

A GIS and Fuzzy AHP-Based Geospatial Approach for Regional Landslide Susceptibility Mapping

Daryoush Ahadi Rosta^{1,*}

¹Department of Civil Engineering, Aeen Kamal Higher Education Institute, Urmia 5715938911, Iran

*Corresponding author: ahadi.daryoush.85@gmail.com

Received: 04 March 2026 / Accepted: 31 March 2026 / Published: 25 May 2026

© The Author(s) 2026

Abstract: The present study aimed to develop a landslide susceptibility map for Khoy County, located in West Azerbaijan Province, northwest Iran. To achieve this, a range of conditioning and triggering factors were considered, including elevation, slope aspect, slope angle, geological formations, precipitation, drainage density, degree of weathering, land use/land cover, proximity to faults, earthquake distribution, distance to roads, and distance to urban areas. For the methodological framework, the Fuzzy Analytic Hierarchy Process (FAHP) was employed to assess landslide susceptibility across the region. The FAHP-based model was applied to the various thematic layers, which were rasterized and integrated into a Geographic Information System (GIS) environment to generate the final susceptibility map. The results revealed a significant landslide risk in the study area, with spatial distribution as follows: very high susceptibility (22.17%), high (25.34%), moderate (13.66%), low (16.63%), and very low (22.20%). This classification highlights that nearly half of Khoy County falls within high to very high-risk zones. Given the considerable extent of susceptible areas, incorporating landslide hazard assessments into regional planning and development strategies is strongly recommended. The findings emphasize the critical need for sustainable land management and hazard mitigation efforts to minimize potential damage and ensure public safety.

Keywords: Landslide susceptibility assessment, Geo-hazards, GIS environment, Fuzzy logic, Khoy County.

I. INTRODUCTION

One of the geological disasters that can occur at different times and spatial scales in mountainous regions are landslides, which frequently result in significant human casualties and property damage worldwide. Rainfall, earthquakes, volcanic eruptions, river slope erosion, and human activities like slope-cutting and excavation all contribute to the occurrence of landslides, which are defined as the downslope mass movements of rock, earth, and debris under the direct influence of gravity (He et al., 2019). It is essential to anticipate

regions that are prone to landslides due to the large number of deaths caused by landslides worldwide (Chanu & Bakimchandra, 2022). Various models to lessen the harm caused by landslides have previously been developed for the purposes of landslide susceptibility mapping and awareness of their distribution (Abay et al., 2019; Panchal & Shrivastava, 2021). Landslide susceptibility mapping (LSM) technique is a useful tool for anticipating and locating landslide events which helping to estimate the probability of landslide occurrence (Nikoobakht et al., 2022). Local governments/councils tend to incorporate the LSM into master development planning due to its usefulness (Mao et al., 2022).

To date, several approaches (qualitative and quantitative) have been proposed for modeling landslide susceptibility (Azarafza et al., 2021). Multiple spatial geoscientific data can be visualized, processed, and analyzed using a geographic information system (GIS), which plays an undeniable role in LSM. Numerous researchers have noticed that advances in GIS software have allowed for the integration of a set of input maps, each showing a distinct geoscientific variable, across dozens of LSM approaches (Es-smairi et al., 2021). In this regard, GIS-based multi-criteria decision-making (MCDM) techniques are useful and inventive ways to transform either spatial or non-spatial data into desired information that, when combined with the subjective judgments of decision-makers, can be used to make important decisions (Okoli et al., 2023). In the meantime, the analytic hierarchy process (AHP), as one of the efficient MCDM-based methods has been widely used in LSM (Do et al., 2020). AHP is a method for making decisions based on multiple factors that can be used in complex decision problems and are broken down into a hierarchy of criteria, sub-criteria, and alternatives. After that, the AHP makes use of pairwise comparisons to assign numerical weights to each part of the hierarchy. These weights are added up to get an overall priority or order of the options (Fan et al., 2022). In LSM, the AHP is used to assess the relative importance of various triggering factors that contribute to the likelihood of a landslide occurrence (Do et al., 2020). Also, AHP has good capability to convert information and categorize the data into the information layers that are usable in GIS to produce LSM maps (Yong et al., 2022).

This study aimed to employ both the AHP and fuzzy logic to develop a LSM model for the Khoy region in Iran. The integration of fuzzy-AHP (FAHP) resulted in enhanced accuracy and reduced uncertainties in the LSM process. Khoy, being a high-risk area prone to earthquakes and landslides, consistently experiences substantial damage from these geological hazards each year (Esmaeili et al., 2019). Given this context, the implementation of LSM becomes imperative for urban sustainable development and planning. The FAHP offers several distinct advantages when applied to Landslide Susceptibility Mapping. One of its primary strengths is its ability to manage and account for uncertainty. LSM involves various factors, such as geology, slope, land use, and rainfall, which often have imprecise or vague data. FAHP is designed to handle these uncertainties by representing factors using linguistic terms and fuzzy numbers, making it a valuable tool for dealing with the inherent ambiguity in LSM data. FAHP excels at incorporating expert knowledge and opinions into the decision-making process. Experts can provide their insights in the form of linguistic variables, which are then translated into fuzzy numbers. This feature allows for a more holistic and informed decision-making approach, as experts' qualitative insights are considered in conjunction with quantitative data. FAHP is also well-suited for multi-criteria decision-making, which is inherent to LSM. It facilitates the simultaneous consideration of numerous criteria and factors, providing a framework for assigning priorities and weights to each factor. In the complex context of landslide susceptibility, this multi-criteria approach is essential for comprehensive and accurate modeling. Lastly, FAHP offers flexibility in terms of adjusting membership functions and fuzzy rules. This adaptability allows the model to be tailored to the specific characteristics of the study area, ensuring that it can be effectively applied in diverse geographic and geological contexts.

While FAHP is a valuable tool, it is essential to recognize its limitations in the context of Landslide Susceptibility Mapping. One significant limitation is its potential for subjectivity. FAHP heavily relies on expert opinions and judgments, which can introduce bias into the modeling process. The definition of linguistic variables and membership functions can vary between experts, leading to differing results. This subjectivity must be acknowledged and addressed to ensure the model's objectivity and reliability. Another limitation is the data requirements of FAHP. Implementing this method necessitates a substantial amount of data and expert input. Gathering such data can be challenging, time-consuming, and costly, particularly in remote or data-scarce regions. The availability of data can significantly impact the feasibility and accuracy of using FAHP in LSM.

Furthermore, the complexity of implementing FAHP should be noted. It can be intricate, especially when dealing with a large number of criteria and linguistic terms. Managing this complexity often requires advanced mathematical and computational skills, which may not be readily available in all research or application settings. Lastly, while FAHP is an effective MCDM tool, it may not fully address the spatial aspects of LSM.

II. LITERATURE REVIEW

Today, various strategies such as qualitative, semi-quantitative, and quantitative methodologies have been developed to identify regions prone to landslide occurrence in literature. The construction of a knowledge-based model is dependent on expert judgment in qualitative or quantitative-based procedures which are practically expert-based methods (Azarafza et al., 2018). Due to the integration of theoretical understanding and accumulated experience, quantitative approaches provide reliable solutions for complex problems in various scientific fields (Nikoobakht et al., 2022). Therefore, these approaches are expected to continue playing an important role in LSM (Nanehkaran et al., 2021). To avoid bias and subjectivity in the evaluation of the significance of criteria, quantitative or data-driven approaches have been developed (Yu & Chen, 2020). In addressing landslide problems, data-driven techniques estimate the likelihood of landslide occurrence by applying statistical or logical models based on the spatial distribution of landslide conditioning factors in landslide-prone areas (Hodasová & Bednarik, 2021). Table 1 presents a list of previous studies that have utilized AHP and fuzzy logic approaches for landslide susceptibility mapping.

A review of previous studies demonstrates the extensive application of AHP, fuzzy logic, and other MCDM techniques in LSM across different geographic regions. For instance, Yalcin (2008) applied the AHP approach in Ardesen, Turkey, and reported that categorizing and statistically evaluating triggering factors can significantly reduce analytical errors in susceptibility assessment. Similarly, Khezri (2011) combined AHP, MCDM, and GIS techniques in the Zab Basin in northwestern Iran, identifying geographical conditions, land use patterns, topographic characteristics, and human activities as the principal factors influencing landslide occurrence. Several studies have also highlighted the advantages of integrating fuzzy logic with AHP within a GIS environment. For example, Pourghasemi et al. (2012) demonstrated in the Haraz watershed of Iran that fuzzy logic methods can outperform conventional AHP models in predicting landslide-prone areas. Likewise, Feizizadeh et al. (2014) reported improved reliability and prediction accuracy when combining AHP with fuzzy set theory for landslide susceptibility mapping in the Izeh River basin.

Comparable findings have been reported in other regions worldwide. Kayastha et al. (2013) produced reliable susceptibility maps for the Tinau watershed in Nepal using AHP and GIS, demonstrating strong agreement between predicted susceptibility zones and historical landslide events. Similarly, Zhu et al. (2014) applied a GIS-based fuzzy logic model in China and showed that knowledge-based approaches can effectively identify landslide-prone areas and remain transferable to other regions with minimal modification. Later studies continued to confirm the robustness of these approaches. For example, Roy & Saha (2019) reported that a combination of AHP, fuzzy logic, and GIS successfully identified highly susceptible zones in Darjeeling, India. More recent investigations, including those by Zhou et al. (2020), Nanehkaran et al. (2021), and Abdi et al. (2021), further demonstrated that fuzzy-AHP-based frameworks provide reliable and accurate results in landslide susceptibility assessments.

Table 1 Several published literatures on fuzzy logic, AHP and GIS method in LSM

Author(s)/Year	Method	Location	Result
Yalcin (2000)	AHP	Ardesen, Turkey	Results showed that identifying and categorizing triggering factors significantly reduces analytical errors in landslide susceptibility assessment.
Khezri (2011)	AHP, MCDM, GIS	Northwest of Iran	Geographical conditions, land use, topography, and human activities were identified as the main controlling factors influencing LSM.
Pourghasemi et al. (2012)	Fuzzy logic, AHP, GIS	Haraz Watershed, Iran	The results indicated that the fuzzy logic approach produced more accurate susceptibility predictions compared with the conventional AHP model.
Kayastha et al. (2013)	AHP, GIS	Tinau watershed, west Nepal	The LSM showed strong agreement with historical landslide occurrences, indicating its reliability for land-use planning.
Feizizadeh et al. (2014)	Fuzzy logic, AHP, GIS	Izeh River basin	Integrating AHP with fuzzy logic significantly improved the accuracy and reliability of LSM.
Zhu et al. (2014)	GIS, fuzzy logic	Kaixian and Gorges, China	The knowledge-based fuzzy approach effectively identified landslide-prone areas and demonstrated good transferability to other regions.
Lorentz (2016)	MCDM	Rio de Janeiro, Brazil	The method successfully identified highly susceptible zones and proved useful for pre-disaster landslide risk assessment.
Zhao et al. (2017)	GIS, fuzzy logic, AHP	Zhen'an County	The integrated model improved the objectivity and accuracy of LSM by combining spatial data with expert knowledge.
Azarafza et al. (2018)	MCDM	South Pars, Iran	High-risk landslide zones were mainly identified in the northern part of the study area near the Assalouyeh and Kangan anticlines.
Roy & Saha (2019)	AHP, Fuzzy logic, GIS	Darjeeling, India	Approximately 34% and 22% of the study area were classified as highly susceptible to landslides.
Zhou et al. (2020)	Fuzzy, AHP, GIS	Kenya	About 31.53% and 29.88% of the study area were categorized as very high and high susceptibility zones, respectively.
Nanehkaran et al. (2021)	Fuzzy, AHP, GIS	Tabriz	The results revealed considerable landslide susceptibility across the Tabriz region due to the influence of multiple triggering factors.
Abdi et al. (2021)	Fuzzy, AHP, GIS	North-East Algeria	Comparative analysis showed that the fuzzy-AHP model achieved higher accuracy than other benchmark methods in LSM.
Saha et al. (2022)	AHP, MCDM, Fuzzy logic	West Bengal, India	The northeastern and eastern parts of the study area were identified as the most landslide-prone zones.
Saygin et al. (2023)	FAHP, Decision Tree, GIS	Turkey	The results showed that integrating MCDM-fuzzy analysis with machine learning improves the accuracy and reliability of landslide susceptibility prediction.
Bhagya et al. (2023)	AHP, FAHP, GIS	Western Ghats, India	The study indicated that the fuzzy-AHP model produced more reliable LSM compared with the conventional AHP method.
Badola et al. (2023)	Fuzzy logic, GIS	Himalayan region, India	The fuzzy rule-based model effectively identified landslide-prone areas and demonstrated strong prediction capability.
Gopinath et al. (2024)	Fuzzy-AHP, GIS	Western Ghats, India	The ensemble fuzzy-AHP approach improved prediction accuracy and reduced uncertainty in landslide susceptibility assessment.
Swain et al. (2024)	GIS-based quantitative modeling	India	The study successfully identified high-risk landslide zones by integrating geomorphological and environmental factors.
An et al. (2024)	AHP, GIS, Fuzzy logic	China	The integration of multi-source geospatial data significantly improved the accuracy of LSM.
Zighmi et al. (2025)	AHP, GIS	Tellian Atlas, Algeria	The GIS-based AHP model effectively identified landslide-prone areas and provided reliable hazard assessment results.
Rebouch et al. (2025)	Remote sensing, GIS, AHP	Souk Ahras, Algeria	The hybrid GIS-AHP model improved landslide susceptibility prediction and accurately delineated unstable zones.
Taş (2025)	AHP, Frequency Ratio, GIS	Kemah-Kömür Basin, Turkey	Both models showed good performance, while AHP provided clearer interpretation for landslide hazard assessment.
Demirel et al. (2025)	AHP, FMEA, GIS	Yalova, Türkiye	The susceptibility map showed that most historical landslides occurred in moderate to very high susceptibility zones, confirming the reliability of the integrated model.
Mersni et al. (2025)	AHP, ANN, GIS	Northwestern Tunisia	The results revealed that rainfall and slope were the most influential factors, and the ANN model produced higher prediction accuracy than the AHP model.
Ali et al. (2025)	AHP, Fuzzy Logic, GIS	Koya, Iraq	The comparison of AHP and fuzzy models indicated that the fuzzy-gamma model achieved higher predictive accuracy in landslide susceptibility assessment.
Kucuker (2025)	AHP, GIS, MCDM	Black Sea Region, Türkiye	The study revealed that a considerable portion of forest roads lies in high-risk landslide zones, indicating the usefulness of AHP for infrastructure risk planning.

III. CASE STUDY

A. Geological Setting

Khoy County is in West Azerbaijan Province (WAP), Iran. The capital of the county is the city of Khoy which is 807 km distance from Tehran's capital. The county is located near several mountains, including Chelekhaneh Mountain and Avrin Mountain, the latter being the highest mountain in West Azerbaijan Province (Aghanabati, 2009). Figure 1 illustrates the location of Khoy County in Iran. The study region has a cold and dry climate, according to the Iranian Meteorological Organization (IMO, 2022). The region's geology is still poorly understood due to its complex geological history. It is known that road and railway construction, seismic activity, groundwater influence, and rock weathering are the primary causes of slope instability in this region. After heavy rainfall, some landslides on road slopes occur in the southwest of Khoy. Along road slopes and residential areas, there have been some historical landslides. The Gougerd landslide, located south of Avrin Mountain, is recorded as one of the major large-scale historical landslides in the Khoy region (Esmaili et al., 2019). Most of the landslides recorded in the region exhibit a rotational failure mechanism, with sliding scales ranging from a few meters to several hundred meters (Aghanabati, 2009). In their general description of the Khoy region's geology, Kamineneni and Mortimer focused primarily on its metamorphic rocks, particularly the presence of high-pressure glaucophane-bearing schists and amphibolites. This region encompasses the junction between the Alborz–Azarbaijan Block (AAB) in the northeast and the Arabian Plate in the southwest, as depicted on Iran's tectonic and magmatic map (Masoudi and Imamali pour, 2019).

Due to its location in the Sanandaj-Sirjan geological zone and geological conditions, the southwest region of Khoy County is one of the most susceptible to landslides (Aghanabati, 2009). Figure 2 shows the geological map of the study area provided by the Geological Survey of Iran (GSI, 2009). As seen in this figure, the most recent geological formations in the region are surface sediments that include young alluviums and older alluviums. Rock units were classified into the following categories: metamorphic rocks (including schist and amphibolite facies), limestone, sandstone, shale, conglomerate, plutonic igneous rocks (including diorite and granite), and alluvium (Aghanabati, 2009).

B. Triggering Factors

One of the most critical phases of landslide studies is the collection, selection, and preparation of a database of triggering factors that influence landslide occurrence for the development of LSM (Fan et al., 2017, 2022; Mallick et al., 2018). In this regard, a comprehensive field survey and remote-sensing observations were conducted. Landsat TM, ETM⁺, Google Maps, Digital Elevation Model (DEM), and GPS data were used. As a result, elevation, slope aspect, slope angle, geology, precipitation, drainage density, weathering, land-use/land-cover, distance to faults, earthquake distribution, distance to roads, and distance to cities were considered as the main acting triggering factors. These conditioning/triggering factors were summarized as follows:

Elevation: Elevation represents spatial variation in terrain height and is considered an important factor influencing landslide occurrence. The influence of elevation on landslides is often indirect and is commonly related to other terrain parameters such as slope angle and slope aspect.

Slope aspect: Slope instability is indirectly influenced by the direction of the sloping terrain in relation to other parameters like sun exposure, rainfall, and dry winds. Slope aspect is commonly classified into nine categories: flat, north, northeast, east, southeast, south, southwest, west, and northwest.

Slope angle: Slope angle is defined as the angle between the horizontal plane and the Earth's surface. Landslides commonly occur when slope angles exceed certain threshold values. The slope values are displayed in degrees of inclination with the horizontal in the slope map layer.

Geology: Lithology significantly influences landslide susceptibility, as different rock units exhibit varying stability conditions. Geological units of the study area were extracted from digitized maps provided by the GSI and classified into igneous, metamorphic, sedimentary rocks, and alluvium.

Precipitation: Rainfall is one of the most significant landslide-triggering factors because it increases soil saturation and pore-water pressure, which reduces slope stability. To produce the rainfall layer, the average annual precipitation data for the previous ten years were extracted for this study. This layer was generated in the GIS environment using the Inverse Distance Weighting (IDW) interpolation method.

Drainage density (distance to rivers): By eroding or saturating the slopes' materials, rivers contribute to their instability. The river network was extracted from topographic maps and digitized in the GIS environment to generate the drainage density layer for LSM. The drainage buffer map was generated using GIS spatial analysis tools.

Weathering: Rock materials gradually weaken, break down, or dissolve over time under geological and meteorological processes. These weathered materials create weak zones that are highly susceptible to mass movements and landslides. So, identifying these weak materials helps determine areas that are more prone to slope instability and mass movements. In this study, weathered materials were identified based on the spectral reflectance characteristics of geological units derived from Landsat satellite imagery.

Land-use/land-cover: Land-use and land-cover are important factors in LSM. Natural vegetation generally stabilizes slopes by reinforcing soil structure and reducing soil moisture through evapotranspiration, whereas human activities such as excavation, deforestation, and uncontrolled construction may increase slope instability and landslide risk.

Distance to faults: The right-lateral strike-slip activity of the Siah Cheshmeh–Khoy fault, one of the major faults in northwestern Iran, has been identified in the study area. Landsat imagery confirms the fault system through deflected river channels and displaced alluvial fans. The displacement of alluvial fans in Dasht-e-Zurabad along the Kamarkassan fault is estimated at about 1.8 km. Fault data were extracted from geological maps, and buffer zones at different distances were generated in GIS to analyze their influence on landslide occurrence.

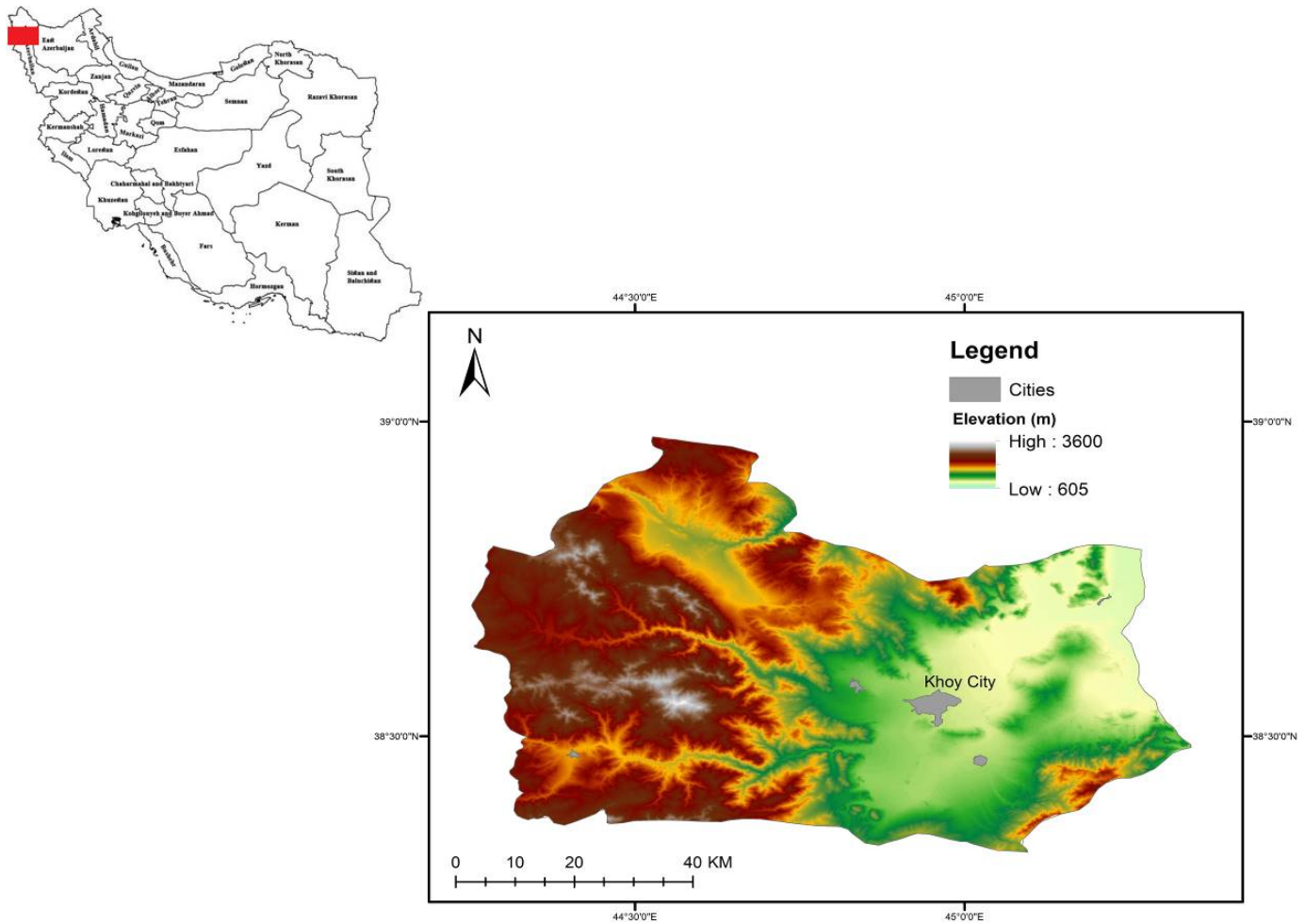


Fig. 1 Location of Khoy County in Iran

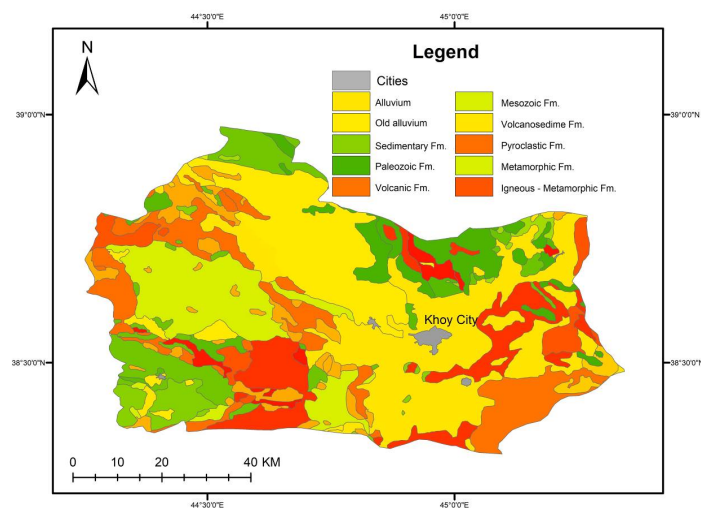


Fig. 2 Geological map of Khoy County (GSI, 2009)

Earthquake distribution: The studied region is seismically active and faced with a large number of earthquakes. Understanding the earthquakes mechanism and surficial distributions helps to provide relative information regarding the suitable area in terms of seismicity which is one of the most important triggering factors for landslide occurrence.

Distance to roads/cities: The development of spontaneous and no principled roads, infrastructures, and urbanism are perhaps the main calculated landslide events. During their development, there are a few normal activities that happen along the street organization, like significant unearthing, vegetation expulsion, and the use of outer burdens. They altogether affect diminishing the obstruction of the slant; the further away from the road or cities the slant is, the steadier it is.

A landslide inventory map should be given to observe the areas and determine landslides that have proactively happened with spatial scales. This map is completed to decide the connection between the elements influencing the rate of landslides and the circulation of landslides in the studied region. Figure 3 is provided with landslide inventory maps regarding the selected main triggering factors for LSM.

IV. MATERIALS AND METHODS

A. Method Basics

The presented study attempted to use coupled AHP, and fuzzy logic methods known as the FAHP to provide LSM for Khoy County. AHP, originally developed by Thomas Saaty, is a semi-quantitative decision-making method used to select the most suitable alternative among several options based on defined criteria and expert judgment (Yu et al., 2021). AHP is a multi-

step decision model that determines the relative importance of factors by prioritizing them through pairwise comparisons (Okoli et al., 2023). A scale of values that identifies the relative importance of various factors is necessary for preference determination. The adoption of a value scale ranging from 1 to 9 (Table 2) allows decision-makers to express their judgments regarding the relative importance of different factors (Pant et al., 2022). The decision matrix was built up based on criteria, sub-criteria, and alternatives based on MCDM principles and checked by the matrix's consistency index (CI) as presented in Eq. 1 (Saaty & Vargas, 1991):

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

where n: number of elements; $\lambda_{\max}$: is the highest Eigenvalue. The consistency ratio (CR) is calculated from CI and random consistency index (RI) values; RI is provided in Table 3 (Saaty & Vargas, 1991).

$$CR = \frac{CI}{RI} \quad (2)$$

If the CR value of the decision matrix is less than 0.1 (10%), the matrix is considered consistent; however, the threshold of 0.1 is generally regarded as a rule of thumb. Lower CR values indicate higher consistency, whereas values greater than 0.1 are generally considered unacceptable (Saaty & Vargas, 1991). On the other hand, fuzzy logic, introduced by Zadeh (1965), is widely used in decision-making processes involving uncertainty. The concept of membership degree allows fuzzy sets to be applied in various information environments, including multi-criteria decision-making problems (Mokarram & Zarei, 2018). Indeed, the expansion of classical sets led to the creation of fuzzy sets. Objects with values of 0 or 1 are considered to be members of classical sets, which have clear boundaries that indicate whether or not they belong to the set. In contrast, fuzzy sets allow partial membership values ranging between 0 and 1, representing gradual transitions rather than sharp boundaries (Zimmermann, 2010).

According to the fuzzy set theory, a membership function that maps all given elements to values between 0 and 1 defines a membership degree as (Zimmermann, 2010):

$$\mu_A(x): U \rightarrow [0, 1] \quad (3)$$

where μ_A is the membership degree, x is the factors, and U is a universal set of components. Fuzzy logic-based techniques commonly apply IF–THEN rules (AND/OR conditions) to derive results. Many spatial phenomena related to landslides involve uncertainty and gradual transitions; therefore, it is difficult to analyze them using classical methods with crisp boundaries. Fuzzy set theory addresses such uncertainties through three main stages: fuzzification, fuzzy inference system (FIS) processing, and defuzzification (Zimmermann, 2010). To integrate membership functions, there are several fuzzy operators. These fuzzy operators can be expressed as follows (Mokarram & Zarei, 2018):

$$\mu_{OR}(X) = \max[\mu_A(X), \mu(x), \dots, \mu_N(x)] \quad (4)$$

$$\mu_{AND}(X) = \min[\mu_A(X), \mu(x), \dots, \mu_N(x)] \quad (5)$$

$$\mu_{SUM}(X) = 1 - \prod_{i=1}^n \mu_i(x) \quad (6)$$

$$\mu_{PRODUCT}(X) = \prod_{i=1}^n \mu_i(x) \quad (7)$$

$$\mu_\gamma(x) = [\mu_{PRODUCT}(x)] \times [\mu_{PRODUCT}(x)]^{1-\gamma} \quad (8)$$

B. Data Preparations

To provide the susceptibility map for the Khoy region, a landslide inventory database was prepared. This database was obtained from field surveys and remote-sensing observations. In this regard, the data were collected based on selected triggering factors from various sources, including satellite imagery, photogrammetric data, geological maps, and meteorological records. Table 4 provides the resources of used data regarding LSM in this study.

C. Model Implementations

The FAHP has been widely applied in LSM due to its relatively low error rate. FAHP is a decision-making tool that involves breaking down a complex problem into smaller, more manageable parts and then evaluating the parts based on their relative importance. FAHP uses both fuzzy logic and AHP methods properly. To implement FAHP for LSM, linguistic variables describing different levels of susceptibility must first be defined. These can include 'very low', 'low', 'moderate', 'high', and 'very high'. Generally, FAHP is an extension of the traditional AHP that incorporates fuzzy logic to deal with uncertainty and imprecision. Here are the steps to implement a FAHP model which is considered in this study:

- Step 1: define the decision problem and criteria (identify the decision problem and the criteria that will be used to evaluate the alternatives).
- Step 2: define the hierarchy (develop a hierarchical structure that represents the decision problem and criteria. The hierarchy should have a goal, criteria, sub-criteria, and alternatives).
- Step 3: define the linguistic variables and fuzzy sets (define the linguistic variables for each criterion and sub-criterion, then, create fuzzy sets for each linguistic variable).
- Step 4: determine pairwise comparisons (use pairwise comparisons to determine the relative importance of the criteria and sub-criteria. Use a scale of 1 to 9 to indicate the degree of importance, with 1 indicating equal importance and 9 indicating extreme importance. For each pairwise comparison, calculate the weighted value using the fuzzy numbers for each criterion).
- Step 5: calculate the fuzzy weights (the fuzzy weights of each criterion and sub-criterion have been estimated by the weighted values obtained from the pairwise comparisons. The fuzzy weights can be calculated using a defuzzification method such as the centroid method).

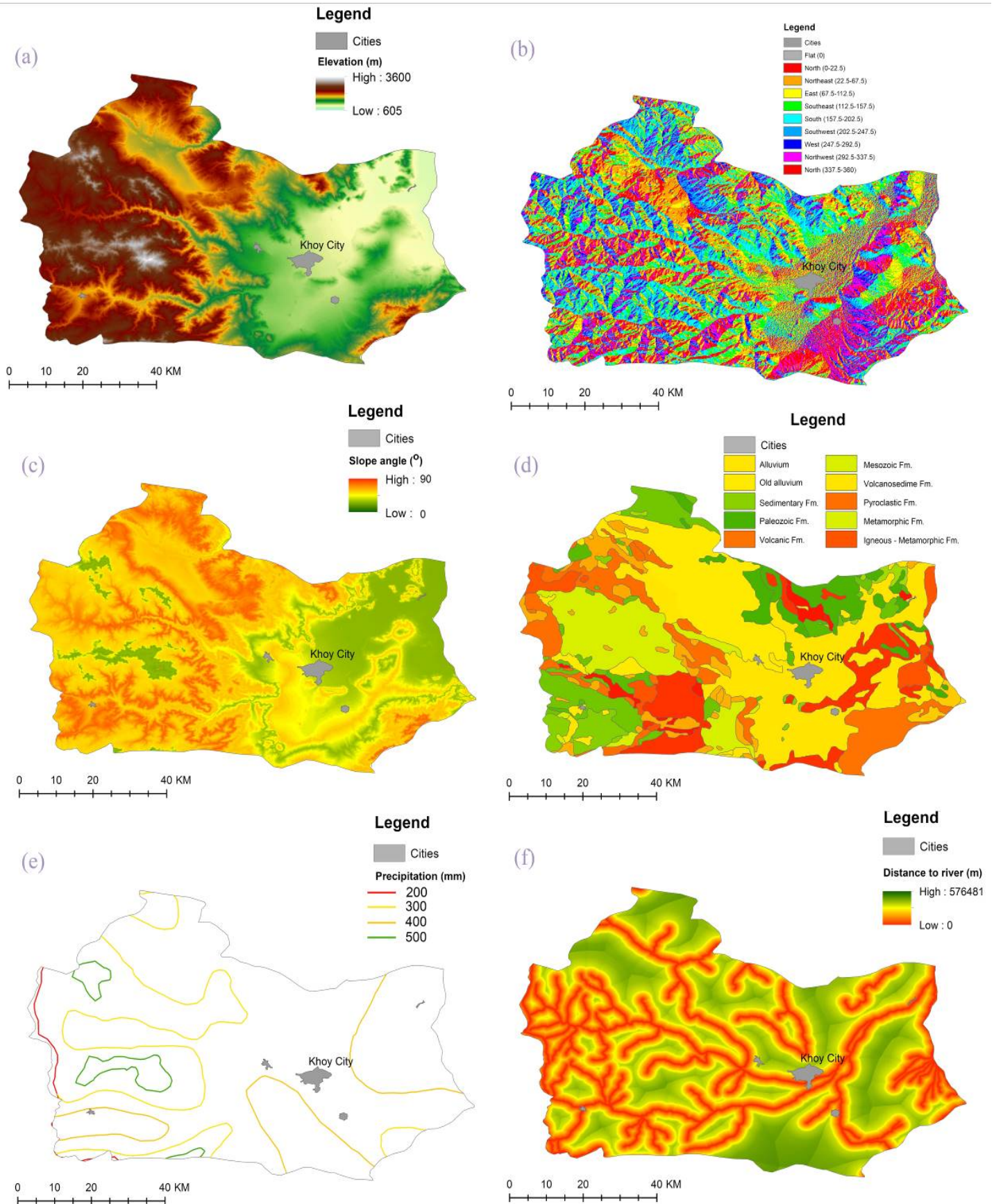


Fig. 3 Landslide triggering factors: (a) elevation, (b) slope aspect, (c) slope angle, (d) geology, (e) precipitation, (f) drainage density, (g) weathering, (h) land-use/land-cover, (i) distance to faults, (j) earthquake distribution, (k) distance to roads, (l) distance to cities

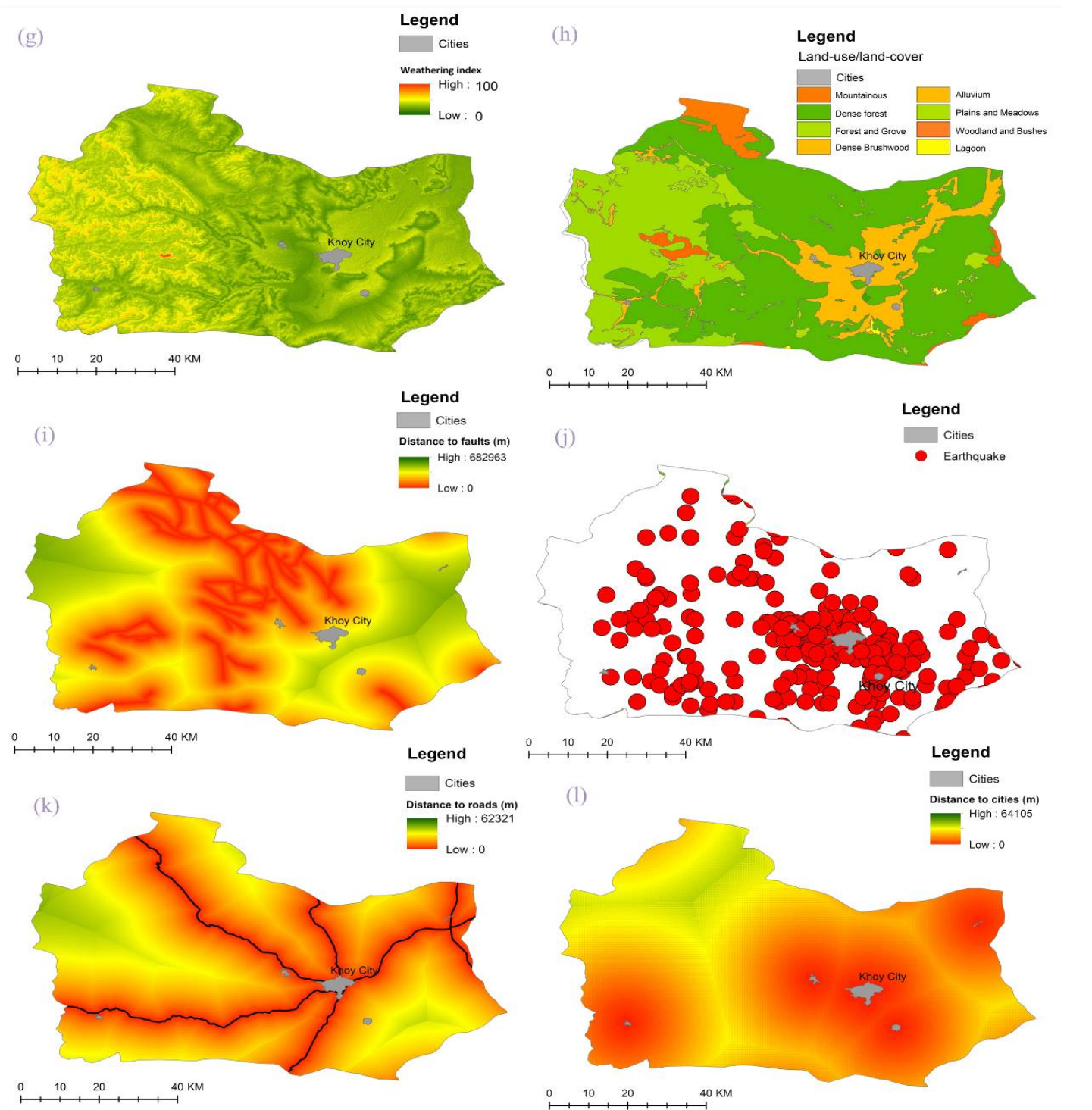


Fig. 3 Continued

Table 2 Fundamental scale for AHP pairwise comparisons (Saaty & Vargas, 1991)

Scale	Degree of preference	Explanation
1	Equally	Two activities contribute equally to the objective
3	Moderately	Experience and judgment slightly to moderately favor one activity over another
5	Strongly	Experience and judgment slightly to moderately favor one activity over another
7	Very strongly	An activity is strongly favored over another, and its dominance is shown in practice
9	Extremely	The evidence of favoring one activity over another is of the highest degree possible of an affirmation
2, 4, 6 and 8	Intermediate values	Used to represent compromises between the references in weights 1, 3, 5, 7 and 9
Reciprocals	Opposites	Used for inverse comparison

Table 3 The RI values for AHP calculations (Millet & Saaty, 2000)

Matrix size	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Table 4 The main used triggering factors and data resources

Main origin	Triggering factors	Data sources	Resolution
Geomorphologic	Elevation	DEM	± 30 m
	Slope aspect	DEM	± 30 m
	Slope angle	DEM	± 30 m
Geologic	Lithology	Geological data	± 30 m
	Drainage density	DEM, Google Map, IWRM*	± 30 m
	Land-use/land-cover	Geological data, Google Map,	± 30 m
	Weathering	Geological data	± 30 m
Meteorological	Precipitation	IMO†	± 30 m
Seismic	Distance to faults	Geological data, Google Map	± 30 m
	Earthquake distribution	IIIES** data	± 30 m
Human works	Distance to roads	DEM, Google Map	± 30 m
	Distance to cities	DEM, Google Map	± 30 m

Note: *Iran Water Resources Management Company (IWRM), † Iran Meteorological Organization (IMO), ** International Institute of Earthquake Engineering and Seismology (IIIES).

- Step 6: calculate the fuzzy scores (calculate the fuzzy scores for each alternative using the fuzzy weights of each criterion and sub-criterion. The fuzzy score is the degree of membership of each alternative to the fuzzy sets of each criterion).
- Step 7: defuzzify the fuzzy scores (defuzzify the fuzzy scores to obtain a crisp value that represents the degree of preference of each alternative. This can be done using a defuzzification method such as the centroid method or the max membership method).
- Step 8: rank the alternatives (ranking of alternatives based on their crisp values obtained from defuzzification).
- Step 9: sensitivity check (perform a sensitivity analysis to evaluate the stability of the results by changing the linguistic variables and fuzzy sets).
- Step 10: rasterize the information data (the input parameters from triggering factors and maps will be rasterized to use in GIS to develop LSM).

These steps provide a framework for implementing a FAHP model to reach a proper LSM. The FAHP model was implemented in MATLAB programming language and data was rasterized for each triggering factor into the GIS environment based on suitability analysis. The Mamdani FIS was used as the core analytical framework, and triangular membership functions were applied for both input and output variables.

V. RESULTS AND DISCUSSION

Landslide susceptibility assessment is an essential component of geo-hazard risk management, as it enables the identification of areas that are more prone to slope failures and helps planners implement preventive strategies. Based on the selected triggering factors, a landslide susceptibility map (LSM) was developed for Khoy County. The factors considered in this study were grouped into five main categories: geomorphological factors (slope angle, slope aspect, and elevation), geological factors (lithology, drainage density, land-use/land-cover, and weathering),

meteorological factors (precipitation), seismic factors (distance to faults and earthquake distribution), and anthropogenic factors (distance to roads and urban areas). Methodologically, the FAHP was applied to evaluate the relative importance of the selected conditioning factors and to generate the LSM.

The FAHP approach combines the structured decision-making framework of the analytic hierarchy process with the capability of fuzzy logic to handle uncertainty and imprecision in spatial data. This integration improves the reliability of susceptibility assessments by incorporating both quantitative data and expert knowledge.

The resulting landslide susceptibility map for Khoy County is presented in Figure 4. The map categorizes the study area into five susceptibility classes: very low, low, moderate, high, and very high. The results indicate that areas with high and very high susceptibility are mainly concentrated in the western part of the county. This region is characterized by mountainous terrain with significant elevation variations, steep slopes, and complex geological conditions, all of which contribute to higher landslide potential.

In contrast, the eastern part of the county is dominated by relatively flat plains, resulting in lower landslide susceptibility. The spatial distribution of susceptibility classes is consistent with field observations and historical landslide records in the region, indicating the reliability of the FAHP-based model. These findings highlight the importance of incorporating landslide susceptibility assessments into regional land-use planning and hazard mitigation strategies. Identifying high-risk zones provides valuable information for local authorities and decision-makers to implement preventive measures, improve infrastructure planning, and reduce potential losses associated with future landslide events. Furthermore, the application of the FAHP approach demonstrates several advantages for landslide susceptibility mapping. By incorporating fuzzy logic, the method effectively addresses uncertainties associated with environmental data and expert judgments. This capability enhances the robustness of susceptibility assessments, particularly in complex mountainous regions such as Khoy County where multiple interacting factors influence landslide occurrence.

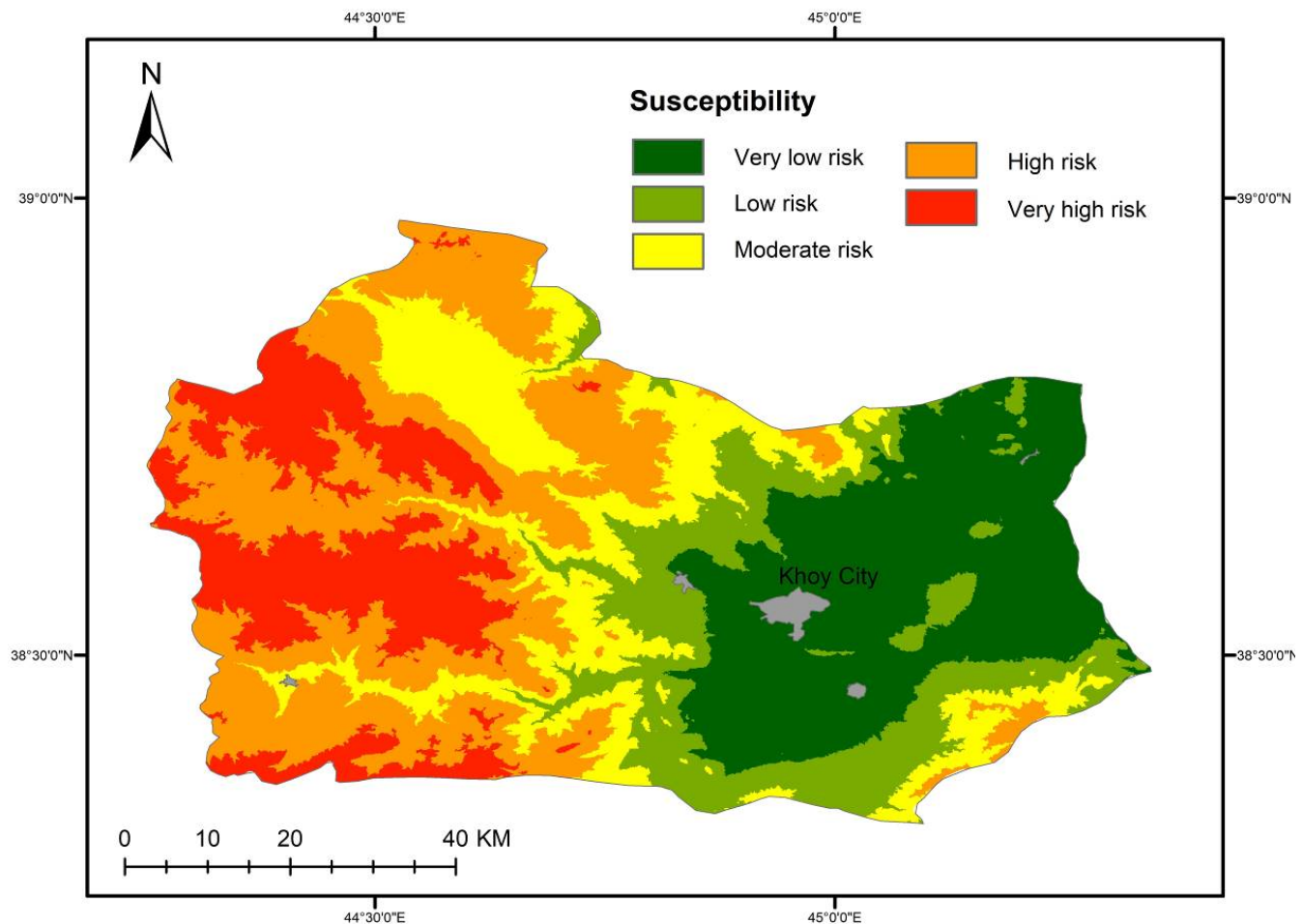


Fig. 4 Landslide susceptibility map for the studied region

The FAHP approach improves landslide susceptibility mapping by incorporating expert knowledge through linguistic variables and fuzzy numbers, which helps reduce uncertainty in decision-making. Given the multi-criteria nature of landslide occurrence in Khoy County, where factors such as slope, geology, rainfall, and land use interact, FAHP enables the simultaneous evaluation of these variables within a unified framework. This capability facilitates the identification of high-risk zones and supports more effective hazard mitigation and land-use planning. Moreover, the flexibility of FAHP in defining membership functions and fuzzy rules allows the model to be adapted to the specific geological and topographical conditions of the study area. Consequently, the application of FAHP enhances the reliability of landslide susceptibility assessments and provides valuable support for sustainable regional planning and disaster risk reduction.

VI. CONCLUSION

Landslides are among the most destructive natural hazards worldwide and are considered the second most significant geohazard in terms of frequency and impact. Similar to other geological phenomena, landslides exhibit recurrence patterns that can be analyzed and predicted by identifying and evaluating their triggering factors. This study applied a FAHP model to assess

landslide susceptibility in Khoy County, located in West Azerbaijan Province in northwestern Iran. The main objective was to produce a reliable landslide susceptibility map to support hazard mitigation strategies and sustainable regional planning. A comprehensive set of environmental and geological conditioning factors was incorporated into the analysis. These factors included elevation, slope aspect, slope angle, lithology, precipitation, drainage density, weathering, land use/land cover, proximity to faults, earthquake distribution, and distances to roads and urban areas. These parameters were integrated within a fuzzy logic-based multi-criteria decision-making framework implemented in MATLAB and spatially analyzed using GIS tools. The generated landslide susceptibility map classified the study area into five categories: very high (22.17%), high (25.34%), moderate (13.66%), low (16.63%), and very low (22.2%). The results indicate that a considerable portion of Khoy County falls within high and very high susceptibility zones, particularly in the western mountainous regions characterized by steep slopes and complex geological conditions. So, the FAHP approach proved to be an effective method for integrating multiple conditioning factors and handling uncertainty in landslide susceptibility assessment. The resulting susceptibility map provides valuable information for planners and decision-makers to support land-use planning, infrastructure development, and hazard mitigation strategies aimed at reducing future landslide risks.

ACKNOWLEDGMENT

We sincerely thank the reviewers for their careful reading and constructive comments, which helped improve the clarity and quality of this manuscript.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available within article. No publicly archived dataset was generated.

ETHICS APPROVAL

This study did not involve human participants, personal data, or animal subjects. No specific ethical approval was required.

FUNDING

This research received no external funding.

AUTHORS' CONTRIBUTIONS

Daryoush Ahadi Rosta performed the main data analysis and contributed to data collection, preprocessing, and interpretation. He also drafted the initial manuscript, provided conceptual guidance, conducted critical revisions, managed the overall project, and approved the final version for publication. All authors read and approved the final manuscript.

CONFLICT OF INTEREST

The authors have not disclosed any competing interests.

USE OF AI

AI tools were not used in data generation, analysis, results, or decision-making.

OPEN ACCESS

This article is distributed under the terms of the *Creative Commons Attribution 4.0 International License*, which allows use, sharing, adaptation, distribution, and reproduction in any medium or format, provided appropriate credit is given to the original author(s) and the source. A link to the Creative Commons license must also be provided, and any modifications should be clearly indicated. Unless otherwise noted in a credit line, images or third-party materials included in this article are covered under the article's Creative Commons license. For material not included in the license or where statutory regulations do not apply, permission must be obtained directly from the copyright holder. To view the full license, visit <http://creativecommons.org/licenses/by/4.0/>.

Publisher's Note: This journal remains neutral with regard to jurisdictional claims in published maps, data, and institutional affiliations.

REFERENCES

- Abay A., Barbieri G., Woldearegay K. (2019). GIS-based landslide susceptibility evaluation using analytical hierarchy process (AHP) approach: The case of Tarmaber District, Ethiopia. *Momona Ethiopian Journal of Science*, 11(1), 14-36. <https://doi.org/10.4314/mejs.v11i1.2>.
- Abdi A., Bouamrane A., Karech T., Dahri N., Kaouachi A. (2021). Landslide susceptibility mapping using GIS-based fuzzy logic and the analytical hierarchical processes approach: a case study in constantine (North-East Algeria). *Geotechnical and Geological Engineering*, 39, 5675-5691. <https://doi.org/10.1007/s10706-021-01855-3>.
- Aghanabati A. (2009). *Geology of Iran*. Geological Survey of Iran press, Tehran, Iran.
- Ali Z., Faqe Ibrahim G.R., Kiss K., Pirisi G. (2025). Comparable analysis of analytical hierarchy process and fuzzy logic methods based on GIS and remote sensing for anticipating landslide susceptibility in the Iraqi Kurdistan Region, Koya district. *Geocarto International*, 40(1), 2540881. <https://doi.org/10.1080/10106049.2025.2540881>.
- An B., Zhang Z., Xiong S., Zhang W., Yi Y., Liu Z., Liu C. (2024). Landslide Susceptibility Mapping Based on Ensemble Learning in the Jiuzhaigou

- Region, Sichuan, China. *Remote Sensing*, 16(22), 4218. <https://doi.org/10.3390/rs16224218>.
- Azarafza M., Azarafza M., Akgün H., Atkinson P.M., Derakhshani R. (2021). Deep learning-based landslide susceptibility mapping. *Scientific Reports*, 11(1), 24112. <https://doi.org/10.1038/s41598-021-03585-1>.
- Azarafza M., Ghazifard A., Akgün H., Asghari-Kalajahi E. (2018). Landslide susceptibility assessment of South Pars Special Zone, southwest Iran. *Environmental Earth Sciences*, 77, 805. <https://doi.org/10.1007/s12665-018-7978-1>.
- Badola S., Mishra V.N., Parkash S., Pandey M. (2023). Rule-based fuzzy inference system for landslide susceptibility mapping along national highway 7 in Garhwal Himalayas, India. *Quaternary Science Advances*, 11, 100093. <https://doi.org/10.1016/j.qsa.2023.100093>.
- Bhagya S.B., Sumi A.S., Balaji S., Danumah J.H., Costache R., Rajaneesh A., Gokul A., Chandrasenan C.P., Quevedo R.P., Abioui M. (2023). Landslide susceptibility assessment of a part of the Western Ghats (India) employing the AHP and F-AHP models. *Land*, 12(2), 468. <https://doi.org/10.3390/land12020468>.
- Chanu M.L., Bakimchandra O. (2022). Landslide susceptibility assessment using AHP model and multi resolution DEMs along a highway in Manipur, India. *Environmental Earth Sciences*, 81(5), 156. <https://doi.org/10.1007/s12665-022-10281-4>.
- Demirel B., Yildirim E., Can E. (2025). GIS-based landslide susceptibility mapping using AHP, FMEA, and Pareto systematic analysis in central Yalova, Türkiye. *Engineering Science and Technology, an International Journal*, 64, 102013. <https://doi.org/10.1016/j.jestech.2025.102013>.
- Do H.M., Yin K.L., Guo, Z.Z. (2020). A comparative study on the integrative ability of the analytical hierarchy process, weights of evidence and logistic regression methods with the Flow-R model for landslide susceptibility assessment. *Geomatics, Natural Hazards and Risk*, 11(1), 2449-2485. <https://doi.org/10.1080/19475705.2020.1846086>.
- Esmaceli C., Khatib M.M., Nazari H., Burg J.P., Gholami E. (2019). Deep-seated gravitational slope deformation in the Siahcheshmeh pull-apart basin: along the Gailatu-Siahcheshmeh-Khoy fault. *Quantitative Geomorphological Research*, 8(1), 199-216.
- Es-smairi A., El Moutchou B., Touhami A.E.O. (2021). Landslide susceptibility assessment using analytic hierarchy process and weight of evidence methods in parts of the Rif chain (northernmost Morocco). *Arabian Journal of Geosciences*, 14, 1-18. <https://doi.org/10.1007/s12517-021-07660-9>.
- Fan H., Lu Y., Hu Y., Fang J., Lv C., Xu C., Liu Y. (2022). A landslide susceptibility evaluation of highway disasters based on the frequency ratio coupling model. *Sustainability*, 14(13), 7740. <https://doi.org/10.3390/su14137740>.
- Fan W., Wei X.S., Cao Y.B., Zheng B. (2017). Landslide susceptibility assessment using the certainty factor and analytic hierarchy process. *Journal of Mountain Science*, 14, 906-925. <https://doi.org/10.1007/s11629-016-4068-2>.
- Feizizadeh B., Roodposhti M.S., Jankowski P., Blaschke T. (2014). A GIS-based extended fuzzy multi-criteria evaluation for landslide susceptibility mapping. *Computers & Geosciences*, 73, 208-221. <https://doi.org/10.1016/j.cageo.2014.08.001>.
- Geological Survey of Iran, GSI (2009). *Geological map for Khoy County*. Geological Survey of Iran press, Tehran, Iran.
- Gopinath G., Jesiya N., Achu A.L., Bhadrar A., Surendran U.P. (2024). Ensemble of fuzzy-analytical hierarchy process in landslide susceptibility modeling from a humid tropical region of Western Ghats, Southern India. *Environmental Science and Pollution Research*, 31, 41370-41387. <https://doi.org/10.1007/s11356-023-27377-4>.
- He H., Hu D., Sun Q., Zhu L., Liu Y. (2019). A landslide susceptibility assessment method based on GIS technology and an AHP-weighted information content method: A case study of southern Anhui, China. *ISPRS International Journal of Geo-Information*, 8(6), 266. <https://doi.org/10.3390/ijgi8060266>.
- Hodasová K., Bednarik M. (2021). Effect of using various weighting methods in a process of landslide susceptibility assessment. *Natural Hazards*, 105, 481-499. <https://doi.org/10.1007/s11069-020-04320-1>.
- Iranian Meteorological Organization, IMO (2022). *Meteorological data for Khoy County*. Khoy station data center, West Azerbaijan province, Iran. Available at: <https://www.irimo.ir/>.
- Kayastha P., Dhital M.R., De Smedt F. (2013). Application of the analytical hierarchy process (AHP) for landslide susceptibility mapping: A case study

- from the Tinau watershed, west Nepal. *Computers & Geosciences*, 52, 398-408. <https://doi.org/10.1016/j.cageo.2012.11.003>.
- Khezri S. (2011). Landslide susceptibility in the Zab Basin, northwest of Iran. *Procedia-Social and Behavioral Sciences*, 19, 726-731. <https://doi.org/10.1016/j.sbspro.2011.05.191>.
- Kucuker D.M. (2025). Analyzing landslide susceptibility of forest roads by analytical hierarchy process (AHP) in of forest planning unit of Turkiye. *Natural Hazards*, 121(2), 2323-2345. <https://doi.org/10.1007/s11069-024-06882-w>.
- Lorentz J.F., Calijuri M.L., Marques E.G., Baptista A.C. (2016). Multicriteria analysis applied to landslide susceptibility mapping. *Natural Hazards*, 83, 41-52. <https://doi.org/10.1007/s11069-016-2300-6>.
- Mallick J., Singh R.K., AlAwadh M.A., Islam S., Khan R.A., Qureshi M.N. (2018). GIS-based landslide susceptibility evaluation using fuzzy-AHP multi-criteria decision-making techniques in the Abha Watershed, Saudi Arabia. *Environmental Earth Sciences*, 77, 1-25. <https://doi.org/10.1007/s12665-018-7451-1>.
- Mao Z., Shi S., Li H., Zhong J., Sun J. (2022). Landslide susceptibility assessment using triangular fuzzy number-analytic hierarchy processing (TFN-AHP), contributing weight (CW) and random forest weighted frequency ratio (RF weighted FR) at the Pengyang county, Northwest China. *Environmental Earth Sciences*, 81(3), 86. <https://doi.org/10.1007/s12665-022-10193-3>.
- Masoudi J., Imamali Pour A. (2019). Application of geological methods for prospecting of podiform chromite deposits in the Khoi ophiolite zone, Northwestern Iran. *Journal of Economic Geology*, 11(2), 285-303. <https://doi.org/10.22067/ECONG.V11I2.70623>.
- Mersni M., Souissi D., Amiri A., Sebei A., Inoubli M.H., Havenith H.B. (2025). Landslide Susceptibility Prediction Using GIS, Analytical Hierarchy Process, and Artificial Neural Network in North-Western Tunisia. *Geosciences*, 15(8), 297. <https://doi.org/10.3390/geosciences15080297>.
- Millet I., Saaty T.L. (2000). On the relativity of relative measures—accommodating both rank preservation and rank reversals in the AHP. *European Journal of Operational Research*, 121(1), 205-212. [https://doi.org/10.1016/S0377-2217\(99\)00040-5](https://doi.org/10.1016/S0377-2217(99)00040-5).
- Mokarram M., Zarei A.R. (2018). Landslide susceptibility mapping using fuzzy-AHP. *Geotechnical and Geological Engineering*, 36, 3931-3943. <https://doi.org/10.1007/s10706-018-0583-y>.
- Nanehkaran Y.A., Mao Y., Azarafa M., Kockar M.K., Zhu H.H. (2021). Fuzzy-based multiple decision method for landslide susceptibility and hazard assessment: A case study of Tabriz, Iran. *Geomechanics and Engineering*, 24(5), 407-418. <https://doi.org/10.12989/gae.2021.24.5.407>.
- Nikoobakht S., Azarafa M., Akgün H., Derakhshani R. (2022). Landslide susceptibility assessment by using convolutional neural network. *Applied Sciences*, 12(12), 5992. <https://doi.org/10.3390/app12125992>.
- Okoli J., Nahazanan H., Nahas F., Kalantar B., Shafri H.Z.M., Khuzaimah Z. (2023). High-Resolution lidar-derived DEM for landslide susceptibility assessment using AHP and fuzzy logic in Serdang, Malaysia. *Geosciences*, 13(2), 34. <https://doi.org/10.3390/geosciences13020034>.
- Panchal S., Shrivastava A.K. (2021). A comparative study of frequency ratio, Shannon's entropy and analytic hierarchy process (AHP) models for landslide susceptibility assessment. *ISPRS International Journal of Geo-Information*, 10(9), 603. <https://doi.org/10.3390/ijgi10090603>.
- Pant S., Kumar A., Ram M., Klockov Y., Sharma H.K. (2022). Consistency indices in analytic hierarchy process: a review. *Mathematics*, 10(8), 1206. <https://doi.org/10.3390/math10081206>.
- Pourghasemi H.R., Pradhan B., Gokceoglu C. (2012). Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. *Natural Hazards*, 63, 965-996. <https://doi.org/10.1007/s11069-012-0217-2>.
- Rebouch N., Belkendil A., Tout F., Dinar H., Benzid Y., Zegmar A., Alliouche A., Farah M.I., Khan N.A. (2025). Landslide susceptibility assessment using hybrid geospatial, frequency ratio, and AHP models in Souk Ahras province, Northeastern of Algeria. *Scientific Reports*, 16, 2288. <https://doi.org/10.1038/s41598-025-32062-2>.
- Roy J., Saha S. (2019). Landslide susceptibility mapping using knowledge driven statistical models in Darjeeling District, West Bengal, India. *Geoenvironmental Disasters*, 6(1), 1-18. <https://doi.org/10.1186/s40677-019-0126-8>.
- Saaty T.L., Vargas L.G. (1991). *Prediction, projection and forecasting: applications of the analytic hierarchy process in economics, finance, politics, games and sports*. Springer.
- Saha A., Villuri V.G.K., Bhardwaj A. (2022). Development and assessment of GIS-based landslide susceptibility mapping models using ANN, Fuzzy-AHP, and MCDA in Darjeeling Himalayas, West Bengal, India. *Land*, 11(10), 1711. <https://doi.org/10.3390/land11101711>.
- Saygin F., Şişman Y., Dengiz O., Şişman A. (2023). Spatial assessment of landslide susceptibility mapping generated by fuzzy-AHP and decision tree approaches. *Advances in Space Research*, 71(12), 5218-5235. <https://doi.org/10.1016/j.asr.2023.01.057>.
- Swain J.B., Singh N.J., Gupta L.R. (2024). Landslide susceptibility zonation of a hilly region: A quantitative approach. *Natural Hazards Research*, 4(1), 75-86. <https://doi.org/10.1016/j.nhres.2023.07.008>.
- Taş M.A. (2025). Comparison Of Analytical Hierarchy Process (AHP) And Frequency Ratio (FR) Methods In Landslide Susceptibility Assessment: A Case Study In Kemah-Kömür Stream Basin, Erzincan. *Ege Coğrafya Dergisi*, 34(2), 337-356. <https://doi.org/10.51800/ecd.1761885>.
- Yalcin A. (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): comparisons of results and confirmations. *Catena*, 72(1), 1-12. <https://doi.org/10.1016/j.catena.2007.01.003>.
- Yong C., Jinlong D., Fei G., Bin T., Tao Z., Hao F., Qinghua Z. (2022). Review of landslide susceptibility assessment based on knowledge mapping. *Stochastic Environmental Research and Risk Assessment*, 36(9), 2399-2417. <https://doi.org/10.1007/s00477-021-02165-z>.
- Yu D., Kou G., Xu Z., Shi S. (2021). Analysis of collaboration evolution in AHP research: 1982–2018. *International Journal of Information Technology & Decision Making*, 20(01), 7-36. <https://doi.org/10.1142/S0219622020500406>.
- Yu, C., Chen J. (2020). Application of a GIS-based slope unit method for landslide susceptibility mapping in Helong City: comparative assessment of ICM, AHP, and RF model. *Symmetry*, 12(11), 1848. <https://doi.org/10.3390/sym12111848>.
- Zadeh L.A. (1965). Fuzzy sets. *Information Control*, 8, 338-353.
- Zhao H., Yao L., Mei G., Liu T., Ning Y. (2017). A fuzzy comprehensive evaluation method based on AHP and entropy for a landslide susceptibility map. *Entropy*, 19(8), 396. <https://doi.org/10.3390/e19080396>.
- Zhou S., Zhou S., Tan X. (2020). Nationwide susceptibility mapping of landslides in Kenya using the fuzzy analytic hierarchy process model. *Land*, 9(12), 535. <https://doi.org/10.3390/land9120535>.
- Zhu A.X., Wang R., Qiao J., Qin C.Z., Chen Y., Liu J., Zhu T. (2014). An expert knowledge-based approach to landslide susceptibility mapping using GIS and fuzzy logic. *Geomorphology*, 214, 128-138. <https://doi.org/10.1016/j.geomorph.2014.02.003>.
- Zighmi K., Zahri F., Faqeh K., Al Amri A., Riheb H., Alamri S.M., Alamery E. (2025). AHP multi criteria analysis for landslide susceptibility mapping in the Tellian Atlas chain. *Scientific Reports*, 15(1), 25747. <https://doi.org/10.1038/s41598-025-10819-z>.
- Zimmermann H.J. (2010). *Fuzzy set theory*. Wiley Interdisciplinary Reviews: Computational Statistics. 2(3), 317-332. <https://doi.org/10.1002/wics.82>.