

Knowledge-Driven Geospatial Techniques for Landslide Susceptibility Mapping: A Case Study in West Siang District, Arunachal Pradesh, India

Victor Saikhom^{1*}, Manoranjan Kalita², M Somorjit Singh³, N William Singh⁴

^{1,2}Civil Engineering Department, Assam Don Bosco University, Guwahati, Assam, India

³North Eastern Space Applications Centre, Umiam, Meghalaya, India

⁴Col Shishupal Security Consultancy & Services, Shillong, Meghalaya, India

¹ victorsaikhom@gmail.com

How to cite this article: Victor Saikhom, Manoranjan Kalita, M Somorjit Singh, N William Singh (2024) Knowledge-Driven Geospatial Techniques for Landslide Susceptibility Mapping: A Case Study in West Siang District, Arunachal Pradesh, India. *Library Progress International*, 44 (2), 899-903.

Abstract

Landslides are frequent natural hazards that cause substantial damage to life, infrastructure, and ecosystems, especially in mountainous areas. The term "landslide" encompasses various processes involving the downward and outward movement of slope-forming materials, including natural rock, soils, artificial fills, or combinations of these materials. This study aims to delineate the landslide susceptibility zones in the West Siang District of Arunachal Pradesh, using a knowledge-driven heuristic approach. By integrating eight geo-environmental factors—lithology, landforms, lineaments, soil texture, drainage, land use/land cover (LULC), slope, and aspect—the weighted overlay method was employed to create a comprehensive landslide susceptibility map in a Geographic Information System (GIS) environment. The rank and weight of each factor, assigned based on expert knowledge, reflect their influence on landslide occurrence, with higher values indicating greater impact. The results categorised the area into five susceptibility classes: very low, low, moderate, high, and very high. The model validation, achieved by overlaying the historical landslide inventory, showed that 80.82% of the historic landslides fell within the high and very high susceptibility zones. The study is a valuable tool for planning, hazard management, and infrastructure development in landslide-prone areas.

Keywords: Landslide susceptibility mapping, geospatial techniques, knowledge-driven method, GIS, AHP, risk assessment.

Introduction

Landslides, or slope failures, are major recurring natural hazards that cause significant loss of life and property in hilly terrains [4]. Historically, the increasing trend of land coming under human utilization has led to land-use development in areas susceptible to landslides, including mountainous regions and steep slopes. While land utilization promotes economic growth, it can also have adverse environmental impacts. The northeastern region of India, particularly the Arunachal Himalayas, falls into the high and medium-to-high categories of the Global Landslide Susceptibility Map [8]. The region is highly susceptible to landslides due to its rugged terrain, heavy rainfall, and active tectonics. Historical data indicate that landslides in this region have caused significant economic losses and human casualties, as reported by Kaur et al. [10]. Landslide susceptibility mapping (LSM) plays a crucial part in mitigating these risks by identifying areas most likely to experience landslides as it provides foundational information for planning and development activities by government organizations and decision-makers.

The heuristic model is an indirect and mostly qualitative mapping method that depends heavily on existing knowledge about the causes and factors of instability in the study area [9]. This model can account for numerous environmental factors, is time-efficient, and is applicable across various scales [6][2][11]. The knowledge-driven heuristic approach relies heavily on expert opinion, where the theoretical understanding of physical processes, combined with field experience, informs the expert knowledge that drives the model's success [15].

In this study, a landslide susceptibility map was generated by integrating various geo-environmental factors, including lithology, landforms, structures/lineament and lineament density, soil, drainage and drainage density, land use/land cover (derived from remote sensing data), slope, and aspect. The study area, spanning from Tato to Monigong, is situated along the international boundary in West Siang district of Arunachal Pradesh (figure 1). These villages are frequently cut off from the rest of the world during monsoon months due to landslides and erosion, which disrupt communication and make it difficult to procure daily necessities. Recognising the need for a landslide susceptibility map is essential for designing alternative routes to bypass landslide-prone areas, a critical concern for the region. The integration of remote sensing, geographic information systems (GIS), and on-site observations was used to develop the landslide susceptibility map.

Objective

The study aims to create a detailed landslide susceptibility map using a knowledge-driven heuristic approach, which can serve as a critical tool for planners and decision-makers, aiding in infrastructure development and hazard management in landslide-prone areas.

Study area

Arunachal Pradesh, located in northeastern India, covers an area of 83,743 sq. km and experiences high rainfall (2500-3000mm annually) and frequent landslides. The study area, from Tato to Monigong in West Siang district of Arunachal Pradesh, spans 788.06 sq. km and lies between latitudes 28°27' N to 28°55' N and longitudes 94°10' E to 94°29' E (Figure 1). The elevation ranges from 749 to 4071 meters, and landslides frequently disrupt the area, particularly during the monsoon season. These disruptions emphasise the need for an accurate landslide susceptibility map to aid safer infrastructure planning and development.

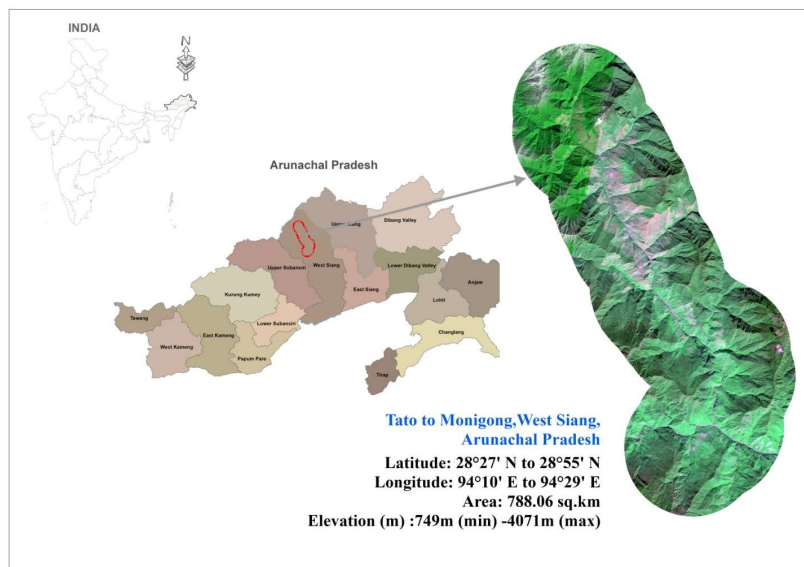


Figure 1: Study area

Data and Methodology

The expert knowledge-based approach to assessing landslide susceptibility generally involves three main steps: (i) gathering insights from domain experts, (ii) identifying and analyzing the conditioning factors, and (iii) forecasting landslide susceptibility [7]. The expert-knowledge-based approach for generating landslide susceptibility maps begins with selecting key geo-environmental factors such as slope, aspect, lithology, land use/land cover (LULC), drainage density, lineament density, soil type, and geomorphology along with the basemap.

Data for these factors are gathered from sources like satellite imagery (IRS-R2 LISS-IV), ALOS DEM (12.5m resolution), soil texture maps with the aid of small-scale maps [12], geological & topographical maps from the Geological Survey of India (GSI) and Survey of India (SOI), and limited field surveys. Preprocessing techniques, such as orthorectification, enhancement techniques and rasterisation, are applied to prepare thematic layers.

The weights and ranks were assigned to geo-environmental factors based on a knowledge-driven heuristic approach [6] in the present analysis of landslide susceptibility. The source of knowledge comes from human expertise, which must be gathered and integrated into a knowledge-based system. Experts require two types of

information: (i) the conditioning factors that influence landslide susceptibility in the area, and (ii) the ways in which these conditioning factors impact landslide susceptibility [9]. In this approach, factors that had a greater influence on the landslide occurrence were assigned higher weights and ranks. On a scale ranging from 1 to 10, factors rank was assigned with 10 being the most influenced and 1 the least. Similarly, further weights of factor subclasses were assigned (table 1).

Table 1: Rank and weightage of geo-environmental factors

Para-meter	Weight	Category	Rank
Slope Gradient	10	0-15	1
		15-25	2
		25-30	4
		30-35	6
		35-40	7
		40-45	8
		45-60	9
		>60	10
Lithology	9.5	Gneiss	3
		Granite (Tourmaline Granite)	4
		Granitoid Gneiss	6
		Schist	7
Structure/ Lineament Density	7.5	Low	4
		Moderate	6
		High	8
Geomorphology	7	Structural Hills Highly Dissected	7
		Structural Hills Moderately Dissected	6
		Structural Hills Less Dissected hills	4
		Structural Hills Highly Dissected - Snow Cover	7
		Channel Bar	0
		Point Bar	0
		Cuesta	3
		River Terrace	0
Drainage Density	6.5	Low	4
		Moderate	6
		High	8
Land Use/ Land Cover	6	Built-up Area	3
		Cropland	1
		Scrub land dense	3
		River/Stream/Drain/Lake/Pond	0
		Shifting Cultivation	5
		Open Forest	4
		Closed Forest	2
		Sandy Area	0

		Transportation	3
		Fallow Land	1
		Landslides	10
		Snow/Glacial Area	5
		Barren rocky	8
Soil	4	Loamy Skeletal Soil	5
		Sandy Skeletal Soil	6
Slope Aspect	2	Flat	0
		North Facing	1
		NE Facing	3
		East Facing	5
		SE Facing	7
		South Facing	8
		SW Facing	6
		West Facing	4
		NW Facing	2

The Analytical Hierarchy Process (AHP) can assist in systematically determining these weights. The landslide susceptibility index (LSI) is calculated as a weighted sum of the factors using the formula:

$$LSI = \sum_{i=1}^n (w_i \times r_i)$$

where w_i is the weight of the i^{th} factor, r_i is the rank of the i^{th} factor, and n is the total number of factors. The weighted overlay analysis (WOA) in a GIS environment combines these thematic layers to generate the final LSI for each pixel. The methodology flowchart used for carrying out this study is shown in *Figure 2*.

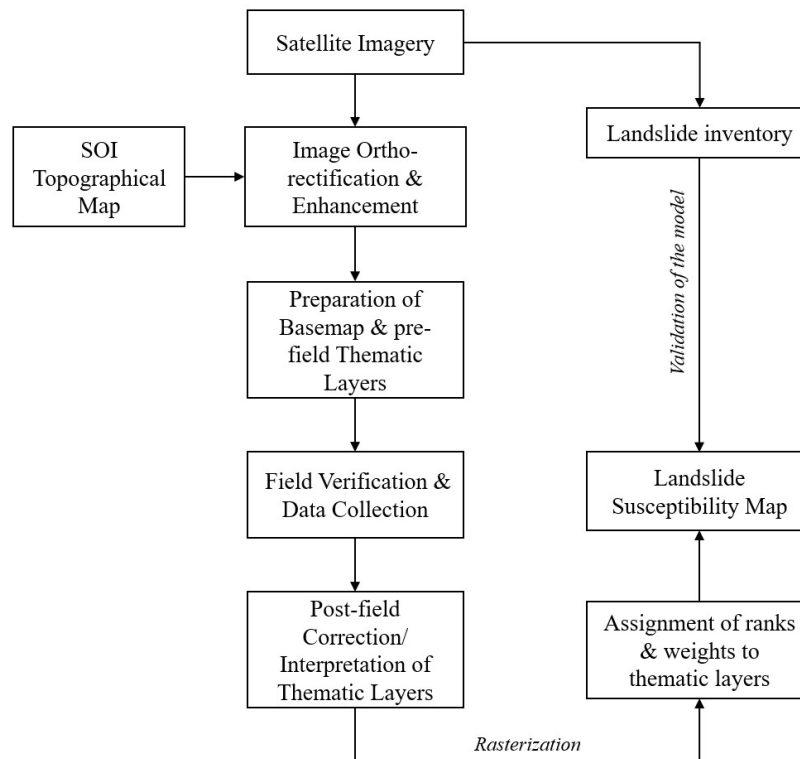


Figure 2: Methodology flow chart

The LSI values are classified into susceptibility zones (very low to very high) using methods like Natural Breaks. The map is validated by overlaying historical landslide events on the susceptibility map. The accuracy was evaluated by calculating the percentage of historical landslides falling into the high and very high susceptibility zones.

Result and Analysis

The analysis for landslide susceptibility in the West Siang District of Arunachal Pradesh utilized GIS and remote sensing data to integrate multiple geo-environmental factors. The study examined various factors such as lithology, slope, aspect, lineament density, drainage density, and land use/land cover to assess their contributions to landslide occurrences. A base map was prepared using satellite imagery (IRS-R2 LISS IV) and topographic maps from the Survey of India (SOI), which included essential geographic features such as roads, settlements, and drainage patterns. This base map served as the foundation for integrating thematic layers critical for analyzing landslide susceptibility.

Lithology significantly influences landslide susceptibility, as the area comprises migmatitic gneisses from the Sela group and schist from the Dirang/ Lumla formation. The presence of younger tourmaline granite intrusions further complicates the geological landscape, increasing the risk of slope failures.

Geomorphology also plays a crucial role as the region features highly dissected structural hills and river terraces, which are inherently unstable. The classification of these landforms based on remote sensing data helped identify high-risk zones.

Lineament density, reflecting fractures and faults in the bedrock, contributes to slope instability. The Main Central Thrust (MCT) and other thrust faults increase landslide susceptibility, as these features create weak zones in the crust.

The drainage pattern, dominated by the Siyom River, influences landslide risk, with areas of high drainage density being more susceptible to failures during heavy rainfall events. The drainage map, prepared using topographic and remotely sensed data, indicated a strong correlation between drainage patterns and landslide occurrences.

Soil texture was categorised into loamy-skeletal and sandy-skeletal soils, impacting water infiltration and slope stability. While the soil texture map was generalised, its influence on landslide susceptibility was acknowledged, though with a lower weight compared to other factors.

Slope and aspect are critical in assessing landslide risks, as steeper slopes are more prone to failure. Slope gradients were classified into eight categories (table 2), with slopes steeper than 45 degrees considered particularly vulnerable. South-facing slopes tend to dry out faster, reducing their risk compared to north-facing slopes, which retain moisture longer.

Table 2: Slope class, area and percentage

Sl. No	Slope Class	Area (Km ²)	Area (%)
1	0-15	32.40	4.06
2	15-25	236.05	29.61
3	25-30	179.13	22.47
4	30-35	154.40	19.37
5	35-40	102.44	12.85
6	40-45	52.55	6.59
7	45-60	39.06	4.90
8	>60	0.95	0.12

Table 3: Slope aspect class, area and percentage

Sl. No	Aspect Class	Area (Km ²)	Area %
1	Flat	0.10	0.01
2	North Facing	35.852	4.49
3	Northeast Facing	92.24	11.57
4	East Facing	104.68	13.13
5	Southeast Facing	99.87	12.53
6	South Facing	90.70	11.38

7	Southwest Facing	122.66	15.39
8	West Facing	137.24	17.21
9	Northwest Facing	113.65	14.25

In its most basic form, land use can be defined as how people in the nation use their property—from farms to golf courses, homes to fast food restaurants, and hospitals to cemeteries. Conversely, land cover describes the topography of the earth, including any plants, objects, water, urban infrastructure, or barren soil. Although both categories are related and interchangeable, land use is often inferred from land cover. Developmental planning starts with data on existing land cover and land use, along with their geographical distribution patterns. The current land use/land cover map (figure 3) was prepared using LISS-IV data acquired on 13 February 2022, and various classes were delineated using the technical manual prepared by the National Remote Sensing Centre (NRSC) for the NRSLULC50K Mapping Project [14]. Adjustments were made by the specifications for susceptibility mapping.

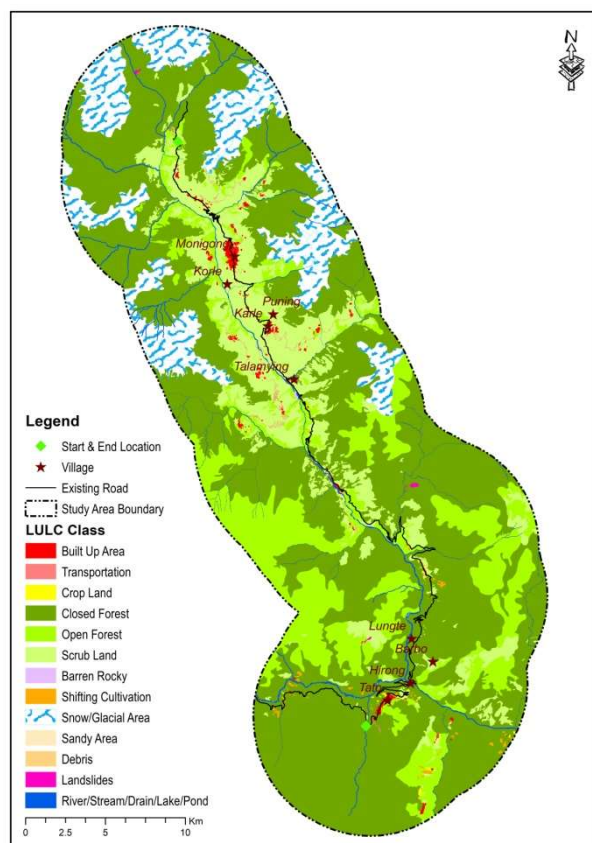


Figure 3: Land use land cover map

Closed forests dominate the Tato to Monigong area, covering 441.16 sq. km (55.94% of the total area), while debris constitutes the least, at 0.04 sq. km (0.01%). The complete data for various land use and land cover classifications in the corridor are displayed in Table 4.

Table 4: LULC class, area and percentage

Sl. No	LULC Class	Area (Km ²)	Area (%)
1	Built Up Area	4.32	0.55
2	Transportation	2.85	0.36
3	Crop Land	0.29	0.04
4	Closed Forest	441.16	55.94
5	Open Forest	135.07	17.13

6	Scrub Land	103.40	13.11
7	Barren Rocky	0.09	0.01
8	Shifting cultivation	1.32	0.17
9	Snow / Glacial area	91.93	11.66
10	Sandy Area	0.27	0.03
11	Debris	0.04	0.01
12	Landslides	0.35	0.04
13	River / Stream / Drain/Lake/Pond	7.51	0.95

Landslide Distribution Map/ Preparation of landslide inventory map

Landslide occurrence is based on the principle that “slope failure is more likely to occur under a condition that led to past instability” [5]. Therefore, it is vital to trace the historical landslides to gain insights and predictions for potential future landslides. Understanding the stability of the hill slopes in the route corridor under investigation is aided by the spatial distribution of the landslide map. The process of interpreting a landslide involves using knowledge of interpretation techniques and diagnostic features, such as crescent shape, light or bright tone head scarp in contrast to the surrounding area, sharp break in slope between the head scarp and displaced mass, etc. The landslide inventory was created by integrating various free open-source high-resolution imagery and IRS-1C LISS IV satellite data, for further accuracy and detail published maps from the Geological Survey of India have been used.

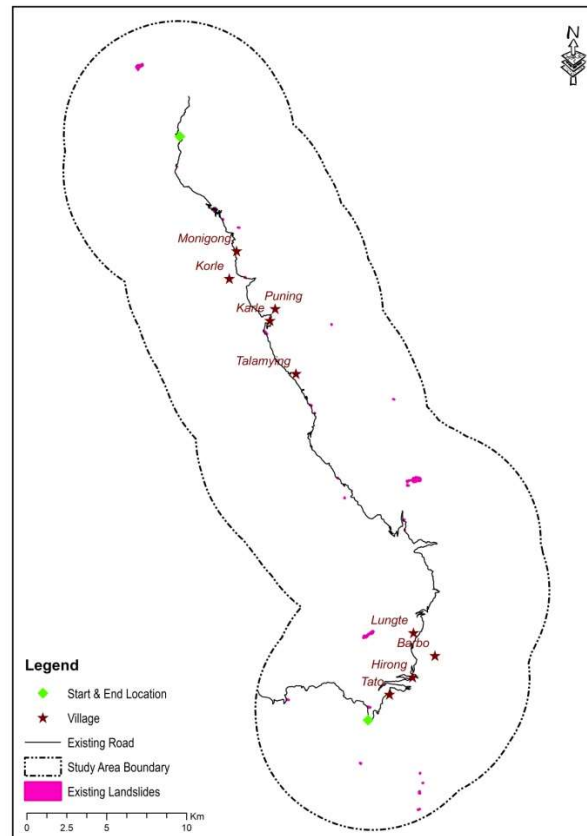


Figure 4: Landslide distribution map

The landslide distribution map of the Tato to Monigong corridor is shown in figure 4. A total of 35.22 hectares of area is covered by the 30 active landslides and the 3 historical landslides. Debris slides account for the majority of landslides seen in the corridor and these slides range in size from 0.07 to 7.87 hectares.

Spatial Data Integration and Landslide Susceptibility Zonation

Several methods or approaches have been developed by experts for creating landslide susceptibility zonation maps. Susceptibility refers to the quantitative or qualitative evaluation of the classification, size (in terms of volume or area), and spatial distribution of existing or potential landslides in a given region. It may also involve an analysis of the velocity and intensity of both current and possible landslide activity [1]. Zonation involves dividing a land surface into uniform areas or zones, which are then ranked based on the varying levels of actual or potential hazard posed by mass movements [17].

Landslide Susceptibility zonation maps can be generated using pure statistical techniques as well as a pure knowledge-based approach [15][3][13]. In the present analysis of landslide susceptibility, a knowledge-driven heuristic approach [6] was adopted. Each geo-environmental parameters or element that affect landslides, such as lithology/rock type, soil texture, slope, aspects, geomorphology/ landform, drainage (density), land use/land cover and structure/ lineament (density) was assigned weights.

Before weight assignment, the drainage density—which is the ratio of all the streams in a basin to its area and lineament density—which is the average length of the lineaments per unit area was calculated. The resulting density map was categorized into three groups: low, moderate, and high. Each group was given a weight based on how much of an impact it had on the likelihood of landslides. The cumulative susceptibility map was then generated by integrating the weight maps with expert opinion and information based on rank in GIS using the Weighted Overlay Method. These weights and rankings are assigned based on their presumed or anticipated significance in triggering mass movements or landslides, as well as the pre-existing knowledge that experts have about the specific study area [9]. The susceptibility pixels are classified into five categories—very low, low, moderate, high, or very high—based on natural cut-off ranges. Once the susceptibility map for both study areas is generated, a majority filter is applied using a 3x3 pixel window. This helps to remove or merge small pixel areas or classes by blending them with the nearest pixels in larger regions or classes.

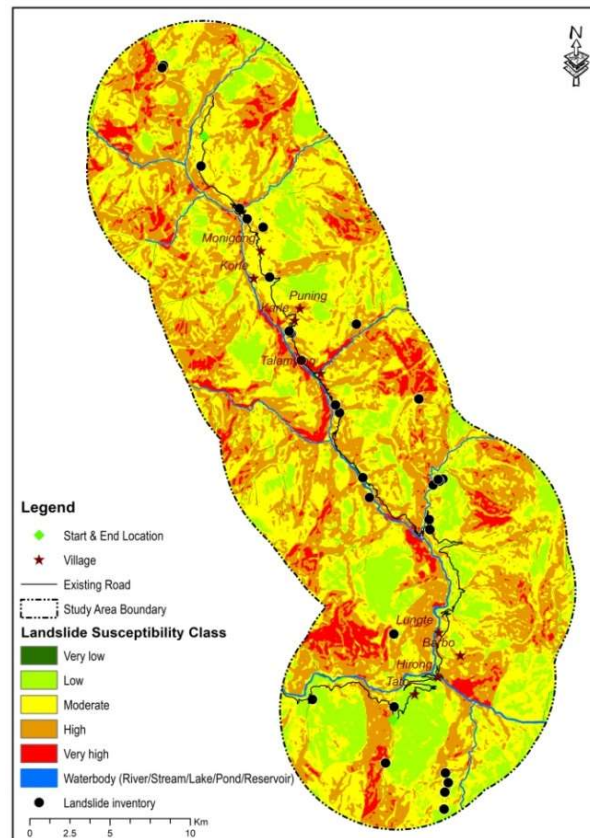


Figure 4: Landslide susceptibility map overlaid with landslide inventory

The landslide susceptibility map of Tato to Monigong area is shown in figure 4. The area and percentage of each landslide susceptibility class or zones within the corridor are given in Table 5. This table shows that the low and moderate classes make up, respectively, 16.26 and 40.70 percent of the total area and 35.92 and 6.54 percent, are occupied by the high and very high susceptibility classes. The very low susceptibility class makes up 0.58 percent

of the total area. This lower class occupies hilltops with a slope of 0 to 15 degrees, valley areas and river beds.

Table 5: Landslide susceptibility class, area and percentage

Sl. No	Susceptibility class	Area (Km ²)	Area %
1	Very Low	4.54	0.58
2	Low	127.39	16.26
3	Moderate	318.97	40.70
4	High	281.44	35.92
5	Very High	51.28	6.54

Model Validation

The landslide inventory generated by using freely available open-source high-resolution imagery and IRS-1C LISS IV satellite data with the aid of published maps from the Geological Survey of India was used for the model validation. The susceptibility map was validated and the current landslide map was superimposed to evaluate the landslide susceptibility map. It is observed that the total area of landslide incidence is highest in the high susceptibility class, which is 24.62 ha, and subsequently in the moderate and very high class, i.e. 6.46 ha and 3.92 ha respectively. The landslide susceptibility map was validated, which comprises 80.82% of the historic landslides in the very high and high landslide susceptibility zones. The details of the model validation are shown in figure 4 & table 6. The method of superimposing the existing landslide map over the landslide susceptibility map is commonly used for validation. If multi-temporal maps of the distribution of hazardous or landslide events are provided, this method can be improved or modified further.

Table 6: Landslide susceptibility class, area and percentage

SL. No	Susceptibility Class	Landslide Area (Ha)
1	Very Low	0
2	Low	0.31
3	Moderate	6.46
4	High	24.62
5	Very High	3.92

Conclusion

The landslide susceptibility map of the study area was generated by implementing a knowledge-driven heuristic approach and adopting the Weighted Overlay Method in a GIS environment. The final results show that the very high and high landslide susceptibility zone comprises 80.82% of the historic landslides which validates the model. The majority of landslides observed within the study area are debris slides which size is ranging from 0.07 to 7.78 hectares. Moreover, from the landslide susceptibility map generated of the study area, it is observed that the moderate susceptible zone makes up the largest area of 318.97 sq. km which is 40.70 percent of the total area and the very low susceptible zone makes up the lowest area of 4.54 sq. km which is of 0.58 percent of the total area. The results show that the major triggering factors for landslides are lithology, landforms, structures/lineament, drainage, land use/land cover, slope and aspects. The landslide susceptibility map will be viable for planners and decision makers providing the strategic planning and developmental activities in the area. This study also further contributes the landslide studies in mountainous areas.

Within the corridor identified in the study area, more than 80% of the areas are inaccessible. Keeping in view of these constrained, field investigations of various parameters used in the study were carried out along the road and other areas wherever possible to reach on foot. It may also be mentioned that the soil texture map used in the study was derived from a small-scale map. Hence, it is highly generalised and arbitrary and it is given lower priority while generating the landslide susceptibility map. The study does not cover the various aspects of geo-engineering characteristics of rocks, such as abrasive resistance, crushing strength, fracture/joint patterns, dip-slope relationship, orientation and tectonic relationships. The landslide susceptibility map generated is qualitative and

only provides a general idea of the spatial possibility of landslide occurrences.

From the preceding findings and observations, future studies must focus on incorporating high-resolution soil and geotechnical data to enhance the model's accuracy. Integrating machine learning and statistical models like random forests or logistic regression could improve the objectivity of factor weighting. Additionally, adding dynamic factors like rainfall intensity and land use changes over time would make the model more adaptable. Advanced remote sensing technologies, such as LiDAR and InSAR, could also be used to monitor slope stability in real time. Expanding field investigations to inaccessible areas through tools like UAVs would improve validation and reliability. Multi-temporal satellite data can be incorporated for continuous model updates, while future work could also include risk and vulnerability assessments to evaluate the socio-economic impact of landslides and guide mitigation efforts.

Conflict of Interests

This paper is an attempt to highlight the efficacy of geospatial technology in the preparation of landslide susceptibility maps for planning and developmental activities with predefined criteria. The authors declared that there is no conflict of interest regarding the work and the publication of this paper.

Acknowledgements

The authors extend their sincere thanks to the North Eastern Space Applications Centre, Umiam, Meghalaya for providing the opportunity to carry out the work.

References

- [1] Australian Geomechanics (Abstract). (2007). Landslide Risk Management. *Journal and News of the Australian Geomechanics Society*, Vol. 42 No. 1.
- [2] Ayalew, L., Yamagishi, H., Watanabe, N., Marui, H. (2004). Land-slide susceptibility mapping using a semi-quantitative approach, a case study from Kakuda-Yahiko Mountains, Niigata, Japan. In: Free, M., Aydin, A. (Eds.), *Proceedings of the 4th Asian Symposium on Engineering Geology and the Environment, Geological Society of Hong Kong*, vol. 7, pp. 99 – 105.
- [3] Carrara, A., Cardinali, M., Guzzetti, F. and Reichenbach, P. (1995). GIS technology in mapping landslide hazard. In: Carrara, A. and Guzzetti, F.(eds.), *Geographical Information Systems in assessing natural hazards*, Dordrecht: Kluwer, pp. 135- 175.
- [4] Champati ray, P.K., and Lakhera, R.C. (2004). Landslide Hazards in India, Proceedings of the Asian Workshop on Regional Capacity Enhancement for Landslide Mitigation (RECLAIM), organised by Asian Disaster Preparedness Centre (ADPC), Bangkok and Norwegian Geotechnical Institute, Oslo, Bangkok, 13-15 Sept. 2004
- [5] Fausto Guzzetti, Alessandro Cesare Mondini, Mauro Cardinali, Federica Fiorucci, Michele Santangelo, Kang-Tsung Chang. (2012). Landslide inventory maps: New tools for an old problem. *Earth-Science Reviews*, Volume 112, Issues 1–2, 2012, Pages 42-66. <https://doi.org/10.1016/j.earscirev.2012.02.001>.
- [6] Guzzetti, F. Carrara, A., Cardinali, M., and Reichenbach, P. (1999). Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. *Geomorphology*, Vol. 31, pp. 181-216
- [7] Harjeet Kaur, Srimanta Gupta, Surya Parkash, Raju Thapa, Arindam Gupta &G. C. Khanal. (2019). Evaluation of landslide susceptibility in a hill city of Sikkim Himalaya with the perspective of hybrid modelling techniques. *Annals of GIS*, DOI: 10.1080/19475683.2019.1575906
- [8] Hong, Y. and Robert F. Adler. (2008). Predicting global landslide spatiotemporal distribution: Integrating landslide susceptibility zoning techniques and real-time satellite rainfall estimates, *Int. J. of Sediment Research*, Vol.23, pp 249-257.
- [9] IIRS, 2008. Landslide Hazard Zonation Mapping Along Shillong-Silchar-Aizawl Highway Corridor In Northeastern Region Of India, *Technical Report and Atlas*, Issue: Dec., 2008
- [10] Kaur, H., Gupta, S. & Parkash, S. (2017). Comparative evaluation of various approaches for landslide hazard zoning: a critical review in Indian perspectives. *Spat. Inf. Res.* 25, 389–398. <https://doi.org/10.1007/s41324-017-0105-7>
- [11] M. Ruff, K. Czurda. (2008). Landslide susceptibility analysis with a heuristic approach in the Eastern Alps (Vorarlberg, Austria), *Geomorphology*. Vol 94, Issues 3–4, 2008, Pages 314-324. <https://doi.org/10.1016/j.geomorph.2006.10.032>.
- [12] NBSS & LUP, (1997). *Soils Arunachal Pradesh for Optimizing Land Use*, NBSS, Publ.55b.

- [13] NRSA, (2001). Technical Report and Atlas: Landslide Hazard Zonation Mapping in the Himalayas of Uttaranchal and Himachal Pradesh using Remote Sensing and GIS techniques, National Remote Sensing Agency, Department of Space, Hyderabad.
- [14] NRSA, (2006). Manual, National Land use Land cover Mapping using Multi-Temporal Satellite Data, National Remote Sensing Agency, Dept. of Space, Govt. of India, Hyderabad NRSC-ISRO, GSI, 2012.
- [15] Van Westen, C.J. (1993). Application of Geographic Information Systems to Landslide Hazard Zonation. *Unpublished Thesis*.
- [16] Van Westen, C.J., Rengers, N. & Soeters, R. (2003). Use of Geomorphological Information in Indirect Landslide Susceptibility Assessment. *Natural Hazards* 30, 399–419 (2003). <https://doi.org/10.1023/B:NHAZ.0000007097.42735.9e>
- [17] Varnes, D. J and the International Association of Engineering Geology Commission on Landslides and Other Mass Movement on Slopes. (1984). *Landslide Hazard Zonation: A Review of Principles and Practice*. UNESCO, Paris.