

Article

A Spatial Study on the Impact of Habitat Quality on Geological Disaster Susceptibility: A Case Study in Pingshan County, China

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Abstract: Habitat quality is a comprehensive index reflecting ecological conditions, land use impact, and human survival. Susceptibility to geological disasters is influenced by factors such as ecology, the geological environment, and human activities. Analyzing the effects of habitat quality on geological disaster susceptibility and its spatial dynamics is crucial for ecological protection and assessing geological disaster risks. This research focused on Pingshan County, using the InVEST 3.7.0 model and ArcGIS to evaluate habitat quality and geological disaster susceptibility for 2020. The spatial relationships were examined with GeoDa to investigate the impact of habitat quality on geological disaster susceptibility. The findings are as follows: (1) Pingshan County generally exhibits high habitat quality, showing significant spatial clustering with geological disaster susceptibility—predominantly high–high in the west and low–low in the east. (2) The geological environment significantly influences the relationship between habitat quality and geological disaster susceptibility, with an overall positive correlation but negative correlations in certain areas. Geological disaster susceptibility is primarily governed by geological factors rather than habitat quality. (3) In mountainous regions with comparable ecological and geological conditions, variations in geological disaster susceptibility are chiefly driven by human activities. Including human activities as a metric significantly enhances the evaluation accuracy. This study provides a scientific foundation for ecological protection, the assessment of geological disaster susceptibility, and the development of mitigation policies.

Keywords: habitat quality; geological disasters; susceptibility; correlation; spatial analysis



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1. Introduction

Geological disasters typically occur in specific areas and include various types, such as collapses, landslides, and mudslides. The formation mechanisms, influencing factors, and impact ranges differ significantly among these disaster types [1,2]. To enhance our understanding of a region's geological environmental conditions and predict the likelihood of geological disasters, assessments of geological disaster susceptibility are conducted for different regions. Such evaluations are crucial not only for assessing the risk and potential impacts of geological disasters but also for devising strategies to mitigate these disasters. They provide a solid foundation for more effective planning and response strategies, aiming to minimize casualties and property losses. Previous research has established that the factors influencing susceptibility to geological disasters include the geological environment, the ecological environment, and human activities [3–6]. These evaluations serve as essential tools for developing preventive measures and formulating robust response strategies for disaster management. In the assessment of geological disaster susceptibility, geological environmental factors are often considered to be primary, while the ecological environment and human activities play a smaller role. Habitat quality serves as a comprehensive indicator that, to a certain extent, delineates the advantages and disadvantages of the

ecological environment and assesses whether the ecosystem can sustain suitable living conditions for individuals or populations [7–10]. It is also significantly influenced by human activities. Habitat quality displays distinct regional and differential characteristics, leading to diverse ecological effects and thus influencing the development of geological disasters to varying degrees. High-quality habitats typically provide superior ecological services, such as soil and water conservation. These services can partially mitigate surface runoff, enhance the stability of rock and soil masses, and thereby contribute to reducing the likelihood of geological disasters. The current research on ecosystem service functions predominantly focuses on extensive areas like regions and provinces [11–14], with less attention given to smaller scales, such as counties and towns. While large-scale studies are instrumental in discerning the overarching patterns and major trends in regional ecosystem services, they may neglect finer ecological processes and details at smaller scales. Conversely, research on habitat quality tends to emphasize the spatiotemporal evolution of regional habitats and analysis of the influencing factors [15–18]. However, studies examining the impact of habitat quality on geological disasters remain relatively scarce. This gap in the knowledge could result in inaccurate risk assessments of geological disasters, potentially increasing both the frequency and severity of these events.

Pingshan County is located in the western part of Hebei Province, East China, at the eastern foot of the middle section of the Taihang Mountains and the upper reaches of the Hutuo River. The region boasts unique ecological advantages. With the acceleration of urbanization in recent years, the area has experienced deteriorating climate conditions, marked by an increase in extreme weather events and a potential rise in geological disasters. Consequently, Pingshan County has emerged as a focal point for ecological environmental protection and geological disaster research within Hebei Province. This study uses Pingshan County as a case to research at a greater scale, integrating geology and ecology to assess its habitat quality and susceptibility to geological disasters in 2020 and to elucidate their spatial relationship. This analysis aids in accurately understanding the status of and challenges in the local ecosystem, enhances our knowledge of the formation mechanisms of geological disasters, and strengthens our understanding of their interrelations. The findings offer both theoretical and practical value for ecological protection, restoration, management, and geological disaster investigation and prevention.

2. Research Area Overview and Data Sources

2.1. Overview of the Research Area

Pingshan County is located in the northwestern part of Shijiazhuang City (Eastern China), spanning from 38°09′ N to 38°45′ N and from 113°30′ E to 114°15′ E (Figure 1). It is bordered by Shanxi Province to the west and lies at the eastern foothills of the Taihang Mountains. The eastern section of the county primarily features plains, low hills, and river valleys, whereas the western section comprises medium-height and low mountain subregions characterized by erosional structures, well-developed fault structures, substantial altitude variations, and significant terrain undulations, coupled with a robust water system. This geographic setting predisposes the area to frequent geological disasters. The county experiences a warm, temperate, semi-humid, monsoon, continental climate with distinct seasons: hot summers and cold winters, large temperature variations, and an annual average temperature of 12.7 °C. The precipitation distribution is uneven in both time and space (Figure 2), with the most precipitation occurring from June to September, and the multi-year average precipitation is approximately 530–690 mm. Overall, the vegetation coverage rate is relatively high.

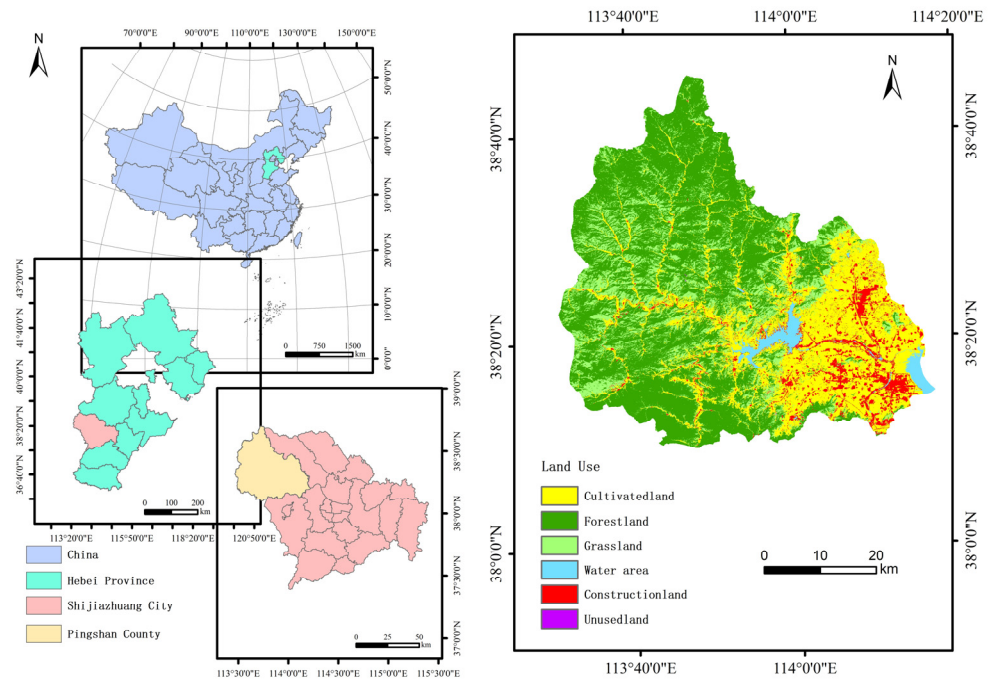


Figure 1. Research area geographical location and land use type diagram.

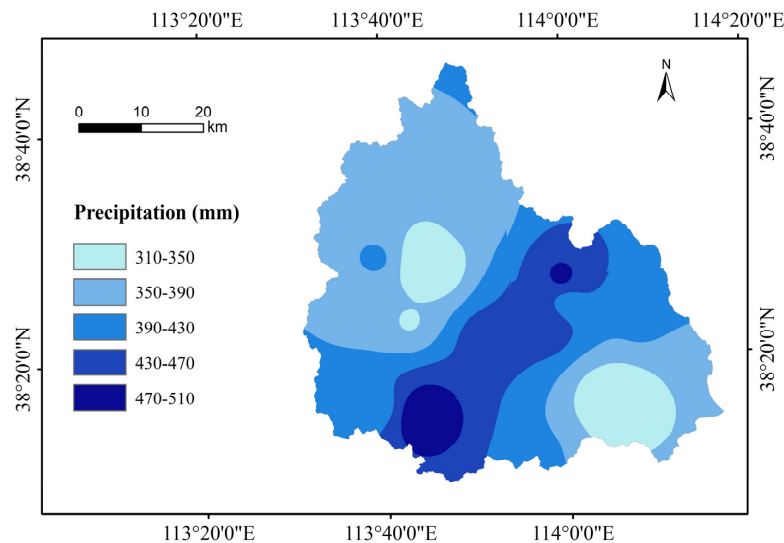


Figure 2. Precipitation distribution map for 2020.

2.2. Data Sources

The 2020 land use data were obtained from the China Land Cover Dataset (CLCD), publicly released by the team led by Professors Yang Jie and Huang Xin at Wuhan University [19], featuring a spatial resolution of $30\text{ m} \times 30\text{ m}$. According to the Land Use Classification Standard of the Ministry of Land and Resources (GB/T21010-2017 [20]), land use in the study area is categorized into six types: cultivated land, forest land, grassland, water bodies, constructed land, and unused land. The 30 m Digital Elevation Model (DEM) topographic data were sourced from the Shuttle Radar Topography Mission (SRTM) elevation data, a collaborative effort between NASA (National Aeronautics and Space Administration) and NIMA (National Imagery and Mapping Agency), available at <http://srtm.csi.cgiar.org/srtmdata/> (accessed on 19 May 2024). The geological disaster data for the year 2020 were provided by the Geological Environment Monitoring Institute of Hebei Province, drawn from their geological disaster risk census materials.

3. Research Methods

3.1. Habitat Quality Assessment

Using the Habitat Quality module of the InVEST model and land use data from the study area, this study conducted an assessment of the habitat quality in Pingshan County. The model considers four primary factors that influence habitat quality: the relative impact of each threat; the distance between the grid cell and the source of the threat; the degree of legal protection afforded to the grid cell; and the relative sensitivity of each habitat type to threats [21,22]. Given the comprehensive nature of our country's laws and regulations on ecological environment protection, the influence of legal protection on habitat quality was not considered in this analysis.

Based on the actual land use conditions in the study area, along with the reference values recommended by the InVEST model guide and associated studies [23–27], construction land, unused land, and arable land have been identified as habitat threat factors. The maximum impact distances of these threat factors, their respective weights (Table 1), and the sensitivity of the habitat to each threat factor (Table 2) have been established.

Table 1. Threat factor parameters.

Threat Factor	Maximum Influence Distance/km	Weight	Spatial Decline Type
Cultivated Land	1.50	0.60	Linear
Construction Land	6.00	1.00	Exponent
Unutilized Land	2.00	0.40	Linear

Table 2. Habitat quality suitability of different land use types and their relative sensitivity to threat factors.

Land Use Type	Habitat Suitability	Threat Factor Sensitivity		
		Cultivated Land	Construction Land	Unutilized Land
Cultivated Land	0.40	0.25	0.50	0.30
Forest Land	1.00	0.80	1.00	0.70
Grass Land	0.80	0.70	0.80	0.80
Water Area	0.70	0.65	0.75	0.75
Construction Land	0.00	0.00	0.00	0.00
Unutilized Land	0.10	0.10	0.30	0.10

Considering that the model attributes habitat quality degradation to increased land use intensity in the vicinity, it is necessary to first compute the degree of habitat degradation. The formula used for this calculation is provided in references [28,29]:

$$D_{xi} = \sum_{r=1}^R \sum_{y=1}^{Y_r} \left(\frac{w_r}{\sum_{r=1}^R w_r} \right) r_y i_{rxy} \gamma_x S_{ir} \quad (1)$$

$$i_{xy} = 1 - \left(\frac{d_{xy}}{d_{rmax}} \right) \quad (2)$$

$$i_{xy} = \exp \left(\frac{-2.99 d_{xy}}{d_{rmax}} \right) \quad (3)$$

$$Q_{xi} = H_i \left[1 - \left(\frac{D_{xi}^z}{D_{xi}^z + k^2} \right) \right] \quad (4)$$

In the specified formula, D_{xi} represents the degree of habitat degradation for grid x within land use type i ; R is the total number of threat factors; w_r is the weight assigned to threat factor r ; Y_r represents the number of grids affected by threat factor r ; r_y denotes the intensity of the threat factor in grid y ; i_{rxy} quantifies the extent of the threat from stressor r_y in grid y to grid x ; γ_x is the disturbance resistance level of grid x ; S_{ir} is the sensitivity of different land use types to threat factor r ; d_{xy} measures the distance between grid x

and grid y ; d_{rmax} is the maximum influence distance for threat factor r ; Q_{xi} indicates the habitat quality of grid x within land use type i ; H_i is the habitat suitability for land use type i ; k is the half-saturation constant, typically set as half of the maximum value of habitat degradation; z is a default parameter for the model, set at 2.5.

3.2. Evaluation of Susceptibility to Geological Disasters

Based on the geological environment and the prevalence of geological disasters in the research area, coupled with insights from previous experiences and related literature [30–32], from the aspects of topography, geological conditions, and ecological environment, nine factors are selected for the evaluation of geological disaster susceptibility: five factors for topography, including slope, degree of relief, elevation, aspect, and landform; three factors for geological conditions, including lithology, distance from faults, and distance from rivers; and the Normalized Difference Vegetation Index (NDVI) for the ecological environment (Figure 3). To comprehensively analyze multiple influencing factors and ascertain their relative importance, the information volume method is integrated with the analytic hierarchy process (AHP). Using ArcGIS, each factor is classified, and data such as the number of disaster points, grid numbers, and other relevant metrics for each level of each factor are collected. The information volume for each level of each factor is then calculated. The 1 to 9 scaling method is applied to rank each factor, facilitating the calculation of the weight for each evaluation index (Table 3). Finally, the weighted information volume for each evaluation index at different levels is derived through weighted processing. The specific calculation formula is as follows:

$$J = \sum_{j=1}^n W_j J_j = \sum_{j=1}^n W_j \ln \frac{S_j / A_j}{S / A} \quad (5)$$

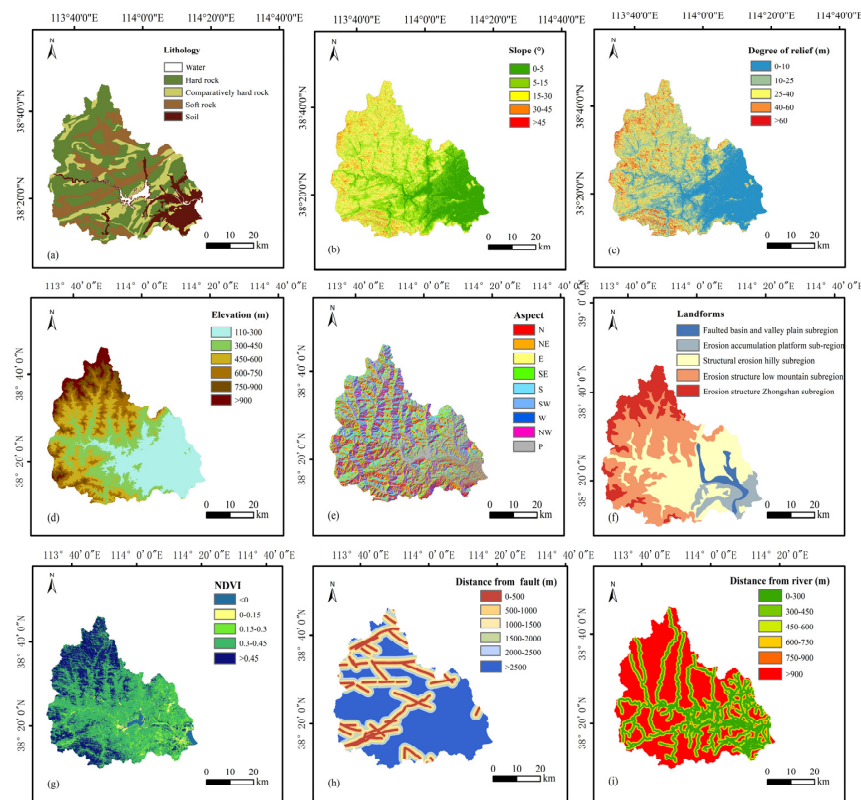


Figure 3. Geological hazard susceptibility evaluation factor map: (a) Lithology; (b) Slope; (c) Degree of relief; (d) Elevation; (e) Aspect; (f) Landforms; (g) NDVI; (h) Distance from fault; (i) Distance from river.

Table 3. Evaluation factor hierarchy analysis ranking result summary table.

Indicator	Lithology	Slope	Degree of Relief	Elevation	Aspect	Landforms	NDVI	Distance from Fault	Distance from River	Weight
Lithology	1	2	3	4	5	6	7	8	9	0.3121
Slope	1/2	1	2	3	4	5	6	7	8	0.2223
Degree of Relief	1/3	1/2	1	2	3	4	5	6	7	0.1555
Elevation	1/4	1/3	1/2	1	2	3	4	5	6	0.1075
Aspect	1/5	1/4	1/3	1/2	1	2	3	4	5	0.0739
Landforms	1/6	1/5	1/4	1/3	1/2	1	2	3	4	0.0507
NDVI	1/7	1/6	1/5	1/4	1/3	1/2	1	2	3	0.0350
Distance from Fault	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1	2	0.0247
Distance from River	1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1	0.0183

In the formula, J represents the total amount of information provided by various factors in the study area for geological disasters. W_j denotes the weight of the j -th factor, while J_j indicates the amount of information provided by the j -th factor for geological disasters. A refers to the total area of the study area, and A_j represents the area occupied by the j -th factor. S is the total number of geological disasters that have occurred in the study area, and S_j specifies the number of geological disasters that have occurred within the area of the j -th factor.

3.3. Bivariate Local Spatial Autocorrelation

Bivariate local spatial autocorrelation is a method used to measure the spatial relationship between two variables at the same or different locations [33,34]. This study utilizes the GeoDa software 1.22 platform to construct the queen contiguity spatial weight matrix and analyzes the spatial distribution characteristics of habitat quality and geological disaster susceptibility using Moran's I index and the Local Indicators of Spatial Association (LISA) cluster map. When the local Moran's I index is greater than zero, this signifies a positive spatial autocorrelation, indicating that similar values cluster together. Conversely, when the index is less than zero, it indicates a negative spatial autocorrelation, suggesting that dissimilar values cluster together [35,36]. Depending on whether the value is positive or negative and its level of significance, the spatial association characteristics can be categorized into different types, such as high–high cluster (H-H), low–low cluster (L-L), high–low cluster (H-L), and low–high cluster (L-H).

4. Results and Analysis

4.1. Habitat Quality Spatial Distribution Characteristics

The habitat quality score in Pingshan County ranges from 0 to 1, where higher scores indicate greater habitat suitability [24]. The overall habitat quality in the county is relatively high, with an average score of approximately 0.70. Consequently, habitat quality in the research area is categorized into four levels—low, medium, high, and very high—using 0.25 as the interval for classification. The very high habitat quality category is the most extensive, comprising about 58.76% of the total county area. Medium and high habitat quality categories together account for approximately 35.53% of the area, while the low habitat quality category covers the smallest proportion (Table 4). There is significant spatial differentiation in habitat quality, which typically exhibits a distribution pattern of “high in the west, low in the east” (Figure 4). This pattern aligns with the spatial distribution of land use (Figure 1) and correlates strongly with the intensity of human activities.

Table 4. Proportion of different habitat quality grades.

Level	Area (km ²)	Area Proportion
Low	151.08	5.71%
Medium	745.24	28.14%
High	195.68	7.39%
Extremely high	1556.00	58.76%

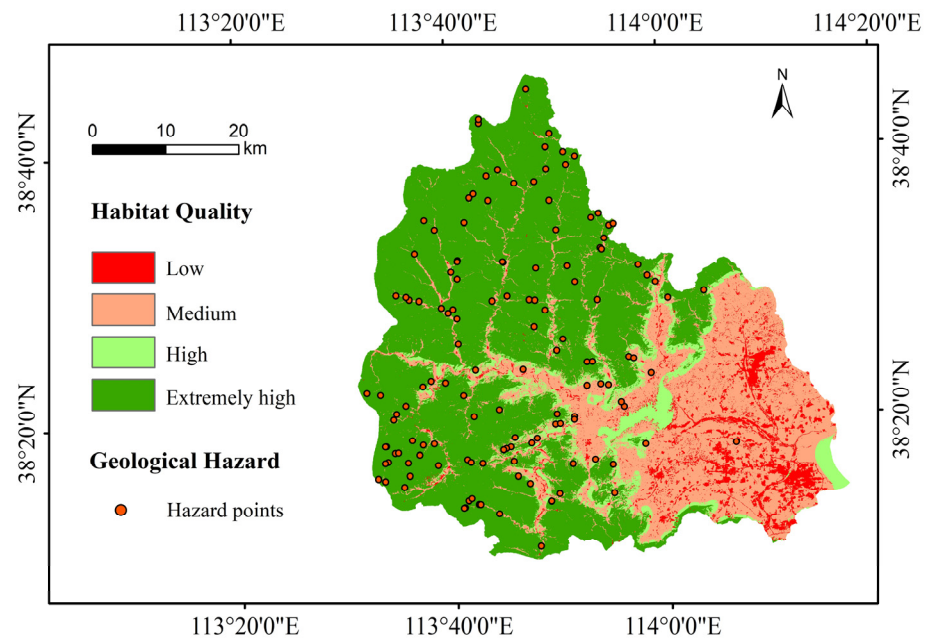


Figure 4. Habitat quality zonation map.

The high-grade areas in Pingshan County are predominantly located in the western part, characterized by forest and grassland land use. This region benefits from a suitable climate with ample precipitation, which fosters vegetation growth and development. Additionally, the low level of human activity disturbance contributes to a high vegetation coverage rate. High-grade areas are primarily situated where farmland intersects with grassland in the west, as well as near water bodies in the east. The terrain in the western areas is generally elevated and steep (elevation > 300 m, slope > 30°). Some slopes have been modified through artificial excavation to create terraced fields, disrupting the original surface vegetation and posing threats to the habitat. Nonetheless, the favorable climate and the absence of industrial pollution support the stability and quality of the farmland habitat, resulting in a relatively high habitat quality. Living near water bodies is the preferred choice for human settlements. The eastern water areas, proximate to farmland and constructed land, face threats from industrial, agricultural, and residential activities, which vary in intensity. Areas with lower habitat quality are concentrated in the east and are sparsely distributed in a tree-like pattern in the west, where farmland is the predominant land use type. Despite the strong influence of human activities, the proximity to water sources and extensive farmland supports soil fertility and biodiversity. Consequently, the habitat quality in these areas ranges between 0.25 and 0.5, classifying them as medium-grade areas. The low-grade areas are primarily composed of constructed and unused land, featuring a high population density. Large expanses of construction land have encroached upon bare land and farmland, fragmenting the continuous natural habitat and leading to significant habitat fragmentation. Construction activities introduce various forms of pollution, including air, water, and noise pollution. The intense human activities in these regions have markedly disrupted the local ecological structure, damaging the integrity of the habitat and reducing the regional habitat quality.

4.2. Characteristics of the Spatial Distribution of Geological Disaster Susceptibility

Pingshan County features a distinctive topography, rising higher in the west and north while descending towards the east and south. It exhibits significant elevation differences, pronounced undulations in the landscape, and a well-developed water system. Given its complex geological environment and the frequent occurrence of geological disasters, the natural breaks method [31] is utilized to categorize the susceptibility of Pingshan County to geological disasters into four levels: low, medium, high, and very high. The areas of

low susceptibility account for approximately 25.21% of the total county area, medium susceptibility covers about 27.02%, high susceptibility constitutes the largest portion, at about 45.12%, and very high susceptibility comprises the smallest fraction, at about 2.65% (Table 5). The distribution of susceptibility to geological disasters exhibits significant spatial characteristics (Figure 5).

Table 5. Different proneness level proportions and disaster point distribution.

Level	Area (km ²)	Area Proportion	Disaster Point Total Density (Count/km ²)
Low susceptibility	667.46	25.21%	0.0045
Medium susceptibility	715.56	27.02%	0.0349
High susceptibility	1194.68	45.12%	0.0804
Extremely high susceptibility	70.29	2.65%	0.1280

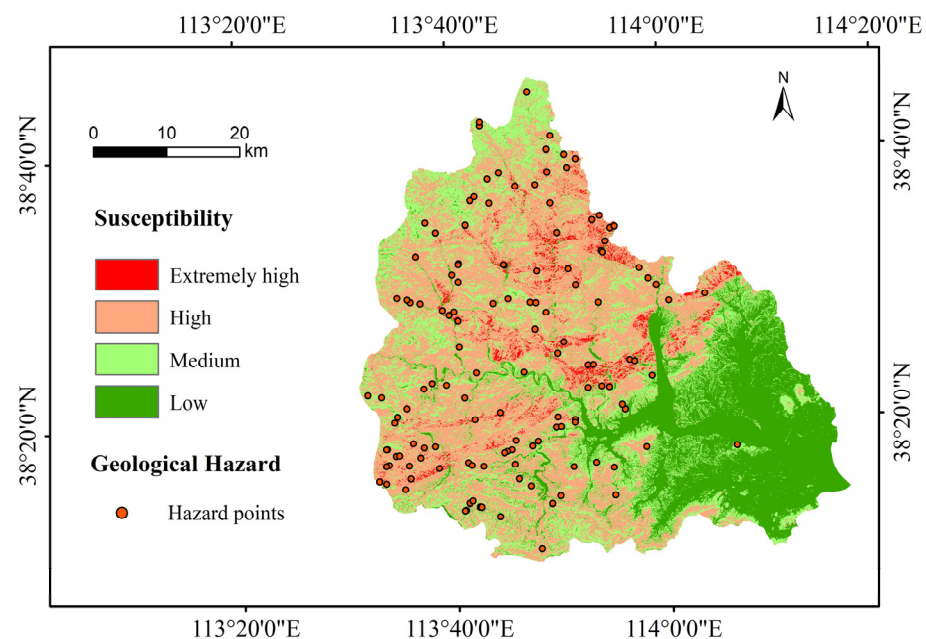


Figure 5. Geological hazard susceptibility zoning map.

The low-incidence areas are predominantly located in the eastern part of the region, falling within the subregion of structurally denuded hills, the erosion accumulation platform subregion, and fault basin and river valley areas. These areas feature less developed fracture structures and are primarily characterized by water bodies, arable land, and construction land. The terrain is generally gentle, with abundant water sources, convenient transportation, and a relatively dense population. Conversely, the medium-incidence areas in the western part of Pingshan County are marked by higher altitudes and greater terrain undulations (elevation > 450 m, degree of relief > 40 m, $15^\circ < \text{slope} < 30^\circ$). This region, part of the erosion structure subregion with medium-height and low mountains, has more developed fracture structures, though the slopes are moderate and the vegetation coverage is high. This area hosts several nature reserves, ecological tourism zones, and scenic areas. Effective monitoring and prevention measures by relevant departments have resulted in fewer disaster points and a relatively lower incidence rate. The high-incidence area spans approximately 1194.68 km², primarily consisting of forest land and grassland in the west. This area is part of the erosion structure subregion of middle-height and low mountains and is characterized by higher altitudes and slopes. Despite numerous disaster points scattered throughout, the density of these points is relatively lower due to the large area of high incidence. The extremely high-incidence area features high terrain, developed fracture structures, and loose and weak rock layers, with the predominant land use being grassland with low vegetation coverage. During the flood season, this area is highly susceptible to

geological disasters due to rainfall. Although this region covers the smallest area, it has the highest density of disaster points at approximately 0.1280 per km² (Table 5). In summary, Pingshan County exhibits an increasing density of geological disasters and higher susceptibility to such events, aligning with the findings from previous research [31]. This confirms the scientific validity and accuracy of the study.

4.3. Analysis of the Spatial Correlation between Habitat Quality and Geological Hazard Susceptibility

Utilizing the GeoDa software platform, a queen contiguity spatial weight matrix was constructed to analyze the bivariate global spatial autocorrelation. Moran's I index for habitat quality and geological disaster susceptibility in Pingshan County for the year 2020, measured at a 30 m grid scale, was calculated to be 0.782 (Figure 6). This index achieved a *p*-value of less than 0.01, indicating statistical significance within a 99% confidence interval. The positive Moran's I index suggests a significant positive spatial correlation between habitat quality and susceptibility to geological disasters in Pingshan County.

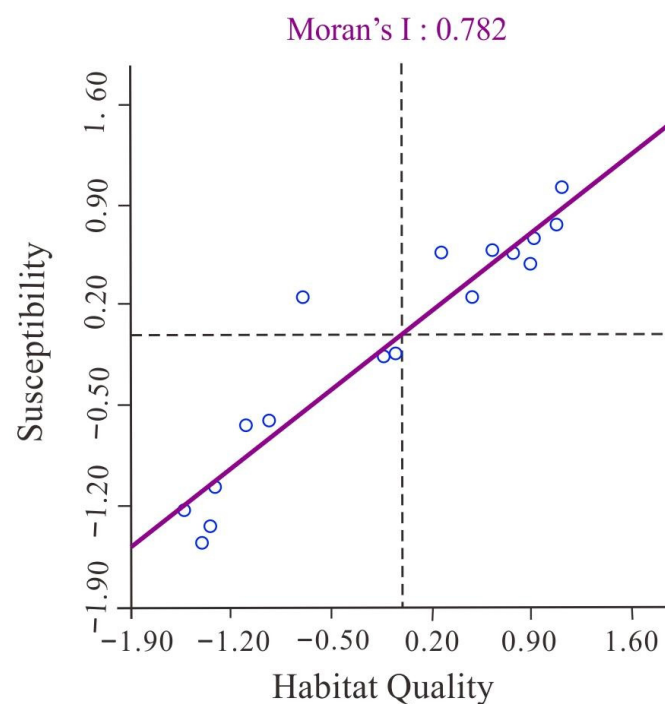


Figure 6. Moran's I index.

The LISA clustering analysis (Figure 7) of habitat quality and geological disaster susceptibility shows that the dominant cluster types in the study area are high–high and low–low. The high–high clusters are mainly located in the northwestern mountainous regions, often at the borders of provinces and counties within the Yanshan–Taihangshan ecological conservation area, which includes various nature reserves and ecotourism zones. In these regions, land use planning prioritizes ecological balance and environmental conservation, characterized by substantial vegetation coverage and a low population density. This configuration minimizes human interference, enhancing habitat quality. However, these areas, noted for their high altitudes, significant topographical variations, and extensive fault structures, are also subject to frequent geological disasters, indicating high susceptibility. Conversely, in the eastern hilly and plain areas, the predominant land uses are agriculture and urban development, with higher population densities. Intense human activity has modified the original environment, and urban development has disrupted the continuity of vast farmland, intensifying habitat fragmentation and degrading habitat quality. Nonetheless, the flatter terrain and more stable soil conditions, combined with effective monitoring and

disaster prevention strategies, render these regions less susceptible to geological disasters, leading to the identification of the low–low cluster type.

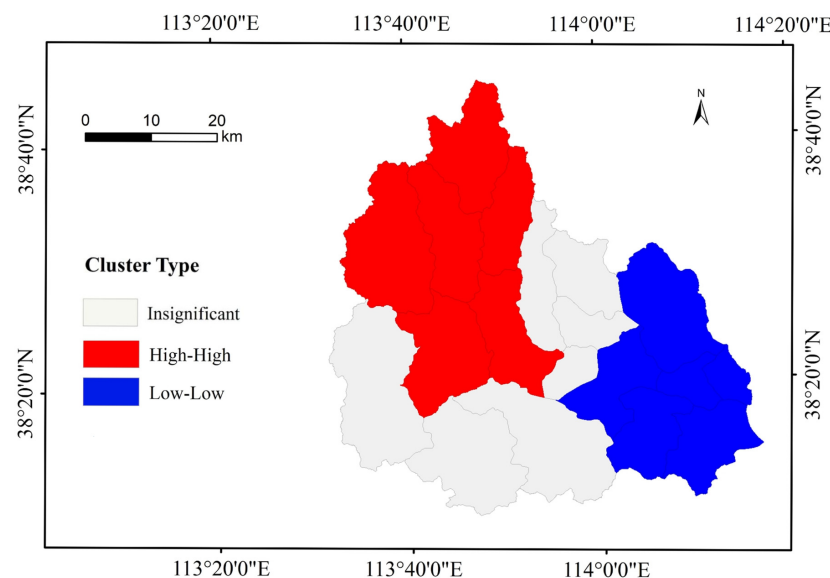


Figure 7. LISA clustering diagram.

As global climate change continues, phenomena such as the degradation of glaciers and permafrost, rising sea levels, increased evaporation, and significant changes in rainfall frequency, periodicity, and intensity have become increasingly apparent. These changes interact with soil and rock masses, leading to various types of geological disasters, such as landslides and mudflows, posing a serious threat to human life. Therefore, there has been an increased focus on the relationship between ecological environments and geological disasters, aiming to provide scientific bases for the prevention and response to geological disasters and the protection of ecological environments [37–40]. The function of habitat quality services closely links human well-being with the ecological environment, not only helping people understand and solve the dilemmas of development and protection but also directly reflecting the state of the ecological environment and its impact on human society. In view of this, this paper uses ArcGIS software 10.6 to count the number and density of geological disasters in areas with different levels of habitat quality (Table 6), deeply studying the impact of habitat quality on susceptibility to geological disasters.

Table 6. Different habitat quality grades and geological disaster number and density.

Level	Area (km ²)	Total Number of Disaster Points (Count)	Disaster Point Density (Count/km ²)
Low	151.08	3	0.0199
Medium	745.24	24	0.0322
High	195.68	18	0.0920
Extremely High	1556.00	88	0.0566

In regions with an extremely high habitat quality, there are 88 disaster points, resulting in the second highest density of 0.0566 points per square kilometer. Conversely, the area with a high habitat quality, despite having the highest density of 0.0920 points per square kilometer, has only 18 disaster points, ranking third. This indicates that geological disasters are more frequent in areas of high habitat quality. In the west, although these regions have comparable geological settings, those with a high habitat quality are smaller and predominantly located at interfaces between farmland and grassland or near construction sites or bodies of water adjacent to farmlands and experience more human activity. The

terrain here is steeper and higher, making transportation challenging. Local construction practices, such as slope undercutting for roads and building directly into slopes, have modified the natural slope configurations, decreasing their stability. Additionally, under conditions of heavy rainfall or other extreme weather, the likelihood of landslides increases significantly. Human activities, including overgrazing and uncontrolled deforestation, have degraded the surface environment, diminishing vegetation cover and the ground's ability to stabilize sand and soil, thereby enhancing the risk of soil erosion. While various factors such as topography, climate, vegetation, geological structure, and human interventions impact susceptibility to geological disasters, it is apparent in areas of generally a high habitat quality that despite a weak negative correlation between habitat quality and disaster susceptibility, the trend of a poorer habitat quality correlating with higher disaster risks persists.

5. Discussion

This study conducted an in-depth exploration of the relationship between habitat quality and geological hazard susceptibility. The research found that there is a close relationship between habitat quality and geological hazard susceptibility. In regions with similar geological environments, they show a negative correlation, which is consistent with previous studies on the relationship between the ecological environment and geological hazards [37–40]. Furthermore, the LISA cluster map revealed that Pingshan County, a region with high vegetation coverage and a good ecological environment, exhibits relatively high geological hazard susceptibility. The possible reason is that the western part of Pingshan County has significant terrain relief, providing good drainage conditions that favor plant growth, resulting in relatively high habitat quality. However, the significant terrain relief affects the spatial distribution of hazard points (Figure 8), leading to a dense distribution of hazard points in this area, while they are relatively dispersed in other regions. The important regulatory role of the geological environment in the relationship between habitat quality and geological hazard susceptibility causes the impact of the ecological environment on geological hazard susceptibility to be lesser in areas with a higher habitat quality. This study further demonstrates the coupled relationship between the geological environment, the ecological environment, and geological hazards [39].

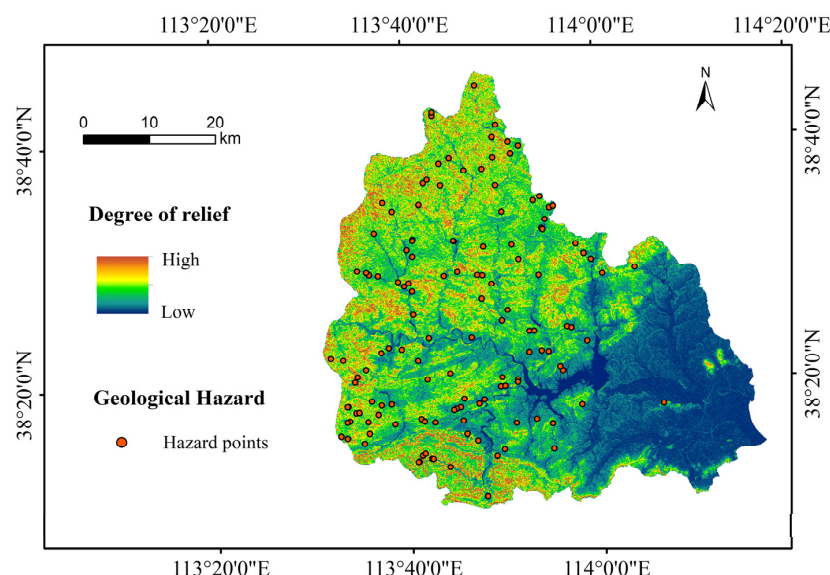


Figure 8. Topographic relief and geological hazard point distribution map.

The geological environment significantly influences the formation and distribution of geological hazards. Relying solely on the assessment of habitat quality is insufficient for fully understanding the characteristics and distribution patterns of geological hazards.

When evaluating susceptibility to geological hazards, it is essential to comprehensively consider the ecological and geological environment of the study area. By assessing the extent to which the ecological environment affects the incubation and occurrence of geological hazards, we can determine the weight of the ecological environment in the evaluation indicators of geological hazard susceptibility. This study helps us to enhance our understanding of the relationship between the ecological environment and geological hazard susceptibility, providing a scientific basis for and new perspectives on the evaluation of geological hazard susceptibility, thereby improving the accuracy and precision of such assessments. It holds significant guidance for planning and disaster prevention and mitigation, as well as ecological environment protection and restoration in mountainous regions.

Effective geological disaster management necessitates the integration of various factors, including geological and natural environments, along with human activities. It is essential to implement scientific monitoring, early warning systems, and preventive measures to safeguard human lives, property, and ecological stability. Factors such as long-term climate variability, geological processes, and human interventions can significantly influence habitat quality and susceptibility to geological disasters. However, short-term studies might not adequately capture these dynamic interactions. This study, focusing solely on data from 2020, may not completely represent the long-term trends and seasonal variations in habitat quality and geological disaster susceptibility. The use of a 30 m × 30 m grid for the analysis offers a detailed spatial resolution but may lack precision in detecting subtle surface and ecological changes, potentially leading to inaccurate assessment outcomes. For future evaluations of habitat quality and geological disaster susceptibility, particularly in smaller regions like counties, it is advisable to base the research on multi-year data and employ remote sensing data with a higher spatial resolution to more accurately capture dynamic changes. When selecting the indicators for susceptibility evaluation, it is crucial to consider environments conducive to geological disasters thoroughly, including both natural and human factors, to enhance the accuracy and reliability of the assessments. Additionally, this study focuses on Pingshan County as the research area. While it provides valuable regional results, its conclusions may not be directly applicable to other areas. Ecological and geological environments vary significantly across different regions, which may result in different relationships between habitat quality and geological hazard susceptibility. Future research can be conducted in different regions to explore the relationship between the ecological environment and the geological environment from multiple perspectives.

6. Conclusions

The assessment of habitat quality and geological disaster susceptibility provides crucial decision support information for local authorities and policymakers, as well as a scientific foundation for land use planning, environmental protection, and strategies to prevent geological disasters. In mountainous areas, disaster prevention policies should account for differences in ecological environments. In zones with a lower habitat quality, it is advisable to implement a combination of engineering and biological measures, enhance ecological protection, expand green areas, and bolster ecosystems' self-restoration capabilities. Conversely, in regions with a higher habitat quality, there should be an intensified focus on geological disaster research and monitoring. It is also essential to encourage rational land development and utilization while strictly prohibiting indiscriminate excavations at slope bases to preserve mountain stability.

On the macro level, the impact of habitat quality on susceptibility to geological disasters is minimal when observing the entire county. However, the ecological environment, the geological environment, and the disaster environment are closely interrelated, influencing and constraining one another. The geological environment significantly affects the relationship between habitat quality and susceptibility to geological disasters. In Pingshan County, regions with similar geological environments exhibit a negative correlation between habitat quality and susceptibility to geological disasters. Therefore, while habitat quality provides

some guidance in assessing susceptibility to geological disasters, it should not be the sole criterion for determining susceptibility levels.

When selecting evaluation indicators for geological disaster susceptibility, it is crucial to thoroughly consider the disaster-bearing environment. For instance, when conducting geological disaster susceptibility assessments in mountainous areas with better ecological environments, it may be appropriate to reduce the weight of the ecological indicators and incorporate measures of human activities, such as land use types, to enhance the accuracy and reliability of the assessment. Conversely, in mountainous regions where high-quality habitats are significantly disturbed by human activities, greater attention and the development of targeted prevention measures are necessary to mitigate potential disaster risks.

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