

RESEARCH ARTICLE

A Multicriteria Approach for Landslide Hazard Zonation in the Lesser Kumaun Himalaya

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ABSTRACT

The socioeconomic prosperity of a region is intricately tied to its infrastructure development, particularly the connectivity provided by highways. Preserving the economic well-being of an area demands meticulous planning and the execution of construction projects with minimal risk. Landslide hazard zonation (LHZ) is a crucial tool for assessing the likelihood of landslide occurrences in specific regions. This study delves into the LHZ of a 171.2 km² area, focusing on critical causative factors such as slope inclination and aspect, slope mass material, Land Use/Land Cover (LULC), distance from fault lines, roads, and drainage systems. The classification resulted in four distinct zones along the National Highway (NH-109) stretch from Bhowali to Almora. Notably, the moderate-hazard zone encompasses 60.4% of the area, followed by the high-hazard zone at 24.4%, the low-hazard zone at 11.9%, and the very high-hazard zone at 3.3%. To enhance the reliability of the study, 63 previously identified landslide locations were marked based on diverse sources, including field studies and landslide inventory data from the Geological Survey of India (GSI). In the validation process, 12 past landslide occurrences were situated within the very high-hazard zone, 32 in the high-hazard zone, 18 in the moderate-hazard zone, and only one in the low-hazard zone. The receiver operating characteristic (ROC) curve yielded a commendable quality with a % area under the curve (AUC) of 71.2%. In summary, this research underscores the importance of LHZ in assessing and mitigating landslide risks along a stretch of the NH-109 corridor. The findings provide valuable insights for informed decision-making in infrastructure development and risk management, contributing to the sustainable growth and protection of the region's livelihood.

1 | Introduction

The United Nations Office has reported a significant increase in global economic losses from natural disasters between 1998 and 2017, surging by 151% compared to the preceding two decades. Notably, India witnessed approximate losses of 79.5 billion USD from such phenomena, with an average annual loss of 1.3 billion USD attributed to landslides (Sidle and

Ochiai 2006; The Wire 2018). Landslides, constituting about 17% of global fatalities, pose a substantial threat, with approximately 66 million people residing in high-risk zones spanning 820,000 km² worldwide (Dilley et al. 2005; Kjekstad and Highland 2009; Pham, Prakash, Khosravi, et al. 2019; Pham, Prakash, Singh, et al. 2019). Haque et al. (2019) asserted that landslides rank as the fourth-highest cause of global natural disaster fatalities, resulting in over 4000 direct and 7800

TABLE 1 | Landslide hazard zonation methods.

S. No.	Methods/Models	References
Quantitative methods		
1.	Frequency ratio	Mersha and Meten 2020 ; Singh et al. 2023
2.	Information value	Chen, Niu, and Jia 2016
3.	Weight of evidence	Bonham-Carter, Cheng, and Wright 1993 ; Guri, Champati ray, and Patel 2015
4.	Logistic regression	Akgun, Dag, and Bulut 2007
5.	Analytic network process (ANP)	Neaupane and Piantanakulchai 2006
6.	Weighted linear combination (WLC)	Ayalew and Yamagishi 2005
7.	Certain factor (CF)	Devkota et al. 2013
8.	Neural-fuzzy	Pradhan et al. 2010
9.	Random Forest (RF)	Kim et al. 2018
10.	Naive Bayes	Tsangaratos and Ilia 2016
11.	Decision trees	Althuwaynee, Pradhan, and Ahmad 2014
12.	Support vector machine	Chawla et al. 2018 ; Bui et al. 2016
13.	Boosted regression trees	Kim et al. 2018
14.	Kernel logistic regression	Bui, Tuan, and Klempe 2016
15.	Artificial neural network	Kanungo, Sarkar, and Sharma 2011
16.	Neighbor-based methods	El-Magd, Ali, and Pham 2021
17.	Random subspace	Pham et al. 2020
18.	Rep tree	Pham, Prakash, Singh, et al. 2019
19.	Bagging	Wu et al. 2020
20.	ANFIS	Polykretis, Chalkias, and Ferentinou 2019
21.	Rotation Forest	Park, Hamm, and Kim 2019
Qualitative methods		
1.	Analytical hierarchy process (AHP)	Yalcin 2008 ; Singha and Sarkar 2024
2.	Fuzzy logic	Kanungo et al. 2006

(Continues)

TABLE 1 | (Continued)

S. No.	Methods/Models	References
Other miscellaneous models		
1.	Landslide hazard evaluation factor (LHEF)	Anbalagan 1992
2.	Integrated approach	Sarkar and Kanungo 2004
3.	Meso scale for town planning	Anbalagan, Chakraborty, and Kohli 2008
4.	Predictive modeling	Dahal et al. 2008
5.	Empirical modeling	Ghosh et al. 2011

indirect life losses annually. In developing countries, economic damage due to landslides can reach 1%–2% of the gross national product (NDMA [2021](#)), and in India, nearly 20% of landslide-related deaths are reported, with approximately 56,000 deaths from 4800 incidents between 2004 and 2016 (Deccan Herald [2019](#); Statista [2023](#)).

Moreover, compared to other Himalayan regions, the Lesser Himalayas are subjected to more human interference, primarily from construction activities, deforestation, mining, cultivation, road construction on mountain slopes, increased vehicular traffic, and additional economic pursuits (Khanduri [2017](#); Singh, Umrao, and Singh [2013, 2014](#); Umrao et al. [2011](#)). These factors collectively contribute to the fragility and susceptibility of the Lesser Himalayan terrain, often exacerbating the occurrence of landslides, particularly during the monsoon season (Khanduri [2017](#)). The Lesser Kumaun Himalaya frequently experiences devastating landslides, particularly in the Bhowali-Almora region, where these events cause recurrent damage to roads, agriculture fields, settlements, and loss of lives. Recent incidents in 2021 and 2023 illustrate the severe impact on connectivity, with landslides cutting off Nainital and disrupting road connections near Bhaurya turn at Khairna, underscoring the vulnerability of the region (Creative News Express, [2023](#); Haldwani Live [2023](#); India Today [2021](#)). Such occurrences impede socioeconomic development, as towns and villages reliant on road networks face disruptions to essential services, leading to casualties due to delayed emergency responses (Amar Ujala [2019](#); Live Hindustan [2021](#); Times of India [2017](#)).

Landslide hazard zonation, as used before, was the division of land based on the likelihood of causing damage (Varnes [1984](#)). These earlier techniques were primarily based on field assessments. A lot of time is required to prepare an inventory of landslides, and landslides in less accessible places are omitted. Emerging as a preferred approach, the data-driven methodology involves analyzing the pixel values of raster data obtained from high-resolution satellite images, the digital elevation model (DEM), and meticulously detailed published secondary data. Consequently, in the contemporary context, the data-driven methodology is acclaimed as the most suitable technique for detecting historical landslide occurrences in any geographic region. Researchers have developed various geospatial and statistical methods to assess landslide

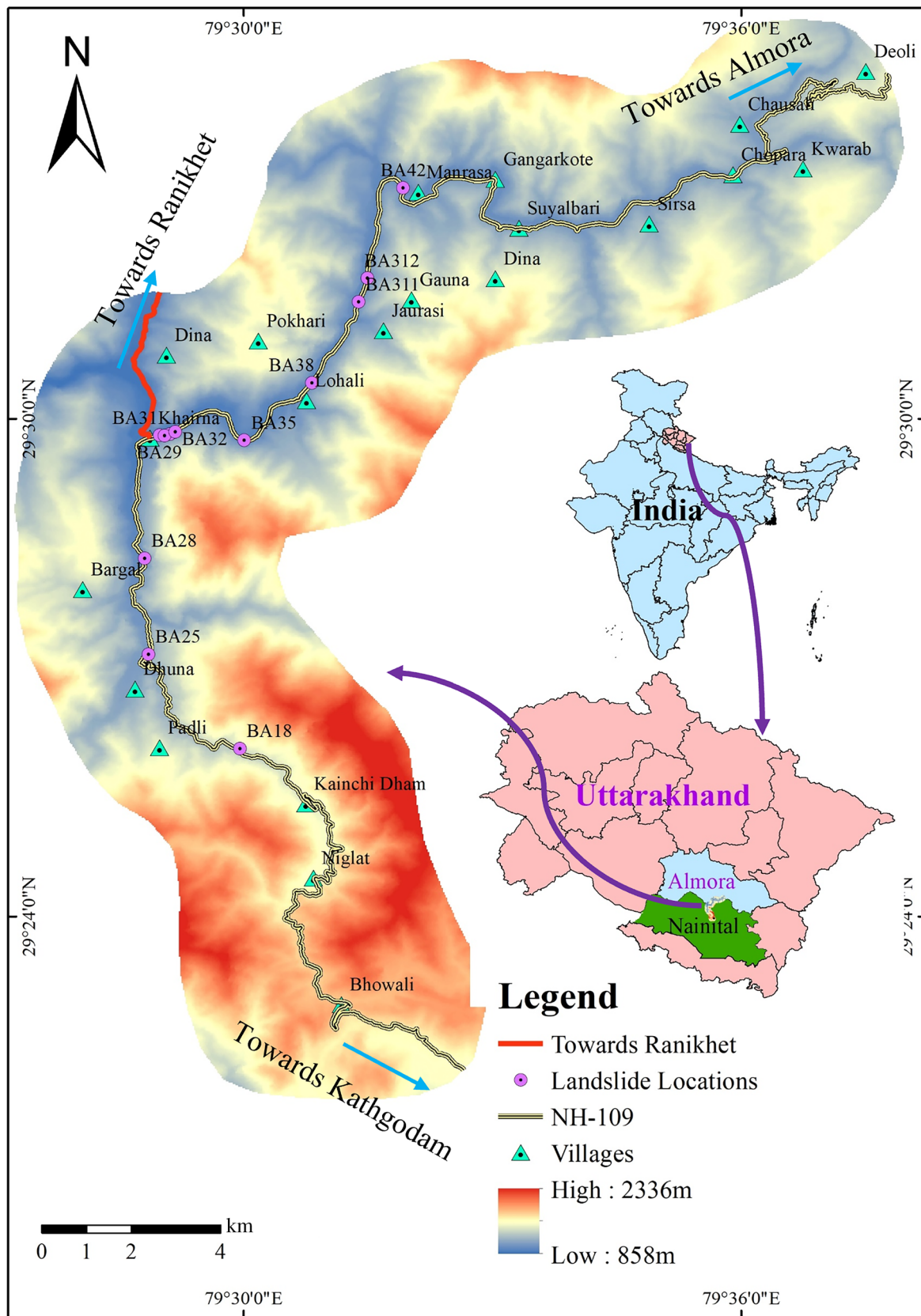


FIGURE 1 | The map of the study area with observed active landslide locations.

probability. Among these methodologies, widely utilized approaches include the integration of fuzzy logic with the likelihood ratio method, the index of entropy method, and the frequency ratio method (Akgun, Dag, and Bulut 2007; Singh et al. 2021).

Various methods employing geographic information system (GIS) technology have been utilized globally to generate landslide susceptibility maps (Table 1). In the Uttarakhand Himalayan terrain, previous studies have applied landslide hazard zonation (LHZ)

TABLE 2 | Data set used.

Agency	Resolution/Scale	Data	Information retrieved
ISRO Portal: Bhuvan	2.5 m	Cartosat 1 DEM	Drainage, slope aspect, slope etc
ISRO Portal: Bhuvan	24 m	LISS III	LULC
Geological Survey of India Portal: Bhukosh	1:50,000	maps	Fault map, lithology, landslides information, etc.
Google Earth Pro		Google map	Highway

TABLE 3 | Description of scales for pair comparison with AHP (Saaty 1990).

Value	Degree of preferences	Description
1	Equally important	Two decision elements equally influence the parent decision element.
3	Marginally important	The influence of one choice factor over the other is somewhat greater.
5	Rather significant	One choice factor has a stronger impact than another.
7	Extremely important	One choice factor greatly outweighs the other in terms of influence.
9	Absolutely important	There is adequate evidence to conclude that a certain factor is genuine.
2, 4, 6, 8	Intermediate values	In between two judgments.

mapping using GIS, analytical hierarchy process (AHP), statistical approaches, soft computing models, and machine learning (Dam et al. 2022; Fayed et al. 2018; Gupta et al. 1999; Juyal and Sharma 2021; Kumar et al. 2017; Kumar and Anbalagan 2016; Pham et al. 2015; Saha et al. 2005; Singh et al. 2023; Sur, Singh, and Meena 2020; Sur, Singh, and Rai 2021; Tran et al. 2021). Gupta et al. (2022) conducted regional-scale landslide susceptibility mapping covering the study area, highlighting the necessity for localized and large-scale planning for socioeconomic development.

This study recognizes the pressing need for effective landslide hazard mitigation in the region, emphasizing that localized LHZ mapping can significantly contribute to socioeconomic development and risk reduction. Landslides, triggered by factors such as earthquakes, rainfall, and cloudbursts, necessitate comprehensive assessments of internal conditioning factors like structural discontinuities, slope geometry, land use/land cover (LULC), and groundwater (Anbalagan 1992; Raghuvanshi, Ibrahi, and Ayalew 2014; Verma et al. 2021).

This study focuses on classifying landslide hazard zones along a stretch of NH-109 in the Bhowali-Almora region, considering factors such as slope, lithology, LULC, fault buffer, aspect, road buffer, and drainage buffer. Thematic layers are assigned weight

values based on their influence on landslides, and subclasses are rated on a scale of 0–9. Integration of these parameters through a multicriteria approach, specifically the AHP, facilitates the creation of a detailed LHZ map. Such mapping aids in informed decision-making for future projects, developments, and settlements, predicting high-hazard zones and guiding authorities to avoid these areas for risk-free development.

This study aims to categorize the various zones for landslide hazard and demarcate the villages with respect to their hazard class. Sustainable development goals in high and very high-hazard zones will be avoided in the future, and guiding authorities will benefit from this research to achieve sustainable development.

2 | Study Area

The research was conducted on a segment of NH-109 in the Nainital and Almora Districts. The Nainital and Almora districts experienced a temperate climate characterized by a warm and short summer, a moist and wet rainy season, and a severe winter. The daily range of minimum and maximum temperature varied from 3.8°C and 29.5°C for the Almora district and 3.6°C and 28.5°C for the Nainital district in a year, respectively (Weather2visit). Identifying vulnerable zones was specifically focused along this stretch of the highway between Bhowali and Almora. To validate the findings, a comprehensive landslide inventory was meticulously recorded. Figure 1 depicts the study area map, highlighting the active landslide locations observed during the field investigation.

3 | Data Used

To use the multiple criterion technique for LHZ, spatial data sets encompassing the landslide causative components: slope, aspect, lithology, fault buffer, road buffer, drainage buffer, and LULC were considered. LISS III images of 24 m spatial resolution and a swath of 141 km were used to prepare LULC (Bhuvan 2020) (Table 2). Cartosat-1 DEM data were used to calculate slope, aspect, and drainage networks (Bhuvan 2020) (Table 2). Cartosat-1 facilitates the acquisition of seven levels of data products utilizing two state-of-the-art panchromatic cameras. These cameras capture black-and-white stereoscopic images with a spatial resolution of 2.5 m in the visible electromagnetic spectrum (Yarrakula, Deb, and Samanta 2013). The other parameters, such as lithological maps, fault maps, and landslide inventory maps, were retrieved from the GSI (Geology Data 2019; Fault Data 2019; Landslide Data 2019) (Table 2). Road data (NH-109)

was manually retrieved from the Google Earth Pro software (Google Earth Pro 2020). Finally, all data sets were rasterized to a 30 m × 30 m grid cell to prepare an LHZ map using AHP.

4 | Methodology

4.1 | Assignments of Weight and Its Normalization Using AHP

The weight values for each thematic layer in this study were assessed utilizing the AHP approach, as introduced by Saaty (1980). AHP methodologies elucidate the hierarchical

structure of multiple criteria through a pairwise comparison technique, aiding in decision-making processes. This approach proves versatile, accommodating both quantitative (objective) and qualitative (subjective) data for decision analysis. In the AHP comparison matrix, scores are recorded on one side of the diagonal, with values of 1 placed on the diagonal itself (Gorsevski et al. 2006). A pairwise comparison matrix was established, where each criterion was compared to every other criterion using a relative dominating scale ranging from 1 to 9 (Table 3).

Relative importance values for each criterion were assigned based on various criteria and preferences, such as equally

TABLE 4 | Pairwise comparison matrix, weight, and consistency ratio of the thematic layers.

Factors	Slope	Lithology	Road buffer	Aspect	LULC	Fault buffer	Drainage buffer	Final Wtg.
Slope	1	1	3	4	6	7	6	0.31
Lithology	1	1	3	5	4	6	5	0.291
Road buffer	1/3	1/3	1	3	4	5	6	0.17
Aspect	1/4	1/5	1/3	1	2	3	3	0.083
LULC	1/6	1/4	1/4	1/2	1	5	4	0.078
Fault buffer	1/7	1/6	1/5	1/3	1/5	1	2	0.035
Drainage buffer	1/6	1/5	1/6	1/3	1/4	1/2	1	0.031

TABLE 5 | Random index value (Saaty 1990).

<i>n</i>	1	2	3	4	5	6	7	8	9	10
RI	0.0	0.0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

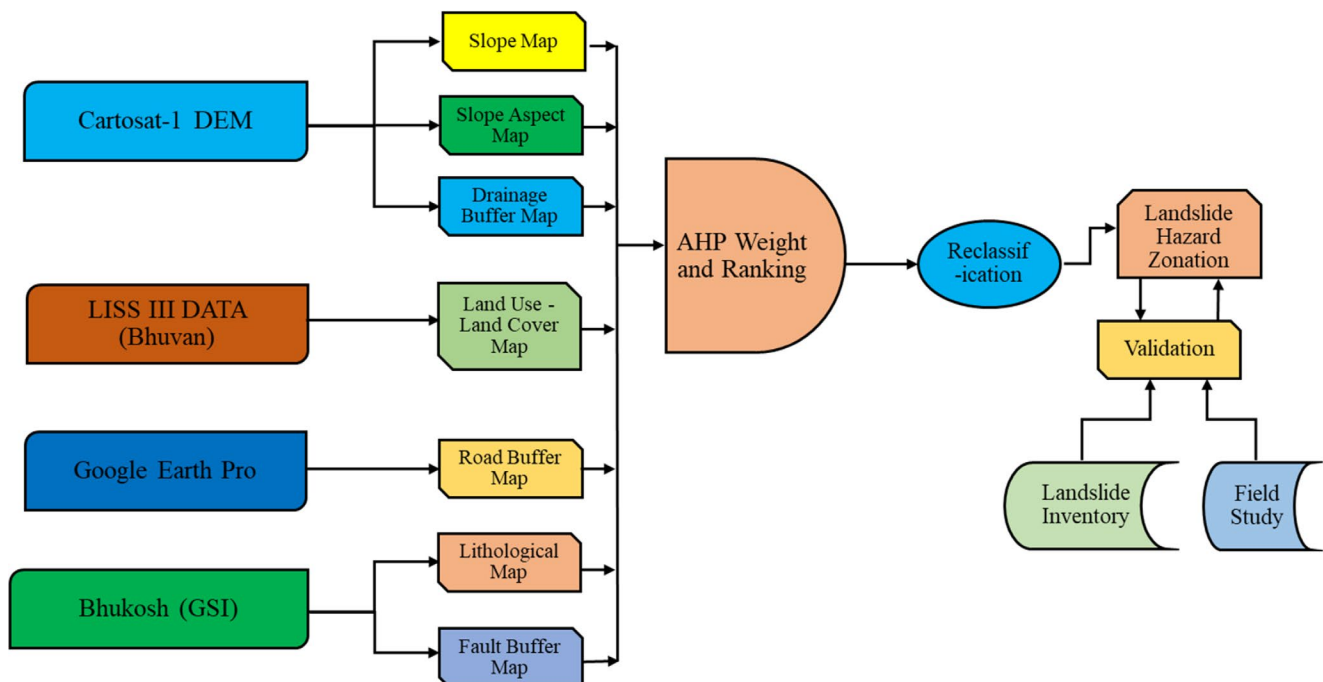


FIGURE 2 | A methodological flow chart adopted for demarcation of landslide hazard zonation map.

TABLE 6 | Landslide hazard weight values and rating system of different thematic map layers (Anbalagan 1992; Bera, Mukhopadhyay, and Das 2019; BIS 14496 (I):2020; El Jazouli, Barakat, and Khellouk 2019; Saha, Gupta, and Arora 2002).

Factor	Classes	Weight	Rating
Slope (degree)	0–5	0.31	1
	5–15		2
	15–25		3
	25–35		5
	35–45		7
	> 45		9
Lithology	Alluvium sediments	0.291	7
	Blaini Formation		6
	Jaunsar (Undiff) Group		3
	Nagthat Formation		2
	Betalghat Formation		8
	Chaura Formation		5
	Gorakhnath Formation		4
	Ramgarh (Undiff) Group		8
	Bhandoli Formation		2
Slope aspect	Flat	0.17	0
	North		1
	North-East		3
	East		7
	South-East		8
	South		9
	South-West		6
	West		4
	North-West		2
Road buffer (m)	0–500	0.083	9
	500–1000		7
	1000–1500		5
	1500–2000		3
	2000–2500		1
LULC	Agriculture	0.078	3
	Vegetation dense		4
	Vegetation moderate		6
	Vegetation sparse		7
	Settlements		8
	River		9
	River bed		9

(Continues)

TABLE 6 | (Continued)

Factor	Classes	Weight	Rating
Fault buffer (m)	0–1000	0.035	9
	1000–2000		8
	2000–3000		7
	3000–4000		5
	4000–5000		3
	5000–6000		2
Drainage buffer (m)	6000–7000	0.031	1
	0–100		9
	100–200		7
	200–300		5
	300–400		3
	400–500		1

important (1), marginally important (3), rather significant (5), extremely important (7), and absolutely important (9), with intermediate values 2, 4, 6, and 8 (Table 3). Subsequently, weighted values for each criterion were computed using an AHP pairwise comparison matrix (Table 4). The matrix's rows signify the inverse values of each criterion and their significance compared to others, with the first row presenting the slope's importance to the remaining seven criteria.

4.2 | Consistency Analysis

To assess the consistency of pairwise comparisons, the consistency ratio (CR) was computed using Equations (1, 2) following the method outlined by Kolat, Ulusay, and Suzen (2012). Despite the AHP method's ability to accommodate inconsistent relationships, the CR measures the degree of consistency or inconsistency, with a value less than 0.10 indicating reasonable consistency. CR is calculated using the following Equations (1, 2).

$$CR = \frac{CI}{RI} \quad (1)$$

$$CI = (\gamma_{\max} - n) / (n - 1) \quad (2)$$

where $\gamma_{\max}$ is the principal eigenvalue and n is the number of factors.

In this study, the resulting CR was 0.072, signifying a high degree of consistency, and the weights were deemed relevant for the LHZ model (Table 4).

The random index (RI) value was computed using randomly generated reciprocal matrices (Saaty 1980). In this study, the random consistency index for the seven factors was 1.32 (Table 5), yielding a principal eigenvalue of 7.57. Figure 2 presents a summarized flow chart detailing the adopted methodology for evaluating the LHZ map. Tables 4 and 6 provide

the pairwise comparison matrix, weight, and CR of the thematic layers and the landslide hazard weight values and rating system for different layers of the thematic map, respectively (Anbalagan 1992; Bera, Mukhopadhyay, and Das 2019; BIS 14496 (I):2020; El Jazouli, Barakat, and Khellouk 2019; Saha, Gupta, and Arora 2002).

4.3 | Topographic Attributes

The slope angle is a critical causative factor for landslides and is widely utilized in susceptibility mapping (Gupta et al. 2008; Kanungo et al. 2006; Nourani et al. 2014). More enormous landslides are frequently caused by steeper slopes because more material crumbles for a given strength (Sur and Singh 2019). The final weight of the slope is 0.31, and its role for LHZ is considered the maximum in this study (Table 4). Six slope classifications were considered (Figures 3a and 4a). In LHZ investigations (Kanungo et al. 2009; Nagarajan et al. 1998; Saha, Gupta, and Arora 2002), the slope aspect is a significant feature that has been considered, and its final weight is 0.083 (Table 4). It is common practice to incorporate the slope aspect, referring to the orientation of the slope face (Poudyal et al. 2010; Pourghasemi, Pradhan, and Gokceoglu 2012), as a conditioning component for landslides. A slope's aspect is defined by its northward-facing orientation, influencing solar warming, soil moisture, and air dryness (Yalcin 2008). The aspect map was created with nine classes (Figures 3b and 4b) (Bera, Mukhopadhyay, and Das 2019).

4.4 | Lithology

Lithology is crucial in landslide vulnerability assessments (Althuwaynee and Pradhan 2016). The study area encompasses various groups such as the Ramgarh Group, Almora Group (Gorakhnath Formation, Chaura Formation), Betalghat Formation, Jaunsar Group (Nagthat Formation), Baliana

Group (Blaini Formation) and Alluvium sediments (Misc. Pub. 2019). Ramgarh Group in this area consists of metabasic and phyllite; the Almora Group consists of schist and gneiss; the Betalghat Formation consists of phyllite; the Jaunsar Group consists of metabasic and quartzite; the Baliana Group consists of slate and alluvium sediments consist of gray sand, silt, and clay (Figure 4c). The final weight of lithology is 0.291, and its role is considered lower than the slope for this study (Table 4).

4.5 | Land Use/Land Cover

Population-related factors significantly influence land utilization, including converting agricultural and forest land into urban areas, transforming forests into agricultural land, and altering slopes for infrastructure development. A critical aspect of landslide hazard mapping involves the land use characterization, and its final weight is 0.078 (Table 4). Seven LULC classes were established through image categorization, encompassing dense vegetation, moderate vegetation, less vegetation, river, riverbed, settlements, and agriculture (Figure 4d). Agriculture dominates the largest land area, followed by dense and moderate vegetation. Riverbeds and settlements are observed as patches, with sparse vegetation mainly concentrated on the northern side of the highway around the Almora region. The LULC distribution is represented in percentages: agriculture (29%), dense vegetation (26%), moderate vegetation (25%), sparse vegetation (15%), river (2%), settlements (2%), and riverbed (1%) (Figure 5).

4.6 | Photolineaments

Photolineaments and linear geological discontinuities can be discerned through multispectral images and DEM. Landslides correlate with photolineaments' proximity (Gupta et al. 1999).

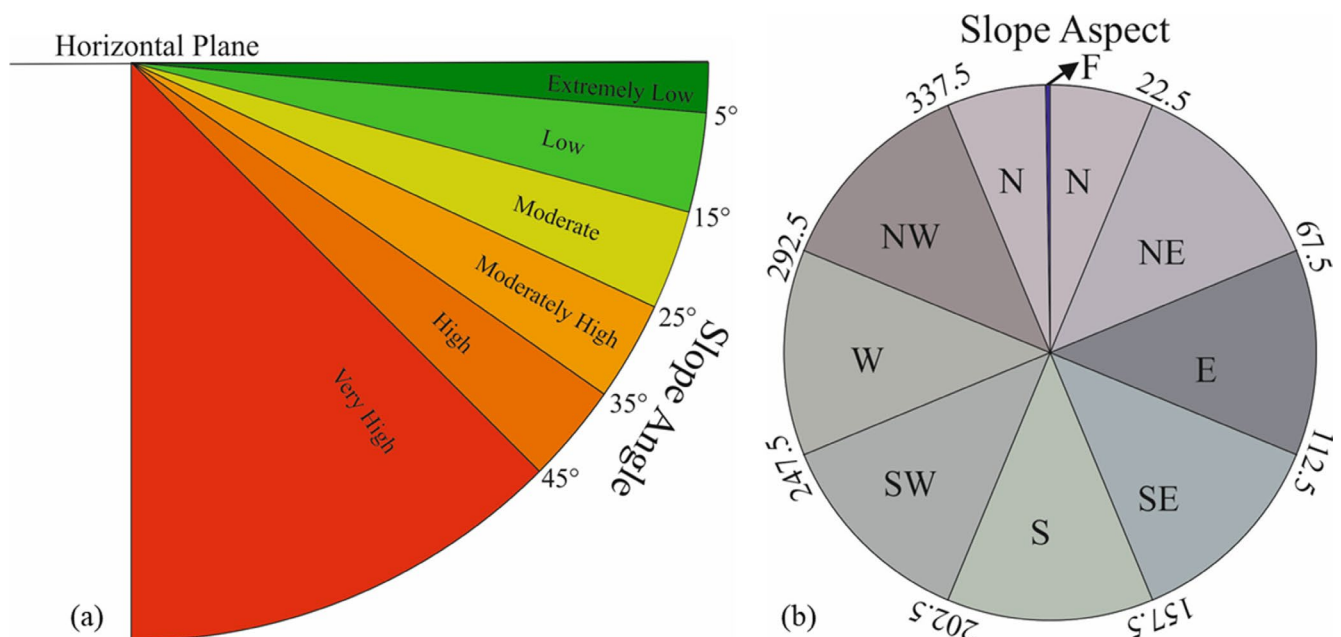


FIGURE 3 | Classification of (a) slope angle, (b) slope aspect (in degree).

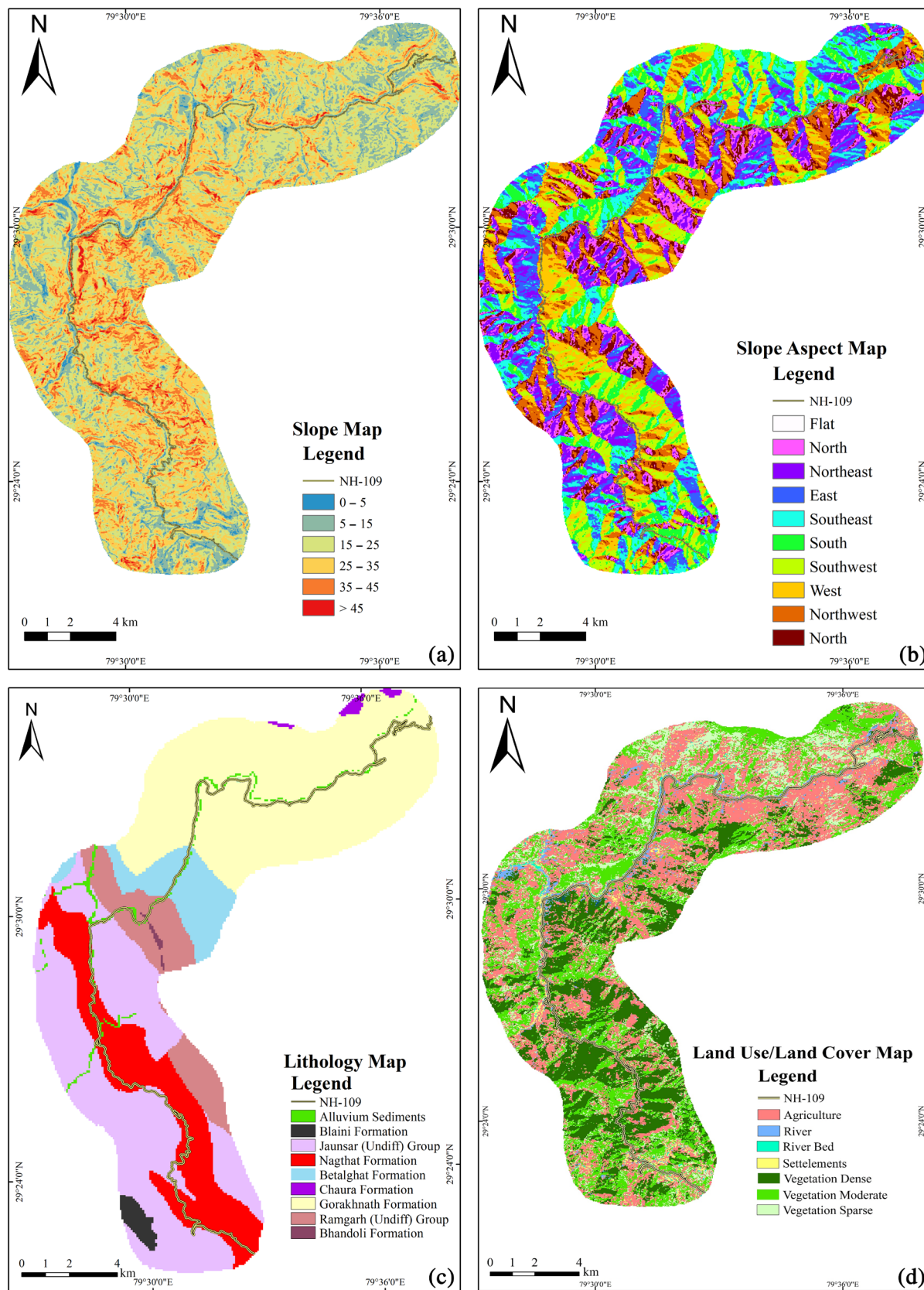


FIGURE 4 | (a) Slope map, (b) aspect map (Source: Cartosat-1 DEM data), (c) lithological map (Source: Geology data, 2019), and (d) Land use/land cover map (Source: LISS III data) of the study area.

Generally, landslides are less likely to occur in geological fault locations due to the weakened strength of the underlying rock resulting from tectonic fractures (Chen et al. 2017). The

final weight of the fault buffer is 0.035 for this study (Table 4). Utilizing the geological map, fault buffers in this study were categorized into seven groups (Fault Data 2019), and a fault

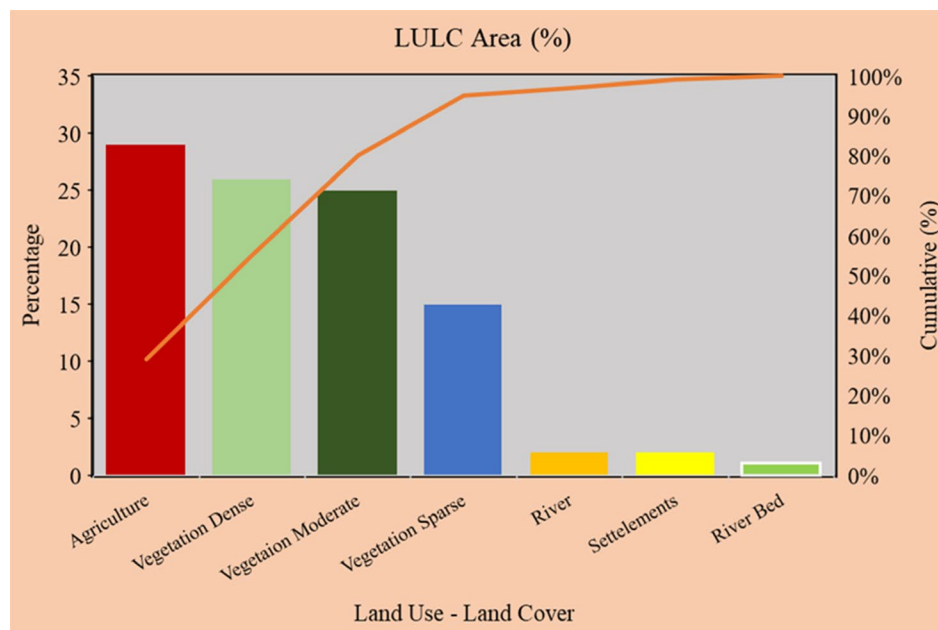


FIGURE 5 | Land use/land cover of the study area (in area percentage).

buffer map was constructed using a multiple-ring buffer tool (Figure 6a).

4.7 | Road and River Buffers

The road buffer is one of the primary anthropogenic variables influencing landslide occurrences, and its final weight is 0.17 in this study (Table 4) (Nourani et al. 2014; Yilmaz 2010). Indeed, several landslides were induced to occur by road construction during fieldwork. Five different buffer zones, each with a 500m interval, were created for the present investigation (Figure 6b).

According to Park et al. (2013), rivers are crucial in landslide occurrences. They can induce bank collapses due to slope undercutting, and gully erosion may alter the terrain, impacting landslide initiation (Bui et al. 2011; Dai and Lee 2002). The final weight of the drainage buffer is 0.031 (Table 4). The drainage network for this study was established using hydrology tools in ArcGIS 10.2 with DEM data. The multiple-ring buffer tool was employed to create five distinct buffers, evaluating the potential impact of streams on bank slopes (Figure 6c). The distance from these structural characteristics has a relative influence on the landslide probability; hence, a buffer map is generated for the zonation of landslide hazard.

4.8 | Landslide Inventory

Every susceptibility assessment study must be grounded in a comprehensive collection of historical records of occurrences, serving as the foundation and guiding the entire process (Abella and Van 2008; Ahmed 2015; Pourghasemi, Pradhan, and Gokceoglu 2012; Van, Castellanos, and Kuriakose 2008). The landslide inventory map was compiled using data obtained from field investigations (Figures 1 and 7 and Table 7) and

information available in the Bhukosh portal of GSI. A total of 63 landslides were documented in the study area. The LHZ map is subsequently validated using this data set (Figure 8a).

5 | Results and Discussion

The landslide causative factors such as slope, lithology, aspect, LULC, fault buffer, road buffer, and drainage buffer have been critical in the study area. The final weights for these causative factors were evaluated using an AHP pairwise comparison matrix (Table 4). The random consistency index for these seven factors was also calculated (Table 5). The findings of this research underscore the importance of LHZ in assessing and mitigating landslide hazards along a section of NH-109. These results provide valuable insights for informed decisions in infrastructure development and risk management, thereby to the region's sustainable growth and the protection of its livelihoods.

5.1 | Landslide Hazard Zonation Mapping

The landslide hazard zonation map of the study area is shown in Figure 8a, in which the Landslide Hazard Index (LHI) values range from 1.99 to 8.44 and are classified into four classes considering manual interval as low (1.99–3.5), moderate (3.5–5.0), high (5.0–6.5), and very high (6.5–8.44) based on the field conditions. Researchers generally rely on their expert judgment to establish class boundaries for continuous data, as there are no universal rules for automatic categorization (Ayalew, Yamagishi, and Ugawa 2004; Sonker, Tripathi, and Singh 2021). The total study area covers 171.2 km². Figures 9 and 10 vividly illustrate that 24.4% (41.77 km²) of the study area exhibits a high hazard potential, while 3.3% (5.65 km²) is classified as having a very high hazard potential. The areas designated as low and moderate hazards constitute 11.9% (20.37 km²) and 60.4% (103.42 km²), respectively. Most of the study area (103.42 km²) falls within the moderate-hazard zone.

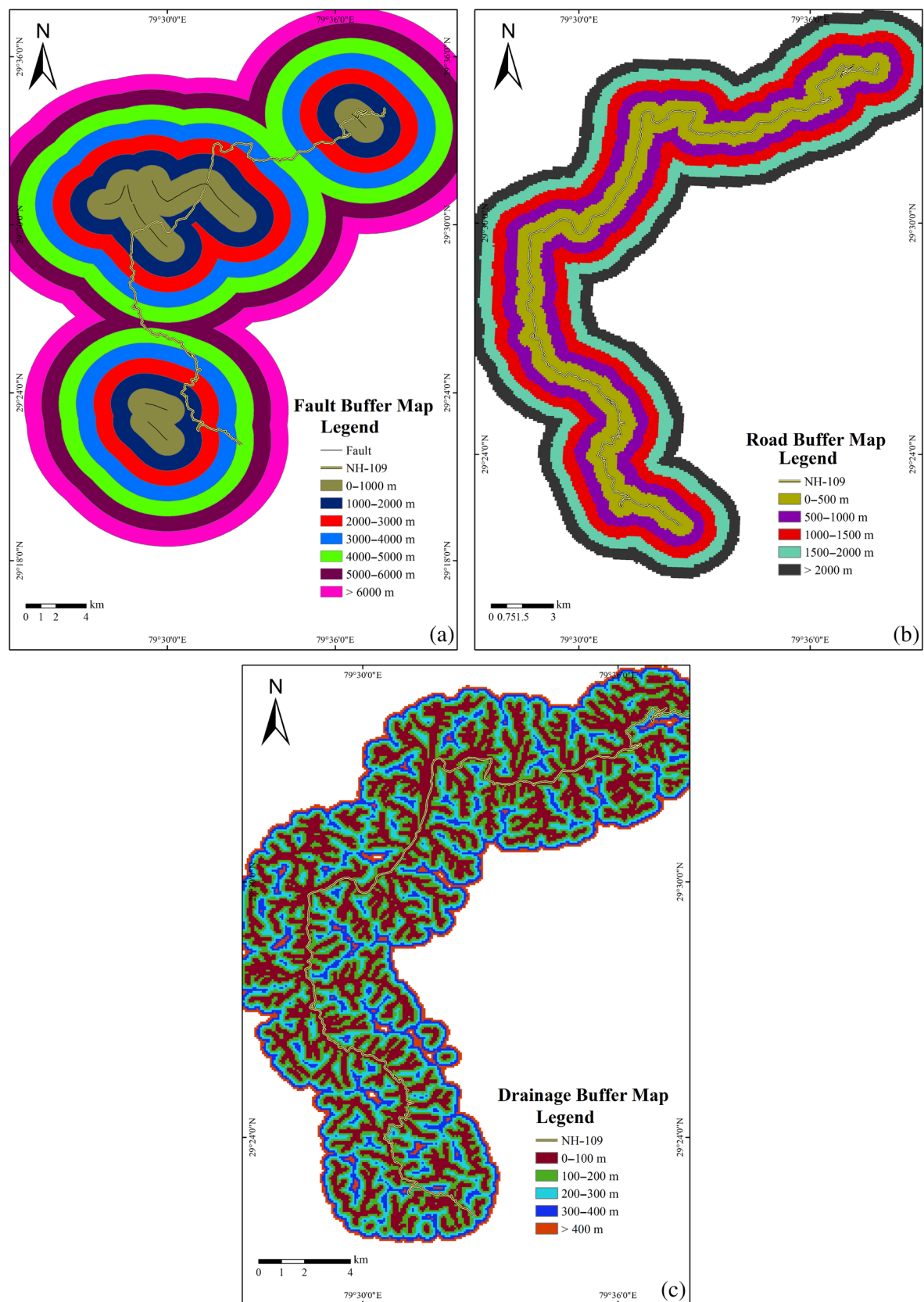


FIGURE 6 | (a) Fault buffer map (Source: Fault Data 2019), (b) road buffer map (Source: Google Earth Pro 2020), and (c) drainage buffer map (Source: Cartosat-1 data) of the study area.

In the proposed Landslide hazard zonation map, high- to very high-hazard zones were estimated in the area along the road stretch from Khairna to Jaurasi. The same conditions,

active landslide incidents, were found at locations BA29, BA210, BA31, BA32, BA35, and BA38 during field investigation within the same stretch of road (Figure 8a). This also validates the

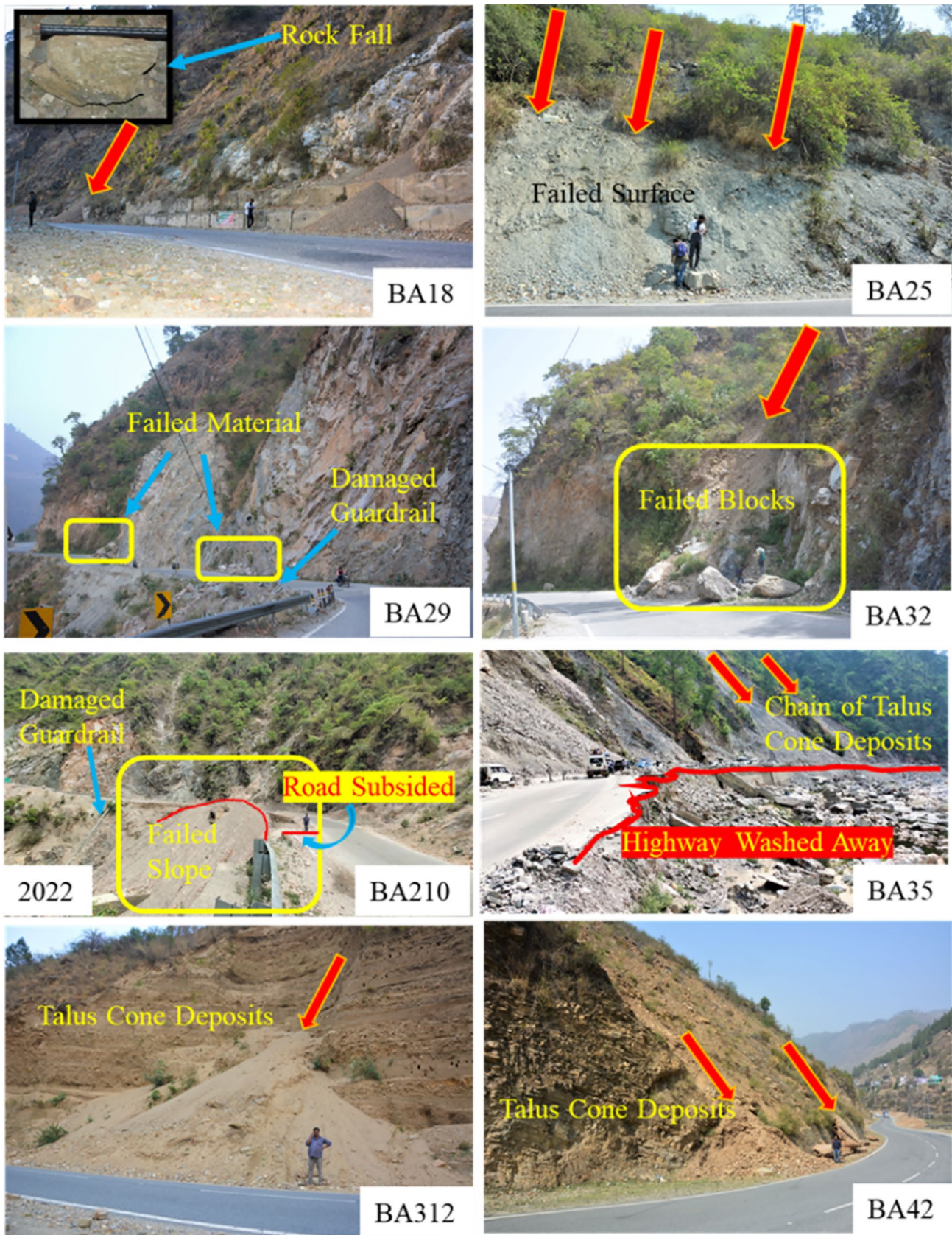


FIGURE 7 | Some demarcated active landslides (locations marked in Figure 1) in the study area.

accuracy of the proposed LHZ map. High- to very high-hazard zones were majorly found along the highway, where road-cut slopes were steep.

Several villages/townships, including Bhowali, Kainchi Dham, Bargal, Dina, Pokhari, Jaurasi, Suyalbari, Gangarkote, Gauna, Manarasa, Chopara, and Chausali are situated in the high hazards

Name	Location	Type of landslide	Affected stretch of the highway
BA18	29° 26' 11" 79° 29' 57"	Rock falls and Talus cones	About 250 m stretch along the highway
BA25	29° 27' 42.6" 79° 28' 45.1"	Circular failure	About 100 m stretch along the highway
BA29	29° 29' 48.1" 79° 28' 59.2"	Rock falls	About 200 m stretch along the highway
BA210	29° 29' 49" 79° 29' 6.8"	Road subsidence	Half of the road subsided during the monsoon in 2022
BA32	29° 29' 50.7" 79° 29' 10.7"	Rock falls	About 100 m stretch along the highway
BA35	29° 29' 40" 79° 29' 27"	Chain of talus cone	About 1 km stretch and newly constructed highway washed away during the monsoon in 2022
BA312	29° 31' 41.9" 79° 31' 29.6"	Talus cone	About 50 m stretch along the highway and half of the road covered by deposits
BA42	29° 32' 47.5" 79° 31' 55.5"	Planar failure and Talus cone	About 100 m stretch along the highway

FIGURE 8 | (a) Landslide hazard zonation map of the study area and (b) villages with landslide hazard zones.

5.2 | Map Authentication and Assessment

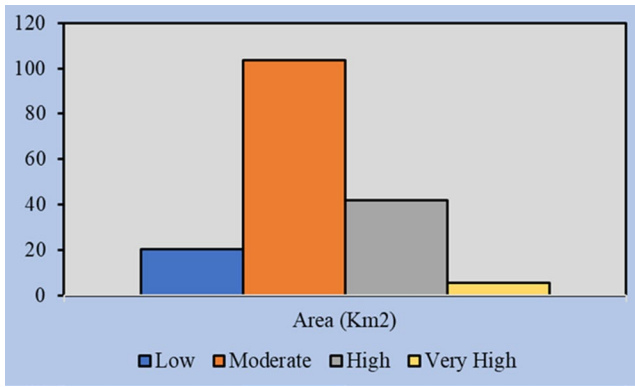


FIGURE 9 | The area (km²) of the hazard zones.

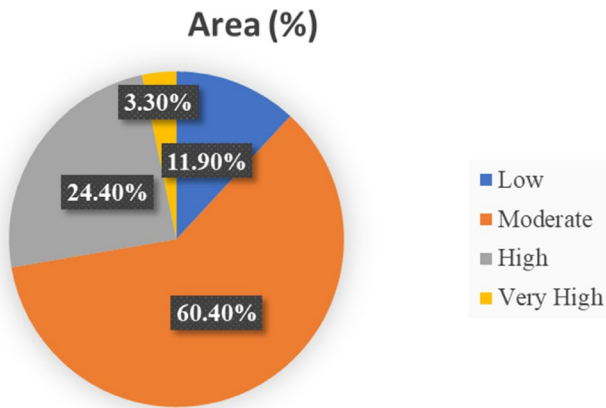


FIGURE 10 | Percentage area of hazard zones.

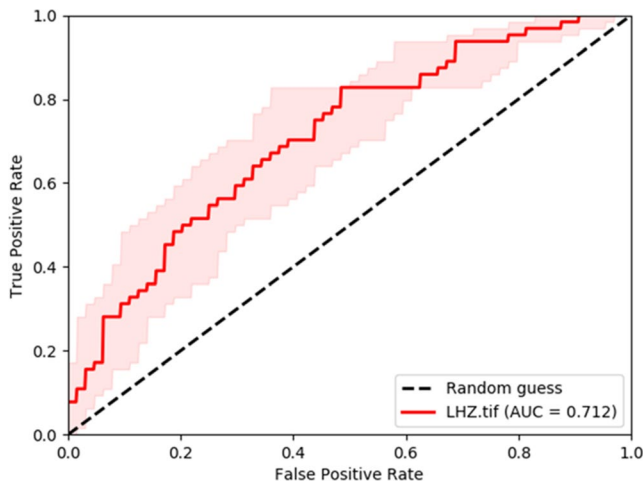


FIGURE 11 | ROC curve for landslide hazard zonation map using AHP.

hazardous zone. Figure 9 visually represents the hazard zones' areal extent and Figure 10 shows distribution percentages.

The very high-hazard zone, covering only 3.3% and 5.65 km² of the total study area, experiences landslides at a higher frequency rate (19% of total landslides). The high-hazard zone, encompassing 24.4% and 41.77 km² of the study area, witnesses over 50% of total landslides. The moderate-hazard zone extends over

TABLE 8 | AUC quality test (Althouse 2016).

AUC value	Quality test
0.9–1.0	Excellent
0.8–0.9	Very good
0.7–0.8	Good
0.6–0.7	Satisfactory
0.5–0.6	Unsatisfactory

60.4% and 103.42 km², with a relatively low landslide frequency (28.57%), and the low-hazard zone covers 11.9% and 20.37 km², with a very low landslide frequency (1.58%). Steep slopes, identified during field investigations (Figure 7), contributed to the highest number of landslides, primarily triggered by heavy rainfall during the monsoon season.

Moreover, the effectiveness of landslide hazard maps derived from AHP was validated using a receiver operating characteristic (ROC) curve (Sonker, Tripathi, and Singh 2021) (Figure 11). The fundamental advantage of the ROC approach as a threshold-independent curve is that it is independent of both the number of thresholds used in calculations and their inter-spaces (Fawcett 2006). For a landslide susceptibility index with n classes, $n + 1$ thresholds are defined. The first threshold ($i = 1$) is lower than the minimum susceptibility detected in the most stable class, while the last threshold ($i = n + 1$) is higher than the maximum susceptibility observed in the most sensitive class. The thresholds create a confusion matrix with four sorts of pixels: true-positive (TP), false-positive (FP), true-negative (TN), and false-negative (FN). Identifying TP and FN pixels helps pinpoint landslides above and below the threshold value. On the other hand, TN and FP pixels signify stable areas below and above the threshold value, respectively. These pixel tallies for each threshold drive the calculation of two crucial statistics: the true-positive rate (TPR) and the false-positive rate (FPR).

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{FPR} = \frac{\text{FP}}{\text{TN} + \text{FP}} \quad (4)$$

In an ROC curve, the TPR and FPR create an engaging visual representation. They represent the point (1, 1) on the curve for the first threshold ($i = 1$), and the point (0, 0) for the last threshold ($i = n + 1$). During the final validation step, the area under the curve (AUC) is calculated as follows:

$$\text{AUC} = \sum_{i=1}^{n+1} \frac{1}{2} \sqrt{(x_i - x_{i+1})^2 \cdot (y_i - y_{i+1})^2} \quad (5)$$

The AUC value can demonstrate the success rate of the model by comparing its performance on the training data set and its predictive ability on the test data set. The success rate indicates how well the LHZ separates the landslides within its hazard zones (Chung and Fabbri 1999).

The ROC curve graphically displays the relationship between TP and false-positive rates (Althouse 2016). AUC values range from

0.5 to 1, with model accuracy increasing as AUC approaches 1. In this study, the ROC tool of ARCSDM was used (ROC tool 2024). The calculated AUC value of 71.2% (Table 8) indicates a good quality test, confirming the predictability of the LHZ map.

6 | Conclusions

The study area, situated in the Lesser Kumaun Himalaya, faces susceptibility to landslide incidents, causing disruptions in road connections and posing threats to the affected region, potentially leading to casualties. To address these challenges and promote sustainable development, a large-scale LHZ was conducted in this region, employing a multicriteria approach with AHP weighting. This mapping technique proves effective in delineating vulnerable landslide zones across expansive areas.

The highway was categorized into low (11.09%), moderate (60.4%), high (24.4%), and very high (3.3%) landslide hazard zones. Despite covering only 3.3% of the total area, the very high-hazard zone exhibited frequent landslide incidents approximately 19% of total landslide incidents in the study area. Results were validated through field studies, landslide inventory, and ROC curve analysis, with the ROC curve yielding an AUC value of 71.2%, indicating good quality in estimating the LHZ.

The high-hazard zone, covering 24.4% of the total area, accounted for over 50.8% of the total landslide incidents. To mitigate the risk of fatalities, authorities responsible for development and planning should exercise caution, particularly in areas classified as high and very high landslide hazard zones (covers area in % = 24.4% + 3.3% and landslide incidents in % = 50.8% + 19%). Any alterations to the natural topography resulting from natural or anthropogenic disturbances, such as seismic activities, deforestation, or road widening, may influence the existing landslide vulnerability in this region. Therefore, continuous monitoring of the LHZ is essential to adapt to changing conditions cyclically caused by these factors.

The present study focuses on classifying landslide hazard zones along a stretch of NH-109 in the Bhowali-Almora region, considering factors such as slope, lithology, LULC, fault buffer, aspect, road buffer, and drainage buffer. The future scope of work in the region lies with the application of artificial intelligence and machine learning approaches for the prediction of rainfall threshold for the initiation of landslides. In addition, site-specific studies on the behavior of slopes with respect to primary and secondary orientations of exposed rocks for landslide susceptibility and site-specific slope modeling should be performed to study the nature of deformation and associated hazards in the region.

Author Contributions

Rahul Kumar Verma: writing – original draft, formal analysis, conceptualization, data curation, methodology, software. **Rajesh Singh:** writing – review and editing, conceptualization, methodology, software, formal analysis. **Prateek Sharma and Ravi Kumar Umrao:** data curation, software, writing – review and editing. **T. N. Singh:** review and suggestions.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Peer Review

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References

- Abella, E. A. C., and C. J. W. Van. 2008. "Qualitative Landslide Susceptibility Assessment by Multicriteria Analysis: A Case Study From San Antonio Del Sur, Guantánamo Cuba." *Geomorphology* 94: 453–466.
- Ahmed, B. 2015. "Landslide Susceptibility Mapping Using Multi-Criteria Evaluation Techniques in Chittagong Metropolitan Area, Bangladesh." *Landslides* 12: 1077–1095.
- Akgun, A., S. Dag, and F. Bulut. 2007. "Landslide Susceptibility Mapping for a Landslide-Prone Area (Findikli, NE of Turkey) by Likelihood Frequency Ratio and Weighted Linear Combination Models." *Environmental Earth Sciences* 54, no. 6: 1127–1143.
- Althouse, A. D. 2016. "Statistical Graphics in Action: Making Better Sense of the ROC Curve." *International Journal of Cardiology* 215: 9–10.
- Althuwaynee, O., B. Pradhan, and N. Ahmad. 2014. "Landslide Susceptibility Mapping Using Decision-Tree Based Chi-Squared Automatic Interaction Detection (CHAID) and Logistic Regression (LR) Integration." *IOP Conference Series: Earth and Environmental Science* 20, no. 1: 012032.
- Althuwaynee, O. F., and B. Pradhan. 2016. "Semi-Quantitative Landslide Risk Assessment Using GIS-Based Exposure Analysis in Kuala Lumpur City." *Geomatics, Natural Hazards and Risk* 8, no. 2: 1–27.
- Anbalagan, R. 1992. "Landslide Hazard Evaluation and Zonation Mapping in Mountainous Terrain." *Engineering Geology* 32: 269–277.
- Anbalagan, R., D. Chakraborty, and A. Kohli. 2008. "Landslide Hazard Zonation (LHZ) Mapping on Meso-Scale for Systematic Town Planning in Mountainous Terrain." *Journal of Scientific and Industrial Research* 67: 486–497.
- Ayalew, L., and H. Yamagishi. 2005. "The Application of GIS-Based Logistic Regression for Landslide Susceptibility Mapping in the Kakuda-Yahiko Mountains, Central Japan." *Geomorphology* 65, no. 1–2: 15–31.
- Ayalew, L., H. Yamagishi, and N. Ugawa. 2004. "Landslide Susceptibility Mapping Using GIS Based Weighted Linear Combination, the Case in Tsugawa Area of Agano River, Niigata Prefecture, Japan." *Landslides* 1, no. 1: 73–81. <https://doi.org/10.1007/s10346-003-0006-9>.
- Bera, A., B. P. Mukhopadhyay, and D. Das. 2019. "Landslide Hazard Zonation Mapping Using Multi-Criteria Analysis With the Help of GIS Techniques: A Case Study From Eastern Himalayas, Namchi, South Sikkim." *Natural Hazards* 96: 935–959. <https://doi.org/10.1007/s11069-019-03580-w>.

- Bhuvan Portal. 2020. October 03, 2024. <https://bhuvan-app3.nrsc.gov.in/data/download/index.php>.
- Bonham-Carter, G. F., Q. M. Cheng, and D. F. Wright. 1993. "Weights of Evidence Modeling and Weighted Logistic Regression for Mineral Potential Mapping." *Computers and Geology* 25: 13–32.
- Bui, D. T., O. Lofman, I. Revhau, and O. Dick. 2011. "Landslide Susceptibility Analysis in the Hoa Binh Province of Vietnam Using Statistical Index and Logistic Regression." *Natural Hazards* 59: 1413–1444.
- Bui, D. T., B. T. Pham, O. P. Nguyen, and N. D. Hoang. 2016. "Spatial Prediction of Rainfall-Induced Shallow Landslides Using Hybrid Integration Approach of Least-Squares Support Vector Machines and Differential Evolution Optimization: A Case Study in Central Vietnam." *International Journal of Digital Earth* 9, no. 11: 1077–1097.
- Bui, D. T., T. A. Tuan, and H. Klempe. 2016. "Spatial Prediction Models for Shallow Landslide Hazards: A Comparative Assessment of the Efficacy of Support Vector Machines, Artificial Neural Networks, Kernel Logistic Regression, and Logistic Model Tree." *Landslides* 13: 361–378.
- Bureau of Indian Standard (BIS). 2020. *IS: 14496, Preparation of Landslide Hazard Zonation Maps in Mountainous Terrains—Guidelines, Part 1 Meso-Zonation BIS*. New Delhi: Bureau of Indian standard.
- Chawla, A., S. Chawla, S. Pasupuleti, A. C. S. Rao, K. Sarkar, and R. Dwivedi. 2018. "Landslide Susceptibility Mapping in Darjeeling Himalayas, India." *Advances in Civil Engineering* 2018: 1–17.
- Chen, M. L., H. W. Jing, X. J. Ma, H. J. Su, M. R. Du, and T. T. Zhu. 2017. "Fracture Evolution Characteristics of Sandstone Containing Double Fissures and a Single Circular Hole Under Uniaxial Compression." *International Journal of Mining Science and Technology* 27, no. 3: 499–505.
- Chen, T., R. Niu, and X. Jia. 2016. "A Comparison of Information Value and Logistic Regression Models in Landslide Susceptibility Mapping by Using GIS." *Environmental Earth Sciences* 75, no. 10: 867.
- Chung, C.-J. F., and A. G. Fabbri. 1999. "Probabilistic Prediction Models for Landslide Hazard Mapping." *Photogrammetric Engineering and Remote Sensing* 65: 1389–1399.
- Dahal, R. K., S. Hasegawa, S. Nonomura, M. Yamanaka, T. Masuda, and K. Nishino. 2008. "GIS-Based Weights-of-Evidence Modelling of Rainfall-Induced Landslides in Small Catchments for Landslide Susceptibility Mapping." *Environmental Earth Sciences* 54, no. 2: 314–324.
- Dai, F., and C. Lee. 2002. "Landslide Characteristics and Slope Instability Modeling Using GIS, Lantau Island, Hong Kong." *Geomorphology* 42, no. 3–4: 213–228.
- Dam, N. D., M. Amiri, N. Al-Ansari, et al. 2022. "Evaluation of Shannon Entropy and Weights of Evidence Models in Landslide Susceptibility Mapping for the Pithoragarh District of Uttarakhand State, India." *Advances in Civil Engineering* 6645007: 1–16. <https://doi.org/10.1155/2022/6645007>.
- Devkota, K. C., A. D. Regmi, H. R. Pourghasemi, et al. 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: 135–165.
- Dilley, M., U. Chen, U. Deichmann, et al. 2005. *Natural Disaster Hotspots: A Global Risk Analysis*. Washington, D.C.: International Bank for Reconstruction and Development/The World Bank and Columbia University.
- El Jazouli, A., A. Barakat, and R. Khellouk. 2019. "GIS-Multicriteria Evaluation Using AHP for Landslide Susceptibility Mapping in Oum Er Rbia High Basin (Morocco)." *Geoenvironmental Disasters* 6: 3. <https://doi.org/10.1186/s40677-019-0119-7>.
- El-Magd, S. A. A., S. A. Ali, and Q. B. Pham. 2021. "Spatial Modeling and Susceptibility Zonation of Landslides Using Random Forest, Naïve Bayes and K-Nearest Neighbor in a Complicated Terrain." *Earth Science Informatics* 14: 1227–1243. <https://doi.org/10.1007/s12145-021-00653-y>.
- Fault Data. 2019. "Geological Survey of India, Government of India, Kolkata, India." April 15, 2019.
- Fawcett, T. 2006. "An Introduction to ROC Analysis." *Pattern Recognition Letters* 27, no. 8: 861–874.
- Fayez, L., B. T. Pham, H. A. Solanki, et al. 2018. "Application of Frequency Ratio Model for the Development of Landslide Susceptibility Mapping at Part of Uttarakhand State." *International Journal of Applied Engineering Research* 13, no. 9: 6846–6854.
- Geology Data. 2019. "Geological Survey of India, Government of India, Kolkata, India." April 15, 2019.
- Ghosh, S., E. J. M. Carranza, C. J. W. Van, V. G. Jetten, and D. N. Bhattacharya. 2011. "Selecting and Weighting of Spatial Predictors for Empirical Modeling of Landslide Susceptibility in Darjeeling Himalaya (India)." *Geomorphology* 131: 35–56.
- Google Earth Pro. 2020. "From Bhowali to Almora, Uttarakhand, India, 29° 22' 40", 79° 31' 50.1"– 29° 35' 37", 79° 39' 10.8", 1589m–1656m."
- Gorsevski, P. V., P. E. Gessler, R. B. Foltz, and W. J. Elliot. 2006. "Spatial Prediction of Landslide Hazard Using Logistic Regression and ROC Analysis." *Transactions in GIS* 10: 395–415.
- GSI Misc. Pub. 2019. "Geology and Mineral Resources of the States of India. Miscellaneous Publication no. 30 Part-XIIIA Uttarakhand, 1 81p."
- Gupta, R. P., D. P. Kanungo, M. K. Arora, and S. Sarkar. 2008. "Approaches for Comparative Evaluation of Raster GIS-Based Landslide Susceptibility Zonation Maps." *International Journal of Applied Earth Observation and Geoinformation* 10: 330–341.
- Gupta, R. P., A. K. Saha, M. K. Arora, and A. Kumar. 1999. "Landslide Hazard Zonation in a Part of the Bhagirathi Valley Garhwal Himalayas Using Integrated Remote Sensing–GIS." *Himalayan Geology* 20: 71–85.
- Gupta, V., S. Kumar, R. Kaur, and R. S. Tandon. 2022. "Regional-Scale Landslide Susceptibility Assessment for the Hilly State of Uttarakhand, NW Himalaya, India." *Journal of Earth System Science* 131, no. 2: 1–18. <https://doi.org/10.1007/s12040-021-01746-4>.
- Guri, P. K., P. K. Champati ray, and R. C. Patel. 2015. "Spatial Prediction of Landslide Susceptibility in Parts of Garhwal Himalaya, India, Using the Weight of Evidence Modelling." *Environmental Monitoring and Assessment* 187: 324. <https://doi.org/10.1007/s10661-015-4535-1>.
- Haque, U., P. F. Da Silva, G. Devoli, et al. 2019. "The Human Cost of Global Warming: Deadly landslides and Their Triggers (1995–2014)." *Science of the Total Environment* 682: 673–684.
- Herald, D. 2019. "Maximum Landslide Deaths in India." <https://www.deccanherald.com/india/maximum-landslide-deaths-in-india-764827.html>.
- Live Hindustan. 2021. <https://www.livehindustan.com/uttarakhand/story-bhowali-almora-nh-opened-after-four-days-closed-due-to-landslide-after-rain-5080729.html>.
- ROC Tool. 2024. "ROC TOOL, arcSDM." <https://github.com/gtkfi/ArcSDM>.
- Creative News Express. 2023. "Creative News Express." <https://www.creativenewsexpress.com/almora-bhawali-road-closed-due-to-debris/>.
- Juyal, A., and S. Sharma. 2021. "A Study of Landslide Susceptibility Mapping Using Machine Learning Approach." In *Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, 1523–1528. Tirunelveli, India: IEEE. <https://doi.org/10.1109/ICICV50876.2021.9388379>.

- Kanungo, D. P., M. K. Arora, S. Sarkar, and R. P. Gupta. 2006. "A Comparative Study of Conventional, ANN Black Box, Fuzzy and Combined Neural and Fuzzy Weighting Procedures for Landslide Susceptibility Zonation in Darjeeling Himalayas." *Engineering Geology* 85: 347–366.
- Kanungo, D. P., M. K. Arora, S. Sarkar, and R. P. Gupta. 2009. "A Fuzzy Set Based Approach for Integration of Thematic Maps for Landslide Susceptibility Zonation." *Georisk* 3, no. 1: 30–43.
- Kanungo, D. P., S. Sarkar, and S. Sharma. 2011. "Combining Neural Network With Fuzzy, Certainty Factor and Likelihood Ratio Concepts for Spatial Prediction of Landslides." *Natural Hazards* 59: 1491–1512. <https://doi.org/10.1007/s11069-011-9847-z>.
- Khanduri, S. 2017. "Landslide Hazard Around Mussoorie: The Lesser Himalayan Tourist Destination of Uttarakhand, India." *Journal of Geography and Natural Disasters* 07, no. 2: 1000200.
- Kim, J. C., S. Lee, H. S. Jung, and S. Lee. 2018. "Landslide Susceptibility Mapping Using Random Forest and Boosted Tree Models in Pyeong-Chang, Korea." *Geocarto International* 33: 1000–1015.
- Kjekstad, O., and L. Highland. 2009. "Economic and Social Impacts of Landslides." In *Landslides—Disaster Risk Reduction*, edited by K. Sassa and P. Canuti, 573–587. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-540-69970-5_30.
- Kolat, C., R. Ulusay, and M. L. Suzen. 2012. "Development of Geotechnical Microzonation Model for Yenisehir (Bursa, Turkey) Located at a Seismically Active Region." *Engineering Geology* 127: 36–53.
- Kumar, D., M. Thakur, C. S. Dubey, and D. P. Shukla. 2017. "Landslide Susceptibility Mapping and Prediction Using Support Vector Machine for Mandakini River Basin, Garhwal Himalaya, India." *Geomorphology* 295: 115–125.
- Kumar, R., and R. Anbalagan. 2016. "Landslide Susceptibility Mapping Using Analytical Hierarchy Process (AHP) in Tehri Reservoir Rim Region, Uttarakhand." *Journal of the Geological Society of India* 87: 271–286. <https://doi.org/10.1007/s12594-016-0395-8>.
- Landslide Data. 2019. *Geological Survey of India, Government of India*. Kolkata, India: Geological Survey of India. April 15, 2019.
- Live, H. 2023. "Haldwani: Bhawali-Almora Road Closed Due to Landslide, Traffic Diverted." <https://haldwanilive.com/almoranews-nh-109-closed-due-to-landslide/>.
- Mersha, T., and M. Meten. 2020. "GIS-Based Landslide Susceptibility Mapping and Assessment Using Bivariate Statistical Methods in Simada Area, Northwestern Ethiopia." *Geoenvironmental Disasters* 7: 20.
- Nagarajan, R., A. Mukherjee, A. Roy, and M. V. Khire. 1998. "Temporal Remote Sensing Data and GIS Application in Landslide Hazard Zonation of Part of Western Ghat, India." *International Journal of Remote Sensing* 19, no. 4: 573–585.
- NDMA. 2021. *Getting a Grip on Landslides: Reducing the Risk of Landslides in India*. New Delhi: A publication of the National Disaster Management Authority, Government of India.
- Neaupane, K. M., and M. Piantanakulchai. 2006. "Analytic Network Process Model for Landslide Hazard Zonation." *Engineering Geology* 85: 281–294.
- Nourani, V., A. H. Baghanam, J. Adamowski, and O. Kisi. 2014. "Applications of Hybrid Wavelet–Artificial Intelligence Models in Hydrology: A Review." *Journal of Hydrology* 514: 358–377.
- Park, S., C. Choi, B. Kim, and J. Kim. 2013. "Landslide Susceptibility Mapping Using Frequency Ratio, Analytic Hierarchy Process, Logistic Regression, and Artificial Neural Network Methods at the Inje Area, Korea." *Environmental Earth Sciences* 68: 1443–1464.
- Park, S., S. Y. Hamm, and J. Kim. 2019. "Performance Evaluation of the GIS-Based Data-Mining Techniques Decision Tree, Random Forest, and Rotation Forest for Landslide Susceptibility Modeling." *Sustainability* 11, no. 20: 5659. <https://doi.org/10.3390/su11205659>.
- Pham, B. T., D. T. Bui, H. R. Pourghasemi, P. Indras, and M. B. Dholakia. 2015. "Landslide Susceptibility Assessment in the Uttarakhand Area (India) Using GIS: A Comparison Study of Prediction Capability of Naïve Bayes, Multilayer Perceptron Neural Networks, and Functional Trees Methods." *Theoretical and Applied Climatology* 128: 255–273. <https://doi.org/10.1007/s00704-015-1702-9>.
- Pham, B. T., I. Prakash, K. Khosravi, et al. 2019a. "A Comparison of Support Vector Machines and Bayesian Algorithms for Landslide Susceptibility Modelling." *Geocarto International* 34, no. 13: 1385–1407. <https://doi.org/10.1080/10106049.2018.1489422>.
- Pham, B. T., I. Prakash, S. K. Singh, A. Shirzadi, H. Shahabi, and D. T. Bui. 2019b. "Landslide Susceptibility Modeling Using Reduced Error Pruning Trees and different Ensemble Techniques: Hybrid Machine Learning Approaches." *Catena* 175: 203–218.
- Pham, B. T., T. Van Phong, T. Nguyen-Thoi, et al. 2020. "Ensemble Modeling of Landslide Susceptibility Using Random Subspace Learner and Different Decision Tree Classifiers." *Geocarto International* 37: 735–757. <https://doi.org/10.1080/10106049.2020.1737972>.
- Polykretis, C., C. Chalkias, and M. Ferentinou. 2019. "Adaptive Neuro-Fuzzy Inference System (ANFIS) Modeling for Landslide Susceptibility Assessment in a Mediterranean Hilly Area." *Bulletin of Engineering Geology and the Environment* 78: 1173–1187. <https://doi.org/10.1007/s10064-017-1125-1>.
- Poudyal, C. P., C. Chang, H. J. Oh, and S. Lee. 2010. "Landslide Susceptibility Maps Comparing Frequency Ratio and Artificial Neural Networks: A Case Study From the Nepal Himalaya." *Environmental Earth Sciences* 61: 1049–1064.
- Pourghasemi, H. R., B. Pradhan, and C. Gokceoglu. 2012. "Application of Fuzzy Logic and Analytical Hierarchy Process (AHP) to Landslide Susceptibility Mapping at Haraz Watershed, Iran." *Natural Hazards* 63: 965–996.
- Pradhan, B., E. A. Sezer, C. Gokceoglu, and M. F. Buchroithner. 2010. "Landslide Susceptibility Mapping by Neuro-Fuzzy Approach in a Landslide-Prone Area (Cameron Highlands, Malaysia)." *IEEE Transactions on Geoscience and Remote Sensing* 48, no. 12: 4164–4177. <https://doi.org/10.1109/TGRS.2010.2050328>.
- Raghuvanshi, T. K., J. Ibrahi, and D. Ayalew. 2014. "Slope Stability Susceptibility Evaluation Parameter (SSEP) Rating Scheme - An Approach for Landslide Hazard Zonation." *Journal of African Earth Sciences* 99, no. 2: 595–612.
- Saaty, T. L. 1980. *The Analytic Hierarchy Process*. New York, USA: McGraw-Hill.
- Saaty, T. L. 1990. "How to Make a Decision: The Analytic Hierarchy Process." *European Journal of Operational Research* 48, no. 1: 9–26.
- Saha, A. K., R. P. Gupta, and M. K. Arora. 2002. "GIS-Based Landslide Hazard Zonation in a Part of the Himalayas." *International Journal of Remote Sensing* 23, no. 2: 357–369.
- Saha, A. K., R. P. Gupta, I. Sarkar, M. K. Arora, and E. Csaplovics. 2005. "An Approach for GIS-Based Statistical Landslide Susceptibility Zonation With a Case Study in the Himalayas." *Landslides* 2: 61–69.
- Sarkar, S., and D. P. Kanungo. 2004. "An Integrated Approach for Landslide Susceptibility Mapping Using Remote Sensing and GIS." *Photogrammetric Engineering and Remote Sensing* 70, no. 5: 617–625.
- Sidle, R. C., and H. Ochiai. 2006. *Landslides: Processes, Prediction, and Land Use. Water Resources Monograph* 18. Washington, D.C.: American Geophysical Union.
- Singh, P., A. Sharma, U. Sur, and P. K. Rai. 2021. "Comparative Landslide Susceptibility Assessment Using Statistical Information Value and Index of Entropy Model in Bhanupali-Beri Region, Himachal Pradesh,

- India." *Environment, Development and Sustainability* 23: 5233–5250. <https://doi.org/10.1007/s10668-020-00811-0>.
- Singh, P., U. Sur, P. K. Rai, and S. K. Singh. 2023. "Landslide Susceptibility Prediction Using Frequency Ratio Model: A Case Study of Uttarakhand, Himalaya (India)." *Proceedings of the Indian National Science Academy* 89: 600–612. <https://doi.org/10.1007/s43538-023-00171-z>.
- Singh, R., R. K. Umrao, and T. N. Singh. 2013. "Probabilistic Analysis of Slope in Amiyani Landslide Area, Uttarakhand." *Geomatics, Natural Hazards and Risk* 4, no. 1: 13–29.
- Singh, R., R. K. Umrao, and T. N. Singh. 2014. "Stability Evaluation of Road-Cut Slopes in the Lesser Himalaya of Uttarakhand, India: Conventional and Numerical Approaches." *Bulletin of Engineering Geology and the Environment* 73, no. 3: 845–857.
- Singha, N., and S. Sarkar. 2024. "Modelling Landslide Susceptibility Along Major Transportation Corridor in Darjeeling Himalayas Using GIS-Based MCDA Approaches." *Modeling Earth Systems and Environment* 10: 1–22. <https://doi.org/10.1007/s40808-023-01942-9>.
- Sonker, I., J. N. Tripathi, and A. K. Singh. 2021. "Landslide Susceptibility Zonation Using Geospatial Technique and Analytical Hierarchy Process in Sikkim Himalaya." *Quaternary Science Advances* 4: 100039.
- Statista. 2023. "Number of Deaths Due to Landslides in India From 2010 to 2022." <https://www.statista.com/statistics/1007663/india-number-of-deaths-due-to-landslides/>.
- Sur, U., and P. Singh. 2019. "Landslide Susceptibility Indexing Using Geospatial and Geostatistical Techniques Along Chakrata-Kalsi Road Corridor, India. Indian Cartographer, Journal of the Indian National Cartographic Association (INCA), 38, 2018. Publication year 2019. ISSN:0927–8392."
- Sur, U., P. Singh, and S. R. Meena. 2020. "Landslide Susceptibility Assessment in a Lesser Himalayan Road Corridor (India) Applying Fuzzy AHP Technique and Earth-Observation Data." *Geomatics, Natural Hazards and Risk* 11, no. 1: 2176–2209. <https://doi.org/10.1080/19475705.2020.1836038>.
- Sur, U., P. Singh, and P. K. Rai. 2021. "Landslide Probability Mapping by Considering Fuzzy Numerical Risk Factor (FNRF) and Landscape Change for Road Corridor of Uttarakhand, India." *Environment, Development and Sustainability* 23: 13526–13554. <https://doi.org/10.1007/s10668-021-01226-1>.
2018. "The Wire." <https://thewire.in/environment/india-lost-79-5-billion-to-natural-disasters-in-20-years-un-report>.
2017. "Times of India." <https://timesofindia.indiatimes.com/city/dehradun/an-entire-hill-in-uttarakhand-is-falling-apart-due-to-road-expansion-on-nh-109/articleshow/61566387.cms>.
2021. "India Today." <https://www.indiatoday.in/india/story/uttarakhand-nainital-floods-landslide-kerala-dams-rainfall-bengal-odisha-bihar-rain-alert-1866782-2021-10-19>.
- Tran, T. H., N. D. Dam, F. E. Jalal, et al. 2021. "GIS-Based Soft Computing Models for Landslide Susceptibility Mapping: A Case Study of Pithoragarh District, Uttarakhand State, India." *Mathematical Problems in Engineering* 19: 9914650. <https://doi.org/10.1155/2021/9914650>.
- Tsangaratos, A., and L. Ilia. 2016. "Comparison of a Logistic Regression and Naïve Bayes Classifier in Landslide Susceptibility Assessments: The Influence of Models Complexity and Training Dataset Size." *Catena* 145: 164–179.
2019. "Amar Ujala." <https://www.amarujala.com/photo-gallery/dehradun/mountain-broken-on-the-bhowali-almora-national-highway-uttarakhand>.
- Umrao, R. K., R. Singh, M. Ahmad, and T. N. Singh. 2011. "Stability Analysis of Cut Slopes Using Continuous Slope Mass Rating and Kinematic Analysis in Rudrapur District, Uttarakhand." *Geomaterials* 1, no. 3: 79–87.
- Van, C. J. W., E. Castellanos, and S. L. Kuriakose. 2008. "Spatial Data for Landslide Susceptibility, Hazard, and Vulnerability Assessment: An Overview." *Engineering Geology* 102: 112–131.
- Varnes, D. J. 1984. "International Association of Engineering Geology Commission on Landslides and Other Mass Movements on Slopes: Landslide Hazard Zonation: A Review of Principles and Practice." *Natural Hazards Series* 3: 63.
- Verma, R. K., P. Sharma, R. Singh, and T. N. Singh. 2021. "Evaluation of Slope Stability Analysis Using Kinematic and Chart Method: A Case Study." *Journal of the Geological Society of India* 97, no. 11: 1387–1395.
- Weather2visit. December 15, 2022. <https://www.weather2visit.com/asia/india/almora.htm>.
- Wu, Y., Y. Ke, Z. Chen, S. Liang, H. Zhao, and H. Hong. 2020. "Application of Alternating Decision Tree With AdaBoost and Bagging Ensembles for Landslide Susceptibility Mapping." *Catena* 187: 104396.
- Yalcin, A. 2008. "GIS-Based Landslide Susceptibility Mapping Using Analytical Hierarchy Process and Bivariate Statistics in Ardesen (Turkey): Comparisons of Results and Confirmations." *Catena* 72: 1–12.
- Yarrakula, K., D. Deb, and B. Samanta. 2013. "Comparative Evaluation of Cartosat-1 and SRTM Imageries for Digital Elevation Modelling." *Geo-Spatial Information Science* 16, no. 2: 75–82. <https://doi.org/10.1080/10095020.2012.747645>.
- Yilmaz, I. 2010. "Comparison of Landslide Susceptibility Mapping Methodologies for Koyulhisar, Turkey: Conditional Probability, Logistic Regression, Artificial Neural Networks, and Support Vector Machine." *Environmental Earth Sciences* 61: 821–836.