DOI:

Hazard Assessment and Zonation of Visitor Risk at Geosites: a Case Study of the Mayan Basin, Binalood Mountain Range, Iran

Sajad Farjadinia[1], Manijeh Ghahroudi Tali[2]

Received: 26 Dec.2025 ***Accepted: 01 Feb.2026***

Original Article

Abstract

INTRODUCTION: The rapid growth of geotourism and the increasing number of visitors to geosites have made visitor safety a critical challenge in geotourism destination management. In many mountainous regions, insufficient spatial hazard assessment and the lack of strategically planned rescue infrastructure can lead to severe consequences for tourists. Accordingly, this study aims to assess and map visitor hazard at geosites and to identify optimal locations for rescue stations in the Mayan Basin of the Binalood Mountain Range.

METHODS: This study employed a descriptive–analytical approach by integrating fuzzy logic, Artificial Neural Networks (ANN), and GIS-based spatial analysis. Geomorphological, topographic, accessibility, land-use, and environmental parameters were collected and fuzzified within a GIS environment. The resulting fuzzy layers were subsequently input into a single-layer neural network model to determine the relative weights of the criteria. Based on the weighted integration of these factors, a continuous hazard index, a hazard zoning map, and an optimal spatial allocation of rescue stations were generated.

FINDINGS: The hazard zoning results indicated that the largest portion of the study area falls within the moderate hazard class, while all 12 selected geosites are located in moderate to very high hazard classes. This pattern reflects the simultaneous occurrence of high geotourism value and potentially hazardous geomorphological conditions. The hazard zoning results indicate that a large proportion of the study area falls within the moderate hazard class, while all twelve identified geosites are located within moderate to very high hazard zones. This distribution highlights the coexistence of high geotourism potential and hazardous geomorphological conditions. Furthermore, the spatial allocation analysis reveals that the proposed rescue stations are primarily situated in moderate hazard zones adjacent to high-risk areas, allowing effective coverage of vulnerable geosites.

CONCLUSION: According to the results, The results underscore the importance of integrating hazard assessment with spatial planning in geotourism management. The proposed framework offers an effective tool for enhancing visitor safety, mitigating natural hazard risks, and supporting the sustainable development of geotourism in mountainous regions.

Keywords: Geosite; Hazard zonation; Artificial Neural Network; GIS; Mayan Basin

How to cite this article: Ghahroudi Tali M, Farjadinia S. **Hazard Assessment and Zonation of Visitor Risk at Geosites: a Case Study of the Mayan Basin, Binalood Mountain Range, Iran**. J Rescue Relief 2026; 18(1): 8-18.

Introduction

Geotourism is a form of tourism based on various aspects of the geological and/or geomorphological heritage of the Earth (1), and is founded on a strong emphasis on sustainability, education, tourism experience, and local communities, all of which represent the core principles of geotourism (2). However, ensuring the safety of visitors and the protection of the environment is crucial for sustainable development and visitor satisfaction (3).

1. PhD Student in Geomorphology, Faculty of Earth Sciences, Shahid Beheshti University, Tehran, Iran.
2. Professor of geomorphology, Department of Physical Geography, Earth Science Faculty, Shahid Beheshti University, Tehran, Iran.
Correspondence to: Manijeh Ghahroudi Tali, Email: m-ghahroudi@sbu.ac.ir

Resource conservation and visitor safety constitute two fundamental elements of sustainability in any tourism destination (4).

Safety and security have become major concerns for tourism stakeholders due to their role in destination attractiveness and their capacity to influence tourists' travel intentions (5).

In the tourism industry, safety and security are essential, and any destination that neglects these responsibilities is likely to fail in the intense competition to attract visitors (6).

Natural hazards and unexpected events are among the factors that exert profound impacts on individuals and societies and, consequently, have significant potential to affect tourism flows (7). Tourists are exposed on a daily basis to a wide range of natural hazards arising from the attractions they visit and the activities in which they engage (8). Natural hazards such as volcanic eruptions, seismic events, landslides, and avalanches in mountainous regions can influence tourism activities and destinations and may substantially alter the geomorphological landscape of a given area (9). Such hazards can negatively affect the image of a tourism destination as well as visitors' trust in the quality and availability of facilities and services in the post-disaster period (10). Given that many geosites are located within active geomorphological environments, they are inherently exposed to natural hazards, and the development of geotourism without proper hazard assessment may pose risks to visitor safety (11).

A considerable number of geotourism attractions are situated in naturally hazardous areas; therefore, researchers emphasize that hazard assessment and the preparation of risk maps can play a vital role in managing visitor safety and designing search-and-rescue infrastructure within geosites (12).

With the expansion of geotourism activities, greater attention to tourist safety, effective risk management planning, and the establishment of search-and-rescue bases have become increasingly important. In practical rescue-base allocation, each base must be capable of serving every demand point—whether or not the point lies within its nominal coverage radius—to prevent increased losses in high-risk areas (13).

Landslide-susceptibility mapping using GIS and data-driven methods has demonstrated that intelligent models can capture complex relationships between environmental factors and natural-hazard occurrences, producing reliable hazard maps (14). Therefore, generating hazard-zonation maps using Artificial Neural Networks represents an appropriate approach for simultaneously analyzing the factors influencing safety in geotourism destinations and identifying suitable locations for establishing search-and-rescue bases. Artificial Neural Networks (ANN), inspired by the structure of the human nervous system (15), are powerful machine-learning methods capable of modeling complex and nonlinear relationships among variables (16). ANN models are widely applied in natural-hazard studies due to their ability to analyze multiple heterogeneous factors simultaneously (17). This approach is particularly valuable in countries with high geomorphological diversity, such as Iran.

Iran, due to its complex geological history and unique geographical setting, encompasses a wide range of landscapes, including mountain ranges, forests, deserts, fertile plains, wetlands, and numerous river systems (18), and is considered one of the countries with high potential for geotourism development (19). Among these regions, the Binalood Mountain Range, as one of the most important geotourism areas in northeastern Iran, is exposed to a variety of natural hazards owing to its distinctive geomorphological conditions and the concentration of active geosites. Despite the extensive body of research conducted on natural hazards, a considerable proportion of these studies has primarily focused on the analysis of geomorphic processes, while comparatively little attention has been paid to risk assessment from the perspective of geosite visitor safety and search-and-rescue management requirements. Moreover, the application of intelligent models such as Artificial Neural Networks (ANN) for visitor-oriented hazard zonation in geotourism destinations—particularly in Iran's mountainous regions—remains limited. Consequently, the need for research capable of addressing this gap has become increasingly evident.

Accordingly, the present study aims to identify geomorphologically high-risk zones as well as safe areas within the study region. To this end, an Artificial Neural Network was employed to generate a continuous hazard index (20), and ultimately a hazard-zonation map of the study area was produced to provide a scientific basis for the optimal location of search-and-rescue bases.

This map also contributes to mitigating the impacts of natural hazards on geotourism activities.

Study Area

The study area is located in the southeastern part of the Binalood Mountain Range and extends between latitudes 36°17′24″ to 36°05′58″ N and longitudes 59°38′09″ to 59°10′56″ E. Covering an area of approximately 607 km², the region includes 25 villages and is considered one of the active geotourism zones due to its numerous geosites, mountainous access routes, and diverse geomorphological landscapes.

From a topographic perspective, the mean elevation of the area is approximately 1,647 m above sea level, with an average slope of 14.5°, indicating the predominantly mountainous and rugged nature of the terrain. The drainage network consists of rivers and channels with a total length of about 178 km, which, in combination with relatively steep slopes, increases the potential for the occurrence of geomorphological hazards.

Geologically, most of the study area is composed of phyllite, shale, quartzite, and sandstone units, locally associated with leucogranite, tourmaline-bearing rocks, and muscovite granite. This lithological diversity, together with the prevailing topographic conditions, plays a significant role in slope instability and heightens the potential risks faced by geosite visitors (Figure 1). Given that the present study focuses on visitor risk assessment and safety management of geotourism activities, the study area was delineated based on the spatial distribution of geosites, access routes, and tourist visitation hotspots. Accordingly, non-watershed-based boundary was adopted to enable a more realistic assessment of hazards affecting visitors and to enhance the practical applicability of the results for safety planning and the optimal siting of search-and-rescue bases.

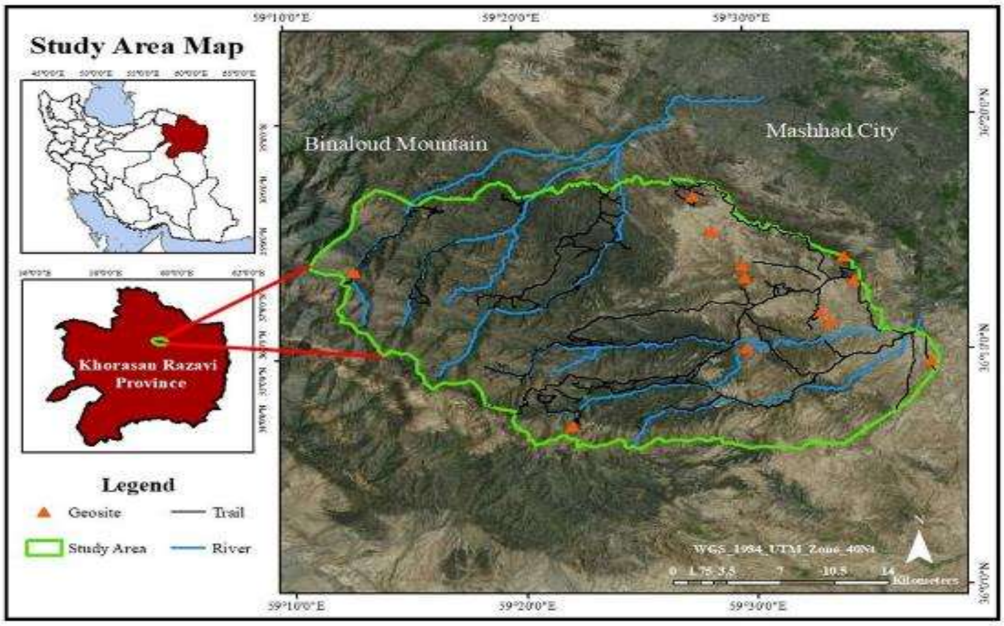

Figure 1. Location of study area in Khorasan Razavi province

Methods

The research materials included a Digital Elevation Model (DEM) with a spatial resolution of 10m, land-use data extracted from Sentinel-2 imagery, precipitation data obtained from regional meteorological stations, geological and geomorphological maps, drainage network layers, faults, roads, villages, and the spatial distribution of geosites. All datasets were pre-processed, standardized to a common scale, and subjected to fuzzy transformation within a GIS environment prior to analysis.

Criteria Fuzzification and Hazard Zonation Process

In this study, the criteria influencing geosite visitor hazard were initially selected, including slope, elevation difference, land use, distance to rivers, distance to roads, distance to villages, distance to faults, distance to geosites, maximum 24-hour precipitation, and landslide occurrence.

Subsequently, all criteria were converted into a standardized range of 0 to 1 through fuzzy membership functions to ensure comparability and integration. Following the fuzzification of thematic layers in the GIS environment, spatial data extracted as point-based samples using a cellular-grid approach, preparing the dataset for subsequent statistical analyses and modeling.

Artificial Neural Network (ANN) Model

The Artificial Neural Network (ANN) model is a mathematical approach inspired by the biological nervous system (21). ANN models consist of a set of interconnected nodes, each functioning as a simple processing unit that responds to weighted inputs received from other nodes (22). These systems operate through the sequential processing of information across interconnected units, where each unit produces an output based on parameters such as weights, thresholds, and mathematical transfer functions (23). Neural networks possess the ability to adapt to variations in input data and enhance model performance by minimizing error throughout the learning process (24).

In this study, a single-neuron Artificial Neural Network with a sigmoid activation function was employed, which is mathematically equivalent to logistic regression (16). This type of model is effective for generating a continuous hazard index in spatial studies (25). The output of the ANN model is a continuous value ranging from 0 to 1, where higher values indicate a greater level of hazard susceptibility. This output is commonly used to classify areas into different hazard levels and to produce hazard maps within a GIS environment (17, 25). The research procedure was conducted through the following steps:

1. The assessment was carried out using ten input variables, each fuzzified within the range of 0 to 1, as presented in Table 1.

Table 1. Fuzzy variables

Variables	Interval (Fuzzy)
Distance to Fault Distance to Geosites Distance to Road Distance to River Distance to Village Slope Rain (24h) Elevation Difference Land use Landslide	Hazard ↑ → 1 Hazard ↓ → 0

2. During the preprocessing stage, Min–Max normalization was applied to each variable across the entire dataset to ensure scale consistency, thereby constraining all values strictly within the [0, 1] interval, according to the following equation:

$$x' = (x - \min(x)) / (\max(x) - \min(x))$$

3. The structure of the Artificial Neural Network was defined such that the model output represents a continuous hazard-susceptibility index ranging between 0 and 1. The network output was computed as follows:

$$z = b + \Sigma (w_i \times x_i') \quad \text{Hazard ANN} = \sigma(z) = 1 / (1 + e^{(-z)})$$

In this project, due to the absence of labeled training data and target outputs required for supervised learning, the network weights were initialized numerically using a fixed random seed to ensure reproducibility, and subsequently used to compute the hazard index. A random sample of 42 points was employed, and the applied bias (b) was equal to 0.020584.

For validation, the spatial consistency of the ANN output was evaluated by comparison with expert knowledge and repeated field observations of the study area. High-hazard zones identified by the model were predominantly located in areas characterized by steep slopes, proximity to river channels, and landslide-prone terrain, which qualitatively supports the reliability of the model. To further examine the agreement between the predicted hazard output and the main controlling factors, correlation coefficients were calculated between the Hazard_ANN variable and the hazard-related factors. The results showed that the highest correlation corresponded to the landslide-susceptibility factor, which is geologically and physically consistent and thus reinforces the validity of the model (Table 2).

Table 2. The correlation between ANN-predicted hazard (Hazard_ANN) and main hazard factors

Factor	Correlation with Hazard_ANN	Interpretation
Slope	0.360	Moderate agreement
River	0.395	Moderate agreement
Road	0.285	Acceptable agreement
Landslide	0.636	Strong agreement
Fault	0.003	No significant effect

Findings

The results obtained from the Artificial Neural Network model indicate that the criteria used in the hazard assessment possess different and statistically meaningful weights. According to the weighting results presented in Table 3 and the corresponding diagram (Figure 2), the distance-to-geosites criterion has the highest contribution to the model output, emphasizing the critical influence of visitor concentration and the intensity of visitation activities in elevating hazard levels.

In contrast, the maximum 24-hour precipitation criterion exhibits the lowest weight, which may be attributed to the relatively uniform spatial distribution of rainfall across the study area or to the overlapping effects of this factor with other geomorphological variables. Other criteria, including landslide susceptibility, elevation difference, land use, and distance to rivers, show moderate to high levels of influence in shaping the spatial hazard pattern.

Table 3. The derived weights of variables

Variable	Weight
Fault	0.374542
Geosite	0.950714
Road	0.731994
River	0.598658
Village	0.156019
Slope	0.155995
Rain	0.058084
Elevation Difference	0.866176
Land use	0.601115
Landslide	0.708073

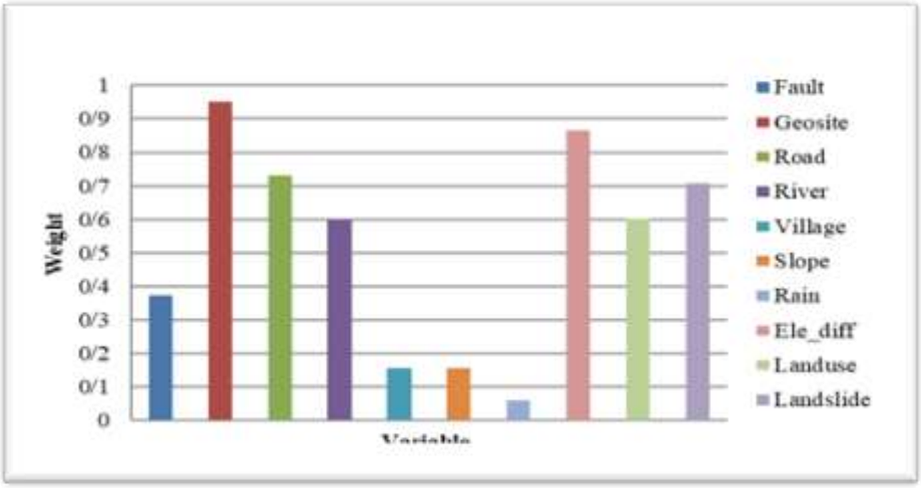

Figure 2. Hazard ANN weights of variables

Table 4. Hazard ANN Histogram

Bin Start	Bin End	Count
0	0.05	0
0.05	0.1	0
0.1	0.15	0
0.15	0.2	0
0.2	0.25	0
0.25	0.3	0
0.3	0.35	0
0.35	0.4	0
0.4	0.45	0
0.45	0.5	0
0.5	0.55	0
0.55	0.6	0
0.6	0.65	10
0.65	0.7	1461
0.7	0.75	5057
0.75	0.8	10119
0.8	0.85	25632
0.85	0.9	16228
0.9	0.95	2970
0.95	1	6

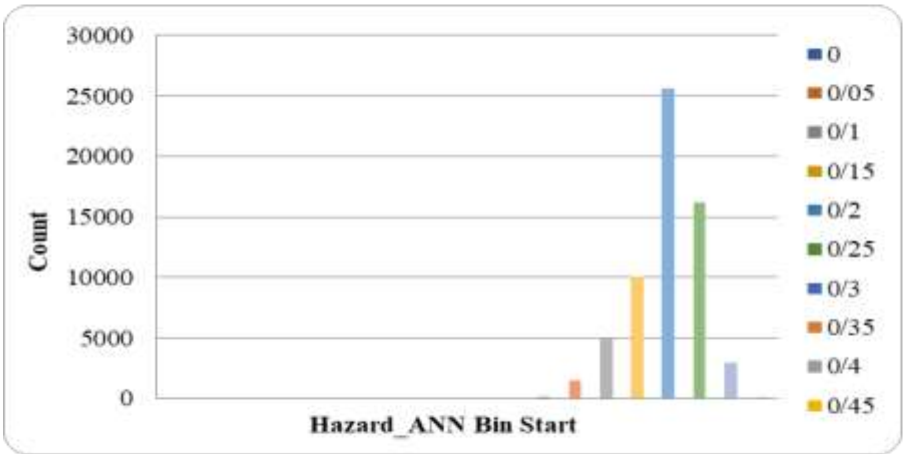

Figure 3. Hazard ANN Histogram

Table 5. Range and Area of Hazard Classes

Class	Range	Area (km²)	Area (%)
Very Low	0.633224 – 0.784424 (inclusive)	57	9.4
Low	> 0.784424 – 0.818042	172	28.3
Moderate	> 0.818042 – 0.839185	296	48.7
High	> 0.839185 – 0.866854	74	12.2
Very High	> 0.866854 – 0.959458	8	1.4

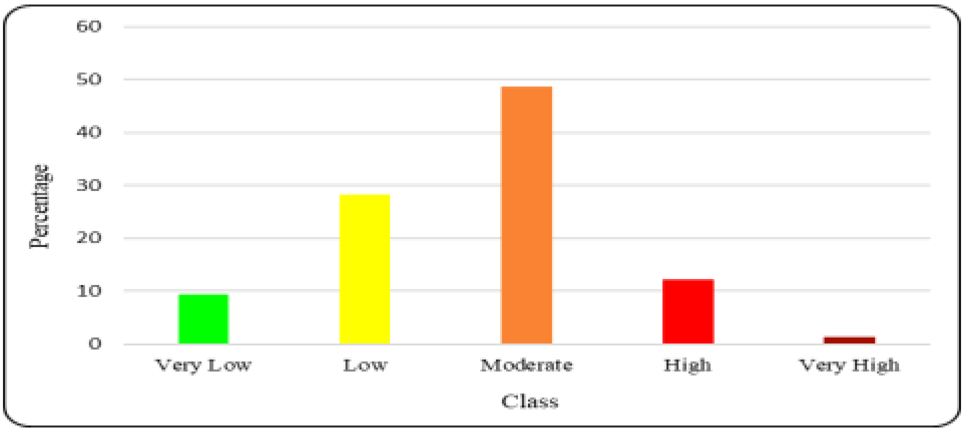

Figure 4. Percentage of area of Hazard Classes

Histogram analysis of the Hazard_ANN index reveals that the distribution of model output values is asymmetric, with the majority of grid cells concentrated within the medium to high ranges of the hazard index. The highest frequency of cells occurs within the 0.80–0.85 interval, whereas values below 0.65 and above 0.95 account for only a small number of cells (Table 4 and Figure 3). This distribution indicates that moderate to relatively high hazard conditions dominate a substantial portion of the study area.

The frequency analysis of hazard classes shows that, following the classification of the continuous hazard index, grid cells are distributed relatively evenly among the different hazard classes. This relatively balanced distribution reflects the effectiveness of the classification method in distinguishing multiple hazard levels across the study area.

The hazard zonation results demonstrate that the spatial distribution of hazard classes across the study area is non-uniform. The largest proportion of the area is assigned to the moderate hazard class, covering approximately 48.7% of the total area, indicating that intermediate hazard conditions dominate much of the region. This is followed by the low hazard class, which accounts for 28.3% of the area and is primarily observed in more stable zones with favorable geomorphological conditions. The high hazard class, representing 12.2% of the total area, occurs mainly in a patchy pattern and is concentrated in areas where multiple hazard-inducing factors overlap. The very low hazard class, comprising

9.4% of the area, is predominantly distributed in regions with minimal geomorphological and environmental constraints. Finally, the very high hazard class exhibits the smallest spatial extent, accounting for only 1.4% of the study area, and is mainly confined to limited locations that are highly sensitive to natural hazards (Table 5 & Figure 4).

An examination of the spatial distribution of geosites relative to the different hazard classes indicates that, among the identified geosites, seven are located within the high hazard class, four within the moderate hazard class, and one within the very high hazard class, while no geosites are situated in the low or very low hazard classes (Table 6).

Table 6. Spatial distribution of geosites within Hazard classes

Class	Number of Geosite
Very Low	-
Low	-
Moderate	4
High	7
Very High	1

These findings highlight the concentration of a significant portion of the region's geotourism attractions within high-hazard zones, reinforcing the necessity of implementing robust safety planning and visitor risk-management strategies. Spatial information on the selected geosites, along with field photographs, is provided in Table 7 and Figure 5. Additionally, Figure 6 illustrates the spatial distribution of geosites and their variability across the different hazard classes.

Table 7. Geosite Information of the Studied area

Area Name	Geosite Name	Geosite Code
Moghan Village	Moghan Cave	G1
Bornabad-Shelgerd	Barnabad Rock Inscription	G2
Takht-e-Mayan	Rock Outcrop	G3
Nocombol	Columnar Basalt	G4
Haft Howz	Sinkhole	G5
Aarefi Village	Granitic Mountain	G6
Kartian	Plunge Pool	G7
Khalaj	Basaltic Outcrop	G8
Haft Howz	Erosional Cliff	G9
Bornabad	Eroded Granitic Mountain	G10
Majooni	Majooni Peak	G11
Sangchin	Bedrock Slope	G12

Figure 5. Images of Geosite in the studied area

Note: Images G6 and G8 were photographed by the researcher, while Images G1–G5, G7, and G9–G11 were photographed by Saeed Heydari, a local mountaineer.

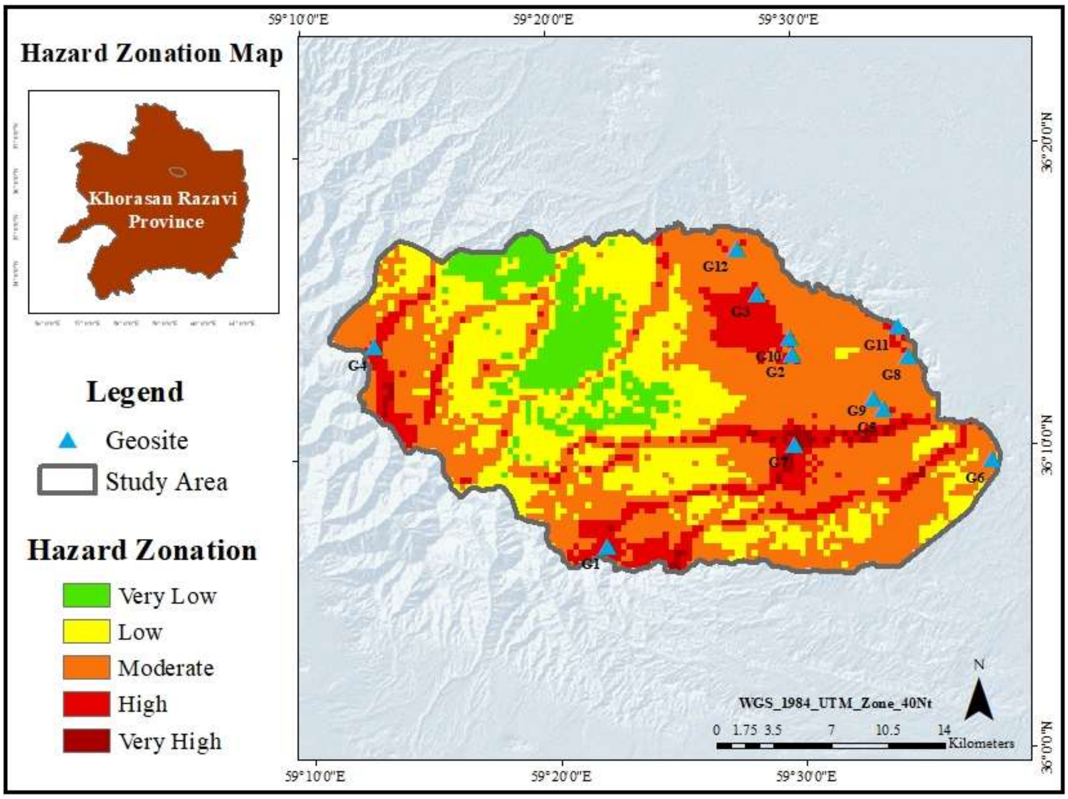

Figure 6. Hazard Zonation Map of the Area Using ANN

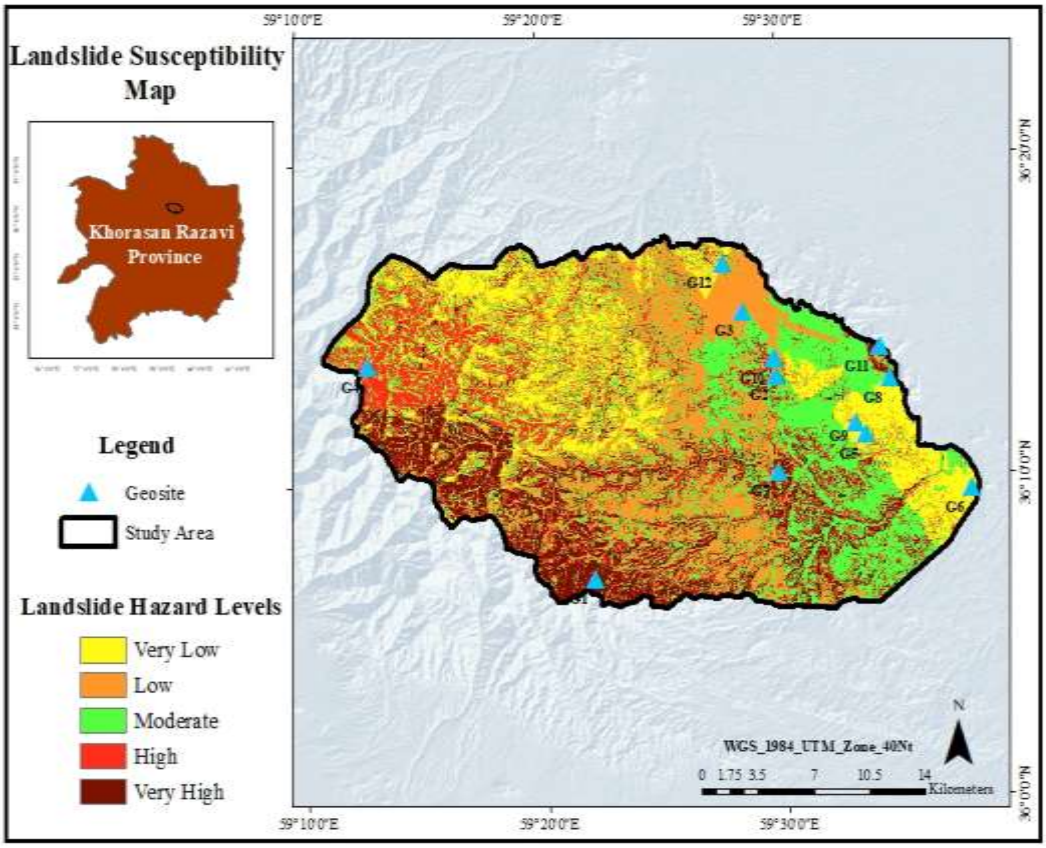

Figure 7. Landslide Susceptibility Map

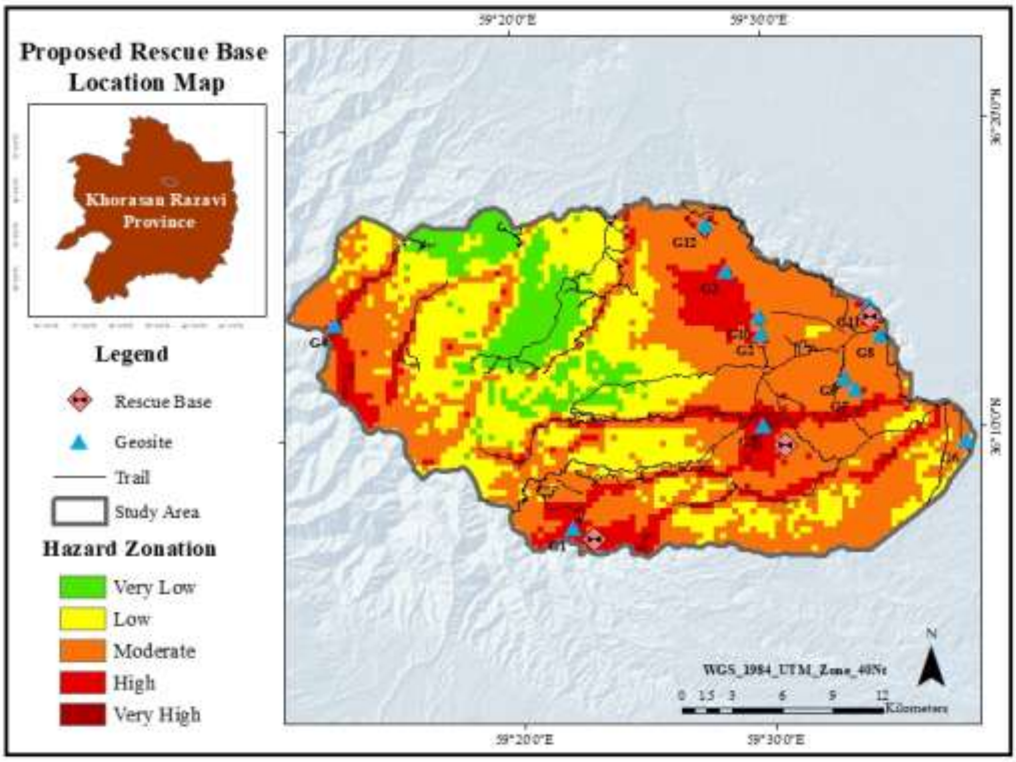

Figure 8. Proposed rescue base location map

Discussion and Conclusion

The analysis of the results indicates that a significant proportion of geosites in the study area are located within moderate to high hazard classes. This pattern suggests that geosites, as features of high scientific, educational, and aesthetic value, are often situated in environments that are geomorphologically unstable and potentially hazardous. The spatial overlap of geosites with the visitor hazard zonation map reveals that factors such as steep slopes, considerable elevation differences, proximity to watercourses, and unstable slopes play a key role in increasing hazard levels. To further elucidate this pattern, a slope-instability susceptibility map was also generated and analyzed (Figure 7). Examination of the geosites' positions within the slope-instability map indicates that certain geosites, including G1, G4, G7, and G11, are located in areas with high to very high landslide susceptibility. This correspondence aligns with their placement in the higher hazard classes on the visitor hazard map, reinforcing the relationship between geomorphological instability and visitor risk. This spatial correspondence underscores the substantial influence of slope-instability processes on elevating hazard levels for visitors and demonstrates that landslide-susceptibility mapping can function as a critical and complementary analytical layer in visitor hazard assessment within geotourism destinations.

The results of the proposed location analysis for rescue and relief stations indicate that most of these points are situated within moderate-hazard zones and in proximity to high-hazard areas. This spatial pattern demonstrates the appropriate spatial logic of the proposed model, as positioning rescue stations in lower-hazard areas reduces risk for emergency personnel while simultaneously providing rapid and effective access to geosites located in high-hazard zones, particularly through proximity to existing access routes (Figure 8).

Overall, the combined analysis of the hazard zonation map and the spatial distribution of geosites suggests that planning for the placement of rescue and relief stations at geotourism destinations should be guided by the spatial logic of hazard levels and accessibility. Rescue stations should be established in low- to moderate-hazard areas while maintaining adequate access to geosites within higher-hazard classes to ensure rapid response in emergency situations. From this perspective, the visitor hazard zonation map serves as an effective decision-support tool for prioritizing the spatial allocation of emergency stations, minimizing response times, and improving visitor safety. Such an approach supports the sustainable development of geotourism by balancing visitor safety with the protection of the natural environment.

The findings obtained from the ANN model in this study indicate that the criteria used for assessing visitor hazard at geosites carry varying and significant weights, with some factors playing a more decisive role in the model output. Due to their nonlinear structure and capability to learn complex relationships, neural networks can extract the relative importance of variables in the model output, distinguishing key factors from less influential ones. This result is fully consistent with the theoretical foundations outlined by Haykin (1999) (15).

Regarding the distance to geosites, which has the highest contribution to hazard levels, this demonstrates the ANN's effectiveness in identifying the most influential variables within complex spatial systems, a concept also emphasized in the theoretical framework of Bishop (2006) (16). Similarly, the minimal weight of the maximum 24-hour precipitation variable aligns with recent studies, as variables with relatively uniform distribution or overlapping effects with other factors typically receive lower weights during the network training process. The asymmetric distribution of model outputs, with most values concentrated in the medium to relatively high range, has been reported in numerous studies on hazard and landslide-susceptibility zonation using ANN (25).

The relatively even distribution of grid cells following the classification of the continuous hazard index is consistent with similar research in geomorphology and hazard management (14,22). The placement of a substantial portion of geosites within high and very high hazard classes aligns with findings reported by Dowling and Newsome (2010) (11), further underscoring that geotourism development without systematic hazard assessment may expose visitors to considerable risk. Therefore, the findings of the present study also hold considerable practical significance, reinforcing the necessity of strategically locating rescue and relief stations to enhance visitor safety and support effective risk-management planning (12).

This study, with a focus on the safety of geosite visitors, presented an integrated analytical framework for hazard assessment and zonation at geotourism destinations. The combined application of Fuzzy Logic (FL), Artificial Neural Networks (ANN), and Geographic Information Systems (GIS) enabled the consideration of the continuous, nonlinear, and heterogeneous nature of the factors influencing visitor hazard, resulting in a realistic and continuous map of the spatial hazard pattern in the Mayan sub-basin of the Binalood mountain range. The overall results indicate that many geosites, despite their high scientific and tourism value, are located in areas with significant hazard levels, highlighting the urgent need for systematic risk management, safer visitation planning, and the development of appropriate emergency infrastructure. In this regard, the visitor hazard zonation map serves as an effective decision-support tool, providing a sound basis for the strategic placement of rescue and relief stations and for reducing emergency response times. The proposed framework not only enhances spatial understanding of hazards at geotourism destinations but also supports tourism managers, emergency agencies, and regional planners in making informed, evidence-based decisions. The adaptability of this approach to other mountainous and geosite-oriented regions demonstrates that the use of intelligent spatial methods can play a pivotal role in promoting safe, responsible, and sustainable geotourism development while improving visitor safety.

Compliance with Ethical Guidelines

There were no ethical considerations in this research.

Funding/Support

This article is extracted from Sajad Farjadinia PhD thesis entitled " Hazard Assessment and Zonation of Visitor Risk at Geosites: A Case Study of the Mayan Basin, Binalood Mountain Range" without financial support in 2026.

Author's Contributions

This article is based on Sajad Farjadinia PhD thesis at Shahid Beheshti University, who was responsible for conducting the research, collecting, and analyzing the data; and the second author, Manijeh Ghahroudi Tali, was responsible for the design and supervision, and the methodology. However, Manijeh Ghahroudi Tali was responsible for correspondence and editing the final manuscript submitted to the journal.

Conflict of Interests

The authors declare no conflict of interest.

Acknowledgments

The authors hereby express their sincere appreciation to Mr. Saeed Heydari, a local mountaineer from the study area, for his valuable cooperation in providing the field photographs.

References

1. Newsome D, Dowling R. Geoheritage and geotourism. In: Geoheritage: assessment, protection, and management. 2nd ed. Elsevier; 2025:479–502. https://doi.org/10.1016/B978-0-443-28997-2.00029-7
2. Štrba Ľ, Bodzáš Palgutová S, Derco J, Kršák B, Sidor C. The geotourism product—what it is and what it is not. Geosciences. 2025;15(7):270. https://doi.org/10.3390/geosciences15070270
3. Herlinawati, Setiawan IF, Rohaendi N, Wahyudi. Safety assessment for geotourism in Ciletuh-Palabuhanratu UNESCO Global Geopark, West Java. IOP Conf Ser Earth Environ Sci. 2025;1451(1):012045. https://doi.org/10.1088/1755-1315/1451/1/012045
4. Sunkar A, Lakspriyanti AP, Haryono E, Brahmi M, Setiawan P, Jaya AF. Geotourism hazards and carrying capacity in geosites of Sangkulirang-Mangkalihat Karst, Indonesia. Sustainability. 2022;14(3):1704. https://doi.org/10.3390/su14031704
5. Muoneke N. Safety and security concerns in Nigeria's tourism sector: the issue of geotourism destinations. Int J Manag Bus Res. 2024;16(3):4014. https://doi.org/10.22610/imbr.v16i3(I).4014
6. Badiora W, Adedotun SB, Oladimeji ST. Safety and security assessment of tourist destinations: a field study in a Nigerian geopark. J Event Tour Hosp Stud. 2022;2:106–149. https://doi.org/10.32890/jeth2022.2.5
7. Rosselló J, Becken S, Santana-Gallego M. The effects of natural disasters on international tourism: a global analysis. Tour Manag. 2020;79:104080. https://doi.org/10.1016/j.tourman.2020.104080
8. Cui A, Fountain J, Espiner S. Communicating natural hazard risks to Chinese visitors: a case study from New Zealand. Front Sustain Tour. 2023;2:1192124. https://doi.org/10.3389/frsut.2023.1192124
9. Ilieş DC, Dehoorne O, Ilieş A. Some examples of natural hazards affecting geosites and tourist activities. GeoJournal Tour Geosites. 2011;7(1):33–38.
10. Salazar J, Hritz N. Measuring the impacts of a natural disaster on visitor confidence. Tour Plan Dev. 2021;21(3):354–362. https://doi.org/10.1080/21568316.2021.1953120
11. Dowling R, Newsome D, editors. Geotourism: the tourism of geology and landscape. Oxford: Goodfellow Publishers; 2010. https://doi.org/10.23912/978-1-906884-09-3-21
12. Ruban DA. Geosite risk and geotourism safety: a conceptual approach. Tour Manag Perspect. 2015;15:97–104. https://doi.org/10.1016/j.tmp.2015.03.005
13. Shan Y, Zhang R. Study on the allocation of a rescue base in the Arctic. Symmetry. 2019;11(9):1073. https://doi.org/10.3390/sym11091073
14. Ayalew L, Yamagishi H. The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, central Japan. Geomorphology. 2005;65(1–2):15–31. https://doi.org/10.1016/j.geomorph.2004.06.010
15. Haykin S. Neural networks: a comprehensive foundation. 2nd ed. Upper Saddle River (NJ): Prentice Hall; 1999.
16. Bishop CM. Pattern recognition and machine learning. New York: Springer; 2006.
17. Pradhan B, Lee S. Landslide susceptibility assessment and factor effect analysis: backpropagation artificial neural networks and their comparison with frequency ratio and bivariate logistic regression modelling. Environ Model Softw. 2010;25(6):747–759. https://doi.org/10.1016/j.envsoft.2009.10.016
18. Zanganehasadi MA, Saadatifar R, Golimokhtari L. Effects of geomorphosites in mountainous areas on tourism development (northwest of Neishabour-Firoozeh City). Geogr Stud Mt Areas. 2020;1(4):69–87.
19. Saadatyfar R, Zanganehasadi MA, Golimokhtari L. Evaluation of tourism land capabilities in the southwest of Binalood Mountain, Khorasan Razavi. Geogr Eng Territ. 2022;6(4):945–962.
20. Pourghasemi HR, Pradhan B, Gokceoglu C. Application of fuzzy logic and artificial neural networks for landslide susceptibility assessment. Catena. 2012;92:1–14. https://doi.org/10.1016/j.catena.2011.10.012
21. Grekousis G. Artificial neural networks and deep learning in urban geography: a systematic review and meta-analysis. Comput Environ Urban Syst. 2019;74:244–256. https://doi.org/10.1016/j.compenvurbsys.2018.10.008
22. Pradhan B, Lee S. Landslide risk analysis using artificial neural network model focusing on different training sites. Environ Geol. 2009;57(2):337–349.
23. Alizadeh M, Ngah I, Hashim M, Pradhan B. A hybrid analytic network process and artificial neural network (ANP-ANN) model for urban earthquake vulnerability assessment. Remote Sens. 2018;10(6):975. https://doi.org/10.3390/rs10060975
24. Sagintayev Z, Atanov S, Gafurov A. Overview of modelling techniques for geo hazard risk assessment. Cent Asian J Water Res. 2017;3(1):35–42.
25. Tien Bui D, Pradhan B, Lofman O, Revhaug I. Landslide susceptibility mapping using support vector machines, decision trees, and neural networks. Geomorphology. 2016;253:55–67.
26. Gorsevski PV, Gessler PE, Boll J, Elliot WJ, Foltz RB. Spatially and temporally distributed modeling of landslide susceptibility. Geomorphology. 2006;80(3–4):178–198. https://doi.org/10.1016/j.geomorph.2006.02.011