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# Landslide Hazard Assessment Induced by Active Tectonics in the Golpayegan Region using AHP

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***Abstract***: The Golpayegan region in central Iran is significantly affected by active tectonic processes, making it highly susceptible to landslides. This study evaluates landslide hazards induced by active tectonics using the Analytical Hierarchy Process (AHP) integrated with a Geographic Information System (GIS). Various conditioning factors were considered, including lithology, slope angle, elevation, proximity to faults, seismic activity, drainage density, land use, and precipitation. These factors were weighted based on expert judgment and previous studies to develop a comprehensive landslide susceptibility map. The results indicate that regions in close proximity to active faults, particularly along steep slopes and weak geological formations, exhibit a higher probability of landslides. The generated susceptibility map classifies the study area into five hazard levels: very low, low, moderate, high, and very high. A validation process was conducted using historical landslide data, revealing a strong correlation between high-risk zones and previously recorded landslide occurrences. The accuracy of the AHP model was further assessed through statistical validation methods, confirming its reliability for hazard assessment.

***Keywords:*** Active tectonics, Landslide hazard assessment, Golpayegan region, Geospatial analysis, AHP.

## I. Introduction

Landslides are among the most destructive natural hazards, causing severe damage to infrastructure, loss of human lives, and environmental degradation (Nanehkaran et al., 2023). A landslide refers to the downslope movement of rock, soil, or debris under the influence of gravity (Cemiloglu et al., 2023). These movements can occur in different forms, including rockfalls, debris flows, translational slides, and rotational slides, each with distinct mechanisms and consequences (Mao et al., 2024). Landslides pose significant risks in mountainous and hilly regions, where steep slopes, unstable geological formations, and external triggers such as rainfall and seismic activity create ideal conditions for slope failure (Broeckx et al., 2018). Understanding the factors influencing landslides and implementing effective risk assessment strategies are essential for minimizing their impact (Sarkar & Kanungo, 2004). Landslides are influenced by a combination of geological, climatic, and anthropogenic factors (Ado et al., 2022). Geological factors include lithology, soil properties, fault lines, and structural weaknesses that determine the natural stability of slopes (Nanehkaran et al., 2021). Climatic factors, such as heavy rainfall, rapid snowmelt, and extreme weather events, contribute to increased soil saturation and slope instability (Fernández et al., 1999). Seismic activity, including earthquakes and fault displacements, can act as a direct trigger for landslides, especially in tectonically active regions (Ayalew & Yamagishi, 2005). Additionally, human activities such as deforestation, road construction, mining, and unregulated urban expansion exacerbate landslide risks by altering natural drainage patterns and weakening slope integrity (Myronidis et al., 2016).

Landslide susceptibility analysis is a crucial step in hazard mitigation, allowing researchers and policymakers to identify high-risk zones and develop preventive measures (Nanehkaran et al., 2023). By assessing the likelihood of landslides occurring in a given area, susceptibility mapping provides essential information for urban planning, infrastructure design, and emergency response (Dias et al., 2021). These maps classify regions into different hazard levels (i.e. very low, low, moderate, high, and very high), helping decision-makers implement land-use regulations, slope stabilization projects, and early warning systems (Liu et al., 2023). Accurate susceptibility analysis reduces the socioeconomic impact of landslides and enhances community resilience (Pourghasemi et al., 2021). Remote sensing technology has revolutionized landslide studies by providing large-scale, high-resolution data for monitoring and analyzing terrain conditions (Stanley & Kirschbaum, 2017). Optical satellite imagery, Light Detection and Ranging (LiDAR), and Synthetic Aperture Radar (SAR) are widely used to detect surface deformations, track land cover changes, and assess slope stability (Mahalingam et al., 2016; Bostjančić et al., 2021). These technologies offer cost-effective, real-time monitoring of landslide-prone regions, making them invaluable tools for risk assessment (Pereira et al., 2023). When integrated with

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Geographic Information Systems (GIS), remote sensing data enhance the accuracy of landslide prediction models, enabling more effective hazard mitigation strategies (Cemiloglu et al., 2023).

Active tectonics play a critical role in landslide occurrences, particularly in seismically active regions (Kamp et al., 2008). Tectonic-induced landslides are often triggered by earthquakes, fault movements, and crustal deformations that destabilize slopes (Rosi et al., 2023). Unlike rainfall-induced landslides, which develop gradually, tectonic-induced landslides can be sudden and catastrophic, resulting in large-scale destruction (Lee & Dan, 2005). These landslides often occur in fault zones where rock fractures and seismic vibrations weaken slope stability. Understanding the impact of active tectonics on landslides is essential for assessing earthquake-related hazards and implementing mitigation measures in high-risk areas (Nefeslioglu et al., 2008). The infrastructure sector is particularly vulnerable to landslides induced by active tectonics (Lee et al., 2008). Roads, bridges, tunnels, and buildings constructed in seismically active regions face significant risks due to sudden slope failures (He & Beighley 2008). Landslides can block transportation networks, disrupt supply chains, and lead to costly repairs or reconstruction efforts (Cemiloglu et al., 2023). In regions with frequent tectonic activity, engineers must incorporate landslide risk assessments into infrastructure planning and design (Pourghasemi et al., 2021). Slope stabilization techniques, such as retaining walls, drainage systems, and rock bolting, are essential for ensuring the long-term safety and functionality of critical infrastructure (Nanehkaran et al., 2023). Figure 1 shows an overall framework for landslides susceptibility analysis. Landslide risk management also involves community engagement and public awareness programs. Educating local populations about landslide hazards, evacuation plans, and early warning systems can significantly reduce casualties and property damage (Parise & Jibson, 2000). Governments and disaster management agencies must invest in training programs, emergency drills, and real-time monitoring systems to ensure rapid response in the event of a landslide. Community-based initiatives, such as afforestation projects and sustainable land-use practices, can also help stabilize slopes and mitigate risks in vulnerable areas (Havenith et al., 2016). The environmental consequences of landslides extend beyond immediate destruction (Roccati et al., 2021). Landslides contribute to soil erosion, loss of vegetation, river sedimentation, and habitat destruction, disrupting ecosystems and biodiversity (Lee & Dan, 2005). The displacement of large amounts of earth alters natural drainage patterns, increasing the risk of flooding and water contamination (Broeckx et al., 2018). Sustainable land management practices, including reforestation, soil conservation, and controlled land development, is necessary to mitigate the long-term environmental impact of landslides (Dias et al., 2021).

Given the increasing frequency and intensity of extreme weather events, climate change is expected to exacerbate landslide risks in many regions (Mao et al., 2024). Rising temperatures, increased rainfall variability, and changing weather patterns contribute to greater slope instability (Nanehkaran et al., 2021). Integrating climate change projections into landslide risk assessments is essential for developing adaptive strategies and ensuring long-term disaster resilience (Myronidis et al., 2016). Governments and scientific communities must work together to monitor climate-induced landslide risks and implement proactive measures to protect vulnerable populations and infrastructure (Chowdhuri et al., 2021). Future research in landslide studies should focus on improving predictive models, enhancing early warning systems, and developing sustainable engineering solutions (Rehman & Azhoni, 2023). The integration of remote sensing data, real-time monitoring networks, and computer-based analysis will further enhance landslide hazard assessments (Stanley & Kirschbaum, 2017). The primary objective of this study is to assess the landslide hazard induced by active tectonics in the Golpayegan region using the Analytical Hierarchy Process (AHP).

Given the region's seismic activity and complex geological conditions, understanding the spatial distribution of landslide susceptibility is essential for disaster risk reduction and sustainable land-use planning. This research aims to identify key triggering factors, analyze their influence on slope stability, and develop a reliable susceptibility map that can guide policymakers, urban planners, and engineers in mitigating landslide risks. By integrating remote sensing data, GIS analysis, and AHP, this study provides a systematic approach to evaluating landslide-prone areas and offers practical insights into risk management strategies. The significance of this study lies in its contribution to both theoretical and applied aspects of landslide hazard assessment. Tectonic-induced landslides pose serious threats to infrastructure, transportation networks, and human settlements, making it imperative to develop predictive models for hazard mitigation. The findings of this research can enhance the resilience of communities in seismically active regions by providing essential data for early warning systems and engineering solutions. Additionally, the integration of AHP in landslide susceptibility analysis improves decision-making by prioritizing critical hazard factors based on expert judgment and empirical data.

## II. AHP in Landslide Susceptibility Analysis

The AHP is a widely used multi-criteria decision-making (MCDM) technique that plays a crucial role in landslide susceptibility analysis (Das et al., 2022). It provides a structured approach to evaluating complex problems by breaking them down into hierarchical levels of criteria and sub-criteria. In landslide studies, AHP enables researchers to systematically assess various conditioning factors, such as topography, geology, hydrology, and land use, by assigning relative weights based on expert judgment (Bhagya et al., 2023). This approach enhances the accuracy of susceptibility mapping, making it an effective tool for identifying high-risk areas (Asmare, 2023). One of the key advantages of AHP in landslide analysis is its ability to integrate both qualitative and quantitative data (Saygin et al., 2023). Landslide susceptibility is influenced by a combination of measurable parameters, such as slope gradient and soil properties, and expert knowledge on terrain stability (Zangmene et al., 2023). AHP allows for the incorporation of expert opinions through pairwise comparisons, ensuring that the most influential factors are appropriately weighted (Nanehkaran et al., 2021).

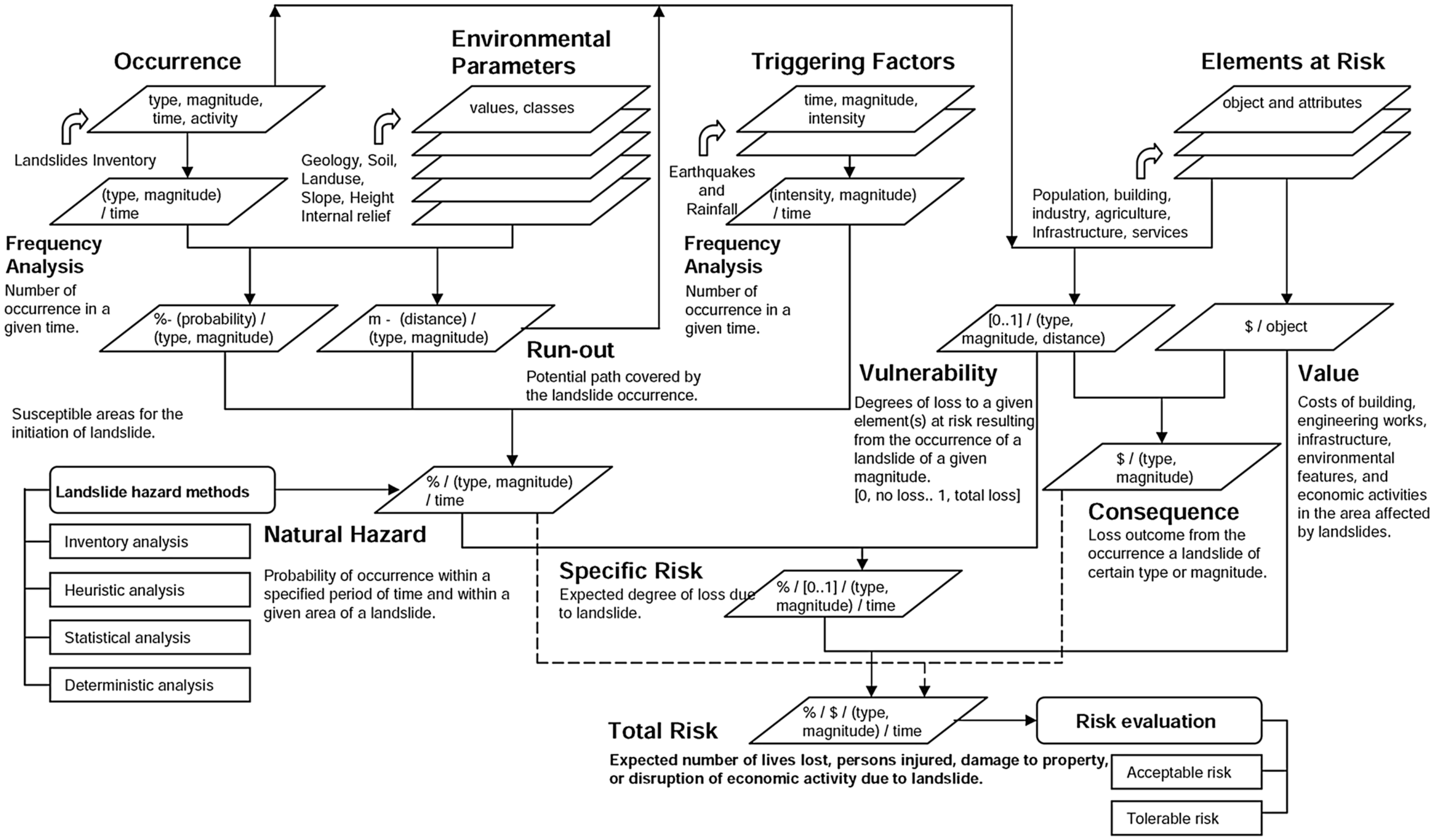


**Fig. 1** Common framework for landslide susceptibility analysis (Abella & Van Westen, 2008; Azarafza et al., 2018)

This makes it particularly useful in regions where field data is limited or where geological conditions require expert interpretation (Asmare, 2023). Another strength of AHP is its flexibility in handling multiple variables simultaneously. Landslides result from a combination of geological, hydrological, and environmental factors, making it essential to evaluate all contributing parameters comprehensively (Asadi et al., 2022). AHP structures the decision-making process by ranking each factor based on its relative importance. This hierarchical breakdown allows researchers to prioritize the most significant triggers of landslides, facilitating more targeted risk assessment and mitigation strategies (Bahrami et al., 2021).

AHP also improves decision consistency by providing a systematic framework for comparing different landslide-triggering factors (Chanu & Bakimchandra, 2022). The method employs consistency ratio (CR) calculations to verify the reliability of expert judgments (Azarafza et al., 2018). If the CR exceeds a certain threshold (typically 0.1), the pairwise comparison matrix needs to be revised to ensure logical consistency. This validation step enhances the credibility of susceptibility models, reducing subjectivity and improving the reliability of the final susceptibility map (Zangmene et al., 2023). The integration of AHP with GIS further enhances its applicability in landslide hazard analysis (Das et al., 2022). GIS provides spatial data on various conditioning factors, which can be overlaid and analyzed using AHP-derived weightings (Mao et al., 2024). By integrating spatial analysis with expert-based decision-making, AHP-GIS models produce high-resolution susceptibility maps that accurately depict landslide-prone areas (Pourghasemi et al., 2021). These maps are essential for urban planning, infrastructure development, and disaster preparedness, allowing authorities to implement proactive measures in high-risk zones (Abella and Van Westen, 2008). AHP is also highly adaptable to different study areas and environmental conditions (Asmare, 2023). Unlike purely statistical models, which rely heavily on large datasets, AHP can be applied in regions with limited historical landslide records by leveraging expert assessments (Parise and Jibson, 2000). This makes it particularly useful in remote or underdeveloped areas where traditional data collection methods are challenging (Biswas et al., 2023). Moreover, AHP can be combined with other MCDM techniques, such as Fuzzy Logic and Machine Learning, to further refine susceptibility models and enhance predictive accuracy (Saha et al., 2022).

The decision-making capabilities of AHP make it a valuable tool for policymakers and disaster management agencies (Mao et al., 2024). Landslide susceptibility assessments are essential for land-use planning and risk reduction strategies (Bahrami et al., 2021). By using AHP, decision-makers can allocate resources efficiently, focusing on the most vulnerable areas. This helps in designing infrastructure projects with appropriate slope stabilization measures, drainage improvements, and early warning systems to mitigate landslide hazards (Asadi et al., 2022). AHP also supports climate change adaptation efforts by evaluating the impact of environmental changes on landslide susceptibility. With increasing rainfall intensity, deforestation, and land-use modifications, landslide risks are evolving (Das et al., 2022).

AHP provides a dynamic framework that can be updated with new data and expert insights to reflect changing conditions (Chanu & Bakimchandra, 2022). This adaptability ensures that susceptibility assessments remain relevant and effective in mitigating emerging risks (Asmare, 2023). The method is particularly beneficial for interdisciplinary research, as it allows geologists, engineers, urban planners, and policymakers to collaborate in hazard assessment (Nanehkaran et al., 2021). Each discipline contributes expertise to the weighting process, ensuring a holistic evaluation of landslide risks (Saygin et al., 2023). This interdisciplinary approach leads to more comprehensive and practical risk management strategies, enhancing resilience to landslide disasters (Nanehkaran et al., 2021).

Landslides triggered by active tectonic processes require specialized assessment techniques due to their sudden and often catastrophic nature (Cengiz & Ercanoglu, 2022). AHP is particularly useful in analyzing the sensitivity of slopes to tectonic-induced landslides by systematically evaluating the role of seismic activity, fault structures, and crustal deformations (Zhou et al., 2023). By assigning appropriate weightings to these factors, AHP helps identify areas with high susceptibility to earthquake-triggered slope failures (Devara et al., 2021). This is crucial for seismic hazard zoning and the development of mitigation strategies in tectonically active regions (Panchal & Shrivastava, 2022). One of the key benefits of AHP in tectonic-induced landslide analysis is its ability to integrate seismic parameters with traditional landslide conditioning factors (Sonker et al., 2021). Unlike rainfall-induced landslides, which develop gradually, tectonic-triggered landslides occur instantaneously, making real-time risk assessment challenging. AHP allows for the incorporation of historical earthquake records, fault density, ground acceleration, and seismic intensity into susceptibility models (Roccati et al., 2021). This provides a more comprehensive understanding of how active tectonics influence slope stability, leading to more effective disaster preparedness measures (Machay et al., 2023). Furthermore, AHP enhances infrastructure resilience by guiding the construction of earthquake-resistant structures in landslide-prone zones (Moragues et al., 2021). By analyzing the sensitivity of slopes to tectonic forces, engineers can design roads, bridges, and settlements with appropriate reinforcement measures (Zangmene et al., 2023). This proactive approach reduces the likelihood of catastrophic failures, protecting lives and minimizing economic losses (Mao et al., 2024). The application of AHP in active tectonic regions is therefore essential for sustainable development and long-term disaster risk reduction, ensuring that infrastructure projects are planned and executed with geohazard considerations in mind (Cengiz & Ercanoglu, 2022).

## III. Studied Location and Geology

The Golpayegan region is situated within the Sanandaj-Sirjan metamorphic zone, along the northern margin of the Zagros mountain range, according to Iran's structural classification (Shahpari et al., 2014). This area has undergone complex deformation over various geological periods. The Sanandaj-Sirjan zone is considered one of the most tectonically active and dynamic regions in Iran (Ahmadi-Bonakda et al., 2022). Up until the Mesozoic era, this region experienced significant metamorphic and magmatic events (Karimi et al., 2012). Figure 2 shows the location of Sanandaj-Sirjan metamorphic zone in Iran. The post-Laramide movements played a crucial role in shaping the structural framework of this zone (Moradi et al., 2022). These movements caused intense compression of all folded and thrusted structures from the Late Miocene to the Pliocene (Mortaza et al., 2013). After the Miocene, due to lateral tension in certain parts of the region, normal faults developed, leading to the formation of basins and depressions along the northern margin of the Zagros (Shahpari et al., 2014).

During the late compressional movements and the collision between the Arabian and Central Iranian plates, in addition to the reverse movements along the northern margin of the Zagros, right-lateral strike-slip movements also emerged (Birjandi et al., 2019). The absence of significant and strong earthquakes in this region has led to the classification of Golpayegan as a relatively stable and inactive part of the northern Zagros margin (Ghanbarian et al., 2021; Moradi et al., 2022). However, morphotectonic evidence suggests the presence of major active faults with NW-SE and NE-SW orientations, either parallel or perpendicular to the main Zagros thrust. Among the parallel faults, the extension of the Shazand Fault can be mentioned, which appears inactive in the Golpayegan area, whereas the Muteh Fault represents an example of a perpendicular fault to the Zagros thrust system (Mirlohi et al., 2015). Morphometry, defined as the quantitative measurement of landform shapes, is a crucial tool in geomorphological studies. It involves measuring parameters such as size, elevation, and slope. These measurements allow geomorphologists to compare landscapes across different regions and establish geomorphic indices (Ahmadi-Bonakda et al., 2022).

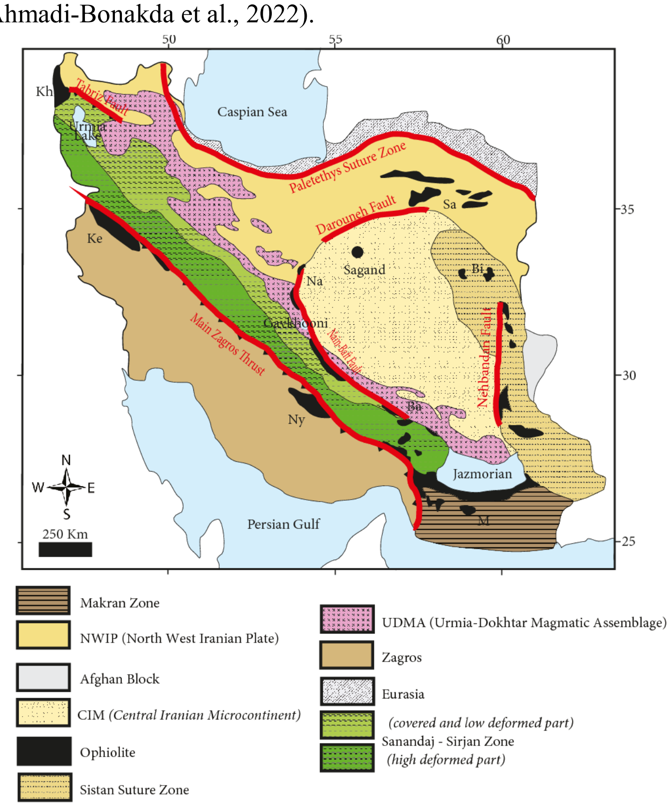


**Fig. 2** The location of the Sanandaj-Sirjan zone in Iran's geotectonic map (Ghazi & Moazzen, 2015)

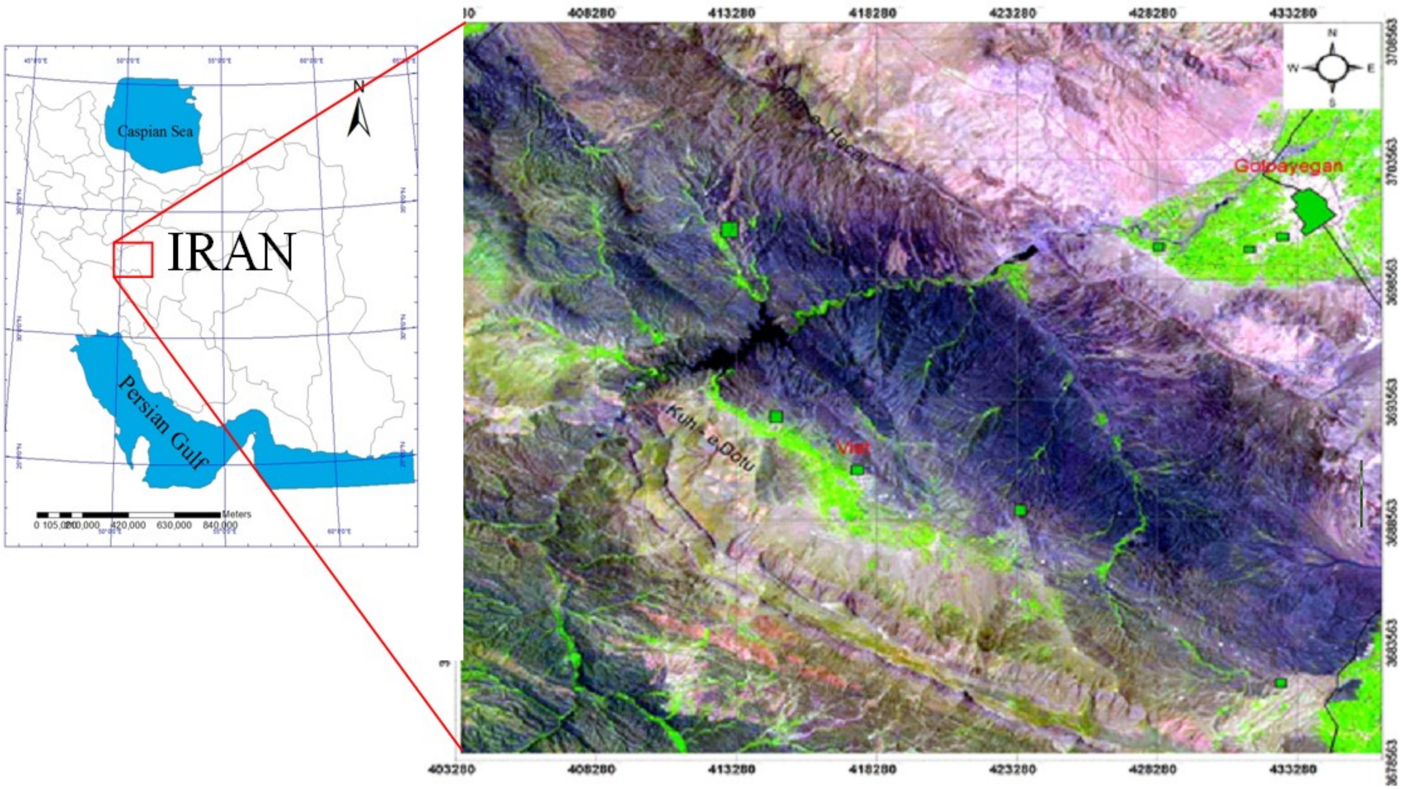


**Fig. 3** Location of studied area

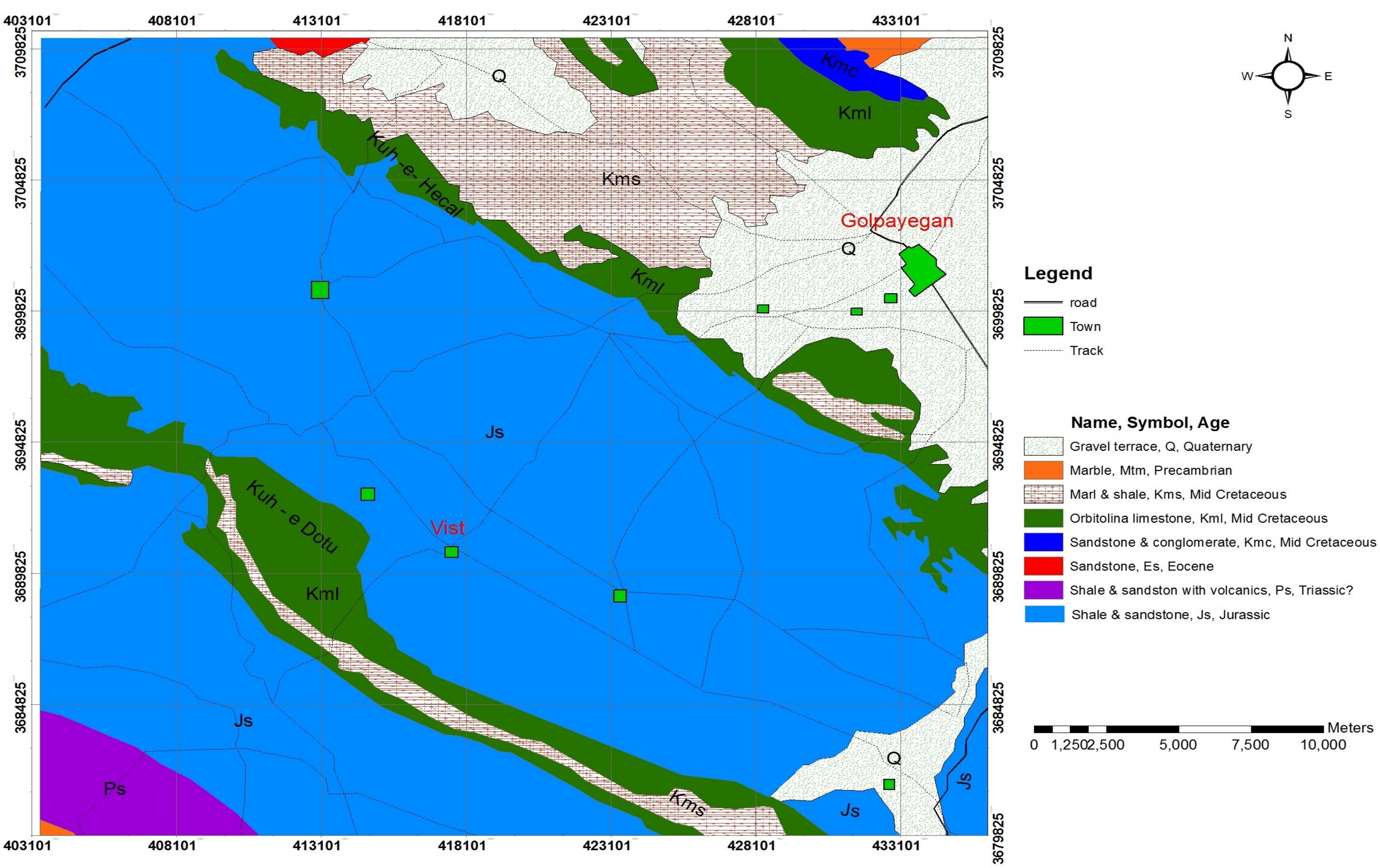


**Fig. 4** Geological map for studied region (Geological Survey and Mineral Exploration of Iran 2012)

From a morphological perspective, the Golpayegan region exhibits distinct geomorphological features indicative of active tectonic processes (Figure 3). The variation in elevation, river drainage patterns, and fault-controlled landforms all provide critical insights into the region's tectonic activity. The presence of linear valleys, triangular facets, and fault scarps suggests recent tectonic movements, challenging the perception of Golpayegan as a stable region. The analysis of morphometric indices, such as the hypsometric integral, valley floor width-to-height ratio, and drainage basin asymmetry, can further reveal the extent of tectonic influences on landscape evolution. These features can be easily encountered on geological map that provided in Figure 4. In this study, the aerial and satellite imagery, along with field evidence, indicate the presence of two main fault systems in the Golpayegan region, ranked by significance and frequency as NW-SE trending and NE-SW trending faults were shaped the geological surface and geomorphology of the studied region (Figure 5).

*NW-SE Trending Fault System*: Faults in this system extend in a northwest-southeast direction, parallel to the main Zagros thrust fault. These faults exhibit both reverse and right-lateral strike-slip components and constitute the dominant fault system in the region (Ghanbarian & Derakhshani, 2022). They have contributed to the displacement and fragmentation of older faults and rock units, eventually forming linear valleys that align parallel to the fault zone. These features are clearly identifiable in the northwestern and southeastern parts of the study area. The movement effects of these faults can be observed through the displacement of rock units, modern alluvial fans, and fault scarps. In the northwestern and southeastern parts of the study area, faults belonging to this system are highly active, with numerous historical and 20th-century seismic records associated with them. One of the most significant faults in this system is the Shazand Fault.

*NE-SW Trending Fault System*: The faults in this system extend in a northeast-southwest direction, almost perpendicular to the Zagros thrust zone. Along these faults, older rock formations and, in some locations, Precambrian basement rocks are exposed. Field investigations and seismic evidence indicate that these faults primarily exhibit normal faulting mechanisms, with some segments also displaying left-lateral strike-slip components. The activity of these faults has led to the formation of uplifted and subsided structures in the central parts of the Golpayegan region. These structures, trending northeast-southwest, have resulted in the uplift of the Muteh block as a horst, while the Golpayegan and Khomein plains on either side have subsided as grabens. This fault system is older than the Zagros-parallel faults mentioned earlier. Notable faults in this system include the eastern and western faults surrounding the Muteh block. The presence of alluvial terraces along these faults indicates vertical displacement.

To highlight morphotectonic features and display fault trends, various maps were created using GIS technology and remote sensing techniques. These maps include (Figures 6 to 8):

- Digital Elevation Model (DEM) for elevation map,
- Geo-aspect map,
- Hillshade map
- 3D Model of the Study Area,

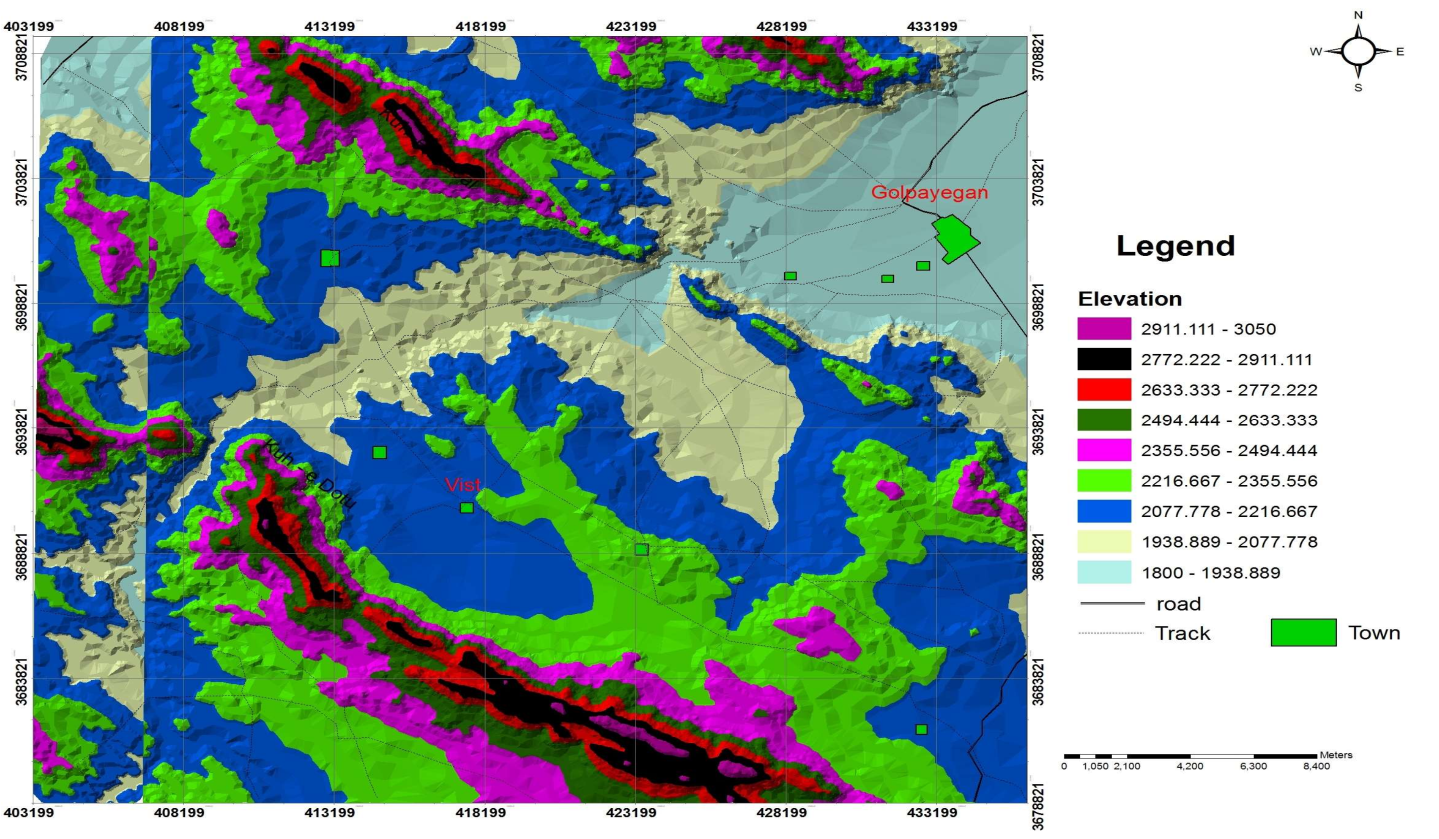


**Fig. 5** The geomorphological variations for studied region (obtain using DEM data, 2018)

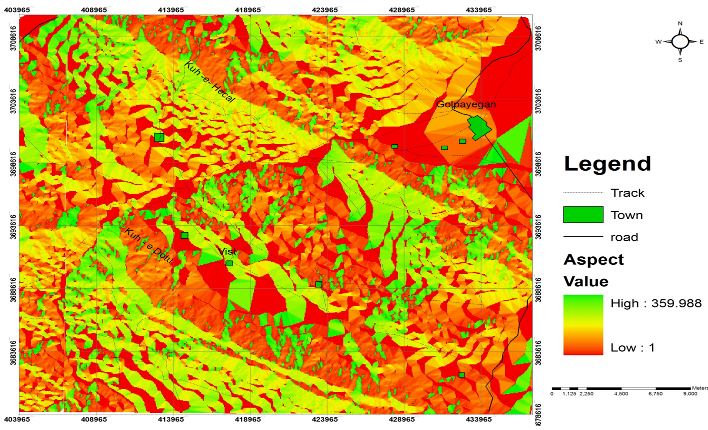


**Fig. 6** Geo-aspect map provided for the study area

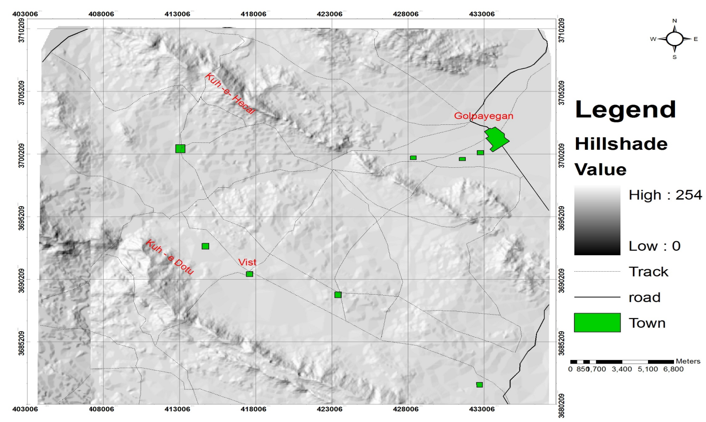


**Fig. 7** Hillshade map for studied area

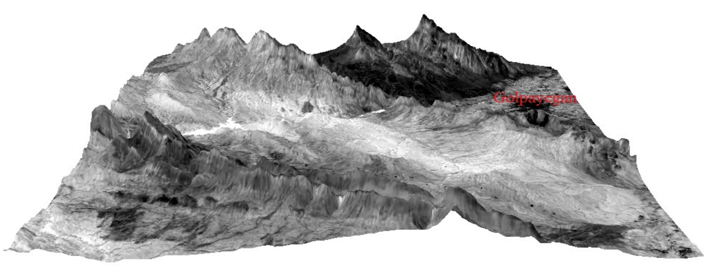

**Fig. 8** The 3D geomorphological map for studied region

## IV. Materials and Methods

The Golpayegan region, located in central Iran, is highly influenced by active tectonic processes, making it susceptible to landslides (Figure 1). This study integrates remote sensing, field surveys, and GIS-based analysis to assess landslide hazards. A comprehensive dataset, including geological maps, topographic data, seismic records, and historical landslide events, was collected from official geological and remote sensing databases. These datasets provided essential information on the physical and geological characteristics of the study area, forming the foundation for landslide hazard assessment. To quantify landslide susceptibility, the AHP was employed. Figure 9 provides a flowchart of the analysis. As known, AHP is a multi-criteria decision-making technique that assigns weights to various landslide conditioning factors based on their relative importance (Roccati et al., 2021). Expert judgment and previous research were utilized to determine the significance of each factor in landslide occurrences (Nanehkaran et al., 2021). By comparing factors in a pairwise manner, priority values were assigned to parameters affecting slope instability (Asmare, 2023). This structured approach ensured that expert knowledge and quantitative analysis was effectively combined (Biswas et al., 2023).

Several morphological, geological, and hydrological parameters were analyzed to construct the landslide hazard susceptibility map. The key conditioning factors included lithology, slope angle, elevation, proximity to faults, seismic activity, and land use (Cengiz & Ercanoglu, 2022). Lithology determines rock resistance and weathering susceptibility, while slope angle and elevation influence gravitational movements (Machay et al., 2023). Proximity to faults and seismic activity significantly contribute to landslides due to tectonic deformations (Mao et al., 2024). Additionally, land-use patterns and vegetation cover affect soil cohesion and slope stability (Devara et al., 2021). Each factor was mapped using GIS tools, and their influence was weighted through the AHP pairwise comparison method (Karimi et al., 2012). A GIS was used to process spatial data and generate thematic maps. The DEM was analyzed to extract slope, aspect, and elevation data, providing key insights into terrain conditions. Additionally, fault and seismic activity mapping highlighted active tectonic zones where ground instability is more likely (see Figure 6 and 7). The land-use classification helped assess vegetation and human impacts on slope stability. By integrating all these datasets, a weighted overlay analysis was performed to generate a landslide susceptibility index, ranking different areas based on their hazard levels.

Using the AHP-derived factor weights, a landslide susceptibility map was created. The region was classified into very high, high, moderate, low, and very low susceptibility zones. Areas with steep slopes and close proximity to active faults exhibited the highest risk. The spatial distribution of susceptibility zones was analyzed to determine critical landslide-prone areas.

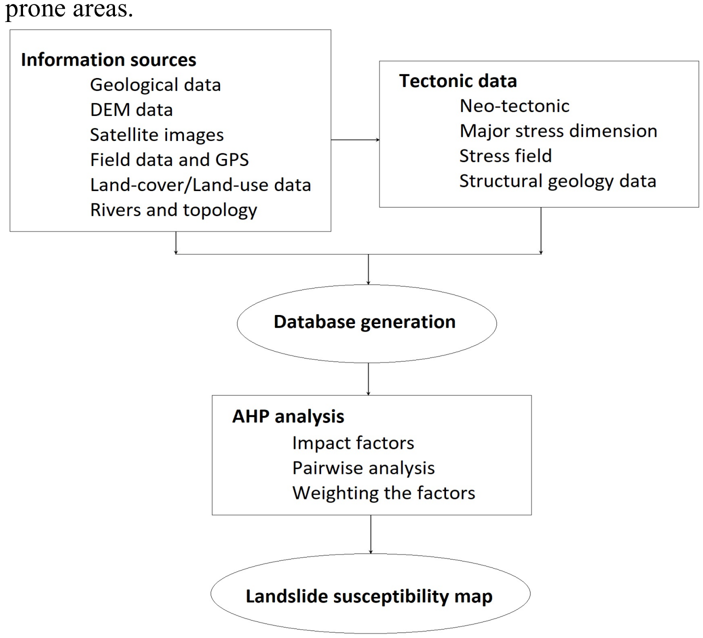


**Fig. 9** Flowchart for analysis process used in this article

This classification provides essential information for disaster management and land-use planners to mitigate future risks effectively. The findings were used to develop land-use planning and hazard mitigation strategies for the Golpayegan region. Key recommendations included restricting infrastructure development in high-risk zones, implementing slope stabilization techniques in vulnerable areas, and strengthening seismic hazard management near active faults. These measures aim to minimize landslide risks, protect infrastructure, and enhance the safety of local communities. While the study provides valuable insights, some limitations exist, such as data resolution constraints and subjective weight assignments in AHP. Future research should explore machine learning-based models to enhance predictive accuracy and incorporate real-time monitoring systems for early warning applications. Integrating AI-driven methods with traditional GIS-based approaches could significantly improve hazard assessments in tectonically active regions. By integrating AHP with GIS, this study successfully identified landslide-prone areas in the Golpayegan region. The methodology offers a systematic approach for assessing tectonically induced landslide hazards, supporting sustainable land-use planning and disaster risk reduction. The results provide critical guidance for policymakers, engineers, and researchers working on hazard mitigation and environmental management in landslide-prone regions.

## V. Results and Discussion

As discussed in the previous sections, this study employs the AHP to assess landslide susceptibility in the Golpayegan region, which is significantly influenced by active tectonic processes. The region is located within the Sanandaj-Sirjan tectonic zone, where seismic activity, fault movements, and morphological changes contribute to the frequent occurrence of landslides. Given these conditions, it is crucial to develop a reliable landslide susceptibility model to identify high-risk areas and support effective hazard mitigation strategies. To achieve this, various geospatial and geological data sources were integrated, including satellite imagery, remote sensing data, and field surveys. These datasets provided essential information for mapping and analyzing key conditioning factors such as lithology, slope angle, elevation, proximity to faults, seismic activity, and land use patterns. Satellite images were used to detect morphological changes, while field surveys validated the occurrence of recent landslides and helped in mapping tectonic lineaments and active fault traces. The observed landslides and their spatial distribution were cross-referenced with known fault zones and structural features to assess the correlation between tectonic activity and slope instability.

Figures 10 and 11 illustrate the tectonic lineaments and landslide occurrences documented in the study area. These visual representations confirm that landslides are predominantly concentrated near active fault zones, where significant displacement has altered slope stability. This observation highlights the necessity of incorporating tectonic parameters as a major component in the landslide susceptibility analysis. By systematically classifying and structuring the collected data, an AHP-based hierarchical assessment was performed to quantify the relative influence of different factors.

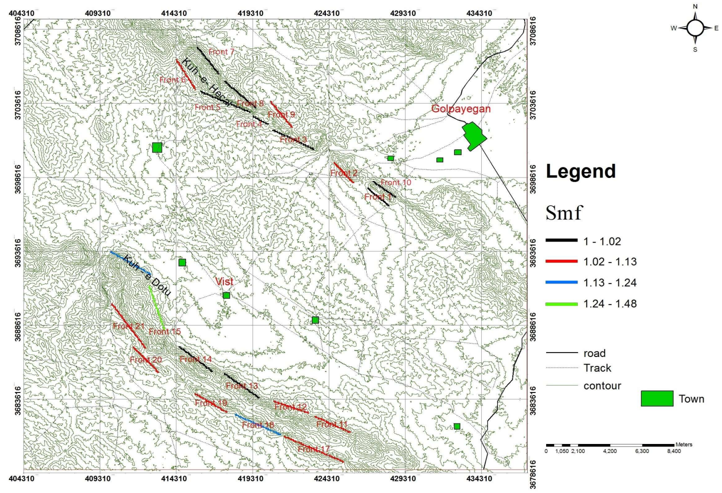


**Fig. 10** The tectonical lineaments recorded align with landslides

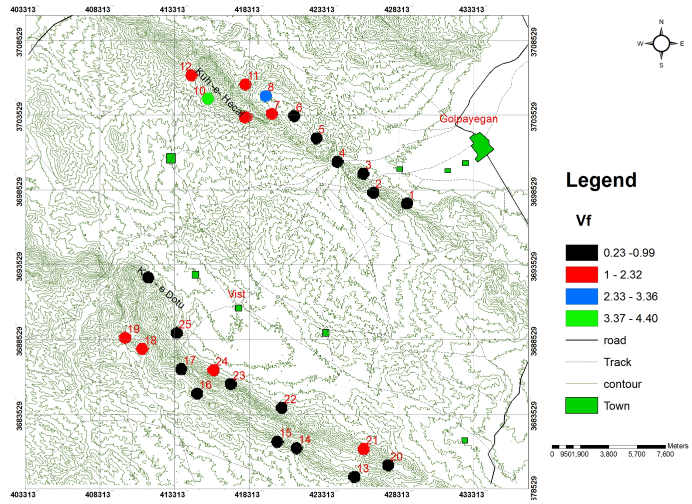


**Fig. 11** The selected point with recorded landslides in the region


**Fig. 12** Example of AHP analysis results for studied region

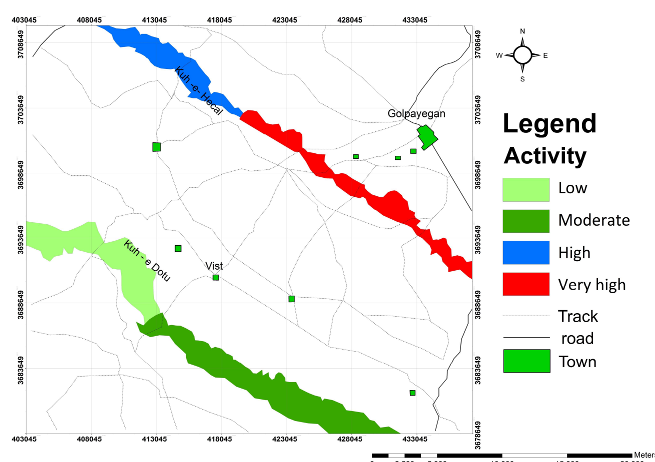


**Fig. 13** Landslide susceptibility map of studied region

For the multi-criteria decision-making process, Expert Choice 11 software was utilized to conduct pairwise comparisons between various landslide-triggering factors. The input parameters were categorized into three primary groups:

- Tectonic-related parameters: These include the Stream Length Gradient Index (SL Index) and the Smf index, which reflect fault activity and river incision as a result of tectonic movements.
- Landslide-related fault parameters: This category incorporates the VF (Valley Floor Width to Valley Height) index, which is used to analyze the role of active faulting in landslide initiation.
- General landslide parameters: This group includes traditional geomorphological and environmental factors such as slope angle, elevation, lithology, proximity to drainage networks, and land use patterns.

Through pairwise comparisons, the relative weights of each factor were determined based on their contribution to landslide susceptibility. The weighting process was structured to prioritize tectonic activity as a key trigger, given the significant correlation observed between faulting and past landslide events. Figure 12 presents an example of the AHP analytical hierarchy structure, showcasing the stepwise process used to assign influence scores to different conditioning factors. The final landslide susceptibility map, shown in Figure 13, categorizes the region into five risk levels ranging from very low to very high susceptibility. The results reveal that high-risk zones are predominantly located near active fault traces and steep slopes, where tectonic movements and gravitational forces contribute to slope instability. Areas with moderate susceptibility correspond to regions with gentle slopes and less pronounced fault activity, while low-risk zones are mainly situated in stable geological formations with minimal external influences. These findings underscore the critical role of active tectonics in landslide occurrence and highlight the importance of integrating geospatial analysis, remote sensing, and field data for comprehensive hazard assessments. The generated maps provide valuable insights for urban planners, engineers, and disaster management authorities, facilitating the development of risk mitigation strategies, land-use policies, and infrastructure planning in the Golpayegan region.

## VI. Conclusion

This study successfully assessed landslide hazards induced by active tectonics in the Golpayegan region using a GIS-based AHP approach. By integrating morphological, geological, and hydrological factors, a comprehensive landslide susceptibility map was generated, classifying the region into different hazard levels. The findings indicate that steep slopes, fault proximity, and seismic activity are the most influential parameters contributing to landslide occurrence. The strong correlation between the predicted high-risk zones and historical landslide records validates the reliability of the AHP model. The results emphasize that tectonically active areas with steep terrain and weak lithological formations are highly vulnerable to slope failures. The generated landslide susceptibility map serves as a key tool for urban planners, engineers, and disaster management authorities to mitigate potential hazards. Effective risk reduction strategies, such as restricted development in high-risk zones, slope stabilization techniques, and seismic hazard management, should be implemented to enhance regional safety. Despite its effectiveness, the AHP method has certain limitations, including subjectivity in weight assignment and data resolution constraints. Future research should explore machine learning-based models to enhance predictive accuracy and incorporate real-time monitoring systems for early warning applications. The integration of AI-driven techniques with traditional GIS-based methods could further improve hazard assessments in tectonically active regions.

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## Authors' contributions

Davoud Birjandi conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and was responsible for drafting the initial manuscript. Reza Derakhshani performed supervision, conceptual guidance, revision of the manuscript, 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.



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