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LNRF-Based Landslide Zonation: Enhancing Risk Assessment in Badakhshan, Afghanistan

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Abstract. Landslides are a major geological hazard with significant annual consequences for humans and the economy. Hence, it is imperative to scrutinize and comprehend the elements that contribute to these occurrences and formulate efficient management strategies. Establishing zoning for risk assessment, damage evaluation, and management is crucial because of landslides' manageable and predictable nature compared to other natural disasters such as floods, volcanoes, and earthquakes. This study aims to examine the factors that contribute to the occurrence of landslides and evaluate their frequency in the Argo district of Badakhshan Province, Afghanistan, using mathematical and quantitative models. This study examined and digitally mapped several vital factors that significantly impact the occurrence of landslides, such as fault lines, proximity to roads, rock type, slope gradient, slope aspect, and land use. This analysis was conducted using the ArcGIS software. ETM and TM satellite images and Google Earth imagery were used for visual examination. The Landslide Numerical Risk Factor (LNRF) model helped generate weighted maps identifying areas with a high landslide risk in the study region. The results showed that west slope shows moderate instability and 12% landslide extent, and southeast slopes, though smaller, are more susceptible to landslides, with instability levels and extents of 15% and 17%, respectively. Most landslides in this region occurred within 100 m of faults. The area affected by landslides is 7 ha or 43% of the total area.

Keywords: Landslide Risk Zoning; Geographic Information System; LNRF Model; Argo-Badakhshan.

1. Introduction

The location of Afghanistan within the Alpine-Himalayan orogeny belt, in conjunction with the country's varied weather conditions, has led to frequent changes in the country's climate, geology, and geomorphology. These changes have resulted in numerous natural disasters, including landslides, which cause significant damage and injuries annually.

Mitigating mountainous hazards requires landslide susceptibility mapping (LSM). The Landslide Nominal Risk Factor (LNRF) method is effective for precise landslide zonation [1,2]. [3] developed the

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

landslide map using LNRF and geographic information systems (GIS). GIS was used in many studies to develop zonation and counters maps based on various properties of soils [4–7]. This method generates susceptibility maps using the lithology, slope, aspect, and fault distance [1]. With an AUC value of 0.77, [2] found that remote sensing and GIS made maps more accurate and reliable. When comparing Landslide Susceptibility Indexes, the LNRF works about the same as the frequency ratio and the Analytical Hierarchy Process. According to [8,9], the maps put areas into groups based on their amount of risk. This helps managers and engineers lower risk. Managing landslide risks depends heavily on understanding the needs of the ground (topography), as emphasized by [10]. [11] developed a systematic dynamics model to emulate and investigate the probable prospective condition of desertification in Egypt. To increase the effectiveness of catastrophe detection and management, [12] created methods for measuring the scale of floods and evaluating damage caused by floods that may be used as guidelines for GIS and RS operations. Landslide disaster mapping helps prioritize risk-mitigation activities in the region. It ranks the area according to the present and anticipated danger from potential slides [13]. [14] used a partially automatically generated landslide inventory and a statistical approach to evaluate the geographical landslide potential in the Garhwal Himalaya, India. Soil erosion is a major contributor to landslides, driven by factors such as environmental and climatic conditions and the soil's chemical properties [15–18]. Landslides typically occur when the soil's shear strength decreases significantly or approaches zero, resulting in slope failure [3,19]. Many maps predicting landslides have also been created recently utilizing statistical techniques based on geographic information systems (GIS), such as Weights of Evidence models and Frequency Ratio [20–25].

Using the LNRF approach, [2] developed a detailed landslide susceptibility map for an area within the Western Ghats region, demonstrating its effectiveness for map preparation. Scale, resolution, and variable selection affect the random forest model's susceptibility mapping of landslips. [26], Studied and evaluated how these attributes (scale, resolution, variable selection) influence landslide susceptibility mapping by using a random forest model. The research conducted by [27,28], and [29] have used the Landslide Nominal Risk Factor (LNRF) method and the Frequency Ratio (FR) model. The researchers applied machine learning algorithms to detect high-risk areas while the authors analyzed demographic NLs attributes (lithology, slope, distance to rivers and roads, land use/thatching). As supported by [28], the closeness to rivers, the distance to highways, and the slope grade are key common factors to landslide occurrence in the Badakhshan Province, Afghanistan. The outcomes as previously mentioned were influenced by various researchers. The AHP area density model has shown to be a higher efficiency in some instances in comparison to each other [30]. Integration of these models with Geographic Information Systems (GIS) may yield valuable tools for creating maps that identify [high-risk areas] landslide susceptible areas and mitigative efforts mainly on sensitive areas (particularly in areas that are sensitive). In conducting landslide susceptibility mapping (for) the Nojian Watershed, which is located side of the Iranian part, [1] utilized the LNRF, FR, and AHP models. According to [31], an extensive evaluation of the possibility of landslides occurring in Afghanistan has been undertaken with the use of effective neural networks and remote sensing techniques. In their study, [32] employed a Frequency Ratio Model, which has been effective in assessing hazard, vulnerability, and the spatial distribution of landslides, based on the geological and topographical factors in the Shahpur Valley, situated in the Eastern Hindu Kush region of Afghanistan. According to [33], among the approaches utilized in determining landslide susceptibility in the Ulus district of Bartın, northern Turkey, the artificial neural network-based method was the best option. Gupta and Joshi (1990) introduced the LNRF model, a method of assigning weights to GIS layers and then integrating the weights to create a zoning map. [34] classified the Himalayan Aglar Basin using weighting, GIS, and landslide factors. According to empirical observations, landslides are positively correlated to the

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

amount of sediment. [35] examined landslide causation in the Kathgodam-Nainital area of the Himalayas. The study utilized LNRF risk assessment to assess causation factors of landslides.

The factors include lithological characteristics, geological composition, marl layering slope, dense tree cover, and a substantial marl soil layer. These factors can significantly contribute to landslides. Identifying and classifying areas for landslide susceptibility and establishing zones of risk is important for the assessment of environmental hazards and watershed management [36]. In a study by Larsen & Parks (1997), the spatial relationship between landslides and roads was examined in a forested mountainous region. landslide risk zoning approaches were evaluated in the Bojnord Urban Watershed, Iran by [37]. Based on the survey, the results obtained from the information value and multivariate regression analyses were deemed acceptable and satisfactory.

Hierarchical analysis and bivariate statistics were used [38] to determine the causes of the landslides in Ardesen, Turkey. According to this study, land use criteria, lithology, slope, and weathering were the main factors affecting landslides. The results also suggest that hierarchical analysis is the best model. [39] examined the effects of rainfall on watershed surface landslides. A model was created to demonstrate how rainfall affects the environmental risk of landslides. [40] Landslide risk zoning in the Zangvan watershed of Ilam province was compared using four information value methods: surface density, hierarchical analysis, and Gopana and Joshi's method. They found that the information value method is more efficient. Assessing domain instability is a highly intricate matter, similar to other environmental and geological issues because it involves multiple factors that influence the occurrence of domain instability [41]. In the Laktrashan basin in Mazandaran province, [42]used the LNRF method and found that 46.75 hectares of the 525.7-hectare basin are unstable for landslides. Downslope collapses are also known as landslides. In addition, it can be used to define a particular category of mass displacement. All slope instability events that cause a significant amount of material to be displaced downhill are included in the scope [43]. Using LNRF, [44]examined landslide zoning in Jae Haraz (Along of Haraz Freeway, Iran) in 2018. Road construction has been found to significantly contribute to landslides. Because of the humidity, the northern and northwestern slopes were more susceptible. In "AHP, LNRF, and FAHP hierarchical analysis methods in landslide risk zoning (a case study of Alang Dareh watershed)," [1]compared the three ways. The LNRF method was chosen as the final model because it fit the environment of the study area. [46] studied "Zoning the risk of domain instability with the LNRF model and GIS in the Kalan Malair basin." Data analysis and mass movement detection in the Kalan dam basin were successfully performed using the LNRF model. Comprehensive field investigations supported these findings. In their study, [46]utilized the LNRF model to investigate landslide risk and damage zoning in the Ziarat watershed of Golestan province. They found that the logistic regression model was more efficient at delineating areas prone to landslides.

1.1. Study Area

The study area is located in the Badakhshan province of northeastern Afghanistan, between 69°86' to 70°85' W and 36°70' to 37°40' N. As shown in the location of the study area in Figure 1. It is distinguished by significant topographical diversity, with elevations varying from 1052 to 3500 m above the mean sea level depicted in the altitude distribution map for the study area in Figure 2. The region's complex land formations and harsh weather conditions are shaped by a significant difference in altitude, spanning around 2448 meters. The range is defined by absolute freezing temperatures, significant daily and seasonal variations, orographic precipitation patterns, and viable microclimates. Numerous geomorphological elements, including steep slopes, escarpments, valleys, gorges, different kinds of rock, geological formations, and soil composition, define the terrain. Several factors play a crucial role in determining the vulnerability of landslides, including the angle and aspect of the slope, lithology, hydrological conditions, vegetation cover, patterns of land use, and seismic activity. The identification

Doi: https://doi.org/10.63333/eem.v1n14
Vol. 1 No. 1 (2025)

of high-risk areas, precise prediction models, the setting of land-use zoning as well as infrastructure development, and disaster preparedness, are all targets that can be accomplished through the comprehensive assessment of the geological landslides and the risk elements that affected them in this region. In order to assess landslide risks in Badakhshan Province, the elevation, climate, and geomorphology of the area must be evaluated together in a detailed manner. The wide variety of elevations and the varied geomorphological features that accompany such diversity are indeed precious datasets that can be used in the observation of landslide risk assessment and the development of targeted strategies for landslide prevention.

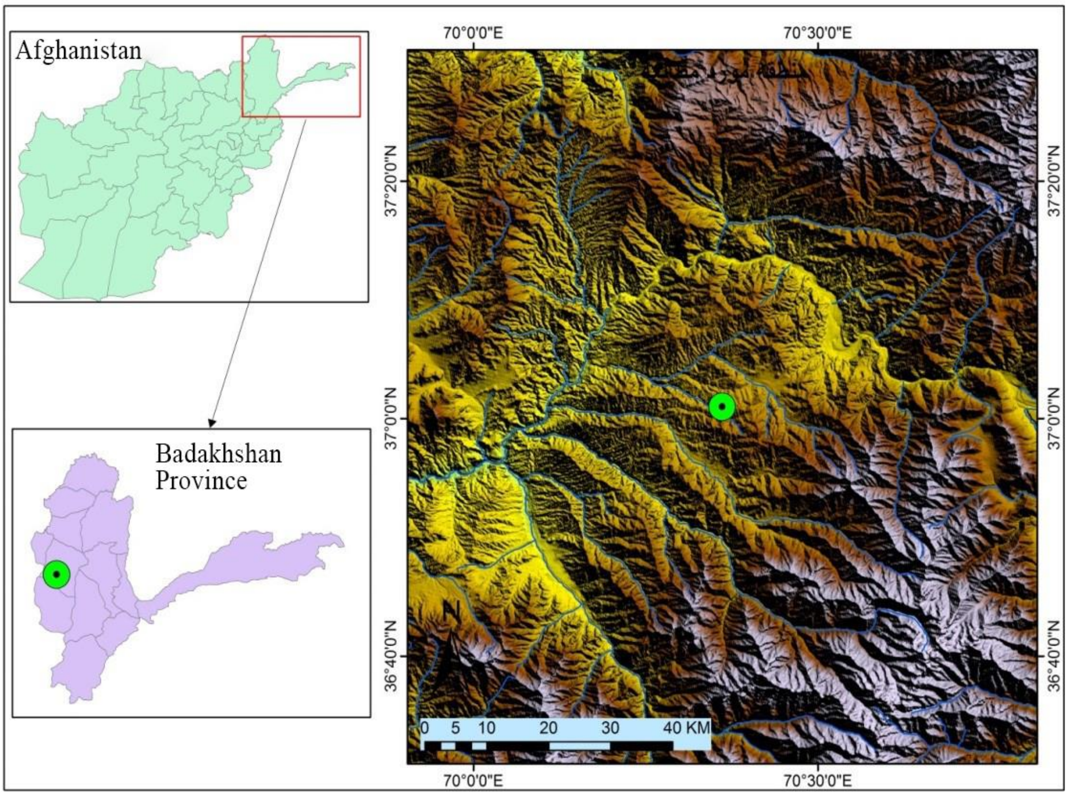

Figure 1. Location of the study area.

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

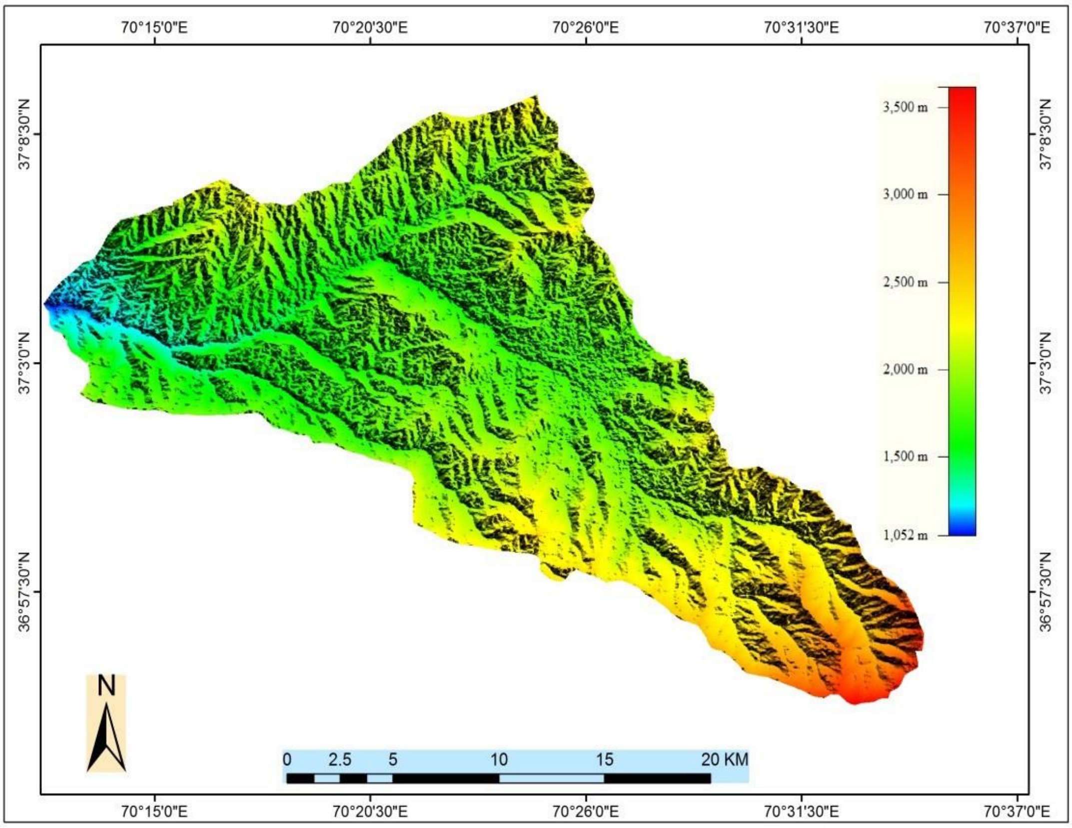

Figure 2. Altitude distribution map for the study area.

2. Materials and methods

The LNRF approach is a commonly implemented method for land sliding susceptibility analysis. It evaluates the influence of various environmental factors, including slope, aspect, geology, land use, and climatic conditions, on land sliding risk assessment [1,2]. The LNRF model assigns different weights to these factors based on their significance in influencing landslide occurrences.

Some of the best weightage for those variables contributing to the loan being Class 1 is assessed using this technique, and we rely on some methods like Info Val (Information Value), FDA (Fisher Discriminant Analysis), and LR (Binary Logistic Regression) [48]. These statistical methods reduce human subjectivity and provide more accurate landslide analysis.

The first part of the methodology focuses on collecting information from various sources, as shown in Figure 3, such as literature and maps. This data makes precise topographical maps with slope and accrediting layers. Land cover maps are created by marking geological strata and measuring the distances to faults. Then, the factors of this mapping are weighed with LNRF weights.

Within each class are weighted factor maps that include the assigned weights for all relevant factors, with the unit's weight calculated as the landslide area in that unit's average landslide size over total landslides. The obtained weight factors allow the modeling of the landslide vulnerability into three groups: low, moderate, and high. Taking the causal relationship defined below as an example, [5] is a simple model based on A: the area affected by landslides in ha, E: is mean area of landslides at all units.

LNRF is a methodology that systematically analyzes patterns in the distribution of landslides concerning environmental factors. This correlation reveals the likelihood of landslides occurring in terms of slope angle, land use, soil type, and distance to faults or rivers, which are assigned weights against each other entirely through historical data. Each of these factors is weighed up through statistical

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

techniques, which have been shown to influence landslide occurrences and are a way the risk may be quantified. These factor maps are then overlaid with their weighted summation to create an overall risk map which can be used for understanding landslide susceptibility within spatial regions Figure 3. The result of the final LNRF values narrowed down highly susceptible zones which are potentially hazardous and hence require focused intervention for landslide mitigation as well as management practices by stakeholders [49]. This organized process improves the precision of landslide vulnerability evaluations and makes it easier to make well-informed decisions about risk reduction and land use planning.

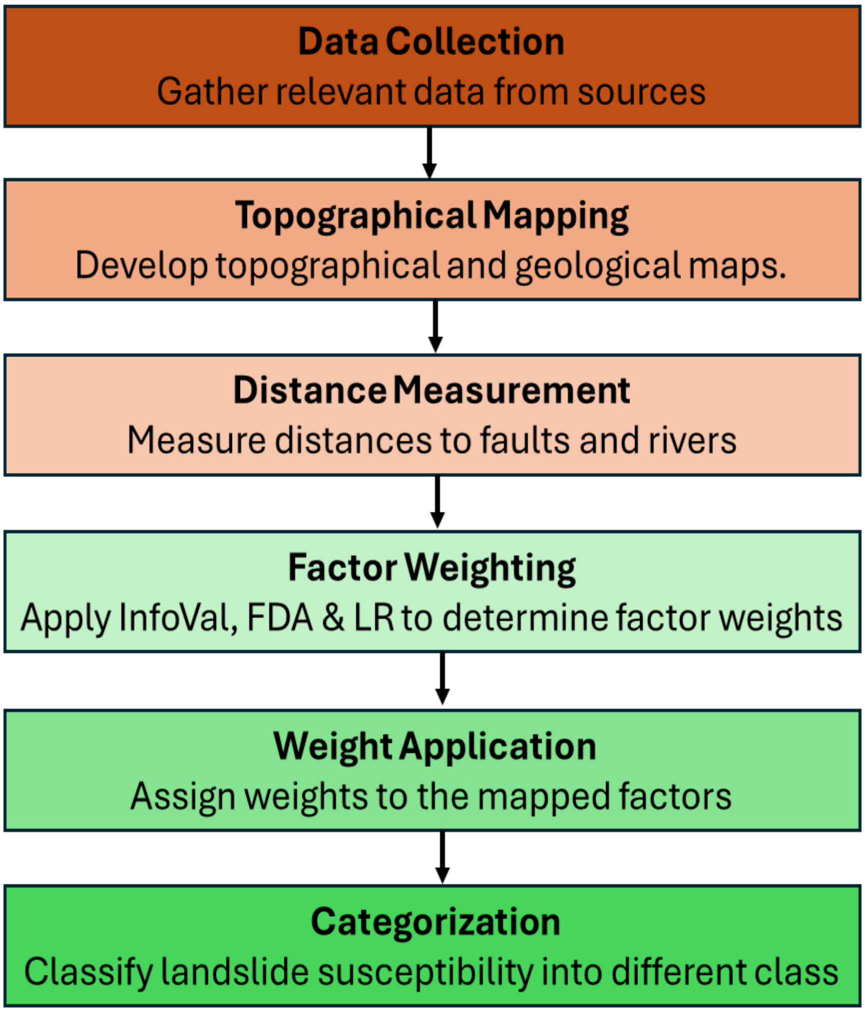

Figure 3. Methodological Flowchart of LNRF.

3. Results and Discussion

3.1. Steep direction

The primary objective of this research was to investigate the relationship between slope orientation and the likelihood of landslides occurring in a specific basin. Based on the slope directions, topographic and geospatial data were used to determine which areas were more likely to experience landslides. Figure 4 classifies slope orientations into ten discrete directions, whereas Figure 5 illustrates the landslide susceptibility levels classified as Low, Medium, and High. Table 1 presents a quantitative assessment

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

of landslide susceptibility considering slope class and orientation. It includes information on the instability levels, weights, influence coefficients, landslide extents, and layer areas. The west slope class covers the most extensive area, measuring 6561.6 hectares, and exhibits a moderate level of instability, along with a 12% extent of landslides. The soil type, hydrological features, or vegetation may cause moderate slope stability because it could help mitigate landslides, but they are still susceptible to severe climate circumstances or seismic. Second, the West-facing slope is possibly going to receive differing areas of sunlight and moistness with some frequency as well, which together might make it a little bit more fatigued over time (over several seasons or years); however, this should still only lead up to mild degrees of instability at most probably. The East and Southeast slopes, although they have smaller coverage areas (4560 and 3910.9 hectares, respectively), display greater susceptibility to landslides with notable levels of instability and landslide extents of 15% and 17%. Several reasons could explain this higher risk. These slopes are likely the most topographically exposed to prevailing wind and rain patterns, causing increased degrees of soil saturation and erosion. The steeper gradients of these slopes likely decrease soil shear strength, thus making them more prone to toppling over. In addition, the geotechnical properties of soil, such as mineral composition or water retention capacity, might have a crucial contribution to making these slopes more prone. The new results, therefore, indicate that how slopes are oriented concerning the local weather patterns could be essential when evaluating which is most likely to produce a landslide [28]. It is important to prioritize these areas with a high risk of danger to implement strategies to reduce the risk and conduct thorough investigations of geological conditions. The moderate-risk zones encompass the Southwest and West orientations, which have substantial areas but relatively low landslide extents. This is possible because of more suitable soil conditions or, in part, a shallower grade that leads to better strength. The descending vulnerability observed in these regions suggests artificial/natural drainage systems that can prevent water infiltration and reduce erosion and landslide activity [50]. Flat and South orientations have reduced instability and landslide extent, making them less urgent for immediate intervention. While south-facing slopes can profit from improved drainage or a lot of greenery working together to strengthen the soils, flat places are resilient since the soil is not as susceptible to gravitational solid pressures. Less significant management intervention will be needed for this kind of land use and others associated with such substantial water sources, but long-term monitoring is necessary to account for changes brought on by a changing climate [28]. This analysis highlights the importance of implementing focused risk-management strategies to effectively address landslide hazards. These strategies should include conducting comprehensive geotechnical surveys, implementing engineering measures to mitigate risks, regularly monitoring the area, and integrating susceptibility data into regional planning.

Table 1. Slope class and orientation landslide susceptibility analysis.

Level of instability	Weight	LNRF	Landslide extent		Area of Layers		Slope layers
			Percent	hectares	Percent	hectares	
Low	1	0.2	2	1	0	5.7	Flat
Medium	2	0.8	10	4	11	4000.0	N
Medium	2	1.2	15	6	11	4073.3	NE
High	3	1.6	20	8	13	4560.0	E
High	3	1.4	17	7	11	3910.9	SE
Medium	2	0.8	10	4	11	3956.4	S
Low	1	0.4	5	2	15	5310.3	SW
Medium	2	1	12	5	18	6561.6	W
Medium	2	0.8	9.8	4	14	5148.2	NW

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

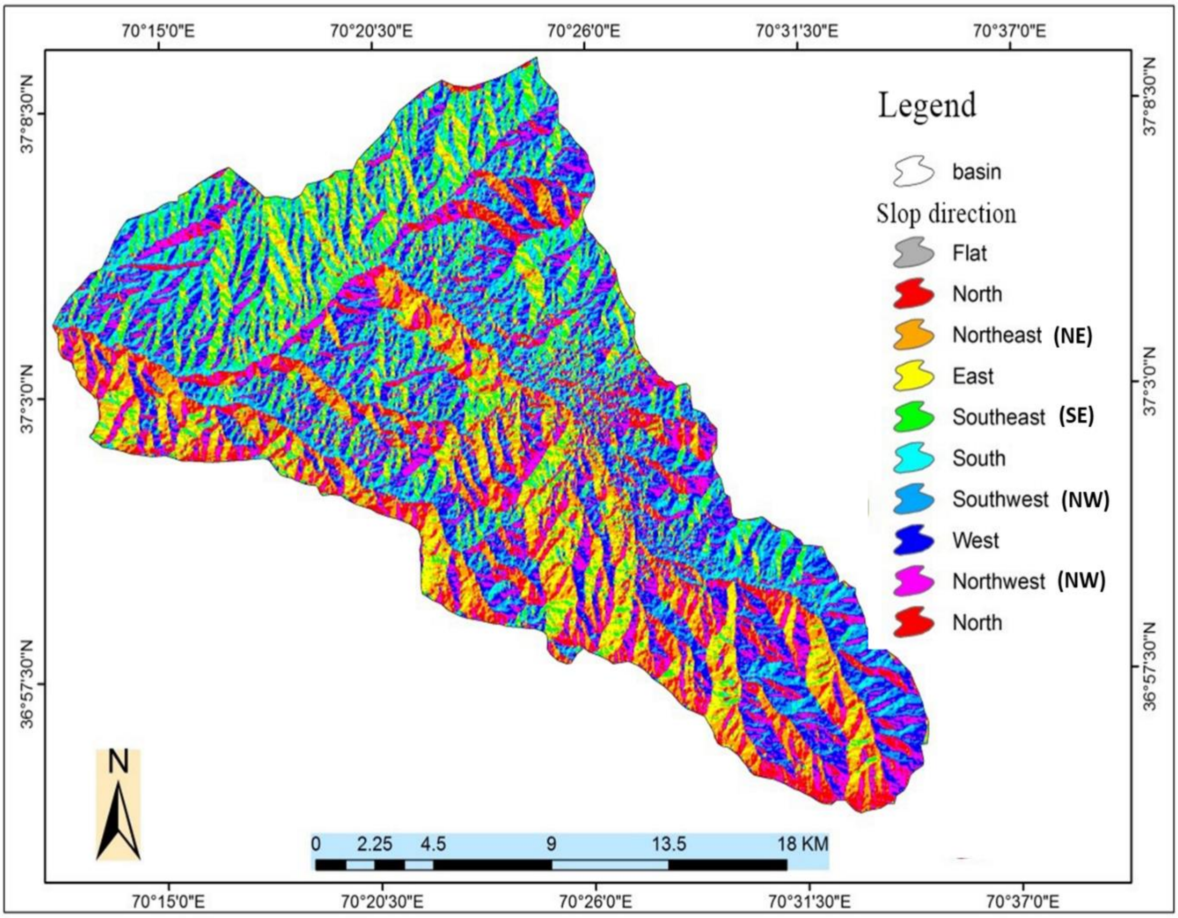

Figure 4. Slope direction of the study area.

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

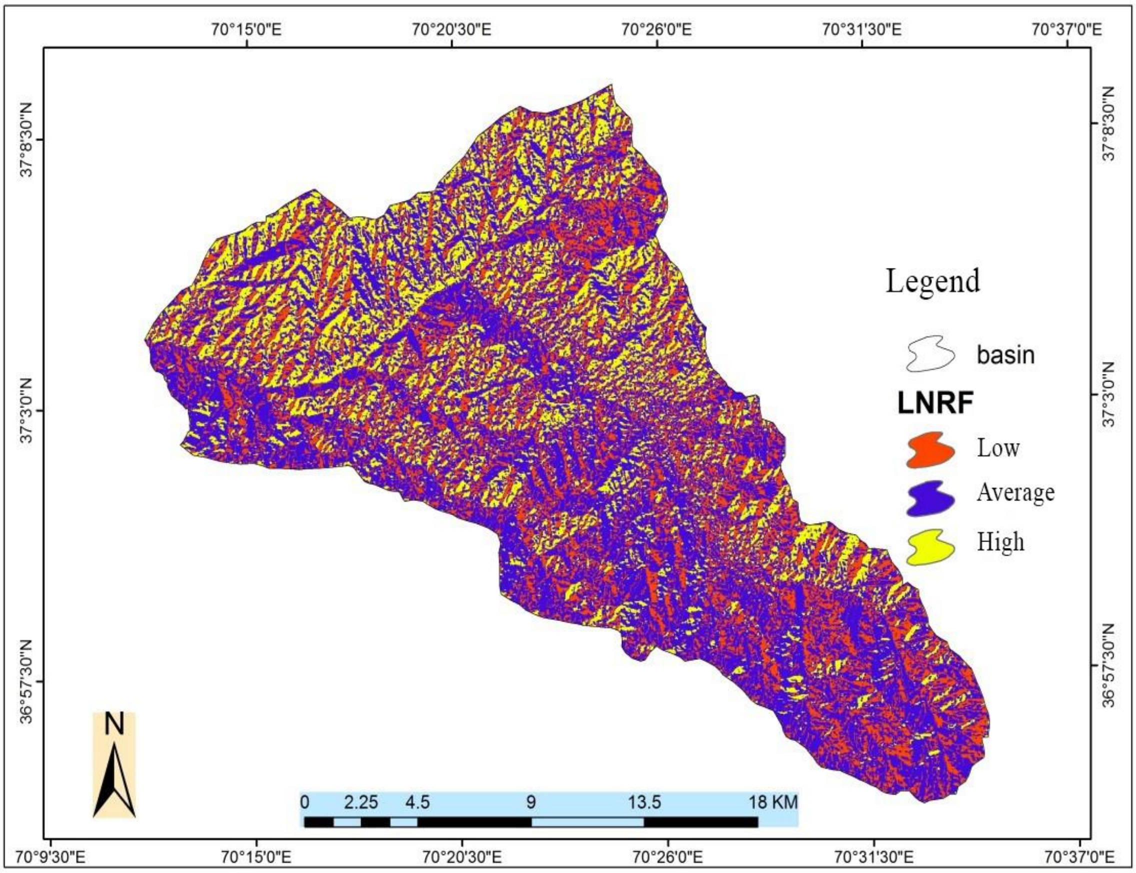

Figure 5. Slope map of the weighted LNRF model.

3.2. Distance from the road

Based on the topographical conditions of the study area, most existing roads are unpaved and primarily constructed in the trough line and along the rivers. Most landslides in this study were observed within a range of 100–200 m from the road. As the distance from the road increased, the friction level decreased. This reduction in friction with distance from the road is crucial to explaining why landslides are so much more likely near roads. For example, roads reduce friction that stabilizes the slope, the more soil dug up or undercut by a road will remove roots, and vegetation prevents erosion. This may be worse in heavy traffic or poor road maintenance, further deteriorating slope stability. Table 2 shows the landslide risks as High, Moderate, and Low, with weights of 3, 2, and 1, respectively. The Landslide Number Risk Factor (LNRF), landslide extent in hectares, geological layers, and affected road layers are included. High-weight highly unstable areas (high) with a weight of 3 have LNRFs (Landslide Non-Recoverable Factors) of 1.83 and 2.08, affecting 5.6% (22 hectares) and 16.7% (25 hectares) of the land and covering 9.5% (2402.3 hectares) and 17.8% (4504.4 hectares) of geological layers within road layers Areas with medium instability, weighted 2, have LNRFs from 1.00 to 1.25 and 0.75, affecting different extents and areas. In contrast, areas with low instability, weighted 1, had LNRFs from 0.17 to 0.58, affecting various extents and regions. These areas have 0–700 road layers.

An LNRF equal to 1.83 and 2.08 in high instability areas foreshadows the direct danger of non-recoverable slides [1]. Given this, it is impossible to eliminate the risk in such a case, but urgent corrective actions such as slope stabilization or road realignment can prevent a permanent slope failure. Medium instability areas with LNRF levels between 1.00 and 1.25 also require preventive interventions, but drainage improvement and regular monitoring levels are enough in this case [30]. Low instability

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

zones tend to have LNRF from 0.17 to 0.58, associated with low landslide occurrence, but regular monitoring is necessary if the situation changes over time. This may happen if human activity or new road construction changes the stable balance in the area.

Table 2. Landslide Risk Factors and Road Infrastructure Attributes Multivariate Analysis.

Level of instability	Weight	LNRF	Landslide extent		Area of Layers		Road layers (m)
			Percent	hectares	Percent	hectares	
High	3	1.83	5.6	22	9.5	2402.3	0-100
High	3	2.08	16.7	25	17.8	4504.4	100-200
Medium	2	1.00	19.4	12	11.6	2931.9	200-300
Medium	2	1.25	8.3	15	11.0	2786.6	300-400
Low	1	0.17	5.6	2	12.0	3036.5	400-500
Medium	2	0.75	16.7	9	9.4	2389.8	500-600
Low	1	0.42	8.3	5	8.5	2154.7	600-700
Low	1	0.58	19.4	7	20.2	5111.5	>700

The road networks and buffer zones in the basin are shown in "Figure 6. Road distance map". The distance from the roads is shown in color-coded intervals: yellow (0-100 meters), orange (100-200 meters), red (200-300 meters), dark orange (300-400 meters), light pink (400-500 meters), dark pink (500-600 meters), purple (600-700 meters), and blue (>700 m). Latitudes 36°30'N to 37°30'N and longitudes 70°9'30"E to 70°37'0"E define the map. The scale bar at the bottom measure’s distances of up to 20 km, while the white outline represents the basin. This map shows road accessibility in yellow for high connectivity and blue for low connectivity. This data can aid in infrastructure planning and environmental assessment. Figure 7 shows the distances calculated by the LNRF model from roads in a basin with weights. The system uses blue for short distances, red for moderate distances, and purple for long distances from the roads. The white lines define the basin, while the black lines indicate roads. The geographic coordinates for the map were 70°9'30"E to 70°37'0"E longitude and 36°57'30"N to 37°9'0"N. The right-side legend shows these symbols. A kilometer-scale bar is placed at the bottom of the display. The northern arrow indicates the orientation.

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

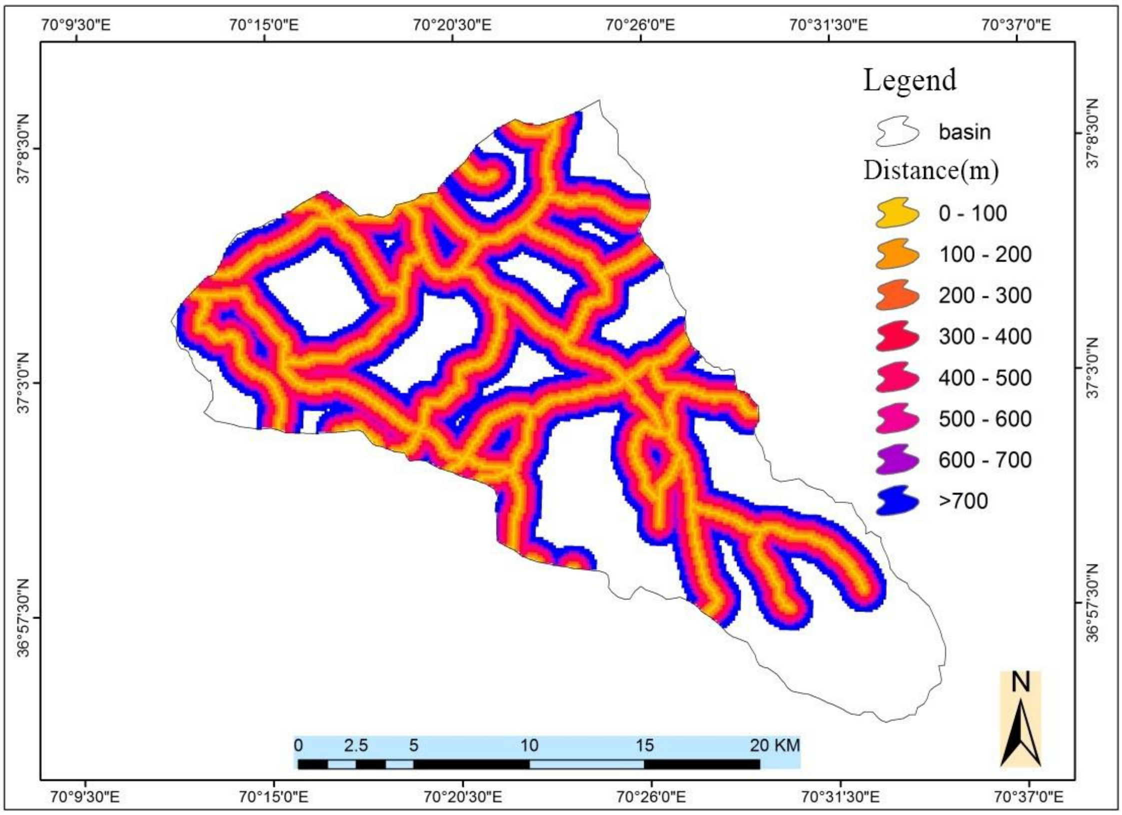

Figure 6. Map indicating the distance from the road.

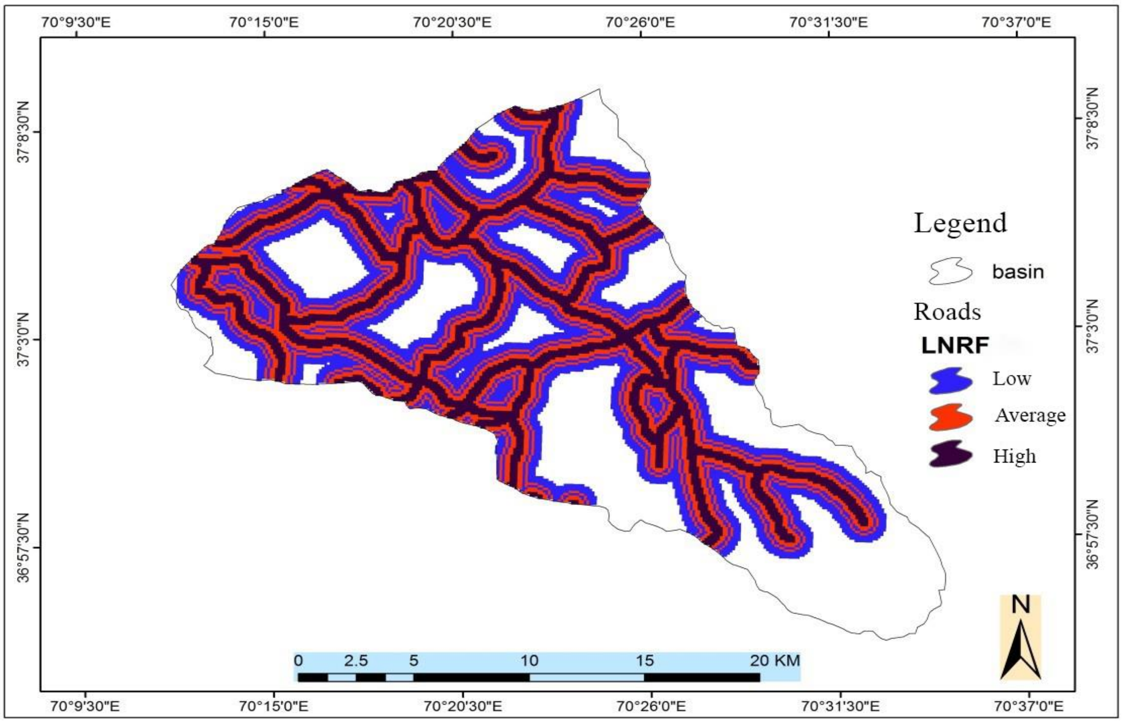

Figure 7. Weighted map of distance from road in LNRF model.

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

3.3. Distance of the fault

The high frequency of landslides within 100 m of faults emphasizes the necessity to consider geological features when assessing slope instability in this region. A high percentage (43%) of the impacted area was situated at/close to these select faults, indicating that they are hazard-prone zones for landslides. This correlation implies that the geological fact itself may cause soil to be more inclined to fail under shear stress adjacent fault lines. Importantly, this relationship is fundamental for effective risk management and mitigation, as monitoring efforts are best focused on areas near faults. Table 3, "Geological and Instability-Based Landslide Risk Analysis", classifies landslides by geological instability into stages. These levels are measured by landslide weight, LNRF, percentage, hectares, and the fault depth distribution of geological layers. By so doing, these classifications provide a better understanding of how geological factors affect the risks of landslides, which is very useful for geotechnical engineers and planners. By analyzing those detailed metrics, stakeholders can pinpoint the areas that need intervention promptly and allocate resources to protect from landslides accurately. The distances between the regions and rivers are shown in Figures 8 and 9, respectively. The figures show river proximity by color. Figure 9 uses the LNRF model to weigh this distance, whereas Figure 8 divides it into intervals (0-700+ meters). The color coding in these figures intuitively illustrates which distances from rivers carry what level of risk. Rivers are a significant aspect that influences soil-moisture conditions, and this influence extends to such processes as erosion, which bears upon slope stability. The clingy relationship between rain and drainage serves as a reminder of the need for careful water flow control in regions subject to landslides, particularly during bouts of heavy rainfall that can exceed the capacity for soil saturation before it all comes tumbling down [50]. This study provided an indicator of soil composition and historic landslide distribution for a region in the southern part of Italy that has been studied very little up to now. Vulnerabilities are linked to soil type, and soils with lower cohesion or higher plasticity, which push the peaks of these curves further into space relative to steeper slope thresholds, can indicate areas that may slide more easily when hit by a heavy rainstorm or seismic event [51,52]. Using geological and soil data along with proximity to rivers or fault lines can thus provide us with an efficient way to manage landslide risks better. Stakeholders can focus on high-risk areas and implement specific interventions, such as improved drainage systems, vegetation management, or infrastructure upgrades to reduce the risk of hazards and protect communities.

Table 3. Geological and instability-based landslide risk analysis.

Level of instability	Weight	LNRF	Landslide extent		Area of Layers		Fault layers (m)
			Percent	hectares	Percent	hectares	
High	3	3.5	43.8	7	7.4	822.2	0-100
medium	2	1	12.5	2	14.5	1612.0	100-200
medium	2	1	12.5	2	10.5	1167.4	200-300
medium	2	1	12.5	2	10.3	1147.8	300-400
Low	1	0.5	6.3	1	11.6	1297.5	400-500
Low	1	0.5	6.3	1	10.0	1117.3	500-600
Low	1	0	0.0	0	9.9	1104.6	600-700
Low	1	0.5	6.3	1	25.8	2879.3	>700

Doi: https://doi.org/10.63333/eem.v1n14
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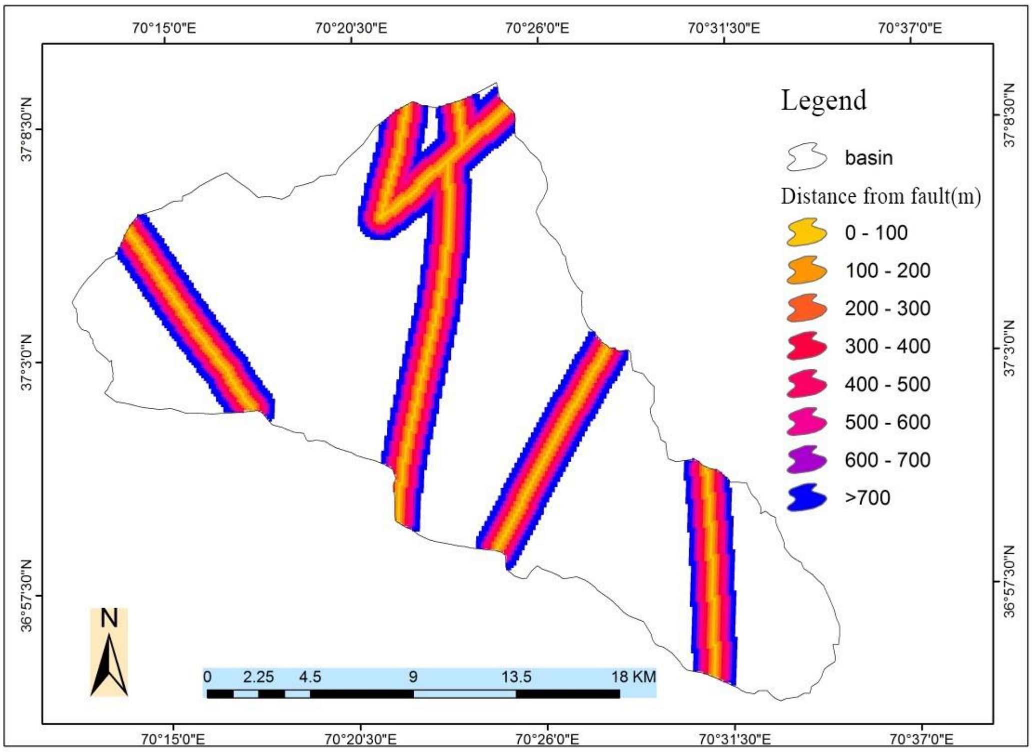

Figure 8. A graphic depicting the distance from the river.

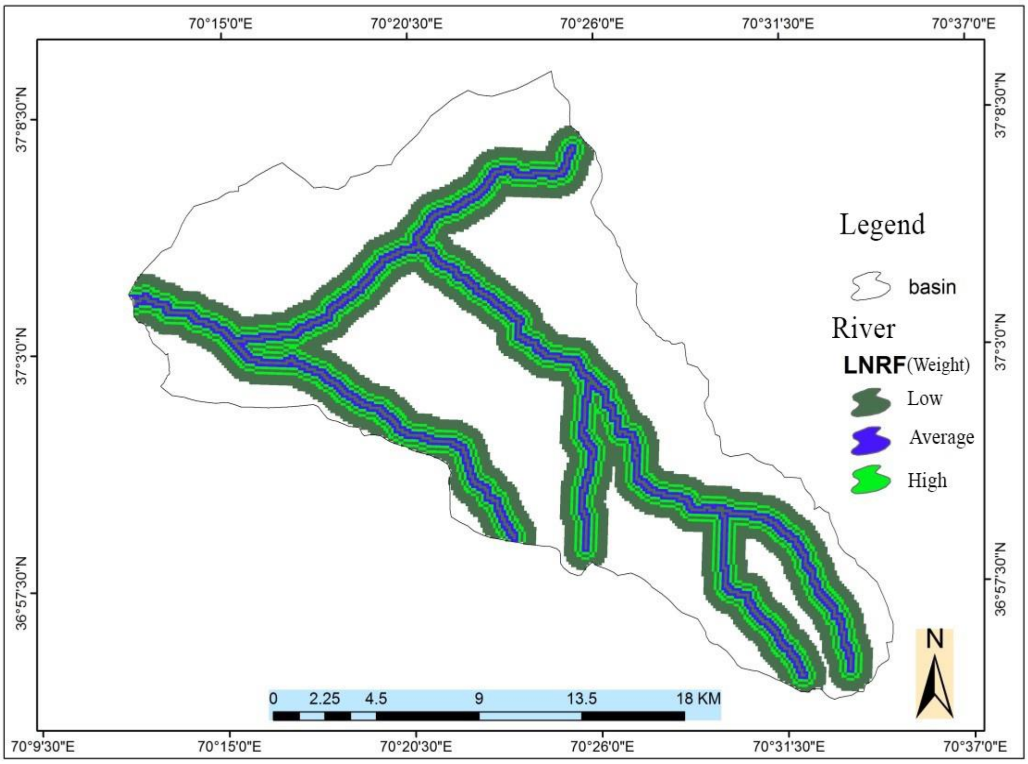

Figure 9. Weighted map of distance from the river in LNRF model.

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

3.4. Discussion on Areas Most Affected by Combined Landslides

Near rivers and near roads were identified as key contributing factors to combined landslides in the study, with a large percentage of those events happening within 100–200m. The risk of landslides is increased when rivers are present, as the water can saturate and slowly move up in soil due to fluctuating moisture levels at intervals over saturated land, which weakens rock/slope stability. Unpaved roads are also more susceptible to landslides as they are typically built-in valleys and along river lines with constant erosion, human activity, and poor drainage. Together with previously recognized human-induced predictors of disease prevalence like poverty, it reinforces those local mitigations are needed in these high-risk regions.

On the other hand, roadside landslides can block access to communities and services needed in transportation networks. Accordingly, the most vital measures are to identify such low forest health areas close to infrastructure, prominent human number places near roads inaccessible reached territories where it is critically crucial not even more massively carrying out restoration operations but just stability increased care enough take kind approach including expanded drainage and permanent soil condition monitoring for provision land degradation prevention. This relationship between tectonic instability, proximity to rivers, and roadbuilding highlights the need to consider these factors in urban planning and construction activities going forward.

Several advantages over previously implemented methods for assessing landslide susceptibility slides can be described by the proposed method, LNRF. In contrast to traditional methods, e.g., deterministic and heuristic models that are built considering a unique factor like slope angle or land cover types or geological formations alone, our LNRF approach unifies control parameters of the studied region including fault line sensitivity besides what is mentioned above (river proximity for example), soil texture among others. It can offer a more comprehensive and realistic reflection of landslide risk in complex terrains [13].

Unlike other techniques, such as the Analytical Hierarchy Process (AHP) or Weight-of-Evidence (WoE), which usually combine proficient review with element weighting schemes, our LNRF method derives weights analytically from physical data where feasible. This minimizes human bias, and hence, the trustworthiness of the output increases. However, the AHP-based model entertains only slope or precipitation as the critical contributing element and readily quantified parameters, while another approach of LNRF determined weight by looking for how much correlation with past events in data. This gave a more plausible risk assessment [53,54]. Models such as logistic regression, traditionally used in landslide vulnerability mapping, tend to emphasize linear associations among elements and the happening of landslides [55]. However, the LNRF method considers non-linear associations between elements, making it a better candidate for accurately detecting landslide-prone areas [3].

One of our proposed method's main benefits is its scalability and flexibility. While some earlier employed techniques have restrictions concerning the scale at which they can be used (only in specific regions) or on small datasets, this is not crucial for an extensive place, and including multiple elements does not influence the precision of LNRF [55]. Also, the utilization of trendy spatial data, mixed with the possibility of updating weights established on new details, permits it to address arising hazard scenarios like climate change.

4. Conclusion

This study highlights a region's landslide susceptibility and the factors that cause it. The area is unstable due to fault line sensitivity, river proximity, and geological features. The strong correlation between these variables and past landslide frequency supports this risk.

The area is primarily residential; therefore, comprehensive urban planning and risk mitigation are required. Geological assessments and risk analyses should guide future development to reduce disaster risk when locating human structures. Severe construction regulations, advanced geological and

Doi: https://doi.org/10.63333/eem.v1n14 Vol. 1 No. 1 (2025)

hydrological assessments to predict and manage landslide risks, and resilient infrastructure projects are required. Furthermore, it is advisable for the community to actively participate in proactive disaster preparedness measures, such as establishing early warning systems and providing residents with education on emergency response procedures. By adopting and executing these strategies, the region can strengthen its ability to withstand and recover from the repeated danger of landslides, thus protecting lives and minimizing financial losses. Implementing comprehensive measures is essential not only for reducing immediate risks but also for guaranteeing sustainable development and the long-term well-being of the population.

Nevertheless, the study has some limitations and could be better. This assessment is an estimate constructed from historical data and likely only identifies recent landslide events because some earlier mapped landslides may have been obscured by erosion, re-vegetation, or other landscape changes. Furthermore, the LNRF model only considers a few environmental factors and may overlook other variables that provide information on landslide risks.

For further research, the authors suggest utilizing more extensive datasets and higher-level modeling tools to achieve better evaluation accuracy about climate change affecting landslide hazards. Long-term monitoring is also needed to assess the success of different mitigation efforts. We must base future development on a careful geological and risk assessment, enforce strict rules regarding building regulations, and conduct advanced hydrological research focused on geology. Community engagement in early warning systems and disaster risk education is equally important. Putting these into practice would enable humanity to bounce back from disaster, safeguard lives, and reduce economic damage while reassuring the world's 570 million city-dwellers of their safety today and tomorrow.

CRediT authorship contribution statement:
Mohammad Amini: conceptualization, validation, visualization, methodology, software and writing—original draft preparation. Longsheng Deng: supervision. Waqas Hassan: methodology, validation, visualization and writing—reviewing and editing. Reza Jafari: methodology, software, and writing—reviewing and editing and Fatima Zahra Zidane: administration and writing—reviewing and editing.

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