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Assessment of Landslide Susceptibility Using Fuzzy Logic: A Case Study of Nur County

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Abstract: Landslides pose a significant threat to human life, infrastructure, and the environment, especially in mountainous regions such as Nur County in northern Iran. Accurate assessment of landslide susceptibility is essential for hazard mitigation and effective land-use management. This study aims to evaluate landslide susceptibility using a fuzzy logic approach integrated with Geographic Information Systems (GIS). Seven key triggering factors were selected based on previous studies and local geomorphological conditions: slope angle, aspect, elevation, lithology, land use, distance from roads, distance from faults, distance from rivers, and rainfall intensity. Each factor was standardized using fuzzy membership functions, allowing the expression of spatial uncertainty and gradual transitions between susceptibility classes. Fuzzy operators were then applied to overlay the thematic layers and produce a comprehensive landslide susceptibility map. The results indicate that areas with steep slopes, fragile lithological formations, intense precipitation, and close proximity to roads and deforested lands exhibit the highest susceptibility. The fuzzy logic model effectively handles complex and uncertain spatial data, offering a reliable tool for predicting potential landslide-prone zones. This methodology can support local decision-makers in planning and implementing risk-reduction strategies.

Keywords: Landslide susceptibility, Fuzzy logic, Spatial analysis, Geographic information system, Nur County.

I. INTRODUCTION

Landslides are a type of mass wasting process involving the downward and outward movement of slope-forming materials such as rock, soil, and debris under the influence of gravity. These natural hazards can be sudden and destructive, often triggered by factors such as intense rainfall, earthquakes, or human activities (Reichenbach et al., 2018). Globally, landslides cause significant loss of life and property each year, particularly in mountainous and tectonically active regions (Huang & Zhao, 2018). The evaluation of landslide susceptibility is a critical step in disaster risk reduction and land-use planning (Guzzetti et al., 2006). Susceptibility mapping identifies areas that are potentially prone to landslides based on the presence of environmental and anthropogenic conditioning factors (Lee & Min, 2001). This information is essential for local authorities, planners, and engineers to design mitigation strategies and allocate resources effectively to vulnerable regions (Broeckx et al., 2018).

Conducting landslide susceptibility analysis is particularly important in regions like Iran, where complex topography, geological diversity, and human development increase the likelihood of slope failures (Nanehkaran et al., 2021). The increasing frequency and severity of extreme weather events, potentially linked to climate change, further amplify the necessity of comprehensive susceptibility assessments (Cemiloglu et al., 2023). Susceptibility analysis, within the context of landslide studies, refers to the assessment of how different input factors contribute to the susceptibility model's outcome (Van Westen et al., 2008). This is crucial for model validation and improving reliability (Ado et al., 2022). It helps identify which conditioning factors exert the most influence on landslide occurrence, thereby guiding data collection priorities and enhancing model interpretation (Zêzere et al., 2017).

Several methods have been developed over the years for landslide susceptibility analysis, which can generally be categorized into qualitative, semi-quantitative, and quantitative approaches (Mao et al., 2024). These include statistical models (e.g., logistic regression, weights-of-evidence), machine learning techniques (e.g., support vector machines, random forest), and multi-criteria decision-making (MCDM) methods, including fuzzy logic and the analytical hierarchy process (AHP) approaches (Frattini et al., 2010). MCDM methods and fuzzy logic have become valuable tools in landslide susceptibility analysis due to their ability to handle complex decision environments involving multiple factors (Bahrami et al., 2021). MCDM techniques, such as AHP, TOPSIS, and PROMETHEE, are commonly used to evaluate and rank the importance of various causative factors (Jam et al., 2021). Fuzzy logic, on the other hand, is applied to manage uncertainties and vagueness in the input data and expert judgments, which are inherent in assessments (Noorollahi et al., 2018).

MCDM methods offer a structured and transparent framework for integrating different criteria, which is particularly beneficial in interdisciplinary problems like landslide analysis (Saygin et al., 2023). They allow the incorporation of both qualitative and quantitative data and enable decision-makers to systematically compare different locations or scenarios based on calculated weights. Their ability to prioritize and rank hazard zones makes them highly practical for land-use planning and risk management (Sur et al., 2020). On the other hand, fuzzy logic excels in dealing with the imprecise nature of environmental data (Pourghasemi et al., 2012). Instead of using crisp boundaries, it models inputs using fuzzy sets, enabling more realistic representation of continuous variables like slope gradients or rainfall thresholds (Saygin et al., 2023). This approach is especially helpful in areas where historical landslide data is scarce or incomplete (Ercanoglu & Gokceoglu, 2004). Fuzzy logic also allows the integration of expert knowledge and linguistic variables, improving the robustness of the susceptibility mapping (Sur et al., 2020). The combination of MCDM and fuzzy logic enhances the overall effectiveness of landslide susceptibility assessments (Saha et al., 2022). For example, fuzzy AHP or fuzzy TOPSIS methods incorporate the strengths of both approaches—structured decision-making and uncertainty modeling (Bhagya et al., 2023). This integrated approach leads to more reliable and interpretable hazard maps, which can be used by policymakers, urban developers, and emergency managers to mitigate potential landslide risks effectively (Wang & Nanehkaran, 2024). Despite their advantages, these methods also have limitations. MCDM methods rely heavily on expert judgment, which can introduce subjectivity and bias (Klai et al., 2024). Similarly, defining appropriate membership functions and rules in fuzzy logic requires careful calibration and expert input (Noorollahi et al., 2018). The accuracy of results is highly dependent on the quality of input data and the assumptions made during the modeling process (Pourghasemi et al., 2012). Additionally, these approaches can be computationally intensive (Nanehkaran et al., 2021).

In this study, fuzzy logic is applied to assess landslide susceptibility in Nur County, using a set of environmental and triggering factors including slope, aspect, elevation, lithology, land use, distance from roads, and rainfall intensity. These factors were selected based on a combination of literature review, expert consultation, and local geoclimatic conditions. The main objective of this research is to develop a spatially distributed landslide susceptibility model using fuzzy logic within a GIS environment. The study aims to explore the relative importance of conditioning factors, improve susceptibility mapping accuracy, and provide a decision-support tool for local authorities and planners. The novelty of this research lies in its integration of fuzzy logic with detailed spatial datasets for a relatively understudied region, employing a systematic methodology to address data uncertainty. By demonstrating the utility of fuzzy logic in landslide studies, this work contributes to the growing body of knowledge on hazard assessment and supports sustainable development initiatives in vulnerable areas.

II. Studied Location

Nur County is one of the counties located in Mazandaran Province, in northern Iran (Figure 1), along the southern coast of the Caspian Sea. It is known for its lush forests, beautiful coastline, and the scenic Alborz Mountains that surround the area (Mirmohammadi et al., 2019). The administrative center of this county is the city of Nur. The county is subdivided into several districts (Sabbaghi, 2024). The county has a mild and humid climate, with dense Hyrcanian forests covering much of its landscape. This makes it a favorite destination for eco-tourism and nature enthusiasts. Nur also has historical sites, such as old mosques, castles, and traditional villages, reflecting the region's rich cultural heritage. This region is experiences mild, humid winter and warm, humid summers. Annual precipitation is relatively high compared to most other regions in Iran, with the majority of rainfall occurring in autumn and winter (Kardavani et al., 2014). The county’s topography varies dramatically from north to south. The northern parts are coastal plains along the Caspian Sea, characterized by low-lying lands and gentle slopes. As one moves southward, the terrain becomes more rugged and mountainous, culminating in the Alborz range. This range creates a natural barrier and contributes to the climatic variation within short distances. The diverse morphology includes coastal plains, rolling hills, steep mountain slopes, and forested valleys (Aghanabati, 2012). Nur County is part of the Hyrcanian forest belt, an ancient deciduous forest region that stretches along the southern Caspian coast (Ghassemi et al., 2023). These forests are recognized for their biodiversity and ecological value. The area’s morphology, with steep gradients and unstable geological formations in the mountainous regions, makes it naturally prone to hazards such as landslides and flash floods, especially during periods of intense rainfall. This ecological richness, however, also makes it an attractive location for tourism and nature conservation efforts (Khairy & Sarfi, 2024).

Nur County lies within the Alborz structural zone, a significant geotectonic unit in northern Iran that has undergone complex geological evolution due to the convergence of the Arabian and Eurasian plates (Aghanabati, 2012). The region represents a transition zone between the stable Caspian coastal plain in the north and the active Alborz mountain belt to the south. This tectonic setting has resulted in a diverse lithological composition, comprising a mixture of sedimentary, volcanic, and metamorphic units from different geological periods, particularly the Mesozoic and Cenozoic eras (Vavsari et al., 2014). The northern parts of Nur, closer to the Caspian Sea, are primarily composed of Quaternary alluvial and marine sediments, deposited by fluvial and coastal processes. These unconsolidated materials include silts, clays, and sands, which are highly susceptible to erosion and slope instability (Aghanabati, 2012). Moving southward, lithology becomes more complex, dominated by Eocene volcanic and pyroclastic rocks, including andesites, basalts, and tuffs, interbedded with sedimentary sequences such as marl, limestone, and shale (Vahidnia et al., 2010). Jurassic and Cretaceous limestone outcrops are also present in higher elevations, contributing to karstic features and varying degrees of rock strength and permeability (Aghanabati, 2012). The geological map of the studied area is illustrated in Figure 2.

The Alborz range's active tectonics and frequent seismicity have led to the development of numerous faults and fractures throughout Nur County, including both thrust and strike-slip systems. These structural discontinuities, combined with steep slopes, weathered rock formations, and high rainfall, significantly increase the potential for landslides and other mass movements (Aghanabati, 2012). Additionally, the juxtaposition of weak, clay-rich layers over harder bedrock contributes to differential weathering and slope deformation. Understanding the geological framework is therefore essential for effective hazard mapping, infrastructure planning, and sustainable land-use management in the region. Given the county's complex terrain, climatic variability, and human settlement patterns, Nur is a suitable case for geohazard assessments, particularly landslide susceptibility analysis. The combination of steep slopes in the south, loose soil structures, high rainfall, and expanding urban and agricultural activities increases the vulnerability to slope instability. Tools like MCDM and fuzzy logic can be effectively applied in this context to identify high-risk zones and inform sustainable development and disaster mitigation strategies.

In the context of landslide susceptibility analysis in Nur County, a set of triggering factors has been selected based on previous geospatial studies and the region's specific geomorphological and environmental characteristics. The selected parameters (i.e. slope angle, aspect, elevation, lithology, land use, distance from roads, distance from faults, distance from rivers, and rainfall intensity), are recognized as the most influential contributors to slope instability in northern Iran's mountainous and coastal transitional zones.

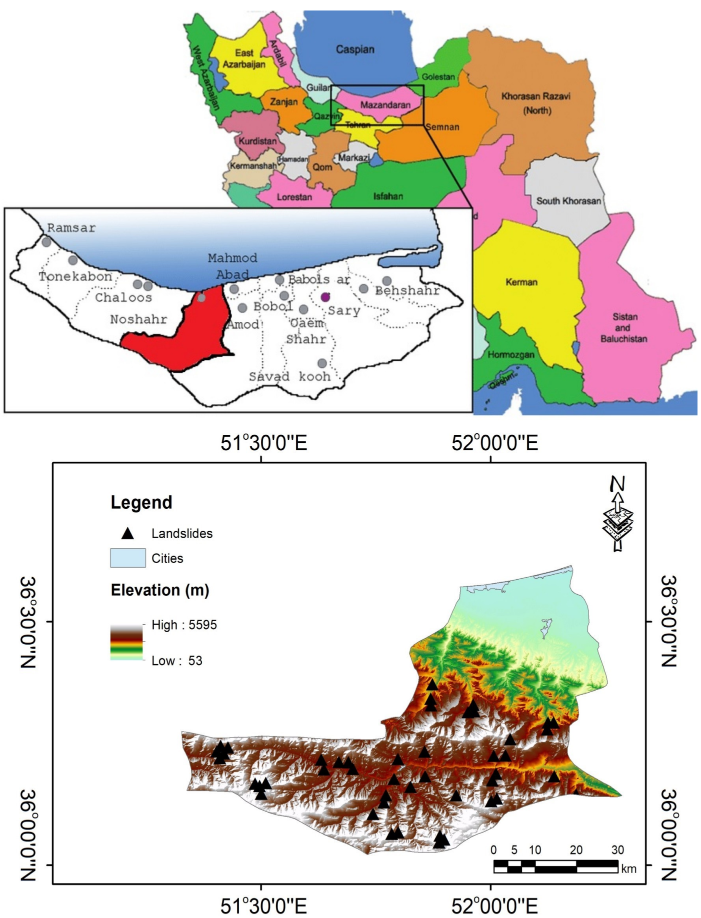

Fig. 1 Location map of the study area in Iran

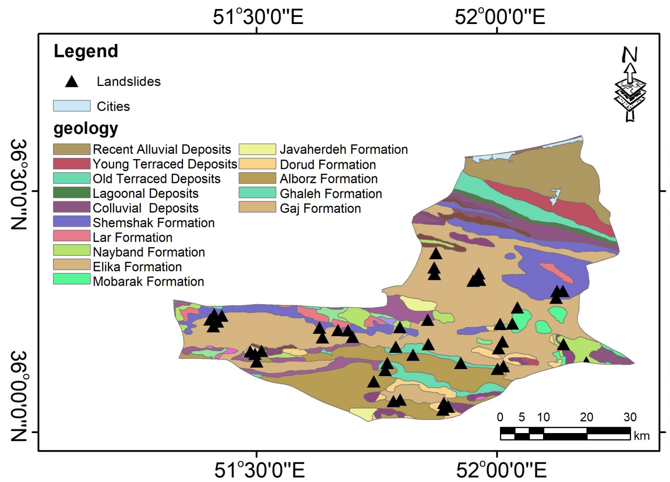

Fig. 2 Geological map of the study area
(adapted from Geological Survey of Iran, 2009)

Slope is a primary factor in landslide initiation, as steeper gradients naturally exert more gravitational force on soil and rock materials, making them prone to movement (Bhagya et al., 2023), especially in the southern mountainous parts of Nur where slopes are more pronounced. Aspect, or direction a slope faces, influences microclimate conditions such as moisture retention, sun exposure, and vegetation cover, all of which affect soil strength and weathering processes (Huang & Zhao, 2018). Elevation plays a role in climate variation and vegetation types, as higher altitudes often experience more intense weathering, freeze-thaw cycles, and precipitation, thus affecting slope stability (Ado et al., 2022).

Lithology is crucial because the type and structure of underlying rock and soil dictate the mechanical strength, permeability, and erosion resistance of the terrain (Noorollahi et al., 2018). In Nur, the mixture of soft sediments in the north and fractured volcanic rocks in the south creates heterogeneous landslide-prone zones. Land use reflects the anthropogenic impact on natural slopes; deforestation, agricultural expansion, and construction can destabilize slopes by altering drainage patterns and reducing root cohesion (Myronidis et al., 2016). Distance from roads is included due to the role of road cuts and slope modifications in triggering failures; road construction often disturbs the natural balance of slopes and increases the likelihood of shallow landslides (Dias et al., 2021). Lastly, rainfall intensity is a well-established triggering factor, particularly in humid regions like Nur, where heavy and prolonged rainfall can saturate soils, reduce shear strength, and initiate mass movements. Figure 3 is provided with the index maps for selected triggering factors that have been used in this assessment. The selection of these factors is essential for producing an accurate and realistic landslide susceptibility model. Each parameter represents a key component of the physical or anthropogenic environment influencing slope stability. Their combined analysis, especially through GIS-based and fuzzy MCDM approaches, allows for a comprehensive and context-specific assessment, enabling local authorities to prioritize risk zones and implement targeted mitigation strategies.

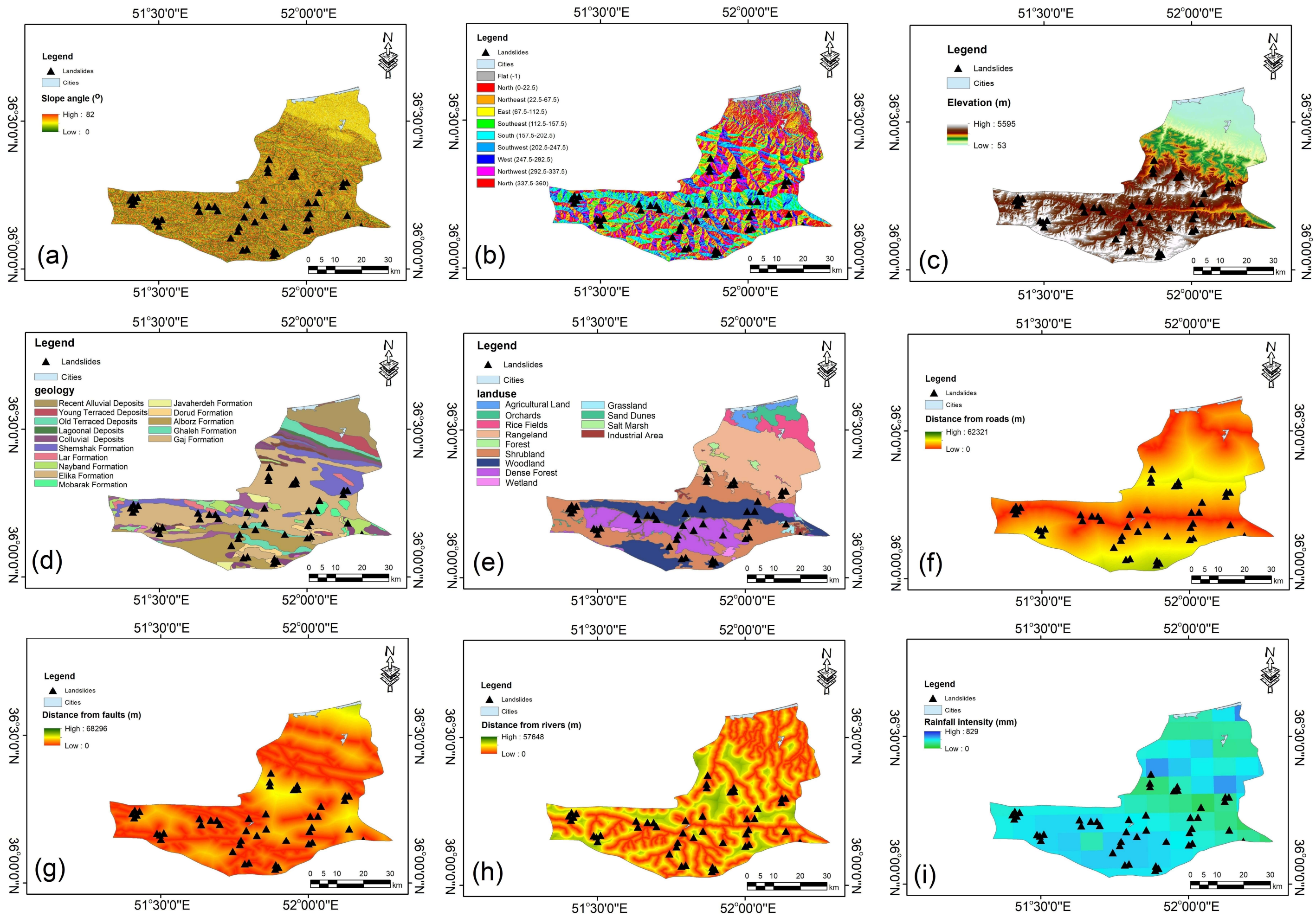

Fig. 3 Triggering factor index maps: (a) slope angle, (b) aspect, (c) elevation, (d) lithology, (e) land use, (f) distance from roads, (g) distance from faults, (h) distance from rivers, (i) rainfall intensity

III. Materials and Methods

The methodology adopted for this study integrates spatial data analysis with fuzzy MCDM techniques to assess landslide susceptibility in Nur County, Mazandaran Province, Iran. This comprehensive approach consists of four main stages: (1) data collection and preprocessing, (2) selection and standardization of landslide-influencing factors, (3) application of fuzzy MCDM techniques (specifically Fuzzy-AHP), and (4) generation of the landslide susceptibility map using GIS-based weighted overlay analysis.

A. Data Collection and Preprocessing

The first stage involved gathering both spatial and non-spatial data from various authoritative sources. Topographic parameters such as slope, aspect, and elevation were derived from a ±30m resolution Digital Elevation Model (DEM). Geological data, including lithological units and fault maps, were obtained from the Geological Survey of Iran. Land use/land cover data were extracted from Sentinel-2 satellite imagery using supervised classification. Road networks and infrastructure layers were acquired from OpenStreetMap and local municipal records. Rainfall data representing annual precipitation and storm intensity were collected from synoptic and climatological stations operated by the Iranian Meteorological Organization. All datasets were georeferenced to the same spatial reference system (WGS84 UTM Zone 39N) and resampled to a uniform resolution for consistency.

In order to ensure comparability among the various landslide conditioning factors, all input data layers were normalized using the Max–Min normalization method (Mao et al., 2024). This method transforms different datasets with varying units and scales into a common range, typically between 0 and 1. Max–Min normalization is especially suitable for multi-criteria analysis, as it preserves the relative distribution of the original values while eliminating the influence of differing measurement units. This step is essential before applying fuzzy logic or MCDM techniques, as it ensures that no single parameter dominates the analysis due to its numerical scale (Cengiz & Ercanoglu, 2022). The Max–Min normalization was applied using the following Eq. 1 (Feizizadeh et al., 2014):

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where, X is the original value of the parameter, X_{min} and X_{max} are the minimum and maximum values of that parameter within the dataset, and X' is the resulting normalized value. This method was applied uniformly to all raster layers, including slope, elevation, rainfall, and distance-based criteria (e.g., distance from roads), using raster calculator tools within ArcGIS (Feizizadeh et al., 2014). As a result, each pixel in the dataset was rescaled to a [0,1] range, facilitating accurate integration and analysis in the subsequent weighted overlay process (Mao et al., 2024).

B. Selection and Standardization of Criteria

In this study, seven primary factors influencing landslide susceptibility were selected based on previous literature, regional expert consultation, and the geomorphological characteristics of Nur County. These include slope, aspect, elevation, lithology, land use, distance from roads, and rainfall intensity. Each of these factors has a documented influence on slope stability and landslide occurrence. For instance, steep slopes and certain lithological formations such as weathered volcanic rocks are known to increase landslide probability, while human-induced changes such as road construction and deforestation significantly alter natural slope conditions. The selection process was driven by the relevance, availability, and spatial resolution of data for each criterion. Prior to standardization, all spatial datasets were normalized using the Max–Min method, which transformed the raw values of each criterion to a common scale ranging from 0 to 1. This step removed the impact of differing units and magnitudes, ensuring that each factor contributes proportionally to the analysis. However, normalization alone does not account for the directionality or effectiveness of each criterion with respect to landslide risk. Therefore, a second stage of standardization was conducted to assign appropriate fuzzy membership values to each normalized layer, reflecting their degree of favorability or susceptibility to landslide occurrence.

For the standardization process, fuzzy logic-based membership functions were applied, which transformed the normalized values into fuzzy suitability scores between 0 (least susceptible) and 1 (most susceptible). Depending on the nature of the relationship between each factor and landslide risk, different types of fuzzy functions were used. For example, a positive linear fuzzy function was used for slope and rainfall (as higher values increase risk), while a negative linear function was used for distance to roads (as risk decreases with increasing distance). Categorical layers such as lithology and land use were reclassified based on expert-based susceptibility ratings. This fuzzy standardization process ensured that all criteria were not only on the same scale but also reflected their appropriate influence direction for accurate landslide susceptibility modeling.

For the standardization process, criteria for which landslide risk increases with higher values (e.g., slope, rainfall); standardized as follows:

$$\mu(x)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a<x<b\\ 1 & x\ge b\end{cases} \tag{2}$$

where, x is normalized value of the parameter, a is lower threshold (least influential value), b is upper threshold (most influential value) and μ(x) is fuzzy membership value (ranging from 0 to 1). Also, the following Eq., were applied to criteria where higher values reduce landslide susceptibility (e.g., distance to roads):

$$\mu(x)=\begin{cases}1 & x\le a\\ \dfrac{b-x}{b-a} & a<x<b\\ 0 & x\ge b\end{cases} \tag{3}$$

In this case, as distance increases, susceptibility decreases, which is reflected in the function (Nanehkaran et al., 2021). In the case of application when the landslide susceptibility is highest within a specific range, the following Eq., are provided:

$$\mu(x)=\begin{cases}0 & c\le x\le a\\ \dfrac{x-a}{b-a} & a<x<b\\ \dfrac{c-x}{c-b} & b\le x<c\end{cases} \tag{4}$$

where, a is minimum acceptable value, b is optimal or peak susceptibility value, c is maximum acceptable value.

C. Fuzzy MCDM/AHP Weighting Procedure

In order to assign accurate and objective weights to the selected landslide conditioning factors, the Fuzzy AHP (a widely recognized MCDM method) was applied. Unlike traditional AHP, the fuzzy version incorporates uncertainty and vagueness in expert judgments using fuzzy logic, which is especially important in geohazard studies where qualitative expert knowledge often guides the decision-making process (Zhao et al., 2017). This makes Fuzzy AHP more robust and suitable for complex natural hazard assessments such as landslide susceptibility mapping (Mallick et al., 2018). The first step in the Fuzzy AHP process is constructing a pairwise comparison matrix among the selected criteria (e.g., slope, lithology, rainfall, land use, etc.). Each pair of factors is compared using linguistic scales such as “equally important”, “moderately more important”, or “extremely more important”. These qualitative judgments are then converted into Triangular Fuzzy Numbers (TFNs), which are expressed as a triplet (l,m,u), where l is the lower bound, m is the most likely value, and u is the upper bound of the expert’s opinion. For example, the linguistic term “moderately more important” may correspond to the fuzzy number (3, 5, 7).

Once the fuzzy pairwise matrix is created, the next step involves calculating fuzzy synthetic extent values for each criterion. This is achieved using Chang’s extent analysis method, which calculates the degree of possibility that one criterion is more important than the others. The formula for the synthetic extent S_i of criterion i is:

$$S_i=\frac{\sum_{j=1}^{n}M_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n}M_{ij}} \tag{5}$$

where, where M_{ij} is the fuzzy comparison value of criterion i with respect to criterion j. These fuzzy sums are computed using fuzzy arithmetic (addition and inversion of triangular fuzzy numbers). Next, the degree of possibility that $S_i \geq S_k$ (i.e., that criterion i is more important than criterion k) is computed using the following formula:

$$V(S_i \geq S_k) = \sup_{x \geq y}\left[\min\left(\mu S_i(x), \mu S_k(y)\right)\right] \tag{6}$$

This step is repeated for all combinations of criteria to construct a possibility matrix, from which the normalized weight vector W= (w_1, w_2, ..., w_n) is derived. These final weights are then defuzzified, typically using the centroid method:

$$w_i = \frac{l_i + m_i + u_i}{3} \tag{7}$$

This results in a crisp weight for each criterion, reflecting its relative importance in triggering landslides in the study area. Finally, the derived weights were incorporated into a GIS-based Weighted Linear Combination (WLC) model to produce the Landslide Susceptibility Index (LSI). Each standardized and fuzzified raster layer was multiplied by its corresponding fuzzy AHP weight, and the sum of all layers yielded the final LSI:

$$LSI = \sum_{i=1}^{n} w_i \cdot X_i \tag{8}$$

where X_i is the standardized fuzzy value for factor i, and w_i is the defuzzified weight. The final susceptibility map was categorized into susceptibility classes (very low to very high) and validated using known landslide inventory data. The Fuzzy AHP approach proved particularly effective in this context, as it combined expert knowledge, addressed uncertainty, and allowed for a nuanced interpretation of multi-source data for landslide hazard analysis.

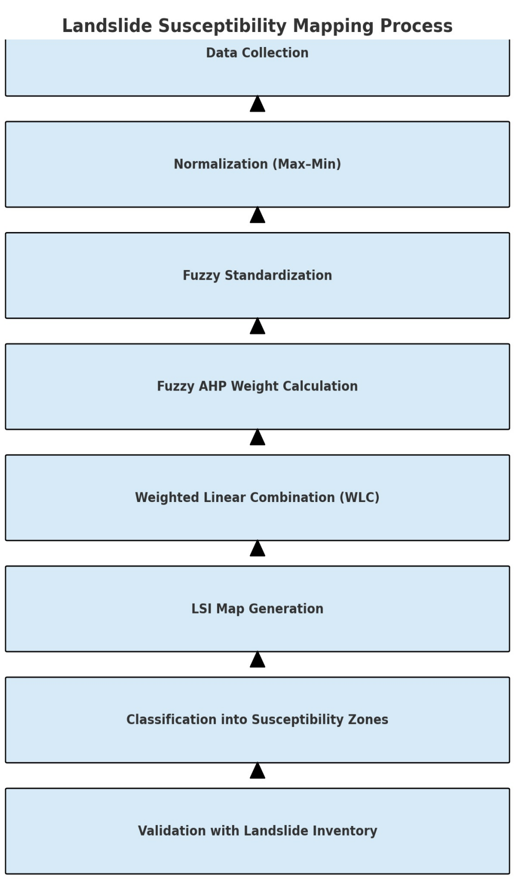

Fig. 4 The flowchart of the study

D. Landslide Susceptibility Mapping

After calculating the weights of the selected factors using the Fuzzy AHP model, the next step involves transferring this information into a GIS environment for spatial modeling. Each thematic layer (such as slope, lithology, rainfall, land use, etc.), which has already been normalized and standardized using fuzzy membership functions, is prepared as a raster dataset in GIS. The weights derived from the Fuzzy AHP process are then assigned to the respective layers. This is typically done using tools like Raster Calculator in ArcGIS, where each standardized raster layer is multiplied by its corresponding fuzzy-AHP weight and all layers are summed to generate a final weighted overlay. The assessment flowchart has been provided in Figure 4. The result of this weighted linear combination is a continuous raster layer known as the LSI, where each pixel represents the degree of landslide susceptibility. This LSI map is then classified into susceptibility using Natural Breaks (Jenks) classification methods.

IV. Results and Discussion

The landslide susceptibility map (Figure 5) generated through the fuzzy logic model revealed distinct spatial variations in hazard levels across Nur County. The southern regions of the county exhibited the highest susceptibility zones, primarily due to the convergence of multiple triggering factors. Steep slopes, prevalent in the southern mountainous terrain, significantly contribute to slope instability, making this area more prone to landslides compared to the northern and central parts. Lithological analysis indicated that fragile rock formations, particularly shale and marl, are extensively distributed in the southern sector. These formations are inherently weak and highly susceptible to weathering and erosion, further exacerbating the landslide risk. The combination of steep slopes and weak lithology creates critical conditions for mass movements, especially during periods of intense rainfall.

Rainfall intensity emerged as another influential factor in the southern regions. Meteorological data showed higher precipitation levels in these areas, increasing soil saturation and reducing shear strength. This hydrological factor, when interacting with geological and topographical vulnerabilities, amplifies the likelihood of landslide occurrences. The fuzzy logic model successfully captured these complex interrelations, highlighting the importance of integrating multiple variables for accurate hazard assessment. Proximity to anthropogenic factors such as roads and deforested lands also plays a vital role in the southern region's susceptibility. Road networks, often carved into steep hillsides, disrupt natural drainage patterns and destabilize slopes. Additionally, deforestation for agricultural and developmental purposes reduces root reinforcement, making soil layers more prone to sliding. The model's sensitivity to these parameters underscores the necessity of considering human-induced changes in susceptibility evaluations.

The fuzzy logic approach demonstrated a robust capability to manage spatial uncertainties inherent in environmental data. Unlike binary classification methods, the fuzzy model allowed for gradual transitions between susceptibility classes, providing a more realistic representation of hazard distribution.

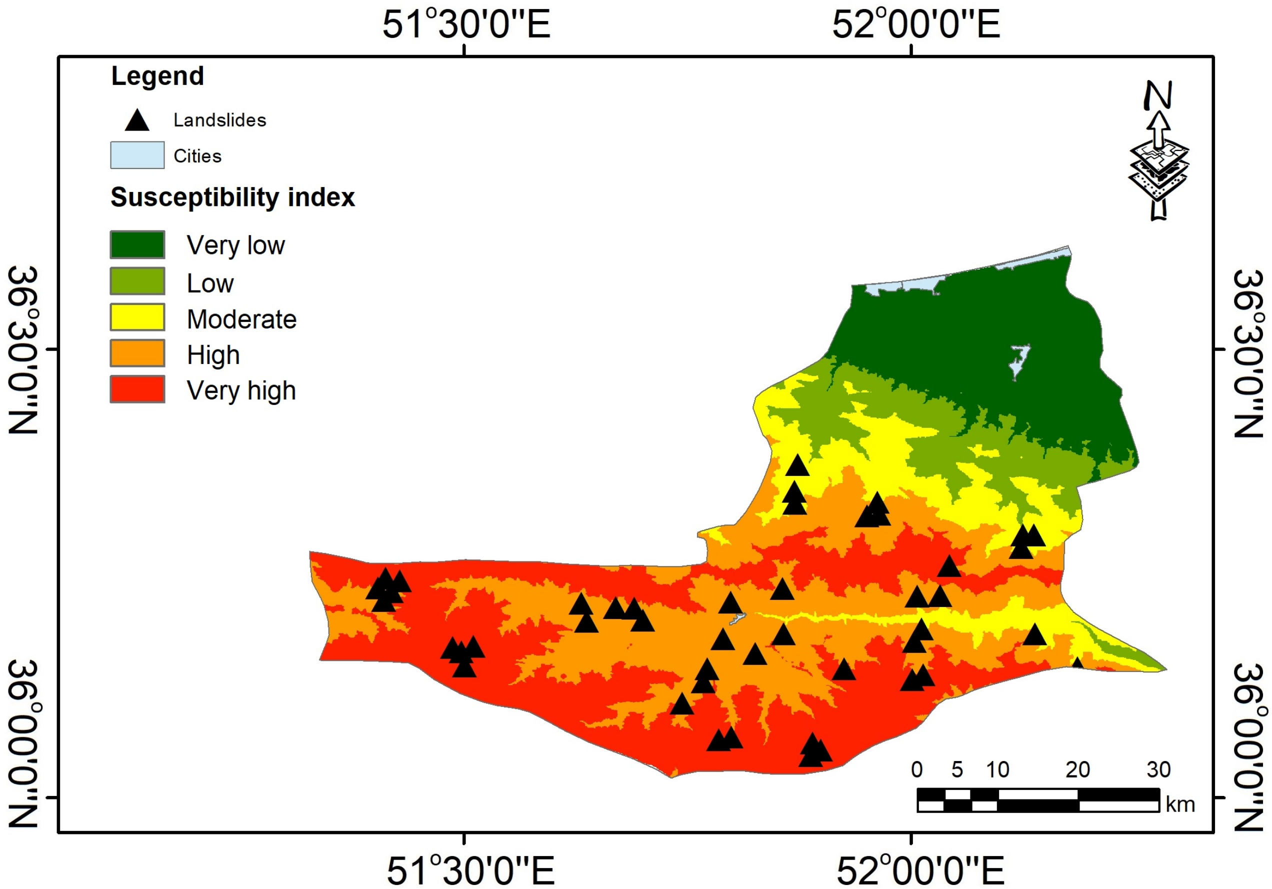

Fig. 5 The landslide susceptibility map for studied region

V. Conclusion

This study highlights the effectiveness of integrating fuzzy logic with Geographic Information Systems (GIS) for assessing landslide susceptibility in mountainous regions, specifically in Nur County, northern Iran. By incorporating nine key factors—slope angle, aspect, elevation, lithology, land use, distance from roads, distance from faults, distance from rivers, and rainfall intensity—the fuzzy logic approach successfully addressed the spatial complexity and uncertainty inherent in landslide hazard mapping. Fuzzy membership functions allowed for the gradual classification of susceptibility, and the use of fuzzy operators enabled the generation of a comprehensive susceptibility map. The findings reveal that areas with steep slopes, fragile lithological formations, high rainfall intensity, and proximity to roads and deforested lands are at the highest risk. This model offers a reliable and flexible framework for predicting landslide-prone areas, supporting local authorities in land-use planning and hazard mitigation. To enhance model precision, future studies can benefit from incorporating multi-criteria decision-making techniques such as the Fuzzy Analytical Hierarchy Process (Fuzzy-AHP). This would allow for more accurate weighting of factors based on expert judgment and improve the robustness of susceptibility analysis. Overall, the methodology presented serves as a valuable decision-support tool for sustainable environmental and infrastructure planning in landslide-prone regions.

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Authors' contributions

Fatemeh Rahimi and Maryam Ebrahimi conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and were responsible for drafting the initial manuscript. Reza Farzi Mehraban performed supervision, conceptual guidance, and critical revision of the manuscript. Reza Farzi Mehraban provided overall project administration and final approval of the version to be published. All authors read and approved the final manuscript.

Conflict of interest

The authors have not disclosed any competing interests.

claims in published maps, data, and institutional affiliations.

REFERENCES

Ado M., Amitab K., Maji A.K., Jasińska E., Gono R., Leonowicz Z., Jasiński M. (2022). Landslide susceptibility mapping using machine learning: A literature survey. *Remote Sensing*, 14(13), 3029. https://doi.org/10.3390/rs14133029.

Bahrami Y., Hassani H., Maghsoudi A. (2021). Landslide susceptibility mapping using AHP and fuzzy methods in the Gilan province, Iran. *GeoJournal*, 86, 1797-1816. https://doi.org/10.1007/s10708-020-10162-y.

Bhagya S.B., Sumi A.S., Balaji S., Danumah J.H., Costache R., Rajaneesh A., Abioui M. (2023). Landslide susceptibility assessment of a part of the Western Ghats (India) employing the AHP and F-AHP models and comparison with existing susceptibility maps. *Land*, 12(2), 468. https://doi.org/10.3390/land12020468.

Broeckx J., Vanmaercke M., Duchateau R., Poesen J. (2018). A data-based landslide susceptibility map of Africa. *Earth-Science Reviews*, 185, 102-121. https://doi.org/10.1016/j.earscirev.2018.05.002.

Cemiloglu A., Zhu L., Mohammednour A.B., Azarafza M., Nanehkaran Y.A. (2023). Landslide susceptibility assessment for Maragheh County, Iran, using the logistic regression algorithm. *Land*, 12(7), 1397. https://doi.org/10.3390/land12071397.

Cengiz L.D., Ercanoglu M. (2022). A novel data-driven approach to pairwise comparisons in AHP using fuzzy relations and matrices for landslide susceptibility assessments. *Environmental Earth Sciences*, 81(7), 222. https://doi.org/10.1007/s12665-022-10312-0.

Dias H.C., Hölbling D., Grohmann C.H. (2021). Landslide susceptibility mapping in Brazil: a review. *Geosciences*, 11(10), 425. https://doi.org/10.3390/geosciences11100425.

Ercanoglu, M., & Gokceoglu, C. (2004). Use of fuzzy relations to produce landslide susceptibility map of a landslide prone area (West Black Sea Region, Turkey). *Engineering Geology*, 75(3-4), 229-250. https://doi.org/10.1016/j.enggeo.2004.06.001.

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.

Frattini P., Crosta G., Carrara A. (2010). Techniques for evaluating the performance of landslide susceptibility models. *Engineering Geology*, 111(1-4), 62-72. https://doi.org/10.1016/j.enggeo.2009.12.004.

Geological Survey of Iran, GSI (2009). *Geological maps of Nur County and vicinity area*. Geological Survey and Mineral Exploration of Iran press, maps unit, Tehran, Iran.

Ghassemi M.R., Allen M.B., Motamedi H. (2023). A Synthesis of the Geology and Petroleum Geology of the Iranian Portion of the South Caspian Basin and Surrounding Areas. *Journal of Petroleum Geology*, 46(4), 487-512. https://doi.org/10.1111/jpg.12848.

Guzzetti F., Reichenbach P., Ardizzone F., Cardinali M., Galli M. (2006). Estimating the quality of landslide susceptibility models. *Geomorphology*, 81(1-2), 166-184. https://doi.org/10.1016/j.geomorph.2006.04.007.

Huang Y., Zhao L. (2018). Review on landslide susceptibility mapping using support vector machines. *Catena*, 165, 520-529. https://doi.org/10.1016/j.catena.2018.03.003.

Jam A.S., Mosaffaie J., Sarfaraz F., Shadfar S., Akhtari R. (2021). GIS-based landslide susceptibility mapping using hybrid MCDM models. *Natural Hazards*, 108, 1025-1046. https://doi.org/10.1007/s11069-021-04718-5.

Kardavani P., Rad A.F., Kavoosi B. (2014). Mazandaran province Geotourism. *Journal of Tourism Hospitality Research*, 3(1), 23-47.

Khairy H., Sarfi M. (2024). Land subsidence in Iran: an omnipresent geohazard. *Geology Today*, 40(5), 187-196. https://doi.org/10.1111/gto.12473.

Klai A., Katlane R., Haddad R., Rabia M.C. (2024). Landslide susceptibility mapping by Frequency Ratio and Fuzzy logic approach: A case study of Mogods and Hedil (Northern Tunisia). *Applied Geomatics*, 16(1), 91-109. https://doi.org/10.1007/s12518-023-00544-5.

Lee S., Min K. (2001). Statistical analysis of landslide susceptibility at Yongin, Korea. *Environmental Geology*, 40, 1095-1113. https://doi.org/10.1007/s002540100310.

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 Y., Li Y., Teng F., Sabonchi A.K., Azarafza M., Zhang M. (2024). Utilizing hybrid machine learning and soft computing techniques for landslide susceptibility mapping in a drainage basin. *Water*, 16(3), 380. https://doi.org/10.3390/w16030380.

Mirmohammadi S.T., Nur, A.G., Mousavinasab S.N., Hosseininejad S.E., Alizadeh H. (2019). Ergonomic Evaluation of the Manual Material Handling Tasks in the Food Industries of Malard County Using the 3D. *Health and Development Journal*, 8(2), 175-186.

Myronidis D., Papageorgiou C., Theophanous S. (2016). Landslide susceptibility mapping based on landslide history and analytic hierarchy process (AHP). *Natural Hazards*, 81, 245-263. https://doi.org/10.1007/s11069-015-2075-1.

Nanehkaran Y.A., Mao Y., Azarafza 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.

Noorollahi Y., Sadeghi S., Yousefi H., Nohegar A.J. (2018). Landslide modelling and susceptibility mapping using AHP and fuzzy approaches. *International Journal of Hydrology*, 2(2), 137-148.

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.

Reichenbach P., Rossi M., Malamud B.D., Mihir M., Guzzetti F. (2018). A review of statistically-based landslide susceptibility models. *Earth-Science Reviews*, 180, 60-91. https://doi.org/10.1016/j.earscirev.2018.03.001.

Sabbaghi A. (2024). Designing an Ecotourism Residence with a Social Sustainability Approach (Case Study: Nur County). *Journal of Civil Aspects and Structural Engineering*, 1(2), 205-219. https://doi.org/10.48314/jcase.v1i2.45.

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.

Sur U., Singh P., Meena S.R. (2020). Landslide susceptibility assessment in a lesser Himalayan road corridor (India) applying fuzzy AHP technique and earth-observation data. *Geomatics, Natural Hazards and Risk*, 11(1), 2176-2209. https://doi.org/10.1080/19475705.2020.1836038.

Vahidnia M.H., Alesheikh A.A., Alimohammadi A., Hosseinali F. (2010). A GIS-based neuro-fuzzy procedure for integrating knowledge and data in landslide susceptibility mapping. *Computers & Geosciences*, 36(9), 1101-1114. https://doi.org/10.1016/j.cageo.2010.04.004.

Van Westen C.J., Castellanos E., Kuriakose S.L. (2008). Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. *Engineering Geology*, 102(3-4), 112-131. https://doi.org/10.1016/j.enggeo.2008.03.010.

Vavsari M.M., Shoaei G., Shajhidi F. (2014). Defining the rainfall intensity–duration threshold to determine the initiation of shallow landslides in Tajan and Nekaroud rivers catchments (eastern Mazandaran province). *Scientific Quarterly Journal of Iranian Association of Engineering Geology*, 7(1 & 2), 15-28.

Wang Y., Nanehkaran Y.A. (2024). GIS-based fuzzy logic technique for mapping landslide susceptibility analyzing in a coastal soft rock zone. *Natural Hazards*, 120(12), 10889-10921. https://doi.org/10.1007/s11069-024-06649-3.

Zêzere J.L., Pereira S., Melo R., Oliveira S.C., Garcia R.A. (2017). Mapping landslide susceptibility using data-driven methods. *Science of the Total Environment*, 589, 250-267. https://doi.org/10.1016/j.scitotenv.2017.02.188.

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.