Assessment on coal mining land subsidence by using an innovative comprehensive weighted cloud model combination PSR conceptual model

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Research Article

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Abstract

The research on land subsidence (LS) is a global topic. In recent years, the environmental problems caused by coal mining have received great attention. In particular, mining land subsidence (MLS) caused damage to villages, buildings, farmland, etc, which seriously threatened the living environment and ecological environment of the mining area. To reasonably evaluate mining land subsidence (MLS) of coal mine, based on characteristics of strata movement in coal mining, this study put forward PSR (Pressure-State-Response) concept model based on MLS to build an evaluation index system of MLS in coal mine. Based on this index system, in view of the uncertainty in the evaluation process, the cloud model is used to represent the index weight and comprehensive evaluation calculations, which fully consider the randomness and ambiguity in the evaluation process. MLS of several important mining areas in China were evaluated and were classified as three grades (Slight-Medium-Strong). The cloud model assessment results are compared with the result of the probability integration method and the actual situation. The assessment results of the cloud model are closer to the actual situation than the probability integration method. It shows that the established MLS evaluation method based on cloud model in this study is reasonable and feasible. The Mining width and height ratio, depth and height ratio and coal seam dip angle are important factors affecting MLS. Therefore, improving the mining method to deal with the goaf reasonably, optimizing the mining design to control the influence range of mining are important measures to reduce the MLS and protect the ecological environment of mining areas.

Highlights

- A new land subsidence concept model in coalmine is proposed the first time.
- Ming land subsidence can be described by the model and 11 indictors.
- An improve Cloud model is used to conduct assessment on mining land subsidence.
- Result of cloud model is more beneficial to assess the danger level of mine land subsidence.

1 Introduction

Land subsidence (LS) refers to the problem of surface subsidence caused by man-made and natural causes. Natural factors mainly include natural compaction of loose strata and man-made factors mainly include human activities such as the exploitation of groundwater, oil and natural gas resources. Research and treatment of land subsidence have been a global problem(Dinar et al., 2021; Galloway et al., 2016; Zoccarato et al., 2018).In recent years, mining land subsidence (MLS) has received extensive attention and research. The mining of coal resources is of great strategic significance to China's long-term development. However, the excessive exploitation of underground coal resources has caused serious secondary disasters, which have had a huge impact on the landscape and ecological environment of the mining area(Zhang et al., 2019). Geological disasters such as surface deformation, fracture, and collapse caused by mining have destroyed a large number of farmland, vegetation, water resources and surface buildings, severely damaged the ecological environment of the mining area, and threatened the sustainable development of the coal industry(Akcin, 2021; Zheng et al., 2020). MLS destroys land resources, causing serious impacts on vegetation and water environment pollution (Ma et al., 2019; Zhao et al., 2020)and at the same time, it has also caused problems such as soil quality degradation and food security (Chen et al., 2019; Sun et al., 2019b). According to a survey conducted by the Bureau of Statistics of the People's Republic of China, 92% of domestic coal production comes from underground mining. It is estimated that 10,000 tons of coal mining underground will cause about 0.2–0.33 hectares of ground surface subsidence. In China, the annual subsidence is expected to increase 2104 hectares (Hu and Xiao, 2013).Accurate prediction and evaluation of MLS is an important prerequisite for preventing mining subsidence damage, reducing subsidence disasters, and protecting the ecological environment, especially the areas with serious potential land subsidence hazards in China (Yuan et al., 2020).For a long time, methods such as probability integral method and influence function method, which focus on the analysis of mining subsidence law and the study of subsidence mechanism, have been the main methods of mining subsidence prediction, which provide theoretical support for subsidence control and disaster prevention.(Chen et al., 2016; Ju and Xu, 2015; Ma et al., 2017; Yan et al., 2018). With the rapid development of the subject of artificial intelligence, many scholars have cited artificial intelligence technology in the prediction and evaluation of MLS(Mohammady et al., 2021; Yan et al., 2021b).Research methods based on numerical simulation are also widely used in the evaluation and analysis of MLS (Liu et al., 2021; Sikora and Wesolowski, 2021). At present, the probability integral method is the most widely used subsidence prediction method in China (Xing et al., 2021; Yuan et al., 2020). The MLS is affected by mining conditions and geological conditions, and it is affected by a large amount of randomness and ambiguity(Li et al., 2021).It can be seen from the above-mentioned literature analysis that MLS is seriously harmful to the environment. There are many research methods for MLS, but they have the following shortcomings in the application:

(1) MLS is closely related to mining and geological conditions and is affected by strata movement and overlying rock activities. It is a complex problem of quantitative and qualitative multi-index coupling, with significant regional and particular characteristics. In the evaluation and analysis, it is difficult to comprehensively analyze complex indicators, and can only simplify the analysis of a large number of qualitative indicators. The traditional predictive evaluation methods established by simplifying complex influencing conditions are difficult to describe the impact of complex factors such as key strata, loose strata, and lithological coupling of different strata. Therefore, the final result often deviates from the actual situation. (2) In the past, few models can well solve the randomness and ambiguity problems in MLS research. Therefore, this study uses the cloud model to solve this long-term problem, based on the establishment of an index system.

Therefore, in view of the shortcomings of traditional evaluation and prediction models, such as difficulty in describing key strata, loose strata, lithological coupling of different strata, and some complex and fuzzy factors, this study adopts the safety evaluation method(Ranjan and Hughes, 2014; Sovacool et al., 2011; Vithayasrichareon et al., 2012) to integrate the quantitative dimensions (the occurrence conditions of the coal seam, mining design parameters), and the qualitative dimensions (the nature of the rock, the impact of key strata) to construct the PSR (pressure-state-response) comprehensive conceptual model of MLS(Fang et al., 2008; Wang and Sun, 2017) based on the characteristics of coal mining, land subsidence, prediction and evaluation, etc. In addition, the comprehensive weighted cloud model of game theory weighted subjective weight and objective weight is introduced for analysis and evaluation, which improves the rationality and safety of mining subsidence evaluation.

2 Research Method

2.1 MLS-PSR concept model

In coal seam mining, the direct roof broke and collapsed, the cracks extended upward, and the overlying rock layer was bent and separated. As the working face advances, the exposed area of the goaf gradually expands, and the impact of mining continues to pass upwards, eventually forming a subsidence basin on the surface, directly leading to a series of serious environmental and ecological problems such as the destruction of ground villages, land, buildings, and the loss of vegetation and water resources. The mining subsidence model is shown in Fig. 1.

As shown in Fig. 1, the activities of the overlying strata caused by human mining activities eventually evolved into land subsidence, and mining is the main factor causing subsidence. The occurrence and mining conditions of coal seams such as coal seam thickness m, mining width l, depth buried H, dip angle a, etc are directly related to land subsidence(Yan et al., 2021a). The activity of the rock strata shows the evolution state of the land subsidence. For coal mining, the lithology of the overlying strata, key strata, the thickness of the loose strata and the slope angle of the terrain have always been the focus of the research on the overburden activity(Sun et al., 2021). In order to predict and control mining subsidence, many scholars have established important indicators for predicting and evaluating mining subsidence through a lot of research and actual measurement. Among them, the maximum subsidence value w_0 is an important index to describe the hazard degree of mining subsidence, which is related to the mining thickness m. dip angle a and the subsidence factor q. The main influence tangent tanβ mainly describes the range distribution of mining subsidence, and the inflection point offset s_0 mainly describes the control distance of the coal roof. In addition, the influence parameters on mining subsidence include the mining influence propagation coefficient and the crushing expansion of rock. Deng Kazhong...Edit. Deformation monitoring and subsidence engineering[M]. China University of Mining and Technology Press, 2014. From the above description and the subsidence model shown in Fig. 1, the study of mining subsidence is a closed-loop system, which is composed of human activities (resource mining), changes in environmental conditions (surface subsidence), and human response measures (prediction and control). It contains a lot of quantitative, qualitative and fuzzy factors.

According to the characteristics of mining land subsidence and referring to the PSR model, this study establishes a MLS-PSR concept model, where P is the pressure exerted by mining on the environment, S is the environmental geological state of the mining area, R is the countermeasure that human beings take to deal with this situation(Fang et al., 2008; Wang and Sun, 2017).The MLS-PSR concept model is shown in Fig. 2.

2.2 Construction of coal mining index system based on MLS-PSR conceptual model

The law of coal mining subsidence has regional characteristics, and the evaluation index system of subsidence mining impact should be different in different mining areas. According to the characteristics of coal mining subsidence, consulting to the existing research, and following principles of representativeness, independence, quantification and systematization of indicators(Peng et al., 2021a), this study built 3 evaluation criteria including the pressure exerted by mining on the environment (P), the geological environmental state of the mining area (S), human response to predict and control this situation (R).The assessment criteria includes 11 assessment indicators, which is shown in Table 1.

Table 1
MLS-PSR assessment indexes and interpretations

Target layer	Criterion layer	Indicator layer	Interpretation	Type
Assessment on MLS-PSR model	Coal resource mining(P)	Mining depth and height ratio	Reflects the relative goaf height of the coal seam in the vertical direction.	+
		Coal seam dip angle	Reflect the shape of the mining influence	+
		Mining width and height ratio	Reflects the sufficiency of mining	+
	Geological environment(S)	Terrain slope angle	Reflects the complexity of the geological environment	+
		Thickness of loose strata	Reflects the complexity of the geological environment	-
		Overlying rock lithology (unidirectional compressive strength)	Reflect the comprehensive properties of the overlying strata	-
		Key strata position	Reflects the ability of key strata to affect subsidence	-
	Predictive research(R)	subsidence factor	Reflect the comprehensive properties of the overlying strata	+
		Main influence tangent	Reflect the range distribution of mining subsidence	+
		Inflection point offset coefficient	Reflect the comprehensive properties of coal roof	-
		Mining propagation coefficient	Reflect the propagation characteristics of mining influence	+

2.3 Evaluation method of MLS based on improved cloud model

Cloud model is an algorithm model based on fuzzy mathematics and random mathematics, with strong qualitative and quantitative analysis capabilities (Pei et al., 2019; Ren et al., 2017; Xu et al., 2020). Let X be a quantitative domain expressed by values of number, and C be a qualitative notion of X. If the quantitative value $x \in X$, and x is a random quantity on C, the membership degree. $\mu(x) \in [0,1]$. x is the cloud droplet of cloud X, then:

$$\mu(x): X \to [0, 1], \forall x \in X, x \to \mu(x)$$

1

The digital characteristics of the cloud consist of element expectations *Ex*, entropy *En*, and super entropy *He* composition (Peng and Deng, 2020b; Xu et al., 2020). Where *Ex* is the central point of domain for cloud droplets. *En* is used to measure its uncertainty and reflect qualitative concepts such as randomness and ambiguity. *He* is used to describe the uncertainty of *En*, that is the entropy of entropy, which is reflected by the dispersion of clouds. The larger the value of *He*, the thicker the cloud appears. The membership cloud and its digital features are shown in Fig. 3.

For an improved cloud model with bilateral constraints[$c_{\min}$, $c_{\max}$](Cao et al., 2020), the formula for its numerical features is:

$$\begin{cases} Ex = \dfrac{c_{\max} + c_{\min}}{2} \\ En = \dfrac{c_{\max} - c_{\min}}{2.335} \\ He = K \end{cases}$$

2

Among them, K is served as a constant, which can be modulated on the grounds of the blur threshold of the variable. The uniform value of K in this study is 0.01.

FCG (Forward cloud Generator) is a cloud generation algorithm that maps from qualitative to quantitative, which generates cloud drops based on the digital characteristics of the cloud[*Ex, En, He*]. The principle of establishing the MLS cloud model is shown in Fig. 4, and concrete step is:

Step 1: Generate a normal random number y_i with En as the expectation and He^2 as the variance

Step 2: Generate a normal random number x_i with Ex as the expectation and y_i^2 as the variance, Delete x that does not meet the objective reality.

Step 3: Calculating $\mu(x_i)$:

$$\mu(x_i) = \begin{cases} 1 & \begin{array}{c} (x_i \in \text{MinDegree}\&x_i < Ex)\ or \\ (x_i \in \text{MaxDegree}\&x_i > Ex) \end{array} \\ \exp\left[-\dfrac{(x_i - Ex)^2}{2y_i^2}\right] & \end{cases}$$

3

Step 4: A cloud droplet (x_i, $\mu(x_i)$) is entered.

Step 5: Step 1–Step 4 are repeated until the Nth cloud droplet that meets requirements is formed into a cloud.

2.4 Calculating the weight of each assessment index for MLS-PSR

2.4.1 Improved analytic hierarchy process

Analytic Hierarchy Process (AHP) is a systematic engineering method from qualitative analysis to quantitative analysis, which is widely used to determine the influence weight of each evaluation index. This study uses the improved 3-scale AHP method, the algorithm is as follows(Peng and Deng, 2020a; Peng and Deng, 2020b; Peng et al., 2021b).

Step 1: Determining the level-structure model

Step 2: Establishing the comparison matrix A

$$a_{ij} = \begin{cases} 2 & \text{Element } i \text{ is more important than element } j \\ 1 & \text{Element } i \text{ is the same important as element } j \\ 0 & \text{Element } i \text{ is less important than element } j \end{cases}$$

4

Step 3: Calculating the ranking index r_i of importance.

$$r_i = \sum_{j=1}^{n} a_{ij}$$

5

r_i is elements' sum of row *i* in matrix *A*, $r_{\max}$= max (r_i), $r_{\min}$ =min (r_i)

Step 4: Establishing judgment matrix *B*

$$b_{ij} = \begin{cases} \frac{r_i - r_j}{r_{\max} - r_{\min}}(b_m - 1) + 1 & r_i > r_j \\ 1 & r_i = r_j \\ \left[\frac{r_j - r_i}{r_{\max} - r_{\min}}(b_m - 1)\right]^{-1} & r_i < r_j \end{cases}$$

6

b_m is the comparison standard of base point, and then the two base point comparison elements are compared according to the judgment scale of level 1–9, to obtain the value of b_m.

Step 5: The optimal transfer matrix *C* of judgment matrix *B* is obtained:

$$c_{ij} = 10^{\frac{1}{n}\sum_{k=1}^{n}\left(\lg \frac{b_{ik}}{b_{jk}}\right)}$$

7

Step 6: The weight *w* is calculated(Duan et al., 2014):

(a) Normalize the matrix by column to get matrix *T*, each element of which is

$$t_{i_j} = \frac{c_{ij}}{\sum_{k=1}^{\mathrm{n}} c_{kj}}$$

8

(b) Calculate the weight value

$$w = \frac{1}{n}\sum_{j=1}^{n} t_{ij}$$

9

2.4.2 Criteria importance though intercrieria correlation (CRITIC) method

There are two fundamental principles in CRITIC: (1) The contrast intensity is introduced, and the standard deviation is used to characterize the value of each evaluation level of the same index. The larger the standard deviation, the larger the index gap. (2) It reflects the conflict of evaluation indicators. If the two indicators have a strong positive correlation, it indicates that the conflict of indicators is smaller(Peng et al., 2021b).The specific calculation steps are as follows:

Step 1: Standardize the original data and normalize the evaluation matrix to eliminate the influence of dimensionality. The calculation formula is as follows:

For positive indicators:

$$y = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}$$

10

For negative indicators:

$$y = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})}$$

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Step 2: Calculate the variability and conflict of the evaluation index, use the standard deviation σ_j of the evaluation index to describe the variability, and the conflict coefficient is calculated by formula 12.

$$c_j = \sum_{m=1}^{n} \left(1 - r_{mj}\right)$$

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In formula 12, c_j is the conflict coefficient of evaluation index, j = 1, 2, …, n, r_{mj} is the correlation coefficient between evaluation indicators, which could be calculated by formula 13:

$$r_{xy} = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 (y - \bar{y})^2}}$$

13

Step 3: Calculating weight coefficient. Finally, the weight coefficient w_j of each index is calculated to obtain the weight matrix W. The weight coefficient could be calculated by formula 14:

$$w_j = \frac{\sigma_j * c_j}{\sum_{j=1}^{n} \sigma_j * c_j}$$

14

Therefore, the weight matrix W of evaluation indicators could be obtained, that is $W = [w_1, w_2, \ldots, w_n]$.

2.4.3 Calculate the combined weight of subjective and objective weights by game theory

After obtaining the subjective and objective weights, game theory is used to comprehensively weight the combined weights. This method combines the advantages of subjective and objective weighting, which not only considers the subjective opinions of decision-makers on the index factors, but also reflects the importance of the index itself to the research object. The steps to determine the combination weight using game theory are as follows:

Step 1: The S method is used to scientifically and reasonably weight the multi-index evaluation problem, and then the combined weight vector is obtained.

$$w(k) = [w_{k1}, w_{k2}, \cdots w_{kn}] \quad (k = 1, 2, \cdots, n)$$

15

$w(k)$ is the weight vector determined by the k-th method, and the weight vector determined by the s methods can be expressed as a linear combination:

$$W^T = \sum_{k=1}^{s} \alpha_k {w_k}^T \quad \alpha_k > 0$$

16

Step 2: According to the idea of the game aggregation model, the optimal combination of different weights is carried out, and the combination coefficient α_k is optimized to obtain the most suitable weight w^*. The countermeasure model is as follows:

$$\min \left\| \sum_{k=1}^{L} \alpha_k w_k^T - w_k \right\|_2 \ (k = 1, 2..., L)$$

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Step 3: According to the differential properties of the matrix, the optimal derivative conditional linear equation system equivalent to Eq. 16 can be obtained:

$$\begin{bmatrix} w_1 \cdot w_1^T & \cdots & w_1 \cdot w_k^T \\ \vdots & \ddots & \vdots \\ w_k \cdot w_1^T & \cdots & w_k \cdot w_k^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_k \end{bmatrix} = \begin{bmatrix} w_1 \cdot w_1^T \\ \vdots \\ w_k \cdot w_k^T \end{bmatrix}$$

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Step 4: Normalizing the solution ().

$$\alpha_{\text{k}}^{*}=\frac{\alpha_{\text{k}}}{\sum\limits_{\text{k}=\text{1}}^{\text{s}} \alpha_{\text{k}}}$$

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Step5: Then comprehensive weight could be obtained:

$$\text{w}^{*}=\sum\limits_{\text{k}=\text{1}}^{\text{L}} \alpha_{k}^{*} w_{k}^{T}$$

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2.5 Determine the degree of comprehensive certainty

The forward cloud generator (FFG) algorithm is used to calculate the certainty μ_{ij} of the index i belonging to the level j. Taking the average after multiple calculations can improve the reliability of the certainty. Finally, combined with the index weight w^* determined by the combination weighting method, the comprehensive certainty c_j of each level of MLS-PRS can be obtained.

$$c_j=\sum\limits_{i=1}^{n} \mu_{ij}\omega_{i}^{*}$$

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2.6 Evaluation criteria division criteria

The evaluation criteria of coal mining land subsidence have different characteristics due to different mining conditions and geological conditions. Considering the current mining status of most coal mines in China, referring to relevant references(Jia et al, 2009) and combining with relevant national regulations, the land subsidence is divided into three levels: Slight, Medium and Strong. The index classification and classification criteria of the body are shown in Table 2.

Table 2
Evaluation index grading standard

Evaluation indicator	I grade	II grade	III grade
Mining depth and height ratio c1	> 200	100–200	0-100
Coal seam dip angle c2(^\circ)	0–25	25–45	45–90
Mining width and depth ratio c3	0-1.2	1.2–1.4	> 1.4
Terrain slope angle c4(^\circ)	< 15	15–30	> 30
Thickness of loose strata c5(m)	< 10	10–40	> 40
Overlying rock lithology (unidirectional compressive strength)c6(MPa)	> 60	30–60	< 30
Key strata position c7(m)	> H_l	H_m-H_l	<H_m
Subsidence factor c8	0.27–0.55	0.55–0.84	0.84-1
Main influence tangent c9	1.20–1.91	1.91–2.40	2.40–3.54
Inflection point offset coefficient c10	0.31–0.43	0.08–0.31	0-0.08
Mining propagation coefficient c11	0.5–0.6	0.6–0.7	0.7–0.8
Note: In the table, H_m is the height of the caving zone and H_l is the height of the fracture zone			

2.7 Specific assessment procedure of MLS-PSR based on combined weighting cloud model

The basic principles of MLS-PSR evaluation based on the combination weighting cloud combination model: Firstly, cloud numerical features of the corresponding grade on the basis of MLS-PSR index grading standards could be calculated; Second, the measured data of each indicator is substituted into the cloud model to calculate the certainty of each indicator, and combined with the combined weights obtained by game theory to determine the comprehensive certainty of each level of MLS-PSR. Finally, the grade of MLS is confirmed according to the “maximum membership degree principle”. The specific procedure is demonstrated in Fig. 5.

3 Case Verification

3.1 Case mining area

In order to verify the applicability of the combined weighting cloud model and the MLS-PSR model in the evaluation of surface subsidence, this study selects typical domestic coal mining subsidence cases in Gansu, Shanxi, and Chongqing mining provinces for analysis. The specific distribution of each mining area is as follows as shown in Fig. 6 (Li, 2019; Li, 2019; Yu, 2015; Wu, 2013; Li, 2010; Wang, 2020; Guo, 2018).

3.2 Model establishment

3.2.1 Calculating cloud model parameters

The expected value *Ex* and the entropy value *En* are calculated according to the boundary values of the different grade evaluation index grade standards in Table 2. In this study, the super entropy *He* is consistently taken as 0.01. The parameters (*Ex, En, He*) of each index of the cloud model are shown in Table 3.

Table 3
Cloud model parameters of MLS in domestic coal mining at different levels based on MLS-PSR

Evaluation indicators	(*Ex, En, He*) of different levels		
	I grade Slight	II grade Medium	III grade Strong
c1	(225, 21.41, 0.01)	(150, 42.83, 0.01)	(50, 42.83, 0.01)
c2	(12.50, 10.71, 0.01)	(35.0, 8.57, 0.01)	(67.50, 19.27, 0.01)
c3	(0.60, 0.51, 0.01)	(1.30, 0.09, 0.01)	(1.70, 0.26, 0.01)
c4	(7.50, 6.42, 0.01)	(22.50, 6.42, 0.01)	(37.50, 6.42, 0.01)
c5	(45.00, 4.28, 0.01)	(25.00, 12.85, 0.01)	(5.00, 4.28, 0.01)
c6	(65.00, 4.28, 0.01)	(45.00, 12.85, 0.01)	(15.00, 12.85, 0.01)
c7	(86.36, 11.68, 0.01)	(50.04, 23.71, 0.01)	(11.18, 9.58, 0.01)
c8	(0.41, 0.12, 0.01)	(0.70, 0.12, 0.01)	(0.92, 0.07, 0.01)
c9	(1.56, 0.30, 0.01)	(2.16, 0.21, 0.01)	(2.97, 0.49, 0.01)
c10	(0.37, 0.05, 0.01)	(0.20, 0.10, 0.01)	(0.04, 0.03, 0.01)
c11	(0.55, 0.04, 0.01)	(0.65, 0.04, 0.01)	(0.75, 0.04, 0.01)
Note: In the table, the C7 digital feature is obtain according to the actual mining area conditions.			

3.2.2 Obtain membership degree

Based on the cloud model theory and the forward cloud generator algorithm (FFG), the MLS-PSR evaluation index cloud model is generated, and the corresponding membership degree is solved. Taking the important evaluation indicators as an example, the cloud model diagram is drawn as shown in Fig. 7.

4 Research Result

4.1 Raw data

The index data involved in this research comes from actual observations and theoretical studies of typical coal mines in China by scholars (Li, 2019; Li, 2019; Yu, 2015; Wu, 2013; Li, 2010; Wang, 2020; Guo, 2018).. The original data and combined weights of each indicator are shown in Table 4.

Table 4
The original data and comprehensive weight of each case mining area evaluation index

Indicators	Chongqing Datong Coalmine	Shanxi Xiadian Coalmine	Shanxi Huangyanhui Coalmine	Shanxi Ganhe Coalmine	Shanxi Majialiang Coalmine	Eight mining area of Chenjiagou Coalmine, Gansu	Third mining area of Chenjiagou Coalmine, Gansu	Combination weight
Mining depth and height ratio	202	70	61	106	66	44	55	0.24
Coal seam dip (°)	10	4	5	7	3	6	15	0.08
Mining width and height ratio	1.67	3.31	1.14	1.3	4.8	0.24	2.4	0.24
Terrain slope angle(°)	14	0	9	8	0	18	40	0.03
Thickness of loose strata (m)	17	19	30	93	264	10.4	12.5	0.03
Overlying rock lithology (unidirectional compressive strength MPa)	46	49.5	36.5	39	81.4	22.8	27.05	0.08
Key strata position (m)	129	182	58	338	182.27	255	240	0.08
Subsidence factor	0.62	0.81	0.82	0.72	0.73	0.13	0.6	0.10
Main influence tangent	1.6	2.5	2.1	2.5	2.98	2.12	2.4	0.07
Inflection point offset coefficient	0.23	0.12	0.06	0.1	0.24	0.06	0	0.01
Mining propagation coefficient	0.62	0.4	0.6	0.6	0.5	0.7	0.6	0.04

4.2 Results

According to the established MLS-PSR evaluation index system, the corresponding forward cloud model is used to indicate the evaluation level corresponding to each evaluation factor, and the comprehensive certainty is calculated, as shown in Table 5.

Table 5
Assessment result of MLS-PSR

number	Mining area	Comprehensive certainty degree			Assessment results
		U(I)	U(II)	U(III)	
1	Chongqing Datong Coal Mine	0.3541	0.3765	0.2529	II
2	Shanxi Xiadian Coal Mine	0.0796	0.2345	0.2848	III
3	Shanxi Huangyanhui Coal Mine	0.2463	0.3463	0.3936	III
4	Shanxi Ganhe Coal Mine	0.2313	0.599	0.2388	II
5	Shanxi Majialiang Coal Mine	0.0865	0.147	0.3091	III
6	Eight mining area of Chenjiagou Coal Mine, Gansu	0.2813	0.1732	0.3585	III
7	Third mining area of Chenjiagou Coal Mine, Gansu	0.139	0.2107	0.3848	III

Table 5 and Fig. 8 show the results of the evaluation using the cloud model. In order to verify the accuracy of the cloud model, the calculated result is compared with the calculated result of the probability integral method. Finally, the conclusions of the two methods are compared with the actual observation results, as shown in Table 6.

Table 6
comparisons of cloud model and probability integral method

Number	Mining area	Model		Actual grade
		Cloud model	Probability integral method	
1	Chongqing Datong Coal Mine	II	II	II
2	Shanxi Xiadian Coal Mine	III	III	III
3	Shanxi Huangyanhui Coal Mine	III	III	III
4	Shanxi Ganhe Coal Mine	II	III	II
5	Shanxi Majialiang Coal Mine	III	III	III
6	Eight mining area of Chenjiagou Coal Mine, Gansu	III	II	III
7	Third mining area of Chenjiagou Coal Mine, Gansu	III	III	II

It can be seen from Table 6 that the cloud model evaluation conclusions of Case 1–6 are basically the same as the actual measurement on site, while the calculation conclusion of the probability integral method is too large in No. 4 and too small in No. 6 case. The conclusions of the cloud model and the probability integral method of Case No. 7 are both level III. The main reason is that the coal seam in this mining area is shallow and the mining area is large, which makes the evaluation and calculation more emphasis on the strong level of III.

This study compares the evaluation results of the cloud model with the results of the probability integral method and the actual on-site. Relatively speaking, the cloud model is more consistent with the actual situation than the probability integral method. The main reason is that the probability integral method is more sensitive to the main calculation parameters such as mining width, depth, and subsidence factor. It is difficult to consider the fuzzy factors in the actual mining process, such as the location of key strata, Overlying rock lithology, etc. However, the cloud model comprehensively considers mining factors, geological conditions and other factors, so its evaluation results are more secure and reliable.

5 Discussion And Suggestion

5.1 Discussion

In recent years, there has been a lot of research on MLS in academia, and fruitful research results have been obtained. The main content is focused on studying the law of MLS activities and internal mechanism analysis, optimizing the accuracy of the prediction model and its adaptability to complex mining conditions. (Chi et al., 2021; Jiang et al., 2021) The ecological environment damage caused by coal mining is a very important subject, and ecological protection and ecological restoration in mining areas are important research areas.(Li et al., 2020; Sun et al., 2019a). The research method based on MLS-PRS is mainly embodied in the comprehensive consideration of actual mining conditions and geological conditions, and the construction of an evaluation model index system and index weights. Research methods have a greater impact on the evaluation results of MLS.

Therefore, it is necessary to consider the actual situation of coal mining and establish a scientific and reasonable evaluation index system. This study uses the cloud model to evaluate the level of MLS, classifies the evaluation index, and obtains the weight of each index, and then determines the weight by the game theory combination. Finally, the grade is obtained through comprehensive certainty, which overcomes the uncertainty degree in the evaluation process to a certain extent.

The establishment of MLS-PSR and the use of cloud models provide new ideas for the evaluation of mining subsidence, which not only fully considers the comprehensive influence of mining conditions and geological conditions, but also comprehensively considers the randomness and ambiguity of the actual situation. However, the pros and cons of the evaluation model are closely related to the construction of the evaluation index system. If some important indexes are ignored, the evaluation results will be biased. This study mainly establishes the evaluation index system from the mining conditions, geological conditions and the laws of rock formations. However, in different mine environments, more indicators need to be considered to improve the reliability of the evaluation results. Therefore, analysis based on actual engineering conditions, in-depth exploration and refinement of index system establishment and grading standards can improve the reliability of model evaluation.

5.2 Suggestion

The control and treatment of mining subsidence is based on accurate subsidence damage assessment. Coal mining is affected by actual mining conditions, geological conditions, hydrological and meteorological factors. The evaluation of mining subsidence in mining areas should be based on familiarity with the regional environment, geological conditions and mining technology, and scientific and reasonable MLS evaluation suggestions should be put forward to provide beneficial countermeasures for the protection and governance of the ecological environment. Main recommendations are as follows:

(1) From the data of various indicators, it can be seen that the mining technology and mining design have a severe impact on the subsidence of mining. Therefore, the government and mining enterprises should actively promote the mining technology with little impact, optimize and improve the design parameters to reduce the environmental impact from coal mining activities.

(2) The movement of the rock strata in coal mining causes the rock strata to appear shear dislocation, bending deformation, separation and fracture, etc., which eventually leads to land subsidence. Therefore, strengthening the control of the movement of the rock strata, filling the separation space, and maintaining the stability of the key strata can effectively prevent surface subsidence.

(3) Pay attention to the coordination of ecological environment protection and restoration with coal mining activities. The government and mining enterprises should strengthen the monitoring of ecological environment indicators in mining areas in coal mining activities. Strictly control the continuous destruction of the ecological environment due to mining subsidence, timely adjust the mining plan and strengthen ecological restoration. In addition, safety monitoring in mining areas should be strengthened to prevent natural disasters induced by coal mining.

(4) Increase investment in science and technology, improve coal mine filling technology, improve technology, reduce filling costs, and promote coal mine goaf filling technology. Fundamentally solve the problem of mining subsidence and realize the sustainable development of the mining area.

6 Conclusions

Prediction and evaluation of coal mining subsidence is the basic work of protecting the ecological environment of mining areas and implementing environmental governance. The purpose of this research is to try to establish a conceptual model of resource extraction and environmental protection based on the PSR model, and introduce the currently widely used cloud model for evaluation and analysis. In the evaluation process, the qualitative factors in the coal mining process are comprehensively considered and quantitatively analyzed. In addition, the proposed conceptual model and cloud model were used for mining subsidence evaluation, and the typical mining area cases in China were analyzed to verify their practicability and rationality. The main conclusions are as follows:

(1) In this study, based on the characteristics of coal mining subsidence, evaluation indexes were selected from coal mining, rock strata movement, and strata control, etc., and the MLS-PSR model of mining subsidence evaluation index system was constructed. Then, the cloud model is used to classify the MLS-PSR level. This study takes typical domestic coal mines as the research object, and evaluates mining subsidence, which has great practicability. The research results can be extended to the scope of MLS research in a large number of mining areas. It has certain research value.

(2) In this study, MLS-PSR and cloud model are used to evaluate coal mining subsidence, combined with the evaluation model of game theory. Taking some mining areas in Shanxi, Gansu, and Chongqing as examples, the comprehensive certainty of MLS is calculated and classified. The evaluation results show that the current impact of mining subsidence in these coal mine are still at a medium and strong level. Among them, Mining depth and height ratio, width and depth ratio are the main factors affecting mining land subsidence. Comparing the evaluation results of the cloud model with the calculation results of the probability integral method and the actual situation on site, the evaluation results are basically the same. It shows that the MLS-PSR evaluation method based on the cloud model established in this study is reasonable and feasible.

(3) The evaluation results show that the overall MLS in the study area is still in a relatively severe situation. Mining technology, plan, etc. are important factors that affect mining subsidence. Therefore, more scientific and reasonable mining techniques should be adopted in the future to reduce mining impacts through effective goaf filling. At the same time, optimize the mining design plan, set up reasonable safety coal pillars, control the scope of mining influence, fundamentally prevent the impact of mining subsidence, and protect the ecological environment of the mining area.

(4) In this study, a conceptual model of mining land subsidence evaluation was established, combined with cloud model and game combination weighting method to evaluate and analyze the mining subsidence of typical domestic mining areas. Due to the fact that there are many influencing factors in the process of coal mining and obvious regional characteristics, some indicators are relatively random. The mining subsidence in mountainous areas, plateaus and other special areas needs further study. In addition, the subsidence data of typical domestic mining areas is used to analyze mining subsidence, and the scale of its scope is relatively small, which cannot well reflect the relationship between land subsidence and coal mining, which needs to be further improved.

Declarations

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Authors Contributions

Chun Xu: investigation, data curation, methodology, writing-original draft, algorithm design and program development. Keping Zhou: funding acquisition, supervision and methodology. Xin Xiong: conceptualization, investigation, data curation, writing-review & editing. Feng Gao: methodology.

Data availability

All data are from the references.

Declarations

Not applicable.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

References

1. Akcin H (2021) A GIS-based building risk assessment for the subsidence due to undercity coal mining activities in Zonguldak, Turkey. Arab J Geosci 14:13
2. Chen G, Wang X, Wang R, Liu G (2019) Health risk assessment of potentially harmful elements in subsidence water bodies using a Monte Carlo approach: An example from the Huainan coal mining area, China. Ecotoxicol Environ Saf 171:737–745
3. Chen LW, Feng XQ, Xie WP, Xu DQ (2016) Prediction of water-inrush risk areas in process of mining under the unconsolidated and confined aquifer: a case study from the Qidong coal mine in China. Environ Earth Sci 75:17
4. Chi S, Wang L, Yu X, Fang X, Jiang C (2021) Research on Prediction Model of Mining Subsidence in Thick Unconsolidated Layer Mining Area. Ieee Access 9:23996–24010
5. Cao Jianli H, Zhiyong R, Fengyu T, Baohui. Rock mass quality classification set-to-cloud algorithm based on index correlation and its application.China Mining,2020,29(11):190–197
6. Dinar A, Esteban E, Calvo E, Herrera G, Teatini P, Tomas R et al (2021) We lose ground: Global assessment of land subsidence impact extent. Sci Total Environ 786:147415–147415
7. Fang SQ, Yang BA, Yu Y (2008) Construction of evaluation index system of national energy security based on CAS theory and PSR model. Kybernetes 37:1297–1307
8. Galloway DL, Erkens G, Kuniansky EL, Rowland JC (2016) Preface: Land subsidence processes. Hydrogeol J 24:547–550
9. Guo Qiang (2018) Characteristics and prevention measures of surface subsidence disasters in thick coal seam slicing and fully mechanized caving mining in Chenjiagou Coal Mine[D]. Xi'an University of Science and Technology
10. Hu Z, Xiao W (2013) Optimization of concurrent mining and reclamation plans for single coal seam: a case study in northern Anhui, China. Environ Earth Sci 68:1247–1254
11. Jiang C, Wang L, Yu X, Wei T, Chi S, Guo Q (2021) Prediction of 3D deformation due to large gradient mining subsidence based on InSAR and constraints of IDPIM model. Int J Remote Sens 42:188–219
12. Ju J, Xu J (2015) Surface stepped subsidence related to top-coal caving longwall mining of extremely thick coal seam under shallow cover. Int J Rock Mech Min Sci 78:27–35
13. Li HJ, Zhu L, Guo GX, Zhang Y, Dai ZX, Li XJ et al (2021) Land subsidence due to groundwater pumping: hazard probability assessment through the combination of Bayesian model and fuzzy set theory. Nat Hazards Earth Syst Sci 21:823–835
14. Li W, Wang D, Du H, An J, Zhao W, Iop (2020) Analysis and evaluation of the instability chain of room and pillar goaf in Western China ecological fragile area. 6th International Conference on Energy, Environment and Materials Science. 585, 2020
15. Liu HF, Sun Q, Zhou N, Wu ZY (2021) Risk Assessment and Control Strategy of Residual Coal Pillar in Room Mining: Case Study in Ecologically Fragile Mining Areas, China. Sustainability 13:13
16. Li Xinyi (2019) Research on the Classification of Geological Environment Destruction Degree in Coal Mining Subsidence Area in Mountainous Region[D]. Chongqing University
17. Li C (2010) Prediction theory and experimental research on the laws of overburden and ground movement and deformation[D]. China University of Mining and Technology (Beijing)
18. Li Lin (2019) Surface Deformation Monitoring and Regular Application Research in Majialiang Mining Area[D]. China University of Mining and Technology
19. Li W et al., Analysis and evaluation of the instability chain of room and pillar goaf in Western China ecological fragile area, in 2020 6th International Conference on Energy, Environment and Materials Science. 2020

20. Ma CQ, Li HZ, Zhang PP (2017) Subsidence prediction method of solid backfilling mining with different filling ratios under thick unconsolidated layers. Arab J Geosci 10:12
21. Ma K, Zhang Y, Ruan M, Guo J, Chai T. Land Subsidence in a Coal Mining Area Reduced Soil Fertility and Led to Soil Degradation in Arid and Semi-Arid Regions. Int J Environ Res Public Health 2019; 16
22. Mohammady M, Pourghasemi HR, Amiri M, Tiefenbacher JP (2021) Spatial modeling of susceptibility to subsidence using machine learning techniques. Stochastic Environmental Research and Risk Assessment
23. Pei J, Liu W, Han L. Research on Evaluation Index System of Chinese City Safety Resilience Based on Delphi Method and Cloud Model. Int J Environ Res Public Health 2019; 16
24. Peng T, Deng H (2020a) Comprehensive evaluation for sustainable development based on relative resource carrying capacity-a case study of Guiyang, Southwest China. Environ Sci Pollut Res Int 27:20090–20103
25. Peng T, Deng H (2020b) Comprehensive evaluation on water resource carrying capacity in karst areas using cloud model with combination weighting method: a case study of Guiyang, southwest China. Environ Sci Pollut Res Int 27:37057–37073
26. Peng T, Deng H, Lin Y, Jin Z (2021a) Assessment on water resources carrying capacity in karst areas by using an innovative DPESBRM concept model and cloud model. Sci Total Environ 767:144353
27. Peng T, Deng HW, Lin Y, Jin ZY (2021b) Assessment on water resources carrying capacity in karst areas by using an innovative DPESBRM concept model and cloud model. Sci Total Environ 767:15
28. Ranjan A, Hughes L (2014) Energy security and the diversity of energy flows in an energy system. Energy 73:137–144
29. Ren Y, Yao J, Xu D, Wang J (2017) A comprehensive evaluation of regional water safety systems based on a similarity cloud model. Water Sci Technol 76:594–604
30. Sikora P, Wesolowski M (2021) Numerical assessment of the influence of former mining activities and plasticity of rock mass on deformations of terrain surface. International Journal of Mining Science Technology 31:209–214
31. Sovacool BK, Mukherjee I, Drupady IM, D'Agostino AL (2011) Evaluating energy security performance from 1990 to 2010 for eighteen countries. Energy 36:5846–5853
32. Sun J, Yuan X, Liu H, Liu G, Zhang G. Emergy evaluation of a swamp dike-pond complex: A new ecological restoration mode of coal-mining subsidence areas in China. Ecological Indicators 2019a; 107
33. Sun S, Sun H, Zhang D, Zhang J, Cai Z, Qin G et al. Response of Soil Microbes to Vegetation Restoration in Coal Mining Subsidence Areas at Huaibei Coal Mine, China. Int J Environ Res Public Health 2019b; 16
34. Sun YJ, Zuo JP, Karakus M, Liu L, Zhou HW, Yu ML (2021) A New Theoretical Method to Predict Strata Movement and Surface Subsidence due to Inclined Coal Seam Mining. Rock Mechanics and Rock Engineering
35. Vithayasrichareon P, MacGill IF, Nakawiro T (2012) Assessing the sustainability challenges for electricity industries in ASEAN newly industrialising countries. Renewable Sustainable Energy Reviews 16:2217–2233
36. Wang L, Sun HQ. Research on the Construction and Application of Auditing Evaluation Index of Ecological Environment Performance in Resource-based Cities. In: McAnally E, Zhang Y, Volodina T, Hou R, Zhang M, editors. Proceedings of the 2nd International Conference on Judicial, Administrative and Humanitarian Problems of State Structures and Economic Subjects. 159. Atlantis Press, Paris, 2017, pp. 240–245
37. Wu Xiaobo (2013) Research on prediction and control measures of surface subsidence in underground coal mines[D]. Beijing Forestry University
38. Wang Z (2020) Research on the law of surface movement and deformation in Chenjiagou Coal Mine with deep mining depth and fully mechanized caving mining[D]. Xi'an University of Science and Technology
39. Xing X, Zhu Y, Yuan Z, Xiao L, Liu X, Chen L et al (2021) Predicting mining-induced dynamic deformations for drilling solution rock salt mine based on probability integral method and weibull temporal function. Int J Remote Sens 42:639–671
40. Xu Q, Xu K, Zhou F. Safety Assessment of Casting Workshop by Cloud Model and Cause and Effect-LOPA to Protect Employee Health. Int J Environ Res Public Health 2020; 17
41. Yan WT, Chen JJ, Tan Y, Zhang WZ, Cai LL. Theoretical Analysis of Mining Induced Overburden Subsidence Boundary with the Horizontal Coal Seam Mining. Advances in Civil Engineering 2021a; 2021
42. Yan WT, Dai HY, Chen JJ (2018) Surface crack and sand inrush disaster induced by high-strength mining: example from the Shendong coal field, China. Geosci J 22:347–357

43. Yan Y, Yan W, Liu J, Guo J. The Prediction Model of Super Large Subsidence in High Water Table Coal Mining Areas Covered with Thick Unconsolidated Layer. Geofluids 2021b; 2021
44. Yuan Y, Li H, Zhang H, Zhang Y, Zhang X. Improving Reliability of Prediction Results of Mine Surface Subsidence of Northern Pei County for Reusing Land Resources. Applied Sciences-Basel 2020; 10
45. Zhang G, Yuan X, Wang K (2019) Biodiversity and temporal patterns of macrozoobenthos in a coal mining subsidence area in North China. PeerJ 7:e6456
46. Yu Y (2015) Study on the breaking dynamic load characteristics of the hard roof and the control of the roadway surrounding rock in the extra-thick coal seam[D]. China University of Mining and Technology
47. Zhao Y, Zheng W, Xiao W, Zhang S, Lv X, Zhang J (2020) Rapid monitoring of reclaimed farmland effects in coal mining subsidence area using a multi-spectral UAV platform. Environ Monit Assess 192:474
48. Zheng L, Zhu L, Wang W, Guo L, Chen B. Land Subsidence Related to Coal Mining in China Revealed by L-band InSAR Analysis. Int J Environ Res Public Health 2020; 17
49. Zoccarato C, Minderhoud PSJ, Teatini P. The role of sedimentation and natural compaction in a prograding delta: insights from the mega Mekong delta, Vietnam. Scientific Reports 2018; 8

Figures

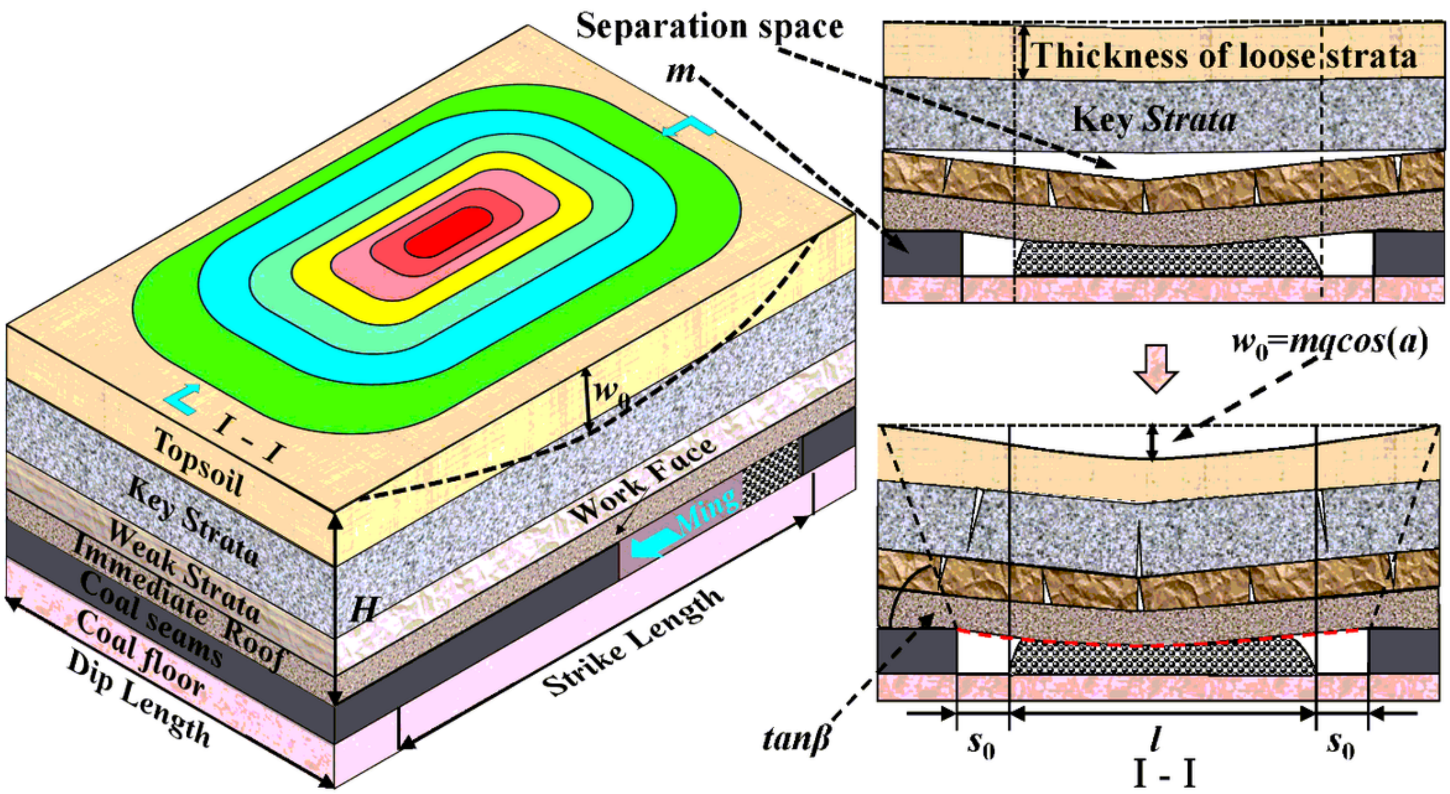

Figure 1

Mining subsidence model

Figure 2

The PSR concept model of MLS

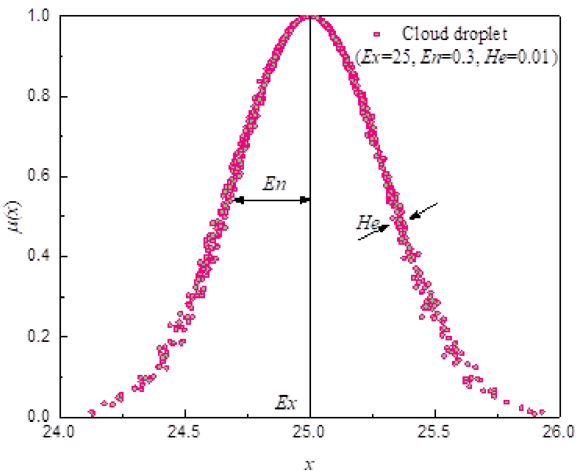

Figure 3

Cloud model and its digital features

Figure 4

The cloud model of Land subsidence

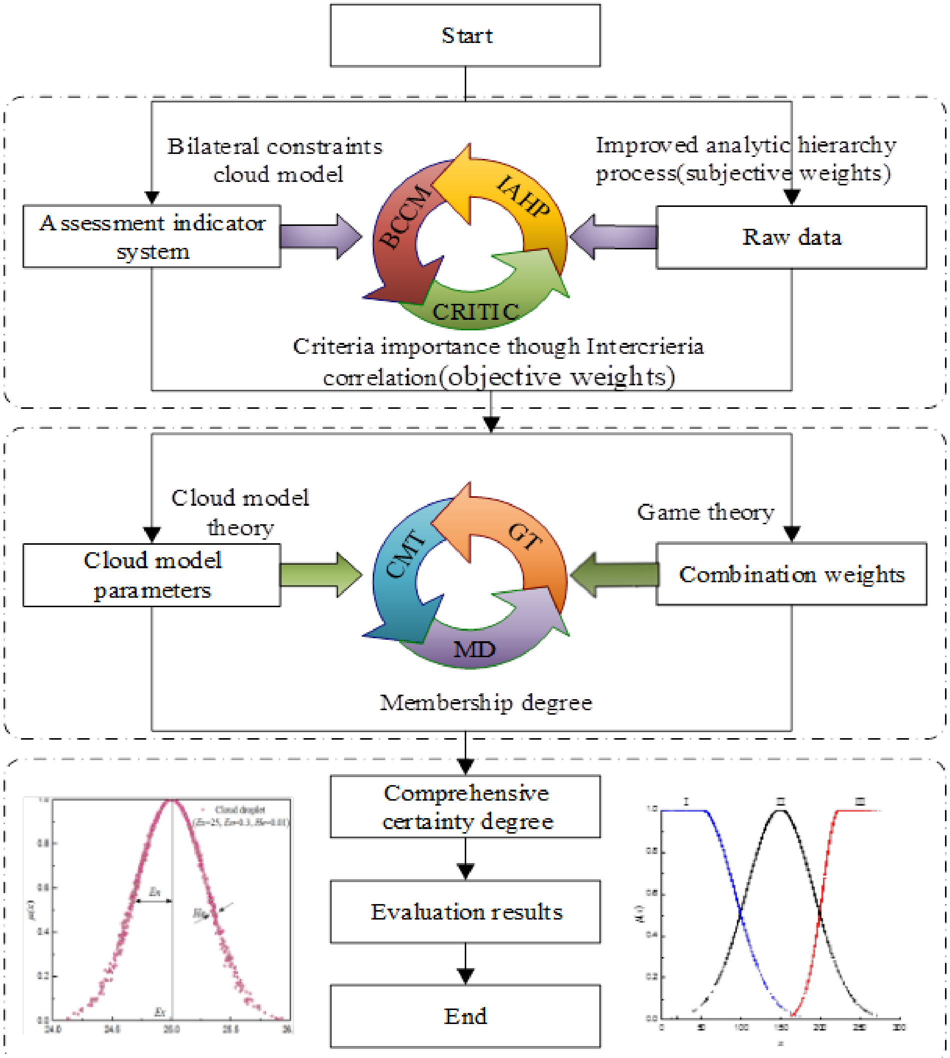

Figure 5

Evaluation process of MLS based on cloud model

Figure 6

Case mining area distribution

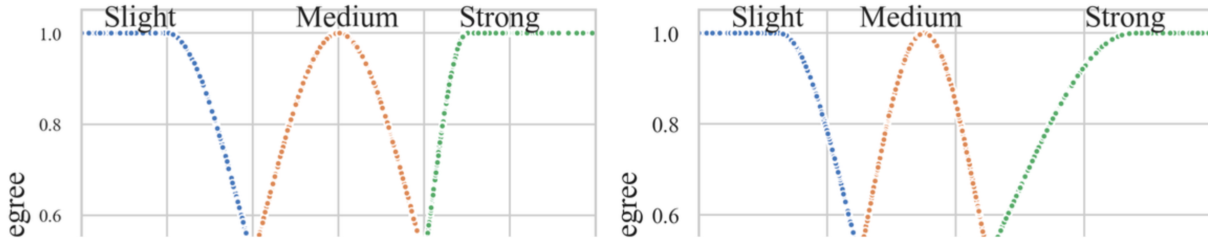

Figure 7

Cloud model diagram of the response subsystem

Figure 8

Assessment result of MLS-PSR in the Case of the mining area