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Article

Mathematical Evaluation on the Control of Mining-Induced Ground Subsidence in Thick Loose Strata

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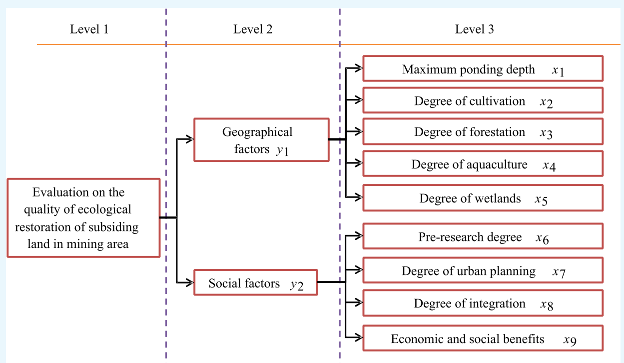
ABSTRACT: Coal mining under thick loose strata in North China leads to ground subsidence, which is a natural result of hydro-mechanical coupling (fluid flow coupled with solid deformation). Therefore, the land surrounding the mining areas is greatly damaged. In this study, the combined weight (CW) method and the fuzzy matter-element analysis (FMEA) method were used to analyze and evaluate the control effect of subsiding land. Overall, 20 sets of geological samples were collected from this area. The influencing factors and the corresponding weights for the control effect of subsiding land were comprehensively analyzed, and an FMEA model was built to predict and verify the results. The results showed that (1) the two evaluation indicators with the most significant impact on land reclamation were the degree of integration and the economic and social benefits and (2) among the 20 sets of samples selected, the predicted conclusions of 17 sets were consistent with the actual engineering situations, which led to an accuracy of 85%. In other words, the CW-FMEA model showed good reliability for evaluating the control effect of subsiding land, which can provide scientific references for control and quality evaluations of land subsidence due to coal mining.



1. INTRODUCTION

Underground mining activities often lead to strata collapse and water flow, causing surface subsidence.[1−4] For coal mining under thick loose strata in the North China Plain, damage to the land is more severe.[5] However, the North China Plain is known to produce a high grain yield (Figure 1a). This region is characterized by high underground phreatic water levels, thick loose strata, and large areas of ponding, resulting in extensive damage across wide areas of cultivated land (Figure 1b).[6] In recent years, as investment by the Chinese government into measures to protect the ecological environment has gradually increased, various coal mine groups have been in active and close contact with relevant scholars and experts, who have subsequently developed methods aimed at controlling subsiding lands that are appropriate to their own local conditions.[7] These control methods include shallow-leveling, deep-digging and shallow-filling, deposition-filling and bulge-cutting, and preset-filling methods. These methods have played an important role in controlling subsiding land processes and have achieved satisfactory results. They are conducive to the rapid restoration of the ecological environment in lands that have undergone subsidence, the establishment of a sound mechanism for controlling subsiding land due to coal mining, and sustainable socioeconomic development. (Figure 1c).[8]

Guo et al.[9] collected values for various influencing factors using ArcGIS software and combined it with a fuzzy analytical hierarchy process (AHP) to comprehensively evaluate the geological environment of the Baoding coal mine. Xiao et al.[10] established a comprehensive ecological risk assessment model for coal mines using ecological risk assessment theory and proposed appropriate risk prevention measures with application to the Dongtan coal mine in Shandong province. Bi et al.[11] conducted field research in the Daliuta coal mine with different inoculation technologies using artificial ecological engineering theory and determined the optimal plants to use for soil restoration of land that has undergone subsidence. Wang et al.[12] observed that drainage is difficult in farmlands where land subsided due to coal mining and also noted the low utilization of solid waste produced by coal mining; they performed permeability and compressive strength experiments using concrete produced from different proportions of waste coal gangue and fly ash, which developed concrete materials that could be applied to farmland drainage ditches. Furthermore, Hu et al.[13] used unpolluted Yellow River sediments for the land

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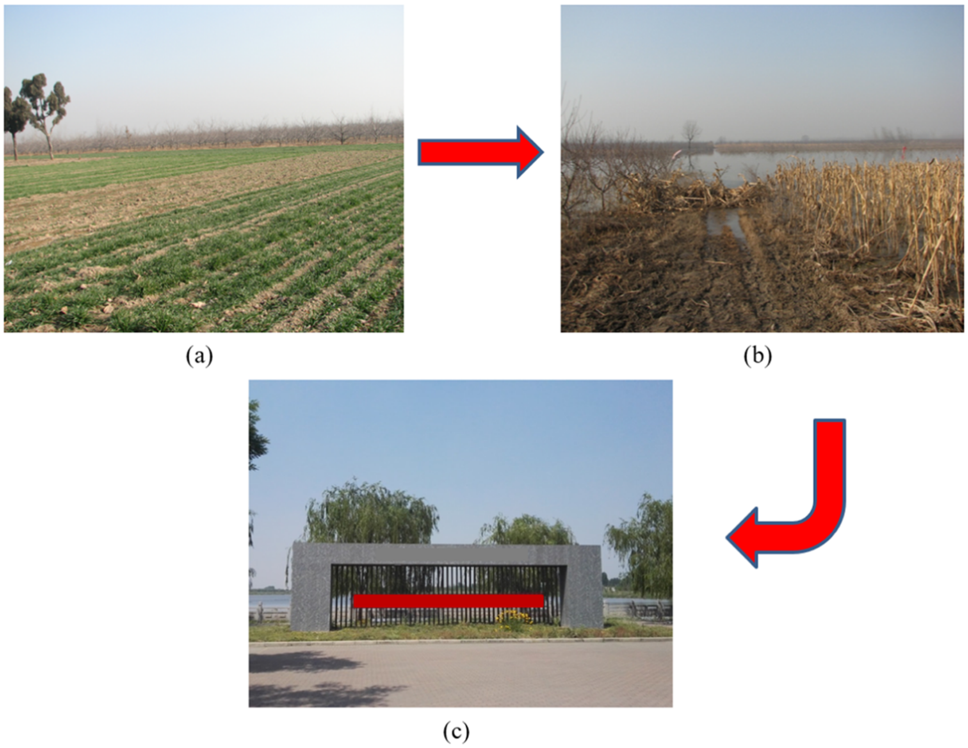

Figure 1. History of subsiding land control. (a) Cultivated land before mining. (b) Water accumulation during land subsidence. (c) Taiping National Wetland Park after the ecological restoration of subsiding land.

reclamation of cultivated land in subsiding land and, by studying corn growth in greenhouse experiments, determined that the optimal soil cover thickness was 70 cm. Yu et al.[14] collected the necessary monitoring data of the surface subsidence in the Hanjiawan coal mine in the Shendong mining area, which was the preparatory work for the experiment. In addition, the comprehensive benefits of land reclamation were studied in this coal mine using the fuzzy comprehensive evaluation method. After the corresponding control measures were proposed, the environmental and economic benefit indexes of the site were increased significantly.

However, most of the research focuses on land reclamation evaluation and ecological restoration. The existing evaluation models also lack important social factors such as the local urbanization level and government investment, which are indexes that cannot be ignored. When calculating the weight value of indexes, the pure qualitative analysis methods were also interfered by human factors. Therefore, many new weight methods should be introduced to make the results more reasonable.

In addition, many new control measures have appeared in the area of surface subsidence in the thick loose strata of the North China Plain. For example, areas with fewer collapsed pits are restored to cultivated land, areas with ponding areas more than 1.5 m deep are used for fishery breeding, and the remaining areas are transformed into wetland parks or woodland.[15,16] Thus, land that has subsided is gradually being developed according to an ecological model that integrates agriculture, livestock breeding, tourism, and sightseeing. By doing this, both economic development and the happiness index of residents can be effectively improved, and the "green lung" function of local areas can also be enhanced. The control practices used vary and have their own characteristics, which are of important practical significance for guiding work to control the land reclamation of subsiding land.[17,18] The evaluation indexes generated during the control of subsidence land have not been used at the same time, and so are the social factors in this case.

In our work, the specific objective of this paper is to build a new comprehensive evaluation system, including the main factors related to the economic, environmental, and social conditions. Among them, the urbanization level and government investment, which are helpful to improve the lives of nearby residents, are the first important factors added to the evaluation system. The calculation process of this paper is divided into the following steps: First, from the perspective of both subjective and objective analyses and incorporated knowledge from land reclamation experts, several key factors influencing the land subsidence control around coal mines in the North China Plain were selected. Then, the comprehensive weights of factors that influence land subsidence control were calculated using the combined weight (CW) method. These values were then used to develop an overall planning strategy. Finally, the fuzzy matter-element analysis (FMEA) theory was used to identify correlations among the various influencing factors. The main contribution of this paper is that it can provide some measures or directions for the control of other coal mine subsidence areas.

2. METHODOLOGY

2.1. Entropy Weight (EW) Method. The EW method[19] is an objective analysis method used to calculate the weights of various evaluation indicators. If the degree of variation is larger and the information entropy is smaller, the weight of the corresponding indicator is larger. The method is based on actual values of the factors influencing the evaluation model, so it is able to produce more reliable results.

The single entropy weight method has little effect on the evaluation of objective things. The application of the improved entropy weight method is increasingly used in research.

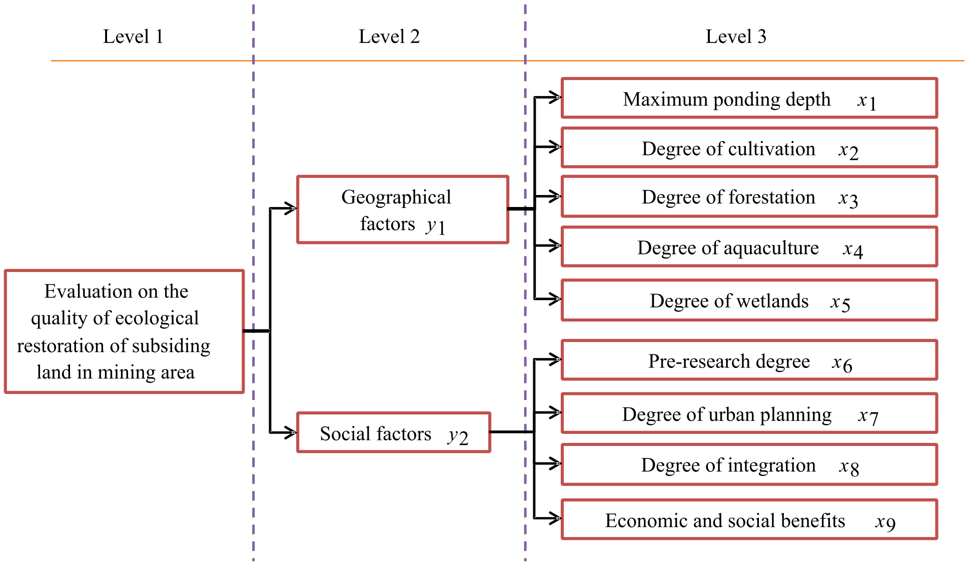

Figure 2. Schematic diagram of the hierarchy of the AHP method.

Nowadays, the entropy weight TOPSIS method,[20] entropy weight and fuzzy C-mean weight method,[21] entropy weight and fuzzy matter-element analysis method,[22] and AHP-entropy weight method[23] are widely used in many aspects of life. These applications can help solve complex problems, such as accident hazards, underground mining risks, and public facility management.

Suppose $m > 1$ evaluation samples and n evaluation indicators are used to establish the evaluation matrix. The matrix is shown as follows

$$B_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

(1) Standardization of indicators

In a multiple indicator evaluation system, it is difficult to calculate the results due to inconsistencies in the units, dimensions, and other factors of each indicator. Thus, to ensure the reliability of the evaluation results, all evaluation indicator parameters should be standardized.

Equation 2 shows the standardization of a positively correlated (beneficial) indicator for column j

$$\bar{x}_{ij} = \frac{x_{ij} - \min_{1\le i\le m} x_{ij}}{\max_{1\le i\le m} x_{ij} - \min_{1\le i\le m} x_{ij}} \ge 0 \tag{2}$$

and eq 3 shows the standardization of a negatively correlated (cost) indicator for column j

$$\bar{x}_{ij} = \frac{\max_{1\le i\le m} x_{ij} - x_{ij}}{\max_{1\le i\le m} x_{ij} - \min_{1\le i\le m} x_{ij}} \ge 0 \tag{3}$$

(2) Weight assignment of each indicator in the matrix according to the following equation

$$Y_{ij} = \frac{\bar{x}_{ij}}{\sum_{i=1}^{m} \bar{x}_{ij}} \tag{4}$$

Thus, Y_{ij} represents the weight of the jth evaluation indicator of the ith evaluation sample in the matrix (i is from 1 to m and j is from 1 to n). Obviously, Y_{ij} satisfies $0 \le Y_{ij} \le 1$ and $\sum_{i=1}^{m} Y_{ij} = 1$ for any j.

(3) Calculation of the entropy value of each indicator using the following equation (k is from 1 to n)

$$Z_k = -\frac{1}{\log m} \sum_{i=1}^{m} Y_{ik} \log Y_{ik} \tag{5}$$

From a basic convex analysis (Lagrange multiplier method for affine constrained maximization), the range of Z_k is between 0 and 1. Note in the actual calculation, the Y_{ik} might be zero or one, and the corresponding $Y_{ik} \log Y_{ik}$ simply vanishes.

(4) Calculation of the entropy weight of each indicator using the following equation (k is from 1 to n)

$$\xi_k = \frac{1 - Z_k}{n - \sum_{k=1}^{n} Z_k} \ge 0 \tag{6}$$

It is easy to see that $\sum_{k=1}^{n} \xi_k = 1$, and the smaller the entropy value Z_k, the greater the entropy weight ξ_k, which means the greater the importance of this evaluation indicator. In this work, the entropy weight vector given by eq 6 is denoted as $\eta_1 \in \mathbb{R}^n$.

2.2. Analytical Hierarchy Process (AHP) Method. The AHP method is a subjective analysis method, proposed by Saaty,[24] to quantify qualitative factors. It is a method that converts nonquantitative factors into numerical values, followed by a series of pairwise comparisons on the importance of each influencing factor, which are used to calculate the weight of each factor.[25,26] The basic procedures are as follows:

(1) A hierarchical structure system is established, which can generally be divided into three layers, namely, the target layer, the intermediate classification layer, and the factor layer (Figure 2).

(2) A judgment matrix (suppose the size is d by d, $d \ge 2$ could be smaller than n due to the hierarchy) is established through mutual comparisons among all of the factors. The element (i, j) in this matrix represents the level of importance of factor i to factor j. The larger the number, the higher the level that factor i is more important than the

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factor j (i.e., escalating differences), and the element (j, i) is the reciprocal of the element (i, j). In solving practical problems, the importance analysis table proposed by Saaty[24] had many limitations. The results calculated were often quite different from those calculated by the entropy weight method or gray relational degree analysis, so it cannot be used to solve problems effectively. After several conversations with other experts, the following proposed Table 1 will be more convincing.

Table 1. Degree of Importance between Two Factors

comparison of the importance of two factors	corresponding quantized value
two factors are of equal importance	1
one factor is a little bit more important than the other	2
the importance of one factor is greater than that of the other	3
the importance of one factor is much larger compared with that of the other	4
the importance of one factor is extremely greater than that of the other	5
intermediate values of the above comparisons such as	3/2, 5/2, 7/2, 9/2

(3) The weight of each factor is then calculated as the non-negative standardized (by $\pm\|\cdot\|_1$) eigenvector corresponding to the largest eigenvalue of the previous judgment matrix.

(4) Consistency test of each (single) judgment matrix. The AHP method requires that the judgment matrix has general consistency, which will ensure a basically reasonable calculated result. The calculation formulae are shown as follows

$$R_C = \frac{I_C}{I_R} \tag{7}$$

$$I_C = \frac{\lambda_{max} - d}{d - 1} \tag{8}$$

where R_C is the consistency ratio, I_C is the consistency index, I_R is the random consistency index whose value is determined according to Table 2 (empirical values provided by Saaty[24]), λ_{max} is the largest eigenvalue, and d is the size of the judgment matrix. The consistency test requires R_C should be smaller than 0.1, otherwise, the judgment matrix should be revised.

(5) Total consistency ratio test. Due to the hierarchical architecture, the total consistency ratio R_C^{total} is also required to satisfy the certain criterion. The R_C^{total} is calculated as follows

$$R_C^{total} = \frac{\sum_{i=1}^{p} w_i I_{C,i}}{\sum_{i=1}^{p} w_i I_{R,i}} \tag{9}$$

where p is the number of factors in the intermediate classification layer and w_i is the weight of factor i in the intermediate classification layer to the target layer. The total consistency ratio should be smaller than 0.1, otherwise, the judgment matrix should also be revised.

(6) Calculation of the final integrated weights of n factors (evaluation indicators), which are known as $\eta_2 \in \mathbb{R}^n$.

2.3. Combined Weight (CW) Method.

The CW method was designed to comprehensively analyze the subjective (AHP) and objective (EW) weight information[27] that influenced the subsiding land control, which enabled a more comprehensive and scientific calculation of the weights of the evaluation indicators.[28,29]

In the most general case, suppose N weight vectors are obtained using N different methods, which are denoted as $\eta_1, \eta_2, ..., \eta_N$. They form a basis weight vector set, and a combined weight vector η^* is simply a linear combination of this set $\eta^* = \sum_{K=1}^{N} \alpha_K \eta_K$. The objective is to minimize the deviation between each of the N weight vectors and η^*. The previous "game theory" (GT) used in other research papers constructed N minimization objectives, and for each objective $\|\eta^* - \eta_K\|^2$, they only take derivative with respect to the α_K and set it to zero, which is not consistent with the necessary condition of a stationary point of a multivariate function. Furthermore, the variables α_1 to α_N are not arbitrary but constrained, thus it is not mathematically correct to do an unconstrained minimization problem (with no specific scalar objective) first and normalize the result later. In this work, a complete convex optimization problem is proposed to resolve the abovementioned issue. The problem is defined as follows

$$\text{minimize}_{\alpha_1, \cdots, \alpha_N} \sum_{K=1}^{N} \beta_K \|\eta^* - \eta_K\|^2 \tag{10}$$

s.t.

$$\sum_{K=1}^{N} \alpha_K = 1 \tag{11}$$

$$\alpha_1 \geq 0, \alpha_2 \geq 0, \cdots, \alpha_N \geq 0 \tag{12}$$

where β_1 to β_N are the prescribed (they were assigned before solving the optimization problem) scalars for deviations, and users could tune them to get satisfying results. In general, if one method is dominant or is preferred by users, the corresponding β should be larger.

2.4. Fuzzy Matter-Element Analysis (FMEA) Method.

The theoretical bases of this method are matter-element theory and extension set theory.[30] Using the qualitative analysis of matter-elements[31] and combining this with the quantitative calculation of the correlation functions,[32] each indicator that influences an evaluation object is converted into a compatible problem[33,34] so that a comprehensive evaluation model,[35−39] which is more in line with objective reality is obtained. The calculation process of the FMEA is described as follows:

(1) Determination of the classical domain. The FMEA model is generally composed of three parts, which are the elements of matter, character, and quantity. If there are L final classes (evaluation levels) and n evaluation indicators, the following n-dimensional matter-element of the kth class will be defined, as shown in the following equation

Table 2. Random Consistency Index Value, I_R

d	1	2	3	4	5	6	7	8	9	10	11
I_R	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

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$$R_k^{\text{classical}} = \begin{bmatrix} d_1 & (a_k^1, b_k^1) \\ \vdots & \vdots \\ d_j & (a_k^j, b_k^j) \\ \vdots & \vdots \\ d_n & (a_k^n, b_k^n) \end{bmatrix} \tag{13}$$

where $k = 1, 2, ..., L$ represents the kth class (evaluation level), d_j represents the jth evaluation indicator ($1 \le j \le n$), and (a_k^j, b_k^j) represents the range ($a_k^j < b_k^j$) of d_j under the kth class (evaluation level).

(2) Determination of the joint domain. The joint domain is given by one n-dimensional matter-element, as shown in the following equation

$$R^{\text{joint}} = \begin{bmatrix} d_1 & (a_{\min}^1, b_{\max}^1) \\ \vdots & \vdots \\ d_j & (a_{\min}^j, b_{\max}^j) \\ \vdots & \vdots \\ d_n & (a_{\min}^n, b_{\max}^n) \end{bmatrix} \tag{14}$$

where $(a_{\min}^j, b_{\max}^j)$ represents the extended range ($a_{\min}^j < b_{\max}^j$) of d_j for all classes (in our application: for all levels of the control effect of subsiding land). It is easy to verify that $a_{\min}^j$ and $b_{\max}^j$ will satisfy $a_{\min}^j \le \min\{a_1^j, a_2^j, \cdots, a_L^j\}$ and $b_{\max}^j \ge \max\{b_1^j, b_2^j, \cdots, b_L^j\}$ for all $j = 1, 2, ..., n$ (all of the evaluation indicators).

(3) Calculation of the correlation function between x_{ij} (sample i with evaluation indicator j) and class k. The expression is shown as follows

$$\Gamma_k(x_{ij}) = \begin{cases} -\dfrac{\rho(x_{ij}, a_k^j, b_k^j)}{|b_k^j - a_k^j|} & \text{if } a_k^j \le x_{ij} \le b_k^j \\ \dfrac{\rho(x_{ij}, a_k^j, b_k^j)}{\rho(x_{ij}, a_{\min}^j, b_{\max}^j) - \rho(x_{ij}, a_k^j, b_k^j)} & \text{else} \end{cases} \tag{15}$$

where the function ρ is given as

$$\rho(x, y, z) = \left| x - \frac{y+z}{2} \right| - \frac{z-y}{2} \tag{16}$$

(4) Then, the vector $\Gamma_k(\boldsymbol{x}_i)$ is constructed as (loop over all of the evaluation indicators)

$$\Gamma_k(\boldsymbol{x}_i) = \begin{bmatrix} \Gamma_k(x_{i1}) \\ \Gamma_k(x_{i2}) \\ \vdots \\ \Gamma_k(x_{in}) \end{bmatrix} \in \mathbb{R}^n \tag{17}$$

where $\boldsymbol{x}_i = [x_{i1}\ x_{i2} \cdots x_{in}]^{\mathrm{T}}$ represents one sample.

(5) Repeat step 3 and step 4 for all of the classes, then choose the weight vector η (EW, AHP, or CW) and assign $\boldsymbol{x}_i$ to the class "$\text{argmax}_k[\eta^{\mathrm{T}}\Gamma_k(\boldsymbol{x}_i)]$".

(6) Repeat step 3, step 4, and step 5 for next sample $\boldsymbol{x}_{i+1}$.

3. MODEL PREPARATION

3.1. Investigation Process of the Evaluation Model. A CW method was used to optimize the evaluation indicator weight vectors obtained by the EW method and the AHP method to provide a more scientific and rational evaluation of the control effect of subsiding land around coal mines. These weight vectors were then introduced into the FMEA model for the comprehensive evaluation of the control effect of each subsiding land.

3.2. Determination of the Evaluation Indicators. By studying the scientific subsiding control methods around the world and the experiences obtained during the subsiding land control at some coal mines, it was concluded that the control processes of subsiding land are influenced by a variety of factors. These factors can be broadly divided into geographical factors (y_1) and social factors (y_2). Geographical factors included the maximum ponding depth (x_1), degree of cultivation (x_2), degree of forestation (x_3), degree of aquaculture (x_4), and degree of wetlands (x_5). Social factors can be divided into preresearch degree (x_6), degree of urban planning (x_7), degree of integration (x_8), and economic and social benefits (x_9).[14,40] That is to say, in our application, $n = 9$. Here, a qualitative analysis of the preresearch degree, degree of integration, and economic and social benefits was required, and the results are shown in Tables 3−5.

Table 3. Evaluation of the Preresearch Degree of Subsiding Land

preresearch level	poor	less poor	ordinary	good	excellent
assignment	0−20	20−40	40−60	60−80	80−100

Table 4. Evaluation of the Degree of Integration of Subsiding Land

degree of integration effect level	poor	less poor	ordinary	good	excellent
assignment	0−10	10−20	20−30	30−40	40−50

Table 5. Evaluation of Economic and Social Benefits of Subsiding Land

economic and social benefit level	poor	less poor	ordinary	good	excellent
assignment	0−10	10−20	20−30	30−40	40−50

3.3. Determination of the Evaluation Classes. To date, there have been few studies on land subsidence control in coal mines. Existing studies have mainly focused on the control of soil on cultivated land or water quality in areas of ponding where subsidence has occurred. No comprehensive evaluation model has been developed to analyze the overall situation of land control that has subsided due to coal mining. To rectify this situation, the results of relevant studies and opinions from land reclamation experts were analyzed. This enabled us to partition efforts to restore subsiding land due to coal mining into five classes, as follows: class I: restoration of subsiding land at a coal mine has not yet started or has only just started. Class II: restoration of subsiding land at a coal mine is limited, and most evaluation indicators are poor (i.e., only land reclamation or simple aquaculture has been carried out). Class III: restoration of subsiding land at a coal mine is not good, and most evaluation indicators are average (i.e., land subsidence has been controlled, but reclaimed land, aquaculture production, forested land, and

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Table 6. Evaluation Indicator Classification Intervals for the Control Effects of Subsiding Lands

evaluation indicator	indicator type	I (poor)	II (less poor)	III (ordinary)	IV (good)	V (excellent)	extended range of I−V
x_1	positively correlated	2−3	3−4	4−5	5−6	6−7	0−7
x_2	positively correlated	0−10	10−20	20−30	30−40	40−80	0−80
x_3	positively correlated	0−6	6−12	12−18	18−24	24−30	0−30
x_4	positively correlated	0−8	8−16	16−24	24−32	32−40	0−40
x_5	positively correlated	0−8	8−16	16−24	24−32	32−40	0−40
x_6	positively correlated	0−20	20−40	40−60	60−80	80−100	0−100
x_7	positively correlated	0−10	10−20	20−30	30−40	40−50	0−50
x_8	positively correlated	0−10	10−20	20−30	30−40	40−50	0−50
x_9	positively correlated	0−10	10−20	20−30	30−40	40−50	0−50

Table 7. Sample Data

shafts	maximum ponding depth (m)	degree of cultivation	degree of forestation	degree of aquaculture	degree of wetlands	preresearch degree	degree of urban planning	degree of integration	economic and social benefits	evaluation level of control effect
Henghe coal mine (early stage)	5.8	9	8	4	11	15	5	5	5	I
Xinglongzhuang coal mine (early stage)	5.7	8	12	5	10	20	5	5	5	I
Yangzhuang coal mine (early stage)	4.1	10	7	3	10	20	5	5	5	I
Wugou coal mine	4	5	10	2	13	20	0	5	5	I
Longgu coal mine (early stage)	6	25	9	10	12	10	10	8	10	II
Beixulou coal mine (early stage)	5.3	7	8	12	21	25	15	15	15	II
Baodian coal mine (early stage)	5.9	17	5	10	14	30	5	10	20	II
Xinglongzhuang coal mine	6	15	16	13	15	35	15	18	15	II
Guotun coal mine	6	15	10	26	10	35	10	15	15	II
Daxing coal mine of Tiemei group	2.3	75	10	10	5	30	5	8	15	II
Chaili coal mine	5.3	19	6	17	12	30	5	18	20	III
Xuchang coal mine	5.5	35	20	18	20	45	25	18	20	III
Nantun coal mine	6	25	11	30	14	60	15	30	25	III
Jiangzhuang coal mine	6.2	27	8	35	10	50	20	30	25	III
Beixulou coal mine	5.5	30	20	29	16	50	15	30	30	III
Binhu coal mine	4.1	16	20	31	28	50	15	35	25	III
Yangzhuang coal mine	4.3	24	19	27	30	60	40	40	35	IV
Henghe coal mine	6	20	20	25	35	70	45	35	40	IV
Jinqiao coal mine	3.6	26	15	35	24	65	40	35	35	IV
Baodian coal mine	6.1	25	21	20	33	80	45	45	40	V

wetlands are independent of one another). Class IV: restoration of subsiding land at a coal mine is relatively good, and most evaluation indicators are good (i.e., land subsidence has been comprehensively controlled; there are complementary effects between reclaimed land, aquaculture, forested land, and wetlands, and a sustainable pattern of development of the social ecosystem has been initiated). Class V: restoration of subsiding land at a coal mine is very good; there is dense vegetation and a variety of bird species in the area, and the economic and social benefits show strong sustainability.[41]

To better analyze the factors influencing the effects of land subsidence control, parameter values were hierarchically structured to establish these evaluation indicator classification intervals for the control effect of subsiding land around coal mines (Table 6). These effects were classified by quantitatively analyzing the data to provide scientific guidance and suggestions for coal mines where there is poor land subsidence control and ensuring sustainable land control.

3.4. Selection of the Sample Data.

Coal mining activities have caused extensive damage to the ground surface; the area of cultivated land has been continuously reduced, soil fertility has decreased, and ponding is a serious problem in areas where subsiding land has occurred. The damage caused by the settlement of land that has undergone subsidence at different coal mines varies according to the coal mining method used, different geological conditions, and inconsistent phreatic water levels. In our work, 20 coal mines from Shandong Province, Anhui Province, and Liaoning Province were selected, as shown in Table 7 and Figure 3. Based on these data, the FMEA model is constructed.

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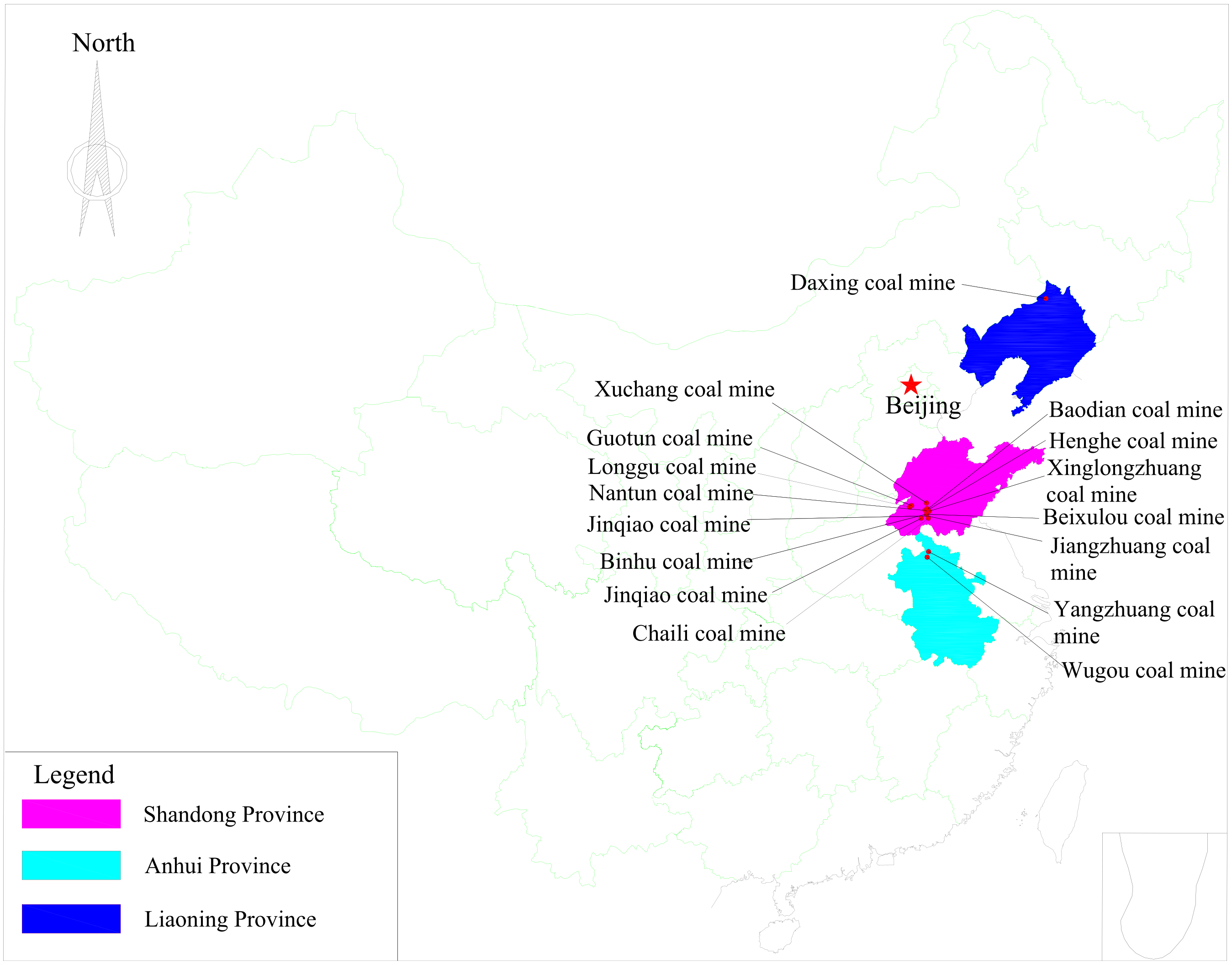

Figure 3. Location map of the study area.

4. RESULTS AND DISCUSSION

4.1. EW Method Calculation Results. The EW method was used to calculate the weights of the main indicators that influence the control effect of subsiding land. Evaluation indicator data during the process of land subsidence control were collected for typical coal mines. In this study, all evaluation indicators were positively correlated with restoration progress. The calculation results are given in Table 8.

Table 8. Calculation Results of Entropy Weight Method

evaluation indicator	entropy value	entropy weight η_1	importance ranking
maximum ponding depth (m)	0.9688	**0.0371**	9
degree of cultivation	0.8906	**0.1302**	4
degree of forestation	0.9114	**0.1055**	6
degree of aquaculture	0.9111	**0.1059**	5
degree of wetlands	0.9206	**0.0945**	7
preresearch degree	0.9224	**0.0924**	8
degree of urban planning	0.8898	**0.1312**	3
degree of integration	0.8594	**0.1674**	1
economic and social benefits	0.8860	**0.1358**	2

As shown in Table 8, the degree of integration has the largest weight, followed by economic and social benefits, degree of urban planning, degree of cultivation, degree of aquaculture, degree of forestation, and degree of wetlands, with the degree of preresearch and the maximum ponding depth. The total weight of the first seven largest evaluation indicators was 0.8705, which plays a decisive role in evaluating the effect of land subsidence control. The weight of the degree of integration is the largest, reflecting that sustainable ecological construction integrating aquaculture and tourism and other industries has positive effects on land subsidence control. The economic and social benefits of land subsidence control are important indicators for us to intuitively evaluate land subsidence control and also a fundamental guarantee for the sustainable development of land subsidence control.

4.2. AHP Method Calculation Results. The AHP method was used to conduct, from a subjective perspective, a qualitative analysis of each evaluation indicator that influenced the land subsidence control. In addition, the degrees of importance of various evaluation indicators were calculated, ranked, and combined with the scores of factors influencing the land subsidence control provided by multiple experts and scholars in the field of land reclamation. The judgment matrices and their corresponding eigenvectors as well as the integrated weight

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vector are summarized in Tables 9–12. Consistency requirements were also met.

Table 9. Establishment of the Grade I Judgment Matrix ($I_C = I_R = 0$)

0	y_1	y_2	eigenvector
y_1	1	1	0.5
y_2	1	1	0.5

Table 10. Establishment of the Grade II Judgment Matrix 1 ($R_C = 0.0022$)

y_1	x_1	x_2	x_3	x_4	x_5	eigenvector
x_1	1	0.4	1/2	2/5	1/2	0.0996
x_2	2.5	1	3/2	6/5	3/2	0.2778
x_3	2	2/3	1	4/5	1	0.1918
x_4	5/2	5/6	5/4	1	1	0.2298
x_5	2	2/3	1	1	1	0.2010

Table 11. Establishment of the Grade II Judgment Matrix 2 ($R_C = 0.0023$)

y_2	x_6	x_7	x_8	x_9	eigenvector
x_6	1	2/3	1/2	0.4	0.1443
x_7	3/2	1	3/4	3/4	0.2285
x_8	2	4/3	1	1	0.3046
x_9	2.5	4/3	1	1	0.3226

Table 12. Integrated AHP Weight Calculation for Each Evaluation Indicator

evaluation indicator	y_1 (0.5)	y_2 (0.5)	integrated weight η_2
x_1	0.0996	0	**0.0498**
x_2	0.2778	0	**0.1389**
x_3	0.1918	0	**0.0959**
x_4	0.2298	0	**0.1149**
x_5	0.2010	0	**0.1005**
x_6	0	0.1443	**0.0721**
x_7	0	0.2285	**0.1142**
x_8	0	0.3046	**0.1523**
x_9	0	0.3226	**0.1613**

4.3. CW Vector. In this paper, $\beta_1 = 1$ and $\beta_2 = 1.5$. The subsequently solved optimal values are $\alpha_1 = 0.4$ and $\alpha_2 = 0.6$. The final combined weight vector η^* is given in the following equation

$$\eta^* = \alpha_1\eta_1 + \alpha_2\eta_2 = 0.4\begin{pmatrix}0.0371\\0.1302\\0.1055\\0.1059\\0.0945\\0.0924\\0.1312\\0.1674\\0.1358\end{pmatrix} + 0.6\begin{pmatrix}0.0498\\0.1389\\0.0959\\0.1149\\0.1005\\0.0721\\0.1142\\0.1523\\0.1613\end{pmatrix} = \begin{pmatrix}0.0447\\0.1354\\0.0997\\0.1113\\0.0981\\0.0802\\0.1210\\0.1584\\0.1511\end{pmatrix}$$

From the value of η^*, the weight of the evaluation indicator x_8 exceeds the weight of the other evaluation indicators, which is the most important factor. The weight of evaluation indicator x_1 is the smallest in the entire model, which can be ignored in future evaluation models. In addition, the total weight of the first seven largest evaluation indicators was 0.8750, which can be used effectively to analyze and evaluate the control effect of subsiding land due to coal mining. Following the effective combination of the EW method and the AHP method, the actual situation in the control process of subsiding land can be accurately interpreted, providing a reliable reference for land subsidence control in other coal mines.

4.4. Discussion. Finally, the comprehensive degrees of correlation were calculated, and the class of each type of subsiding land after land reclamation was determined, as shown in Table 13. The model accuracy was 85%, which indicates the rationality of our CW-FMEA model used in this study. The predicted category also gives insights into the restoration and reclamation measures or directions. For example, it reveals that the ecological restoration (x_3, x_4, x_5) is also very useful in addition to the agricultural reclamation (x_2), by comparing the Daxing coal mine and the Beixulou coal mine. In practice, ecological restoration includes various measures such as planting trees, constructing wetland parks, and carrying out aquaculture. In addition, it is necessary to develop wetland tourism industries such as ecological tourism, leisure vacation, fishing folk culture, wetland science education, and urban cultural theme parks in the coal mine subsidence area. These measures are conducive to the development of local cities and produce more obvious economic, social, and environmental benefits.

However, some coal mines subsiding land of class I and class II have not been restored significantly, with control work carried out only in a few regions. The area of restored cultivated land and aquaculture was small, and the layout was poor. Wetland parks and forestry construction were not included in the plan. The annual income level of residents has not increased a lot and the local living environment has not been improved. All of these factors will inhibit the social urbanization and the development of local villages and towns. These coal mines should, based on their own local damage conditions caused by subsiding land, refer to more highly appraised control methods of land subsidence control.

For coal mines given the wrong predicted category, the comprehensive correlation degrees K_{III} and K_{IV} are pretty close to each other for the Beixulou coal mine and the Binhu coal mine. This suggests that the true ecological restoration significance should lie between class III and class IV, and there might be other influencing factors that dominate the decision in the "actual category" of Table 13.

5. CONCLUSIONS

In this study, the CW and FMEA methods were used to comprehensively analyze the main factors influencing the control effect of subsiding land in coal mines, and a model to evaluate the class of the control effect of subsiding land was established. In the CW method, a new minimization objective was developed that fixes the inconsistency in the previous game theory used in other mining engineering projects. The CW method was used to reasonably allocate the weights of the evaluation indicators obtained using the EW and AHP methods, which not only avoided the objective impact of a single factor but also reduced the impact of subjective factors. Through the CW method, the order of importance of influencing factors was determined and the most important factor was the degree of integration. The FMEA model established in this study was characterized by good reliability and can provide scientific references for evaluating the control effect of subsiding land around coal mines. Furthermore, all of the data and calculation processes are shown clearly in tables and mathematical formulae,

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Table 13. List of Evaluation Results of the Control Effect of Each Coal Mine Subsiding Land[a,b]

shafts	K_{I}	K_{II}	K_{III}	K_{IV}	K_{V}	combined weight	actual category
Henghe coal mine (early stage)	**0.2322**	−0.2613	−0.6128	−0.7061	−0.7815	I	I
Xinglongzhuang coal mine (early stage)	**0.2043**	−0.2849	−0.5732	−0.6767	−0.7648	I	I
Yangzhuang coal mine (early stage)	**0.2159**	−0.2451	−0.5950	−0.7287	−0.7951	I	I
Wugou coal mine	**0.1833**	−0.3569	−0.6272	−0.7477	−0.8091	I	I
Longgu coal mine (early stage)	−0.0805	**0.0026**	−0.3371	−0.5508	−0.6519	II	II
Beixulou coal mine (early stage)	−0.1937	**0.2437**	−0.2567	−0.4769	−0.6210	II	II
Baodian coal mine (early stage)	−0.1132	**0.0276**	−0.3426	−0.5289	−0.6426	II	II
Xinglongzhuang coal mine	−0.3119	**0.2575**	−0.1439	−0.4008	−0.5414	II	II
Guotun coal mine	−0.2763	**0.2241**	−0.2714	−0.4103	−0.5730	II	II
Daxing coal mine of Tiemei group	−0.0882	**−0.0868**	−0.5103	−0.6622	−0.6053	II	II
Chaili coal mine	−0.1909	**0.0483**	−0.2006	−0.4389	−0.5911	II**	III
Xuchang coal mine	−0.3922	−0.1313	**0.0969**	−0.0748	−0.3852	III	III
Nantun coal mine	−0.4277	−0.1204	**0.0283**	−0.1601	−0.3904	III	III
Jiangzhuang coal mine	−0.4246	−0.1824	**−0.0171**	−0.2558	−0.3273	III	III
Beixulou coal mine	−0.4611	−0.2168	−0.0527	**−0.0092**	−0.3553	IV**	III
Binhu coal mine	−0.4647	−0.1675	−0.0666	**0.0025**	−0.3651	IV**	III
Yangzhuang coal mine	−0.5961	−0.4594	−0.1758	**0.1221**	−0.2144	IV	IV
Henghe coal mine	−0.6471	−0.5144	−0.3394	**0.0240**	−0.0940	IV	IV
Jinqiao coal mine	−0.5680	−0.4138	−0.1251	**0.0853**	−0.1957	IV	IV
Baodian coal mine	−0.6841	−0.5788	−0.3066	−0.1477	**0.0390**	V	V

[a]Note 1: Numbers in the first five columns of this table (known as the comprehensive degree of correlation) are for the combined weight vector. [b]Note 2: "**" indicates the wrong case of discrimination.

which can be regarded as a benchmark example for other engineering projects that adopt weight modeling and FMEA.

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Notes

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LIST OF SYMBOLS

$B_{m\times n}$	the evaluation matrix
Y_{ij}	weight of the jth evaluation indicator of the ith evaluation sample in the matrix
Z_k	the entropy value of each indicator
ξ_k	the entropy weight of each indicator
η_1	the entropy weight vector
R_{C}	consistency ratio
I_{C}	the consistency index
I_{R}	the random consistency index
$\lambda_{\max}$	the largest eigenvalue
d	the size of the judgment matrix
$R_{\mathrm{C}}^{\mathrm{total}}$	the total consistency ratio
p	number of factors in the intermediate classification layer
η_2	the weight vector of AHP method
η^*	the combined weight vector
k	the kth class of evaluation level
d_j	the jth evaluation indicator
$R_k^{\mathrm{classical}}$	the classical domain
R^{joint}	the joint domain
$\Gamma_k(x_{ij})$	the correlation function

REFERENCES

(1) Shao, J.; Zhang, Q.; Zhang, W.; Wang, Z.; Wu, X. Effects of the borehole drainage for roof aquifer on local stress in underground mining. *Geomech. Geoeng.* **2021**, *24*, 479−490.

(2) Wang, Z.; Zhang, Q.; Shao, J.; Zhang, W.; Wu, X.; Zhu, X. New type of similar material for simulating the processes of water inrush from roof bed separation. *ACS Omega* **2020**, *5*, 30405−30415.
(3) Zhang, Q. Hydromechanical modeling of solid deformation and fluid flow in the transversely isotropic fissured rocks. *Comput. Geotech.* **2020**, *128*, No. 103812.
(4) Zhang, Q.; Yan, X.; Shao, J. Fluid flow through anisotropic and deformable double porosity media with ultra-low matrix permeability: A continuum framework. *J. Pet. Sci. Eng.* **2021**, *200*, No. 108349.
(5) Zhang, W. Q.; Wang, Z. Y.; Zhu, X. X.; Li, W.; Gao, B.; Yu, H. L. A risk assessment of a water-sand inrush during coal mining under a loose aquifer based on a factor analysis and the fisher model. *J. Hydrol. Eng.* **2020**, *25*, No. 04020033.
(6) De, S.; Mitra, A. K. Reclamation of mining-generated wastelands at Alkusha-Gopalpur abandoned open cast project, Raniganj Coalfield, eastern India. *Environ. Geol.* **2002**, *43*, 39−47.
(7) Dong, H. M.; Sun, J. M.; Arif, M.; Golsanami, N.; Chao, W. C.; Zhang, Y. H. A novel hybrid method for gas hydrate filling modes identification via digital rock. *Mar. Pet. Geol.* **2020**, *115*, No. 104255.
(8) Tremblay, P. Y.; Thiffault, E.; Pinno, B. D. Effects of land reclamation practices on the productivity of young trembling aspen and white spruce on a reclaimed oil sands mining site in northern Alberta. *New Forests* **2019**, *50*, 911−942.
(9) Guo, Q.; Zhang, H.; Liu, H. C. Comprehensive evaluation of the geological environment in Baoding mine based on fuzzy analytic hierarchy process. *Metal Mine* **2017**, *8*, 193−198. (in Chinese).
(10) Xiao, W.; Li, S. C.; Wang, Z.; Y Yang, Q.; Wang, T. Ecological risk identification and assessment for a coal mine with a high groundwater table. *Acta Ecol. Sin.* **2016**, *36*, 5611−5619. (in Chinese).
(11) Bi, Y. L.; Wang, K.; Wang, J. Effect of different inoculation treatments on AM fungal communities and the sustainability of soil remediation in Daliuta coal mining subsidence area in northwest China. *Appl. Soil Ecol.* **2018**, *132*, 107−113.
(12) Wang, J. M.; Qin, Q.; Hu, S. J.; Wu, K. N. A concrete material with waste coal gangue and fly ash used for farmland drainage in high groundwater level areas. *J. Cleaner Prod.* **2016**, *112*, 631−638.
(13) Hu, Z. Q.; Duo, L. H.; Shao, F. Optimal thickness of soil cover for reclaiming subsided land with yellow river sediments. *Sustainability* **2018**, *10*, No. 3853.
(14) Yu, X.; Mu, C.; Zhang, D. Assessment of Land Reclamation Benefits in Mining Areas Using Fuzzy Comprehensive Evaluation. *Sustainability* **2020**, *12*, 2015.
(15) Quanyuan, W.; Pang, J.; Qi, S.; Li, Y.; Han, C.; Liu, T.; Huang, L. Impacts of coal mining subsidence on the surface landscape in Longkou city, Shandong Province of China. *Environ. Earth Sci.* **2009**, *59*, 783−791.
(16) Xiao, W.; Hu, Z. Q.; Li, J.; Zhang, H. Y.; Hu, J. L. A study of land reclamation and ecological restoration in a resource-exhausted city—a case study of Huaibei in China. *Int. J. Min., Reclam. Environ.* **2011**, *25*, 332−341.
(17) Duque, J. F. M.; Tejedor, M.; Moreno, C. M.; Nicolau, J. M.; Díaz, J. M. G. Geomorphic landscape design integrated with progressive mine restoration in clay quarries of Catalonia. *Int. J. Min., Reclam. Environ.* **2020**, *35*, 399−420.
(18) Golsanami, N.; Zhang, X. P.; Yan, W. C.; Yu, L. J.; Dong, H. M.; Dong, X.; et al. NMR-based study of the pore types contribution to the elastic response of the reservoir rock. *Energies* **2021**, *14*, No. 1513.
(19) Sahoo, M. M.; Patra, K. C.; Swain, J. B.; Khatua, K. K. Evaluation of water quality with application of Bayes' rule and entropy weight method. *Eur. J. Environ. Civ. Eng.* **2017**, *21*, 730−752.
(20) Wang, Y. H.; Wen, Z. G.; Li, H. F. Symbiotic technology assessment in iron and steel industry based on entropy TOPSIS method. *J. Cleaner Prod.* **2020**, *260*, No. 120900.
(21) Alafeef, M.; Fraiwan, M.; Alkhalaf, H.; Audat, Z. Shannon entropy and fuzzy C-means weighting for AI-based diagnosis of vertebral column diseases. *J. Ambient Intell. Humaniz. Comput.* **2020**, *11*, 2557−2566.
(22) Lv, H.; Guan, X. J.; Meng, Y. Comprehensive evaluation of urban flood-bearing risks based on combined compound fuzzy matter-element and entropy weight model. *Nat. Hazards* **2020**, *103*, 1823−1841.
(23) Du, Y. B.; Zheng, Y. S.; Wu, G.; Tang, Y. Decision-making method of heavy-duty machine tool remanufacturing based on AHP-entropy weight and extension theory. *J. Cleaner Prod.* **2020**, *252*, No. 119607.
(24) Saaty, T. L. How to make a decision: The analytic hierarchy process. *Eur. J. Oper. Res.* **1990**, *48*, 9−26.
(25) Zhang, W. Q.; Wang, Z. Y.; Shao, J. L.; Zhu, X. X.; Li, W.; Wu, X. T. Evaluation on the stability of vertical mine shafts below thick loose strata based on the comprehensive weight method and a fuzzy matter-element analysis model. *Geofluids* **2019**, *2019*, No. 3543957.
(26) Pilevar, A. R.; Matinfar, H. R.; Sohrabi, A.; Sarmadian, F. Integrated fuzzy, AHP and GIS techniques for land suitability assessment in semi-arid regions for wheat and maize farming. *Ecol. Indic.* **2020**, *110*, No. 105887.
(27) Zhao, J.; Jin, J. L.; Zhu, J. Z.; Xu, J. C.; Hang, Q. F.; Chen, Y. Q.; Han, D. H. Water resources risk assessment model based on the subjective and objective combination weighting methods. *Water Resour. Manage.* **2016**, *30*, 3027−3042.
(28) Dai, S. Y.; Niu, D. X. Comprehensive evaluation of the sustainable development of power grid enterprises based on the model of fuzzy group ideal point method and combination weighting method with improved group order relation method and entropy weight method. *Sustainability* **2017**, *9*, No. 1900.
(29) Zhang, Q.; Wang, Z. Spatial prediction of loose aquifer water abundance mapping based on a hybrid statistical learning approach. *Earth Sci. Inform.* **2021**, *14*, 1349−1365.
(30) Cai, W. The extension set and incompatibility problem. *J. Sci. Explor.* **1983**, *1*, 81−93. (in Chinese).
(31) Zhang, W. Q.; Li, B.; Yu, H. L. The correlation analysis of mine roof water inrush grade and influence factors based on fuzzy matter-element. *J. Intell. Fuzzy Syst.* **2016**, *31*, 3163−3170.
(32) Li, S. Q.; Li, R. R. Energy sustainability evaluation model based on the matter-element extension method: a case study of Shandong province, China. *Sustainability* **2017**, *9*, No. 2128.
(33) Wang, Q.; Li, S. Q. Shale gas industry sustainability assessment based on WSR methodology and fuzzy matter-element extension model: The case study of China. *J. Cleaner Prod.* **2019**, *226*, 336−348.
(34) Wang, Q.; Li, S. Q.; He, G.; Li, R. R.; Wang, X. F. Evaluating sustainability of water-energy-food (WEF) nexus using an improved matter-element extension model: A case study of China. *J. Cleaner Prod.* **2018**, *202*, 1097−1106.
(35) Golsanami, N.; Bakhshi, E.; Yan, W. C.; Dong, H. M.; Mahbaz, S.; et al. Relationships between the geomechanical parameters and archie's coefficients of fractured carbonate reservoirs: a new insight. *Energy Sources, Part A* **2020**, *10*, 1−25.
(36) Wang, C. L.; Wu, A. X.; Lu, H.; Bao, T. C.; Liu, X. H. Predicting rockburst tendency based on fuzzy matter-element model. *Int. J. Rock Mech. Min. Sci.* **2015**, *75*, 224−232.
(37) Li, P. Y.; He, S.; He, X. D.; Tian, R. Seasonal hydrochemical characterization and groundwater quality delineation based on matter element extension analysis in a paper wastewater irrigation area, northwest China. *Exposure Health* **2018**, *10*, 241−258.
(38) Li, B.; Yang, G. S.; Wan, R. R.; Hörmann, G. Dynamic water quality evaluation based on fuzzy matter−element model and functional data analysis, a case study in Poyang Lake. *Environ. Sci. Pollut. Res.* **2017**, *24*, 19138−19148.
(39) Liu, D. J.; Zou, Z. H. Water quality evaluation based on improved fuzzy-matter-element method. *J. Environ. Sci.* **2012**, *24*, 1210−1216.
(40) Li, X. D.; Chen, Z. T.; Liu, Z.; Yang, H.; Garg, H. Decision-Making on reuse modes of abandoned coal mine industrial sites in Beijing based on environment-economy-society matter-element models. *Math. Probl. Eng.* **2021**, *2021*, No. 9941182.
(41) Zhang, J.; Sun, Q.; Fourie, A.; Ju, F.; Dong, X. Risk assessment and prevention of surface subsidence in deep multiple coal seam mining under dense above-ground buildings: Case study. *Hum. Ecol. Risk Assess.* **2019**, *25*, 1579−1593.

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