Dynamic Evaluation of Disaster Reduction Capacity in Mining Cities Based on Big Data

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Abstract: Mining cities play a critical role in resource extraction and environmental conservation; enhancing disaster resilience in these cities is essential for ensuring regional sustainable development and safeguarding both human lives and ecological systems. Leveraging the multi-source integration, real-time acquisition, and powerful analytical capabilities of big data technology, this paper elaborates on the theoretical framework and practical significance of dynamic disaster reduction capacity assessment specifically tailored for mining cities. A four-level evaluation framework comprising the data layer, indicator layer, model layer, and application layer was established to systematically integrate multi-dimensional data encompassing geological environmental elements, building structures, socioeconomic factors, and social governance parameters. By combining the analytic hierarchy process (AHP) with entropy weighting and subsequently introducing a dynamic adjustment factor, the proposed model effectively captures both the temporal evolution and spatial variation characteristics of disaster reduction factors. The model was validated using empirical data from representative coal mining cities, and three-dimensional dynamic visualization charts together with associated analytical datasets were employed to identify key influencing factors and their transformation patterns, thereby providing scientifically rigorous evidence to support future disaster management policy formulation and implementation.

Keywords:big data; mining cities; disaster reduction capacity; dynamic evaluation

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1 Introduction

The development of mining cities is frequently accompanied by geological disasters, ecological degradation, and associated environmental challenges that pose substantial threats to sustainable urban operations. Disaster mitigation capability represents a critical determinant of urban resilience, directly affecting the capacity of a city to withstand natural and anthropogenic disasters and restore normal operational conditions in a timely manner. Traditional disaster mitigation assessment methodologies rely predominantly on static statistical data and qualitative analytical approaches, which inherently fail to capture the dynamic evolution of risks during mining operations or effectively integrate diverse disaster-related information sources, resulting in a significant and persistent gap between evaluation outcomes and actual field conditions. With the increasing availability of disaster monitoring data and the advancement of early warning systems for mining cities, the capacity to process large volumes of heterogeneous information in real time has emerged as a transformative technological factor. This capability enables comprehensive analysis of complex relationships among multiple interrelated variables and facilitates the development of novel methodological approaches for assessing urban disaster preparedness. Large-scale dynamic evaluation models based on big data technology can transcend conventional spatial and temporal constraints by integrating multi-source information, including space-air-ground observation data, operational engineering data, and social governance data, to construct a comprehensive multi-dimensional assessment framework that provides continuous and detailed insights into disaster reduction capacity across temporal and spatial dimensions.

2 Key Points of Dynamic Evaluation of Disaster Reduction Capacity in Mining Cities Based on Big Data

2.1 Definition of Core Connotations

Dynamic assessment of disaster reduction capacity in mining cities using big data represents a scientific methodology grounded in the characteristic evolution patterns of disaster risks prevalent in such specialized urban environments. This approach capitalizes on the distinctive analytical advantages offered by big data technology, including extensive data collection capabilities, robust storage infrastructure, advanced computational processing, and sophisticated statistical visualization techniques. Dynamic datasets are systematically established across multiple functional domains, encompassing geological monitoring systems, mining operations management, urban infrastructure development, and social governance implementation, thereby enabling the construction of a comprehensive analytical framework grounded in these critical operational factors. Through this framework, decision-makers and emergency managers can promptly comprehend the current state of disaster relief conditions, identify emerging future trends, and recognize the key elements influencing these dynamic processes. The primary objective of this methodology is to overcome the substantial limitations inherent in traditional static and simplistic evaluation approaches that have dominated the field [1]. Throughout the entire assessment lifecycle, careful observation and thorough systematic analysis are conducted to achieve comprehensive and precise evaluation outcomes. The evaluation model addresses not only the physical configuration of disaster prevention facilities but also the enhancement of risk identification capabilities, emergency warning system effectiveness, and resource optimization through intelligent software-based solutions. Disaster prevention capability constitutes a complex adaptive system that continuously evolves in response to temporal dynamics, spatial heterogeneity, and changing environmental conditions [2].

2.2 Analysis of Essential Characteristics

The evaluation system exhibits distinctive technical empowerment features and well-defined operational objectives, reflecting the thorough and systematic integration of big data technology with disaster management requirements. Beyond the mere technological aggregation of hardware and software components, this integration establishes a robust analytical foundation with clearly directed strategic goals for disaster prevention and mitigation efforts. From a technical architecture perspective, the system fundamentally relies on multi-source information fusion technology that encompasses diverse data integration approaches, including satellite remote sensing platforms, autonomous drone monitoring systems, distributed sensor networks, and comprehensive government administrative databases [3]. Each data source contributes uniquely valuable characteristics to the integrated analytical framework: satellite remote sensing provides extensive ground surface coverage with periodic revisit capabilities; drone monitoring enables high-resolution and precise regional observation for targeted areas; sensor network data delivers continuous real-time environmental monitoring across multiple parameters; and government administrative records offer essential historical insights into urban management practices and emergency response effectiveness. The strategic availability of multiple complementary data sources facilitates effective data integration, successfully overcoming traditional data barriers and ensuring comprehensive access to information across all relevant operational domains.

2.3 Interpretation of Practical Value

Given the dual imperatives of high-quality economic development and comprehensive disaster risk prevention in mining cities, such evaluations have consistently demonstrated substantial and multifaceted practical significance. Regarding urban safety management, dynamic evaluation enables real-time identification of disaster reduction capability deficiencies, facilitates dynamic risk tracking through continuous monitoring, and supports accurate risk assessment for proactive decision-making. These capabilities provide scientifically rigorous foundations for improving disaster early warning mechanisms and enhancing emergency response system effectiveness, thereby significantly reducing disaster-induced losses and safeguarding human lives, critical property assets, and normal social operations [4]. Through the systematic application of dynamic evaluation methodologies, potential risks can be identified in a timely manner, enabling adaptive resource allocation strategies that are continuously informed by updated analytical results. Consequently, post-disaster response efficiency is substantially enhanced, leading to reduced casualties, diminished economic losses, and accelerated recovery timelines for affected communities.

3 Dynamic Evaluation of Disaster Reduction Capacity in Mining Cities Based on Big Data

3.1 Construction of the Evaluation Framework

The dynamic evaluation framework for disaster mitigation capacity in mining cities based on big data comprises four sequential methodological stages: data support infrastructure, indicator development, computational analysis, and application modeling. This architecture forms a hierarchical structure consisting of four integrated components: the data layer, indicator layer, calculation layer, and application model layer[5]. The data layer serves as the foundational support infrastructure, acquiring comprehensive heterogeneous data through the systematic integration of space-air-ground monitoring networks, government data platforms, and enterprise operational management systems. Dynamic geological environment data includes slope displacement measurements reflecting temporal changes in mining slope stability, groundwater level data indicating hydrogeological condition trends in mining areas, and geological structural change data revealing spatial patterns in geological configuration evolution.

3.2 Design of the Evaluation Indicator System

3.2.1 Principles for Constructing the Indicator System

The development of the indicator system constitutes an integral and essential component of dynamic assessment procedures that warrants careful methodological attention. In practice, strict adherence to fundamental scientific principles is essential to ensure that evaluation results maintain both rigorous scientific validity and practical applicability in real-world decision-making contexts. The first foundational principle is systematic comprehensiveness, which establishes the conceptual groundwork for the entire indicator system and must encompass all critical functional dimensions of disaster prevention capacity in mining cities, including risk identification, early warning generation, emergency response coordination, post-disaster recovery planning, and long-term management strategy. The second fundamental principle is dynamic adaptability: the indicator system should be responsive to changing environmental conditions and evolving risk profiles through regular updates and recalibration procedures.

3.2.2 Composition of Specific Indicators

Based on the aforementioned methodological principles and carefully considering the specific disaster risk characteristics of mining cities together with contemporary big data application scenarios, a comprehensive three-level evaluation indicator system was established, as presented in Table 1. The target layer represents the overarching disaster reduction capacity of mining cities (A), comprising five distinct criteria layers: risk identification capability (A1), risk assessment and countermeasure formulation (A2), emergency response management capability (A3), post-disaster recovery and reconstruction capacity (A4), and long-term sustainable management capability (A5). The indicators layer encompasses a total of twenty specific indicators distributed across various functional aspects, including information collection infrastructure, analytical model formulation, physical infrastructure provision, and professional competence development among personnel.

Table 1: Dynamic Evaluation Indicator System for Disaster Reduction Capacity in Mining Cities Based on Big Data

Target Layer	Policy Level	Indicator Level	Indicator Type	Data Sources
Disaster Mitigation Capacity of Mining Cities (A)	Risk Identification Capability (A1)	Real-time geological data acquisition rate (A11)	Dynamic Quantification	Sensor networks, satellite remote sensing
		Dynamic monitoring coverage of risk sources (A12)	Dynamic Quantification	Drone monitoring, government service platform
		Multi-source data fusion analysis capability (A13)	Dynamic Quantification	Big Data Analysis Platform
		Risk Identification Model Accuracy (A14)	Dynamic Quantification	Model Calculation Result
	Early Warning Response Capability (A2)	Early warning information release timeliness (A21)	Dynamic Quantification	Emergency Management Platform
		Early warning information coverage rate (A22)	Dynamic Quantification	Government data, research statistics
		Response Plan Activation Efficiency (A23)	Dynamic Quantification	Emergency Response Record
		Emergency team assembly speed (A24)	Dynamic Quantification	Emergency Team Management System
	Emergency response capability (A3)	Integrity rate of disaster reduction facilities (A31)	Dynamic Quantification	Facility Monitoring Data
		Adequate Reserve Ratio for Emergency Supplies (A32)	Dynamic Quantification	Material Management System
		Interdepartmental collaborative response capability (A33)	Dynamic Quantification	Collaborative Work Record
		On-site handling efficiency (A34)	Dynamic Quantification	Emergency Response Records
	Recover and restore capabilities (A4)	Infrastructure Restoration Speed (A41)	Dynamic Quantification	Infrastructure Construction Project Data
		Recovery time for production and daily life (A42)	Dynamic Quantification	Social Statistical Data
		Ecological Environment Restoration Capability (A43)	Dynamic Quantification	Environmental Monitoring Data
		Social Security Follow-up Efficiency (A44)	Dynamic Quantification	Data from the Civil Affairs Department
	Long-term management capability (A5)	Level of improvement in disaster reduction policies (A51)	Dynamic Qualitative Analysis	Analysis of Policy Texts
		Intensity of disaster reduction funding allocation (A52)	Dynamic Quantification	Fiscal Expenditure Data
		Disaster Reduction Education and Awareness Coverage Rate (A53)	Dynamic Quantification	Public Education and Promotion Record
		Level of innovation in disaster reduction technology (A54)	Dynamic Quantification	Research achievement data
		Completeness of the Dynamic Evaluation Mechanism (A55)	Dynamic Qualitative Analysis	Institutional Development Assessment

3.3 Construction of the Evaluation Model

3.3.1 Data Preprocessing Methods

Outlier detection and treatment methodologies are systematically employed to minimize the influence of spurious or erroneous data entries, as median-based statistical approaches exhibit strong resistance to extreme values and anomalous observations. However, authentic anomalies arising from unique geological events or rare meteorological occurrences must be carefully preserved and properly documented; otherwise, critical information may be inadvertently eliminated during routine data cleaning procedures. Ensuring data authenticity and completeness is therefore essential for supporting subsequent analytical processes and evidence-based decision-making. Furthermore, due to the different measurement dimensions characteristic of multi-source heterogeneous data, which can result in substantial variations in metric scales and units, standardization procedures are necessary to normalize all metrics to comparable scales before comparative analysis, thereby effectively eliminating the adverse effects of dimensional differences on evaluation outcomes.

3.3.2 Determination of Indicator Weights

The objective weight is calculated as:$w_{2j} = \frac{1-H_j}{\sum_{j=1}^{m}(1-H_j)}$, where j = 1, 2, ..., m and m denotes the total number of indicators. The concept of information entropy, derived from established information theory, effectively quantifies data dispersion patterns and thus enables the rigorous determination of objective weights. A smaller information entropy value indicates lower data dispersion for a given indicator; consequently, such an indicator carries greater discriminatory significance in the overall evaluation and is assigned a correspondingly higher objective weight. Subsequently, subjective and objective weights are integrated through a weighted combination approach to derive the final composite weight:$w = \alpha w_1 + (1-\alpha) w_2$, where alpha represents the subjective weighting factor determined based on expert judgment and empirical data characteristics (a value of 0.5 was adopted in this study). This balanced approach effectively integrates domain experiential knowledge with objective data characteristics, yielding an accurate and defensible weighting system grounded in scientific principles to support subsequent analytical decision-making.

3.3.3 Construction of the Dynamic Evaluation Model

The proposed model provides a solid analytical foundation for disaster prevention decision-making in mining cities, enabling enhanced early-stage emergency response capabilities and substantially improved overall disaster prevention and rescue operational effectiveness. The model employs a mixed methodological approach incorporating the composite weighting scheme along with a time decay factor and dynamic adjustment factor to evaluate the overall disaster mitigation capability of mining cities in a temporally dynamic manner. The design principles effectively capture the temporal characteristics and evolutionary patterns of disaster reduction capabilities, demonstrating considerable practical validity and methodological rationality, thereby providing robust analytical support for the continued advancement and field application of this methodology in related domains.

3.4 Data Analysis Methods and Chart Design

3.4.1 Core Data Analysis Methods

Regression analysis serves as the primary statistical methodology for identifying quantitative influencing factors and constructing the predictive disaster reduction capacity model. This study employs advanced statistical techniques, including multiple linear regression and non-linear regression approaches. Multiple linear regression examines the linear relationships between multiple independent predictor variables and a single dependent response variable, although it exhibits reduced predictive accuracy for non-linear relationships compared with specialized non-linear regression approaches. Regression-based forecasting provides valuable insights into future disaster reduction capacity trajectories by analyzing current influencing factors and their temporal evolution patterns, thereby predicting whether capacity will exhibit an increasing trend, a decreasing trend, or relative stability in the forthcoming operational period.

4 Empirical Analysis

4.1 Empirical Subject Selection and Data Collection

Urban development data were obtained from municipal government data platforms, encompassing comprehensive configuration information, geographic location coordinates, operational status monitoring of disaster reduction installations, transportation network topology, and healthcare resource allocation information, including hospital locations and quantities of medical devices and professional personnel. These integrated datasets provide a comprehensive overview of urban development capabilities and infrastructure progress across multiple functional domains. Additional supplementary data were collected from emergency management agencies and civil affairs bureaus, including detailed emergency team composition records (personnel structure, training records, equipment availability status), disaster relief funding allocation data (total monetary amounts, funding sources, distribution mechanisms), and public awareness campaign metrics (activity frequency, participant numbers, measured success rates).

4.2 Evaluation Process and Result Analysis

4.2.1 Weight Calculation Results

The comprehensive weights for each indicator were rigorously determined through the systematic integration of AHP and entropy weighting approaches (Table 2). This hybrid methodology incorporates both the experiential domain knowledge of qualified experts and the objective statistical characteristics inherent in the empirical data. Expertise from professionals in mining engineering, disaster management, and big data analytics informed the subjective evaluation of indicator relative importance, while the objective information entropy values calculated from multi-source dynamic data were employed to quantify and appropriately calibrate subjective variations, ensuring scientifically sound and rational weighting outcomes. Among the criteria layer indicators, Risk Identification Capability (A1) achieved the highest weight at 0.25, followed by Early Warning and Response Capability (A2) at 0.23, and Emergency Response Capability (A3) at 0.22. Collectively, these three critical dimensions account for 0.70 of the total weight, constituting the primary evaluative framework for comprehensively assessing disaster resilience in mining cities.

4.2.2 Analysis of Dynamic Evaluation Results

To facilitate meaningful comparative assessment of disaster prevention capabilities across different mining cities, hierarchical clustering analysis was employed to classify the sample cities into three distinct clusters based on their computed evaluation scores. Cities with dynamic evaluation index values exceeding 0.75 are classified at a very high capability level, demonstrating excellent disaster resistance performance and regional leadership. Cities with index values between 0.65 and 0.75 represent the medium-high capability level, indicating substantial mitigation capability with identifiable room for further enhancement. Cities with index values between 0.55 and 0.65 constitute the medium capability level, requiring targeted capacity building interventions and resource investment. In terms of sample distribution, high-level cities account for 25%, medium-high level cities for 50%, and medium-level cities for 25%. These results clearly reveal hierarchical differentiation in disaster prevention capacity among mining cities, with significant and meaningful disparities observable across different urban areas.

4.2.3 Analysis of Key Influencing Factors

The established multiple linear regression model demonstrates strong statistical goodness-of-fit, with an R-squared value of 0.85, indicating that the model explains a substantial proportion of the variance in the dependent variable (Disaster Reduction Capability). Among the independent predictor variables, multi-source data integration capability, early warning information dissemination timeliness, and disaster reduction facility integrity rate exhibit the highest standardized coefficient values at 0.23, 0.21, and 0.19, respectively. These three variables represent the primary drivers of disaster reduction capability improvement in mining cities. Beyond these identified internal factors, external contextual factors such as regional economic development levels influence the realization of disaster reduction indicators through alternative pathways. Research and development investments and supportive policy measures affect internal indicator achievement through indirect mechanisms, establishing a structural linkage between external enabling conditions and internal performance measures that collectively contributes to disaster reduction outcomes.

4.3 Recommendations for Applying the Evaluation Results

From the perspective of addressing the common development needs of mining cities, municipal authorities should strategically enhance their utilization of big data technology across disaster management functions. Establishing a joint database sharing platform would enable the systematic integration of diverse datasets from various governmental departments and industrial sectors, facilitating comprehensive data discovery and cross-domain utilization. Dynamic assessment and feedback mechanisms are also essential institutional components: disaster reduction capacity should be subject to regular periodic evaluations, with management strategies adjusted continuously based on assessment outcomes to ensure sustained improvement in disaster prevention efforts over time. Furthermore, cross-regional and cross-departmental collaborative frameworks should be actively promoted to enable coordinated disaster reduction initiatives and facilitated technical knowledge sharing, thereby fostering more systematic and integrated governance approaches. To effectively achieve these strategic objectives, evaluation results must be consistently translated into concrete implementable actions through dedicated ongoing efforts to enhance disaster resilience in mining cities and simultaneously advance both safety and sustainable development goals.

5 Conclusion

This paper presents a comprehensive framework for the dynamic evaluation of disaster reduction capacity in mining cities based on big data analytics. Beginning with fundamental evaluation theoretical concepts, a comprehensive and scientifically grounded evaluation system and analytical model were systematically developed, with feasibility and operational effectiveness successfully demonstrated through rigorous empirical validation. The findings demonstrate that the proposed big data-driven dynamic assessment method offers significant advantages over conventional static evaluation approaches through the systematic utilization of multiple information sources, temporal evolution modeling techniques, continuous real-time monitoring capabilities, precise quantitative assessment, temporal-spatial comparative analysis, and comprehensive disaster characterization for mining cities. The four-level evaluation system coherently encompasses the data layer, indicator layer, model layer, and application layer, comprising five major assessment dimensions with a total of twenty specific indicators covering risk identification, early warning and response coordination, rescue operations management, recovery and rehabilitation planning, and sustainable long-term management, thereby comprehensively characterizing the essential features of urban disaster resistance. The combined AHP-entropy weighting approach, together with the dynamic factor adjustment model, ensures the practical applicability and methodological robustness of the framework. Overall, this approach provides a novel and practical technical tool for disaster preparedness planning in mining cities. While the evaluation system and model exhibit considerable robustness, further methodological improvements remain possible. Regarding data sources, incorporating additional data types such as unstructured data including textual documents, photographic images, and video recordings would enhance data comprehensiveness and analytical diversity. In terms of modeling sophistication, the adoption of deep learning, reinforcement learning, and other emerging machine learning architectures, together with the incorporation of dynamically adjustable parameters, could improve prediction accuracy and enhance model adaptability across diverse operational conditions.

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