**Proceedings of 14th IOE Graduate Conference**
*Peer Reviewed*
Year: 2023 Month: December Volume: 14
ISSN: 2350-8914 (Online), 2350-8906 (Print)

# Support Vector Machine Based Landslide Susceptibility Mapping: A Case study of Doti, Nepal

Chakra Bhandari [a], Indra Prasad Acharya [b], Mandip Subedi [c]

[a, b, c] *Department of Civil Engineering, Pulchowk Campus, IOE, Tribhuvan University, Nepal*

[a] rcbhandari42@gmail.com, [b] indrapd@ioe.edu.np, [c] mandip.subedi@gmail.com

**Abstract**
Landslides are among the most common natural hazards, particularly occurs in the Hilly area known for complex geological formations and steep slopes. The landslide risk increases during the monsoon due to prolonged rainfall, causing significant infrastructure damages and economic losses annually. Therefore, landslide assessment is essential for disaster risk management. Current study seeks to prepare a reliable landslide susceptibility map over the diverse geography of Doti district by analyzing the geospatial relationship between past events and landslide conditioning factors. Landslide susceptibility mapping is a crucial tool employed worldwide for landslide management. It relies on existing landslide characteristics. A total of 13 landslide conditioning factors and inventory map containing 7869 landslide events were employed for the study. The landslide susceptibility assessed using the Support Vector Machine (SVM) algorithm. SVM is a flexible supervised machine learning technique that makes predictions from a small number of samples. The results revealed that the district characterized by varying level of susceptibility with 9.35% of the area identified as very high, 13.7 % as high, and 21.4 % as moderately susceptible to landslide. Further, feature importance analysis indicated the rainfall and slope as main landslide contributing factors in the district. The model was evaluated using area under the Receiver operating curve (AUC-ROC) and confusion matrix. The model provided a good prediction rate of 83 % which indicates SVM could be a promising option for precise hazard prediction. Although most part of area is characterized by low landslide susceptibility, future occurrences are still possible due to human activities, earthquake and rainfall. Therefore, improving the warning system and enhancing landslide preparedness is crucial. The generated map will be helpful to the local government in planning land use and preventing future possible landslide damages.

**Keywords**
Landslide Susceptibility, Support Vector Machine, land use planning, Receiver operating curve, geographical information system

## 1. Introduction

Landslides rank as the third most fatal natural disaster globally, contributing to 9 % of the world's natural disasters [1, 2]. Nepal ranks within the top 20 countries globally that are highly vulnerable to multiple hazards. As per data analysis between 1978 and 2005, an annual average of 78 landslide related fatalities occurs in Nepal [3]. A complicated interplay between earthquakes, climate change, and road construction operations has resulted in a sharp rise of the number of landslides in Nepal. Among Nepal's 77 districts, 49 are at risk of floods and landslides, including Doti [4].

Landslides, among the most common natural hazards in mountainous country, involves debris, rock and earth movement due to gravity. These landslides result in significant ecological and economic losses annually [5]. The occurrence of landslides is influenced by various causative factors including human activities [6]. Rainfall is a leading trigger of landslides and causes frequent landslides in hilly area [7]. Geomorphological factors such as Digital Elevation Model (DEM), elevation, slope, aspects, Curvature, ans Topographic Wetness Index (TWI) all can influence landslide occurrence. Areas with slopes >5° are considered landslide-prone [8]. Aspects has effect on processes like hydrology and weathering [9]. TWI has an influence on soil moisture [10]. Hydrological factors are significant, especially in streamside areas are prone to slope instability due to saturation [11]. Factors like Land use/land cover (LULC), normalized difference vegetation index (NDVI), road constructions etc. alters landscapes and slope stability [9, 12]. Geological factors such as lithology, soil types, fault proximity can also make area prone to landslide [13].

Landslides occurs frequently in Doti, especially during the monsoon, primarily due to its steep terrain and location in a seismically active region. The district is identified as a climate-related Disaster Hotspot, ranking third in terms of total disaster factor and second in terms of the highest estimated loss [14, 15]. Heavy rainfall and slopes weakened by earthquakes increase the landslide risk, making early warning systems and landslide prediction tools Imperative. The 2015 rainfall - triggered landslides in Toleni and Daud village of Doti exemplify this situation. Prevention and Avoidance are often the best solution for landslides, but not possible for poor local areas of Nepal like Doti. Alerting and careful planning can help now. However, neither of these approaches has been applied due to limited budget and lack of planning. Despite of several fatal landslide events, no comprehensive regional-level studies have been conducted. These findings highlight the district has low level of preparedness for disaster risk reduction.

Landslide susceptibility assessment involves predicting the potential locations of future landslides in a specific area.

Various qualitative and quantitative approaches, including machine learning (ML) algorithms, can be used for landslide susceptibility modeling. The combination of the Geographical Information System (GIS) and machine learning has significantly improved landslide and slope failure-related studies [16, 17]. Machine Learning is a distinct field in computer science that employs algorithm to learn from various disciplines like mathematics and Artificial Intelligence. ML is gaining traction in landslide assessment due to its proficiency in handling complex data, improvement in accuracy, flexibility, and adaptability in mapping and forecasting. However, data quality and factor selection remain crucial for precise results.

In this study, a commonly used supervised ML method known as Support Vector Machine is applied to determine spatial correlation between factors contributing to landslides and past landslide events. The model was developed considering 13 conditioning factors with the assumption that landslides are more probable in areas resembling previous landslide locations. The study aims to map the susceptibility for the future landslide occurrences over the diverse geographic area of Doti district and identify factors contributing the landslides and slope failures in Doti. Assessment of landslide susceptibility and their mapping is vital for land use management, disaster preparedness and proactively safeguard landslide-prone areas. Such mapping tasks do not eliminate hazards but holds practical utility in making decisions on the strategic application of landslide mitigation approaches. They act as the initial step for disaster preparedness and management and prevent future possible damages. However, further studies and development projects are desperately needed for accurate landslide prediction and susceptibility assessment.

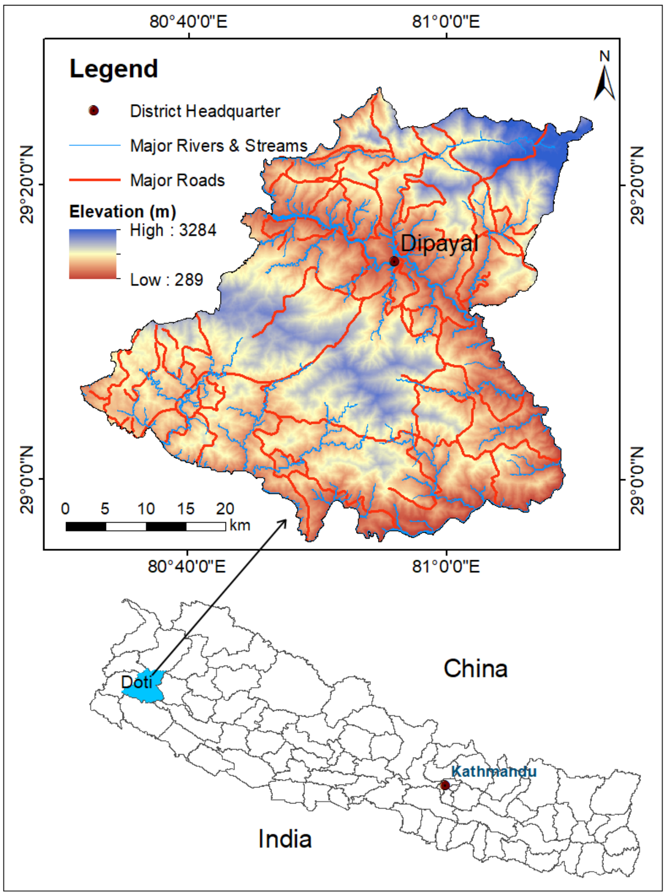


**Figure 1:** Map showing the location of study area with major rivers, roads, and elevation

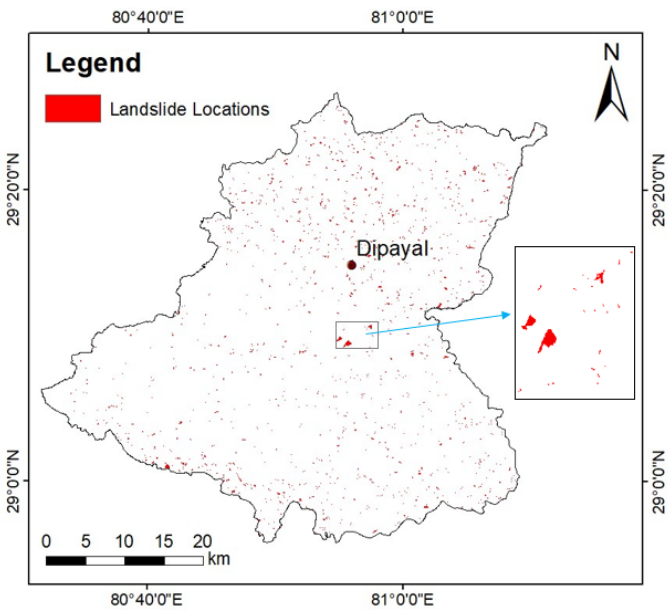


**Figure 2:** Map showing distribution of landslide events in the study area

## 2. Study Area

Doti is situated in Sudurpaschim province of Nepal, with an elevation difference of 2995 m (lowest: 289 m and highest: 3284 m), covering roughly 2025 sq. km area. The district lies between the Ramganga River in the west and the Karnali River in the east with headquarter Dipayal Silgadhi lying on the bank of the Seti River flowing in the middle. The district experiences an average seasonal rainfall of about 670.7 mm from July to November and the mean annual temperature of 22.84 °C [18]. The majority of areas of district are covered by forests and grasslands. Geologically, it features Khaptad Gneiss Klippe in the north; the Dandeldhura Crystallines in the south; and an extension of the Karnali Klippe and the Doti Schist (a green mica schist) in between [19]. The area is seismically active due to Main Frontal Thrust (MFT) passing nearby the southern boundary of the district [20]. The location map of the study area is shown in **Fig. 1**.

## 3. Material and Methods

### 3.1 Data collection

Landslide is complex process. The reliability of landslide susceptibility assessment depends on sound inventory data and causal factors. Understanding the landslide causative factors and making inventory mapping are crucial steps for assessment of landslide hazard. Therefore, a total of 7869 past landslides locations spanning the period from 1992 to 2020 collected as inventory data. Notably, 44 of these locations, pertaining to the period from 2019 to 2020 were digitized using Google Earth, while the remaining locations were

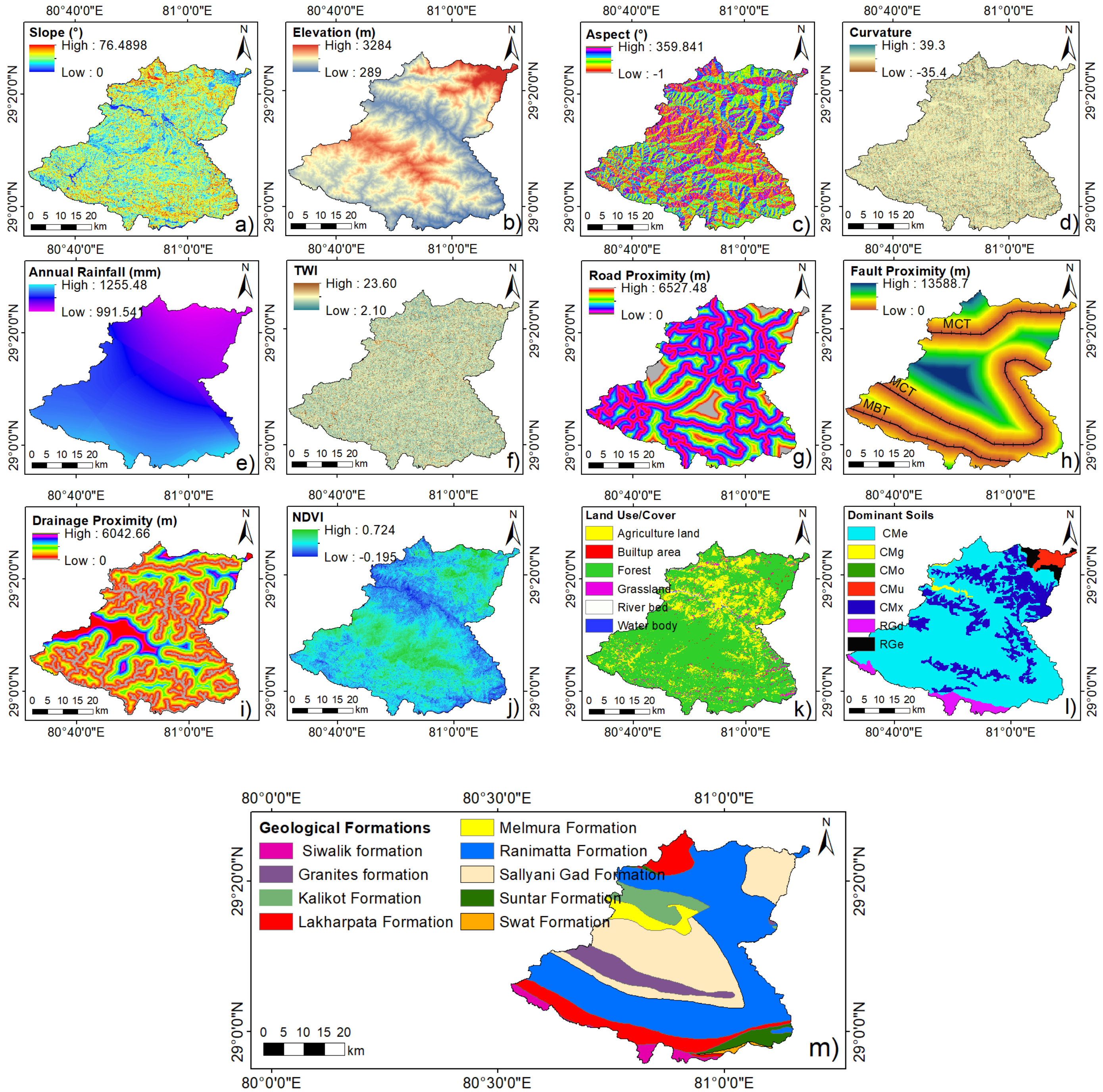


**Figure 3:** Thematic maps of various landslide factors: (a) Slope, (b) Elevation, (c) Aspect, (d) Curvature, e) Annual Rainfall, f) TWI, (g) Proximity to Roads, (h)Proximity to Faults, i) Proximity to Drainages, (j) NDVI, (k) Land use and land cover, (l) Dominant Soil types (RGe: Eutric Regosols; CMe: Eutric cambisols; CMu: Humiic cambisols; CMx: Chromic cambisols; CMg: Gleyic cambisols; RGd: Dystric Regosols; CMo: Ferralic cambisols), and (m) Geological formations

extracted from the previous study 'Multi-Temporal Landslide Inventory for the Far-Western region of Nepal' [21, 22]. These datasets comprises of three decade landslide events digitized in form of polygons through remote sensing technique. The duplication of data were manually checked using spatial analyst tool and landslide inventory map prepared (**Fig. 2**).

Additionally, 13 landslide conditioning factors (**Fig. 3**) with the common spatial reference ' WGS 1984 UTM 44N ' and resolution of 30 m were considered based on the literature review [10, 23, 24]. Factors such as elevation, slope, aspect, and curvature were obtained using the Shuttle Radar Topography Mission (SRTM) DEM of 30 m resolution. The land use map of Nepal for the year 2019 was acquired from the International Centre for Integrated Mountain Development (ICIMOD), and the geological data were obtained from the national geological map of 1,000,000 scale published by the Department of Mines and Geology (DMG) in 1994. Fault data were digitized from previous study [25]. The NDVI was calculated using free satellite images like the Landsat series in Google Earth Engine (GEE). Rainfall data provided by the Climate Research Unit (CRU) for the period 2011 to 2020 were used to prepare precipitation map. The Topographic map of

1:25,000 scale were obtained from survey Department, Nepal. The thematic mapping of landslide factors was done in geographical information system (GIS) environment.

### 3.2 Methodology: Support Vector Machine

SVM is a powerful binary classifier in the field of machine learning. It is based on supervised learning principles rooted in statistical theory and aims to find the optimum n-dimensional hyperplane by maximizing the margin of the training data. This boundary separate different classes of data points i.e, it serves as decision boundary [26]. SVM relies on two key concepts: first, it aims to find an optimal linear separator to distinguish patterns within the data. Second, it incorporate kernel functions to transform non-linear data into a format that can be separated by a linear boundary in a higher-dimensional space [10, 26].

For a given set of input vectors $x_i$ (where, i = 1, 2,...,n ), which are linearly separable into two classes label denoted as $y_i = \pm1$, SVM identifies the hyperplane that separates the classes ensuring maximum margin (**Fig. 4**(a)).

Mathematically,

$$\frac{1}{2}\|w\|^2 \tag{1}$$

Subjected to the constraints:

$$y_i\left((w\cdot x_i)+b\right)\geq 1 \tag{2}$$

where, $\|\mathbf{w}\|$ is the weight vector also called norm of the hyperplane, $b$ is a scalar base (shifts the decision boundary from the origin), $x_i$ indicates input features, $y_i$ indicates the label, and $(\cdot)$ denotes the scalar product operation.

The Lagrangian Multiplier can be used to define cost function represented by equation (3).

$$L=\frac{1}{2}\|\mathbf{W}\|^2-\sum_{i=1}^{n}\lambda_i\left(y_i\left((\mathbf{w}\cdot\mathbf{x}_i)+b\right)-1\right) \tag{3}$$

where, $\lambda_i$ is the Lagrangian multiplier.

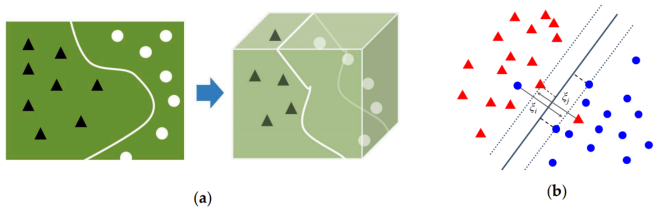

**Figure 4:** Explanation of SVM principle. (a) optimum n – dimensional Hyperplane differentiating binary datasets with maximum gap (b) non - separable case and slack variables $\xi_i$ [7, 27]

The solution of equation (3) can be obtained through a dual minimization process with respect to both 'w' and 'b'. In cases where data points are non-separable (**Fig. 4**(b)), the slack variables $\xi_i$ can be introduced to modify the Equation (2) [26].

$$y_i\left((w\cdot x_i)+b\right)\geq 1-\xi_i \tag{4}$$

Then, Equation (1) becomes:

$$L=\frac{1}{2}\|W\|^2-C\sum_{i=1}^{n}\xi_i \tag{5}$$

where, C is introduced in order to account for misclassification.

Additionally, a kernel function K($x_i$, $x_j$) is introduced by Vapnik, [28] to take into account the nonlinear decision boundary. It computes the dot product between transformed data points $\phi(x)$ in higher dimensional space for a given feature vector 'x'i.e.,

$$K(x_i,x_j)=\Phi(x_i)\cdot\Phi(x_j) \tag{6}$$

Where, $x_i$, $x_j$ are input features in original space and $\phi$ is a transformed basis vector called mapping function.

The SVM classifier support four kernel: Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid. The present study is focused on the RBF kernel as it is commonly used kernel and various studies have shown that it provides good agreement for landslide prediction [26]. Radial basis function is represented as:

$$K(x_i,y_i)=e^{-\gamma(x_i-x_j)^2} \tag{7}$$

where, $\gamma$ is kernel function parameters.

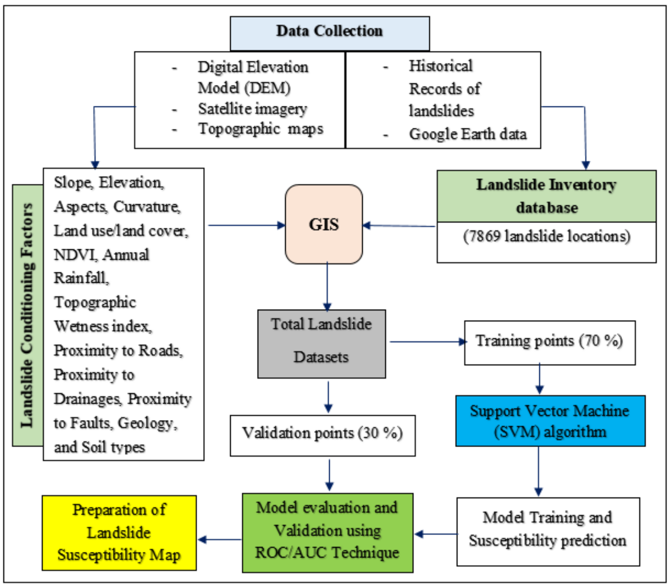


**Figure 5:** Flowchart of the methodology

Landslide susceptibility mapping requires both landslide and non-landslide locations data [29]. The choice of non-landslide (absence-data) is typically arbitrary. Therefore, an equal number of non-landslide data (to avoid biasness) as that of landslides were randomly generated in GIS based on the assumption that landslides are more likely to occur in situations similar to those of past landslides.

There are two techniques of data sampling: the pixel-based and object-based method [30]. In this study, pixel-based method was adopted and the value of each landslide conditioning factors extracted for each landslide and non-landslide pixels. The datasets pre-processed for outliers and missing values and divided randomly into two groups:

Training (70 %) and validation (30 %) data. The training group were applied to train SVM model with RBF kernel and testing group used to measure prediction rate and model accuracy. Landslide susceptibility indexes (LSI) were computed as the probability prediction of model for landslide occurrence and susceptibility visualized in GIS. The detail workflow chart to perform the landslide susceptibility assessment using SVM is shown in **Fig. 5**.

### 3.3 Model Performance Analysis

The support vector machine model for landslide prediction was developed in python environment using training landslide datasets and landslide susceptibility index for each pixel predicted. The result was visualized with the help of spatial analyst tool GIS. Performance and Prediction accuracy of the models was evaluated using Area Under the Receiver operating Curve and confusion matrix using testing datasets. The ROC is a commonly used graphical representation that shows the relationship between true positive and false positive. The Area Under curve (AUC) ranges from 0.5 to 1, with a value greater than 0.5 indicating the model's validity and acceptability. AUC provides a measure of the model accuracy and determine its predictive power.

## 4. Results and Discussion

The SVM model was trained using training datasets and the probability of landslide occurrence predicted for each pixels.The landslide susceptibility map (LSM) was generated in GIS using these probability as susceptibility index. The generated map was subsequently divided into five distinct categories to represent different level of landslide susceptibility, ranging from very low (VL) to very high (VH). The categorization was accomplished using a natural break classifier in the GIS software and the occurrence of landslide visualized in color gradient with green shades indicating very low susceptibility region and dark red indicating very high landslide susceptibility zone (**Fig. 6**). The spatial distribution of landslide susceptibility indicated that 9.35 % of the area has very high, 13.7 % of area has high (H), and 21.4 % of the area has moderate susceptibility (M). The most part of area ( 55 %) especially area south and west to Dipayal was found very low to low category of landslide susceptibility. The performance of model was evaluated using area under ROC and the prediction rate was found 83 % (**Fig. 7**). This indicates the accuracy is high enough, displaying validity of the model.

The results revealed that the district characterized by varying level of landslide susceptibility. From the visualisation of susceptibility map, it can be seen that majority area of Shikhar Municipality and Jorayal Rural Municipality have lower susceptibility. Whereas, most part of Adarsha Rural Municipality, Sayal Rural Municipality, and Purbichauki Rural Municipality observed highly susceptibility to landslide hazard. The area around Dipayal has been seen to have varying level of susceptibility. Similarly, South Khaptad NP, South-West of Badikedar and south Jorayal Rural Municipality also demonstrated as higher landslide susceptibility zone.

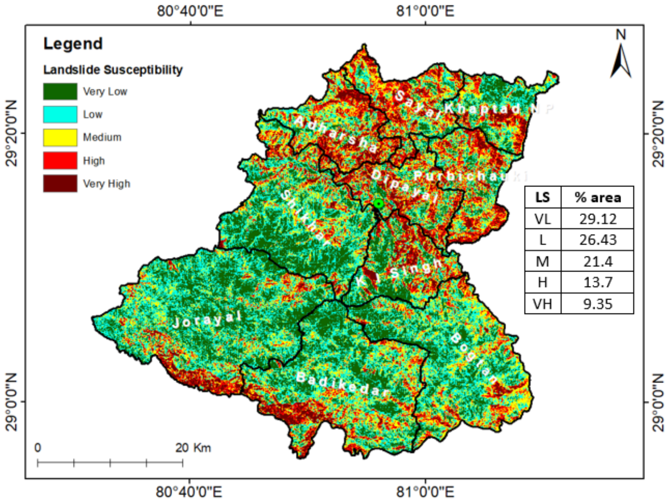


**Figure 6:** Landslide susceptibility map of Doti district developed by using Support Vector Machine method

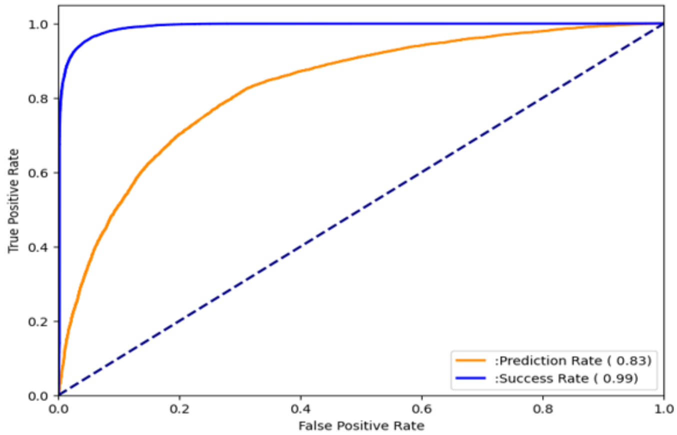


**Figure 7:** ROC Curve for Susceptibility simulation

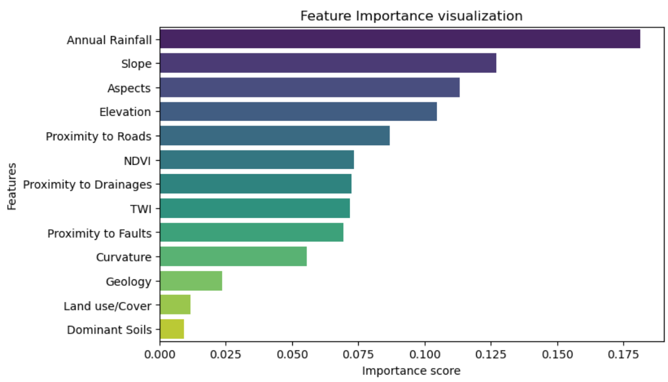


**Figure 8:** Feature importance score of each landslide causative factors

This variation may be attributed to the higher slope and elevation in Northern area and higher precipitation in southern part of doti. Moreover, higher road construction activities and agriculture in the north and south area, as opposed to the middle part of the district with dense forest/vegetation cover might be responsible for to this vulnerability. Also, the region has become more vulnerable to multiple hazards including landslides and slope instability, due to seismic activities along the main thrusts of Nepal. The area near the Seti River is identified as having a higher susceptibility to landslides, potentially influenced by infrastructure like roads construction along the valley bottom and hydropower projects.

From the feature importance analysis (**Fig. 8**), rainfall (18.2 % contribution) and slope (12.9 % contribution) were observed as the two main factors contributing landslides in Doti. The factors like dominant soils, geology and land cover have very low contribution (< 2.5%) to landslides occurrence. The feature importance score reveals that Rainfall, Slope, Aspect, Elevation, Road construction, NDVI, Drainage proximity, TWI, and Fault proximity as the main landslide contributing factors in Doti.

## 5. Conclusions

Landslides pose a severe and widespread natural threat. Evaluating landslide susceptibility is crucial for the disaster risk management. Such mapping tasks do not eliminate hazards; however, enhance future landslide preparedness, acting as the initial step for the landslide risk management. The study illustrates the landslide susceptibility mapping over the diverse geography of Doti district by analyzing the geospatial relationship between past events and landslide conditioning factors. The fundamental purpose of study is to identify areas prone to landslide and factors contributing landslide. Following are some conclusions drawn from this study:

a) The study revealed varying levels of landslide susceptibility in the district with 9.35 % of the area categorized as very high, 13.7% as high, 21.4 % as moderate, and 55 % of the area showing lower susceptibility to landslides.

b) The feature importance score highlights Rainfall, Slope, Aspect, Elevation, Road construction, NDVI, Drainage proximity, TWI, and Fault proximity as the main contributing factors to landslides in Doti.

c) The prediction rate of model 83 % clearly demonstrated that machine learning method like SVM could be a promising option for precise hazard prediction.

Even though most part of the district is identified having lower level of landslide susceptibility, future occurrences are still possible due to human activities, earthquake and rainfall. Hence, enhancing machine learning techniques for landslide prediction and mapping might be a promising option for disaster management in a country like Nepal.

## Acknowledgments

The authors are grateful to Institute of Engineering [IOE], Pulchowk Campus, and like to extend special thanks to the colleagues Rajan K.C., Swati Acharya, and Krishna Bhattarai. Their co-ordination and guidance for data collection and paper writing were indispensable.

## References

[1] Bayes Ahmed. Landslide susceptibility modelling applying user-defined weighting and data-driven statistical techniques in cox's bazar municipality, bangladesh. *Natural Hazards*, 79(3):1707–1737, 2015.

[2] Nida Kanwal, Muhammad Atif Randhawa, and Zafar Iqbal. A review of production, losses and processing technologies of guava. *Asian Journal of Agriculture and Food Sciences (ISSN: 2321–1571)*, 4(02), 2016.

[3] Brian G McAdoo, Michelle Quak, Kaushal R Gnyawali, Basanta R Adhikari, Sanjaya Devkota, Purna Lal Rajbhandari, and Karen Sudmeier-Rieux. Roads and landslides in nepal: how development affects environmental risk. *Natural Hazards and Earth System Sciences*, 18(12):3203–3210, 2018.

[4] Narayan Paudyal, Ram B Khadka, and Ranjana Khadka. Agricultural perspectives of climate change induced disasters in doti, nepal. *Journal of Agriculture and Environment*, 14:149–159, 2013.

[5] David Milne Cruden. Cruden, dm, varnes, dj, 1996, landslide types and processes, transportation research board, us national academy of sciences, special report, 247: 36-75. *Landslides Eng. Pract*, 24:20–47, 1993.

[6] Melanie J Froude and David N Petley. Global fatal landslide occurrence from 2004 to 2016. *Natural Hazards and Earth System Sciences*, 18(8):2161–2181, 2018.

[7] Qigen Lin, Pedro Lima, Stefan Steger, Thomas Glade, Tong Jiang, Jiahui Zhang, Tianxue Liu, and Ying Wang. National-scale data-driven rainfall induced landslide susceptibility mapping for china by accounting for incomplete landslide data. *Geoscience Frontiers*, 12(6):101248, 2021.

[8] Bahareh Kalantar, Biswajeet Pradhan, Seyed Amir Naghibi, Alireza Motevalli, and Shattri Mansor. Assessment of the effects of training data selection on the landslide susceptibility mapping: a comparison between support vector machine (svm), logistic regression (lr) and artificial neural networks (ann). *Geomatics, Natural Hazards and Risk*, 9(1):49–69, 2018.

[9] Rajesh Khatakho, Dipendra Gautam, Komal Raj Aryal, Vishnu Prasad Pandey, Rajesh Rupakhety, Suraj Lamichhane, Yi-Chung Liu, Khameis Abdouli, Rocky Talchabhadel, Bhesh Raj Thapa, et al. Multi-hazard risk assessment of kathmandu valley, nepal. *Sustainability*, 13(10):5369, 2021.

[10] Tri Dev Acharya. Regional scale landslide hazard assessment using machine learning methods in nepal. *esis for: Doctor in EngineeringAdvisor,, esis for: Doctor in EngineeringAdvisor*, 2018.

[11] FC Dai, Chin Fei Lee, and Y Yip Ngai. Landslide risk assessment and management: an overview. *Engineering geology*, 64(1):65–87, 2002.

[12] Renata Pacheco Quevedo, Andrés Velastegui-Montoya, Néstor Montalván-Burbano, Fernando Morante-Carballo, Oliver Korup, and Camilo Daleles Rennó. Land use and land cover as a conditioning factor in landslide susceptibility: a literature review. *Landslides*, 20(5):967–982, 2023.

[13] Trinh Quoc Ngo, Nguyen Duc Dam, Nadhir Al-Ansari, Mahdis Amiri, Tran Van Phong, Indra Prakash, Hiep Van Le, Hanh Bich Thi Nguyen, and Binh Thai Pham. Landslide susceptibility mapping using single machine learning models: a case study from pithoragarh district, india. *Advances in civil engineering*, 2021:1–19, 2021.

[14] MoFE. *Vulnerability and Risk Assessment and Identifying Adaptation Options in Disaster Risk Reduction and Management (DRRM)*. 2021. [Online].

[15] ADPC, NGI, CECI, and GFDRR. Nepal hazard risk assessment, 2010. [Online]. Available: `https://www.adpc.net/igo/category/ID276/doc/2013-b27Iym-ADPC-NHRA_Report.pdf`.

[16] M Marjanović. *Advanced methods for landslide assessment using GIS*. PhD thesis, Palackỳ University Olomouc Olomouc, Czechia, 2013.

[17] Abdelaziz Merghadi, Ali P Yunus, Jie Dou, Jim Whiteley, Binh ThaiPham, Dieu Tien Bui, Ram Avtar, and Boumezbeur Abderrahmane. Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. *Earth-Science Reviews*, 207:103225, 2020.

[18] Govinda Bhandari. Trends in seasonal precipitation and temperature–a review in doti and surkhet districts of nepal. *International Journal of Environment*, 2(1):269–279, 2013.

[19] Daigoro Hayashi. *Geological reconnaissance around Silgarhi-Doti, West Central Nepal*. PhD thesis, 1984.

[20] Ram Krishna Tiwari and Harihar Paudyal. Spatial mapping of b-value and fractal dimension prior to november 8, 2022 doti earthquake, nepal. *Plos one*, 18(8):e0289673, 2023.

[21] Alberto Muñoz-Torrero Manchado. Multi-temporal landslide inventory for the far-western region of nepal (version 01). Zenodo, 2020.

[22] Alberto Muñoz-Torrero Manchado, Simon Allen, Juan Antonio Ballesteros-Canovas, Amrit Dhakal, Megh Raj Dhital, and Markus Stoffel. Three decades of landslide activity in western nepal: new insights into trends and climate drivers. *Landslides*, 18:2001–2015, 2021.

[23] Yimin Li, Xuanlun Deng, Peikun Ji, Yiming Yang, Wenxue Jiang, and Zhifang Zhao. Evaluation of landslide susceptibility based on cf-svm in nujiang prefecture. *International Journal of Environmental Research and Public Health*, 19(21):14248, 2022.

[24] Bikash Phuyal, Prem Bahadur Thapa, and Krishna Chandra Devkota. Characterization of large-scale landslides and their susceptibility evaluation in central nepal himalaya. *Journal of Nepal Geological Society*, pages 109–122, 2022.

[25] Dilli Ram Thapa. *Seismic zoning for Nepal*. PhD thesis, 2018.

[26] Saro Lee, Soo-Min Hong, and Hyung-Sup Jung. A support vector machine for landslide susceptibility mapping in gangwon province, korea. *Sustainability*, 9(1):48, 2017.

[27] X Yao, LG Tham, and FC Dai. Landslide susceptibility mapping based on support vector machine: a case study on natural slopes of hong kong, china. *Geomorphology*, 101(4):572–582, 2008.

[28] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20:273–297, 1995.

[29] A-Xing Zhu, Yamin Miao, Junzhi Liu, Shibiao Bai, Canying Zeng, Tianwu Ma, and Haoyuan Hong. A similarity-based approach to sampling absence data for landslide susceptibility mapping using data-driven methods. *Catena*, 183:104188, 2019.

[30] Yu Huang and Lu Zhao. Review on landslide susceptibility mapping using support vector machines. *Catena*, 165:520–529, 2018.