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Risk management for mine closure: A cloud model and hybrid semi-quantitative decision method

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Abstract: Mine closure is associated with many negative impacts on society and the environment. If these effects are not rationally addressed, they would pose risks of mine closure. Thus, a risk management method is needed to mitigate these adverse impacts and address mine-closure issues. An integral framework for mine-closure risk management that includes risk assessment and risk treatment was proposed. Given the fuzziness and randomness of the transformation between qualitative and quantitative knowledge in the risk assessment process, a novel risk assessment method based on the cloud model was presented, which fully considers the uncertainty in risks themselves and in the reasoning process. Closed mine reutilization is an effective risk treatment option in response to the identified high risks, but it requires selecting optimal reutilization strategies for the successful implementation of the reuse plan. To this end, a hybrid semi-quantitative decision method is proposed to optimize decision-making. The results of a case study showed that this risk management methodology can help budget planning for risk treatment and provide an instructional framework to effectively reduce the negative effects of closed mines.

Keywords: mine closure; risk assessment; risk treatment; cloud model; risk matrix

1. Introduction

A common misconception is that mine closure means the end of mining operations and abandonment without any risk [1]. However, long-term maintenance and monitoring of derelict mines are far from over. Mining enterprises still need to address various social and environmental impacts to mitigate the unwanted outcomes that occur in closed mines, such as ensuring that the staff and mining area residents receive compensation and settlement [2–3], restoring a viable ecosystem that is healthy and safe [4], and handling the assets and liabilities reasonably [5]. Immature mine-closure management greatly increases the possibility and consequence of adverse effects associated with such closures, thereby causing numerous risks of potential mine closure [6].

Mine closure results from various reasons. Mine closure caused by resource depletion is defined as mature closure, whereas that precipitated by economic, social, or policy reasons is called premature closure [7]. Compared with the former type, the latter would result in more serious negative effects due to uncontrollability. Particularly in resource-rich countries with weak governmental management and immature mine-closure plans, premature closure leads to multiple crises, such as breakdowns of local and regional public health and livelihoods, destruction of the natural environment, and a sharp decline in local finance [5,8]. These crises could worsen and become much more common with a prolonged period of mine closure, and some of the potential and emerging dangers are long-term and even fatal. Therefore, risk management for mine closure should be examined seriously [9].

With rigorous initiatives of “mine closure and production reduction campaign” implemented in China, a large number of coal mines prematurely closed in a short time (from 87000 in 1995 to approximately 5800 in 2018) [10–11]. As the coal mining method in China is still dominated by underground mining (accounting for 90% of production), the closed coal mines mainly comprise underground ones. Unfortunately, at

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the present stage, China still has neither effective regulatory policies for mine-closure management nor operational risk management methodologies for reference [12–13]. A large number of closed mines without supervision have been abandoned, posing an excessive economic burden to the country and society [14]. Many coal mines were closed without adequate preparation, resulting in unknown disasters and limitations for future use [15]. With this problem, setting up an integrated mine-closure risk (MCR) management system to guide the reduction of potential negative effects of closing mines has become an urgent problem to solve. This study uses closed underground coal mines (hereafter referred to as "closed mines" or "mine closure") as the research object to investigate risk management.

The MCR management system comprises risk assessment and risk treatment [16–17]. The purpose of this system is to mitigate the impacts of closed mines and offset the increased environmental and social costs. MCR assessment aims to identify the critical risks associated with mine closure by evaluation outcomes. Considering that effective risk assessment is the precondition for targeted reutilization pattern implementation, we need to accurately determine the significant risks. Thus, selecting a scientific and practical assessment method is a very important research topic in risk management. As MCR assessment inevitably involves pervasive uncertainty and imprecision, such as fuzziness and randomness, which appear in the probability or consequence evaluation of a hazard event, accurately determining the risk levels is difficult [18]. A number of assessment methods have been proposed for risk-level determination, such as fuzzy extended analytic hierarchy process, which Koulinas *et al.* [19] adopted to assess safety risk in worksites; the evaluation model based on set pair analysis that Chong *et al.* [20] implemented for assessing occupational hazards in coal mines; the fuzzy synthetic evaluation method that Akter *et al.* [21] applied to evaluate the vulnerability of climate-related hazards; and the risk assessment model combining neural networks and a genetic algorithm that Kaeeni *et al.* [22] provided for assessing derailment accident risk. Although these methods have made progress in the reasoning of risk-level determination, they still have the unresolved problem of how to incorporate the randomness and fuzziness of indicators when assessing risk levels. Due to the shortage of data and uncertainty of risks, these models only considered fuzziness or randomness in assessment, causing deviation between evaluation results and practical situation. Moreover, using a single value in these methods to represent the level of risk does not adequately reflect the fuzziness and randomness of risk factors. Considering that risk has two dimensions (often referred to as the probability and consequence of hazard events), the risk matrix approach (RMA), which combines the probability and consequence of a hazard event, is an essential tool for risk assessment [23–24]. Nevertheless, this method faces two prominent problems that are yet unresolved and seriously affect the credibility of the results. First is that this method classifies risk grades by quantitative calculation, which belongs to the hard division without considering the fuzziness of the boundary. The other one is that this method determines the risk level according to the risk matrix table, failing to render a scientific and reasonable uncertain reasoning mechanism. Moreover, as evaluators are accustomed to using natural language rather than numerical methods when expressing the probability of occurrence and severity of consequences of risk events, the RMA method cannot effectively solve the problem of the fuzziness of the natural language description and randomness of the occurrence of events [25]. Consequently, an essential task is searching for a novel method that can solve the uncertain knowledge representation and present a clear reasoning mechanism.

The cloud model proposed by Li *et al.* [26] is an uncertainty analysis model based on fuzzy set theory and probability theory. It adopts membership degree to describe fuzziness and uses event occurrence probability to express its randomness, which provides an effective tool in transforming between natural language and quantitative expressions [18]. Currently, the cloud model has been applied in many aspects. Guo *et al.* [25] proposed a risk assessment method based on cloud model theory and applied it to the risk assessment of natural gas pipelines, which verifies the feasibility and rationality of the cloud model for risk assessment. Wu *et al.* [27] employed the cloud model in the risk assessment of drought hazards, and Zhang *et al.* [28] assessed the risk of adjacent buildings in tunneling environments based on the cloud model, greatly enhancing the robustness of the cloud model in risk assessment. Therefore, this paper proposes an improved risk matrix based on the cloud model (IRMCM) method to assess MCR.

Risk treatment is the second step in risk management. It aims to provide effective treatment strategies for the identified risks [29]. Compared with the reactionary monitoring and control of closed mine risks, closed mine reutilization (CMR) has been recognized as the most proactive measure for risk action because it not only modifies mine-closure problems but also brings economic benefits for companies and communities [30]. CMR is an important aspect of cleaner coal production practices because it can fully tap the potential and vitality of idle resources, save social costs, minimize closure and post-closure costs, and provide employment opportunities for the unemployed [31]. As the recovery budget of abandoned mines is limited, it needs to determine which reutilization strategy is best for treating the critical risks [32]. In general, deciding on optimal reutilization options involves multiple complex environmental and socioeconomic factors and mine conditions [33–34]. In this context, multi-criteria decision-making (MCDM) method is the most common approach to solve decision problems [35–36].

Various MCDM methods are known, such as analytic hierarchy process (AHP) [19,32], technique for order preference by similarity to ideal solution (TOPSIS) [36], preference ranking organization method for enrichment evaluation [37], grey correlation method [38], and rank sum ratio [39]. Compared with other methods, the TOPSIS method can make the most use of the original data information and accurately depict the gaps among all the evaluation schemes. In addition, this method has other advantages, such as no strict limit on the number of indicators and a simple calculation process. In decision-making problems, the indicators' weights are commonly determined by the AHP method [40]. However, for frameworks with a large number of indicators, the weight determination by traditional AHP involves a relatively large amount of computation in judgment matrix consistency testing. Therefore, the AHP method should be improved to enhance its performance in weight determination. This study used the scale expansion instead of pairwise comparison to improve the judgment matrix construction (called the IAHP method) [38], which can avoid coincidence examination and define the weighing scientifically. Combining the IAHP and TOPSIS methods, this study presented a hybrid semi-quantitative decision method to provide a quantitative and transparent process for optimal ordering of the reutilization patterns.

To illustrate the functionality of the proposed risk management methodology in terms of closed mine impact reduction, this study took a typical suburban closed mine named Muchengjian coal mine as the research object. The main issues addressed in this study can be summarized as follows: (1) how to establish an organized MCR framework and a CMR suitability analysis indicators system, (2) how to achieve robust and visual assessment results on the MCR, and (3) how to select the optimal reutilization options for responding to the critical risks. The rest of this paper is organized as follows. Section 2 introduces the methodologies of the risk assessment and risk treatment. Section 3 provides a case study for verifying the proposed methods. Section 4 presents the results and discussion. Section 5 provides the conclusions and policy implications.

2. Methodology

2.1. General framework for this study

A complete MCR management approach includes three steps: risk identification, risk assessment, and risk treatment. Risk identification involves three tasks. The first is to determine the mine-closure hazard events and assess the probability and consequences of such events through an expert group. The composition of an expert team directly affects the quality of risk assessment, so the most relevant decision-makers with mine memory and different interests have to be selected. The second step is to apply the IRMCM method to determine the magnitude of risks and identify the critical risks. In the third step, the two-level IAHP is employed to calculate the weights of the attributes of the CMR suitability analysis framework and then input these weights into the TOPSIS method to select the targeted reutilization patterns. These reutilization patterns are regarded as the best ways to deal with the high risks assessed in the second step. The fundamental framework of this study is summarized in Fig. 1.

2.2. Risk assessment

2.2.1. Mine closure risk classification

Identifying the major adverse events related to mine closure and judging the likelihood and consequences of each event are the prerequisites for risk assessment. The legacy issues associated with closed mines are usually complex because each mine has its own unique natural conditions. Therefore, the risk list of a closed mine should be obtained by a questionnaire survey on the negative effects of mine closure. The questionnaires should be completed by an expert group involving mining companies, governments, stakeholders, and communities [41]. The MCR classification has been extensively researched in various studies such as [5,6,8,14,16–17], among which the research results by Laurence [6] are the most widely acknowledged in application. In this study, an MCR list was commenced with a literature review and then supplemented and perfected by an expert group. The final MCR types in this study are shown in Table 1. The risk categorization was summarized as technical, health and safety, environmental, community, and legal and financial risks.

2.2.2. Improved risk matrix based on cloud model (IRMCM)

The risk matrix method requires a team of the most relevant decision-makers to quantify the probability and consequences of each risk. Then, the magnitude of risks can be determined by the risk matrix. The expression of this approach is shown as follows:

$$R = P \times C \tag{1}$$

where R represents the risk, P indicates the probability of the risk occurring, and C indicates the consequences of the risk occurring.

This equation does not show a multiplication representation of P and C, but indicates a combined relationship between the probability and consequences of a risk. Based on the risk matrix method proposed by Garvey and Lansdowne [42], this study constructed a risk assessment matrix, as shown in Table 2. In this matrix, the risk levels are defined as I, II, III, IV, and V. The levels of probability are divided into "almost certain," "likely," "possible," "unlikely," and "rare"

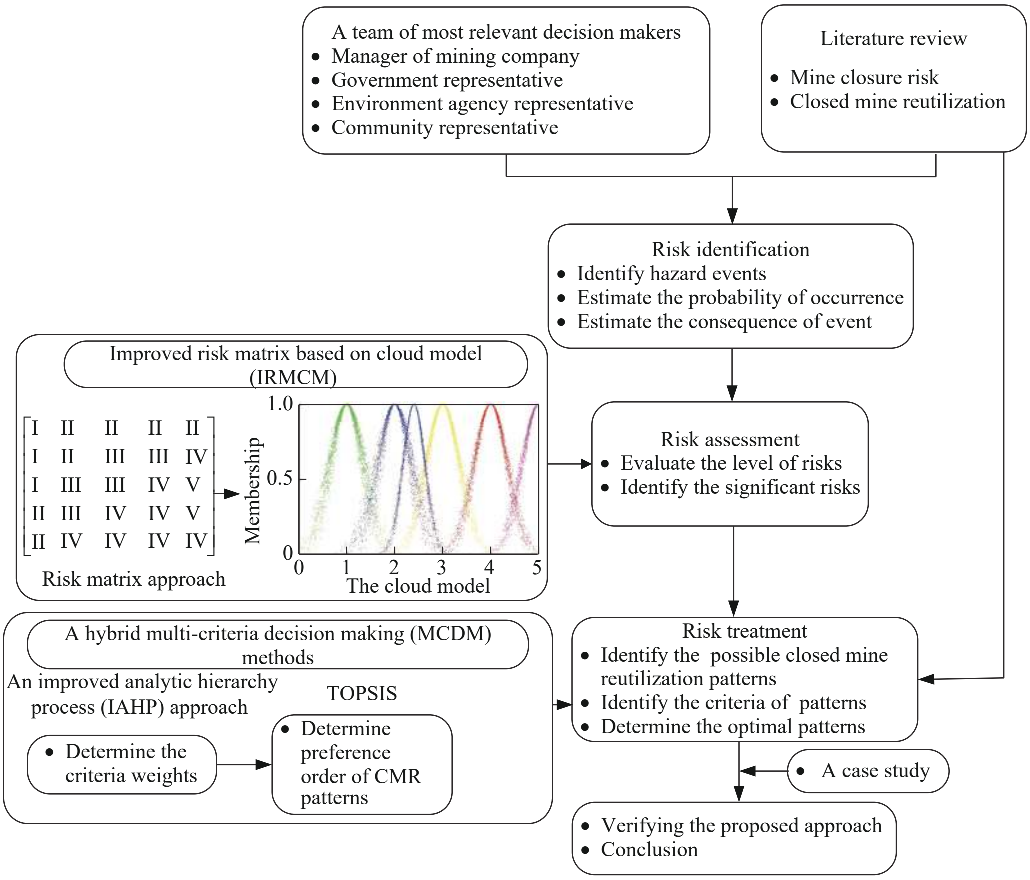

Fig. 1. Research framework for the study.

and the severity of consequences are classified into five categories: “catastrophic,” “major,” “moderate,” “minor,” and “insignificant,” as demonstrated in Table 3. The values for each level of R, P, and C were assigned according to [43].

On the basis of RMA, the cloud model was applied to improve the traditional risk matrix methods. Compared with the RMA method, the cloud model can realize the soft classification of concept level, which effectively integrates the fuzziness, randomness, and relevance of qualitative concepts. On this basis, the uncertainty reasoning mechanism is established to overcome the limitations as ignoring uncertainty in the process of assessment. As the most widely used model, the normal cloud model applies three numerical features, namely, expectation (E_x), entropy (E_n), and super entropy (H_e) to implement the transformation between qualitative concepts and quantitative descriptions. The definition of each parameter and the algorithm of the forward cloud generator are based on [44], and operating the forward cloud repeatedly can generate a cloud figure. For example, the cloud parameters are (0.5, 0.1, and 0.02), and the corresponding cloud figure is shown in Fig. 2. To illustrate the randomness of the risk grade value, we operated the forward cloud generator 3000 times on MATLAB software. In this figure, the value 0.5 represents the expectation and its variation range is (0.2–0.8) based on the “$3E_n$ criterion,” which means that the assessment result is a range and not a single numeric value [18]. The span of the cloud image reflects the fuzziness of the level and cloud image thickness manifests the randomness. The procedures of the IRMCM method are as follows [18,25]:

Step 1: Grading R, P, and C by cloud model to achieve soft partition of index boundary.

According to the risk matrix method, R, P, and C are divided into five grades, and each grade corresponds to a numerical range, as shown in Table 3. As the boundary value of the adjacent level is fuzzy, this classification belongs to a “hard division.” The cloud model can achieve a “soft division” of five levels with three cloud parameters, as shown in Table 4. The normal cloud figures of R, P, and C are shown in Fig. 3.

Step 2: Construction of reasoning rule base.

Rules are the basis of inference in the process of uncertain reasoning. In this study, the two-condition rule is constructed by P and C. The inference rule can be expressed by natural language as R_{ij}: if P_i and C_j, then R_{ij}; i, j, k = 1–5, where R_{ij} is the qualitative rule and represents the evaluation level of the risk when the risk probability level is P_i and the risk occurrence consequence level is C_j. In this study, the rule base

Table 1. Classification of MCR

Risk type	No.	Events	Illustration
Technical	TR_1	Mine-closure plan	No existing mine-closure plan or only an old mine-closure plan existed before mine-closure
	TR_2	Remediation progress	Reclamation activities or abandoned mine reutilization progress slowly
	TR_3	Shortage of a professional team for mine closure	Lack of professional or expert personnel for mine-closure treatment imposes risks on the project
	TR_4	Documentation	The closed mine data are incomplete or untrue, resulting in difficulties in implementing the subsequent reutilization process
Health and safety	HR_1	Falling into unsealed or unfenced mine shaft	Injuries due to person or animal falling into the closed mines
	HR_2	Subsidence	Safety problems caused by subsidence (residential building deformation and road damage)
	HR_3	Toxic gas emission	Toxic gas emission causing safety problems
	HR_4	Problem of mine water accumulation	Accumulation of closed mine drainage induces geological disaster in mining area
	HR_5	Gangue hill failure	Gangue hill collapse caused by rainstorm erosion damage to homes and agricultural lands
	HR_6	Toxic elements in water	Toxic elements released into the surrounding water resources cause diseases
Environmental	ER_1	Acid drainage	Contamination of water caused by acid drainage
	ER_2	Soil contamination	Destruction of soil fertility caused by heavy metal pollution
	ER_3	Degradation of water quality	Water pollution due to mine effluent
	ER_4	Dewatering	Decline in groundwater level caused by extraction
	ER_5	Air pollution	Air pollution due to greenhouse gas emission and dust suspended by the wind
	ER_6	Aesthetic values	Destruction of natural landscape caused by mining activities
Community	CR_1	Employees' compensation claim	Problems due to workers' insurance and long-term labor contracts (retraining and relocation)
	CR_2	Damage to income of residents around the mine	Economic depression because of the closure of mining-related industries and high local unemployment
	CR_3	Conflict between residents and mine owners	Residents' dissatisfaction due to lack of fair distribution of wealth in the community
	CR_4	Impact on mining area attraction	Negative effects on attracting capital and labor of mining town
Legal and financial	LR_1	Regulatory compliance	Problems caused by non-compliance with relevant laws (regulations of mine-closure policy and environmental protection policy)
	LR_2	Financial provisioning for rehabilitation	Failure to finance reclamation activities during mining operations or inaccurate estimation of reclamation cost
	LR_3	Financial risk for employees	Problems caused by unpaid wages
	LR_4	Financial risk for government	Problems due to unpaid taxes and royalties

Table 2. Risk assessment matrix

Probability level	Consequence level				
	Insignificant	Minor	Moderate	Major	Catastrophic
Rare	I	II	II	II	II
Unlikely	I	II	III	III	IV
Moderate	I	III	III	IV	V
Likely	II	III	IV	IV	V
Almost certain	II	IV	IV	IV	V

is constructed according to the risk matrix table (as shown in Table 2). The antecedent and action of a rule are qualitative concepts described in natural language; P and C are input variables and C is output variable. Table 3 shows that the probability P and consequence C are divided into five grades; therefore, 25 rules can be constructed according to the combination principle. These 25 rules form the reasoning rule base with double conditions (as shown in Eq. (2)). In the process of risk grade reasoning, each rule needs successively calculation to complete the uncertain reasoning.

Table 3. Levels of quantitative description of risk, probability and consequence

Risk level	Risk scale	Probability	Probability scale	Consequence	Consequence scale
I	1	Rare	0–0.1	Insignificant	0–1
II	2	Unlikely	0.1–0.4	Minor	1–2
III	3	Moderate	0.4–0.6	Moderate	2–3
IV	4	Likely	0.6–0.9	Major	3–4
V	5	Almost certain	0.9–1.0	Catastrophic	4–5

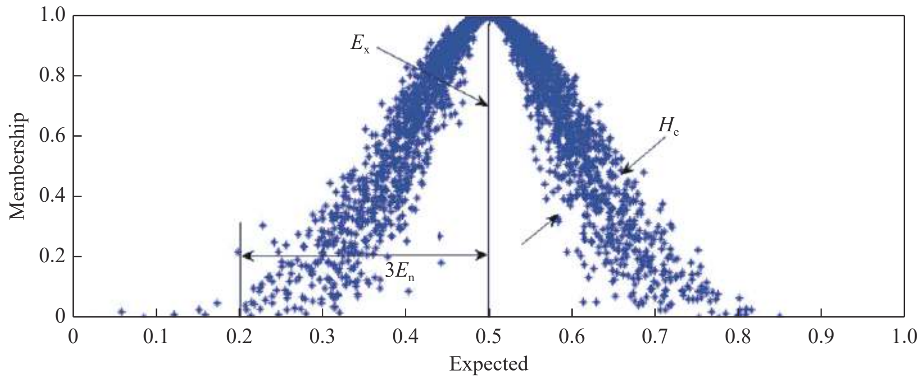

Fig. 2. MCR level description by normal cloud model.

$$\boldsymbol{R} = (\boldsymbol{R}_{5\times5}) = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{15} \\ R_{21} & R_{22} & \cdots & R_{25} \\ \cdots & \cdots & \cdots & \cdots \\ R_{51} & R_{52} & \cdots & R_{55} \end{bmatrix} = \begin{bmatrix} \mathrm{I} & \mathrm{II} & \mathrm{II} & \mathrm{II} & \mathrm{II} \\ \mathrm{I} & \mathrm{II} & \mathrm{III} & \mathrm{III} & \mathrm{IV} \\ \mathrm{I} & \mathrm{III} & \mathrm{III} & \mathrm{IV} & \mathrm{V} \\ \mathrm{II} & \mathrm{III} & \mathrm{IV} & \mathrm{IV} & \mathrm{V} \\ \mathrm{II} & \mathrm{IV} & \mathrm{IV} & \mathrm{IV} & \mathrm{V} \end{bmatrix} \quad (2)$$

Step 3: Uncertainty reasoning based on cloud model.

Based on the expert group decision, the probability and consequence of MCR are evaluated and scored based on Table 3. Then, the probability cloud model $P\,(E_{xp}, E_{np}, H_{ep})$ and consequence cloud model $C\,(E_{xc}, E_{nc}, H_{ec})$ should be examined according to Table 4. Finally, the final cloud model of the probability and consequence of the risk should be synthesized by the evaluation results of all experts with the weighted average method as interpreted in Eq. (3):

$$\begin{cases} x_p = x_{p_1}\times\lambda_1 + x_{p_2}\times\lambda_2 + \cdots + x_{p_k}\times\lambda_k \\ x_c = x_{c_1}\times\lambda_1 + x_{c_2}\times\lambda_2 + \cdots + x_{c_k}\times\lambda_k \end{cases} \quad (3)$$

where x_p is the final value of probability, x_c indicates the final value of consequences, and λ_k refers to the weight of each expert. This study selected four experts to form an expert group and set each expert with an equal weight of 0.25.

Thereafter, the calculation processes of uncertainty inference by the normal cloud are as follows:

(1) Generating two-dimensional (2D) random numbers.

Based on Eq. (4), a 2D random value (x_p, x_c) is generated, which conforms to a 2D normal distribution; for each evaluation rule in the rule base, Eq. (5) is used to generate a random value (E_{npi}, E_{nci}), which also conforms to a 2D normal distribution.

$$(x_p, x_c) = \mathrm{NORMINV}[\mathrm{Rand}\,(), (E_{xp}, E_{xc}), (E_{np}, E_{nc})] \quad (4)$$

$$(E_{npi}, E_{nci}) = \mathrm{NORMINV}[\mathrm{Rand}\,(), (E_{np}, E_{nc}), (H_{ep}, H_{ec})] \quad (5)$$

(2) Calculating membership matrix $\boldsymbol{\mu}$.

The results of Eqs. (4) and (5) are substituted in Eq. (6) to obtain the corresponding membership values under the condition that the pre-input condition of each rule is (x_p, x_c). As 25 rules exist in the rule base, 25 membership values are generated, thereby forming the membership matrix $\boldsymbol{\mu}$. The ele-

Table 4. Normal cloud parameter of *P*, *C*, and *R* levels

Variable	Parameter	I	II	III	IV	V
	E_x	1	2	3	4	5
R	E_n	0.33	0.33	0.33	0.33	0.33
	H_e	0.02	0.02	0.02	0.02	0.02
	E_x	0.05	0.25	0.5	0.75	0.95
P	E_n	0.04	0.13	0.08	0.13	0.04
	H_e	0.02	0.02	0.02	0.02	0.02
	E_x	0.5	1.5	2.5	3.5	4.5
C	E_n	0.42	0.42	0.42	0.42	0.42
	H_e	0.02	0.05	0.05	0.05	0.02

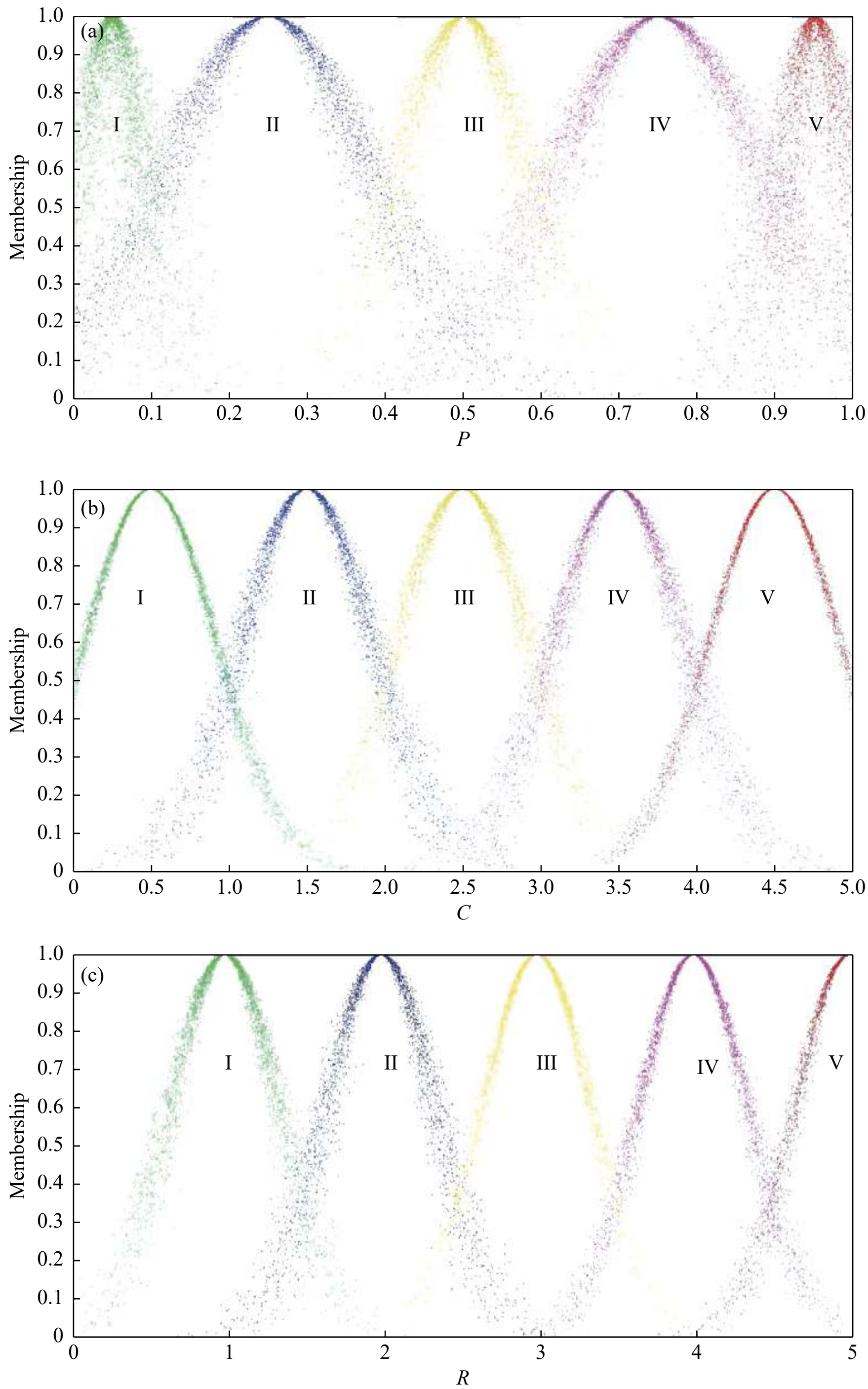

Fig. 3. Normal cloud figure of (a) *P*, (b) *C*, and (c) *R*. Green represents I, blue represents II, yellow represents III, magenta represents IV, and red represents V.

ments values μ_i ($i = 1, 2, \ldots, 25$) in the matrix can be calculated as:

$$\mu_i = \exp\left[-\left(\frac{(x_\text{p} - E_{\text{xp}i})^2}{2(E_{\text{np}i})^2} + \frac{(x_\text{c} - E_{\text{xc}i})^2}{2(E_{\text{nc}i})^2}\right)\right] \tag{6}$$

(3) Calculating cloud droplets (y, μ_i).

This step involves taking the maximum μ_1 and second-maximum μ_2 from the matrix $\boldsymbol{\mu}$ and then adopting Eq. (7) to generate the one-dimensional (1D) normal random values E'_{nR} of the grade cloud model with maximum and next-maximum correspondence rules. Thereafter, Eq. (8) is used to calculate four y values inversely under the condition of μ_1, μ_2, and E'_{nR}, so we can obtain four groups (y_{11}, μ_1), (y_{12}, μ_1), (y_{21}, μ_2), (y_{22}, μ_2).

$$E'_{\text{nR}} = \text{NORMINV}(\text{Rand}\ (),\ E_{\text{nR}},\ H_{\text{eR}}) \tag{7}$$

where E_{nR} is the entropy of risk, E_{xR} is the expectation of risk, and H_{eR} represents the super entropy of risk.

$$\mu_i = \exp\left[-\frac{(y-E_{xR})^2}{2(E'_{nR})^2}\right], i = 1,2 \tag{8}$$

(4) Constructing a virtual cloud.

The two closest cloud droplets, for example, (y_{11}, μ_1) and (y_{21}, μ_2) are selected to construct a virtual cloud concept by the geometric methods. The numerical characteristics (E_x, E_n) of the virtual cloud are calculated using Eq. (9) and (10), and the super entropy is 0. The virtual cloud is considered as the cloud model for the final evaluation risk-level (R), where the expectation E_x can be regarded as the final evaluation level of the risk event.

$$E_x = \frac{y_1\sqrt{-2\ln\mu_2} + y_2\sqrt{-2\ln\mu_1}}{\sqrt{-2\ln\mu_2} + \sqrt{-2\ln\mu_1}} \tag{9}$$

$$E_n = \frac{|y_1 - y_2|}{\sqrt{-2\ln\mu_2} + \sqrt{-2\ln\mu_1}} \tag{10}$$

2.3. Risk treatment

2.3.1. Determination of reutilization modes

Risk treatment means that certain effective strategies are adopted to eliminate or mitigate the unaccepted hazard events that have been identified in the risk assessment. CMR, as a proactive measure, refers to the integration of idle resources such as underground space, land, surplus resources, culture, and other resources through engineering and biological measures to make them available [45–48]. However, reusing these coal mines is difficult because of serious deformation of underground spaces and many disasters such as mine water and gas accumulation. As these mines are too expensive to rehabilitate for reuse, they are no longer considered for reutilization. A review of hundreds of articles and examples has revealed that closed mines can be reused for various purposes, such as constructing entertainment centers [49], energy storage (pumping storage, wind, and compressed air) [50], abandoned mine methane extraction [51], geothermal energy recovery [52], renewable energy production [53], and underground storage [54–55]. Based on the review of different CMR options, the reutilization modes can be divided into six categories with 19 sub-patterns, as shown in Fig. 4. Each reutilization pattern corresponds to multiple MCRs, which have potential conflicts in terms of the suitability and effectiveness of risk management. Notably, not all 19 reutilization patterns are feasible in a closed mine. The initial reutilization patterns should be determined by comprehensively evaluating the mine conditions, natural and geological conditions, and socio-economic factors. To simplify and facilitate research, we can confirm the seven reutilization alternatives from Fig. 4 for the present study cases with research on the surrounding CMR situation and expert consultation.

2.3.2. Restricted condition identification of closed risk mine (CMR) patterns

The selection of an optimal reutilization pattern involves various internal and external restricted conditions of a closed mine. However, a large number of indicators on the survey forms may be confusing. Therefore, an integrated indicator system that involves the most important criteria should be established to identify the suitability of CMR. At present, the existing studies on suitability evaluation mainly focus on mined land [34,45,56]. Papers that directly take closed mines as research objects and provide a general analytical framework for reutilization pattern selection have not been found. As mining land is an important mine-closure legacy resource, its reclamation suitability evaluation shares many of the same economic, social, and environmental restriction factors with the whole idle resource cycle of closed mines. The main difference lies in the mine and technical conditions. According to the suitability analytical framework of mining land reclamation in the literature [16,41,46], this study identified the most important restricted factors related to CMR pattern selection and grouped them into five aspects with 17 sub-attributes, as shown in Table 5. The economic factors refer to the most

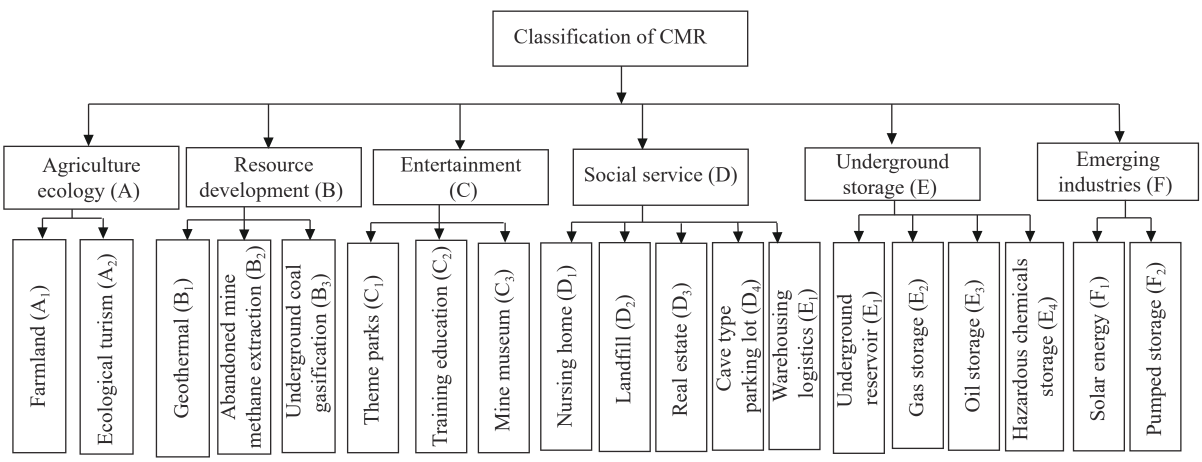

Fig. 4. Classification of reutilization modes of closed mines.

important cost and benefit attributes related to the economic characteristics of the CMR modes. The social factors indicate the positive impacts and public acceptance in the process of CMR suitability analysis. The landscape and environmental factors comprise criteria related to the positive effects and environmental acceptability of CMR on landscape and environment. The technical factors mean the constraints that affect the reutilization mode selection. Finally, the mine factors refer to constraints from mine characteristics, which include the size of the mine, surrounding geological conditions, and hydrological conditions.

2.3.3. Ranking of CMR patterns

This paper adopted the IAHP–TOPSIS method to obtain the potential CMR pattern preference order based on the CMR restricted conditions framework (Table 5). The procedure of IAHP weighting can be seen in section 2.3.4, and the steps of the TOPSIS method are as follows:

Step 1: Constructing the decision matrix $\boldsymbol{A}$.

As shown in Eq. (11), the elements are derived from the experts scoring of these restricted conditions (Table 5). Due to the low quantification of some social and technical factors, this study used a 1–9 scale defined by Saaty and Tran to assign scores of the restricted conditions, where 1 indicates the lowest and 9 is the highest condition of each indicator to patterns [57].

$$\boldsymbol{A}^k = \begin{bmatrix} a_{11}^k & a_{12}^k & \cdots & a_{1j}^k \\ a_{21}^k & a_{22}^k & \cdots & a_{2j}^k \\ \cdots & \cdots & \cdots & \cdots \\ a_{i1}^k & a_{i2}^k & \cdots & a_{ij}^k \end{bmatrix} \tag{11}$$

where k refers to the number of experts, i can be interpreted as the i-th alternative, and j indicates the j-th constraint. In this study, $k = 1,2,3,4$; $i = 1,2,\ldots,7$; $j = 1,2,\ldots,17$.

Step 2: Creating the normalized decision matrix.

This step involves normalizing matrix $\boldsymbol{A}$ to acquire matrix $\boldsymbol{Z}^k$, where the elements $\boldsymbol{Z}_{ij}^k$ are obtained based on Eq. (12):

$$\begin{cases} \boldsymbol{Z}_{ij}^k = \dfrac{a_{ij}^k}{\sqrt{\sum_i^n a_{ij}^{k\,2}}} \quad \text{(For benefit attribute)} \\ \boldsymbol{Z}_{ij}^k = \dfrac{1/a_{ij}^k}{\sqrt{\sum_i^n \left(1/a_{ij}^k\right)^2}} \quad \text{(For cost attribute)} \end{cases} \tag{12}$$

Step 3: Obtaining the weighted normalized decision matrix.

Creating a weighted decision matrix $\boldsymbol{Z}^{k'}$, where its elements $\boldsymbol{Z}_{ij}^{k'}$ are calculated by Eq. (13):

$$\boldsymbol{Z}_{ij}^{k'} = W_j \times Z_{ij}^k \tag{13}$$

In Eq. (13), W_j is denoted as the weight of constraint j, and $j = 1,2,\ldots,17$.

Step 4: Acquiring positive and negative ideal solutions.

This step involves calculating the positive and negative ideal solutions according to Eq. (14) and (15):

$$\boldsymbol{Z}^{k'+} = (Z_1^{k'+}, Z_2^{k'+}, \ldots, Z_m^{k'+}) = \left\{\max_i Z_{ij}^{k'+} \,|\, j = 1,2,\ldots,17\right\} \tag{14}$$

$$\boldsymbol{Z}^{k'-} = (Z_1^{k'-}, Z_2^{k'-}, \ldots, Z_m^{k'-}) = \left\{\min_i Z_{ij}^{k'-} \,|\, j = 1,2,\ldots,17\right\} \tag{15}$$

Step 5: Determining distances of ideal point and negative ideal point.

This step involves calculating the distances (S) from the ideal point and negative ideal by Eq. (16) and (17):

Table 5. Decision-making constraints in CMR

Criteria layer	Index layer	Cost	Benefit	Weight
Economic factors (E)	Capital cost E_1	√	—	0.1017
	Maintenance cost E_2	√	—	0.1281
	Potential of investment absorption E_3	—	√	0.0388
	Creating income for local E_4	—	√	0.0307
Social factors (S)	Employment opportunities S_1	—	√	0.0228
	Consistency with local concerns and needs S_2	—	√	0.1291
	Changes in livelihood quality S_3	—	√	0.0114
	Public participation S_4	—	√	0.0457
	Conformity with government policy S_5	—	√	0.0646
Landscape and environmental factors (L)	Environmental acceptability L_1	—	√	0.1152
	Landscape quality improvement L_2	—	√	0.0634
Technical factors (T)	Availability of reutilization techniques T_1	—	√	0.0373
	Distance to nearest water supply T_2	—	√	0.0913
	Market availability T_3	—	√	0.0218
Mine factors (M)	Surrounding geology M_1	—	√	0.0535
	Hydrology of surface and groundwater M_2	—	√	0.0268
	Size M_3	—	√	0.0178

Note: The "√" is used to indicate the confirmation of these indicators' attributes.

$$S_i^{k+} = \sqrt{\sum_j^m \left(Z'_{ij} - Z'^{+}\right)^2} \quad (16)$$

$$S_i^{k-} = \sqrt{\sum_j^m \left(Z'_{ij} - Z'^{-}\right)^2} \quad (17)$$

Step 6: Acquiring group decision results of ideal point and negative ideal point.

Aggregating each individual separation measure is conducted based on Eq. (18) to acquire group decision results:

$$\begin{cases} S_i^{+} = (S_i^{k+},1)^{\lambda_1} \times (S_i^{k+},2)^{\lambda_2} \times \cdots \times (S_i^{k+},k)^{\lambda_k} \\ S_i^{-} = (S_i^{k-},1)^{\lambda_1} \times (S_i^{k-},2)^{\lambda_2} \times \cdots \times (S_i^{k-},k)^{\lambda_k} \end{cases} \quad (18)$$

where λ_k refers to the weight of each expert, which is equal to 0.25 in this study.

Step 7: Calculating and ranking the relative proximity C_i based on Eq. (19):

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (19)$$

where $0 \le C_i \le 1$, $i = 1, 2, \cdots, 7$.

2.3.4. Weighting constraints with an improved AHP

The improvement of consistency of the comparison matrix is a difficult problem in the AHP. The improved AHP (IAHP) adopts scale-extending to construct the judgment matrix, causing the adjusted judgment matrix to have a satisfactory consistency. The basic idea of the IAHP is to compare the importance of indicators in the same hierarchy and rank them as a sequence according to the expert preferences, and then calculate the value of other elements according to the importance transitivity of each indicator to obtain the judgment matrix. The judgment matrix constructed in this way has consistency and does not require a consistency test. The method is commenced by ranking all the criteria layer indicators according to the order of their importance, which is based on an individual expert's judgment. The acquired indicator sequence is defined as $x_1 > x_2 > x_3 > \cdots > x_n$, where the importance of the adjacent index is quantitatively described according to Saaty and train's nine-point scale [57]. The judgment matrix $\boldsymbol{R}'$ constructed by the IAHP can be seen in Eq. (20). Thus, based on this, the indicators' weight can be calculated by Eq. (21). After performing the criteria layer indicators' weight calculation, the same algorithm was adopted to calculate each indicator weight in the index layer. The final step is to multiply the weights of the criteria layer and index layer to acquire the global weights of all the constraints.

$$\boldsymbol{R}' = \begin{vmatrix} 1 & t_1 & t_1t_2 & t_1t_2t_3 & \cdots & t_1t_2\cdots t_{n-1} \\ \frac{1}{t_1} & 1 & t_2 & t_2t_3 & \cdots & t_2t_3\cdots t_{n-1} \\ \frac{1}{t_1t_2} & \frac{1}{t_2} & 1 & t_3 & \cdots & t_3t_4\cdots t_{n-1} \\ \frac{1}{t_1t_2t_3} & \frac{1}{t_2t_3} & \frac{1}{t_3} & 1 & \cdots & t_4t_5\cdots t_{n-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{1}{t_1t_2\cdots t_{n-2}} & \frac{1}{t_2t_3\cdots t_{n-2}} & \frac{1}{t_3t_4\cdots t_{n-2}} & \frac{1}{t_4t_5\cdots t_{n-2}} & \cdots & t_{n-1} \\ \frac{1}{t_1t_2\cdots t_{n-1}} & \frac{1}{t_2t_3\cdots t_{n-1}} & \frac{1}{t_3t_4\cdots t_{n-1}} & \frac{1}{t_4t_5\cdots t_{n-1}} & \cdots & 1 \end{vmatrix} \quad (20)$$

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} r_{ij}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} r_{ij}}} \quad (21)$$

where w_i is the weight value of the i-th indicator by an individual expert, and r_{ij} is the value of the preference of the i-th compared with the j-th element.

As the weight determination is performed by a group of experts, it is needed to aggregate each individual judgment in group decision-making. The weighted geometric average method is the most common method to aggregate all experts' judgment matrixes into one judgment matrix. The element in the final judgment matrix $\boldsymbol{A}$ (Eq. (11)) can be calculated as Eq. (22):

$$a_{ij} = (a_{ij},1)^{\lambda_1} \times (a_{ij},2)^{\lambda_2} \times \cdots \times (a_{ij},17)^{\lambda_k} \quad (22)$$

where k indicates the number of experts, (a_{ij},k) is the matrix element of the k-th expert, and λ_k represents the weight of each expert. When the weights of experts are the same as 0.25, Eq. (22) can be simplified as Eq. (23):

$$a_{ij} = \sqrt{(a_{ij},1) \times (a_{ij},2) \times \cdots \times (a_{ij},17)} \quad (23)$$

3. Study area and data sources

3.1. Background

To verify the feasibility and correctness of the novel risk management method, we selected the Muchengjian coal mine, a closed mine in the Beijing west mining area, as the study object. The terrain of Beijing west mining area is complicated and the elevation difference is great. The mine shares the advantages of superior geographical location and well developed transportation networks. The Muchengjian mine is a simple hydrogeological mine and the relative gas emission volume of the mine is 2.73 m^3/min, which is a low-gas mine. The average solar radiation in this region is 5763.82 MJ/m^2. It is the largest coal mine in the Beijing west mining area with an annual capacity of 1.7×10^6 t and more than 7400 employees before shutting down. It has provided more than 70×10^6 t of coal resources for the country and the remaining resources can still be mined for nearly 60 years. However, according to the government provisions "Reduction Coal Overcapacity Implementation Plan in Beijing", all the coal mines in Beijing west mining area should be closed by 2020. In 2018, the Muchengjian coal mine was completely closed, leaving many socio-economic problems. After many years of mining activities, a gangue of nearly 1.2×10^6 m has been formed in the mine site. The gangue not only occupies the land but also causes different impacts on the surrounding environment. At present, the closed Muchengjian coal mine actively nurtures new economic growth points, such as ecological agriculture, aquaculture, and tourism.

3.2. Data sources

The recognition and preference of experts play a critical role in risk management considering the incomplete knowledge historical statistical data and limitations of expert competence. In this study, the expert team consists of the four most relevant stakeholders: (1) manager of the mining company, (2) government representative (official of National Energy Administration), (3) environment protection agency representative, and (4) community representative, to fully consider various professional competencies and roles of those involved in mine closure. Although these experts represent a small sample without statistical significance, this feature is not a fatal flaw in group decision-making because the aim of the survey is to identify all significant risks from key persons. Considering the difficulty of comparing the level of competence of experts, this study sets the weight of each expert as equal to 0.25.

4. Results and discussion

4.1. CMR assessment of study area

According to the IRMCM method, the outcomes of risk assessment were obtained in Table 6. As shown in the first column in Table 6, the risk levels were reflected by cloud parameters, where the expectation value represents the most likely level and the entropy shows the uncertainty of the risk level range. Fig. 5 shows the cloud figure of each risk grade, intuitively reflecting the expectation grade and fluctuation range of the risk level. Therefore, Table 6 and Fig. 5 can fully show the fuzziness and randomness of risk assessment. This method proposes a simple, efficient, and visual new model for resolving the uncertainty of a CMR control system.

As shown in the second column in Table 6, the risk-level determination based on IRMCM is a range. The risk whose

Table 6. Results of MCR by IRMCM and RMA

Risk	IRMCM	Level ranges	Level distribution	$\mu > 0.5$	Level determination (μ >0.5)	RMA
TR_1	4.7558, 0.0978, 0	4.46–5.05	V	4.64–4.87	V	V
TR_2	1.6683, 0.0612, 0	1.48–1.85	II	1.60–1.74	II	II
TR_3	2.6119, 0.2126, 0	1.97–3.25	II, III, IV	2.36–2.86	III	III
TR_4	1.8855, 02269, 0	1.20–2.57	II, III	1.62–2.15	II	I/II
HR_1	1.5552, 0.1735, 0	1.03–2.08	II, III	1.35–1.76	II	II
HR_2	2.6818, 0.1470, 0	2.24–3.12	III, IV	2.51–2.85	III	III
HR_3	2.5618, 0.1000, 0	2.26–2.86	III	2.44–2.68	III	II/III
HR_4	4.3832, 0.1304, 0	3.95–4.73	IV, V	4.18–4.49	V	IV
HR_5	2.3789, 0.1299, 0	1.99–2.77	II, III	2.23–2.53	III	III
HR_6	3.5237, 0.1547, 0	3.05–4.00	III, IV	3.34–3.71	IV	III
ER_1	3.2971, 0.1330, 0	2.90–3.70	III, IV	3.14–3.45	IV	III/IV
ER_2	1.6354, 0.1064, 0	1.31–1.95	II	1.51–1.76	II	II
ER_3	2.3754, 0.1356, 0	1.97–2.78	II, III	2.22–2.54	III	II
ER_4	3.5832, 0.1105, 0	3.25–3.91	IV	3.45–3.71	IV	IV
ER_5	3.0000, 0.2753, 0	2.17–3.83	III, IV	2.68–3.32	III	III
ER_6	4.6276, 0.1380, 0	4.21–5.04	V	4.34–4.47	V	V
CR_1	4.7471, 0.1124, 0	4.41–5.08	V	4.61–4.88	V	V
CR_2	3.5715, 0.1752, 0	3.05–4.10	IV, V	3.37–3.78	IV	IV
CR_3	3.6172, 0.1830, 0	3.07–4.17	IV, V	3.40–3.83	IV	IV
CR_4	3.2360, 0.1159, 0	2.89–3.58	III, IV	3.10–3.37	IV	III/IV
LR_1	2.5651, 0.2957, 0	1.68–3.45	II, III, IV	2.22–2.91	III	III
LR_2	3.9499, 0.2839, 0	3.10–4.80	IV, V	3.62–4.28	IV	IV
LR_3	2.5526, 0.2294, 0	1.86–3.24	II, III, IV	2.29–2.82	III	III
LR_4	2.2295, 0.1031, 0	1.92–2.54	II, III	2.11–2.35	III	II

Note: The levels of risks are indicated by the depth of shade.

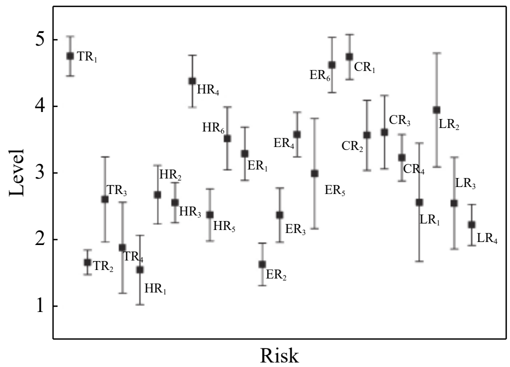

Fig. 5. Level range of all risks assessed using normal cloud model. The "average" value represents the expectation of each risk level. The range of error is determined based on the "3E_n criterion".

level fluctuates within a range of one grade is called high certainty risk, including TR_1, TR_2, HR_3, ER_2, ER_4, ER_6, and CR_1, indicating that the decision-makers have a high degree of certainty in these risk judgments. An analysis of these high certainty risks shows that most of them are at the high level (V), which reflects that the decision-makers have certain cognition of the critical risk identification. The risk whose level fluctuates within two grades is called low uncertain risk involving TR_4, HR_1, HR_2, HR_4, HR_5, HR_6, ER_1, ER_3, ER_5, CR_2, CR_3, CR_4, LR_2, and LR_4. The risk level, which could be fluctuated more than two grades, is defined as the most uncertain risk, containing TR_3, LR_1, and LR_3. The determination of these uncertain risk levels needs to elevate the degree of membership, indicated by μ_i, $i = 1, 2, \ldots, 25$ in Eq. (6), to narrow the confidence interval. In this study, the evaluation levels of each risk were determined when the membership degree was greater than 0.5 ($\mu_i > 0.5$), and the results are shown in the third column of Table 6. The consistency rate of risk grade assessed by IRMCM and RMA results was 66.7% (in the same color) when the membership degree was greater than 0.5. Regarding the risks with inconsistent grades in the two methods, the grades determined by IRMCM were a grade higher than those determined by RMA, indicating that the evaluation results of IRMCM were cautious and conservative in practical application. Thus, we can recognize that the results of risk matrix evaluation are not entirely plausible. Especially for engineering with potentially high risks, underestimation of these risk levels may lead to incorrect decision-making [56].

The grades of TR_4, HR_3, ER_1, and CR_4 in the last column of Table 6 were difficult, judging by the traditional risk matrix method. In comparison, these risk grades can be effectively determined by IRMCM under the condition of membership degree greater than 0.5, which illustrates that the IRMCM method has a stronger applicability for the determination of potential higher-level risk events.

From the analysis of the grade distribution ($\mu_i > 0.5$), it can be found that TR_1, HR_4, ER_6, and CR_1 were in the highest risk grade (V), and HR_6, ER_1, ER_4, CR_2, CR_3, CR_4, and LR_2 were in the higher risk grade (IV). These risks were mainly related to society (community and health) and the environment, indicating that the main sources of MCR were derived from environmental pollution and regional economic shocks. As shown in Table 6, the high-level risks (V, IV) ratio in the Muchengjian closed coal mine is 46%; thus, this entire MCR level was considered at a high level and should receive special attention. Due to the different risk levels of mine closure, it is meaningful to determine which closed mine should receive intervention given the circumstances of the large number of abandoned mines in China and the recovery budget restrictions. The MCR assessment by the proposed method not only assists in identifying the harmful effects of mining activities but also providing guidance for selecting the priority for mines recovery.

4.2. CMR treatment in the study area

The outcomes of CMR pattern preference order are demonstrated in Table 7. The table shows that ecological tourism was considered the best reutilization mode for the Muchengjian coal mine. As the high-level risks were mainly in the environmental and social aspects, this reutilization mode not only strengthens environmental protection (ER_1, ER_6) and improves the health and safety conditions (HR_4, HR_6) but also increases local income (CR_2 and CR_4) and solves the problem of unemployment (CR_1 and CR_2) relative to other reutilization patterns. Therefore, this reutilization pattern was the best choice for treating the significant identified risks.

According to the "Beijing City Overall Plan (2016–2035)", the function orientation of the Mentougou district is a

Table 7. Priorities of CMR patterns by IAHP–TOPSIS method

ID	Mode	Pattern	Description	S_i^+	S_i^-	C_i	Ranking
1	F	Solar power plant	F_1	0.0766	0.0561	0.4227	4
2	D	Landfill	D_2	0.1077	0.0292	0.2135	7
3	C	Entertainment center	C_1, C_2, C_3	0.0562	0.0892	0.6134	2
4	D	Real estate	D_3	0.0910	0.0421	0.3163	6
5	A	Ecological tourism	A_2	0.0208	0.1115	0.8429	1
6	D/E	Commercial use	D_1, E_1	0.0806	0.0500	0.3828	5
7	A	Agriculture	A_1	0.0556	0.0879	0.6127	3

Note: The classifications of reutilization patterns in Table 7 are based on the reutilization modes listed in Fig. 4.

key ecological conservation area [58]. As shown in the reference [58], the Muchengjian mine is located in the ecological conservation area but not within the scope of the planned construction region. That is, all the reutilization types should be consistent with the construction of the ecological conservation function. As this mining area is a restricted development zone (located in the ecological conservation base), it is not suitable for industrial construction (which can improve regional revenues). However, the critical risks CR_1–CR_4 (mainly about the residents' economic demands and regional development) are high. Thus, the core problem in this area is to balance the economy's sustainable development with ecological construction after mine closure. That is, the key point of risk treatment is to resolve the contradiction between environmental protection and local economic development. Therefore, it is important to find a reutilization way that not only protects the ecological environment but also makes full use of the advantages of the surrounding ecological dominance and cultural resources to meet the needs of economic and social development. Compared with other reutilization patterns, ecological tourism is the best form of combining economic benefits and ecological benefits. In addition, it provides the opportunity to perfect the compensation mechanism of forestry ecological benefits in China. According to "Implementation Opinions on Accelerating the Transformation and Development of the Western Region" published by the Beijing government, authorities began to draft plans for a new Jingxi, with ecological tourism as its pillar industry. Based on the preceding analysis, the result that ecological tourism is the best option was verified clearly and authoritatively.

The A_5 and A_7 are ecological development patterns based on ecological conservation area construction. The difference in these reutilization options' preference order may be related to economic benefits. In addition, the nearest water resource supply indicator also plays an important role in restricting agriculture development because it has a higher requirement for water sources than other alternatives. In fact, this region has experimented with growing plants such as cherry trees and other drought-tolerant crops, which can improve the ecology and increase community income. In addition, based on the Transformation and Upgrading Plan of JINGMEI Group (TUPJMG, 2017), the Muchengjian coal mine will be built into a ski industrial park (A_2) that integrates ski equipment research and development, ski training, ski leisure, and tourism (A_5), which demonstrates that this decision method is effective.

The weights of indicators fully express the preferences of decision-makers. Fig. 6 shows that the weights of economic factors accounted for a large proportion (30%) followed by social indicators (27%) in the total weight, reflecting that decision-makers pay more attention to economic costs and social benefits in the decision of CMR modes. The reasons are that the uncontrollability of economic indicators plays a decisive role in reutilization project demonstration. The social concerns are also critical in determining the CMR pattern because the alternative must meet the local demand and be accepted by society.

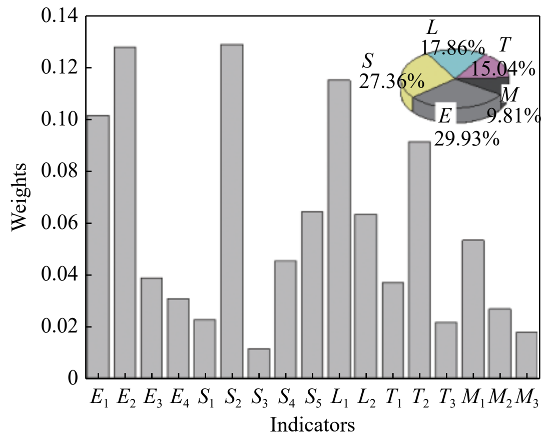

Fig. 6. Global weights based on IAHP.

5. Conclusions and implication

(1) When determining risk levels, the traditional risk matrix method does not consider the ambiguity and uncertainty of the boundary and lacks a scientific and reasonable uncertainty reasoning mechanism, which seriously affects the accuracy of risk assessment. This study developed a novel risk assessment approach based on a cloud model to manage MCR. Compared with other risk assessment methods, the proposed method comprehensively considered the uncertainties of risk grading by clouding the risk probability and consequences, thereby realizing soft classification of the level of risk events. Combined with expert group decision-making, this method effectively integrates the fuzziness and randomness of qualitative concepts, which achieves the transformation between quantitative description and qualitative concept. On this basis, this study deduces the uncertainty reasoning process based on constructing a rule base, making the evaluation results more reliable and intuitive. This study employs three normal cloud parameters to characterize the risk levels instead of using a single indicator to represent the results of risk assessment in the traditional risk assessment methods. This approach greatly improves the robustness of the risk assessment by comprehensively considering the center value and fuzziness and randomness of the evaluation results. This study provides a simple and effective new method for the quantitative analysis of MCRs, which is helpful for managers to determine the key points of risk control and realize economic and reasonable risk management according to the results of the cloud model of risk level. Therefore, the most important theoretical contribution of this study is a proposed universally accepted risk assessment method.

(2) This study employed the IAHP–TOPSIS method to acquire a preference ranking list of CMR patterns, which provides a hybrid multidimensional decision-making method for responding to the significant risks involved in closed mines. Compared with other methods, TOPSIS fully utilizes the original data information and accurately reflects gaps among all the evaluation schemes. The improved AHP avoids the coincidence examination and adjustment of the judgment matrix, simplifies the calculation, and defines the weighing scientifically and properly. The results of this method can be used as a reference for effectively reusing the idle resources of closed mines to achieve cleaner production in post-mining regions. The reutilization simplification should be avoided by combining and coordinating these suitable patterns to achieve more efficient allocation of idle resources.

(3) For the policy implications, a valid MCR management method can provide policy implications and formulate targeted mine-closure plans to address the adverse social and economic impacts. When a mine is closed, in addition to dealing with the environmental problems, another important consideration is achieving smooth production transition of the mining corporation and the sustainable development of society and economy in the mining area. Therefore, the key points of mine-closure management are to determine the risk level accurately and treat the identified high-level risks at the minimum cost on the premise of meeting the needs of all stakeholders and regional characteristics.

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