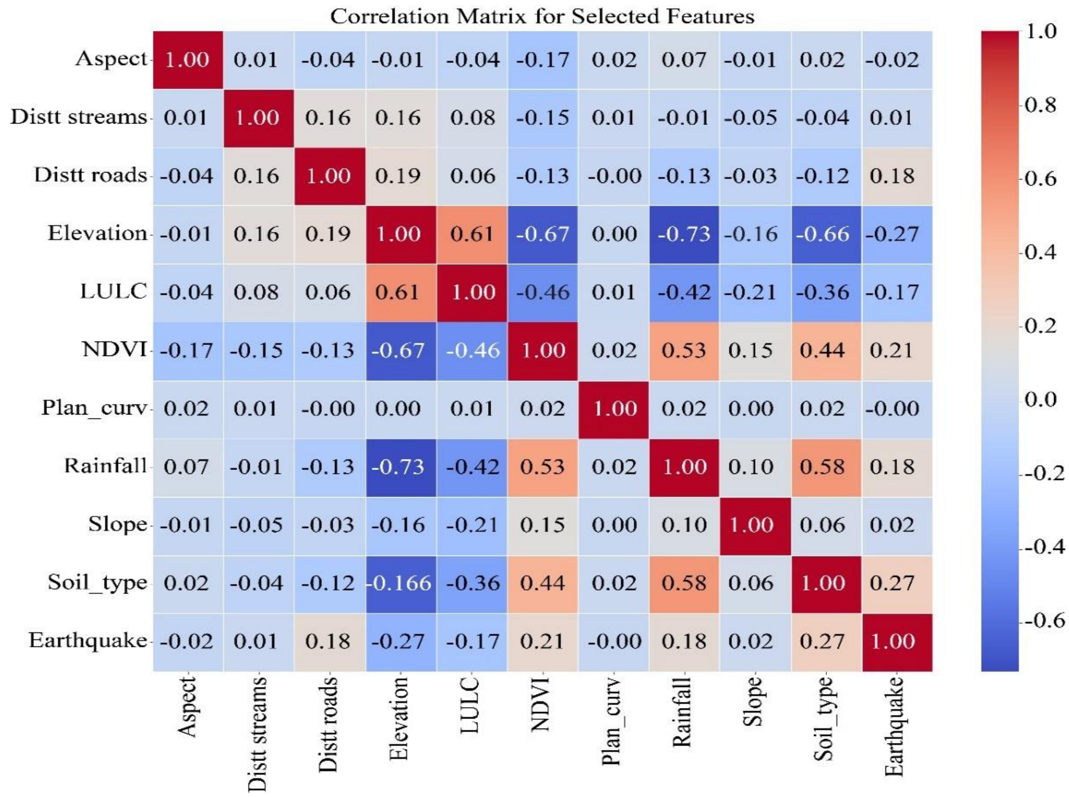


Fig. 4 Correlation matrix of conditioning factors

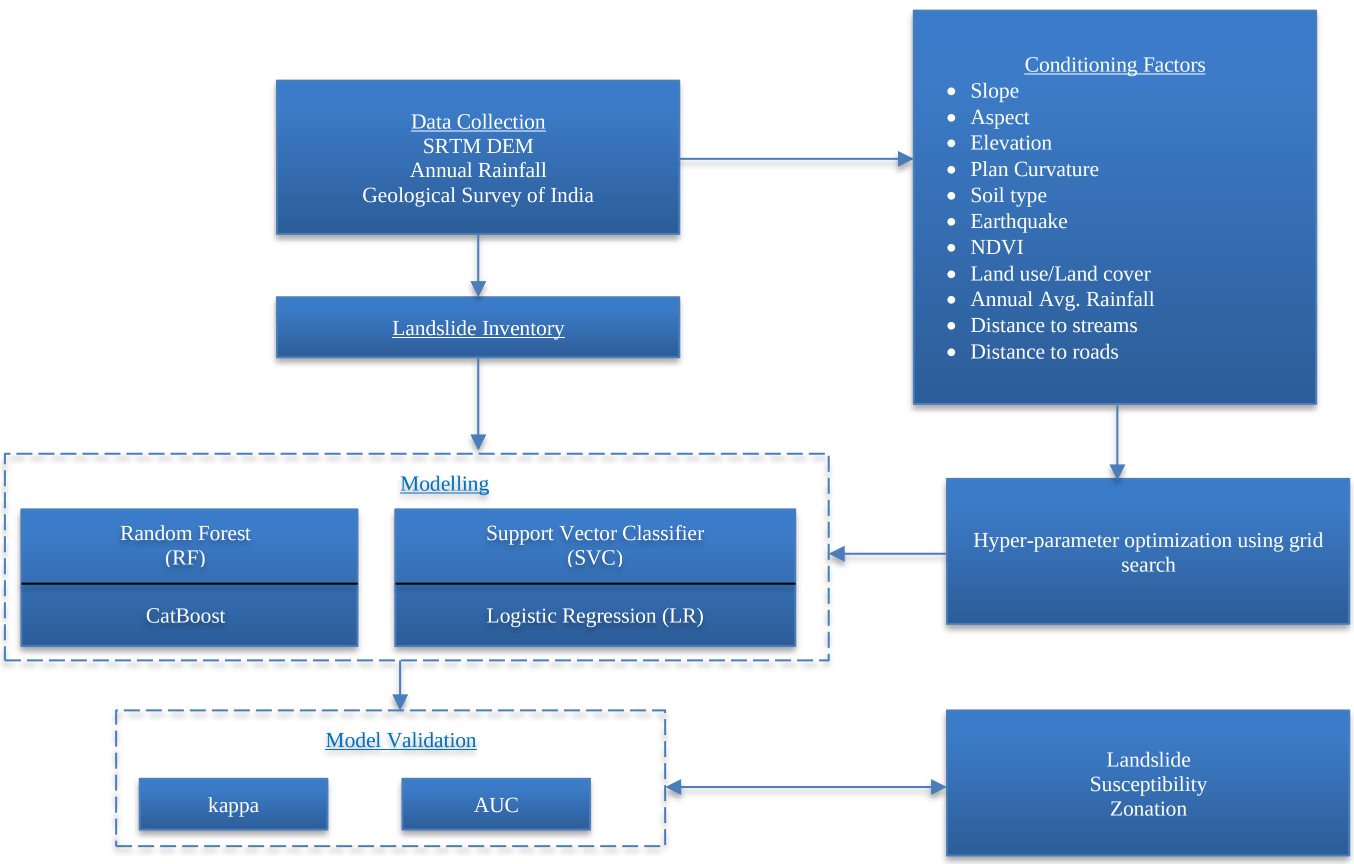


Fig. 5 Methodology of the study

Table 1. Optimal hyperparameters using grid search

Model	Hyperparameters Range	Optimal Values
LR	C = [1-200]; Step Size = 5	1
RF	n_estimators = [1 - 200]; Step Size = 5	31
	max_depth = [1-10]; Step size = 1	8
SVC	Kernel = [linear, polynomial, rbf]	rbf
	C = [1-200]; Step Size = 5	56
	Degree = [1,2,3]	nil
Catboost	n_estimators = [1 - 200]; Step Size = 5	76
	depth=[1-10]	8
	learning_rate=[0.1,0.01,0.001]	0.1

Upon establishing the optimal hyperparameters, susceptibility maps for the study area were generated utilizing the calibrated models. These maps illustrate the likelihood of landslides occurring throughout the region. The results derived from the various models were subsequently compared to assess their performance. This comparative analysis aimed to identify the most accurate and reliable model for landslide susceptibility mapping, thereby ensuring robust and meaningful outcomes for decision-making and risk assessment purposes.

5. Results and Discussion

The study employed four machine learning techniques—Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF) and CatBoost—for landslide susceptibility mapping. The hyperparameters for each model were meticulously optimized through a grid search, as detailed in Table 1. Utilizing these optimal hyperparameters, comparative results were generated, and corresponding maps were produced.

It is important to highlight that the performance of the classifiers is significantly influenced by the Area Under the Curve (AUC), with a value of 1.0 representing optimal performance. The ROC curves in Figure 6 illustrate the classification performance of the models, with the AUC values highlighting their ability to distinguish between classes. The AUC values for the models are 0.743 for Logistic Regression (LR), 0.753 for Support Vector Classifier (SVC_RBF), 0.765 for Random Forest (RF), and 0.762 for CatBoost. The variation in these AUC values reflects differences in the models' underlying algorithms, levels of complexity, and effectiveness in capturing the relationships between features and the target variable.

The ROC curves of RF, CatBoost, and SVC are closer to the plot's top-left corner than LR, indicating better classification performance. Notably, these models achieve AUC values exceeding 0.75, suggesting superior discriminatory power and overall performance compared to LR. Additionally, the evaluation of the model is based on other metrics, including training score, testing score, sensitivity, specificity, and kappa, as shown in Figure 7. In addition to the ROC and evaluation metrics analysis, Figure 8 presents the confusion matrices of the models, revealing their predictive accuracy. The total number of misclassifications for each model further substantiates the AUC findings. Logistic Regression exhibits the highest number of misclassifications at 966, while Random Forest has the fewest at 889, followed by CatBoost with 897 and SVC (RBF kernel) with 929. These results underscore the enhanced performance of RF, CatBoost, and SVC over LR, as evidenced by their higher AUC values and fewer misclassifications. This combined evaluation demonstrates the strengths of RF, CatBoost, and SVC in accurately predicting landslide susceptibility, making them more reliable choices for this task.

The landslide susceptibility maps generated for the models mentioned earlier are presented in Figure 9. Figure 10 illustrates the area distribution for each class across the various machine learning models. In the case of Logistic Regression, the highest area classification, at 24.62%, falls within the High susceptibility category. This indicates that a significant portion of the study area is predicted to be at a relatively elevated risk for landslides.

For the Random Forest model, the largest proportion, 30.49%, is categorized as Moderate susceptibility, suggesting a greater emphasis on regions at moderate risk. Similarly, the SVC (RBF) model assigns the highest area percentage of 26.01% to the High susceptibility class, aligning closely with the Logistic Regression model, albeit with a minor difference in magnitude. In contrast, the CatBoost model also classifies the largest area, 30.68%, into the Moderate susceptibility category, similar to the Random Forest findings but slightly higher in percentage.

These results reveal the distinct focus of Random Forest and CatBoost on moderate-risk areas compared to the other models. The variations in classification outcomes underscore the impact of the underlying algorithms on the results, with each model highlighting different susceptibility levels based on its capacity to discern patterns within the dataset. This variability emphasizes the significance of evaluating multiple models to thoroughly understand landslide susceptibility within the study area.

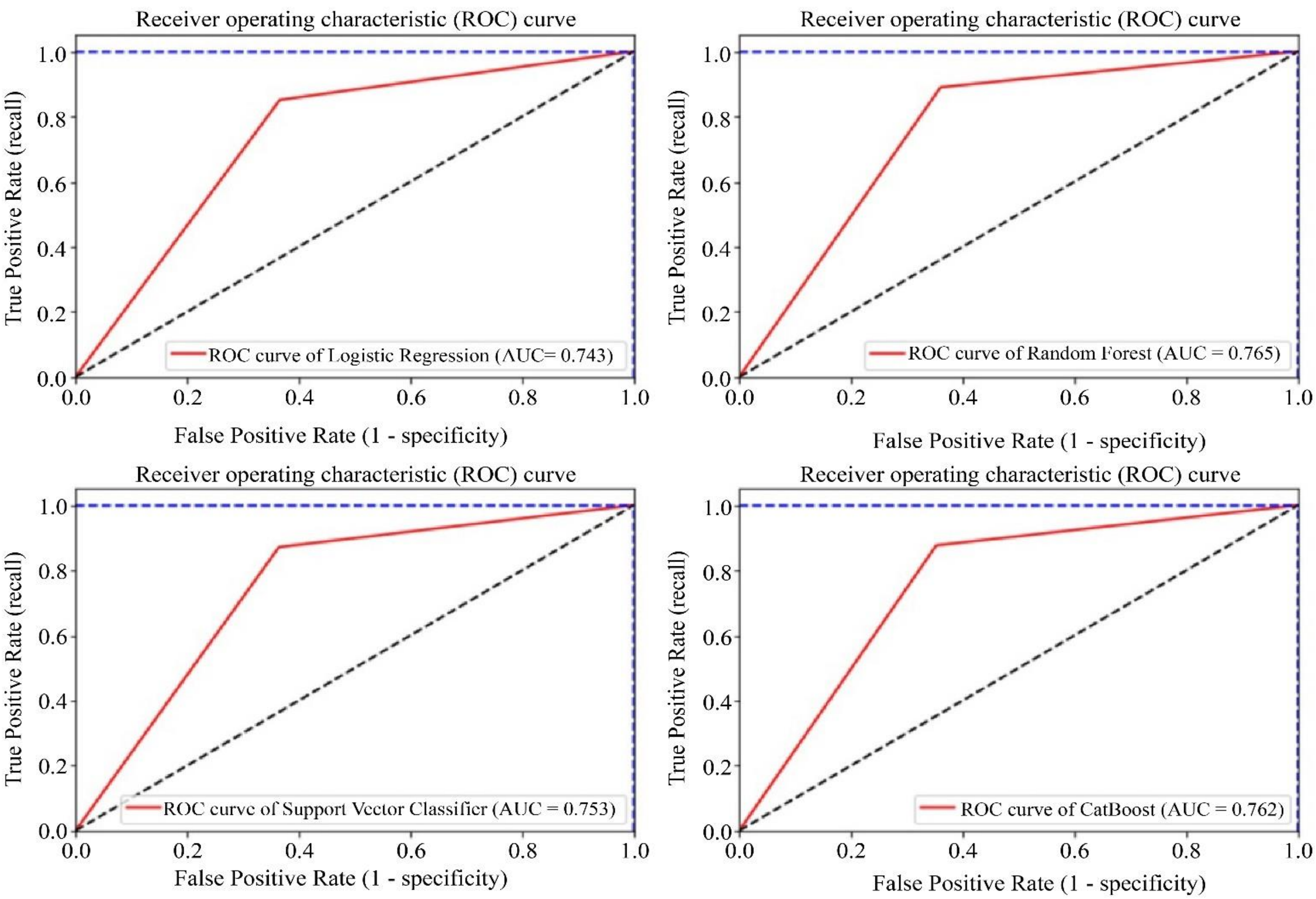


Fig. 6 ROC curves of all ML models

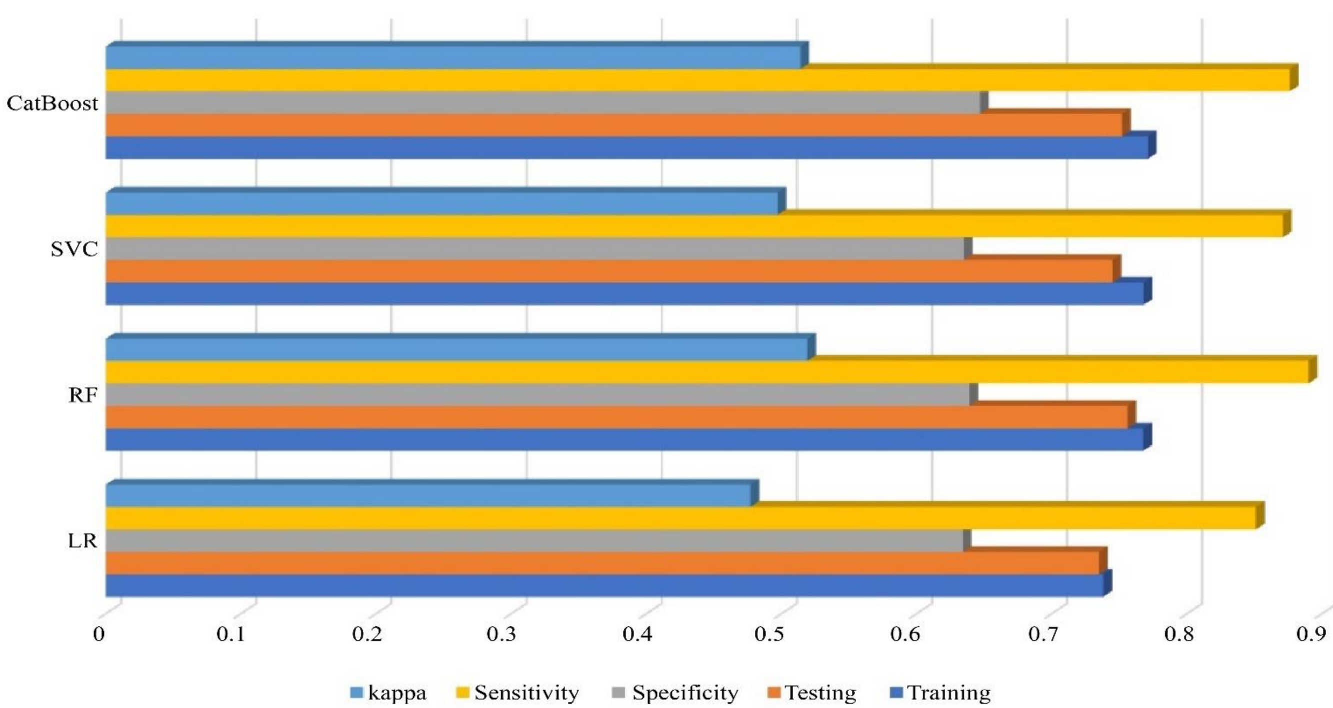


Fig. 7 Evaluation metrics for the ML model

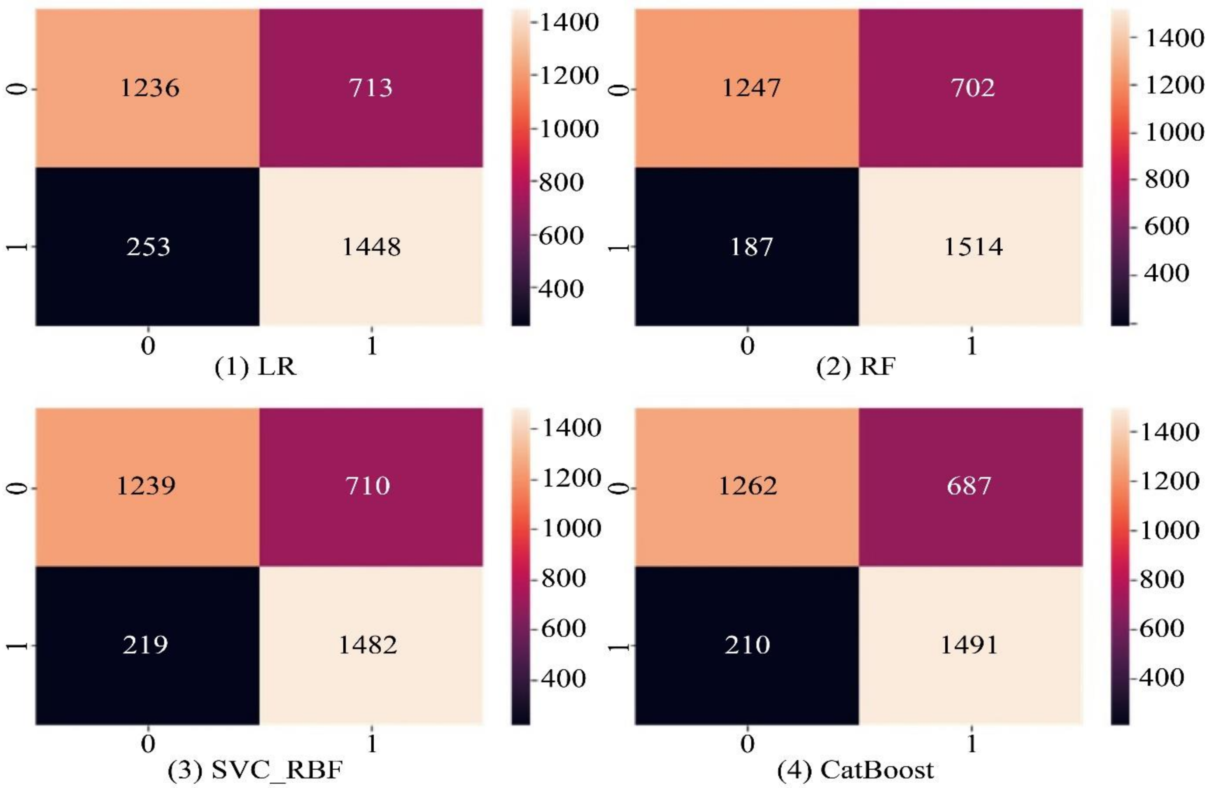


Fig. 8 Confusion matrix of classification models

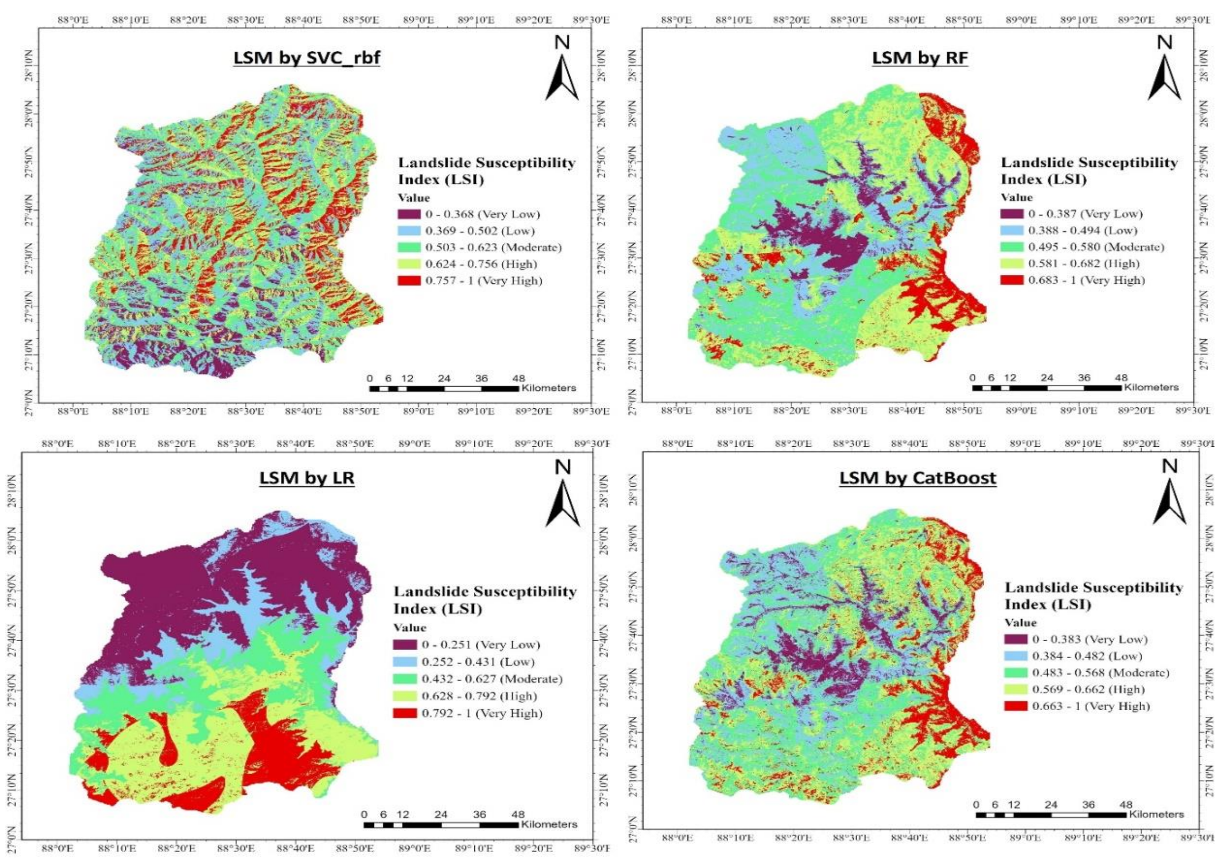
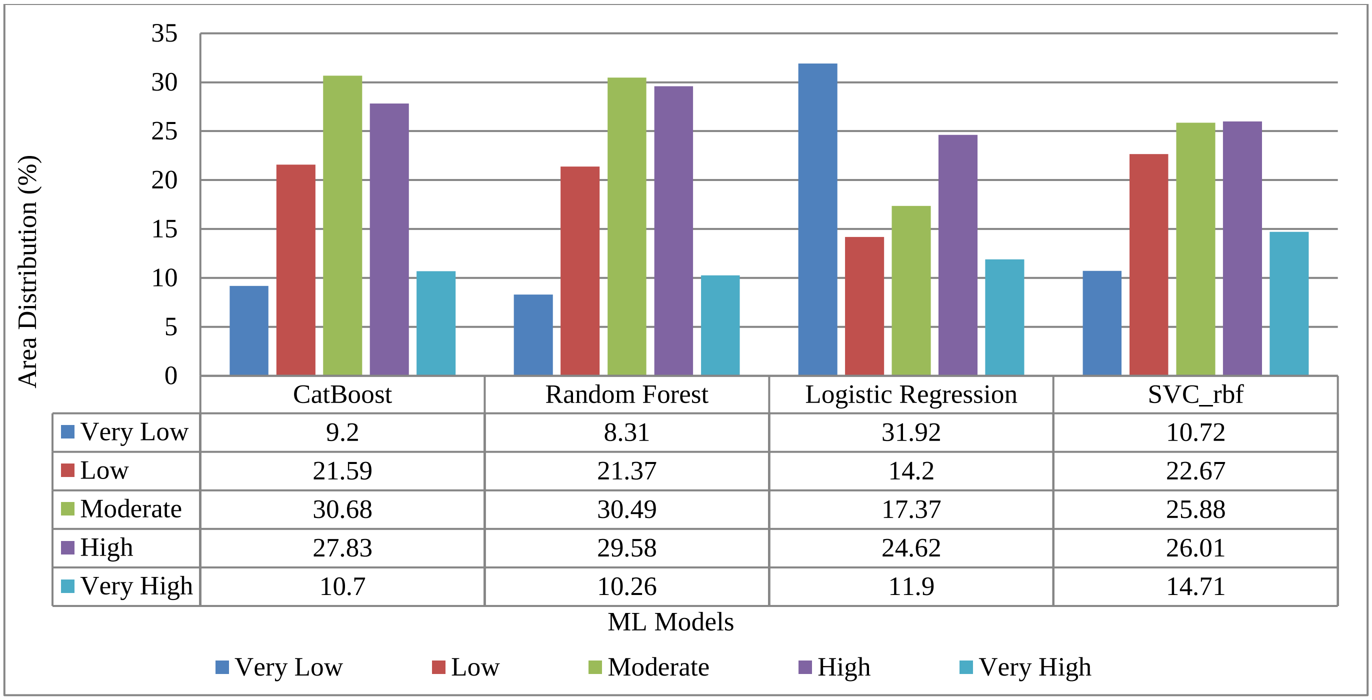


Fig. 9 Generated LSM by all ML models



	CatBoost	Random Forest	Logistic Regression	SVC_rbf
Very Low	9.2	8.31	31.92	10.72
Low	21.59	21.37	14.2	22.67
Moderate	30.68	30.49	17.37	25.88
High	27.83	29.58	24.62	26.01
Very High	10.7	10.26	11.9	14.71

Fig. 10 Area distribution of the study area by ML models

6. Conclusion

Identifying regions at risk of landslides and accurately determining their locations based on specified susceptibility levels are crucial for effective planning activities. Various methodologies have been proposed in the literature for developing landslide susceptibility maps. This study evaluates the effectiveness of GIS-based techniques, specifically Logistic Regression (LR), Random Forest (RF), Support Vector Classifier (SVC), and CatBoost, in creating a landslide susceptibility map for Sikkim, India. These methodologies were applied to utilize a range of factors, including aspect, slope, land use and land cover (LULC), elevation, distance to roads, distance to streams, Normalized Difference Vegetation Index (NDVI), plan curvature, soil type, rainfall, and earthquake. In this study, a comprehensive set of evaluation metrics was employed to assess and compare the performance of the models, including training score, testing score, kappa coefficient, specificity, sensitivity, and Area Under the Curve (AUC). These metrics provided a robust framework for analyzing each model's predictive accuracy and reliability in classifying landslide susceptibility. Based on the evaluation results, the Random Forest (RF) model demonstrated superior performance compared to the other models.

It achieved the highest kappa coefficient of 0.519, which reflects a strong agreement between predicted and actual classifications, accounting for any chance agreement. Additionally, the RF model recorded the highest AUC value of 0.756, indicating its exceptional ability to distinguish between classes and reliably predict landslide susceptibility.

Furthermore, the confusion matrix analysis revealed that the RF model had the least misclassifications, with 889 incorrectly classified instances, making it the most accurate among the evaluated models. This result underscores the RF model's ability to minimize prediction errors and highlights its robustness in handling complex datasets with multiple conditioning factors. Overall, the combination of high kappa, superior AUC, and minimal misclassifications establishes the RF model as the most reliable and effective tool for landslide susceptibility mapping in this study, making it an optimal choice for such predictive analyses.

Author Contribution Statement

SKA: Dataset collection, Conceptualization, Methodology, Analysis and Drafting; DK: Review and Comments; SKA and DK: Final drafting and proofreading.

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