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Assessment of clean production level in phosphate mining enterprises: Based on the fusion group decision weight and limited interval cloud model

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ABSTRACT

To develop a robust cleaner production level assessment model for phosphate mining enterprises, this study investigated the key factors influencing their cleaner production levels. The model incorporates integrated group decision weights and a limited interval cloud model. Based on the comprehensive life cycle of phosphate mining production, we constructed a detailed evaluation index system to assess the cleaner production level of these enterprises. This system defined the quantitative ranges for each level and revealed the interrelationships among the indicators. To ensure comprehensive weight determination, we proposed a method that integrates the expertise of multiple stakeholders. This method leveraged group decision-making principles to effectively resolve conflicts in expert judgments during the weight determination process. In addressing the characteristics of evaluation indicators for the cleaner production level of phosphate mining enterprises, we proposed employing a finite interval cloud model to accurately characterize the distribution of the indicators. Leveraging the finite interval cloud model, we obtained numerical characteristics for various indicators and incorporated the weights of the integrated group decision-making attributes. This approach enabled us to determine the cleaner production level of phosphate mining using a finite interval cloud generator. Validation using five phosphate mining enterprises in Hubei Province, China, confirmed the model's high accuracy. This model demonstrated its applicability in evaluating cleaner production levels for phosphate mining enterprises, offering a theoretical foundation for developing targeted environmental management policies.

1. Introduction

Driven by economic and societal growth, the demand for phosphate mining resources is steadily rising. However, this increased mining activity also generates significant concerns. Wastewater, waste residue, and waste rock pose a growing threat of regional environmental pollution and ecological damage, prompting urgent attention (Safhi et al., 2022; Amar et al., 2023). Implementing cleaner mining production practices can improve overall efficiency, mitigate the adverse impact of mines on human and ecological environments, and maximize the utilization of resources and their associated resources (Zhou and Zhao, 2016; Dong et al., 2019). Therefore, by evaluating the cleaner production level of phosphate mining enterprises, it becomes feasible to significantly enhance corporate management, reduce environmental pollution, and improve the ecological environment, thereby accomplishing the objective of sustainable mine development.

Building on in-depth research on cleaner production in phosphate mines, scholars have achieved promising results. For instance, Wu et al. (2022) explored clean processing technologies for phosphogypsum, a by-product of the phosphorus industry, with the aim of guiding future by-product development directions. Pu et al. (2021) investigated the current applications of phosphogypsum in geotechnical engineering, further exploring its potential for wider use in the field. However, research has primarily concentrated on comprehensive resource utilization and harmless treatment. There is a paucity of studies on the evaluation of the cleaner production level of phosphate mining enterprises. The challenges in evaluating the cleaner production level of phosphate mining enterprises primarily arise from three key aspects: the selection of key influencing factors, the calculation of indicator weights, and the construction of evaluation models (Oliveira et al., 2017).

An accurate and scientifically sound evaluation index system is fundamental for effectively assessing cleaner production levels in phosphate mining. Therefore, establishing such a comprehensive and objective system is crucial. Dong et al. (2018) established a

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comprehensive evaluation index system for cleaner production in phosphate mining by selecting 31 indicators across six aspects: enterprise management, environmental protection, mining technology, mining economy, comprehensive utilization, and processing technology. Wang et al. (2018) developed an ecological environment assessment index system using the Driving Forces-Pressure-State-Impact-Response (DPSIR) model and determined the weights of each indicator using the analytic hierarchy process (AHP). Liu et al. (2023) developed an Index system for green mining evaluation, that encompassed eight key aspects: management level, mining technology, corporate culture, environmental protection measures, comprehensive utilization, energy conservation and emission reduction, land reclamation, and community environment. They further integrated the AHP and the Analytic Network Process (ANP) to allocate weights to the indicators. He et al. (2017) established a five-aspect geological and ecological environmental assessment index system for phosphate mining that considers geological conditions, geological hazards, natural environment, mining intensity, and ecological environment restoration. AHP was employed to determine the weights of each indicator. While these research findings provide a reference for studying cleaner production index systems in the phosphate resource mining industry, these methods often involve subjective indicator selection that relies heavily on decision-makers' subjective experiences and personal preferences. In addition, they lack consideration of the correlation and hierarchy of indicators, resulting in a lack of overall integrity and comprehensiveness in the index system.

Furthermore, the subjective, vague, and uncertain division of indicator intervals under different grades in the cleaner production level of phosphate mines is a crucial consideration in assessing cleaner production levels in phosphate mining. Hu et al. (2019) used the AHP to weigh the indicators, conducted ecological technology evaluation with a logistic regression model, and broadened its application in this field. Wang et al. (2023) examined the ecological environment and human safety threats of pollutants in phosphogypsum. They developed a comprehensive risk model for phosphogypsum treatment, that covered hazard identification, risk analysis, and hazard characteristics. Zhang et al. (2023) introduced the theory of Interval 2-tuple q-rung orthopair fuzzy sets (I2q-ROFSs) to better describe the ambiguity of environments. Vafadarnikjoo et al. (2020) constructed an improved BWM multicriteria decision-making model by reducing the number of pairwise comparisons and identifying inconsistencies that arise during the comparison process. Chen et al. (2023) proposed a mixed grey evaluation model for mine ecological environments, addressing ambiguity in the ecological environment assessment process based on grey AHP and grey clustering method. Lombardi and Todella (2023) introduced a multi-criteria decision analysis (MCDA) approach for evaluating the sustainability and circularity of solid waste management. Phosphate mining involves significant uncertainty factors. These methods partially addressed deficiencies in traditional risk assessment, thereby expanding the applicability of current methods. However, challenges remain in representing the ambiguity between model accuracy and the level of cleaner production in phosphate mining. This underscores the ongoing need for a more practical and reasonable evaluation method to achieve a cleaner production level of phosphate mining.

In summary, the challenges inherent in evaluating the cleaner production level of phosphate mining enterprises can be summarized as follows: (i) there is a need for more profound research into the scientific rigor and comprehensiveness of indicator selection, the interrelationships, and causal connections among indicators, and the classification of indicator levels; (ii) Crucial to the analysis results is the determination of indicator weights. Presently, the most commonly employed AHP and its associated improved models excessively depend on the subjective awareness and experience of decision-makers, demonstrating significant subjectivity; (iii) the relationships between cleaner production levels in phosphate mines are ambiguous and uncertain. Despite significant efforts to improve the understanding of system elements through the collection of representative data, challenges persist in representing, propagating, and interpreting ambiguity and uncertainty. These challenges need to be addressed when evaluating cleaner production levels in phosphate mines. This study aims to address the aforementioned issues by establishing a scientific hierarchical index system for the cleaner production levels of phosphate mines. This study proposes a reasonable method for determining index weights and an accurate representation of fuzzy relationships, ultimately achieving a precise evaluation of the cleaner production level of phosphate mines. Building upon this and considering the characteristics of phosphate mining, a hierarchical index system for the cleaner production levels of phosphate mines will be established across the entire product life cycle. The evidence theory will be integrated with the AHP to calculate the weights of the evaluation indicators. This approach combines the differing opinions of multiple experts, to resolve conflicts among indicators that may lead to adverse effects. Finally, a fusion group decision-making weight finite interval cloud model will be constructed based on finite interval theory. This model characterizes the realistic distribution characteristics of the index grading results and analyzes the uncertainty of the cleaner production system in phosphate mines. This represents the fuzziness and uncertainty inherent in evaluating the cleaner production level of phosphate mines. This study aims to provide a reliable basis for comprehensively understanding the cleaner production level of phosphate mining enterprises. This will aid in improving the environmental management level of these enterprises, ultimately contributing to the enhancement of the ecological environment in phosphate mining areas.

The paper is structured as follows: Section 2 constructs a hierarchical index system for evaluating the cleaner production level in phosphate mines considering the entire life cycle of production and determining the quantification range of indicators at different levels. Section 3 provides a further analysis of the interrelationships among these indicators. In section 4, a weight determination method is introduced, employing group decision-making attributes in conjunction with the finite interval cloud model, thereby establishing a finite interval cloud model based on integrated group decision-making weights. Section 5 validates and discusses the model using five phosphate mining enterprises in Hubei Province, China, as a case study. Finally, section 6 summarizes the conclusions drawn from this study.

2. Construction of an evaluation index system for cleaner production levels of phosphate mines

2.1. Selection of evaluation indicators for cleaner production levels of phosphate mines

Constructing a cleaner production index system is not merely an arbitrary addition and combination of indicators. A scientific, comprehensive, and open index system is necessary to adapt to changes in economic and social environments that objectively and truthfully reflect the cleaner production level of phosphate mining enterprises. Considering the entire life cycle of phosphate mining production, we constructed a cleaner production level evaluation index system applicable to the phosphate mining industry. It integrates four aspects: ore deposit exploitation, pollutant emissions, resource recovery, and environmental protection while accounting for the interrelationships among the indicators. This system is based on the advanced level of production equipment (X_1), the level of mining process technology (X_2), ore recovery rate (X_3), ore dilution rate (X_4), cutting ratio (X_5), electricity consumption (X_6), water consumption per ton of phosphate ore mined (X_7), explosive consumption (X_8), diesel consumption (X_9), dust (X_{10}), sulfur dioxide (X_{11}), chemical oxygen demand (COD) (X_{12}), suspended solids (SS) (X_{13}), total phosphorus (TP) (X_{14}), on-site noise (X_{15}), solid waste emissions (X_{16}), comprehensive utilization rate of gangue (X_{17}), comprehensive utilization rate of mineral resources (X_{18}), comprehensive utilization rate of associated mineral resources (X_{19}), comprehensive utilization rate of wastewater (X_{20}), land reclamation rate (X_{21}), subsidence land management rate (X_{22}), dust control compliance rate

(X_{23}), noise control compliance rate (X_{24}), and wastewater treatment compliance rate (X_{25}). The specific structure is shown in Fig. 1.

Accurately classifying cleaner production levels in phosphate mining is essential for assessing the cleaner production level of enterprises in this industry (Thammaraksa et al., 2017; Wu et al., 2022a). By referencing relevant laws and regulations, standards, and expert experiences, the cleaner production level in phosphate mining can be categorized into four levels, as described below.

Grade I (Advanced cleaner production level): Phosphate mines at this level have implemented advanced cleaner production technologies and management practices. This includes efficient resource utilization, reduction of waste and pollutant emissions, and adoption of clean energy. Comprehensive assessments of environmental impacts during production processes are regularly conducted, and effective control and improvement measures are implemented.

Grade II (Relatively high cleaner production level): At this level, phosphate mines employ advanced cleaner production technologies and management measures to reduce resource consumption and environmental impact. This is achieved through partial resource recycling, reduced waste emissions, and measures to reduce pollutant discharge.

Grade III (Basic cleaner production level): At this level, phosphate mines have implemented basic cleaner production technologies and management measures to minimize resource waste and environmental pollution. These measures involve simple resource conservation and pollution control, but they fall short of the requirements for higher-level cleaner production.

Grade IV (Traditional cleaner production level): At this level, phosphate mines operate with a relatively low cleaner production level, primarily utilizing traditional production technologies and management practices. This results in low resource utilization efficiency, higher waste and pollutant emissions, and a certain level of environmental impact.

Classification of cleaner production levels in phosphate mines plays a crucial role in assessing and guiding production practices. It facilitates the transition of phosphate mines toward cleaner and more efficient production models. In conjunction with environmental regulations specific to phosphate mines, a standardized grading system has been developed for cleaner production levels of phosphate mines. The quantified results of this grading are presented in Table 1.

In Table 1, the quantified results for the advanced level of production equipment and mining process technology are categorized into four levels based on the following quantification rules: When internationally advanced mining equipment is used, the value falls within the range of 0.75–1; when domestically relatively advanced mining equipment is used, the value lies between 0.5 and 0.75; when traditional domestic mining equipment is used, the value ranges from 0.25 to 0.5; and when obsolete mining equipment is used, the value ranges from 0 to 0.25. Similarly, when the mining process technology reaches the internationally advanced level, the value ranges from 0.75 to 1; when it reaches the domestically advanced level, the value ranges from 0.5 to 0.75; when traditional process technology is used, the value ranges from 0.25 to 0.5; and when outdated process technology is used, the value ranges from 0 to 0.25.

2.2. Determining the weight of indicators for group decision-making attributes

Assessing the cleaner production levels in phosphate mines presents a multi-objective group decision-making problem, aiming for an accurate reflection of the importance of each indicator in cleaner production. The AHP model exhibits adaptability and flexibility, making it suitable for decision-making criteria of various scales and types, without compromising the method's robustness. It provides us with a simple yet powerful tool, allowing for the decomposition of complex decision-making issues into more manageable sub-problem hierarchies (Vafadarnikjoo et al., 2020). By employing group decision-making, the AHP can integrate qualitative and quantitative analyses while fully considering the relative importance of multiple indicators. The method selected involves obtaining the weights of each indicator through a combination of the AHP (Shang et al., 2015; Shen et al., 2015) and evidence theory fusion (Ruan et al., 2019), by consulting expert opinions, taking into consideration the characteristics of the evaluation index system for cleaner production in phosphate mining.

To ensure that the assessment was more practical and relevant, experts from professional evaluation agencies were invited along with 10 specialists from the phosphorus mining production field, including on-site safety officers and university professors. An evidence theory

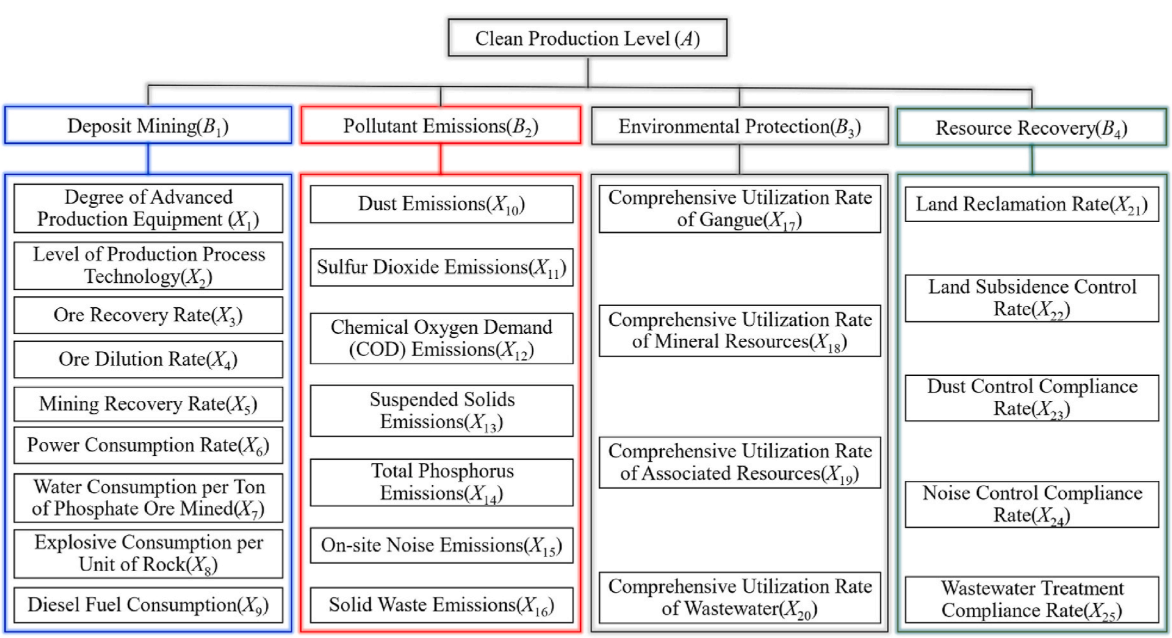

Fig. 1. The structural model of cleaner production index system for phosphate mines.

Table 1
Phosphate mine cleaner production level index grading results.

Evaluation Indicators	Evaluation Index Grading Standards			
	Grade I	Grade II	Grade III	Grade IV
X_1	Internationally Advanced Mining Equipment	Relatively advanced domestic mining equipment	Typical domestic mining equipment	Outdated and obsolete mining equipment
X_2	Internationally advanced technological process level	Domestically advanced technological process level	Typical technological process level	Outdated technological process level
X_3/%	$X_3 > 90$	$60 < X_3 \leq 90$	$40 < X_3 \leq 60$	$X_3 \leq 40$
X_4/%	$X_4 \leq 5$	$5 < X_4 \leq 7.5$	$7.5 < X_4 \leq 10$	$10 < X_4$
X_5	$X_5 < 10$	$10 \leq X_5 < 15$	$15 \leq X_5 < 20$	$X_5 \geq 20$
X_6/(kW·h·t^{-1})	$X_6 < 10$	$10 \leq X_6 < 15$	$15 \leq X_6 < 20$	$X_6 \geq 20$
X_7/m^3	$X_7 \leq 5$	$5 < X_7 \leq 10$	$10 < X_7 \leq 15$	$15 < X_7$
X_8/ (kg/t)	$X_8 \leq 0.5$	$0.5 < X_8 \leq 0.75$	$0.75 < X_8 \leq 1$	$1 < X_8$
X_9 (kg/t)	$X_9 \leq 0.4$	$0.4 < X_9 \leq 0.7$	$0.7 < X_9 \leq 1$	$1 < X_8$
X_{10}/(mg·m^{-3})	$X_{10} \leq 1$	$1 < X_{10} \leq 3$	$3 < X_{10} \leq 5$	$5 < X_{10}$
X_{11}/(mg·m^{-3})	$X_{11} \leq 1$	$1 < X_{11} \leq 2$	$2 < X_{11} \leq 3$	$3 < X_{11}$
X_{12}/(mg·L^{-1})	$X_{12} \leq 10$	$10 < X_{12} \leq 30$	$30 < X_{12} \leq 50$	$50 < X_{12}$
X_{13}/(mg·L^{-1})	$X_{13} \leq 20$	$20 < X_{13} \leq 60$	$60 < X_{13} \leq 100$	$100 < X_{13}$
X_{14}/(mg·L^{-1})	$X_{14} \leq 0.1$	$0.1 < X_{14} \leq 0.2$	$0.2 < X_{14} \leq 0.3$	$0.3 < X_{14}$
X_{15}/((Leq)/dB(A))	$X_{15} \leq 50$	$50 < X_{15} \leq 60$	$60 < X_{15} \leq 70$	$70 < X_{15}$
X_{16}/(t)	$X_{16} \leq 0.4$	$0.4 < X_{16} \leq 0.5$	$0.5 < X_{16} \leq 0.6$	$0.6 < X_{16}$
X_{17}/%	$X_{17} > 95$	$80 < X_{17} \leq 95$	$60 < X_{17} \leq 80$	$X_{17} \leq 60$
X_{18}/%	$X_{18} > 95$	$80 < X_{18} \leq 95$	$70 < X_{18} \leq 80$	$X_{18} \leq 70$
X_{19}/%	$X_{19} > 100$	$85 < X_{19} \leq 100$	$70 < X_{19} \leq 85$	$X_{19} \leq 70$
X_{20}/%	$X_{20} > 90$	$65 < X_{20} \leq 90$	$40 < X_{20} \leq 65$	$X_{20} \leq 40$
X_{21}/%	$X_{21} > 100$	$75 < X_{21} \leq 100$	$50 < X_{21} \leq 75$	$X_{21} \leq 50$
X_{22}/%	$X_{22} > 90$	$75 < X_{22} \leq 90$	$60 < X_{22} \leq 75$	$X_{22} \leq 60$
X_{23}/%	$X_{23} > 95$	$70 < X_{23} \leq 95$	$50 < X_{23} \leq 70$	$X_{23} \leq 50$
X_{24}/%	$X_{24} > 85$	$60 < X_{24} \leq 85$	$30 < X_{24} \leq 60$	$X_{24} \leq 30$
X_{25}/%	$X_{25} > 95$	$70 < X_{25} \leq 95$	$50 < X_{25} \leq 70$	$X_{25} \leq 50$

model was introduced to analyze the degree to which the decision-making and strategic choices of different participants influence the outcome in the weight determination process. This is done in the process of determining the importance of indicators by multiple experts to quantify and allocate the weights or influences of different participants. Consequently, evidence theory is employed to assess each expert's value contribution to the overall weight determination process. The evidence theory can reduce biases in the comprehensive weight determination imposed by various expert groups and attribute decision-making authority. It identifies consistency and compromise among different weight values, resolving conflicts between different weights and achieving Nash equilibrium, thereby enhancing the weights' accuracy and distinctiveness. Below is the particular modeling process for the indicator weights considering the attributes of group decision-making (Groselj et al., 2015; Rahman et al., 2019).

Step 1: Expert assessment. A nine-level scale ranging from 1 to 9 is to be used by multiple experts from relevant fields to determine the pairwise comparison scores between different evaluation indicators of the cleaner production level of phosphate mines. The range of values for the degree of influence, considering the direction of causality, is [1, 9], where 1 indicates equal importance between two indicators, 9 indicates that indicator X_i is extremely more important than indicator X_j, and so on. A higher score indicates an indicator's relatively higher level of importance.

Step 2: Construction of the judgment matrix. Eq. (1) presents a formulation for the corresponding judgment matrices, which are constructed based on the direct mutual importance of different indicators as assessed by experts.

$$A = (a_{ij})_{n\times n} = \begin{bmatrix} X_1/X_1 & X_1/X_2 & \cdots & X_1/X_n \\ X_2/X_1 & X_2/X_2 & \cdots & X_2/X_n \\ \cdots & \cdots & \cdots & \cdots \\ X_n/X_1 & X_n/X_n & \cdots & X_n/X_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{11} & \cdots & a_{11} \\ a_{11} & a_{11} & \cdots & a_{11} \\ \cdots & \cdots & \cdots & \cdots \\ a_{11} & a_{11} & \cdots & a_{11} \end{bmatrix} \tag{1}$$

Step 3: Integration of expert opinions. The evidence theory is used to integrate the diverse opinions of multiple experts while fully accounting for the group decision-making attributes when determining the weights of evaluation indicators for the cleaner production level of phosphate mines. The set of mutually exclusive and exhaustive elements is represented by the identification framework Θ in the D-S evidence theory, as shown in Eq. (2). Where an event within the recognition framework Θ is represented by θ_i; the number of elements in the recognition framework is denoted by n.

$$\Theta = \{\theta_1, \theta_2, \cdots, \theta_n\} \tag{2}$$

where θ_i represents an event within the recognition framework Θ; n denotes the number of elements in the recognition framework.

The scores of the 1 to 9 scale method, which determines the relative importance of indicators, are represented by the recognition framework Θ. A mapping of the power set 2^{Θ} of all subsets of the recognition framework Θ to the interval [0, 1] is the basic probability assignment. That is, $m{:}2^{\Theta}\rightarrow[0,1]$, where $m(A)$ is the basic probability assignment of subset A. Here, A is any subset of the recognition framework Θ, satisfying Eq. (3) and Eq. (4).

$$m(\varnothing) = 0 \tag{3}$$

$$\sum_{A\subseteq\Theta} m(A) = 1 \tag{4}$$

where $m(A)$ represents the level of trust in subset A, indicating the probability distribution of the relative importance of indicators for the phosphate mining cleaner production level assigned to a specific score.

The distribution of comprehensive opinions on the relative importance of the indicators is constructed by utilizing evidence theory to integrate the diverse opinions of multiple experts, as illustrated in Eq. (5).

$$D_{ij} = \{(\theta_1, d_1(ij)), (\theta_2, d_2(ij)), \ldots, (\theta_9, d_9(ij))\} \tag{5}$$

Suppose that the identification framework Θ has two belief functions, Bel_1 and Bel_2, with corresponding basic probability assignments

m_1 and m_2, and focal elements $A_1, A_2, \ldots, A_i$, as well as $B_1, B_2, \ldots, B_i$. The basic probability assignment of the function $m{:}2^{\Theta}\rightarrow[0,1]$ is shown in Eq. (6).

$$m(A)=\frac{\sum_{A_i\cap B_i}(r_1m_1(A_i))(r_2m_2(B_j))}{1-\sum_{A_i\cap B_i=\varnothing}m_1(A_i)m_2(B_j)},\forall A\subseteq\Theta \tag{6}$$

In the equation, r_i represents the proportion of experts' opinions on the distribution of the comprehensive opinions regarding the relative importance of the assessment indicators for cleaner production in phosphate mines.

The D-S evidence theory is applicable to the problem of data fusion. Basic probability assignments can be used to represent diverse opinions from various experts regarding the interrelations between different indicators when integrating information from multiple sources. Additionally, evidence synthesis can be conducted based on Eq. (7).

$$\begin{cases} \forall A\subseteq\Theta, A\neq\varnothing \\ m(A)=K\sum_{\substack{A_1,\cdots,A_i\subseteq\Theta \\ A_1\cap\cdots\cap A_i\subseteq A}} m_1(A_1)\cdots m_n(A_n) \end{cases} \tag{7}$$

The degree of conflict between the items of evidence is represented by calculating K in Eq. (7), as shown in Eq. (8).

$$K=\left(\sum_{\substack{A_1,\cdots,A_i\subseteq\Theta \\ A_1\cap\cdots\cap A_i\subseteq A}} r_1m_1(A_1)\cdots r_nm_n(A_n)\right)^{-1} \tag{8}$$

Eq. (7) and Eq. (8) state that $Bel_1, Bel_2, \ldots, Bel_n$ are amenable to the fusion of evidence if the cores $\delta_1, \delta_2, \ldots, \delta_n$ corresponding to the trust functions $Bel_1, Bel_2, \ldots, Bel_n$ satisfy $\delta_1\cap\delta_2\cap\ldots\cap\delta_n\neq\Phi$.

Step 4: The geometric mean of each row in the judgment matrix A' based on the integrated opinions of multiple experts is calculated after integrating the opinions of multiple experts, as shown in Eq. (9).

$$\omega_i=n\sqrt{\prod_{j=1}^{n}a'_{ij}}(i=1,2,\ldots,n) \tag{9}$$

The corresponding vectors are constructed based on ω_i, as shown in Eq. (10).

$$\overline{W_i}=(\omega_1,\omega_2,\cdots,\omega_n)^T \tag{10}$$

where i and j are the row and column positions of the characteristic vectors in the matrix, and n is the number of vectors.

Eq. (11) shows the corresponding characteristic vectors of the judgment matrix.

$$W_i=\frac{\overline{W_i}}{\sum_{j=1}^{n}\overline{W_{ij}}} \tag{11}$$

The characteristic vector W_i in the equation, denotes the weights of various indicators after integrating the opinions of multiple experts.

Step 5: Consistency check. First, we calculate the maximum eigenvalue of the judgment matrix, as shown in Eq. (12).

$$\lambda_{max}=\frac{1}{n}\sum_{i=1}^{n}\frac{(A'W)_i}{W_i} \tag{12}$$

where $(A'W)_i$ is the i-th element of the vector $A'W$ in the judgment matrix.

The maximum eigenvalue can be used to obtain the consistency index value CI, as shown in Eq. (13).

$$CI=\frac{\lambda_{max}-n}{n-1} \tag{13}$$

When CI is 0, the matrix is completely consistent; as the CI value increases, the consistency of the matrix deteriorates. In order to test the high reliability of the consistency of the judgment matrix, CI is compared with the average random consistency index RI.

The judgment matrix exhibits satisfactory consistency when both the average random consistency index RI and the consistency index CI satisfy Eq. (14) together. If it does not meet this criterion, the judgment logic must be readjusted until Eq. (14) is satisfied.

$$CR=\frac{CI}{RI}<0.1 \tag{14}$$

Step 6: Hierarchical ranking. There are two categories of hierarchical ranking: overall ranking and individual ranking. Individual ranking refers to the relative importance of each factor within each level to the specific factors in the previous level based on the characteristic vector of the judgment matrix. Overall ranking is determined by the calculation of the total ranking value for each level or the calculation of the relative importance coefficient of each scheme in the scheme level to the target in the target layer. this process is based on hierarchical ranking. The consistency test for overall ranking satisfies both Eq. (15) and Eq. (16).

$$CI^{(k)}=\left(CI_1^{(k)},CI_2^{(k)},\cdots,CI_{n_{k-1}}^{(k)}\right)W^{(k-1)} \tag{15}$$

$$RI^{(k)}=\left(RI_1^{(k)},RI_2^{(k)},\cdots,RI_{n_{k-1}}^{(k)}\right)W^{(k-1)} \tag{16}$$

The consistency ratio $CR_j^{(k)}$ at level k is calculated as shown in Eq. (17) after the consistency index $CI_j^{(k)}$ and the average random consistency index $RI_j^{(k)}$ of indicator j at level k are obtained.

$$CR^{(k)}=\frac{CI^{(k)}}{RI^{(k)}} \tag{17}$$

When $CR^{(k)}<0.1$, it indicates that all judgment hierarchies above the structural hierarchy are considered to have overall satisfactory consistency.

Following the aforementioned steps, the weights of each indicator at the indicator level relative to the overall objective level in the evaluation of cleaner production levels in phosphate mining can be obtained, as shown in Table 2.

Based on the above results, the importance of evaluation indicators for the cleaner production level of phosphate mining is ranked as X_3, X_{20}, X_6, X_1, X_{19}, X_7, X_{16}, X_2, X_{18}, X_{25}, X_{12}, X_4, X_8, X_{13}, X_{14}, X_{17}, X_9, X_{22}, X_5, X_{10}, X_{23}, X_{11}, X_{24}, X_{15}, and X_{21}, with their corresponding influence degrees of 0.1769, 0.0039, and 0.002. Accordingly, to enhance the cleaner production level of phosphate mining, improvement plans, and measures can be developed from the perspectives of technological enhancement, equipment renewal, management optimization, and rationalization of resource utilization.

3. Hierarchical and correlation analysis of factors influencing the level of cleaner production in phosphate mines

There is a lack of clarity in the hierarchical structure and relationships between the various indicators in the evaluation indicators developed for cleaner production levels in phosphate mining. These indicators interact and depend on one another to form a complex network that directly impacts the cleaner production level of phosphate mines. Therefore, further analysis of the identified indicators is necessary to reveal the causal relationships between them and quantify their mutual influences. To achieve this, the Decision-Making Trial and

Table 2
The weight coefficients of various indicator levels relative to the overall objective level.

indicator	weight	indicator	weight	indicator	weight	indicator	weight	indicator	weight
X_1	0.0850	X_6	0.1207	X_{11}	0.0053	X_{16}	0.0419	X_{21}	0.0020
X_2	0.0408	X_7	0.0651	X_{12}	0.0287	X_{17}	0.0145	X_{22}	0.0135
X_3	0.1769	X_8	0.0234	X_{13}	0.0151	X_{18}	0.0310	X_{23}	0.0066
X_4	0.0254	X_9	0.0145	X_{14}	0.0147	X_{19}	0.0694	X_{24}	0.0040
X_5	0.0120	X_{10}	0.0081	X_{15}	0.0039	X_{20}	0.1485	X_{25}	0.0289

Evaluation Laboratory (DEMATEL) method is employed for the relational analysis of cleaner production indicators in phosphate mining, offering a comprehensive and in-depth perspective to comprehend and manage the complexity of the cleaner production system in phosphate mining (Qi et al., 2020; Bao et al., 2023).

The degree of direct mutual influence among the indicators is determined using a four-level scale ranging from 0 to 3, taking into account the direction of causal relationships This results in the mutual interaction matrix encoding of the cleaner production level evaluation indicators for phosphate mining, as illustrated in Fig. 2.

From Fig. 2, the mutual influence relationships among the various indicators can be clearly and intuitively observed. Standardization processing is applied to the direct impact matrix. The comprehensive impact matrix T is derived using the standardized direct impact matrix and Eq. (18).

$$T = \left(t_{ij}\right)_{n\times n} = \sum\nolimits_{n=1}^{\infty} X^n \approx X(\boldsymbol{I} - X)^{-1} \tag{18}$$

where t_{ij} represents the overall impact of indicator i on indicator j, including both direct and indirect effects; X denotes the standardized direct impact matrix; and $\boldsymbol{I}$ represents the identity matrix.

The impact degree and the degree of being influenced for each indicator are then obtained separately using Eq. (19) and Eq. (20), based on the comprehensive impact matrix.

$$D_i = \sum\nolimits_{j=1}^{n} t_{ij} \quad i = 1, 2, \cdots n \tag{19}$$

$$R_j = \sum\nolimits_{i=1}^{n} t_{ij} \quad j = 1, 2, \cdots n \tag{20}$$

where D_i and R_j represent the impact degree and the degree of being influenced, respectively.

Indicators such as centrality and causality are used to assess the influence and susceptibility of indicators on the entire system. The relationships between indicators can be better understood using centrality and causality. Eq. (21) and Eq. (22) can be used to determine centrality and causality.

$$P_i = D_i + R_j \quad i = j \tag{21}$$

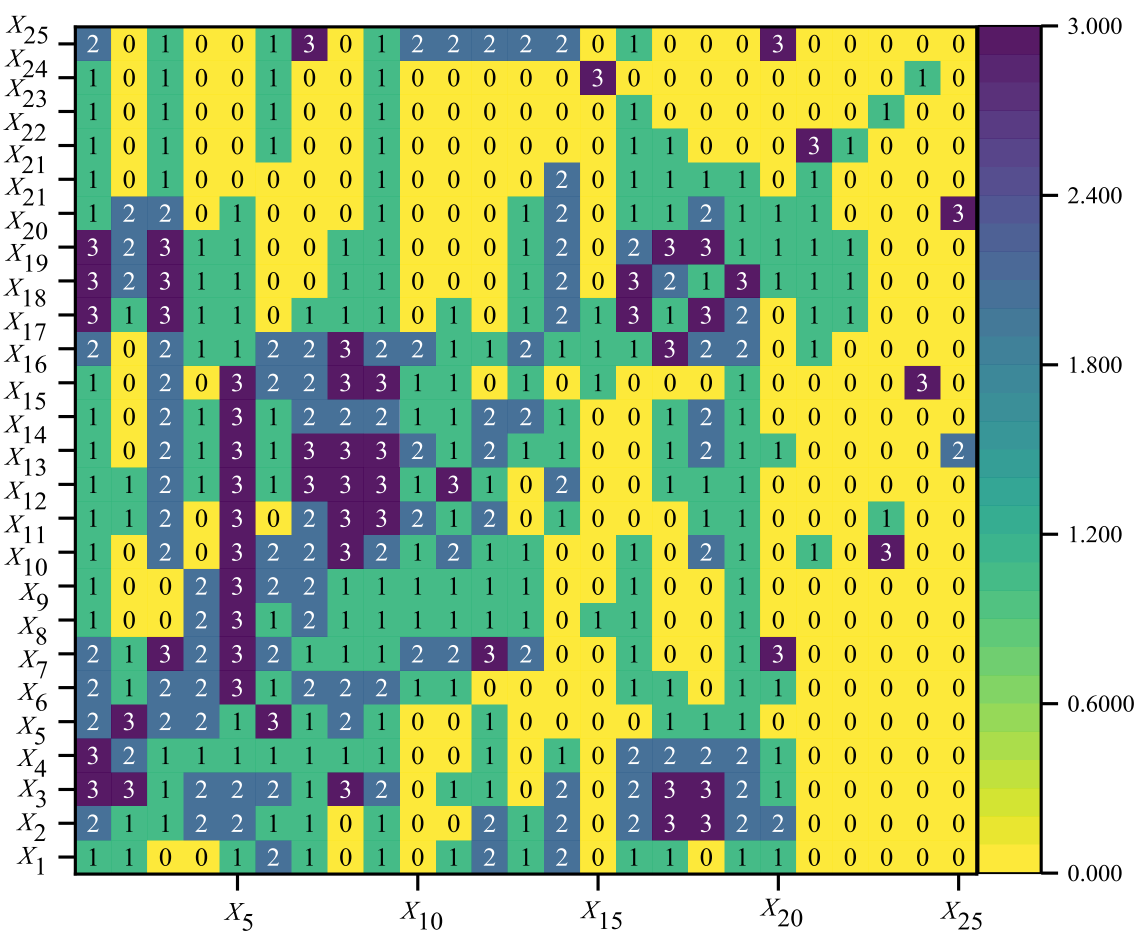

Fig. 2. The direct impact matrix encoding of cleaner production level evaluation indicators.

$$C_i = D_i - R_j \quad i = j \tag{22}$$

The centrality (P_i) and causality (C_i) of the evaluation indicators for the cleaner production level of phosphate ore are shown in Table 3.

A higher centrality in Table 3, indicates a greater impact of the indicator on the cleaner production system of phosphate mines. The following is a ranking of centrality ranking: X_3, X_5, X_7, X_{16}, X_{18}, and X_{19}, which are the core factors influencing the cleaner production of phosphate mines. Causality is the difference between the degree of being influenced and the degree of influence. An indicator has three primary effects: it primarily affects the "causes" of other indicators if the casualty is positive; it is primarily influenced by the "results" of other indicators if the causality of an indicator is negative; and it affects both the "causes" of other indicators and is influenced by the "results" of other indicators if the causality of an indicator is zero. To further analyze the relationship between centrality and causality, the distribution graphs of both indicators are plotted. The distribution of centrality and causality relationships for the evaluation indicators of cleaner production levels in phosphate mines is shown in Fig. 3.

According to their distribution, the evaluation indicators for the cleaner production level of phosphate ore in Fig. 3 were divided into four regions, each representing different characteristics of the indicators. The majority of the indicators in Region I, such as X_1, X_5, X_8, and X_9, belong to the criteria layer of mining deposit exploitation. These indicators are typically system-driven factors or inputs that have a significant impact on the level of clean production in phosphorus mining. High centrality and causality close to 0 are demonstrated by the indicators in Region II. X_3, X_4, X_6, X_7, X_{14}, X_{18}, and X_{19} are the main indicators in Region II. These indicators may represent important results or response variables. High centrality implies that these indicators hold significant importance in the cleaner production system of phosphate ore, representing key nodes within the system. Variations in these indicators may reflect important changes in the system's state. The causality values for indicators in regions III and IV are negative. X_3, X_{10}, X_{11}, X_{12}, X_{16}, X_{20}, X_{21}, X_{22}, X_{23}, and X_{24}, among others, are the main indicators in these regions. These indicators exhibit negative causality and high centrality. This indicates that these indicators act as result factors, being significantly influenced by other indicators and holding high importance within the system.

A better understanding of the interaction patterns among these

Table 3
The parameter distribution results of the indicator relationships.

Indicators	D_i	R_i	P_i	C_i	Rank (P_i)
X_1	4.3746	1.8388	6.2134	2.5358	4
X_2	2.6153	3.0727	5.6880	−0.4573	9
X_3	3.9930	3.6028	7.5959	0.3902	1
X_4	2.7490	2.4876	5.2366	0.2615	15
X_5	4.5686	2.2394	6.8081	2.3292	2
X_6	3.0207	2.4031	5.4238	0.6177	13
X_7	3.2684	3.2228	6.4912	0.0455	3
X_8	3.6311	1.8868	5.5179	1.7442	11
X_9	3.6837	1.8898	5.5735	1.7938	10
X_{10}	1.6355	2.7411	4.3766	−1.1056	18
X_{11}	2.0539	2.4555	4.5094	−0.4016	17
X_{12}	2.5421	2.9397	5.4818	−0.3977	12
X_{13}	1.9553	3.2665	5.2219	−1.3112	16
X_{14}	2.6017	2.6956	5.297	−0.0937	14
X_{15}	0.5119	2.3010	2.8129	−1.7892	20
X_{16}	2.8050	3.4045	6.2096	−0.5995	5
X_{17}	2.9519	3.0050	5.9569	−0.0530	8
X_{18}	3.1487	2.8976	6.0463	0.2511	6
X_{19}	3.1510	2.8865	6.0375	0.2645	7
X_{20}	1.6561	2.1606	3.8168	−0.5045	19
X_{21}	0.8046	1.0581	1.8627	−0.2534	22
X_{22}	0.4016	0.8884	1.2900	−0.4869	23
X_{23}	0.3624	0.5800	0.9424	−0.2175	24
X_{24}	0.1677	0.7466	0.9143	−0.5788	25
X_{25}	0.4082	2.3919	2.8001	−1.9837	21

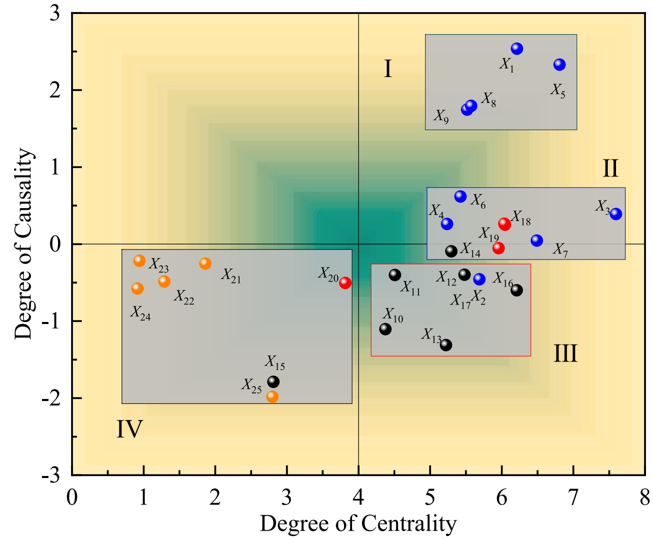

Fig. 3. The distribution of interrelationships among the evaluation indicators.

indicators and their comprehensive impact on the cleaner production system of phosphate ore can be achieved by analyzing the relationships among various indicators within the system. This aids in the more effective management of environmental issues within phosphate ore enterprises by providing vital information and guidance for the management of the cleaner production system of phosphate ore.

4. Construction of a cleaner production evaluation model for phosphate mines

4.1. Numerical characteristics of the finite interval cloud model

The management status of the cleaner production system of phosphate mines is linked to the cleaner production level of phosphate mines in addition to the inherent properties of the system. It possesses characteristics such as complexity, dynamics, and correlation. It demonstrates both the general characteristics of traditional-grade uncertainty and the essential attributes of indicator uncertainty. The evaluation system for the cleaner production level in phosphate mines is fuzzy and uncertain due to subjectivity in both the indicators and the cleaner production level grades, as seen from the perspective of the characteristics of the cleaner production system in phosphate mines(Wu et al., 2022b). In addition to handling incomplete and imprecise information, By handling incomplete and imprecise information and overcoming the deficiencies of uncertainty modeling such as insufficient subjective cognition and unknowability, cloud models can transform the qualitative and quantitative relationships between indicators (Cui et al., 2020; Bai et al., 2017). Consequently, it is appropriate to consider the adoption of cloud theory to express the fuzziness and uncertainty within this context. However, while traditional cloud models are capable of transforming qualitative concepts and quantitative values of uncertainty for the assessment indicators of the safe operation status of tailings dams, they assume that each indicator will transform uncertain information according to a Gaussian distribution. Several indicators exhibit unilateral constraint grade intervals of $[-\infty, X_{min}]$ and $[X_{max}, +\infty]$, which do not entirely conform to a Gaussian distribution within these unilateral constraint intervals, as can be seen from the grading results of the cleaner production assessment indicators for phosphate mines in Table 1. Using a traditional normal cloud model would lead to errors in grade determination. Thus, a finite interval cloud model based on the principle of finite intervals was developed considering the actual conditions of the cleaner production indicators in phosphate mines. According to the central limit theorem (DeRiggi, 2019), as long as the sample size is sufficiently large, the distribution will tend to approximate a normal distribution. Consequently, the distribution of intervals with bilateral constraints follows a normal distribution on the whole.

The numerical characteristics (E_x, E_n, H_e) of the cleaner production assessment indicators for phosphate mines with bilateral constraints were obtained based on Eq. (23), considering the lengths of the grade intervals of the indicators.

$$\begin{cases} E_x^D = \left(X_{max}^D + X_{min}^D\right)/2 \\ E_n^D = \left(X_{max}^D - X_{min}^D\right)/6 \\ H_e = K \times E_n^D \end{cases} \tag{23}$$

where X_{max}^D and X_{min}^D represent the range of the cleaner production capacity assessment indicators for phosphate mines with bilateral constraints in the corresponding grade D interval. K is a constant, typically set to 0.01.

For the grade intervals with unilateral constraints, the numerical characteristics of the cleaner production capacity assessment indicators for phosphate mines are shown in Eq. (24).

$$\begin{cases} E_{x^-}^D = 2E_x^{D-1} - X_{min}^{D-2} \\ E_{x^+}^D = \left(2E_x^{D+1} - E_x^{D+2} + X_{max}^D\right)\Big/2 \\ E_n^D = \left(X_{max}^D - X_{min}^D\right)/6 \\ H_e = K \times E_n^D \end{cases} \tag{24}$$

where $E_{x^-}^D$ and $E_{x^+}^D$ represent the expected values corresponding to the assessment grades with right and left constraints, respectively. A uniform distribution with a membership degree of 1 obeys the corresponding half-interval if the actual numerical value of the grade differs significantly from the determined expected value. The corresponding transformation results, using indicator X_3 as an example, are shown in Fig. 4.

4.2. Determining membership degrees of grades using the finite interval cloud model

A finite interval cloud forward generator is required to determine the membership based on the finite interval cloud model. Using the digital features of the finite cloud model and setting the generated number of cloud droplets, the membership of different indicators to a certain level is determined by integrating the characteristics of the cleaner production capacity evaluation index levels of phosphate mines.

The finite interval cloud model can be expressed mathematically as follows (Jiang et al., 2021). Let U be a quantitative set denoted by precise values, $U = \{u_1, u_2, \ldots, u_n\}$, referred to as the universe of discourse, and let Q be a qualitative concept on U. For any variable x, there exists a stable tendency random number $\mu(x) \in [0, 1]$, referred to as the determinacy of x to Q, and the distribution of x on the universe of discourse U is termed as a cloud. The mapping of uncertainty between qualitative concepts and quantitative values is represented by the cloud droplet generation process.

Using various digital features, a finite interval cloud model is developed based on the finite interval cloud generator. This model simulates the status levels of different indicators belonging to a certain state level of cleaner production in phosphate mines. The finite interval cloud model can be used to generate n cloud droplets and a random normal distribution function $Y \sim N(E_n, H_e^2)$ by inputting the current data of phosphate mining enterprises. Subsequently, the membership of phosphate mining enterprises at different levels of cleaner production can be obtained by inputting the variable value x and the expected value E_x, according to Eq. (25).

$$\mu(x) = exp\left(-(x - E_x)^2 / \left(2E_n'^2\right)\right) \tag{25}$$

where E_n' is a normal random number with E_n as the expectation and H_e as the standard deviation, denoted as $E_n' \sim N(E_n, H_e^2)$; x represents the current status value of the corresponding index of the phosphate mining enterprises.

The numerical characteristics (E_x, E_n, H_e) of the finite cloud model for each evaluation indicator are calculated using Eq. (23) and Eq. (24), as presented in Table 4, in conjunction with the hierarchical results of the cleaner production assessment indicators for phosphate mines in Table 1.

The most intuitive indicators for assessing cleaner production capacity in phosphate mines are pollutant emissions B_2 and environmental protection B_4. For illustrative purposes, using secondary indicators B_2 and B_4 as examples, the corresponding cloud plots generated from tertiary indicators such as dust X_{10}, sulfur dioxide X_{11}, chemical oxygen demand (COD) X_{12}, suspended solids (SS) X_{13}, total phosphorus (TP) X_{14}, onsite noise X_{15}, solid waste emissions X_{16}, land reclamation rate X_{21}, subsidence land management rate X_{22}, dust control compliance rate X_{23}, noise control compliance rate X_{24}, and wastewater treatment compliance rate X_{25} are shown in Fig. 5.

The abscissa in the cloud diagrams of the finite interval cloud models in Fig. 5, represents the value range of different indicators, while the ordinate represents the membership degree of each indicator under different levels of cleaner production capacity in phosphate mines. Here, E_x denotes the expectation of the cloud; E_n denotes the dispersion of the cloud; and H_e denotes the thickness of the cloud. All of these can be

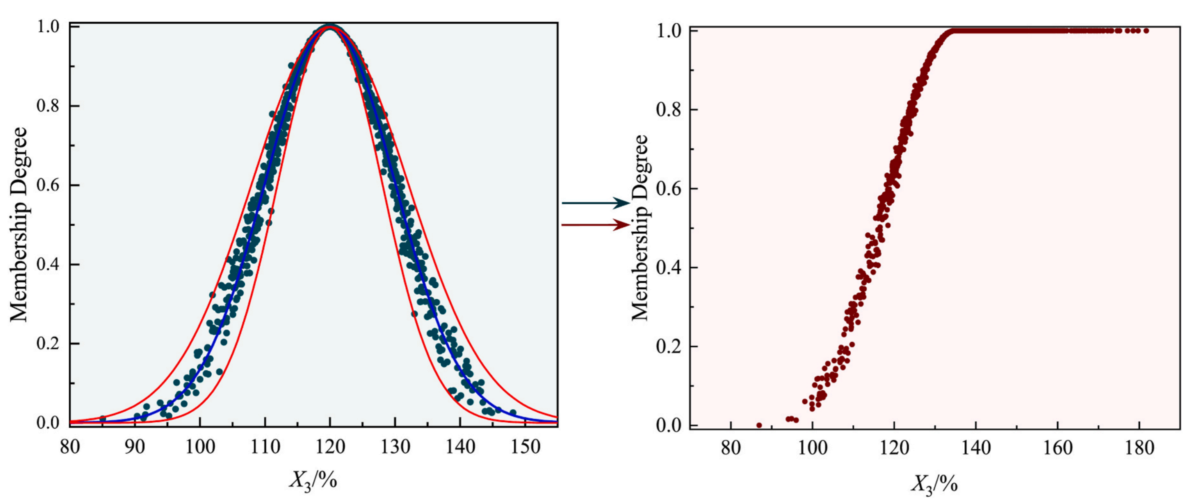

Fig. 4. The finite interval distribution transformation of unilateral constraint intervals.

Table 4
The numerical characteristics of the finite interval cloud model for indicators under different levels of cleaner production.

Indicators	The Numerical Characteristics of the Finite Cloud Model			
	Grade I	Grade II	Grade III	Grade IV
X_1	(0.88, 0.04, 0.01)	(0.63, 0.04, 0.01)	(0.38, 0.04, 0.01)	(0.13, 0.04, 0.01)
X_2	(0.88, 0.04, 0.01)	(0.63, 0.04, 0.01)	(0.38, 0.04, 0.01)	(0.13, 0.04, 0.01)
X_3	(120.00, 10.00, 0.10)	(75.00, 5.00, 0.05)	(50.00, 3.33, 0.03)	(20.00, 0.6.67, 0.07)
X_4	(2.50, 0.83, 0.01)	(6.25, 0.41, 0.01)	(8.75, 0.41, 0.01)	(12.50, 0.83, 0.01)
X_5	(5.00, 1.67, 0.02)	(12.50, 0.83, 0.01)	(17.50, 0.83, 0.01)	(25.00, 1.67, 0.02)
X_6	(5.00, 1.67, 0.02)	(12.50, 0.83, 0.01)	(17.50, 0.83, 0.01)	(25.00, 1.67, 0.02)
X_7	(2.50, 0.83, 0.01)	(7.50, 0.83, 0.01)	(12.50, 0.83, 0.01)	(20.00, 1.67, 0.02)
X_8	(0.25, 0.08, 0.01)	(0.63, 0.04, 0.01)	(0.83, 0.04, 0.01)	(1.25, 0.08, 0.01)
X_9	(0.20, 0.67, 0.01)	(0.55, 0.05, 0.01)	(0.85, 0.045, 0.01)	(1.25, 0.08, 0.01)
X_{10}	(0.50, 0.17, 0.01)	(2.00, 0.34, 0.01)	(4.00, 0.34, 0.01)	(7.50, 0.83, 0.01)
X_{11}	(0.50, 0.17, 0.01)	(1.50, 0.17, 0.01)	(2.50, 0.17, 0.01)	(4.00, 0.34, 0.01)
X_{12}	(5.00, 1.67, 0.02)	(20.00, 3.33, 0.03)	(40.00, 3.33, 0.03)	(65.00, 5.00, 0.05)
X_{13}	(10.00, 3.33, 0.03)	(40.00, 6.67, 0.07)	(80.00, 6.67, 0.07)	(125.00, 8.33, 0.08)
X_{14}	(0.05, 0.02, 0.01)	(0.15, 0.02, 0.01)	(0.25, 0.02, 0.01)	(0.40, 0.03, 0.01)
X_{15}	(25.00, 8.33, 0.08)	(55.00, 1.67, 0.02)	(65.00, 1.67, 0.02)	(85.00, 5.00, 0.05)
X_{16}	(0.20, 0.07, 0.01)	(0.45, 0.02, 0.01)	(0.55, 0.02, 0.01)	(0.80, 0.07, 0.01)
X_{17}	(125.00, 8.33, 0.08)	(90.00, 2.50, 0.03)	(70.00, 3.33, 0.03)	(30.00, 10.00, 0.10)
X_{18}	(125.00, 8.33, 0.08)	(90.00, 2.50, 0.03)	(75.00, 2.50, 0.03)	(35.00, 11.67, 0.12)
X_{19}	(107.50, 2.50, 0.03)	(92.50, 2.50, 0.03)	(77.50, 2.50, 0.03)	(35.00, 11.67, 0.12)
X_{20}	(105.00, 5.00, 0.05)	(77.50, 4.17, 0.04)	(52.50, 4.17, 0.04)	(20.00, 0.6.67, 0.07)
X_{21}	(110.00, 3.33, 0.03)	(87.50, 4.17, 0.04)	(62.50, 4.17, 0.04)	(25.00, 8.33, 0.08)
X_{22}	(105.00, 5.00, 0.05)	(82.50, 2.50, 0.03)	(67.50, 2.50, 0.03)	(30.00, 10.00, 0.10)
X_{23}	(107.50, 4.17, 0.04)	(82.50, 4.17, 0.04)	(60.00, 3.33, 0.03)	(25.00, 8.30, 0.08)
X_{24}	(102.50, 5.83, 0.06)	(67.50, 4.17, 0.04)	(45.00, 5.00, 0.05)	(15.00, 5.00, 0.05)
X_{25}	(107.50, 4.17, 0.04)	(82.50, 4.17, 0.04)	(60.00, 3.33, 0.03)	(25.00, 8.30, 0.08)

obtained through Eq. (23) or Eq. (24). The membership degrees of various indicators of cleaner production capacity in phosphate mines belonging to different levels can be calculated using Eq. (25).

4.3. Determining the comprehensive membership of the aggregated group decision attribute weights

The assessment of cleaner production capacity in phosphate mines involves complex interrelationships among factors., There exists a certain level of randomness and subjectivity among various indicators because of cognitive limitations and the practical constraints of mining operations. The indicator weights adequately account for significant differences in weight opinions while also integrating subjectivity in the process of weight determination considering group decision-making attributes, as determined in Section 2.2. Consequently, it is considered to integrate the weights determined through group decision-making for different indicators to determine the degree of membership of each indicator in different levels of cleaner production capacity in phosphate mines.

The membership degrees of the evaluation factors for cleaner production capacity in phosphate mines can be obtained based on calculations using the limited cloud model. The comprehensive membership degrees of each indicator can be derived by combining the associated weight values, as shown in Eq. (26). The principle of maximum membership degree allows for the determination of the cleaner production capacity level of phosphate mines considering comprehensive weight factors.

$$W(\theta) = \sum_{j=1}^{m} \left[\omega_j \times \mu(x)\right] \tag{26}$$

where ω_j represents the weight value of the cleaner production capacity evaluation indicators in phosphate mines, as determined in Section 2.2; $W(\theta)$ denotes the comprehensive membership degree of the indicators.

The degree of uncertainty or fuzziness between indicator levels is quantified using the limited cloud model. This approach can quantify uncertainty into numerical values, thereby facilitating further analysis and decision-making.

5. Empirical study of a cleaner production evaluation model in phosphate mines

5.1. Collection of production data from phosphate mines

China possesses an abundance of phosphate resources, with over 80% of the country's reserves found in the Yangtze River Basin. Among Chinese provinces, Hubei has confirmed phosphate ore reserves exceeding 7 billion tons, mainly distributed in the western region of the province, including the cities of Yichang, Jingmen, and Shiyan. Phosphate ore mining is a large-scale and long-term process that not only poses safety threats to the mines but also results in serious environmental pollution in the surrounding areas. The current cleaner production indicators for five phosphate mining enterprises were obtained using Yichang City, Hubei Province, China as an example. These include Hubei Guangyuan Chemical Group Co., Ltd: Liushangou Phosphate Mine (#1), Yichang Dongsheng Jiunv Mining Co., Ltd: Jiunv Phosphate Mine (#2), Hubei Dongsheng Chemical Group Co., Ltd: Shaiqihe Mining Co., Ltd. (#3), Yichang Yihua Yinjiaping Mining Co., Ltd. (#4), Yinjiaping Phosphate Mine and Hubei Shanshuya Mining Co., Ltd: Shanshuya Phosphate Mine (#5). These data were obtained following on-site investigations and expert assessments. The final research findings are presented in Table 5.

5.2. Assessment of cleaner production levels in phosphate mining enterprises

The current status of five phosphate mining enterprises, namely Liushangou Phosphate Mine, Jiunv Phosphate Mine, Shaiqihe Phosphate Mine, Yinjiaping Phosphate Mine, and Shanshuya Phosphate Mine, was investigated. Using Eq. (19), the subordination degrees of various evaluation indicators for the cleaner production level of phosphate mines were calculated. The distribution of subordination levels for various indicators is shown in Fig. 6.

The abscissa in Fig. 6 represents different current status indicators of the phosphate mine, while the ordinate represents the basic probability distribution of different indicators subordinated to the cleaner production level of the phosphate mine. Based on the principle of maximum subordination degree, the final cleaner production capacity level of the phosphate mine is determined by integrating all indicators and transforming them into the overall subordination degree of the cleaner production level for the phosphate mining enterprise. The basic probability distribution of the cleaner production level subordination of the phosphate mine, without considering the factor of indicator weights, is shown in Table 6.

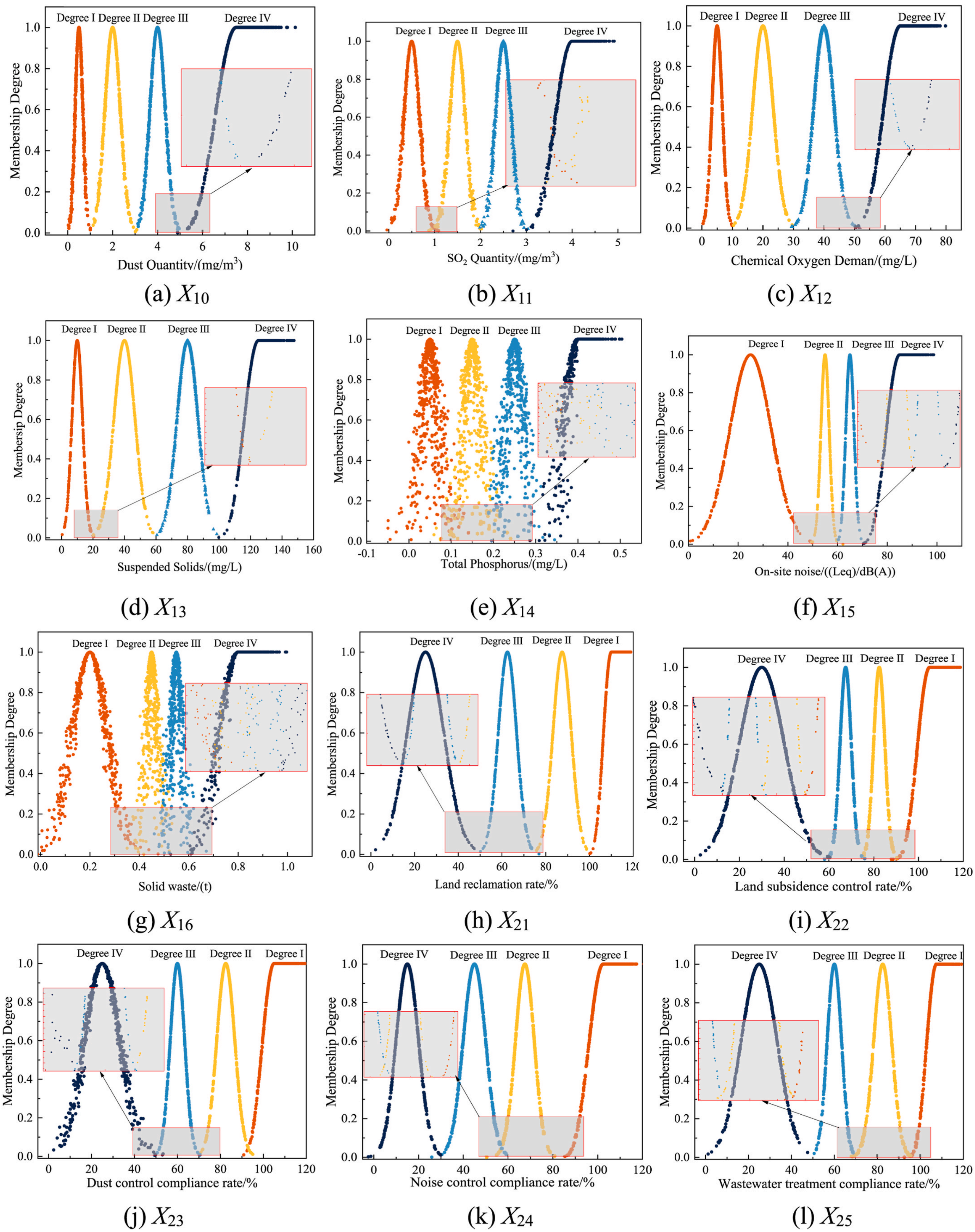

Fig. 5. The finite interval cloud models for different indicators at various levels.

Table 5
Research findings on the current status of hosphate mines in Yichang City, Hubei Province.

Indicators	Actual Values of Phosphate Mining Enterprise Indicators				
	#1	#2	#3	#4	#5
X_1	0.1	0.9	0.7	0.7	0.7
X_2	0.4	0.9	0.9	0.7	0.9
X_3/%	75	76	78	76.2	81.4
X_4/%	10	4	7	4.21	2
X_5	10	11.4	16	6.34	8.7
X_6/(kW·h·t^{-1})	10	6.5	16	4.18	8.5
X_7/m^3	6	15	4	0.3	0
X_8/ (kg/t)	0.8	0.45	0.5	0.392	0.41
X_9 (kg/t)	0.5	0.65	0.8	0.528	0.56
X_{10}/(mg·m^{-3})	0.039	2.8	3.2	3	2.8
X_{11}/(mg·m^{-3})	0.001	2.6	3	3	2.8
X_{12}/(mg·L^{-1})	7	8.6	3	50	50
X_{13}/(mg·L^{-1})	0.6	21.3	27	70	70
X_{14}/(mg·L^{-1})	0.037	0.16	0.18	0.2	0.3
X_{15}/Leq/dB(A)	50	50	50	55	50
X_{16}/(t)	0.5	0.28	0.3	0	0
X_{17}/%	85	100	90	95	100
X_{18}/%	75	76	95	76.2	85
X_{19}/%	75	100	100	100	100
X_{20}/%	98	50	96	36	30
X_{21}/%	95	60	90	81.62	100
X_{22}/%	80	100	92	100	100
X_{23}/%	85	50	95	82	100
X_{24}/%	80	60	90	95	100
X_{25}/%	95	90	98	100	100

Without considering the attribute weights, Table 6 presents the results of the evaluation of the cleaner production equality level of phosphate mining enterprises. This, combined with the weights of various indicators of the cleaner production level of phosphate mines, is represented as ω_j =(0.0310, 0.0694, 0.1485, 0.0020, 0.0135, 0.0066, 0.0040, 0.0289). As indicated in Table 7, the probability distribution of the cleaner production level of phosphate mining with the integrated multi-attribute decision weights is obtained, according to Eq. (20).

This is evident from Table 6 and Table 7, that the determination result of the cleaner production level of phosphate mining, integrating the multi-attribute decision weights, is consistent with the on-site investigation results of the phosphate mine, and the credibility is relatively high, indicating the rationality of the method. In the determination results of the interval-valued cloud model without considering weights, the result of the Shaiqi River phosphorus mine in Hubei Dongsheng Chemical Group Dongda Mining Co., Ltd. does not match the actual situation. However, in the determination results of the normal cloud model, the result of the Yinjiaping phosphorus mine does not match the actual situation. In determining the level of clean production in phosphorus mining, this indirectly reflects the applicability and accuracy of the interval-valued cloud model based on the fusion of group decision attributes. Treating each indicator as having the same level of impact is evidently unreasonable because of the varying degrees of influence of each indicator on the overall cleaner production level of phosphate mining enterprises. Multi-attribute decision weights integration, on the other hand, can comprehensively reflect the influence of each risk indicator on the evaluation results. The assessment results are consistent with the actual level, and the distinguishability between grade memberships is more pronounced, making the results more reasonable.

5.3. Results and discussion

Assessment of the cleaner production level of phosphate ore resources has become critically important because of the significance of phosphate ore resources and the potential environmental issues associated with their extraction. Each of the crucial assessment indicators for the phosphate mining industry provided by the evaluation index system for the cleaner production level of phosphate ore holds its importance and degree of influence on the cleaner production level of phosphate mines. Enhanced attention and control measures should be implemented for indicators of high importance. The following measures can be considered to elevate the cleaner production level of phosphate mining enterprises.

Ore Recovery Rate (X_3): Improving ore recovery rate can be achieved through refining mining and beneficiation processes, optimizing equipment operation, and enhancing management and monitoring methods. Comprehensive utilization rate of wastewater (X_{20}):

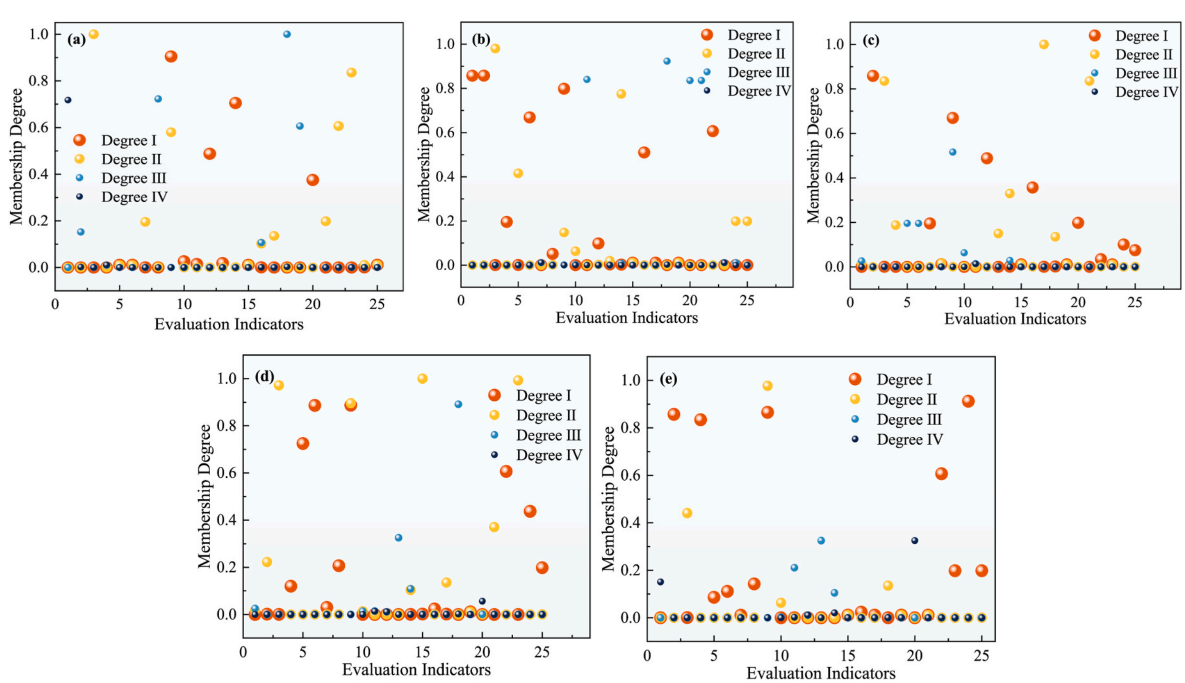

Fig. 6. The distribution of membership grades of various indicators in different phosphate mining enterprises: (a) Liushangou phosphate mine; (b) Jiunv phosphate mine; (c) Shaiqihe phosphate mine; (d) Yinjiaping phosphate mine; (e) Shanshuya phosphate mine.

Table 6
Probability distribution of cleaner production level for phosphate mines without considering weighting factors.

Phosphate mining enterprise	Basic probability distribution of subordination level				Maximum subordination degree	Subordination level
	I	II	III	IV		
#1	0.26791	0.38567	0.26989	0.07653	0.38567	II
#2	0.42522	0.25660	0.31594	0.00224	0.42522	I
#3	0.39668	0.46513	0.13642	0.00178	0.46513	II
#4	0.39987	0.45776	0.13435	0.00802	0.45776	II
#5	0.63466	0.21427	0.08487	0.06619	0.63466	I

Table 7
Probability distribution of cleaner production level of phosphate mining with integrated multi-attribute decision weights.

Phosphate mining enterprise	Fused weighted subordination level probability distribution				Subordination level	Actual level	Normal cloud
	I	II	III	IV			
#1	0.19997	0.46029	0.21089	0.12884	II	II	II
#2	0.39911	0.33336	0.26606	0.00147	I	I	I
#3	0.53822	0.35361	0.10796	0.00021	I	I	I
#4	0.37789	0.51141	0.08934	0.02136	II	II	I
#5	0.39257	0.35458	0.02871	0.22414	I	I	I

Optimizing wastewater treatment and reuse systems, including increasing water reuse rates, reducing wastewater discharge, and implementing water recycling systems. Electric power consumption (X_6): Adopting energy-saving technologies and equipment, refining production processes, optimizing equipment operating parameters to reduce energy consumption. Advanced level of production equipment (X_1): Upgrading and modernizing production equipment, introducing advanced production technologies and equipment to enhance production efficiency and reduce environmental impact. Comprehensive utilization rate of by-product mineral resources (X_{19}): Developing comprehensive utilization technologies for by-product mineral resources to minimize resource wastage. Water consumption per ton of phosphate ore extraction (X_7): Optimizing mining processes, improving water resource utilization efficiency, and reducing water consumption. Solid waste emissions (X_{16}): Implementing technologies for solid waste reduction and resource utilization to minimize solid waste emissions. Technological level of mining processes (X_2): Introducing advanced mining process technologies to enhance efficiency and reduce environmental impact.

The group decision weight determination method based on evidence theory proposed in the evaluation of cleaner production levels in phosphate mining integrates qualitative and quantitative factors in the weight determination process. It uses evidence theory to perform multi-source data fusion, taking into full consideration the diverse opinions of multiple experts in the weight determination process, effectively mitigating the adverse effects caused by direct conflicts between different indicators. Furthermore, the developed finite interval cloud model for integrating group decision weights comprehensively considers the uncertainty and fuzziness among the evaluation indicators. For cleaner production levels in phosphate mining, the finite interval cloud model can develop more reasonable distribution functions tailored to the characteristics of evaluation indicators. This validates the rationality of the method because compared to traditional cloud models, it better reflects the actual distribution features of the indicators (which do not entirely conform to Gaussian distribution within one-sided constrained intervals). By integrating group decision weights, the finite interval cloud model embodies the fuzzy uncertainty transformation of the cleaner production level grading for phosphate mining enterprises, thereby bringing the model's predictive results closer to actual conditions. This has also been verified in the determination results at actual mines. With the integration of group attribute decision weights, the finite interval cloud model provides a theoretical reference for the safety and environmental management of phosphate mining enterprises by enabling a more accurate assessment of the cleaner production level of phosphate mining enterprises.

6. Conclusion

Assessing the cleaner production level in phosphate mining enterprises contributes to enhancing the overall environmental production efficiency of phosphate mines, reducing the environmental impact of phosphate mining, and improving the utilization of resources and associated resources. A finite interval cloud model integrating group decision weights for evaluating the cleaner production level of phosphate mining enterprises has been proposed to enhance the environmental management level of phosphate mining enterprises and improve the ecological environment of phosphate mining areas. The proposed model leads to the following conclusions.

(1) The comprehensive consideration of the entire lifecycle of phosphate mining production, which encompasses four aspects, including ore extraction, pollutant emissions, resource recovery, and environmental protection, led to the selection of 25 cleaner production influencing factors. This facilitated the development of an evaluation index system for the cleaner production level of phosphate mining, while also establishing grading standards for the assessment indicators based on relevant regulations, standards, and expert opinions. Quantification ranges corresponding to each grade were determined. Based on this foundation, the hierarchical and correlated nature of the evaluation indicators for cleaner production levels in phosphate mining were revealed, laying the groundwork for the accurate assessment of cleaner production levels in phosphate mining enterprises.

(2) A method for determining weights that incorporates group decision-making attributes has been proposed through the comprehensive integration of the AHP and the expert consultation method, considering the opinions of multiple experts in the weight determination process. This method effectively resolves the adverse effects caused by direct conflicts between different indicators, reduces the biases of different experts in determining comprehensive weights, reconciles conflicts among expert opinions, optimizes the group decision-making structure, and enhances the accuracy of the weights. The top five indicators with the highest weights are ore recovery rate, comprehensive utilization rate of wastewater, energy consumption, level of production equipment advancement, and the utilization rate of associated mineral resources. Accordingly, phosphate mining

enterprises should enhance resource allocation and control levels for these indicators.

(3) A finite interval cloud model was proposed to reflect the actual distribution characteristics of the cleaner production level evaluation indicators of phosphate mining enterprises. These indicators do not entirely conform to a Gaussian distribution within a unilateral constraint interval, so the model combines their characteristics. Simultaneously integrating the weights determined through group decision-making, a cleaner production level evaluation model for phosphate mining enterprises based on the finite interval cloud model of fused group decision-making weights has been developed. This model objectively and accurately describes the fuzziness and uncertainty in the evaluation of the cleaner production level of phosphate mining enterprises. The developed model has been applied to five phosphate mining enterprises in Yichang City, Hubei Province, China. The evaluation results obtained for the cleaner production level of phosphate mines are consistent with the actual research findings from the enterprises. This demonstrates the rationality and reliability of using the finite interval cloud model integrated with group decision-making weights to evaluate the cleaner production level of phosphate mines.

Availability of data and materials

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

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CRediT authorship contribution statement

Menglong Wu: Writing – original draft, Visualization, Methodology, Conceptualization. **Yang Liu:** Supervision, Funding acquisition, Data curation. **Yicheng Ye:** Resources, Project administration. **Binyu Luo:** Validation, Investigation.

Declaration of competing interest

The authors declare no conflicts of interest.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.142398.

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