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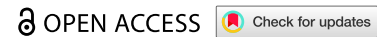


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RESEARCH ARTICLE



Resilience assessment of geohazard emergency system based on the 'hazard–impact–drive' model

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ABSTRACT

To objectively reflect historical patterns, future trends, and internal drivers of geohazard risk, this paper proposes the 'hazard–impact–drive' (HID) model for resilience assessment. The HID model advances conventional approaches by establishing causal linkages between hazard characteristics (H), exposure vulnerability (I), and driving mechanisms (D), enabling bidirectional analysis that integrates historical recognition with prospective forecasting. By extending risk assessment ($R = H \times I$) into a resilience framework, the model ensures methodological continuity for intervention design. To quantify resilience, a comprehensive assessment model is constructed using the improved G1-CRITIC method, integrating multi-dimensional socio-economic and natural factors for indicator weighting to balance analytical rigor with operational tractability. By applying this method to Huanggu Town, Shaanxi Province (2013–2022) using remote sensing and field data, the following results are obtained: (1) Resilience exhibits temporal regularity, where major turning points align with policy and social events, validating the HID model's causal identification; (2) evolution follows a dual-timescale pattern –short-term fluctuations are driven by instantaneous natural factors, while long-term trajectories are shaped by cumulative socio-economic reconfiguration; and (3) dynamic feedback between natural and socio-economic systems creates a non-monotonic resilience trajectory, necessitating the coordination of immediate response mechanisms with multi-level long-term governance.

ARTICLE HISTORY

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KEYWORDS

Geohazard emergency system; resilience assessment; remote sensing; internal driving mechanism; dual-control system

1. Introduction

Owing to strong geological structure and seismic activities, complex topography and geological conditions, diverse climate types, and intense human engineering activities, geological disasters in China are prone to occur frequently (Xu et al. 2019). At present, the prevention and control of geological disasters in China still focuses on 'holding' known potential hazard points. The identification, evaluation, and control of regional risks are at an initial stage. Risk surveys and evaluations have not yet been properly linked with territorial spatial planning and usage management, and the source of risk is not adequately managed. Improving the ability to prevent and control geohazards requires a better understanding of the current status of regional geohazard risks, as well as the structural characteristics, stability trends, scope of threat, and risk level of geohazards and potentially disaster-causing bodies. Regional geological disaster risk assessment is important for relevant departments to understand the current state of the geological environment in the region, predict the trend of changes in the geological environment, formulate policies and measures, and construct a dual-control system of hazard sites + risk zones'.

Although the concept of landslide hazard assessment was proposed earlier, it was not until the 1980s that relatively mature technical methods and assessment procedures for quantitatively evaluating the hazard of a single given slope site were clearly defined (Varnes 1984). During this period, pioneering studies employed multiple regression methods to assess landslide hazards in regional contexts, marking the initial application of mathematical and statistical approaches to geological disaster evaluation. Subsequently, the mid-1980s witnessed the development of fundamental methodologies and theoretical

frameworks for hazard assessment and regional zoning. This period saw the gradual emergence of various quantitative research methods, including evidence-based models, binary statistical approaches, artificial neural network algorithms, logistic regression models, and support vector machine models. (Carrara 1983; Brabb 1984; Degg 1992; Fell 1994; Hearn 1995; Carrara et al. 1999; Forste 2005). In the 21st century, further refinement of GIS technology has expanded its application scope in geological disaster assessment. Research efforts have increasingly focused on understanding the instability mechanisms and movement patterns of various landslide types to improve the accuracy of regional hazard assessments. (Lee and Pradhan 2007; Promper and Glade 2016). The integration of GIS with advanced analytical models has enabled comparative evaluations of different assessment methodologies, enhancing the reliability of hazard predictions. More recently, the maturation of GIS platforms, coupled with the emergence of unmanned aerial vehicle (UAV) technology and enhanced remote sensing capabilities, has facilitated the development of comprehensive multi-index evaluation systems (Psomiadis et al. 2020). Contemporary approaches increasingly favour the integration and comparison of multiple assessment methods rather than reliance on singular techniques, yielding results that demonstrate improved accuracy and closer alignment with observed field conditions. However, the interconnection and reciprocal influence between assessment methodologies and their applicability across diverse geological contexts still require further clarification.

With the development of the aforementioned theories and technologies, geological disaster research has shifted from hazard assessment to risk assessment. This is also a transformation from the engineering approach of disaster point treatment to the emergency management approach of disaster risk control. Geological disaster risk assessment work has achieved increasing results, theoretical knowledge has become increasingly rich, and technology development has become increasingly mature (Xu et al. 2023). The reasons for the increasing international interest in geological disaster risk are twofold: firstly an increasing awareness of the socio-economic significance of geological disasters and secondly, the increased pressure of development and urbanisation on the environment (Aleotti and Chowdhury 1999). From a technical and theoretical aspect, the existing geological disaster risk assessment model faces challenges in fully meeting the requirements of the dual control system of the 'hidden danger point + risk area'. First, the accuracy of the assessment model is strongly dependent on the accuracy of the selected evaluation indicators and the reliability of the evaluation data sources. Additionally, traditional assessment models, regardless of the methodology or theory, still tend to use 'expert scoring' methods, such as the analytic hierarchy process or principal component analysis, to determine the weights of certain key indicators in some of the most critical modelling steps. This results in the accuracy of the evaluation model being highly dependent on the theoretical foundation and engineering experience of the modeler, and the evaluation results are also difficult to objectively verify. Second, the assessment model based on natural indicators can assess only the current level of regional geohazard risk. It cannot study the historical change process, disclose the internal driving mechanism, predict the development trend, or optimize control measures (Xu and Yordanov, 2024). As a result, developing the 'long-term dynamic prevention and control' of the dual control system of 'hazard sites + risk zones' of geological disasters is difficult, as is accurately evaluating the effectiveness of government department governance and making targeted adjustments to their risk prevention and control planning, policies, and measures.

Nevertheless, the complexity of landslide mechanisms under natural conditions remains significant, with highly variable and location-specific controlling factors. The degradation process of slopes is intricate and influenced by multiple interacting factors, including climatic conditions, geomorphological characteristics, geotechnical properties, and vegetation cover. Consequently, existing research on landslide hazard assessment has not achieved sufficient comprehensiveness, making it challenging to establish unified evaluation frameworks across different geological settings. In addition to accurately grasping the current risk situation from the potentially disaster-causing bodies point of view only by geological disaster risk assessment, accurate predictions of future trends should also be made in order to formulate reasonable measures from the disaster prevention and control system's point of view via geological disaster resilience assessment. In other words, resilience assessment should be introduced in the field of geological disaster prevention as a supplement to risk assessment to objectively reflect the historical patterns and future trends of risk change, as well as the internal driving factors of such changes.

The notion of resilience, which originated in the realm of ecosystems, has been expanded to include parts of sociology, disaster science, and psychology, and has piqued the interest of many geohazard

researchers. (Holling 1973; Janssen et al. 2006; Cutter et al. 2008; Alexander 2013). The study of ‘resilience’ in the field of engineering initially emerged due to the rapid development of industries, which led to the formation of engineering systems. The failures of these engineering systems were also inevitable (Fallah-Aliabadi et al. 2020). People began to study the failures of the systems and restore them to normal operation. With the accumulation of research experience, the ability of systems to return to normal was referred to as resilience. The concept of resilience has been incorporated into disaster management, providing additional perspectives for geohazard disaster prevention and control (Burton 2015; Cimellaro et al. 2016). In 2021, Parsons et al. conducted a resilience assessment of disasters in Australia, mainly focusing on eight aspects, such as economy and society, and divided the regions into high-resilience areas, medium-resilience areas, and low-resilience areas (Parsons et al. 2021).

The HID model differs from existing resilience assessment frameworks in several aspects: theoretically, it establishes causal linkages between hazard characteristics, vulnerability of exposed elements, and underlying driving mechanisms, compared to the descriptive-aggregative approach of some index-based systems (Rus et al. 2018; Cheng et al. 2022); temporally, it incorporates the Drive component to enable analysis of both historical patterns and prospective trends, extending beyond the primarily retrospective orientation of system function curves (Bruneau et al. 2003); and methodologically, it positions resilience evaluation as an extension of risk assessment ($R = H \times I$), attempting to address the conceptual separation between risk and resilience assessment in some existing frameworks. This tripartite structure aims to balance analytical capability with practical applicability for geological disaster management contexts.

The notion of resilience has been introduced into disaster management, offering fresh perspectives on geohazard disaster prevention and control. For the first time, ‘China’s 14th Five-Year Plan’ and ‘Vision 2035 programmes’ included the notion of resilience in national strategic planning. Geohazard resilience is defined as a system’s ability to resist, reduce, and absorb the effects of disturbances (shocks, disruptions, or disasters), maintain an acceptable level of service (static resilience), and return to normal and smooth operations within a reasonable time and cost (dynamic resilience). A geohazard-resilient system reflects the system’s pace of recovery after a geohazard disruption as well as the amount of external aid required to restore its former functional state. Nonetheless, there is no specific construction plan for geohazard resilience in China. Research into disaster resilience ability is important for establishing safer natural geologic settings, and geologic disaster resilience capacity requires further development.

Overall, resilience assessment does not aim to replace risk assessment. Risk assessment remains important for identifying and prioritizing known threats. The core advantage of resilience assessment lies in its focus on a system’s ability to absorb shocks, maintain core functions, recover rapidly, and adapt and learn following disruptions (including both known and unknown risks), rather than merely identifying and quantifying potential threats. The two are complementary and mutually reinforcing.

To objectively reflect the historical patterns and future trends of changes in geohazard risk, as well as the internal driving factors of such changes, this paper comprehensively analyzes the multifaceted natural and socio-economic factors of geohazards and then systematically reveals the coupling and feedback mechanisms among the three components of the geological disaster system, namely, the disaster-causing body, the exposed elements, and the driving force. Based on the proposed assessment model and integrating the resilience theory, while considering natural indicators, socio-economic indicators are also introduced to ensure that the resilience assessment model can explore the high-dimensional complex nonlinear relationships between geological disasters and various triggering factors, as well as reveal the interrelationships among different triggering factors. Then, the ‘hazard–impact–drive’ model (HID) is proposed for geohazard emergency system resilience assessment by combining the subjective improvements of the improved G1 method and the objective entropy method. A geohazard emergency system resilience assessment model is constructed to obtain the historical change process and evolution law of geological disaster prevention and control resilience levels in the study area and to clarify the main controlling factors and their coupling and feedback relationships, revealing the internal driving mechanism of resilience changes. As a case study, this paper focuses on Huangu Town, which is located in Ankang City, Shaanxi Province, and extracts multi-source evaluation indicators by interpreting, analyzing, and filtering objective natural data and socio-economic data from remote sensing images, official statistics, and field surveys. These datasets are then subjected to the proposed model to evaluate changes in the resilience of the geohazard emergency system in the region. Finally, the accuracy of the methodology was

validated against the historical records. This approach can provide reasonable references for the government to understand the current geohazard risk and emergency management level situation in the region, predict the trend of change, and formulate policy measures.

2. Data and methods

2.1. Geological disaster resilience assessment model

2.1.1. 'Hazard-impact-drive' model (HID)

Risk refers to the probability of a specific adverse result occurring within a particular context and timeframe. When evaluating risk, it is important to consider not only the likelihood and scale of the accident but also the extent of the harm to the entity affected by the disaster following its occurrence (see Equation 1):

$$R = H \times I \quad (1)$$

In Equation 1, R represents the level of risk. H represents the disaster hazard of the disaster-causing body, or rather, the possibility of a disaster occurring, which can be obtained through the susceptibility assessment and I represents the potential loss of the exposed elements.

While geological disaster risk assessment focuses on evaluating the current risk situation of potentially disaster-causing bodies, geological disaster resilience assessment can be used to analyze future trends and inform disaster prevention and control measures. In other words, resilience assessment should be introduced in the field of geological disaster prevention as a supplement to risk assessment to objectively reflect the historical patterns and future trends of risk change, as well as the internal driving factors of such changes. Therefore, in addition to the disaster-causing body and the exposed elements, the drive also needs to be taken into consideration to establish the 'hazard-impact-drive' model (HID) for geological disaster resilience assessment on the basis of risk assessment. The resilience assessment model proposed in this paper is shown in Figure 1.

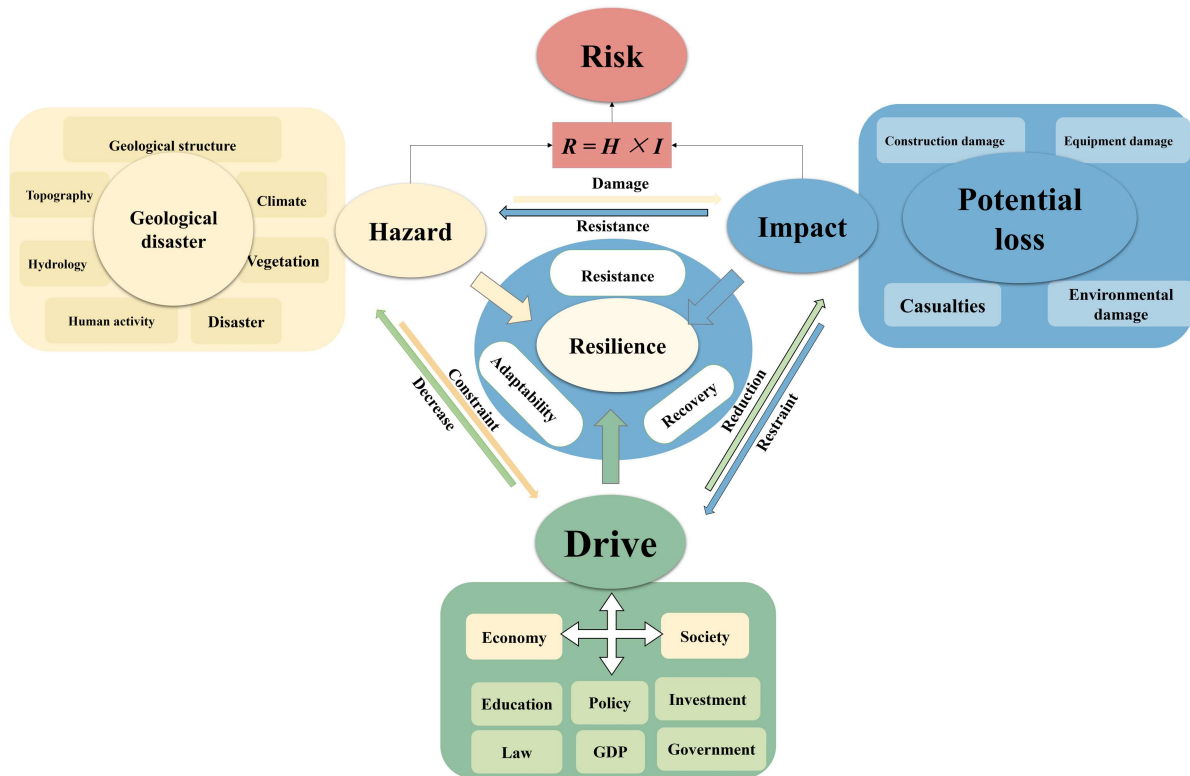


Figure 1. 'Hazard-impact-drive' (HID) model.

As shown in [Figure 1](#), resilience assessment and risk assessment are both crucial management tools, but they differ significantly in perspective, objectives, and application. The core advantage of resilience assessment lies in its focus on a system's ability to absorb shocks, maintain core functions, recover rapidly, and adapt and learn following disruptions (including both known and unknown risks), rather than merely identifying and quantifying potential threats.

2.1.2. Relationship between resilience assessment and risk assessment

The concept of resilience has emerged as a critical concept in complex, adaptive systems in a range of disciplines. Originally rooted in the fields of ecology and natural science (Barthel et al. 2010), resilience has evolved into a versatile analytical tool employed across diverse domains because of its capacity to address environmental, socioeconomic, and political uncertainties (Kolars 2016; Meerow et al. 2016). The widespread adoption of resilience thinking reflects its fundamental value in helping systems – whether ecological, social, or technical – prepare for, respond to, and recover from various disturbances and disruptions. On the other hand, resilience is attained when the energy system is prepared for diverse and partially ‘unpredictable’ factors by increasing its ability to withstand and recover from various disruptions.

The main advantages of the geohazard resilience assessment based on the HID model proposed in this paper are as follows:

1. Transcending prediction of the unknown: coping with ‘Black Swans’ and ‘Gray Rhinos’

In risk assessment discourse, two significant metaphors have emerged: Black Swan events, coined by Taleb, referring to high-impact, unpredictable, and rare occurrences characterized by nonlinear and stochastic emergence; and Gray Rhinos, termed by Michele Wucker, denoting obvious yet systematically neglected high-impact threats. These phenomena present fundamental challenges to conventional risk management frameworks.

Risk assessment focuses primarily on identifying and quantifying known or foreseeable risks through probability and impact analysis. Its heavy reliance on historical data, models, and empirical experience limits its effectiveness in addressing unprecedented Black Swan events or systematically overlooked Gray Rhino threats.

Resilience assessment offers a distinct advantage by eliminating the requirement for precise risk prediction. It concentrates on the system's inherent capacities to withstand, adapt, and recover from shocks regardless of their origin – whether from known risks, unknown threats, or concurrent multiple disruptions. This approach emphasizes survival and flourishing capabilities within uncertain environments.

2. Emphasis on proactive adaptation & learning evolution, not passive defense

Risk assessment typically generates prevention and mitigation strategies, such as risk avoidance, probability reduction, and impact minimization. While necessary, this approach can prove insufficiently dynamic when risks cannot be completely eliminated or mitigated.

Resilience assessment emphasizes response, recovery, and adaptation capabilities. It directs organizations to consider rapid response mechanisms for maintaining critical functions during unavoidable shocks, efficient recovery strategies to minimize losses and downtime, and learning mechanisms to strengthen structural and procedural frameworks through adaptation. This represents a more proactive, dynamic, and forward-looking analytical perspective.

3. Focus on maintaining system function & rapid recovery, not just loss minimization

Risk assessment primarily aims to minimize potential losses across financial, reputational, and safety domains. Success metrics typically measure whether losses remain below anticipated thresholds.

Resilience assessment centers on maintaining the continuity of core functions and services alongside recovery speed and efficiency following disruptions. It emphasizes system survivability and bounce-back capability under stress conditions. Success metrics include critical service downtime, the time required for

functional restoration, and service level recovery rates. This framework acknowledges inevitable losses while prioritizing functional continuity and recovery efficiency.

4. More holistic system perspective

Risk assessment frequently examines specific, isolated threats or discrete risk categories, such as individual landslide hazards.

Resilience assessment requires systems thinking to analyze organizations, communities, or infrastructure. It examines interdependencies among system components – physical, natural, economic, and social – and their behavioural responses under stress. This approach recognizes that shocks propagate through complex cascading effects, necessitating comprehensive capacity development.

5. Empowers organizations to operate & develop continuously in turbulent environments

Risk assessment focuses on preventing adverse outcomes or reducing negative impacts within relatively stable operational contexts.

Resilience assessment acknowledges operation within increasingly complex, interconnected, and uncertain environments (VUCA: volatile, uncertain, complex, and ambiguous). Its ultimate objective is enabling systems –whether organizations or communities – to survive ongoing change, disruption, and crises while learning from experience to strengthen adaptability for future challenges, thereby facilitating sustainable development. This concerns long-term organizational viability and competitive advantage.

6. Provides a foundation for innovation and transformation

The pursuit of resilience frequently reveals systemic vulnerabilities and inefficiencies. Resilience enhancement often yields improved operational efficiency and innovation opportunities.

Complementary relationship in geohazard management:

Resilience assessment does not supplant risk assessment; rather, risk assessment remains essential for identifying and prioritizing known threats. The two approaches are complementary and mutually reinforcing:

Risk assessment as a foundation: identifies major threats and informs targeted resilience building, particularly for high-probability, high-impact risks requiring prevention and preparation.

Resilience assessment as enhancement: builds upon risk assessment to develop comprehensive system capabilities for managing all disruption types, especially unknown and complex shocks, with emphasis on post-failure recovery and adaptation.

The primary advantage of resilience assessment lies in its future-oriented nature, acceptance of uncertainty, and emphasis on systemic adaptability, recoverability, and evolutionary capacity. It enables organizations and communities to develop inherent shock absorption and bounce-back capabilities in contexts where complete risk prediction remains impossible, thereby maintaining competitiveness, reliability, and viability amid turbulence.

In summary, risk assessment identifies potential failures and their severity, while resilience assessment determines system capacity to withstand disruptions, recover expeditiously, and emerge strengthened. In an era characterized by profound uncertainty, the latter has become increasingly indispensable for sustainable geohazard management.

2.2 Assessment indicator system characteristics

Traditional geohazard susceptibility assessment and geohazard risk assessment rely mainly on the inherent natural indicators of the disaster-causing body to establish models and conduct current situation evaluations. Nevertheless, a geohazard emergency system is dynamic and constantly evolving, because this system is determined by its composition of the disaster-causing body, the exposed elements and the drive. It is essential not only to examine the system's static state at a specific point in time, but also to focus on understanding its dynamic trajectory and the underlying mechanisms driving its evolution. Therefore, the

proposed ‘hazard–impact–drive’ (HID) model for geohazard emergency system resilience assessment comprehensively analyzes multifaceted natural and socio-economic indicators of geohazard. Summarizing the indicator data in Figure 1, this paper can further analyze the characteristics of different attribute evaluation indicators, as shown in Figure 2.

In the context of the entire geohazard emergency system, the influence of the natural dimension is direct and immediate, whereas the impact of the socio-economic dimension is predominantly indirect and gradual. The mechanism through which the latter affects the geohazard emergency system primarily involves altering certain natural factors first, which then mediate the subsequent systemic impacts. This

Indicator categories	Common indicators	Assessment	
Nature	Topography	Susceptibility assessment <i>[Hazard (H)]</i>	$R = H \times I$
	Geological structure		
	Vegetation		
	Hydrology		
	Climate		
	Disaster		
	Human activity		
Economy & Society	Potential loss <i>[Impact (I)]</i>	Risk assessment <i>[Risk (R)]</i>	Resilience assessment
	Law		
	Policy		
	Investment		
	Education		
	Execution		
	GDP		
	Government		

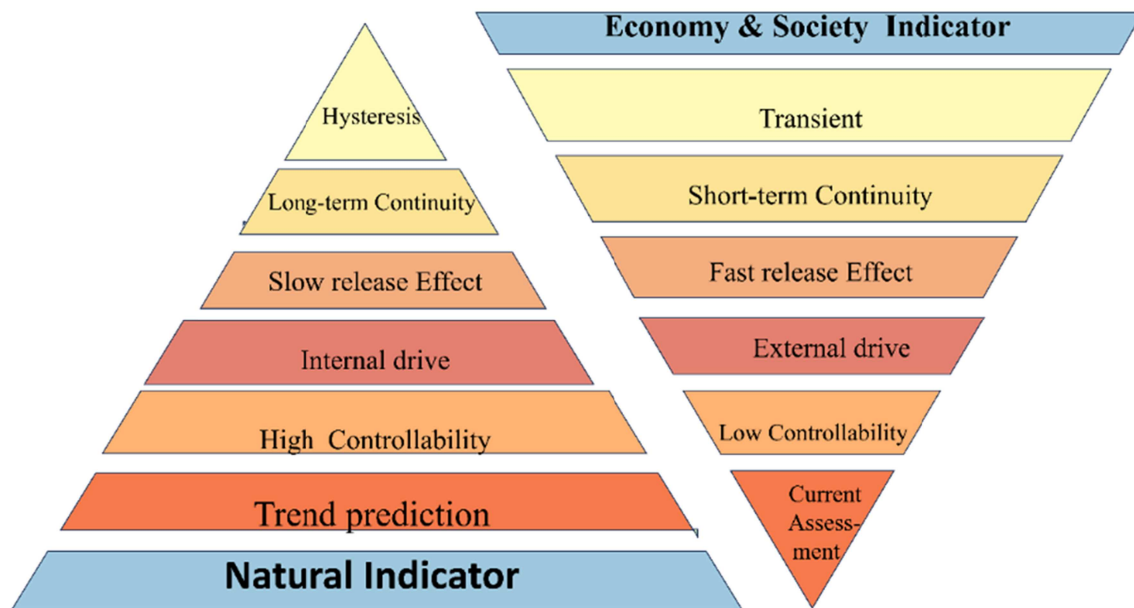


Figure 2. Indicator characteristics.

process highlights the delayed effect of the socio-economic dimension on the geohazard emergency system. As human awareness of environmental changes increases, adjustments within the social and economic domains are initiated, largely in response to changes occurring at the natural level. In essence, the natural dimension tends to produce more immediate outcomes and conditions, while the social and economic dimension functions as an internal driver that shapes these outcomes. Understanding these mechanisms not only deepens our comprehension of geohazard emergency system dynamics but also supports the selection and modelling of relevant indicators.

According to the current national guidelines and national standard specifications, summarizing social indicators, economic indicators and natural indicators, a comprehensive diagram of the geological disaster indicator system most commonly used is obtained, as shown in Figure 3.

As shown in Figure 3, the geological disaster indicator system selects 21 social indicators, 18 economic indicators, and 48 natural indicators and jointly establishes an aggregated indicator system. Among them, the natural indicators can provide a selection basis for subsequent geohazard risk assessment, while the social indicators and economic indicators can provide a selection basis for the resilience assessment and serve as a guide for the construction of a dual-control system.

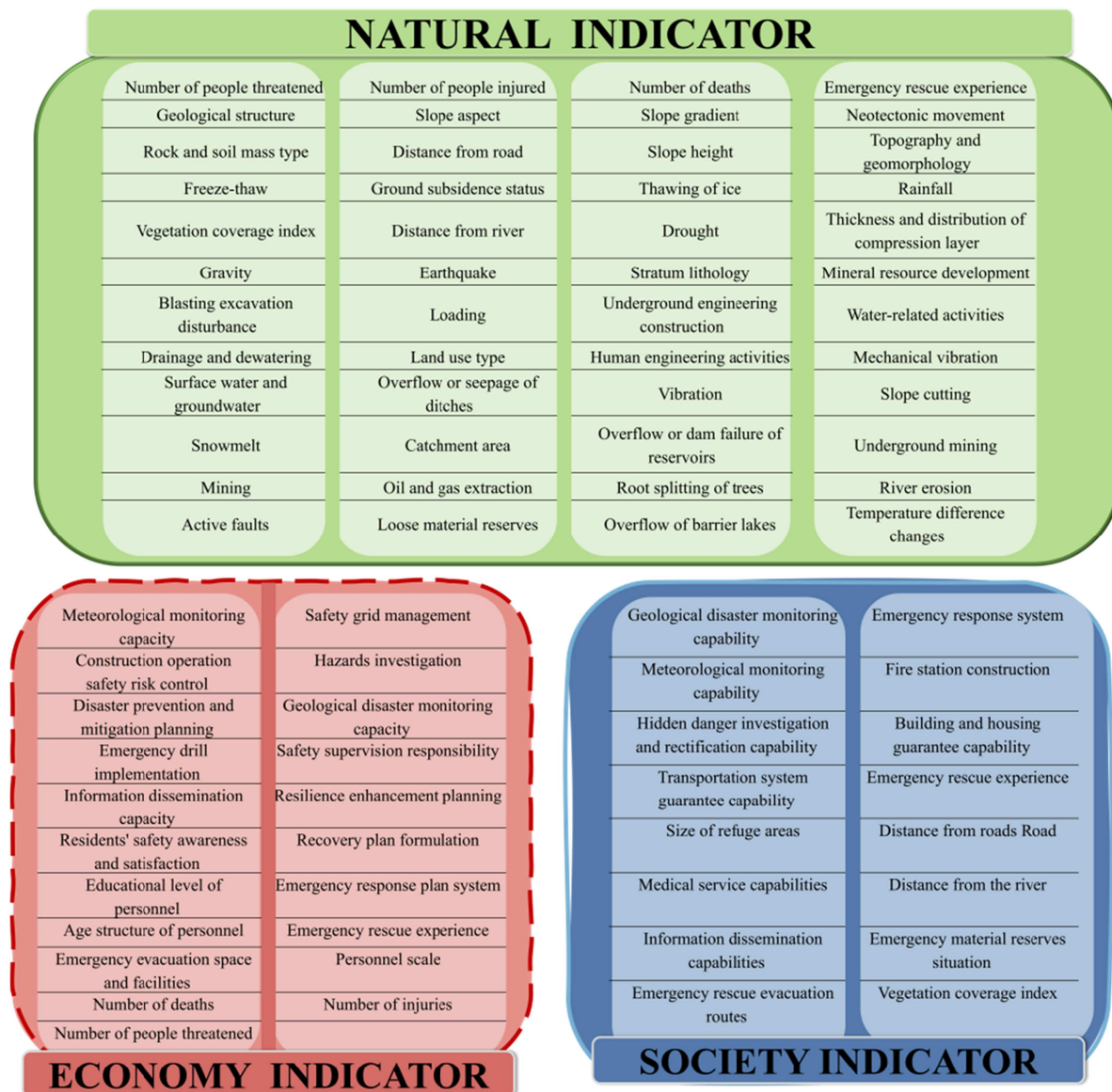


Figure 3. Geological disaster assessment indicator system.

2.3. Assessment unit

The present study adopts a universal geohazard assessment framework, employing evaluation indicators derived from eight generic categories of geohazards. Notably, this work transcends conventional case study methodologies. The Huanggu Town represents an application instance of the HID model rather than the research focus itself. The constraint to a single site reflects the intensive data requirements of slope-unit-based modelling, which demands comprehensive historical datasets and extensive field surveys. Future research will extend the HID model to multiple sites across varying geological settings to rigorously examine its transferability and universal validity.

The division of assessment units influences the accuracy and application of the geohazard risk assessment results. The assessment units need to be precisely divided during the geohazard emergency system resilience assessment process based on the scientific and quantifiability evaluation principles while considering geological and natural environment characteristics. Currently, the grid cell is the most often used technique for splitting evaluation units of regional evaluation in the fields of environmental and risk assessment, but it is not suitable for the field of geohazard because of the fundamental characteristics of the disaster-causing body. Geohazard assessment focuses on analysing or assessing specific geological units, while grid cells cannot adequately represent geological conditions.

This paper uses Huanggu Town, Ziyang County, Ankang City, Shaanxi Province of China, as an example to compare and illustrate the different effects of the two types of units. Figure 4(a) shows that the shape of each unit is regular when utilising the grid cell. Still, the divided grid lines do not align accurately with the real ridgelines and gully lines. Additionally, the evaluation unit does not conform to the mountain morphology and fails to represent the slope geological information accurately. The slope units refined based on UAV-acquired 3D vector data are regional units calibrated using 1:2000 scale drone-derived 3D vector datasets. These units exhibit irregular geometries that better align with actual geographical conditions. The refinement method ensures complete conformity to real slope morphologies, delivering high accuracy and minimal margin of error. Thus, this research employs the depth identification approach of 3D vector high-precision remote sensing data to automatically divide slope units, creating 647 slope units, as depicted in Figure 4(b).

The comparison between the three slope units and the actual slopes in Figure 4(b) demonstrates that the automatic slope unit division technique used in this paper accurately divides the units in accordance with the mountain. This technique effectively reflects the geographic environment and the factual information of the slopes.

2.4. Data source

As shown in Figure 2, the proposed ‘hazard–impact–drive’ model (HID) classifies the assessment indicators into two types: natural and socio-economic. This is partly due to the composition of the

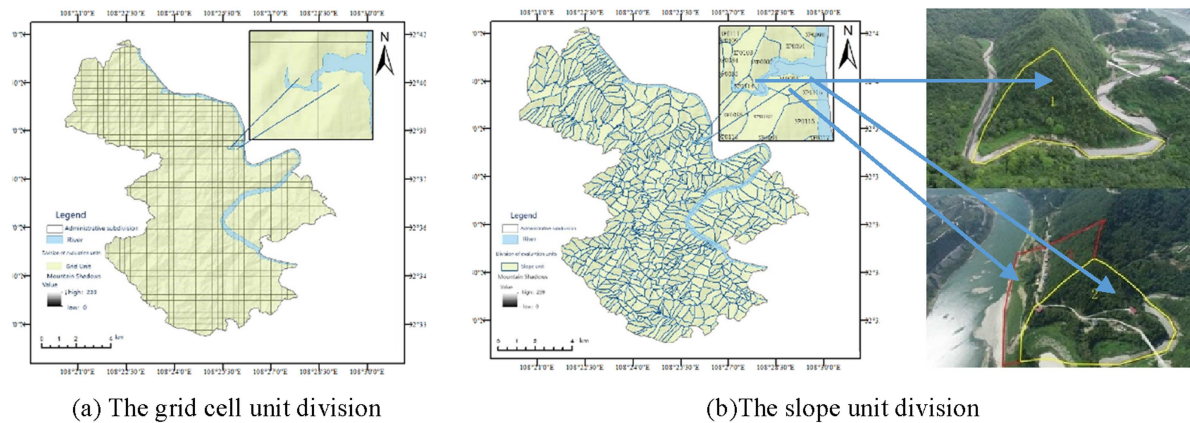


Figure 4. Comparison chart of evaluation unit division.

disaster-causing body, the exposed elements and drive, and partly because of the data sources. The accuracy of the assessment model is strongly dependent on the accuracy of the selected evaluation indicators and the reliability of the evaluation data sources. The data used in this paper are from three main sources. Most of the data for natural indicators come from remote sensing, while most of the data for socio-economic indicators are derived from official statistics and field investigations. Some examples of data sources are shown in Figure 5.

Remote sensing is the main source of natural indicator data. Remote sensing images must be pre-processed before being extracted and quantitatively analyzed to minimize or limit the impacts of geometric distortion, radiometric distortion, and other factors. The primary steps are radiometric correction, atmospheric adjustment, geometric correction, and image cropping (Xu et al. 2024). The calibrated remote sensing image overlay is compared and interprets multi-period picture data with digital elevation model (DEM) data, satisfying the need for thorough geological disaster research and judgment. Figure 5 depicts the extraction findings of the primary remote sensing indicators in Huangu Town in 2022.

For the greenness index (NDVI), considering its influence on forest fire danger, the most vigorous time of the forest between June and August each year was selected to extract the remote sensing image of Huangu Town. Initially, the pictures were radiometrically calibrated, atmospherically corrected, and vector-cropped to generate the remote sensing images of Huangu Town using ENVI 5.3. Secondly, using Equation (1.1) NDVI calculation function to obtain the NDVI data value through the observation data to determine the confidence interval. According to the characteristics of the study area, the Huangu town confidence interval as the cumulative regional percentage of 5%–95%. The NDVI values were normalized using the resulting confidence intervals, and the tif TIFF-format image of the NDVI was imported into ArcGIS to generate the results displayed in Figure 3a.

$$NDVI = \frac{NIR - R}{NIR + R}$$

where NIR is the near-infrared band and R is the red light band.

Of course, different types of data sources are not completely absolute. For instance, some key data about the exposed elements, such as housing data, can be derived directly from remote sensing, but official statistics and field investigations are needed for verification. To put it more clearly, although basic

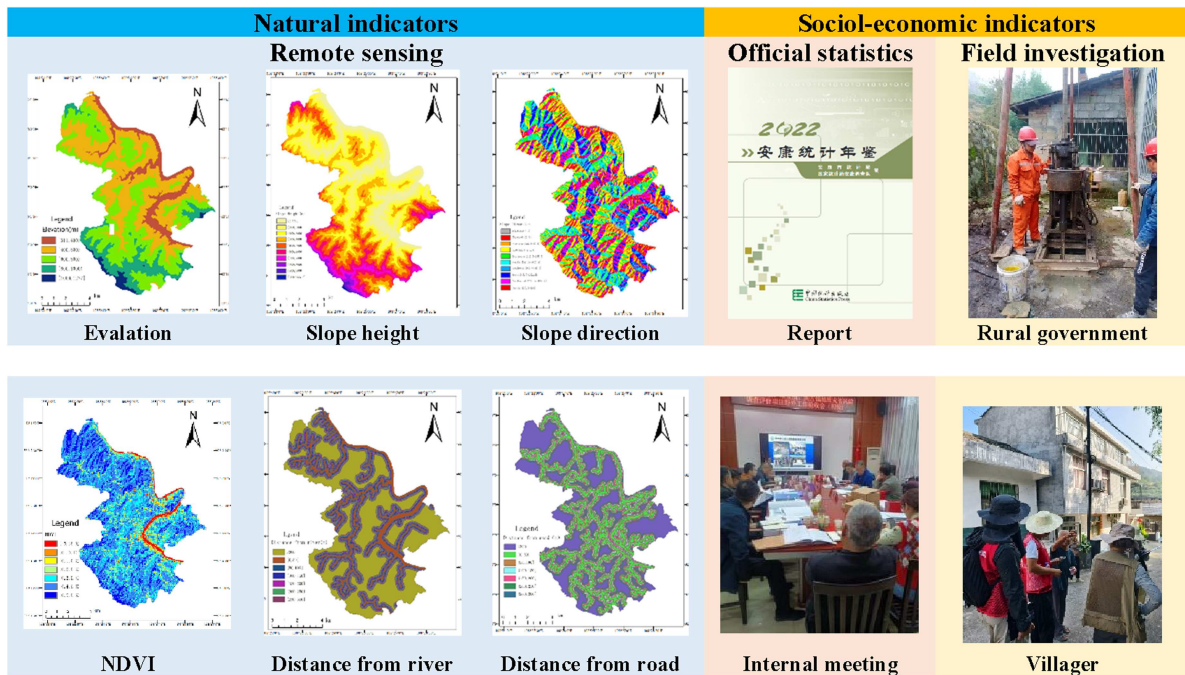


Figure 5. Data sources.

information about the houses can be directly obtained through remote sensing, whether the houses are still in use or if their purposes have changed still requires the latest version of the resident census report and field interviews for confirmation. Another example is that although rainfall data are a type of natural indicator data, they are obtained mainly through official websites of meteorological stations and annual reports, etc.

This research selects numerous natural and socio-economic data as evaluation indicators. However, further normalization is required because of the different units of the chosen evaluation factors. Normalization involves the application of mathematical formulas to regulate the values of assessment indicators within the range of 0–1. Furthermore, normalized data aids model training by accelerating data convergence and increasing computational accuracy. This normalised data processing selects the maximum–minimum normalization method, which is shown in Equation (2):

$$Y = (X - X_{\min}) / (X_{\max} - X_{\min}) \quad (2)$$

Y represents the normalised data, X represents the evaluation factor data, $X_{\max}$ represents the maximum data in the evaluation factor, and $X_{\min}$ represents the minimum data in the evaluation factor.

Data statement: Ethical approval was not required as the study used only secondary data from publicly available, de-identified sources. This study does not include any human or animal experiments. This study was conducted in compliance with data protection regulations. The investigation and use of resident data were approved by the Ankang Municipal Bureau of Natural Resources, ensuring that all the data were anonymized and securely stored. All participants were informed and provided verbal consent. All the data do not contain any personal information.

2.5. Weighing values of assessment indicator

After sufficient data are collected, the proposed ‘hazard–impact–drive’ (HID) model needs to determine the weights of each indicator through specific calculation methods. Overall, each method possesses distinct advantages and disadvantages.

1. Improved G1 method (IG1)

The improved G1 (IG1) method is a subjective weighting technique that extends the analytic hierarchy process (AHP) by incorporating sequential relationships among evaluation indicators (Xu 2013). The method employs a three-stage procedure: (1) decision-makers rank indicators by relative importance, (2) pairwise importance ratios between adjacent indicators are determined, and (3) indicator weights are computed based on these ratios. This approach leverages expert judgment to establish systematic indicator prioritization.

2. CRITIC method

The criterion importance through intercriteria correlation (CRITIC) method, developed by Diakoulaki et al. (1995), is an objective weighting technique grounded in two fundamental principles. First, the contrast principle quantifies variability within each indicator using standard deviation; greater temporal variance indicates higher discriminatory power and thus greater weight. Second, the conflict principle assesses inter-indicator relationships through correlation coefficients, where a lower correlation implies greater independence and information content. Weight assignment integrates both dimensions to balance discriminative capacity and informational diversity.

3. Matrix idea integration method (MIIM)

The matrix idea integration method (MIIM) applies matrix-based reasoning to multi-model fusion problems. The approach decomposes complex systems into constituent elements, organizing outputs from multiple models or data sources into matrix form. Integration proceeds through matrix operations (e.g. weighted summation, matrix multiplication) to generate consolidated predictions. An iterative

optimization process refines both matrix construction and fusion strategies based on performance feedback, thereby enhancing decision accuracy and providing a consolidated judgment.

The objective assessment method stands out for its reliance on data analysis and computational processes, which contribute to greater objectivity and accuracy in the results. The entropy method is the mainstream approach among objective assessment methods (Xu 2013). The entropy method is a mathematical evaluation technique grounded in the principles of information theory. It determines index weights by analyzing the degree of dispersion across indicators. The core principle of this method suggests that an index with lower information entropy exhibits reduced uncertainty, thereby having a greater influence on the overall evaluation process. The procedure typically involves key steps such as data standardization, entropy computation, and derivation of the difference coefficient. It is widely applied in fields such as economic management and engineering decision-making, where objective weight assignment is essential. Together with the factor score method, it forms a mainstream approach for determining index weights in multi-criteria decision-making frameworks. However, the entropy method, like other objective assessment methods, falls short in incorporating individual experience, subjective perceptions, and value judgments.

In contrast, the subjective assessment method, such as the improved G1 method, integrates human value judgments and enhances the traditional analytic hierarchy process. The improved G1 method is optimized based on the traditional ordinal relationship method, rejecting the condition of the original ordinal relationship method that requires the evaluation indicators to satisfy strong consistency among them, and proposing the view that the evaluation indicators satisfy weak consistency (Chen et al. 2011). Simultaneously, when the weights of the indicators are defined, objective information on the indicator data is coupled with subjective expert assessment. Nevertheless, as it primarily depends on subjective assessments, its persuasiveness may be limited, so the improved G1 method needs to be combined with traditional objective assessment methods.

To address this issue, the matrix idea integration method is employed to integrate these two approaches. Importantly, the proposed HID model is inherently non-linear in nature. The weight calculation process integrates the subjective judgment of experts (improved G1 method) and the objective information of indicator data (entropy method) through the matrix idea integration method, which involves complex non-linear operations such as pairwise importance comparison, information entropy calculations, and matrix fusion. This non-linear mechanism enables the model to capture the complex relationships between geohazard factors that cannot be reflected by simple linear superposition. The relatively intuitive linear presentation of the final resilience results is a simplification for engineering application convenience – aiming to facilitate policy makers and practitioners quickly grasping risk distribution and formulating targeted measures, rather than indicating that the model itself relies on linear superposition logic. This combined method benefits from both subjective insights and objective data extraction (Zhang and Wei 2012). It creates matrices that combine information from numerous models or data sources, hence improving decision accuracy and stability. The outputs of several models or information from data sources are first organized into a matrix, and the information in the matrix is then fused using matrix operations (e.g. weighted summation, matrix multiplication, etc.) to provide a consolidated judgment. Finally, based on the performance feedback from the fusion results, the matrix construction and fusion technique are modified to further enhance the integration impact.

Based on the preceding discussion and the finalization of the findings on the concepts, the concepts and methodologies outlined in this paper are synthesized here, as depicted in Figure 6, to offer a more comprehensive illustration of the construction of the evaluation model.

As shown in Figure 6, objective weighing can occasionally provide misleading results due to sample data; however, subjective weighting can be heavily influenced by human experience. To address these issues, a combination of the subjective improvement of the improved G1 method and the objective entropy method was applied, with the resulting assessment indicators merged and weighted using the matrix idea integration method. This technique aims not only to achieve uniformity in the weighting of evaluation markers across different assignment mechanisms but also to ensure consistency in the evaluation process. It also aims to minimize the disparity between the aggregate weights of each assessment indicator and the individual weights calculated by each assignment technique, thereby creating a more scientifically rational system.

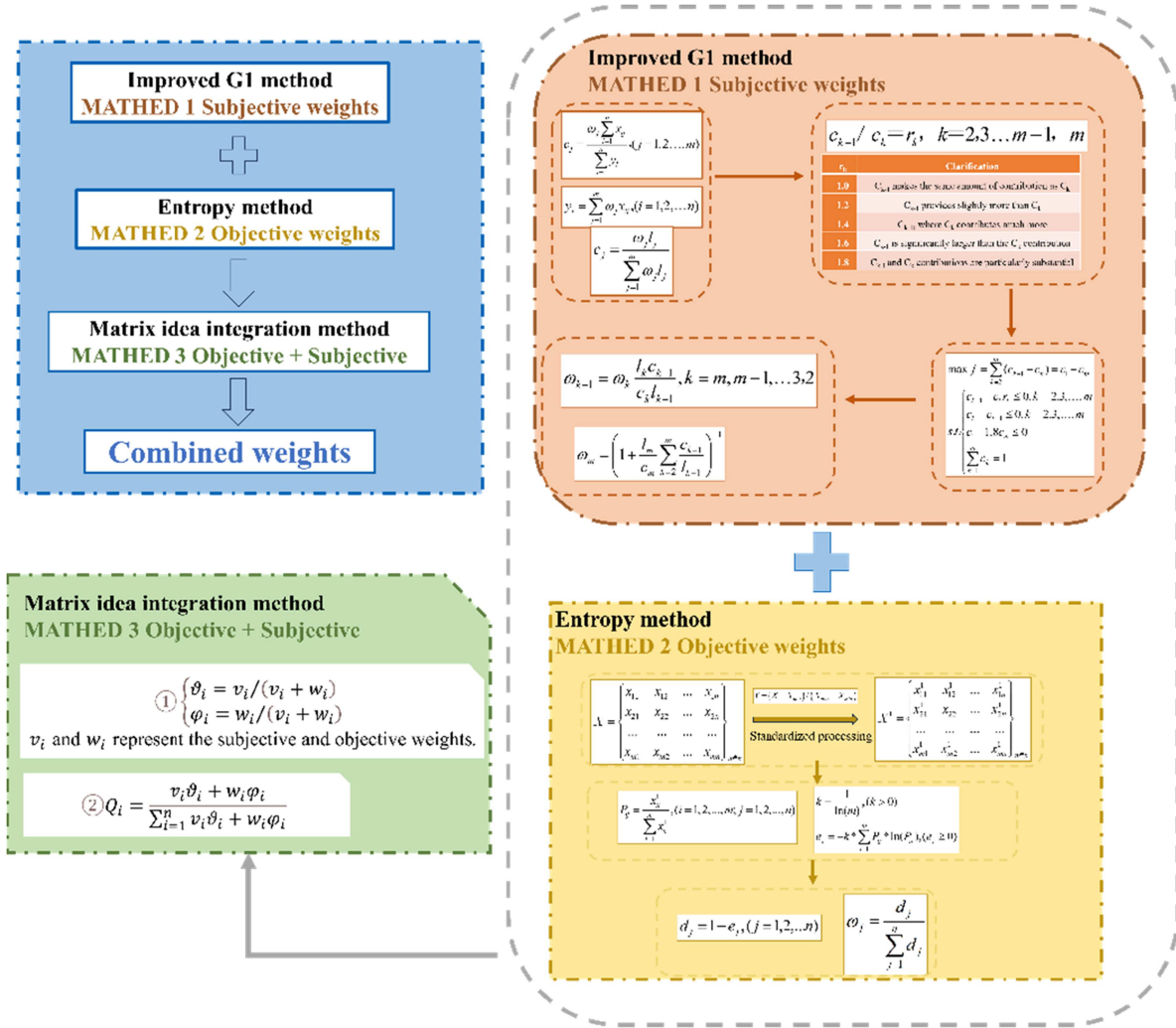


Figure 6. Assessment model construction diagram.

3. Example applications

3.1. Study area

Huanggu Town is in Zi Yang County, Ankang City, Shaanxi Province, China. It is situated in the northwestern portion of Ziyang County, bordering Artemis Town and Shuang'an Town to the east, Chengguan Town and Xiangyang Town to the south, Hongchun Town and Dongmu Town to the west, and Hanwang Town to the north (as shown in Figure 7). Eleven administrative villages govern Huanggu Town and have a north-south length of 10.1 km, an east-west breadth of 18.5 km, and a total area of 108.58 square kilometers, with the town covering 102 square kilometers. The Qinling Mountains in the north and the Ba Mountains in the south form a screen, with overlapping mountains and gullies within their territory, which has a typical subtropical humid monsoon climate.

Huanggu Town is in the Qin-Ba mountainous area, with high mountains, deep ditches, steep slopes, and a wide distribution of slippery stratum. Because the geological environment is fragile, the territory experiences regular occurrences of landslide risks, with all listed geohazard sites in the town experiencing landslide hazards.

Based on the geological and ecological characteristics of Huanggu Town, the selection of evaluation indicators needs to consider the following aspects:

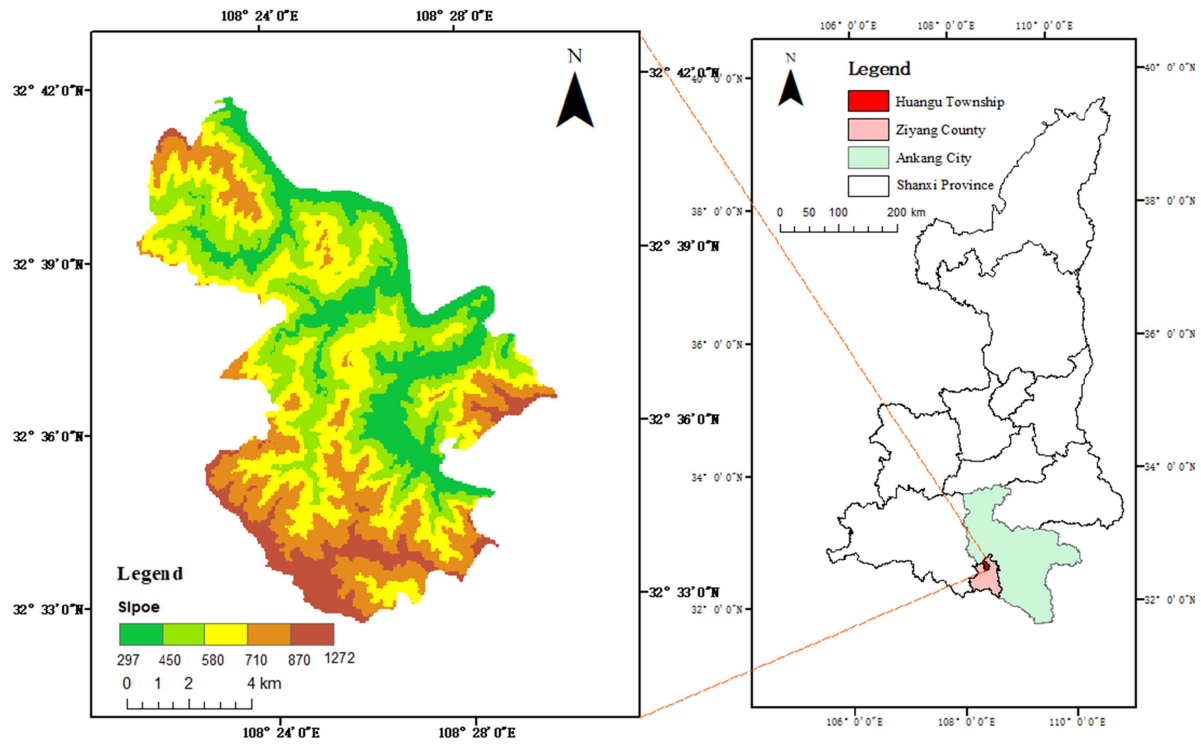


Figure 7. Geographical location of Huanggu Town.

1. Weather. The Huanggu Town is located in a northern subtropical humid monsoon climate zone. The Qin-Ba mountains in the north block the cold current, while the warm and humid airflow in the south ensures ample rainfall and a mild climate. There are more rainstorms in the district, which are characterized by their suddenness, short duration, small coverage area, and concentrated rainfall. This occurs primarily between June and September, with July and August being the most common months. Sudden geologic disasters caused by short-term severe rainstorms are common (Xu et al. 2024); hence, Huanggu Town experiences a high frequency of landslide geologic disasters during the summer and fall.
2. Topographic landforms. Huanggu Town has a low hilly topography with steep slopes ranging from 20° to 40°, making it susceptible to high rainfall and natural calamities.
3. Rock soil mass type. Harder, thinly laminated slate, with a more fragmented rock body, exhibits easy weathering. The area is characterized mainly by the accumulation of soil on slopes and the accumulation of gravel on residual slopes, which are prone to causing landslides and geological catastrophes.
4. Human activity. The Huanggu town is involved in various activities, including agricultural development, road construction, and slope cutting for housing purposes. They are vulnerable to geological disasters and disrupt the natural ecosystem (Hou et al. 2024).

3.2. Resilience assessment indicator system

Combining the impact factors of disaster prevention and mitigation in the previous literature, indicators of natural, economic, and social categories are selected, and appropriate indicators are screened from the three levels of resistance, adaptability, and recovery to construct an evaluation index system of disaster mitigation power. Based on the characteristics of Huanggu Town, the evaluation indicators shown in Figure 3 were screened and integrated, and 31 indicators were ultimately extracted. The established assessment indicator system is shown in Table 1.

The selection of the indicator system for this study is based on theoretical support and empirical verification. Following the principles of orientation, comprehensiveness, and feasibility, a four-tiered

Table 1. Resilience assessment indicator system for Huangu town.

Target layer	Criterion layer	Element layer	Indicator layer
Resilience	Resistance (A1)	Infrastructure resilience (B1)	Housing security capacity (C1)
			Transportation security capacity (C2)
		Risk control capacity (B2)	Geohazard investigation and rectification (C3)
			Meteorological and geological disaster monitoring (C4)
			Disaster information release capacity (C5)
			Geological disaster monitoring capabilities (C6)
		Natural geography (B3)	Road distance (C7)
			River distance (C8)
			Slope height (C9)
			Slope direction (C10)
			NDVI(Normalized vegetation Index)(C11)
			Slope (C12)
	Adaptability (A2)	Self-rescue and mutual rescue capability (B4)	Personnel size (C13)
			Personnel age structure (C14)
			Educational attainment of personnel (C15)
		Emergency awareness and capability (B5)	Emergency rescue experience (C16)
			Emergency shelter size (C17)
			Residents' safety awareness and satisfaction (C18)
		Management system construction (B6)	Emergency equipment configuration (C19)
			Responsibility for geological disaster safety supervision (C20)
			Special Plan for Disaster Prevention and Mitigation (C21)
			Resilient Rural Enhancement Plan (C22)
	Recovery (A3)	Emergency support capacity (B7)	Development of village-level recovery plans (C23)
			Emergency response system (C24)
			Emergency drills carried out (C25)
			Rural safety grid (C26)
			Fire facility construction status (C27)
			Emergency material reserves (C28)
			Understanding of emergency shelters and facilities (C29)
			Emergency rescue evacuation access status (C30)
			Medical service personnel (C31)

structure was gradually developed at the levels of target, criteria, elements, and indicators to reflect the features and genuine needs of geohazard resilience fully.

The criterion layer is chosen based on the theoretical foundation of the catastrophe resilience model and is divided into three dimensions: ‘resistance’, ‘adaptability’, and ‘recovery’ (Zhou et al. 2010; Aydin et al. 2018; Ismail-Zadeh 2024).

The ‘Resistance’ evaluates the ability of a system area to tolerate the severity of geohazard risk and respond to external threats to manage the damage to the system produced by geohazard disruptions. ‘Adaptability’ refers to the system's stability as well as its ability to understand and prepare for hazards during the planning and building phase, allowing it to react better to future dangers. ‘Recovery’ refers to the ability of a disaster area to return to its original social, economic and environmental conditions following a geologic hazard.

The element layer's design is based on the natural geographic environment characteristics as well as the current catastrophe risk conditions in Huangu town. It is broken down into seven components: infrastructure resilience, risk prevention and control capacity, natural geographic indicators, self-rescue and mutual help ability, emergency response awareness and capacity, management system development, and emergency response security capacity.

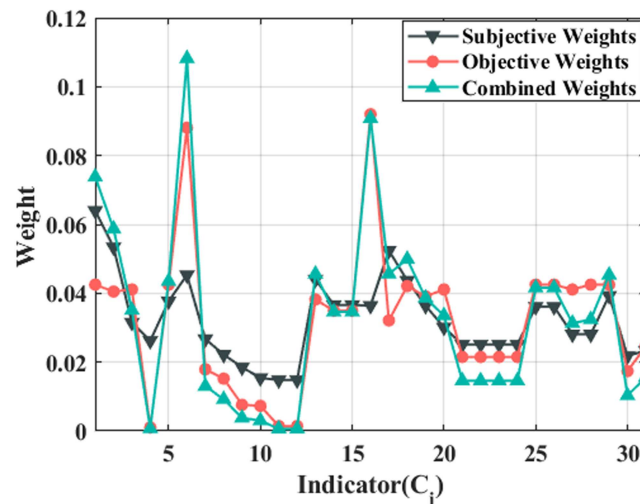
3.3. Resilience assessment indicator system

According to the data in Table 1, the subjective weights of the indicators were computed using the improved G1 method, while the objective weights were derived using the entropy method. Finally, using the ‘matrix idea’ integration method, subjective and objective weights are combined to generate a comprehensive weight, making the final weight assignment more acceptable and precise. The weight assignment table is presented below (Table 2).

Figure 8 depicts the weight fitting method.

Table 2. Assignment of weights to assessment indicators.

Criterion layer	Element layer	Weight			Indicator layer	Weight		
		Subjective	Objective	Combined		Subjective	Objective	Combined
A1	B1	0.1174	0.083	0.1324	C1	0.064	0.0425	0.0738
					C2	0.0534	0.0405	0.0587
	B2	0.1407	0.1727	0.1875	C3	0.0315	0.0411	0.0351
					C4	0.0262	0.001	0.0007
					C5	0.0377	0.0425	0.0435
					C6	0.0453	0.0881	0.1082
					C7	0.0267	0.0179	0.013
					C8	0.0222	0.0152	0.0092
	B3	0.1124	0.0508	0.0301	C9	0.0185	0.0076	0.0038
					C10	0.0154	0.0073	0.003
					C11	0.0148	0.0014	0.0006
					C12	0.0148	0.0014	0.0006
					C13	0.044	0.0382	0.0456
					C14	0.0366	0.0349	0.0346
A2	B4	0.1172	0.108	0.1149	C15	0.0366	0.0349	0.0346
					C16	0.0364	0.092	0.0908
	B5	0.1689	0.2053	0.2249	C17	0.0524	0.0321	0.0456
					C18	0.0437	0.0421	0.0499
					C19	0.0364	0.0391	0.0386
					C20	0.0301	0.0411	0.0335
					C21	0.0251	0.0215	0.0146
					C22	0.0251	0.0215	0.0146
	B6	0.2027	0.2121	0.1753	C23	0.0251	0.0215	0.0146
					C24	0.0251	0.0215	0.0146
					C25	0.0361	0.0425	0.0416
					C26	0.0361	0.0425	0.0416
					C27	0.0281	0.0411	0.0313
					C28	0.0281	0.0425	0.0324
A3	B7	0.1407	0.1681	0.1349	C29	0.0393	0.0425	0.0453
					C30	0.0218	0.0174	0.0103
					C31	0.0234	0.0246	0.0156

**Figure 8.** Weight-fitting procedure.

4. Results

4.1. Geohazard emergency system resilience

4.1.1. Resilience values of each slope unit

The proposed ‘hazard–impact–drive’ (HID) model, combined with the data in Table 2, was used to calculate the geohazard emergency system resilience index of each slope unit within the study area using the ArcGIS raster calculator to assign reasonable weights to each index. Weighting the toughness level values of each slope unit using the weight values generated by the enhanced ordinal relationship and

entropy value methods. The resilience level values are partitioned proportionally based on the Resilience Evaluation Guide's scoring ranges. The resilience values are grouped into resilience levels, which are labelled from low to high as low resilience, middle resilience, high resilience, and extremely high resilience, and are represented by four colours: red, yellow, cyan, and blue.

The reclassification function of ArcGIS was utilized to obtain a zoning map for the toughness evaluation of slope units, as shown in Figure 9.

For ease of interpretation, the colour scheme of the resilience map is adapted from the four-zone security diagram. However, since resilience exhibits an inverse relationship with security risk, regions with lower resilience values are marked in red – consistent with the high-risk zone in the security colour scheme – to draw attention to areas requiring prioritized management and intervention.

Figure 8 shows that places with low levels of resilience are largely uninhabited and roadless, remote, sparsely populated, inadequately secured, and dominated by high hilly terrain, which usually has poor infrastructure and planning. The majority of high-resilience areas are highways and places where people congregate because they are easy to manage, have strong protection capabilities, complete infrastructure, convenient transportation, and high villagers' awareness of emergency response, and they can swiftly activate prevention and response.

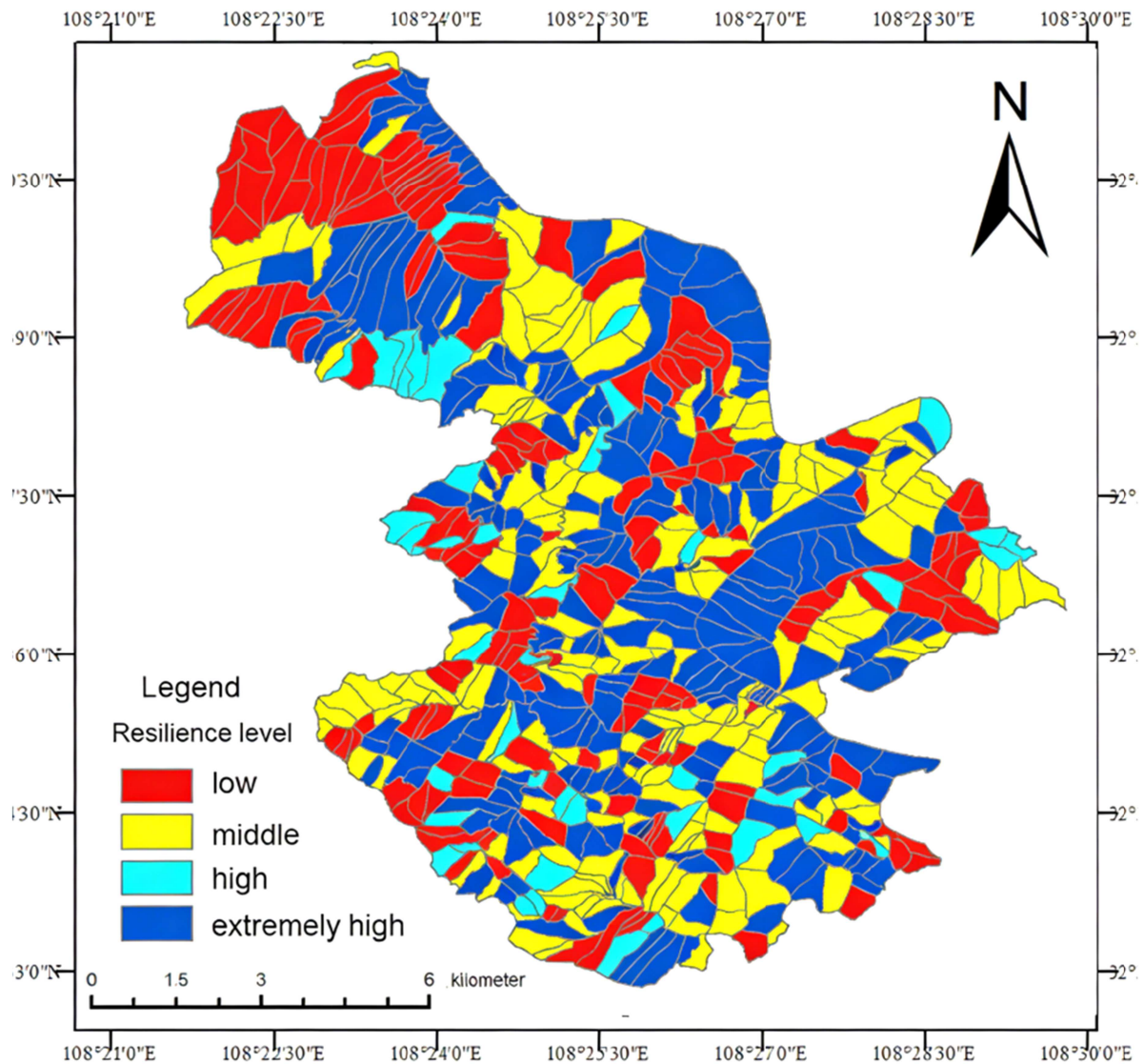


Figure 9. Resilience value and four-colour chart of each slope unit in Huangtu town in 2022.

4.1.2. Resilience values of village unit

Geohazard emergency system resilience is used mainly to evaluate the emergency management capabilities of various levels of administrative departments, especially those at the township level and village level. Therefore, it is necessary to calculate the resilience level values for each village in Huanggu town. By weighting and averaging the resilience level values of all slope units in each village according to their unit areas, the resilience evaluation zoning map of administrative villages is obtained using ArcGIS's reclassification tool based on the toughness level value of each slope unit, as illustrated in Figure 10.

As shown in Figure 10, Miaoxi Village, Chunyan Village, Liujiahe Village, Huanggu Village, Donghe Village, and Lazu Village are examples of areas with high resilience levels. These six villages typically have a large population, well-developed infrastructure, well-developed delivery, and a strong emergency response capability that enables quick prevention and response. The outstanding features included the building of emergency shelters in Huanggu and Lazhu villages (C18), emergency evacuation drills in Liujiahe village (C25), and the awareness of disaster prevention among the inhabitants in Chunyan village (C17).

This related to Ziyang County's post-disaster reconstruction project, which was completed in 2021. This involves removing landslides from the system village's main road and rebuilding the transportation

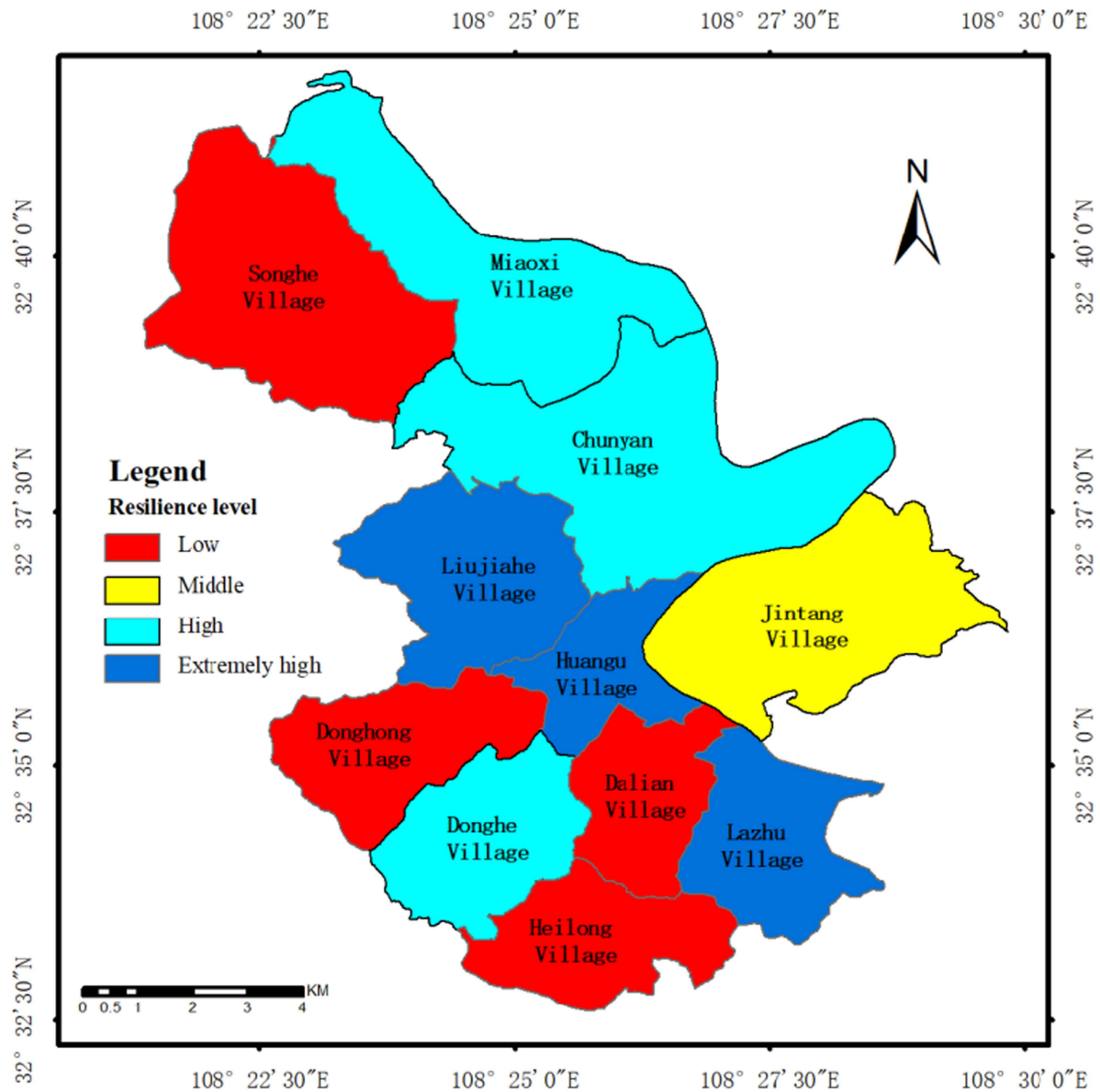


Figure 10. Resilience zoning map of administrative villages in Huanggu Town in 2022.

infrastructure, including retaining walls, pavement, bridges, and security. The development of a comprehensive catastrophe prevention and relief system that makes use of public underused assets, such as abandoned school buildings and recreation plazas, in order to completely construct emergency shelters and emergency material depots in towns and villages. Comprehensively pushing the building of the emergency broadcasting system, ensuring that emergency broadcasting is available in villages and villages, enhancing the ability to distribute emergency information, and doing well in terms of risk prevention and control capacity indication (B2).

Emergency evacuation drills in Liujiahe Village (C25) and villagers' disaster prevention awareness in Chunyan Village (C17) are linked to the village's experience with a landslide geological disaster in 2022. Following the disaster, villagers' perceptions of risk and awareness of disaster prevention were increased, and they became more familiar with the village shelter. Fire safety facilities in densely populated areas following a disaster should be improved, emergency drills and related knowledge publicity and training should be conducted on a regular basis, town and village emergency response teams should be established, the emergency management system should be improved, and good performance should be achieved on the management indicator system (B6).

The Village of Pine River has the lowest level of resilience, having completed construction of the Migrant Security Housing Project in 2017. It has more developed transportation networks and a high Infrastructure Resilience (B1) score. However, the overall hill is steeper, and human engineering operations such as building houses and roads, mining, and clearing land for planting have affected the structure and vegetation conditions of the slopes, which have a worse natural geography indication (B3) compared to other settlements; economic development is more backward, staff size is small, the ability to endure shocks is limited, and the self-rescue and mutual help indicator score (B4) is poor. The management indicator system (B6) received a low score because the villages have had the majority of their migrants relocated, the infrastructure configuration was not perfect, and the emergency protection capacity was limited, preventing timely prevention and response to geologic hazards. To strengthen disaster resilience, the Village of Pine River began construction on an emergency security project in 2021, which is expected to increase the ability of the Emergency Security Capacity Indicator (B7).

4.2. Resilience change trend

To analyze the process of change and development trend of geohazard risks and geohazard emergency system resilience in the study region, the transition of the development of 'long-term dynamic prevention and control' should be realized. This paper gathers resilience index data from 647 slope units in Huangu town from 2013 to 2022, and the resilience evaluation is carried out using the aforesaid approach to obtain the geohazard resilience indices of 647 slope units over the decade 2013–2022. Figure 11 depicts the changing process of geohazard resilience in Huangu town over the decade from 2013 to 2022, which was weighted and averaged based on the real area of each slope.

To enhance the visual interpretation of the figure, the vertical axis representing resilience values has been inversely oriented. Accordingly, higher positions on this axis correspond to lower resilience scores, meaning that greater distances from the x-axis (years) indicate diminished resilience.

As shown in Figure 11, the resilience index of Huangu town generally remains steady throughout the decade from 2013 to 2022, with slight fluctuations. However, the risk index in Huangu town sharply decreased to approximately 0.07 in 2021 and then recovered to the normal range the following year. The change process of the resilience index is consistent with the change in the number of disaster occurrences and their direct economic losses, as counted in the *Ankang Statistical Yearbook* published by the Ankang Municipal Government, confirming the accuracy of the evaluation method proposed in this paper.

Changes in the resilience index are frequently influenced by both internal drivers of the socio-economy and external triggers of the natural environment. Because the proposed 'hazard–impact–drive' model (HID) for geohazard emergency system resilience assessment comprehensively analyzes multifaceted natural and socio-economic indicators of geohazard, the influences of natural and socio-economic factors on the changes in resilience indicators can be clearly observed in Figure 11.

As shown in Figure 10, in terms of the influence of natural factors, owing to the continuous improvement in the geological environment in the Qin-Ba mountains, the resilience index generally

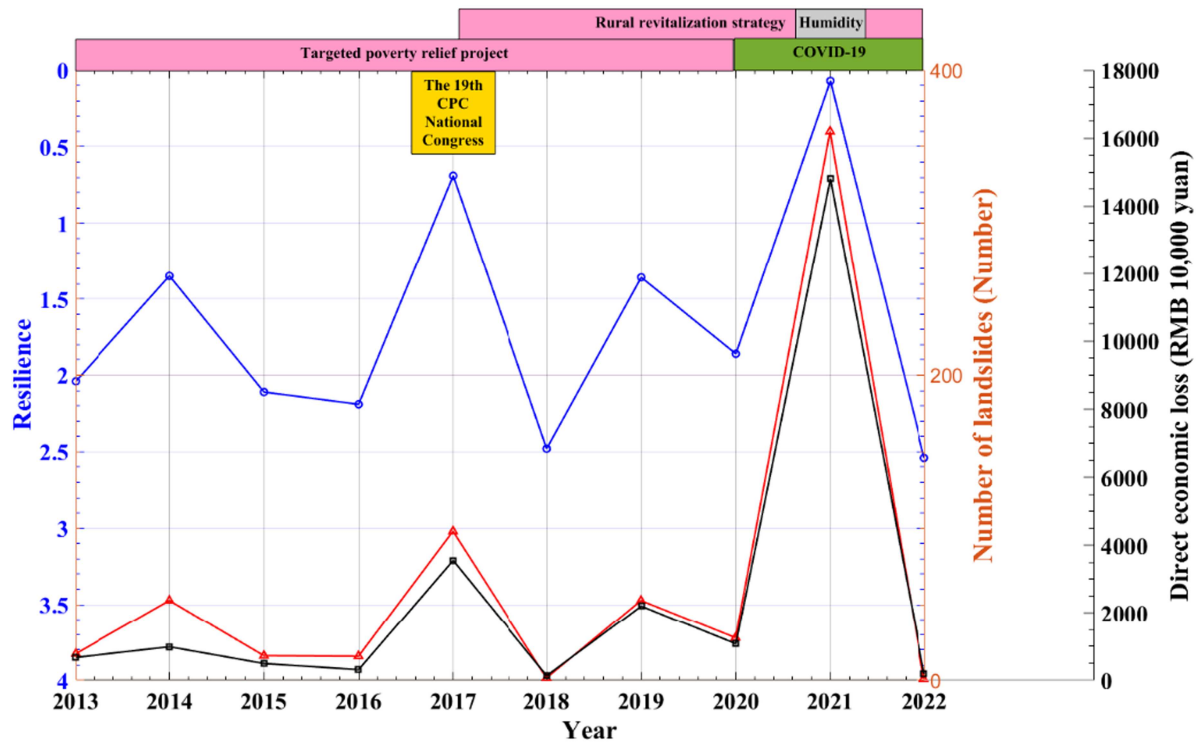


Figure 11. Resilience and factor changes.

shows a continuous and stable trend. Only in 2021, when the highest rainfall occurred in Huanggu town over the past ten years, due to a rare rainstorm disaster, did the resilience index suddenly accelerate to its lowest value. Around the same period in 2021, owing to the indirect impact of the sudden outbreak of the COVID-19 pandemic in early 2020 on geohazard emergency management work, this delay effect further led to the lowest resilience index value in 2021, and as the COVID-19 pandemic ended, the resilience index rebounded and rose in 2022. The examples of the impact of natural factors on resilience mentioned above indicate that the effects of natural factors are direct and immediate, but they can quickly recover once the natural event is over.

The economic factors have shown an overall upward trend. This is attributed not only to the steady development of the national economy as a whole, but also to the influence of economic policies and measures, such as the ‘Targeted Poverty Relief Project’ initiated in 2012 and the ‘Rural Revitalization Strategy’ launched in 2016, etc. Due to the external shock of the COVID-19 pandemic in 2020, the economic index suddenly decreased, but it soon recovered in a ‘V’ shape in 2021 and returned to the original upward trajectory.

The multi-scale policy architecture demonstrated hierarchical effectiveness patterns. National-level strategic directives (19th National Congress environmental mandates) establish overarching frameworks that cascade through provincial regulations (Shaanxi Geological Disaster Prevention Programme) to local implementation mechanisms (Ziyang County ‘two areas and two lines’ action). Each administrative tier introduces additional implementation delays while also providing opportunities for context-specific adaptation and resource concentration. The designation of Ziyang County as a priority prevention zone exemplifies how targeted resource allocation within broader policy frameworks can accelerate localized resilience improvements.

Social factors are influenced mainly by government policies and their implementation effects. With the convening of the *19th National Congress of the Communist Party of China* in 2017, the urbanization process accelerated significantly, and investment in various rural industries strengthened markedly. With the convening of the *19th National Congress* in 2017, the State strengthened the direction of environmental protection, sustainable development, and green development by promulgating a series of laws and

regulations on geological ecological protection, such as the *Implementation Opinions on Accelerating Green Mines*. In 2017, the Shaanxi Provincial Land Department announced the *2017 Shaanxi Province Geological Disaster Prevention and Control Programme*, which identified Ziyang County as a significant geological disaster prevention county. In the same year, Ziyang County implemented the ‘two areas and two lines’ unique prevention and control action, focusing on ‘urban residential concentration areas, mining areas, highways, and railway lines,’ which initiated a gradual decrease in the level of riskiness starting in 2017.

Although various laws and regulations were promulgated by the government at all levels in 2017, the regulations and policy measures have characteristics such as long-term effectiveness, gradual release, and lag. Therefore, the effects of these policies did not become apparent until the following year. Additionally, the sudden outbreak of the COVID-19 pandemic in 2020 affected the normal operation of society and its management work, resulting in the adverse impact of social factors on resilience being quite obvious. However, with the end of the epidemic and the manifestation of the effects of the policies, the social factor is expected to show a gradually positive trend in the future.

Moreover, policy resilience itself – the capacity of governance frameworks to maintain effectiveness under external shocks – emerged as a critical factor. The COVID-19 pandemic disrupted the continuity of policy implementation continuity during 2020–2021, demonstrating that even well-designed disaster resilience policies remain vulnerable to concurrent systemic shocks. This finding highlights the necessity for adaptive governance mechanisms that can maintain core prevention and mitigation functions during periods of broader societal disruption, potentially through redundancy in implementation pathways and decentralized operational capacity.

From 2022 to 2023, people will be more conscious of the necessity of disaster prevention and control, and counties will conduct a geological disaster risk census and develop a dual-control system of ‘hidden hazard points + risk zones’ for geological catastrophes. An 80% increase in geohazard monitoring, a 50.03% increase in emergency response inputs, and a 100% increase in housing security inputs improved the ability to prevent and avoid disasters, and resilience increased by 97.2%. All these efforts also led to a rapid recovery of the resilience index after 2022.

The dynamic and predictive capabilities of the HID model are prominently reflected in the Drive component, which enables the model to go beyond the description of historical and current risks and realize the prediction of future resilience evolution trajectories. The socio-economic factors in the Drive component (such as government policies, economic investment, and social management systems) have obvious forward-looking and guiding characteristics: for example, the ‘Rural Revitalization Strategy’ launched in 2016 not only promoted the steady growth of economic indicators but also indirectly improved the regional resilience level through the construction of rural infrastructure and the enhancement of disaster prevention capabilities; the designation of Ziyang County as a key geological disaster prevention county in 2017 laid the foundation for the subsequent improvement of risk prevention and control capabilities (B2) and emergency support capabilities (B7). By analyzing the historical change rules of these driving factors and their coupling effects with natural factors, the HID model can effectively predict the future resilience change trend of the geohazard emergency system, providing a scientific basis for the formulation of long-term dynamic prevention and control strategies.

Short-term fluctuations are driven mainly by instantaneous natural factors (such as an abnormal climate directly increasing the risk), while long-term trends are deeply regulated by the cumulative reconfiguration of the socio-economic system (such as the long-term and lagging characteristics of the implementation effect of regulations and policies, and the complex impact of the epidemic on economic activities and social operations). This law confirms the driving mechanism of the geohazard emergence system: the natural system directly and instantaneously affects risk through explicit and instantaneous means, while the socio-economic system gradually reconfigures and cumulatively alters the risk base through implicit and cumulative changes. The dynamic feedback of these two systems jointly shapes the phased turning points and non-monotonic trajectory of the resilience index, highlighting the systematic need for coordinating immediate response and long-term governance.

In summary, the changes in the resilience index are the result of the dynamic coupling between the natural system and the socio-economic system. In other words, the changes in the resilience index are

often influenced by both internal drivers of the socio-economy and external triggers of the natural environment.

The temporal validation approach employed in this study demonstrates methodological robustness through multi-period resilience assessment. By comparing the resilience indices across the decade-long observation period (2013–2022) against documented geohazard losses and occurrence frequencies, we establish an empirical correspondence between the calculated indices and the observed disaster impacts. This longitudinal validation is critical for two reasons: first, it confirms that the proposed HID model captures actual disaster impact trajectories rather than merely reflecting statistical artifacts; second, the temporal analysis reveals that our resilience indices exhibit characteristic resilience-related properties, including absorption capacity during shock periods, degradation under sustained stress, and recovery potential following disturbance cessation. The non-linear response patterns observed – particularly the sharp decline in 2021 followed by rapid recovery in 2022 – demonstrate that the assessment framework successfully captures the dynamic, non-monotonic nature inherent to resilience systems, distinguishing it from static vulnerability assessments that fail to reflect temporal adaptation and recovery dynamics.

4.3. Correlation analysis

Correlation analysis constitutes a fundamental component of disaster resilience modelling, as it facilitates the identification of key determinants and elucidates model uncertainty. To evaluate the robustness and sensitivity of this rural disaster resilience assessment framework, this study conducts a comprehensive examination of the correlations between each assessment indicator and the geohazards resilience index, as well as their sensitivity. The analytical results demonstrate that indicators with higher composite weights exhibit stronger statistical associations with the DRI, which aligns closely with the fundamental principles of risk modelling – factors exerting greater influence on outcome variables typically receive proportionally higher weights.

A strong positive correlation is observed between the overall resilience index and key capacity indicators such as emergency rescue experience (C16, $r = 0.888$) and geological disaster monitoring capabilities (C6, $r = 0.663$), underscoring their central role in shaping resilience outcomes. Housing security capacity (C1, $r = 0.600$) also shows a notable association, reflecting the importance of basic infrastructure.

Within the topographic domain, slope-related indicators – slope height (C9), slope direction (C10), and slope (C12) – demonstrate near-perfect intercorrelations ($r \approx 1.0$), indicating a high degree of multicollinearity. This suggests that these variables capture overlapping aspects of terrain morphology and may be consolidated in subsequent modelling.

The Infrastructure and planning indicators exhibit moderate to strong positive correlations. For instance, housing security capacity (C1) is positively correlated with transportation security capacity (C2, $r = 0.356$) and emergency shelter size (C17, $r = 0.351$), reflecting synergistic development in physical infrastructure. Similarly, institutional planning indicators – including the Special Plan for Disaster Prevention and Mitigation (C21), Resilient Rural Enhancement Plan (C22), and Emergency response system (C24) – show consistent interrelationships ($r = 0.364$ – 0.418), indicating that governance mechanisms tend to be implemented in an integrated manner.

Monitoring and information-related capacities – such as meteorological and geological disaster monitoring (C4), disaster information release capacity (C5), and geological disaster monitoring capabilities (C6) – also form a coherent cluster with correlations ranging between 0.401 and 0.495, supporting the notion of complementary technological and informational subsystems.

Notably, the correlation analysis identifies minimal associations between certain variable pairs, providing evidence of dimensional independence. Topographical indicators (slope height, slope direction, and slope gradient) show near-zero correlations with institutional variables (emergency response system, disaster prevention plans, and emergency drill frequency), with correlation coefficients less than 0.10. This pattern confirms that physical terrain characteristics remain independent of policy interventions and institutional developments, validating the multi-dimensional structure of the assessment framework. The model appropriately distinguishes between immutable geographical attributes and mutable socioeconomic factors.

These correlation patterns validate the multi-dimensional structure of the resilience framework, where indicators within the same thematic domain co-vary meaningfully, while cross-domain independence helps avoid redundant information. The results provide a robust empirical basis for subsequent variable selection, model specification, and composite indicator construction.

In addition to the statistical correlation characteristics, the HID model further emphasizes the dynamic interaction mechanisms among factors, which is a key difference from static descriptive assessment methods. For example: (1) Housing security capacity (C1) and transportation security capacity (C2) are core components of infrastructure resilience, and their improvement is closely linked to institutional factors such as the Special Plan for Disaster Prevention and Mitigation (C21) and emergency drills carried out (C25). The government formulates targeted construction standards for disaster-resistant housing and emergency evacuation routes through C21, and allocates funds to upgrade rural housing structures (C1) and optimize transportation networks (C2); meanwhile, regular emergency drills (C25) based on the upgraded infrastructure help residents familiarize themselves with evacuation paths and improve the efficiency of disaster response, forming a 'management system construction → infrastructure upgrading → emergency capacity enhancement' interactive chain. (2) Geohazard investigation and rectification (C3) and meteorological and geological disaster monitoring (C4) provide key risk information support for the improvement of residents' emergency capabilities. The risk points identified through C3 and real-time monitoring data from C4 enable the targeted configuration of emergency equipment (C19) and emergency material reserves (C28), while the improvement of residents' educational attainment (C15) and emergency rescue experience (C16) enhances their ability to use monitoring early warnings and emergency resources, and their feedback on practical problems in disaster prevention further optimizes the focus of C3 and C4 work – forming a positive feedback loop between risk control measures, emergency support capabilities, and human capital factors. These interactive mechanisms are not static linear relationships but rather dynamic coupling processes that evolve with time and space, which are effectively captured by the HID model's three-dimensional structure (H–I–D) and multi-source data integration logic.

4.4. Internal driving mechanism

To examine the current status of a geohazard system, contemporary evaluation relies significantly on the natural indicators inherent in the issue under consideration. Geohazards, on the other hand, have complex and changeable cause mechanisms that are frequently linked to internal indicator drivers and exterior natural indicator triggers. Only by knowing the triggering mechanisms of past geohazards will we be able to properly prevent and minimize future geohazard-related losses.

Natural indicators have a direct impact on geohazard systems in general, whereas social and economic indicators have a more indirect and gradual impact. The latter process of influencing geohazards works primarily by changing specific natural components, which subsequently influence the geohazard system. This phenomena demonstrates the socio-economic dimension's lagged influence on the geohazard system. As people become more conscious of natural variability, adjustments in the socio-economic realms are being made in response to natural shifts. In essence, the natural dimension manifests more immediate consequences and conditions, but the socio-economic aspects are the internal catalysts that shape these 'outcomes and conditions'. In-depth study of these mechanisms not only improves our understanding of geohazard systems, but also helps in choosing and modelling key indicators. This approach not only provides a thorough understanding of the complexities of geohazards, but also can serve as a reference point for developing a robust geohazard evaluation system and selecting associated indicators.

Changes in the resilience data of Huangtu town over the years have proven that, in response to geohazards, even if the natural environmental conditions change abruptly, the regional system will be able to recover from changes in the disaster faster and reduce the impact of geologic hazards on the regional system because it has a certain degree of resistance and adaptability in the face of disasters.

Summarizing the indicator data in Table 2 and combining with the analysis of the changing trend shown in Figure 11, this paper can further analyze the characteristics of different attribute evaluation indicators, as shown in Figure 12.

As shown in Figure 12, the weights of each indicator are different, indicating that some socio-economic indicators play a very important role in the assessment results. The weight ranking at the element layer is

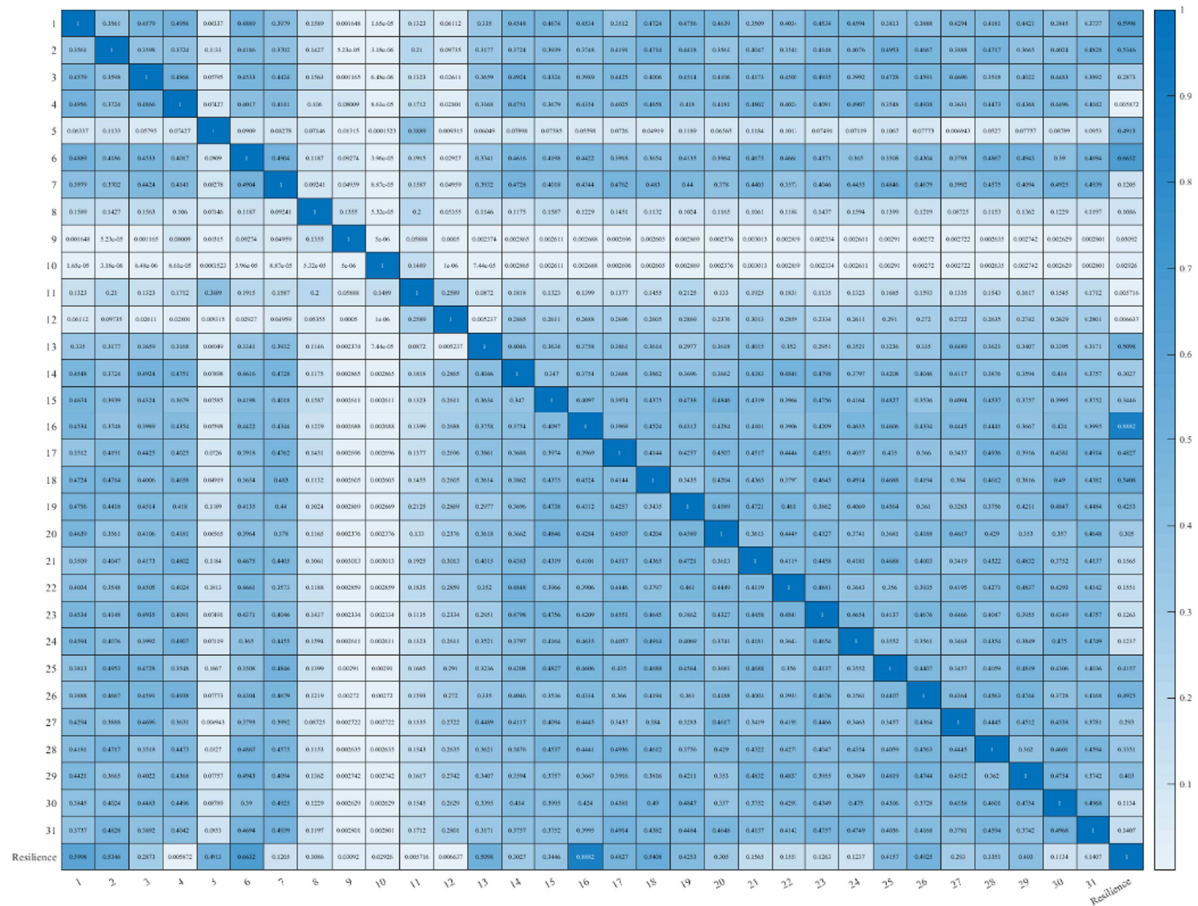


Figure 12. Dual-control system.

as follows: emergency awareness and capability (B5), risk prevention and control capability (B2), management system construction (B6), emergency support capability (B7), infrastructure disaster resistance capability (B1), self-rescue and mutual rescue capability (B4), and natural geographical indicators (B3). The indicators with the greatest influence on geological disasters are emergency awareness and capability, as well as risk prevention and control capability. This stage is also the most important stage for preventing geological disasters and reducing the impact range of the disasters.

Specifically, at the indicator layer, the weight rankings of the first three indicators are as follows: geological disaster monitoring capability (C6) > emergency rescue experience (C16) > and housing security capability (C1). This finding indicates that the geological disaster monitoring capability indicator is the internal driving and controlling factor. Decomposed to specific indicators, the weight of C6 is the highest, indicating that the geological disaster monitoring capability is particularly important in terms of the resilience to geological disasters. Additionally, the weights of emergency rescue experience and housing security capability are the second and third, respectively, suggesting that the severity of geological disasters and the monitoring and early warning of disasters have a significant impact on the level of geological disaster resilience.

4.5. Tiered control measures

As the internal driving force, socio-economic indicators are often directly influenced by factors such as government laws and regulations, policies, investment, implementation intensity, and the efficiency of emergency response to unexpected events. They have certain foresight and long-term effects, not only having a significant effect on the current assessment results, but also having a decisive control effect on the

future development trend of risks. Moreover, socio-economic factors often have the characteristic of controllability, so through analysis, adjustment and improvement of the internal driving mechanism help relevant departments master the current situation of geohazard risk and emergency system resilience in the region, predict the change trend, and formulate reasonable and applicable policies and measures, ultimately achieving the transformation from hazard disposal to 'long-term dynamic prevention and control'.

Based on the internal driving mechanism theory of resilience evaluation, the above top five indicators in Figure 12 were selected and ranked from high to low. Control measures suggestions were proposed from five aspects: county, town, village, inspectors, and villagers. These suggestions provide reference value for government planning of prevention and control, policy adjustments, and measure implementation, as shown in Figure 13.

'Hazard Sites' and 'Risk Zones' emerged as distinct concepts in geological disaster management during the late 20th century, particularly following the UN's International Decade for Natural Disaster Reduction (1990–2000), to differentiate between locations with geological threats (hazard sites such as fault lines or unstable slopes) and areas where these threats actually endanger human populations and assets (risk zones). There is increasing recognition that the field of emergency management should be dynamic and continually evolving to remain constant with the changing nature of hazards, risk, and vulnerability.

This separation is necessary because it distinguishes natural phenomena from their potential consequences, recognizing that a hazard becomes a risk only when vulnerable elements are exposed. Different strategies for hazard-prone areas versus areas with actual risk to communities can be enabled. The framework offers dynamic management capabilities since risk zones can change with development patterns even when hazard sites remain constant. This approach has become the international standard for modern disaster management and land-use planning.

In the case of Heilong Village, disaster risk regions were identified based on the resilience assessment results. The river basin surrounding the Village of Black River is fragmented, with multiple ditches, generally steep topography, and dense vegetation cover, creating ideal circumstances for the growth of geologic hazards. Heilong Village currently has five catastrophe hazard sites, and it is recommended that the associated disaster risk regions be identified based on the distribution characteristics of the sites and

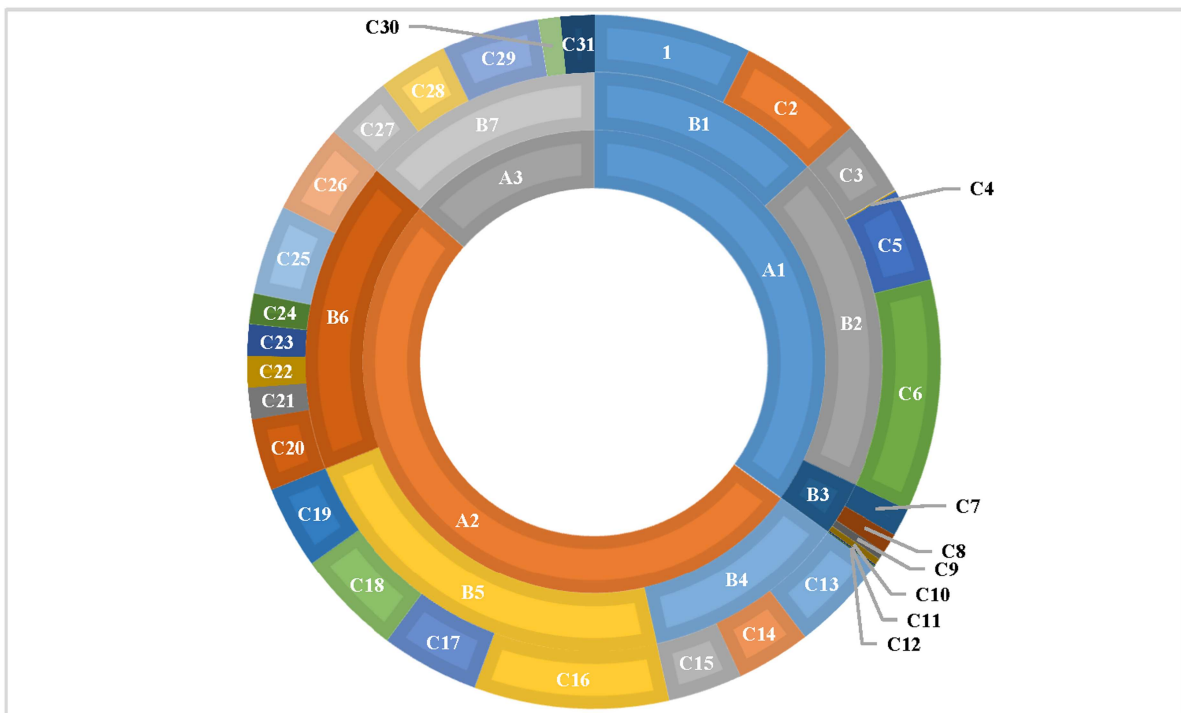


Figure 13. Driving mechanism.

the threatened population. The resilience evaluation results indicate that Heilong Village in Huanggu Town has one high-risk zone and three medium-risk zones, with the high-risk zone serving as an example for the control and planning of geohazard site prevention and avoidance, as shown in Figure 14. A dual-control system of 'hazard sites + risk zones' (Figure 15) is built.

As shown in Figure 14, this system is based on a dual-control system of 'hazard sites + risk zones', disaster prevention and mitigation planning in the region focuses on two aspects:

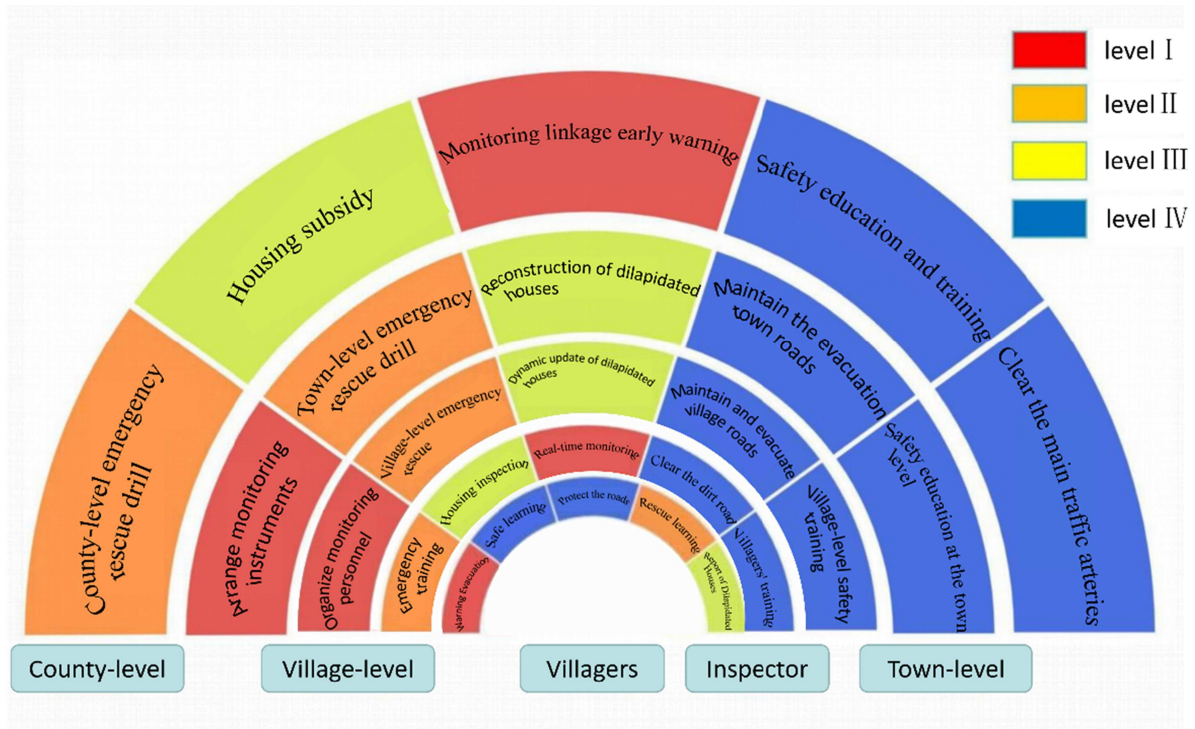


Figure 14. Tiered control measures proposal.

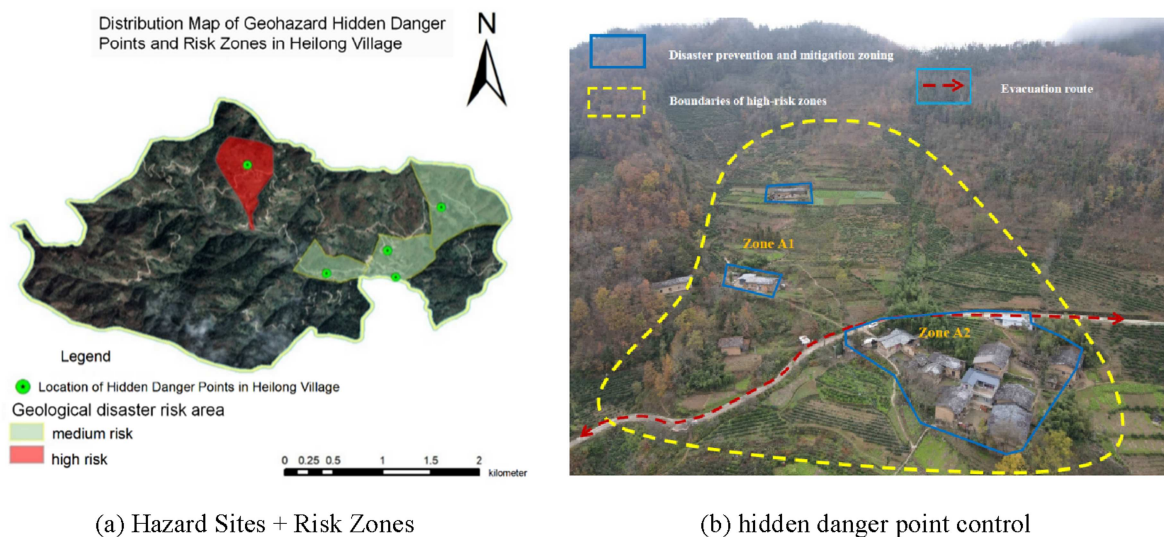


Figure 15. Dual-control system.

- (1) Retrofitting outdated and old structures, improving the seismic performance of buildings, and increasing the resilience of the living system.
- (2) Emergency shelter evacuation space optimization, including emergency shelters and emergency evacuation channels; Zone A1, which is primarily a management and control zone, with disaster prevention and mitigation planning centered on real-time monitoring of landslide hazards and threatened settlement management. The main measures include encouraging structural reinforcement of existing buildings, reinforcing building facades, strengthening slope interception and drainage, and improving emergency escape routes near buildings to reduce damage from landslides and heavy rainfall. Zone A2 is located at the bottom of the slope, on lower ground, and is a densely populated area in the high-risk area of the Helong Village. The quality of housing building varies greatly, and the focus of disaster prevention and mitigation differs from that of Zone A1. It should be unloaded on the slope and compacted at the bottom of the slope. High and steep slopes can be unloaded in stages, with a heavy object placed at the slope's base. Do an excellent job of avoiding and evacuating following the publication of early warning information on flash floods, severe rainfall, geologic hazards, and other emergencies.

5. Discussion

5.1. Advantages of HID assessment model for geohazards

Index-based systems (Rockefeller Foundation and ARUP 2014; Cutter and Derakhshan 2021), system function curves (SFC) (Bruneau et al. 2003; Henry and Ramirez-Marquez 2012), and quantitative simulation platforms are the most common machine resilience assessment approaches utilized. While index-based frameworks are effective for multidimensional aggregation across socioeconomic, infrastructural, and environmental domains, they predominantly adopt descriptive-aggregative paradigms that capture current conditions but lack explicit mechanistic linkages between system components (Sharifi and Yamagata 2016; Saja et al. 2019; Lv et al. 2024; Lv et al. 2024). Compared with existing resilience modelling approaches, SFC methods have been widely implemented for tracking performance trajectories through disaster phases; however, these approaches remain predominantly retrospective-reactive, focusing on the post-disturbance system response rather than anticipating future risk evolution. Furthermore, while quantitative simulation platforms, while offering sophisticated computational capabilities, they often require extensive data inputs and complex parameterization, potentially limiting their applicability in data-scarce geological disaster contexts, particularly in developing regions.

The proposed hazard–impact–driven (HID) model addresses these limitations through its parsimonious three-parameter structure that maintains analytical rigor while reducing data requirements (Holling 1973; Walker and Holling, 2004). The model's non-linear nature is guaranteed by the hybrid weighting system and matrix integration method, which avoids the limitation of linear superposition in capturing complex factor relationships. Meanwhile, the Drive component endows the model with forward-looking predictive capabilities – by identifying the internal driving mechanisms of resilience change (such as policy implementation, economic development, and social management optimization), the model can not only explain the historical evolution of geohazards but also predict the future risk trajectory, making up for the gap in static descriptive assessment methods in dynamic prediction. The model's characteristic lies in its explicit tripartite causal framework (H–I–D), which delineates hazard probability, vulnerability exposure, and underlying driving mechanisms, establishing resilience assessment systematically on the basis of risk assessment ($R = H \times I$) (Folke et al. 2010). This configuration extends beyond conventional status assessment by embedding causal attribution directly into the analytical framework, addressing the limitation that index-based systems ‘may assume better subsystem conditions automatically lead to greater resilience’ without explicating underlying drivers (Linkov et al. 2018; Cutter and Derakhshan 2021). Moreover, the HID model provides enhanced superior temporal scope through its dual analytical orientation, enabling both historical pattern recognition and prospective trend forecasting by incorporating the Drive component that identifies internal forcing factors governing risk dynamics. This temporal bidirectionality contrasts with SFC approaches that predominantly emphasize retrospective analysis (Bruneau et al.

2003). The model achieves methodological parsimony comparable to index-based frameworks while providing clear intervention entry points (reducing hazard exposure, minimizing impact severity, or modifying underlying drivers), thus supporting targeted policy formulation. By positioning resilience as a systematic extension rather than a parallel construct for risk assessment, the HID model creates methodological continuity from hazard susceptibility to adaptive capacity, enabling practitioners to transition seamlessly from current risk characterization to forward-looking intervention design. This integrated architecture facilitates scenario-based planning where interventions targeting specific drivers can be evaluated for their effects on overall risk trajectories (Cox 2012; Han and Semnani 2025), supporting the shift from reactive disaster management to proactive resilience enhancement particularly suited for geological disaster contexts where tight integration of physical hazard analysis, vulnerability assessment, and policy-driven adaptation is important (Johnson 2021; Wu et al. 2025).

5.2. Resilience assessment of geohazards

Beyond traditional risk assessment, which focuses primarily on hazard identification and probability quantification, resilience assessment has emerged as an important framework for governmental disaster prevention and emergency management systems (Bruneau et al. 2003; Reimann et al. 2024). Unlike conventional expert-based evaluation methods that rely heavily on subjective weighting approaches such as the analytic hierarchy process (AHP) and Delphi techniques, resilience assessment integrates objective temporal analysis of disaster evolution patterns and recovery trajectories (Promper and Glade 2016; Feng et al. 2025). This development enables government agencies to transition from reactive point-based treatment to proactive area-wide governance, addressing not only geological conditions but also the dynamic interactions between natural hazards and socio-economic factors (Tai et al. 2024). In particular, resilience assessment incorporates anthropogenic drivers, including risk control capacity, emergency awareness and capability and management system construction, which influence both disaster occurrence probability and community recovery capacity (Zscheischler et al. 2018). Furthermore, the framework allows for systematic evaluation of policy effectiveness by tracking how governmental interventions – such as engineering mitigation measures, land use regulations, early warning systems, and emergency response protocols – modify regional resilience over time (Xu and Yordanov, 2024). This capability is particularly useful for the dual control system of ‘hazard sites + risk zones,’ where decision-makers must optimize resource allocation across multiple spatial scales and temporal horizons. Therefore, integrating resilience assessment into geological disaster prevention systems provides a more comprehensive and objective foundation for formulating adaptive management strategies that account for both natural processes and human–environment interactions, ultimately enhancing long-term disaster prevention effectiveness and regional sustainability.

The evolution of geological disaster assessment from hazard evaluation to risk quantification represents a transition shift from engineering-based point treatment to emergency management-oriented risk control (Brabb 1984; Varnes 1984). Traditional risk assessment models, which were developed from the 1980s–2000s using mathematical and statistical methods, including logistic regression, artificial neural networks, and support vector machines (Carrara 1983; Dai et al. 2002; Lee and Pradhan 2007; Lu et al. 2024;), have provided valuable insights into current risk conditions. Recent advances in machine learning techniques, particularly ensemble methods and deep learning algorithms, have significantly improved the accuracy of landslide susceptibility assessments, with studies demonstrating prediction accuracies exceeding 90% (Xu and Yordanov, 2024; Liu and Norbu 2024). However, these conventional approaches exhibit methodological limitations in the context of dual control systems of ‘hazard sites + risk zones’. This is due to their heavy reliance on subjective expert-based weighting methods, such as the analytic hierarchy process (AHP) and principal component analysis (PCA), which determine indicator weights in critical modelling steps (Guzzetti et al. 1999; Xu et al. 2023). The accuracy of the evaluation results thus becomes highly dependent on the theoretical foundation and engineering experience of individual modelers, making objective verification difficult (Xu and Yordanov, 2024). Moreover, traditional natural indicator-based models can assess only current regional geohazard risk levels but cannot study historical change processes, disclose internal driving mechanisms, predict development trends, or optimize control measures.

Moreover, the transition from traditional disaster treatment to modern resilience-based governance raises questions about the adequacy of current assessment frameworks. The dual control system of ‘hazard sites + risk zones’ represents a change in governmental disaster prevention policy, moving from reactive point-based remediation to proactive area-based risk management (De Angeli et al. 2022; Lee et al. 2025). Recent developments in infrastructure resilience assessment emphasize the integration of multi-criteria decision frameworks that account for cost-benefit analysis and the side effects of implementable actions, providing practical guidance for critical infrastructure managers (Lv et al. 2024). Under this emergency management paradigm, government agencies must not only identify and mitigate specific hazard points through engineering interventions but also delineate and regulate broader risk zones where potential disasters may emerge due to combined natural and anthropogenic factors. However, traditional assessment models lack the capacity to evaluate policy effectiveness, track the temporal evolution of risk under different governance strategies, or optimize resource allocation across the hazard-risk spectrum. The integration of socio-economic drivers and policy interventions as endogenous factors is important for understanding how governmental disaster prevention measures, land use regulations, and emergency response capabilities interact with natural hazard processes to shape overall regional resilience trajectories (Reimann et al. 2024; Tai et al. 2024).

6. Conclusion

This study contributes to the development of geohazard risk assessment methodologies by establishing a comprehensive ‘hazard–impact–drive’ (HID) model that systematically integrates the disaster-causing body, exposed elements, and driving forces within geological disaster systems. The analytical framework reveals coupling and feedback mechanisms that govern geohazard evolution, offering potential improvements over traditional assessment approaches that often treat these components in isolation.

- (1) The HID model demonstrates methodological development through its hybrid weighting system, which combines the subjective Improved G1 Method with the objective Entropy Method, subsequently integrated via Matrix Idea Integration. This approach reduces discrepancies between aggregate and individual indicator weights, showing improved accuracy compared to single-method assessments. The validation in Huangtu Town, incorporating 647 automatically divided slope units derived from 3D vector high-precision remote sensing data and 31 assessment indicators, supports the model's predictive capability, with results closely aligning with historical geohazard records.
- (2) The temporal analysis of geohazard emergency system resilience reveals that major inflection points in resilience indices consistently coincide with policy interventions and significant social events, suggesting the important role of human-driven mechanisms in geohazard system dynamics. This finding complements purely physically-based models and highlights the value of integrating socio-economic factors into risk assessment frameworks. The identification and ranking of key indicators provide empirical evidence for prioritizing intervention strategies across multiple governance scales – from county-level planning to individual villager awareness programs.
- (3) The multi-scale control framework proposed, encompassing county, town, village, inspector, and villager levels, represents a shift from centralized to distributed geohazard management. This hierarchical approach acknowledges that effective resilience building requires coordinated actions across different administrative and social strata, with each level possessing distinct responsibilities and intervention capabilities.

However, several limitations warrant consideration. The model's reliance on historical data may constrain its applicability to regions with sparse geohazard records or under unprecedented climate scenarios. The automated slope unit delineation, while efficient, requires validation across diverse geological settings beyond the study area. Furthermore, the temporal scope of analysis may not fully capture long-term resilience trajectories, particularly under accelerating climate change and urbanization pressures.

Given these data limitations, future work should prioritize collaborative implementation of the HID model with governmental agencies. Through sustained multi-year assessment periods, such partnerships would enable validation of the model's applicability and verification of the underlying driving mechanisms across diverse operational contexts. This iterative validation process not only refines the model's predictive

capabilities but also strengthens its credibility as a decision-support tool. By providing evidence-based insights into disaster resilience dynamics, the HID framework could inform more precise policy interventions and resource allocation strategies, ultimately enhancing governmental capacity for proactive disaster risk management. Such government-research collaboration represents an important approach toward translating theoretical advancements into tangible improvements in community disaster resilience and adaptive governance. Given the constraints of data quality and limited sample size, the current study did not incorporate machine learning methods. In subsequent research, we aimed to enhance data quality and expand the dataset, anticipating the potential for more robust and insightful findings.

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R. Xu was responsible for conceptualization, funding acquisition, resources, methodology and writing (original draft); B. Song was responsible for investigation, methodology and writing (original draft); L. Ma was responsible for data curation, formal analysis, methodology and visualization; H. Cheng was responsible for data curation, funding acquisition and investigation; T. Yang was responsible for methodology, project administration and software; Y. Song was responsible for data curation, methodology and visualization; Y. He was responsible for data curation, investigation, project administration and writing (review & editing). All the authors reviewed the manuscript.

Author contributions

CRediT: **Rui Xu**: Conceptualization, Funding acquisition, Resources, Writing – original draft, Writing – review & editing; **Bin Song**: Investigation, Methodology, Writing – original draft; **Lijuan Ma**: Data curation, Formal analysis, Methodology, Visualization; **Hui Cheng**: Data curation, Funding acquisition, Investigation; **Tiantian Yang**: Methodology, Project administration, Software; **Yixuan Song**: Data curation, Methodology, Visualization; **Youshan He**: Data curation, Investigation, Project administration, Writing – review & editing.

Disclosure statement

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Data availability statement

The data are owned by the research laboratory and cannot be disclosed for copyright reasons. The raw data were generated at Rui Xu. Derived data supporting the findings of this study are available from the corresponding author, Rui Xu, upon request.

Ethical approval

Ethical approval was not required as the study used only secondary data from publicly available, de-identified sources. This study does not include any human or animal experiments. This study was conducted in compliance with data protection regulations. The investigation and use of resident data were approved by the Ankang Municipal Bureau of Natural Resources, ensuring that all the data were anonymized and securely stored. All participants were informed and provided verbal consent. All data do not contain any personal information.

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