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Research Paper

GIS-based MCDM Approach for Landslide Susceptibility Hazard Mapping Case study: Mehran Roud Basin, Iran

Tohid Rahimpour[1*], Mohammad Hossein Rezaei Moghaddam[2]

1. Post Doctoral Researcher, Department of Geomorphology, University of Tabriz, Tabriz, Iran. rahimpour1990@gmail.com
2. professor of Geomorphology, Department of Geomorphology, University of Tabriz, Tabriz, Iran. rezmogh@tabrizu.ac.ir

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A B S T R A C T

Landslide is one of the destructive hazards that causes much damage to residential zones and natural resources such as forests and farmlands every year. This phenomenon is noticeable in Iran because most of the areas in this country are mountainous, especially in the northern parts. This study determined susceptible zones with landslide incidence potential in the Mehran Roud basin, located in the northwestern part of Iran. For achieving this aim, the information layers related to 8 factors that are effective in landslide incidence, including Geology, land use, slope, aspect, elevation classes, precipitation, distance to stream, and distance to fault, were prepared under the ArcGIS platform. Then, rating the factors was done using the analytic network process (ANP) method in the Super Decisions software. The study results showed that the weights of the mentioned eight factors are 0.331, 0.080, 0.117, 0.036, 0.055, 0.233, 0.112, and 0.032, respectively. Finally, landslide susceptibility zonation map was obtained by integrating weighted layers in GIS software. The zonation map divides the basin in terms of landslide occurrence into five classes, including very high susceptibility (21 km^2), high (134 km^2), moderate susceptibility (94 km^2), low (60 km^2), and very low susceptibility (51 km^2), which high susceptibility areas cover the largest area of the basin. A comparison between the zonation map and the scattered landslide points obtained from field activities shows that 85.7% of the landslides have occurred in high and very high susceptibility zones. Thus, the ANP model can be considered as an appropriate method for zoning the hazard of landslide in the Mehran Roud basin due to its ability to distinguish hazard zones.

*Correspondin Author: Tohid Rahimpour, rahimpour1990@gmail.com
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مقاله پژوهشی

تهیه نقشه خطر وقوع زمین‌لغزش با استفاده از روش تصمیم گیری چندمعیاره و GIS مطالعه موردی: حوضه مهران‌رود، ایران

توحید رحیم‌پور[1]، محمدحسین رضائی‌مقدم[2]

۱- پژوهشگر پسادکتری، دانشکده برنامه‌ریزی و علوم محیطی، دانشگاه تبریز، تبریز، ایران. rahimpour1990@gmail.com
۲- استاد گروه ژئومورفولوژی، دانشکده برنامه‌ریزی و علوم محیطی، دانشگاه تبریز، تبریز، ایران. rezmogh@tabrizu.ac.ir

کلیدواژه‌ها

زمین‌لغزش،
فرایند تحلیل شبکه‌ای،
Super Decisions،
GIS،
حوضه آبریز مهران‌رود،
استان آذربایجان شرقی.

چکیده

زمین‌لغزش‌ها سالانه باعث آسیب‌های قابل توجهی به مناطق مسکونی و محیط‌زیست، از جمله جنگل‌ها و مزارع می‌شوند. این مخاطره در ایران اهمیت ویژه‌ای دارد، چون بخش زیادی از کشور، به‌ویژه نواحی شمالی، کوهستانی است. این تحقیق با هدف تهیه نقشه خطر وقوع زمین‌لغزش در حوضه آبریز مهران‌رود، واقع در شمال غربی ایران، انجام شده است. برای دستیابی به این هدف، لایه‌های اطلاعاتی مرتبط با ۸ عامل مؤثر در وقوع زمین‌لغزش، شامل زمین‌شناسی، کاربری اراضی، شیب، جهت شیب، طبقات ارتفاعی، بارش، فاصله از رودخانه و فاصله از گسل، در محیط نرم‌افزار ArcGIS تهیه شدند. سپس، وزن‌دهی این عوامل با استفاده از روش فرآیند تحلیل شبکه‌ای (ANP) در نرم‌افزار Super Decisions انجام شد. نتایج تحقیق نشان داد که وزن‌های این هشت عامل به ترتیب ۰/۳۳۱، ۰/۰۸۰، ۰/۱۱۷، ۰/۰۳۶، ۰/۰۵۵، ۰/۲۳۳، ۰/۱۱۲ و ۰/۰۳۲ هستند. در نهایت، نقشه پهنه‌بندی خطر زمین‌لغزش با ادغام لایه‌های وزندار تهیه شد که حوضه مورد مطالعه را به پنج کلاس خطر شامل مناطق با پتانسیل خیلی زیاد (۲۱ کیلومترمربع)، زیاد (۱۳۴ کیلومترمربع)، متوسط (۹۴ کیلومترمربع)، کم (۶۰ کیلومترمربع) و خیلی کم (۵۱ کیلومترمربع) تقسیم می‌کند. مناطق با پتانسیل زیاد بیشترین مساحت حوضه را پوشش می‌دهند. مقایسه نقشه پهنه‌بندی با نقاط پراکنده زمین‌لغزش که از بررسی تصاویر ماهواره‌ای و فعالیت‌های میدانی به‌دست آمده‌اند، نشان می‌دهد که ۸۵/۷ درصد از زمین‌لغزش‌ها در مناطق با پتانسیل بالا و بسیار بالا رخ داده‌اند. بر اساس نتایج به‌دست‌آمده، لازم است در سیاست‌گذاری‌های محیطی، اقدامات لازم برای مدیریت این پدیده و کاهش پیامدهای انسانی و مالی آن در مناطق حساس در نظر گرفته شود.

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*نویسنده مسئول: توحید رحیم‌پور
رایانامه: rahimpour1990@gmail.com

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Introduction

Landslide, a natural hazard, involves the rapid downward movement or detachment of cohesive sediment masses along slopes. This process leads to significant economic losses, affecting forests, agricultural lands, infrastructure such as power lines and pipelines, mining operations, engineered constructions, roadways, and residential areas (Moazzez et al., 2019). Recognized as one of the most destructive natural disasters in mountainous regions, landslides can result in sudden fatalities and extensive property destruction (Bui et al., 2011). Understanding the causal mechanisms behind these events can help mitigate their impacts (Intarawichian & Dasananda, 2010). According to Varnes (1984), landslides typically involve multiple movement types, forming complex mass-wasting processes. Various external triggers contribute to their occurrence, including heavy rainfall, seismic activity, fluctuations in water levels, coastal wave action, and rapid river erosion (Dai & Lee, 2002). While tectonic forces such as earthquakes and fault movements can induce landslides, they often interact with climatic conditions, particularly precipitation (Feizizadeh et al., 2013). Key factors commonly utilized in landslide susceptibility mapping include slope, aspect, elevation, geology, rainfall patterns, land cover, distance to stream, and distance to Fault (Bai et al., 2011; Feizizadeh & Blaschke, 2013; Ghorbanzadeh et al., 2018; Anis et al., 2019; Wang et al., 2020).
Northwestern Iran is highly prone to landslides because of its unique topography and consistent rainfall throughout the year. An effective method to mitigate landslide risks and reduce their impact is through landslide hazard mapping. This process involves dividing the land into different zones and ranking them based on the actual or potential landslide threats on slopes (Shariat Jafari, 1996). Developing advanced geomorphological techniques to evaluate landslide susceptibility is crucial for achieving cost-effectiveness and reliable scientific results (Piacentini et al., 2012). Typically, landslide susceptibility models fall into four main groups: a) inventory-based assessments, b) heuristic approaches, c) statistical evaluations, and d) algebraic or deterministic techniques (Carrara et al., 1995; Guzzetti et al., 1999; Ermini et al., 2005). The choice of methodology must align with the research objectives and the scope of the analysis. Landslide inventories and heuristic models rely on expert judgment and are typically employed in preliminary assessments of large areas. Statistical models, which provide a more systematic and consistent evaluation of the relationship between landslides and causative factors, are better suited for regional-scale studies. In contrast, deterministic models, grounded in mathematical principles, require highly detailed data and are thus only applicable at a local scale (Piacentini et al., 2012). In recent years, advancements in science have enabled the creation of diverse GIS techniques for assessing landslide hazards (Bui et al., 2012). Disaster management evaluation is a key area where GIS-based multicriteria decision analysis (GIS-MCDA) is applied. GIS-MCDA offers robust methods for assessing and forecasting natural disasters (Feizizadeh & Blaschke, 2013). In the context of environmental hazards such as landslides and floods, a number of studies have applied multi-criteria decision analysis (MCDA) as an investigative tool. Examples that can be referenced are: Rahimpour eta al (2018) in Sardool Chay Basin, Moazzez et al (2019) in Nahand Chai Basin, Mokhtari et al (2020) in Ghomnab Chai Basin, Lajmorak and Piri (2023) in Baghmalek County, and Ildoromi and spehri (2024) in Kurdistan dam watershed. The stated objective of this research is to systematically assess landslide susceptibility and analyze the causative factors contributing to landslide occurrences in the Mehran Roud basin, situated in northwestern Iran. To achieve this, the study employs an integrated methodological approach combining: Analytical Network Process (ANP) – A multi-criteria decision-making (MCDM) technique that accounts for complex interdependencies among landslide-triggering factors, providing a weighted evaluation of their relative importance. Geographic Information System (GIS) – A spatial analysis tool used to process, overlay, and visualize geospatial data, facilitating the generation of a landslide susceptibility map. Zhou et al. (2018) explain that landslides result from the interplay of a slope's inherent geological properties and external environmental influences. Therefore, this study, drawing on prior research and field surveys, identified eight key factors contributing to landslides: geology, land use, slope, aspect, elevation, precipitation, distance to stream, and distance to fault.

The Study Area

Mehran Roud basin is located in geographic coordinates of 37°43′12″ to 38°07′12″ North latitude and 46°15′03″ to 46°34′24″ East longitude in the Eastern Azerbaijan province (Figure 1). This basin has an area of 360 km^2, and it is situated in the northwestern part of Iran. The area is part of Sahand Mountain, with a varying altitude from 1340 m in the river bed of Mehran Roud to 3511 m above sea level in the Sahand Mountains. Also, this basin is one of the sub-basins of the Urmia Lake basin, and its surface waters are drained into the Urmia Lake after meeting the Aji Chai River. In the bottom section of the basin, Tabriz city is located, which is known as the largest city in the north-western part of Iran with about 2 million inhabitants. Based on De Martonne's climate classification, the research region experiences a semi-arid climate characterized by cold, snowy winters (Alijane, 2000), with an average yearly rainfall of around 300 mm. The highest precipitation typically falls during April and May (Feizizadeh & Blaschke, 2013).

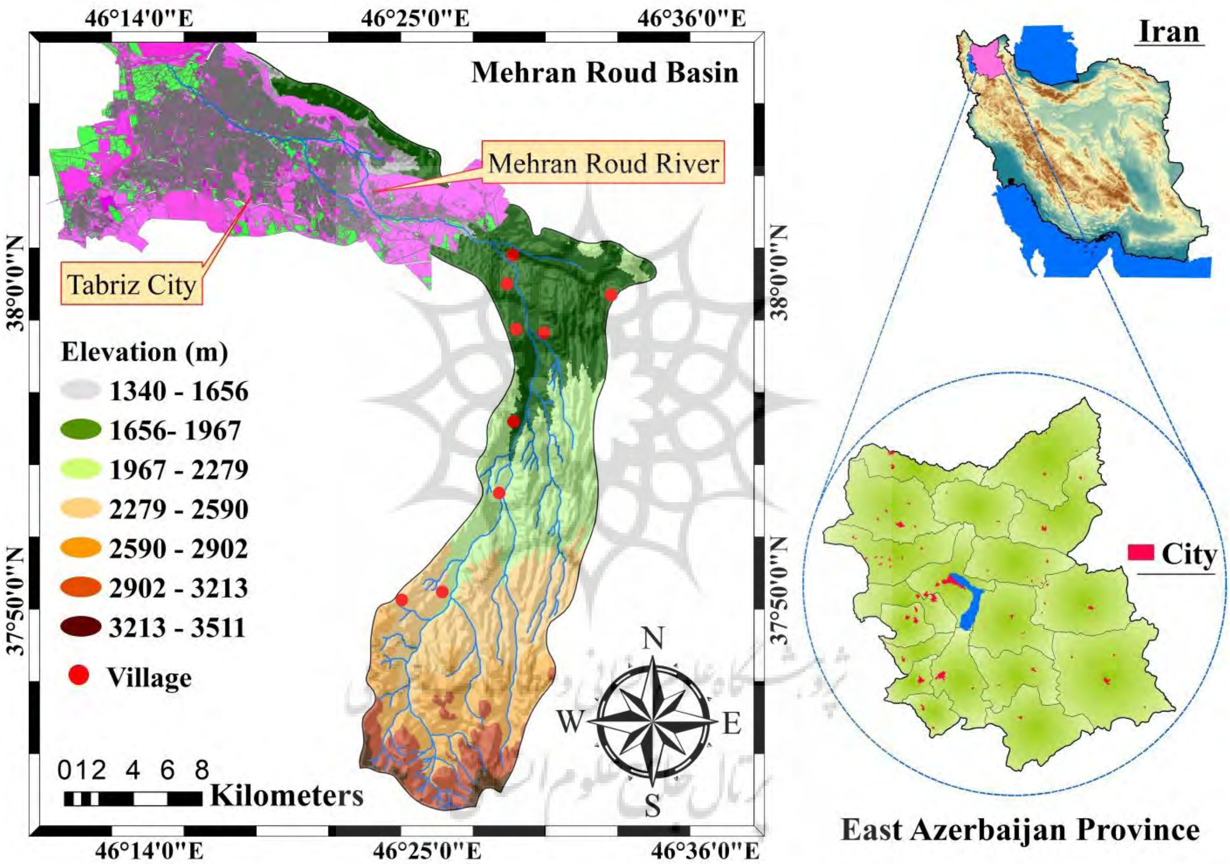

Figure 1. The study area location in the North-west of Iran

Research Data and Tools

In this research, the following data and software have been used to generate a map of landslide hazards in the Mehran Roud basin.

- A frame of Landsat 8 satellite image OLI scanner with path of 168 and row of 34, in 30m spatial resolution, was captured for Juan 9th, 2022, covering all the study area to prepare the land use map.
- Geological maps in 1: 100,000 scale from Tabriz and Ousku, provided by the Geological Organization of Iran.
- Topographic maps in 1: 50000 scale from Tabriz city produced by mapping organization of Iran.

- Data on rainfall over a 23-year period (2000–2022) was gathered from meteorological stations inside and adjacent to the study area, covering locations like Tabriz, Sahand, Varzaghan, and Bostan Abad, sourced from the East Azerbaijan Provincial Meteorology Office.
- ASTER Global Digital Elevation Model (ASTGTM) in 30m spatial resolution (https://gdex.cr.usgs.gov/gdex/).
- ArcGIS (http://www.esri.com) and Super Decisions software (http://www.superdecisions.com) to generate maps.

Methods Applied

The ANP was applied to the relational database to weight data layers and define functional criteria and factors. Developed by Saaty (1980), ANP is a multi-criteria decision-making method that incorporates interdependent elements across clusters (Keeney & Raiffa, 1976). The model features a network of connections between elements of different clusters (outer dependency) and within the same cluster (inner dependency), reflecting reciprocal relationships (Saaty, 1999; Saaty & Vargas, 2006).

ANP implementation involves four stages:

Defining the decision problem and modeling it as a network: After identifying the problem, relevant parameters are structured into a network model (Figure 2), including criteria, factors, and their dependencies. Methods like brainstorming, Delphi, DEMATEL, or nominal group techniques can define this structure (Zebardast, 2010). Figure 2 illustrates the criteria, factors, and clusters used for landslide susceptibility mapping in the study area.

Formation of the pairwise comparison matrices and extracting priority vectors: In this step, similar to the AHP model, numbers 1 to 9 and their reverse are used for expressing preference in pairwise comparison matrices.

After determining the preferences in pairwise comparison matrices, the inner importance vector, representing the relative importance of factors and classes, should be calculated using Eq. (1).

$$AW = \lambda_{max}.W \qquad (1)$$

Where A is a pairwise comparison matrix of factors and classes, W is the eigen vector (importance coefficient), and λ_{max} is the maximum eigenvalue of the judgment matrix.

Consistency ratio (CR) is used for validity determination of pairwise comparisons.

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (2)$$

In Eq. (2), CI is the consistency index, and n is the number of compared components in the matrix, as shown by Eq. (3).

$$CR = \frac{CI}{RI} \qquad (3)$$

CR is the consistency ratio, and RI is the random index that depends on the number of the compared components. If the consistency ratio is less than 0.1, the pairwise comparison will be acceptable and constant (Malczewski, 1999; Saaty, 1980; Neaupane and Piantanakulchai, 2006).

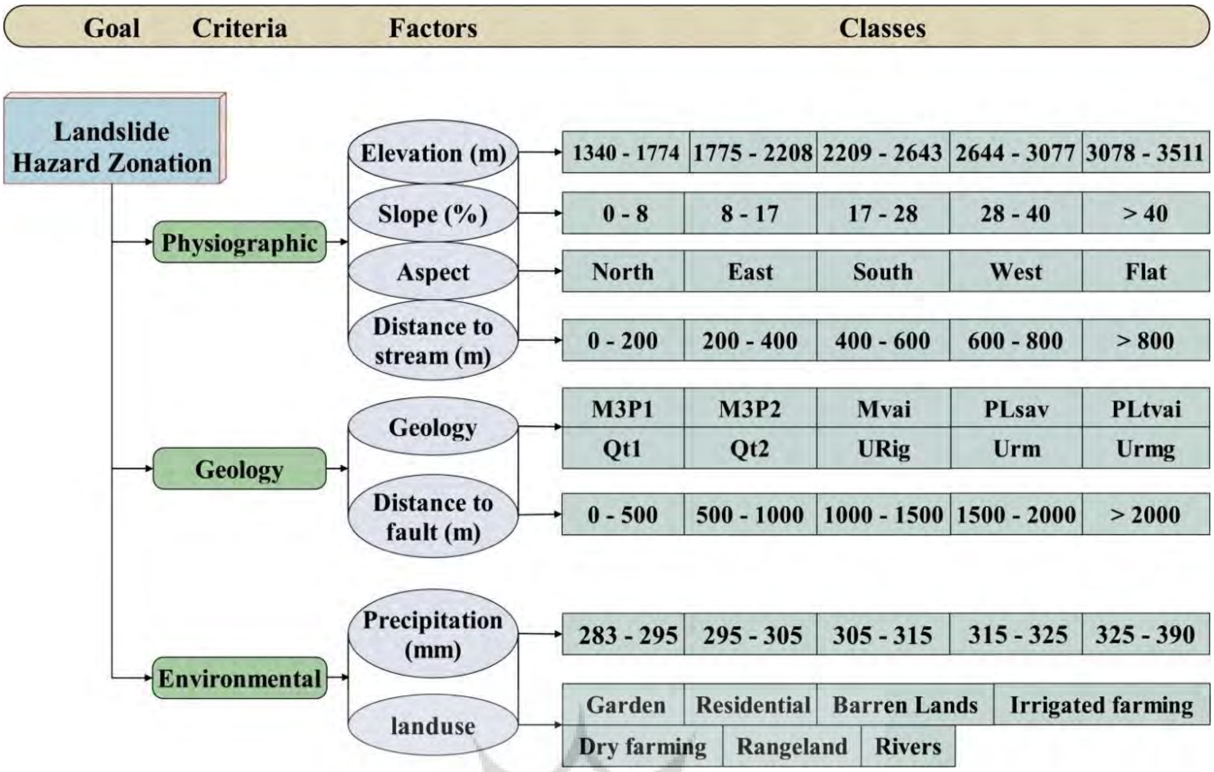

Figure 2. Criteria, Factors and Classes Applied in the ANP Model

The Super matrix: In this step, the available relations in network structure and relative calculated weights in the second step are presented by a super-matrix. A super matrix is obtained by the union of all priority vectors calculated for each pairwise comparison matrix in one matrix (Lami and Abastante, 2014).

Determination of the best alternatives: In this study, Super Decision software was used to calculate the weights of the factors and classes. After determining the weights, the weight of each class is assigned to it in its reclassed factor. Finally, landslide susceptibility zonation map was produced in ArcGIS software by overlapping the weighted layers. Layers weighted sum was applied to prepare the final map (Eq. 5).

$$LS_i = \sum_{i=1}^{n} (S_{ij} \,.\, W_{ij}) \tag{5}$$

Where LH_i is the amount of landslide susceptibility in pixel I (by overlapping weighted layers in ArcGIS software), S_{ij} is the weight of pixel i in classes j, and W_{ij} is the weight of pixel i in factors j.

The Analytic Network Process is a widely used GIS-based multi-criteria decision analysis (MCDA) method that has been effectively implemented in various decision-making systems.

Results and Discussions

In this study, 8 data layers (Including Land use, Precipitation, Geology, Distance to fault, Elevation classes, Slope, Aspect, and Distance to stream) have been provided in a GIS setting, as they are regarded to be significantly important factors in landslide occurrence in Mehran Roud basin. All layers were prepared as raster maps and reclassified in a UTM coordinate system. These data layers have been analyzed in this section.

The land use map

The land use map was extracted from the Landsat 8 images process using the supervised classification method and Maximum Likelihood Algorithm in ENVI software (Figure 3a). There are 7 land use types in the Land Use map of the study area: (1) Garden, (2) Residential, (3) Barren lands, (4) Irrigated farming, (5) Dry farming, (6) Rangeland, and (7) Rivers. The correlation of land use types with landslide density indicates that the high landslide density is concentrated on the rangeland and vicinity of the streams.

The precipitation map

Rainfall is considered as the most important factor of landslide occurrence. The information from synoptic and climatology stations (Tabriz, Sahand, Varzaghan, and Bostan Abad) was used to prepare the precipitation layer. The precipitation map was prepared by interpolation of the stations' point data (the average annual precipitation from the year 2000 to 2022) using the inverse distance weighting (IDW) method under the ArcGIS platform. This method was selected because of its better accuracy than other interpolation methods. Finally, the precipitation map of the study area was divided into five categories, e.g., 283-295, 295-305, 305-315, 315-325 and 325-390mm. The precipitation situation of the study area has been shown in Figure 3b.

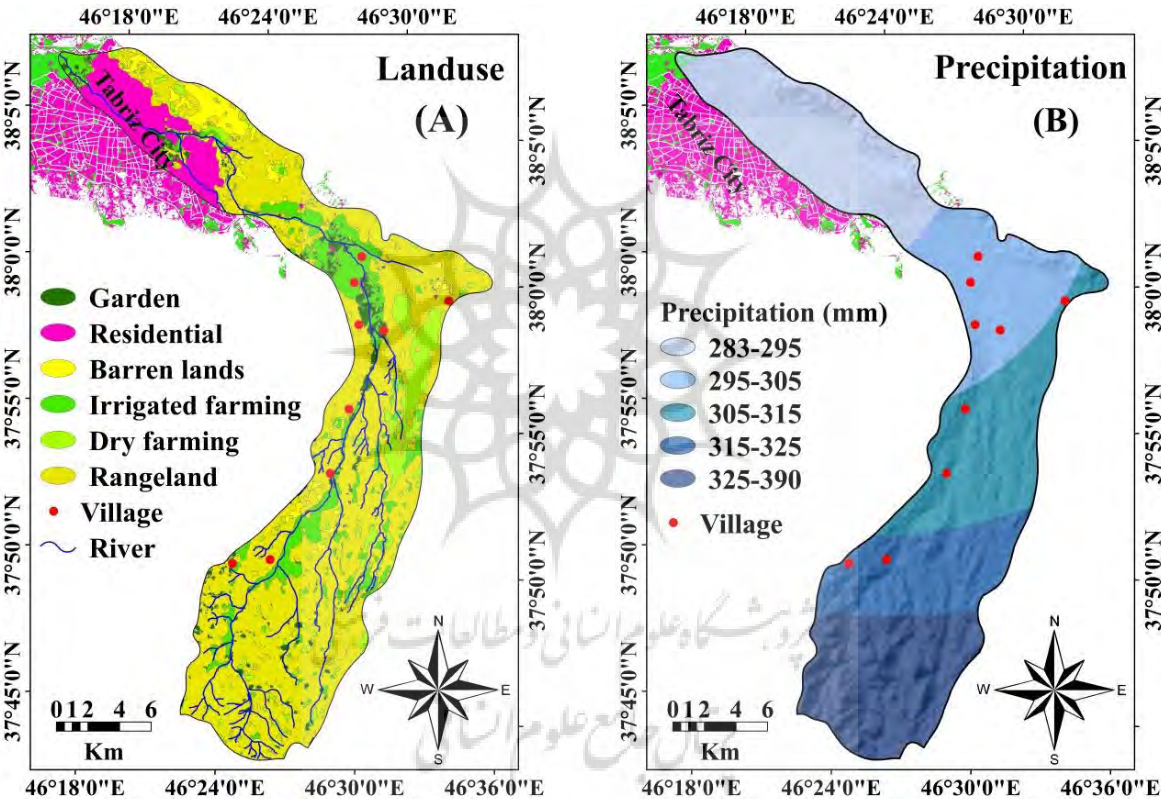

Figure 3. Land use and precipitation maps

Slope, aspect and elevation maps

In this study, slope, aspect, and elevation maps were prepared based on a digital elevation model (DEM) (pixel size = 30 m) and using GIS techniques. The slope gradient is an important factor of the slope consistency analysis and is mainly used in landslide susceptibility studies. The more the slope gradient increases, the more it will correlate with an increased likelihood of failure (Bui et al., 2011). The range of slope has been found between 0 and 63%, and the highest rating was assigned with steep slope class, and the lowest rating was assigned with the lowest slope in the ANP model (Figure 4a). The slope map was grouped into five different categories, e.g., 0-8, 8-17, 17-28, 28-40, and > 40%.

Aspect can be defined as the compass direction that a slope faces measured in degrees from the north in a clockwise direction, ranking from 0º to 360º (Bui et al., 2011). Aspect is a vital factor influencing slope inconsistency due to aspect-related parameters, such as exposure to sunlight and drying winds, which control the concentration of soil moisture, which is a determinant for the occurrence of landslides (Magliulo et al., 2008). In the study area, on the north and west aspects, the landslide number is relatively high (Figure 4b).

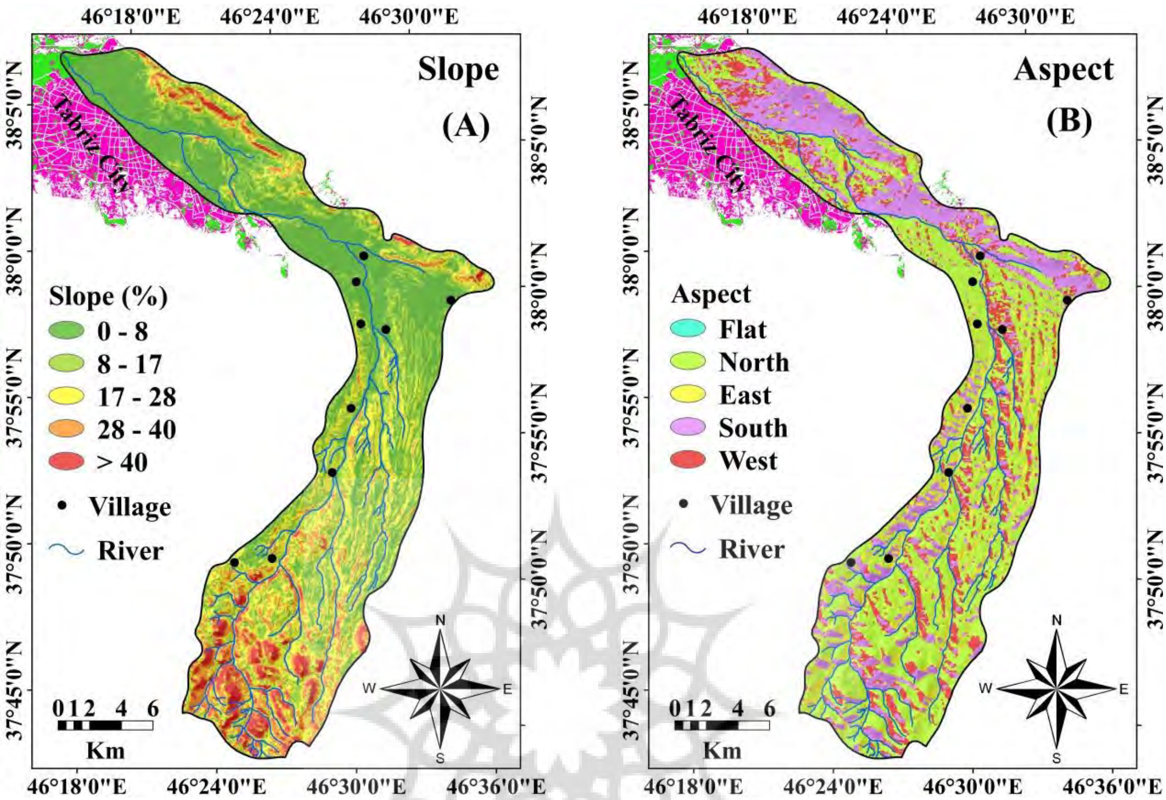

Figure 4. Slope and Aspect map

The distance to rivers map

Vicinity to the drainage network is an important factor in controlling the occurrence of landslides (Gokceoglu and Aksoy, 1996). The reason can be related to the fact that land modification caused by gully erosion may influence the occurrence of a landslide (Dai and Lee, 2002). In order to provide the river layer, first, the drainage network of the study area was extracted from the topography map in 1: 50000 scale from Tabriz city. Then, the distance to the map of the rivers was prepared under the ArcGIS platform (Figure 5b).

The Geology and distance to faults maps

Geology, with its structural and property variations, may cause differences in the strength and permeability of rocks and soils (Ayalew and Yamagishi, 2005). According to subdivisions of the structural-sedimentary units (Stoecklin, 1968), the geological maps of Tabriz and Ousku, which it is located in the northwest of Iran, are considered as a part of the central Iran zone or the Alborz- Azerbaijan zone (Nabavi, 1976). In this study, the lithology map was extracted from geological maps in 1: 100,000 scale from Tabriz and Ousku under the ArcGIS platform provided by the Geological Organization of Iran (Figure 6a). The geological formations of the region include

Qt1 (Old terraces and gravel fans),

Qt2 (Young terraces, plain deposits, and gravel fans),

Urm (Light-red to brown marl with sandstone),
URig (Red marl, sandstone, and conglomerate),
Urmg (Gyps and marl),
M3P1 (Conglomerate with lahar, Tuff, Pumice, Volcanic ashes, and freshwater Limestone),
PLtvai (Dacitic andesite and quartz andesite),
PLsav (Pliocene rhyolitic to rhyodacitic sub volcanic),
M3p2 (Ash flows and associated rocks), and
Mvai (Dacitic to andesitic sub-volcanic rocks).

Distance to faults has been identified as a critical factor affecting landslide susceptibility. According to Varnes (1984), the extent of rock fracturing and shear deformation plays a significant role in slope stability assessment. To analyze this relationship, a fault distance map was created using buffer analysis in ArcGIS 10.3, categorizing the area into five distinct zones: 0–500, 500–1000, 1000–1500, 1500–2000, and beyond 2000 m (Figure 6b). The findings indicate that zones within 0–500 m of faults exhibit the highest landslide susceptibility in the study area.

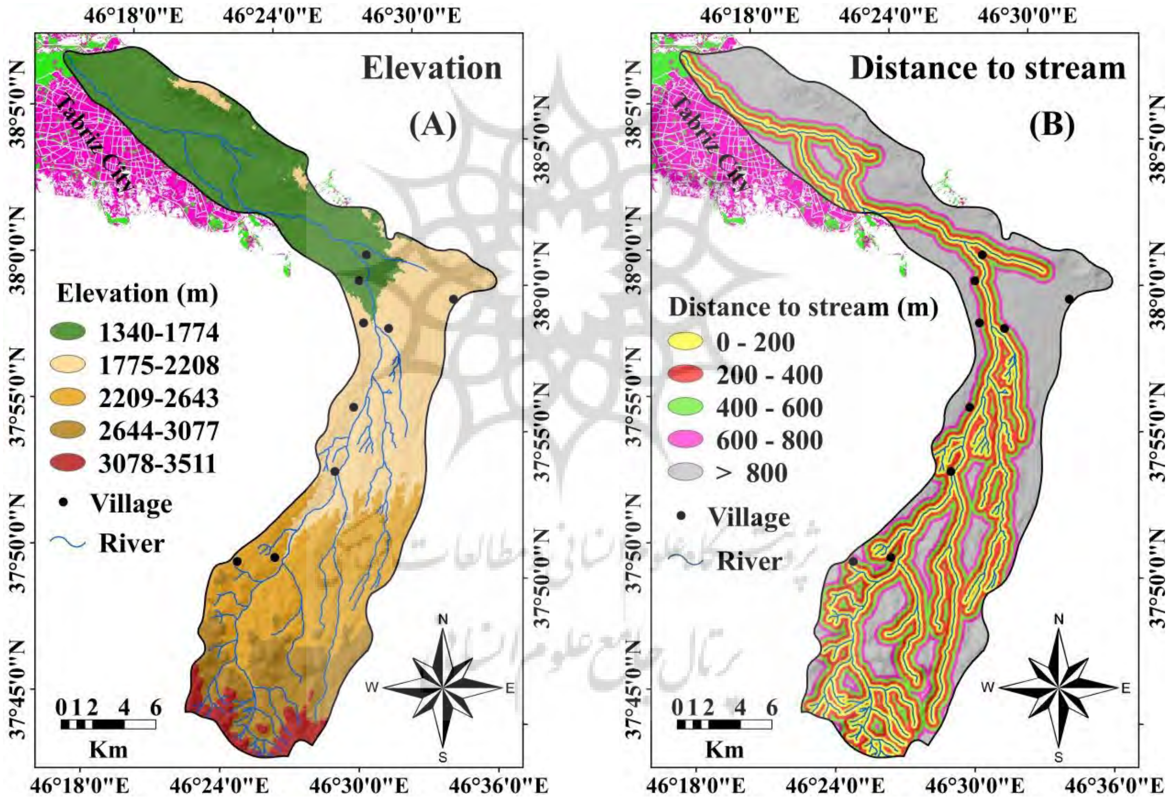

Figure 5. Elevation classes and distance to rivers maps

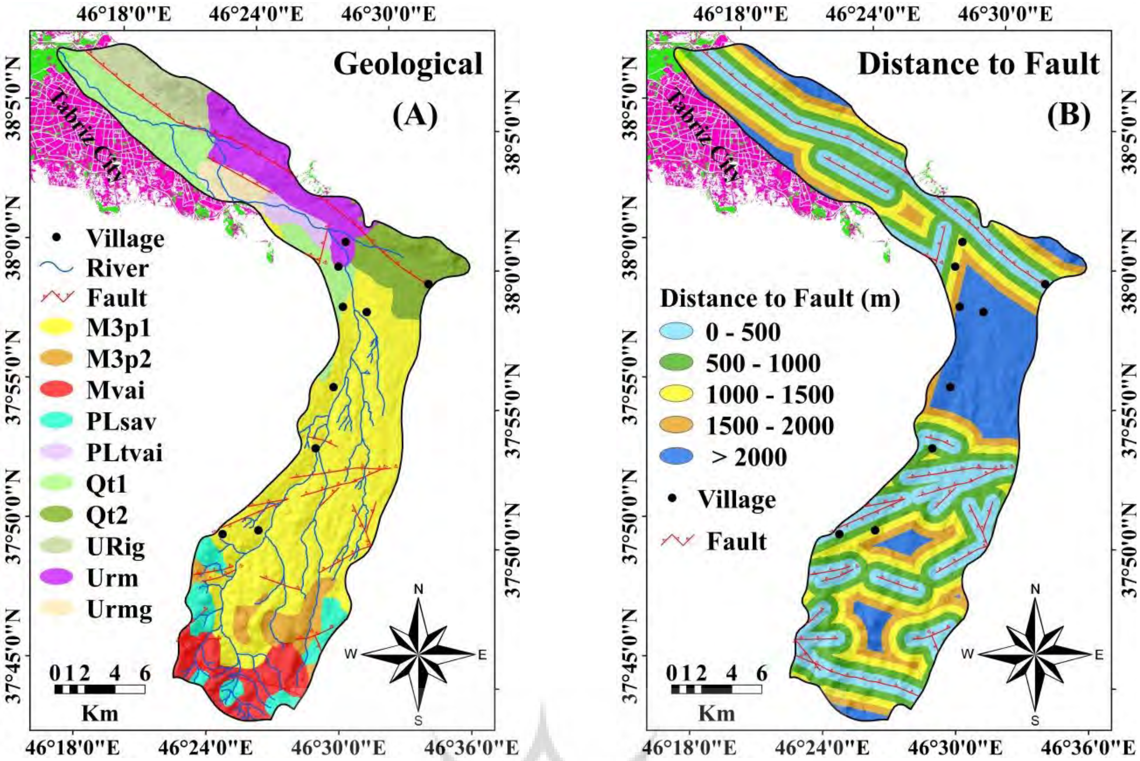

Figure 6. Geological and distance to faults maps

Weighting to information layers

After determining the effective parameters on landslide occurrence in the study area, all necessary weights were calculated for factors and classes using the analytic network process in Super Decisions software (Table 1, 2). According to a comparison between classes, it was specified that aspect with north class (weighted as 0.576), distance to fault with ranging from 0 to 500 m (weighted as 0.441), distance to stream with ranging from 0 to 200 m (weighted as 0.420), precipitation with ranging from 325 to 390 mm (weighted as 0.418) have the highest impacts on landslide occurrence. Two factors, including slope (ranging from 17 to 28%) and land use (Barren lands and Dry farming), have the second highest importance. Moreover, elevation classes between 2209-2643m (weighted as 0. 372) and geology (M3P1, M3P2, and PLsav geological formations) show the highest weight.

Table 1. The weights calculated for Factors using ANP model

Factors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Eigenvalue
(1) Geology	1	2	5	3	4	6	9	4	0.331
(2) Precipitation (mm)	1/2	1	4	2	4	3	5	7	0.233
(3) Slope (%)	1/5	1/4	1	2	2	3	3	3	0.117
(4) Distance to stream (m)	1/3	1/2	1/2	1	2	3	3	4	0.112
(5) Land use	1/4	1/4	1/2	1/2	1	2	4	3	0.080
(6) Elevation classes (m)	1/6	1/3	1/3	1/3	1/2	1	2	3	0.055
(7) Aspect	1/9	1/5	1/3	1/3	1/4	1/2	1	2	0.036
(8) Distance to Fault (m)	1/4	1/7	1/3	1/4	1/3	1/3	1/2	1	0.032
Inconsistency index: 0.05									

Table 2. The weights calculated for classes using ANP model

Factors	Classes	Eigenvalue	Inconsistency index
Precipitation (mm)	283-295	0.061	0.01
	295-305	0.097	
	305-315	0.159	
	315-325	0.262	
	325-390	0.418	
Land use	Garden	0.046	0.05
	Residential	0.043	
	Barren lands	0.226	
	Irrigated farming	0.100	
	Dry farming	0.302	
	Rangeland	0.181	
	Rivers	0.102	
Slope (%)	0-8	0.067	0.03
	8-17	0.099	
	17-28	0.264	
	28-40	0.148	
	> 40	0.42	
Aspect	flat	0.002	0.04
	North	0.576	
	West	0.280	
	East	0.087	
	South	0.055	

Table 2. The weights calculated for classes using ANP model

Factors	Classes	Eigenvalue	Inconsistency index
Elevation classes (m)	1340-1774	0.103	0.04
	1775-2208	0.277	
	2209-2643	0.372	
	2644-3077	0.166	
	3078-3511	0.079	
Distance to stream (m)	0-200	0.420	0.01
	200-400	0.252	
	400-600	0.162	
	600-800	0.098	
	> 800	0.066	
Distance to Fault (m)	0-500	0.444	0.005
	500-1000	0.261	
	1000-1500	0.152	
	1500-2000	0.088	
	> 2000	0.052	
Geology	M3P1	0.172	0.08
	M3P2	0.163	
	Mvai	0.147	
	PLsav	0.148	
	PLtvai	0.089	
	Qt1	0.005	
	Qt2	0.008	
	URig	0.078	
	Urm	0.094	
	Urmg	0.096	

Mapping of landslide susceptibility

In order to build landslide susceptibility map, the raster layer of each parameter was multiplied by its weighted vector. Finally, the landslide susceptibility map was prepared through the sum of the layers related to geology, physiographic, and environmental parameters. Landslide susceptibility map was produced using the GIS-MCDM technique, including ANP (Figure 7). Based on the effective parameters, landslide occurrence inside the Mehran Roud basin could be separated into 5 distinguished classes, from very high to very low landslide susceptibility, as given in Table 4. According to the ANP-based landslide susceptibility map, 155 km^2 (43%) of the study area have high and very high potential, 111 km^2 (30.9%) have low and very low susceptibility and 94 km^2 (26.1%) have Moderate potential toward landslide susceptibility occurrence. At a glance, Figure 7 indicates that the areas with high landslide susceptibility are located on the north and west aspect, near the river and faults, and slopes with higher 17%. Also, regions with high landslide susceptibility are located in the elevation from 2209 to 3511 m based on the elevation classes.

The distribution of 7 landslide events that occurred inside the study area during the past ten years is shown in Figure 7. In specifying details, the number of landslides for individual landslide susceptibility classes and their contributions inside the study area are indicated in Table 3.

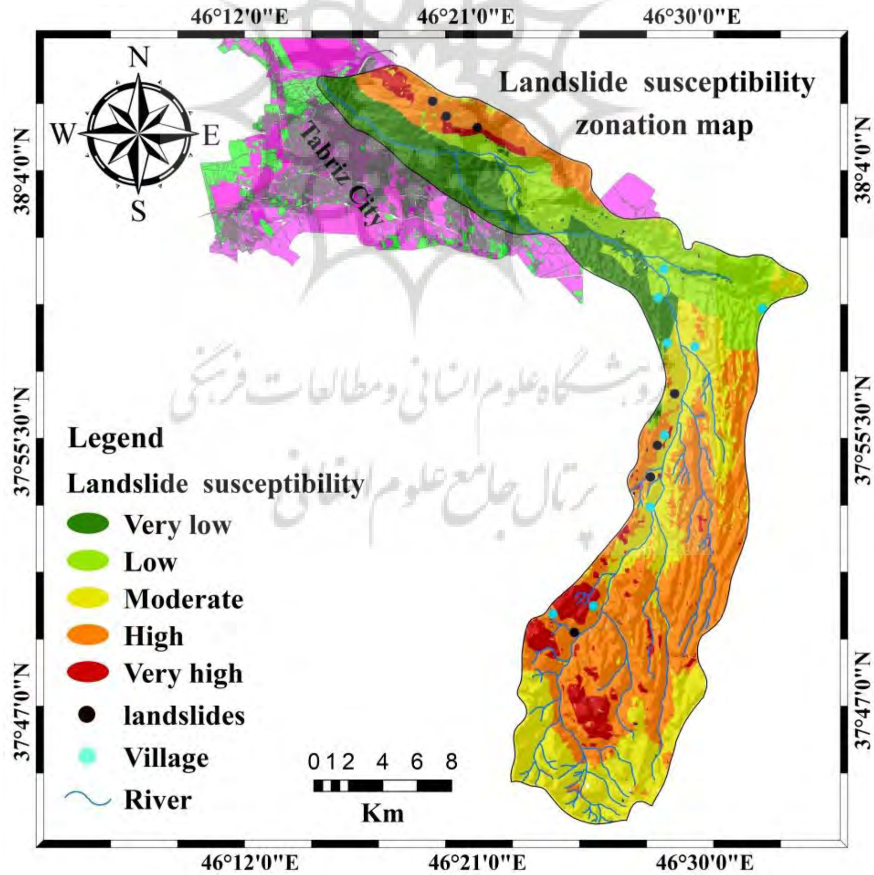

Figure 7. Landslide susceptibility zonation map of Mehran Roud basin based on the ANP model

Table 3. The areas of Landslide susceptibility classes

Landslide susceptibility	Area (Km^2)	Area (%)	Landslides Occurred	Landslides Occurred (%)
Very low	51	14.2	-	-
Low	60	16.7	-	-
Moderate	94	26.1	1	14.3
High	134	37.2	5	71.4
Very high	21	5.8	1	14.3
Total	360	100	7	100

In order to assess which classes contribute most to the landslide risk potential in the region, the final map was cross-validated with each output (Table 4).

Table 4. the most effective classes of each criteria in the potential risk of landslides in the area

factors	the most effective classes
Precipitation (mm)	The rainfall ranges of 315–325 mm and 325–390 mm are associated with higher landslide susceptibility.
Slope (%)	Steeper slopes, particularly those exceeding 20%, exhibit a greater likelihood of landslides.
Distance to stream (m)	Three classes, 0-200, 200-400, and 400-600 of rivers are more prone to landslides.
Land use	Dry farming and rangeland areas are identified as highly susceptible to landslides based on susceptibility mapping.
Elevation classes (m)	Regions at elevations above 2,200 m demonstrate increased landslide vulnerability.
Aspect	North- and west aspects show significantly higher landslide susceptibility.
Distance to Fault (m)	Locations within 0–600 m of fault zones are at elevated risk of landslides.
Geology	Certain geological formations, including M3P1 (conglomerate with lahar, tuff, pumice, volcanic ash, and freshwater limestone), M3P2 (ash flows and related rocks), PLsav (Pliocene rhyolitic to rhyodacitic sub-volcanic deposits), and Mvai (dacitic to andesitic sub-volcanic rocks), are highly prone to landslides.

Conclusion

Identifying regions with a high hazard of landslides can assist environmental planners, natural resource agencies, and other relevant organizations in taking preventive measures, thereby reducing costly damages and the loss of valuable resources after a landslide event. Overall, the benefits of preventing landslides encompass both anthropogenic and environmental dimensions. In this study, an attempt was made to identify areas with potential for landslide occurrence in the Mehran Roud basin. The key factors influencing landslide occurrence in the study region —such as geology, precipitation, land use, distance to stream, slope, distance to fault, elevation classes, and aspect layers —were were prepared under the ArcGIS platform. The ANP method was applied to assign weights to the factors and classes, after which the weighted layers were combined to generate the landslide susceptibility zoning map. In the region, geological conditions (weight: 0.331) and rainfall (weight: 0.233) have been the most significant factors contributing to landslides. The research area was categorized into five levels of landslide susceptibility: very low, low, moderate, high, and very high. Based on the preliminary models, approximately 37% of the area falls under high susceptibility, while about 5.8% is classified as very high susceptibility. Comparing past landslide locations with the landslide susceptibility zonation map revealed that 85.7% of these points fall within the high and very high-hazard categories. This indicates that the ANP model is a suitable approach for landslide risk zoning in the Mehran Roud basin, as it effectively identifies hazard-prone areas. Additionally, the GIS play a significant role in processing and combining various data layers, demonstrating its strong capabilities in spatial analysis.

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