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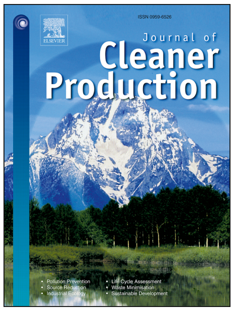

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Assessing industrial ecosystem vulnerability in the coal mining area under economic fluctuations

Delu Wang[a, *], Jianping Zheng[a], Xuefeng Song[b], Gang Ma[a], Yun Liu[c]

[a] School of Management, China University of Mining and Technology, Xuzhou, Jiangsu 221116, P. R. China

[b] School of Management Science and Industrial Engineering, Nanjing University of Finance and Economics, Nanjing, Jiangsu 210003, P. R. China

[c] Management School, Lancaster University, Lancaster LA2 0PJ, United Kingdom

ABSTRACT

In the context of the depth adjustment of the global economy and wild fluctuations in energy prices, the vulnerability issue of the coal mining industrial ecosystem (CMIES) has seriously affected the sustainable development of the regional economy. Comparisons of CMIES health status at a regional level are worthy of being conducted. This not only contributes to understanding a particular coal mining area's situation in regards to CMIES vulnerability, but also helps to discover a meaningful benchmark to learn the experiences in terms of action programmes formulation. In this study, based on the analysis of the vulnerability response mechanism of CMIES to economic fluctuations, an initial indicator system for vulnerability assessment of CMIES was constructed. Ultimately, 14 vulnerability-evaluating indicators and their weights were obtained using rough set attribute reduction. Based on a composite CMIES Vulnerability Index (CVI), the Rough Set-Technique for Order Preference by Similarity to Ideal Solution-Rank-sum Ratio (RS-TOPSIS-RSR) methodology is proposed to conduct the CMIES vulnerability assessment process from an overall perspective. Using this methodology, 33 coal mining areas in China are ranked as well as grouped into three specific groups based on the CVI score. The results demonstrate the feasibility of the proposed method as a valuable tool for decision making and performance evaluation with multiple alternatives and criteria.

Keywords industrial ecosystem; vulnerability; composite index; integrated assessment; coal mining area

1. Introduction

For a long time, the coal industry has caused an increasingly serious ecological crisis as well as numerous inevitable social problems under the one-way linear production model of 'resources-products-waste' (Kuai et al., 2015), despite the fact that it contributed significantly to economic development (Moran et al., 2014). Under the background of ecological civilization construction, the industrial metabolism model of 'resources- products-regenerated resources' has become the basic pattern for the green and intensive development of coal mining areas (Li and Wang, 2015; Ren, 2011). In fact, industrial enterprises mostly focused on their core business, and could not ensure that the secondary activities of value chain, such as pollution prevention and control, receive adequate attention. However, integrating resources through an industrial symbiosis network could relieve the finiteness of

* Corresponding author. Tel.: +8613813460366
E-mail address: dlwang@cumt.edu.cn (D.L. Wang)

the resources and ability of environment governance, which also provides the most suitable way for intensive industry development (Korhonen et al., 2004; Yu et al., 2015a). Recently, the United Nations Industrial Development Organization has advocated and promoted a regional ecological development strategy in the world. The Chinese government has focused on ecological modernization, green growth, and low-carbon development and made the circular economy development as a part of the national ecological security strategy. (Geng et al., 2013). Under the guidance, intervention, and even dominance of government bodies at all levels, more than 40 large-scale mining areas in China have constructed coal mining industrial ecosystem (CMIES) by building circular economy parks.

CMIES[1] is formed by optimizing industrial chains vertically and horizontally according to the principle of material cycling and harmonious symbiosis between biology and industry in a coal mining area (Zhang et al., 2013). CMIES is an open and complex giant system. In such a complex system, a minor change in economic or environmental factors can trigger enormous changes in the mining areas' economic development (Martin and Sunley, 2015). CMIES vulnerability has restrained the sustainable development of coal mining areas. According to the theory of vulnerability, CMIES does not always demonstrate vulnerability under any kind of disturbance. It displays different characteristics of vulnerability in facing different types of disturbance. Therefore, CMIES vulnerability is always closely related to certain disturbances imposed on the system. The major industries of CMIES (e.g., coal, electronics, and coal chemical industry) are all the fundamental industries of the national economy. According to the Morgan Stanley Capital International Index, these industries are more sensitive to economic fluctuations and are relatively more affected by fluctuations compared with general light industries. Thus, economic fluctuations play an important role in many disturbance factors which affect the healthy development of CMIES. For example, as coal prices have been falling since 2012, many coal mining areas such as Changzhi, Hauibei, Panzhihua, Qitaihe, and Jincheng have suffered an economic slowdown and even fell into serious crisis, with unemployment rates of more than 800, 000.

In recent years, many challenge-seeking researchers among both academia and industry have spent considerable efforts on the CMIES' development strategy (Muduli et al., 2013a), evolution mechanism (Van Beers et al., 2007), efficiency evaluation (Kulshreshtha and Parikh, 2002), and resource metabolism (Salmi, 2007). However, literature shows that studies on the composite index and method of CMIES vulnerability assessment are limited, despite the fact that they are the key processes affecting the success of comprehensive management of CMIES. Evaluating vulnerability is an interesting and challenging problem, and always an important concern for both managers and policymakers. Therefore, we attempt some exploratory research on the vulnerability assessment related to CMIES under economic fluctuations scenario. This study contributes to the literature in three ways. First, we propose a new RS-TOPSIS-RSR methodology to assess CMIES vulnerability. The integration of three isolated models can give full play to each other's advantages as well as overcome their disadvantages. Second, we introduce a hierarchical structure of CMIES Vulnerability Index (CVI). The CVI

[1] CMIES - Coal Mining Industrial Ecosystem; CVI - CMIES Vulnerability Index; RS - Rough Set; TOPSIS - Technique for Order Preference by Similarity to Ideal Solution; RSR - Rank-sum Ratio.

captures a multitude of risk information in a comprehensive way instead of considering isolated indicators, and offers advantages in terms of benchmarking and decision making. Third, the 33 coal mining areas of China are ranked and classified into three groups, and the causes of high-vulnerability pattern are revealed. This is favorable for policymakers in drawing up targeted programmes.

The remainder of this paper is structured as follows. After the introduction, Section 2 reviews the related literature. Section 3 introduces a hierarchical structure of the composite CMIES Vulnerability Index (CVI) of coal mining areas as well as the study areas and data sources. Section 4 presents the integrated RS-TOPSIS-RSR methodology for CMIES vulnerability evaluation. Section 5 reports the application of the methodology and computational results. Section 6 discusses the corresponding results and implications. Finally, Section 7 summarizes the key conclusions and outlook.

2. Literature Review

The concept of vulnerability originated from studies about natural disaster in 1960s (Janssen et al., 2006). As a new analysis tool in the area of sustainability science, the vulnerability research has been applied to disaster management (Zhang and Huang, 2013), ecology (Collin and Melloul, 2003), economics (Serwa and Bohl, 2005), etc. Among them, some natural science fields such as climate change and natural disaster always take up a dominant position. In recent years, as many research institutions (e.g. Intergovernmental Panel on Climate Change) increasing emphasis on the response and adaptation of human society to global change (Marshall et al., 2014), the researches on the vulnerability of human system and social-economic-natural complex ecosystem have become a new trend. From the point of view of research in different fields, natural sciences consider that the disturbance imposed on the system, the exposure degree and sensitivity of the system to disturbance are the determinants of system vulnerability. However, humanities take the vulnerability of human system as an intrinsic property originated from the internal of the system. And they focus on the discussion of the system, economic and culture factors that cause the human society to be easily damaged. The researches on the vulnerability of complex ecosystem explain emphatically the interaction among nature, society, and economic systems.

In order to better carry out vulnerability assessment, scholars have proposed many vulnerability analytical frameworks, such as risk-hazards (RH) model, Pressure–State–Response (PSR) model (Wolfslehner and Vacik, 2008), the Exposure–Sensitive–Adaptation (ESA) model (Polsky et al., 2007), and airlie house vulnerability (AHV) (Turner et al., 2003). In terms of evaluating method, most of the extant studies adopt composite index method (Zhang and Huang, 2013). However, based on different analytical frameworks, the vulnerability assessment indexes built by the scholars are different from each other. For example, when assessing the impact of disasters or climate change based on RH model, the exposure and sensitivity of hazard-affected body to environment change are often emphasized. According to the models of PSR and ESA, the vulnerability depends on how the system can respond to disasters. Therefore, compared to RH model, these two models more emphasize that the resilience has the decisive significance for disaster vulnerability.

The extant studies suffer from a few limitations. The first issue is related to the assessment indicators of

CMIES vulnerability. The existing studies tend to describe industrial ecosystem property from different points of view (Chopra and Khanna, 2014; Li and Shi, 2015). They doesn’t presents an overall perspective on the industrial ecosystem health by capturing a multitude of vulnerability information in one index score (Jiao and Boons, 2014; Wang et al., 2013). Comparing each indicator individually doesn’t account for the aggregation of indicators. This may then make coal mining areas have different evaluation results using different exposure information. It is unfavorable for policymakers in assessing their own relative CMIES vulnerability and drawing up targeted programmes. Consequently, it is attractive, desirable and necessary to create an overall CMIES vulnerability index. Further more, the combination of CMIES vulnerability indicators into an index is a methodologically intensive process. It includes assigning weights of indicators and aggregating these indicators. In this respect, new methods are worthwhile exploring and testing for the CMIES vulnerability case.

3. Indicators and data

3.1. Composition of CMIES

Coal mining areas are the economic geography areas which are formed during the process of coal mining and processing and have common features in economic characteristics, social functions, and environmental attributes. According to Mathews and Tan (2011) and Yao et al. (2015), CMIES consists of four subsystems (as shown in Fig.1), namely, original industrial subsystem, extended industrial subsystem, resources and environment subsystem, and social service subsystem. The original industrial and extended industrial subsystems constitute the living system of CMIES, while the resources and environment and social service subsystems constitute the life-support system of CMIES.

- The original industrial subsystem refers to the production system of the coal mining and coal processing industries.
- The extended industrial subsystem is the collection of industries which use coal to produce directly and their corresponding downstream industries, such as chemicals, electronics, building materials, metallurgy and manufacturing industries.
- The resources and environment subsystem is the material base of the mining industrial ecosystem’s development, including an exhaustible resource (coal) as well as regenerated resources such as land, water, creatures and atmosphere.
- The social service subsystem provides all kinds of services to ensure the normal operation and development of the above three subsystems, including ecological restoration, landscape design, public administration, research institutes, finance and insurance, circulation service, mediation service, etc.

The development and evolution of CMIES is the collective effect of collaborative development of the above four subsystems. In other words, the overall evolution and healthy development of CMIES can be actually promoted only if each subsystem is organized, reasonable, orderly, and coordinates with other subsystems.

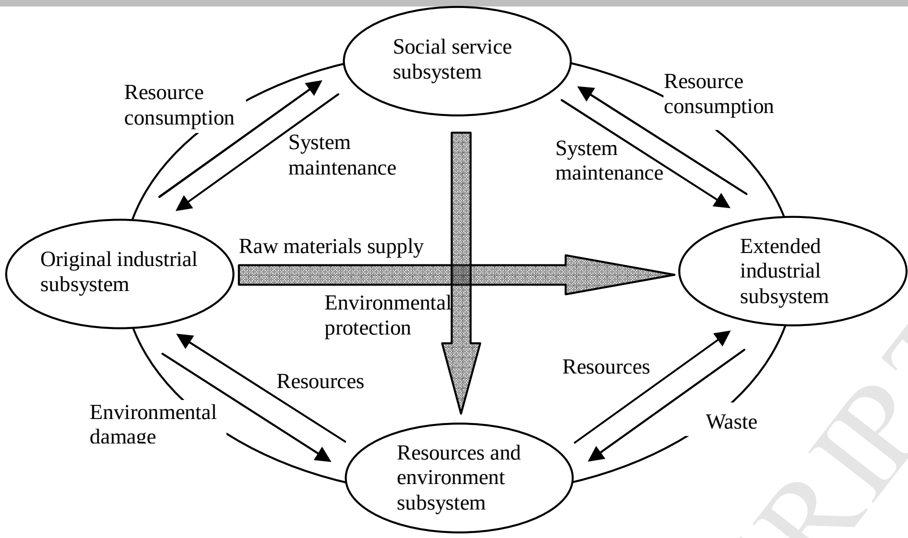

Fig.1. The basic structure of coal mining industrial ecosystem

3.2. Vulnerability response mechanism of CMIES

In recent years, many analytical frameworks are proposed to explore the causes of vulnerability, such as the PSR model (Wolfslehner and Vacik, 2008) and the ESA model (Polsky et al., 2007). The principle of the PSR model is to explore the relationships among pressure, state, and response in terms of the causal relationship. More specifically, external disturbances imposed certain pressures on the system. Owing to these pressures, the system changed its original nature or status. Then in order to restore the system function or prevent system degradation, people responded to these changes by adopting some coping strategies. Although the PSR conceptual model helps to clarify the causal relationship, it is difficult to have a rigorous classification of these indices. For example, a non-biological index in status indicators can be regarded as a status of the ecosystem when it is affected, or as a certain kind of pressure. The ESA model can make up for the defect. According to this model, vulnerability is divided into three dimensions (namely exposure, sensitive, and adaptation) in terms of the system's comprehensive vulnerability properties (e.g. sensitivity, fragility, adaptive capacity, and even degradation). Therefore, we combine PSR model and ESA model to analyze the vulnerability response mechanism of CMIES to economic fluctuations, as shown in Fig.2.

The structural characteristics of CMIES are the direct cause for vulnerability, while external disturbances or pressures as well as interactions between these disturbances and CMIES are the driving factors of the evolution of vulnerability. Finally the vulnerability is reflected by exposure, sensitivity, and response capacity of the system. To be specific, in the context of economic fluctuations, disturbance factors (e.g. energy prices, market demands, and government policy) will break the original balance of supply and demand within the system, or provoke the significant strategic adjustment of focal enterprises. Then this could change the internal structure and trigger the inherent vulnerability of CMIES. However, as an open, complex, and adaptive system, CMIES tends to demonstrate three kinds of defense mechanisms under external shocks. First, it is sensitive to the external changes to give the system more response time. Second, it could take effective resistance to maintain the system's stability and to reduce the degree of danger or disaster. Third, if the system is destroyed, it can repair itself to a certain extent.

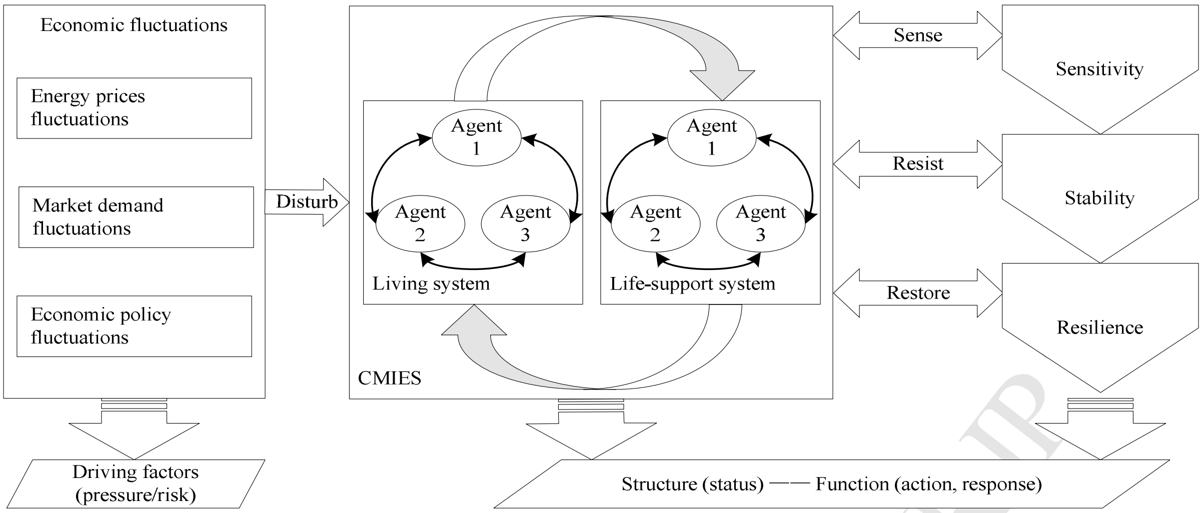

Fig.2. The vulnerability response mechanism of CMIES to economic fluctuations

3.3. Identification of vulnerability indicators

We argue that, among the three kinds of defense mechanisms, sensitivity and resilience are the main functions of living system, while stability is the main function of life-support system. The reasons are as follows. First, the carriers of economic fluctuations are the industries in coal mining area. Sensitivity and resilience reflect the abilities of the industries to perceive and respond to environmental changes, which is a proactive defense behavior. And the behavioral agent of them is mainly the industrial system, including original industries and extended industries, which has the characteristics of ‘life body’. Second, when macroeconomic environment changed greatly, the living system should cope with this change positively rather than maintaining the status quo (that is stability). Meanwhile, for life-support system, it should have a certain stability to provide living system with various resources and services continuously. Based on the above analysis and a wide literature review, the important indicators related to CMIES vulnerability have been selected to construct a hierarchical structure of the CMIES Vulnerability Index (CVI). The reasons for selecting indicators and the references are presented in Table A in Appendix.

The CVI is then used to measure the degree of healthy development of CMIES in terms of four dimensions: economic fluctuations risk, sensitivity of living system, resilience of living system, and stability of life-support system. Economic fluctuations risk is the risk caused by the changes in energy prices, market demands, and government policy in the context of economic fluctuations. Sensitivity of living system is defined as the degree to which it is affected by environment changes such as market, policy, and so on. Resilience of living system refers to the capacity of the industrial system to continue to survive when facing disturbance factors. Stability of life-support system denotes the ability of resources and environment as well as social service subsystems to support the healthy development of the living system. Each sub-dimension is broken down into several indicators. The hierarchical structure of CVI is presented in Fig.3.

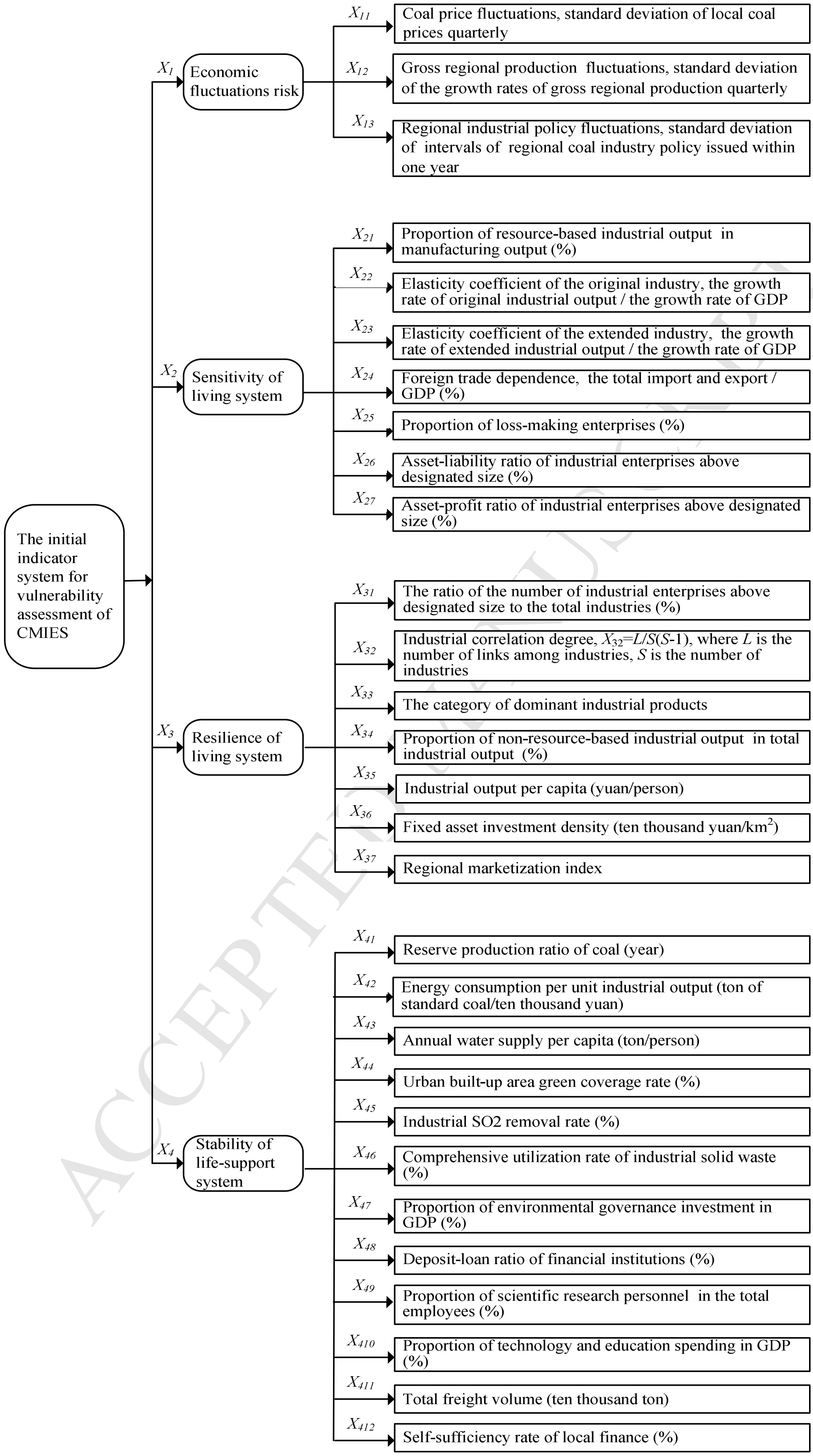

Fig.3. The initial indicator system for CMIES vulnerability assessment

3.4. Data collection

There are 46 major large coal mining areas in China, mainly distributed in Hebei, Henan, Guizhou, Shanxi, Xinjiang, Shaanxi, Sichuan, Shandong, Liaoning, and other provinces. Considering the availability of data, we mainly selected 33 coal mining areas as objects for vulnerability assessment. The location and distributions of these areas are shown in Fig.4. These areas include Ordos (OR) and Baotou (BT) of the Inner Mongolia Autonomous Region, Fuxin (FX) of Liaoning Province, Liaoyuan (LY) of Jilin Province, Shuangyashan (SY), Jixi (JX), and Qitaihe (QT) of Heilongjiang Province, Xuzhou (XZ) of Jiangsu Province, Huainan (HN) and Huaibei (HB) of Anhui Province, Panzhihua (PZ) of Sichuan Province, Qujing (QJ) of Yunnan Province, Yulin (YL) and Xianyang (XY) of Shaanxi Province, Yinchuan (YC) of the Ningxia Hui Autonomous Region, Urumqi (UR) and Ili (IL) of the Xinjiang Uygur Autonomous Region, Lanzhou (LZ) of Gansu Province, Tangshan (TS) and Handan (HD) of Hebei Province, Taian (TA), Jining (JN), and Zaozhuang (ZZ) of Shandong Province, Shangqiu (SQ), Zhengzhou (ZH), Pingdingshan (PD), and Sanmenxia (SM) of Henan Province, Taiyuan (TY), Yangquan (YQ), Shuozhou (SZ), Changzhi (CZ), Datong (DT), and Jincheng (JC) of Shanxi Province. In order to reveal the evolution laws of CMIES vulnerability in the context of economic fluctuations, we assessed the vulnerability of the industrial ecosystem of 33 coal mining areas for years of 2007, 2010, and 2013.

Data pertaining to X_{11}, X_{12}, X_{13}, and X_{37} were obtained from the China Coal Market net (www.cctd.com.cn), the China Economic Net (www.ce.cn), China Coal Industry Yearbook (2007-2013), and Marketization Index of China's Province (2007–2013), respectively. The remaining index data were obtained from each regional statistics yearbook (2006–2014). In general, indicators have different positive and negative effects on CMIES vulnerability. For some indicators, the higher values indicate a higher level of vulnerability in a coal mining area, and these indicators are regarded as positive indicators (X_{11}, X_{12}, X_{13}, X_{21}, X_{24}, X_{25}, X_{26}, X_{42}). Nevertheless, for some other indicators, the higher values indicate a lower level of vulnerability in a coal mining area, and these indicators are regarded as negative indicators (X_{22}, X_{23}, X_{27}, X_{31}, X_{32}, X_{33}, X_{34}, X_{35}, X_{36}, X_{37}, X_{41}, X_{43}, X_{44}, X_{45}, X_{46}, X_{47}, X_{48}, X_{49}, X_{410}, X_{411}, X_{412}).

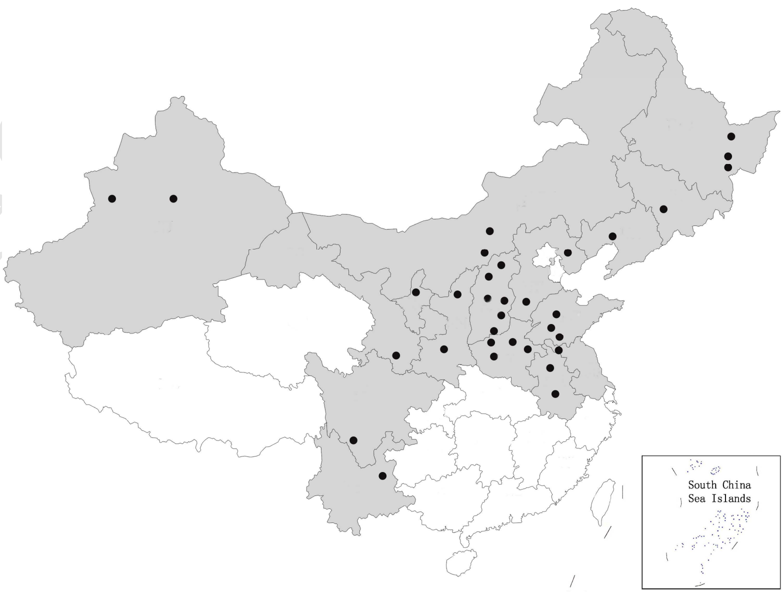

Fig.4. Location and distributions of the 33 coal mining areas in China

4. Methodology

4.1. Framework

We proposed the CMIES vulnerability assessment model based on the RS-TOPSIS-RSR methodology, as shown in Fig.5. The basic flow of this assessment model is shown as below. First, the importance of each indicator in the initial indicator system for vulnerability assessment of CMIES was different. What's more, the correlations among indicators easily make the result distorted. Therefore, we conducted attribute reduction based on the rough set method, which can eliminate redundant information and keep the ability of classification. Thus, we obtained the final indicators and their corresponding weights for vulnerability assessment. Considering that the rough set can only deal with discrete values, we discretized the continuous attributes using fuzzy c-means (FCM) clustering algorithm first. Then, after normalization of the final indicators, we calculated the relative closeness of each evaluation object to the object with highest vulnerability as the CMIES Vulnerability Index (CVI) by adopting the TOPSIS method. The coal mining areas are ranked based on the CVI. Finally, we introduced CVI into the RSR model to calculate the distribution of the RSR for each evaluation object and the corresponding regression equation, thus obtaining the vulnerability grade of each evaluation object.

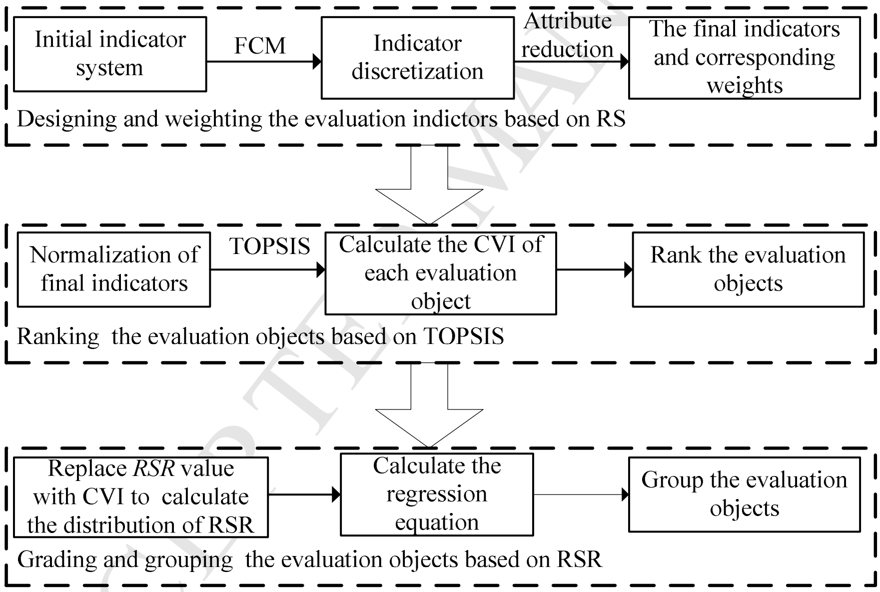

Fig.5. The basic principle of CMIES vulnerability assessment model

4.2. Attribute reduction and weighting based on RS

In general, indicator weights can be determined by principal components analysis (PCA) (Gitelman et al., 2010), experts' opinions (e.g. analytic hierarchy process (AHP) (Chen et al., 2014; Ren et al., 2015a), analytic network process (ANP) (Kilic et al., 2015), Delphi (Makkonen, 2016)), fuzzy set theory (e.g. fuzzy AHP (Tadic et al., 2013; Ren and Sovacool, 2014), fuzzy ANP (Ren et al., 2015b)), etc. For these methods, indicator weights are mostly determined by experts' opinions. This requires them to have a wide spectrum of knowledge and experience. Owing to the subjective nature of these methods, inconsistency is inevitable (Hermans et al., 2008). In addition, the existing studies usually use the designed index system as input to the evaluation model directly and ignore correlations among indicators. This would cause distortions in the evaluation results.

Rough set (RS) is an effective mathematical tool to deal with vagueness and uncertainty (Pawlak, 1982), which can eliminate redundant information without the loss of key information and evaluate data dependencies effectively (Wang et al., 2015; Zheng et al., 2014). Therefore, we simplified the indicator system and weighted the effective indictors based on the RS theory. Because the variables selected for vulnerability assessment of CMIES are mostly continuous attributes and the rough set can only deal with discrete data, the clustering algorithm should be applied to discretize the continuous data. For this, we combined fuzzy clustering algorithm with information entropy to discretize the continuous attributes, and then obtained the final indictor system based on the RS theory.

(1) Discretization of continuous attributes

The discretization algorithm based on Fuzzy c-mean (FCM) clustering is widely used in machine learning and data mining, which group a collection of objects into a limited number of categories in terms of the similarity among objects (Coletta et al., 2012). Compared with other algorithms, this algorithm does not require a mass amount of prior knowledge, and can combine the users' language description habits for the research object with data processing (Bose and Chen, 2015).

In fuzzy clustering, the number K of the cluster should be set in advance, which is difficult to ensure the clustering quality. To address this problem, we adopted the size of information entropy to judge the number K by combining the pedigree clustering method to successively select different numbers for clustering (Wang et al., 2015). The distribution of the data points is similar to that of the atoms; moreover, the more reasonable the clustering division is, the more certain the attribution of data points in a cluster and the smallest the clustering information entropy. Therefore, if the data point attribute is identified as accurately as possible and minimum information entropy clustering results are obtained, the purpose of clustering can be realized.

The range of clustering numbers $[C_{\min}, C_{\max}]$ and accuracy threshold ε, a decimal value between 0 and 1, should be defined first when we adopted the pedigree method. The values of ε usually range from 0.01 to 0.2; here, smaller values reflect more accurate results, although this process may be time consuming. Every cluster number k would produce a membership matrix u^k which corresponds to the information entropy value H_k ranging from $C_{\max}$ to $C_{\min}$. If the column value is set to data point i and the train value is set to cluster category j, then $H_k(x) = \sum_{i=1}^{N} H_{ki}(x)$, in which $H_{ki}(x) = -\sum_{j=1}^{k} u_{ij} \bullet \log_2 u_{ij}$ is the information entropy of each data point. Selecting the cluster number k of the minimal $H_k(x)$ as the ultimate cluster number C, the result is finally obtained by FCM algorithm.

(2) Heuristic attribute reduction based on discernibility matrix

Attribute reduction based on discernibility matrix was first put forward by Skowron and Rauszer (1992). We define information system as $S = (U, A, V, f)$, where $U = \{x_1, x_2, \cdots, x_n\}$ is the non-empty finite set of objects, $A = \{a_1, a_2, \cdots, a_n\}$ is the non-empty finite set of attributes, P is the attribute subset and $P \subset A$. Let $a_i(x_j)$ be the value of sample x_j at attribute a_i. Then, the discernibility matrix M can be defined as $c_{ij} = \{a_k \mid a_k \in p \wedge a_k(x_i) \neq a_k(x_j)\}$, where $i, j = 1, 2, \cdots, n$. The classical Skowron method based on discernibility matrix should convert conjunctive normal forms of non-empty elements in the matrix into the minimal disjunctive norm form. This process is quite complex and difficult to realize by computer programming. Therefore, we adopted a heuristic attribute reduction algorithm based on discernibility matrix. The basic flow of this algorithm is shown as follows.

Step 1: Initialization. Let $CORE = \phi$, a reduction $RED = \phi$.

Step 2: Calculate the discernibility matrix $M = (c_{ij})_{n \times n}$ of the information table.

Step 3: Check each item for $c_{ij} \neq \phi$, and if $|c_{ij}| = 1$, let $CORE = CORE \cup \{c_{ij}\}$.

Step 4: Let $RED = CORE$.

Step 5: For each $c_{ij} \neq \phi$, if $RED \cap c_{ij} \neq \phi$, let $c_{ij} = \phi$, else count the frequency of each attribute in c_{ij} and define the attribute with maximum frequency as c_k.

Step 6: If $\forall c_{ij} = \phi$, stop and input $RED, CORE$, else let $RED = RED \cup c_k$ and turn to Step 5.

(3) Weighting based on knowledge information quantity

According to the RS theory, the indictor weights can be obtained by calculating the attribute importance which is determined by the amount of knowledge information it contains. First, the knowledge information quantity of the equivalence relation *P* can be defined as $I(P) = 1 - \frac{1}{|U|^2}\sum_i^l |X_i|^2$. After the attribute *r* is eliminated, the knowledge information quantity of $P\{r\}$ can be represented as $I(P - \{r\}) = 1 - \frac{1}{|U|^2}\sum_i^k |X_i|^2$. Then the importance of attribute *r* can be calculated by the attribute importance formula $S_p(r) = I(P) - I(P - \{r\})$. Finally, the weight of each indictor is obtained by normalizing the importance of all attributes

4.3. Ranking the evaluation objects based on TOPSIS

Multiple criteria decision making is a well-established methodology aggregating indicators. The main methods include data envelopment analysis (DEA) (Ren et al., 2013), preference ranking organization method for enrichment evaluations (PROMETHEE) (Corrente et al., 2013; Ren et al., 2016), elimination et choice translating reality (ELECTRE) (Chen, 2014), VlseKriterijuska Optimizacija I Komoromisno Resenje (VIKOR) (Yang et al., 2013), and weighted product (WP). These methods have their own set of advantages and disadvantages. For example, DEA does not need to set the weights of inputs and outputs in advance, which reduce the influence of subjective factors (Ren et al., 2014). However, this method takes all random disturbance items as the efficiency factors, and is easy to be affected by the extreme values. In this study, we integrate TOPSIS and RSR models in a systematic way. TOPSIS (Hwang and Yoon, 1981), one of the well-known classical multiple criteria decision making methods, is investigated. The RSR is integrated to group coal mining areas with inherent similarity in their practices (Chen et al., 2015).

TOPSIS is a kind of effective multiple attribute decision making method (Hwang and Yoon, 1981) that has been used in many research fields (Guo and Zhao, 2015; Tavana et al., 2015). The basic principle of this method is to rank the evaluation objects according to the relative closeness degree.

Step 1: Define the evaluation object with the highest vulnerability (the ideal solution) as $Z^+ = (z_1^+, z_2^+, \cdots, z_n^+)$, and define the evaluation object with the lowest vulnerability (the negative solution) as $Z^- = (z_1^-, z_2^-, \cdots, z_n^-)$, where $z_j^+ = \max_{1 \le i \le m}\{z_{ij}\}$, $z_j^- = \min_{1 \le i \le m}\{z_{ij}\}$ $j = 1, 2, \cdots, n$.

Step 2: Calculate Euclidean distance D_i^+ between the evaluation object with the highest vulnerability and other evaluation objects, as well as D_i^- between the evaluation object with the lowest vulnerability and other evaluation objects respectively. And then calculate the relative closeness of each evaluation object to the evaluation object with the highest vulnerability $C_i = \frac{D_i^-}{D_i^- + D_i^+}$. We denote C_i as the CVI. Thus, the higher the value of CVI, the higher the vulnerability level of the evaluation object.

Step 3: Rank the evaluation objects based on CVI.

4.4. Grading and Grouping the evaluation objects based on RSR

Rank-sum Ratio (RSR) is a kind of synthetic evaluation method, which integrates the classical parametric statistics and modern nonparametric statistics (Chen et al., 2015). It represents the average of the decision attribute's rankings. It is a nonparametric metric and has the characteristics of 0-1 interval continuous variables. The basic idea of this method is to obtain the dimensionless statistics RSR_i through rank transformation in a $m \times n$ matrix. On this basis, the distribution of RSR_i can be determined by using the parametric analysis method, and then the evaluation objects can be ranked or grouped by their RSR_i value. By replacing RSR_i value in the RSR model with C_i, the information loss in the process of rank transformation in the RSR model can be effectively avoided (Chen et al., 2015). Then the evaluation objects can be ranked by their RSR_i value. In doing so, the ranking and grouping of evaluation objects can be combined, and more basis could be provided for the CMIES vulnerability assessment. The basic flow of this algorithm is shown as follows.

Step 1: Determine the distribution of the RSR for each evaluation. RSR distribution refers to the specific downward cumulative frequencies of RSR values, which is expressed by probit. Replace RSR_i value with the relative closeness degree C_i. Arrange the evaluation objects in ascending order according to RSR_i value. List the frequencies f_i and cumulative frequencies $f_{\downarrow i}$. Calculate the percentiles P_i and convert them into probit Y. The probit Y corresponding to percentiles P_i is presented in Table B.1.

$$f_{\downarrow i} = i\ ;\quad P_i = \frac{f_{\downarrow i}}{m},\quad i = 1,2,\cdots,\ m-1\ ;\quad P_m = (1 - \frac{1}{4m}) \times 100\% \tag{1}$$

Step 2: Calculate the regression equation. Take the probit Y corresponding to cumulative frequencies as the independent variable and the RSR value as the dependent variable to calculate the regression equation.

$$RSR = a + bY \tag{2}$$

where a and b are regression coefficients.

Step 3: Group the evaluation objects. Choose the appropriate number of grouping according to the amount of evaluation objects. Then the percentiles P^* and probit Y^* will be determined according to Table B.2. Subsequently, calculate the interval of grouping RSR^* by means of the regression equation (2)

$$RSR^* = a + bY^* \tag{3}$$

Group the evaluation objects by their RSR_i value, taking the RSR^* as the interval of grouping. Then conduct analysis of variance to ensure that the grouping is statistically significant.

5. Results

5.1. Reduction and weighting

The fuzzy clustering algorithm based on information entropy is adopted to discretize the continuous data, and this process is realized by programming in Matlab7.0. The final discretization results were obtained by solving the fuzzy clustering algorithm, as shown in Table 1. The data results show that compared to the other methods (e.g.

the equal frequency and equidistance discretization), the discretization results of fuzzy clustering algorithm based on information entropy are more consistent with objective reality. The discrete indictors are reduced and weighted based on the RS theory, and then a relative smallest reduction set { X_{11}, X_{22}, X_{23}, X_{27}, X_{32}, X_{33}, X_{37}, X_{42}, X_{45}, X_{47}, X_{48}, X_{410}, X_{411}, X_{412}} and the weight of each attribute can be obtained. That is the final indicator system for CMIES vulnerability assessment with corresponding weights, as shown in Table 1.

Table 1 Discretization, reduction and weights of indicators

Type	Symbol	Discretization result	Reduction result	Weight
Economic fluctuations risk X_1	X_{11}	4 classes	retain	0.0976
	X_{12}	3 classes	delete	—
	X_{13}	2 classes	delete	—
Sensitivity of living system X_2	X_{21}	2 classes	delete	—
	X_{22}	2 classes	retain	0.0976
	X_{23}	3 classes	retain	0.0244
	X_{24}	2 classes	delete	—
	X_{25}	2 classes	delete	—
	X_{26}	2 classes	delete	—
	X_{27}	2 classes	retain	0.0976
Resilience of living system X_3	X_{31}	2 classes	delete	—
	X_{32}	2 classes	retain	0.0488
	X_{33}	2 classes	retain	0.0488
	X_{34}	2 classes	delete	—
	X_{35}	2 classes	delete	—
	X_{36}	2 classes	delete	—
	X_{37}	2 classes	retain	0.0488
Stability of life-support system X_4	X_{41}	2 classes	delete	—
	X_{42}	2 classes	retain	0.1220
	X_{43}	2 classes	delete	—
	X_{44}	2 classes	delete	—
	X_{45}	2 classes	retain	0.0976
	X_{46}	2 classes	delete	—
	X_{47}	2 classes	retain	0.0488
	X_{48}	3 classes	retain	0.0732
	X_{49}	2 classes	delete	—
	X_{410}	3 classes	retain	0.0732
	X_{411}	2 classes	retain	0.0976
	X_{412}	3 classes	retain	0.0244

5.2. Ranking based on CVI score

By means of the RS-TOPSIS–RSR model introduced in Section 3, the overall index score (CVI score) of the 33 coal mining areas in three years of 2007, 2010, and 2013 is obtained, and each coal mining area can be ranked based on its score. The results and the corresponding rankings are shown in Table 2.

The results present a broader picture of CMIES vulnerability degree, and will help coal mining areas to assess their industrial ecosystem health status in comparison to other areas. It can be seen that OR, XZ, JN, ZZ, and ZH are the top five best-performing coal mining areas, with the lowest industrial ecosystem vulnerability, since they obtain the optimal CVI score in the model in three years of 2007, 2010, and 2013. While some coal mining areas such as JX, QT, HN, HB, PZ, IL, YQ, and JC are low-ranked in three years, and considered to be under-performing. Consequently, these mining areas face greater challenges in industrial ecosystem vulnerability. In other words, there is still sufficient room for these mining areas to improve their industrial ecosystem health status.

Table 2 Rankings based on CVI score

	2007		2010		2013	
Mining area	CVI score	Ranking	CVI score	Ranking	CVI score	Ranking
OR	0.4964	9	0.4237	3	0.3688	1
BT	0.5282	16	0.4986	16	0.4334	7
FX	0.5475	19	0.4874	14	0.5154	21
LY	0.4458	3	0.4650	11	0.5074	19
SY	0.6411	30	0.6162	31	0.4540	11
JX	0.7540	33	0.6412	33	0.5527	27
QT	0.6201	29	0.6152	30	0.6149	32
XZ	0.4584	4	0.3616	1	0.3832	2
HN	0.6441	31	0.5520	25	0.5473	25
HB	0.5675	24	0.5559	26	0.5717	30
PZ	0.5816	26	0.6373	32	0.5732	31
QJ	0.4882	6	0.4935	15	0.5078	20
YL	0.5248	15	0.4601	9	0.5193	23
XY	0.5482	20	0.4433	6	0.4514	9
YC	0.4939	8	0.4590	8	0.4573	12
WL	0.6648	32	0.6117	29	0.4448	8
IL	0.5737	25	0.6032	28	0.5505	26
LZ	0.5546	21	0.5203	22	0.5047	17
TS	0.5136	12	0.4688	12	0.5066	18
HD	0.6029	27	0.4782	13	0.5540	28
TA	0.4656	5	0.4621	10	0.4871	14
JN	0.3931	1	0.4316	5	0.4168	4
ZZ	0.4428	2	0.3911	2	0.4311	6
SQ	0.4991	10	0.5048	18	0.4164	3
ZH	0.4907	7	0.4240	4	0.4275	5
PD	0.5552	22	0.5216	23	0.4785	13
SM	0.5204	13	0.5036	17	0.4894	15
TY	0.5076	11	0.4542	7	0.5173	22
YQ	0.5657	23	0.5282	24	0.5441	24
SZ	0.5362	17	0.5128	20	0.4519	10
CZ	0.5222	14	0.5191	21	0.5633	29
DT	0.5400	18	0.5096	19	0.4949	16
JC	0.6050	28	0.5989	27	0.6666	33

5.3. Grouping coal mining areas

It is possible to make comparisons between all the mining areas as a single group. However, it should be taken into account that differences exist between the mining areas concerning industry development, environment variables, etc. Therefore, it is more realistic to compare mining areas with similar backgrounds (e.g. industry systems, ecological level). In conclusion, it is preferable to group comparable mining areas and then to compare the mining areas within a specific group.

In this study, coal mining areas are classified with inherent similarity in their industrial ecosystem status and operation to enable comparisons between mining areas within similar backgrounds. Based on the CVI score, the distribution of the RSR values of coal mining areas is shown in Tables C.1, C.2, and C.3, and the regression equations are determined as follows:

$$RSR^{*}(2007)=0.07148Y+0.1796 \quad (4)$$

$$RSR^{*}(2010)=0.07053Y+0.1498 \quad (5)$$

$$RSR^{*}(2013)=0.06574Y+0.1635 \quad (6)$$

The confidence limits were calculated at a 95% level. At 0.05 significance level, the three regression equations above are all statistically significant ($P < 0.001$).

It is appropriate to compare the coal mining areas within three groups, due to the fact that the amount of coal mining areas would be too large for accurate comparisons to be made were they contained within a too small number of groups. The corresponding percentiles P^* and probit Y^* are determined accordingly. Then, the interval of grouping RSR^* is calculated by means of the above regression equation. Finally, the coal mining areas are classified into three groups by their RSR_i value, taking the RSR^* as the interval of grouping. The three groups of coal mining areas are presented in Table 3.

As shown in Table 3, 33 coal mining areas are divided into three categories from the most preferable to the least preferable. It can be seen that in 2013, OR, XZ, SQ, and JN are classified in Group I, exhibiting the most favorable level of industrial ecosystem health status. CZ, HB, PZ, QT, and JC are classified in Group □, with high vulnerability compared to other groups. The remaining coal mining areas are classified in Group Ⅱ with medium vulnerability. Additionally, we can find that, according to the CVI score, some areas (e.g. OR, SQ, ZH, CZ, HB, IL, LY) exhibit distinct levels of vulnerability and are assigned to different groups in different years.

Table 3 Three groups of coal mining areas.

Group	P^*	Y^*	2007		2010		2013	
			RSR^*	Coal mining area	RSR^*	Coal mining area	RSR^*	Coal mining area
Low (I)	<15.866	<4	<0.465	JN, ZZ, LY, XZ	<0.432	XZ, ZH, OR, ZZ, JN	<0.426	OR, XZ, SQ, JN
Medium (II)	15.866-	4-	0.466-	TA, QJ, ZH, YC, OR, SQ, TY, TS, SM, CZ, YL, BT, SZ, DT, FX, XY, LZ, PD, YQ, HB, IL, PZ, HD, JC	0.432-	XY, TY, YC, YL, TA, LY, TS, HD, FX, QJ, BT, SM, SQ, DT, SZ, CZ, LZ, PD, YQ, HN, HB	0.426-	ZH, ZZ, BT, WL, XY, SZ, SY, YC, PD, TA, SM, DT, LZ, TS, LY, QJ, FX, TY, YL, YQ, HN, IL, JX, HD
High (III)	84.134-	6-	0.608-	QT, SY, HN, WL, JX	0.572-	JC, IL, WL, QT, SY, PZ, JX	0.558-	CZ, HB, PZ, QT, JC

6. Discussions

6.1. Comparisons of vulnerability of coal mining areas

On the basis of the CVI scores derived from the RS-TOPSIS-RSR method, the comparison of mining areas' rankings in different years is shown in Fig.6. The following observations can be made:

- From the time dimension point of view, there are 5 coal mining areas whose industrial ecosystem vulnerability degree decreased year by year, including OR, BT, JX, HN, and UR; there are 10 coal mining areas whose vulnerability degree increased year by year, including LY, QT, HB, QJ, YC, TS, TA, ZZ, YQ, and CZ; there are 8 coal mining areas whose vulnerability degree decreased first and then increased, including FX, XZ, YL, XY, HD, ZH, TY, and JC; there are 10 coal mining areas whose vulnerability degree increased first and then decreased, including SY, PZ, IL, LZ, JN, SQ, PD, SM, SZ, and DT.
- From the horizontal comparison point of view, there are 5 coal mining areas whose CVI scores always remained at a low level (which were ranked in the top 10 for the 3 years), including OR, XZ, JN, ZZ, and ZH. These areas were mostly distributed in eastern China, where the economy is relatively developed. There are 5 coal mining areas whose CVI scores always remained at a high level (which were ranked in

the bottom 10 for the 3 years), including JX, QT, HN, HB, PZ, IL, YQ, and JC. These areas were mostly distributed in western China and northeast China, where the economy is relatively undeveloped.

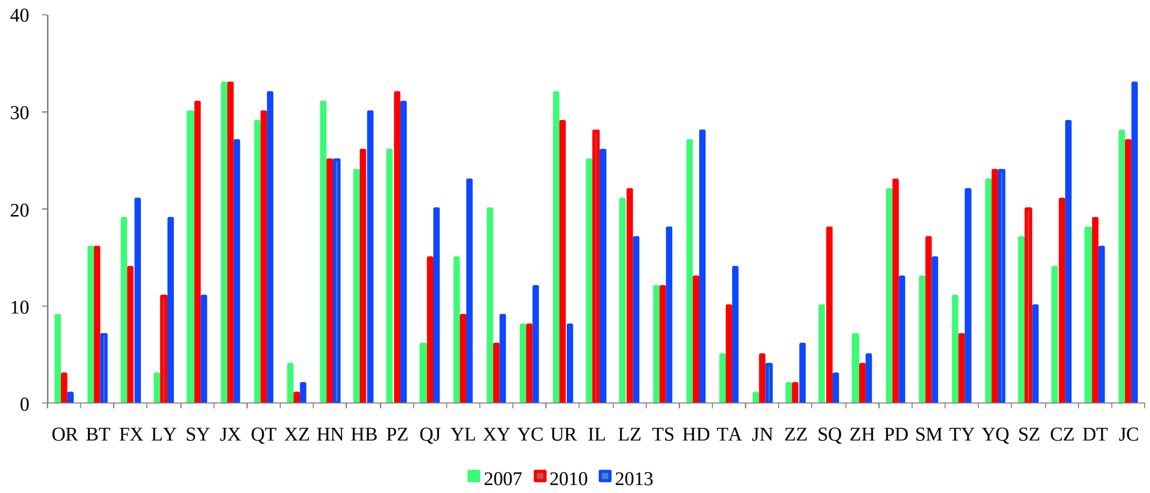

Fig.6. Rankings of coal mining areas based on CVI score

In order to explore the major determinants of vulnerability pattern, we further calculated the following indices: Sensitivity Index (SEI) of living system, Resilience Index (RI) of living system, and Stability Index (STI) of life-support system respectively. The results are presented in Tables D.1, D.2, and D.3. The coal mining areas' rankings based on the scores of SEI, RI, and STI are shown in Figures 7, 8, and 9. The following observations can be made:

- Even though the vulnerability degree of some coal mining areas always remained at a low level and demonstrated a gradual downward trend, they face certain problems, some of which are very serious. For example, Ordos mine's industrial ecosystem vulnerability degree decreased year by year (it has risen from ninth to first place in the ranking), but its resilience of living system was relatively weak (ranked 23rd in 2007, 24th in 2010, and 13rd in 2013 respectively). As the largest and the most important coal industry base of China, Ordos has found a number of large, competitive coal enterprises (e.g. Shenhua Group, Yitai Group) in recent years. These enterprises still maintain a high level of profit, even in the condition of the current coal market downturn. Meanwhile, Ordos improves the ecological environment of the mining areas steadily by developing its circular economy, implementing scientific innovation, and strengthening ecological restoration. However, while the above achievements have been obtained, the mining area still faces certain problems and challenges. According to the Ordos statistics yearbook (2001–2014), the added value of the coal industry has accounted for over 70% of the GDP since 2001. It indicated that the economic development of Ordos relies heavily on the coal industry. However, the other underdeveloped industries, especially non-resource-based industries, has reduced the resilience of CMIES. This is worse for the sustainable development of Ordos.
- Some coal mining areas share similar overall vulnerability degree, whether with high vulnerability or with low vulnerability. However, the causes of their vulnerability patterns are different. In 2013, for example, although OR and JN are all in the top 4 in the CVI ranking, the low vulnerability level of OR is mainly

due to its low sensitivity of living system (ranked 2nd) and high stability of life-support system (ranked 1st), while the low vulnerability level of JN is mainly due to its high resilience of living system (ranked 1st) and high stability of life-support system (ranked 4th). Furthermore, although PZ, QT, and JC are all in the bottom 4 in the CVI ranking, the causes of their vulnerability are not the same. The vulnerability level of PZ and QT are relatively high mainly owing to their high sensitivity of living system (ranked 23rd and 26th respectively) and low stability of life-support system (ranked 28th and 32nd respectively), in spite of their relatively high resilience of living system (ranked 10th and 6th respectively). As for JC, it performed poorly in three aspects, which led to its highest vulnerability degree.

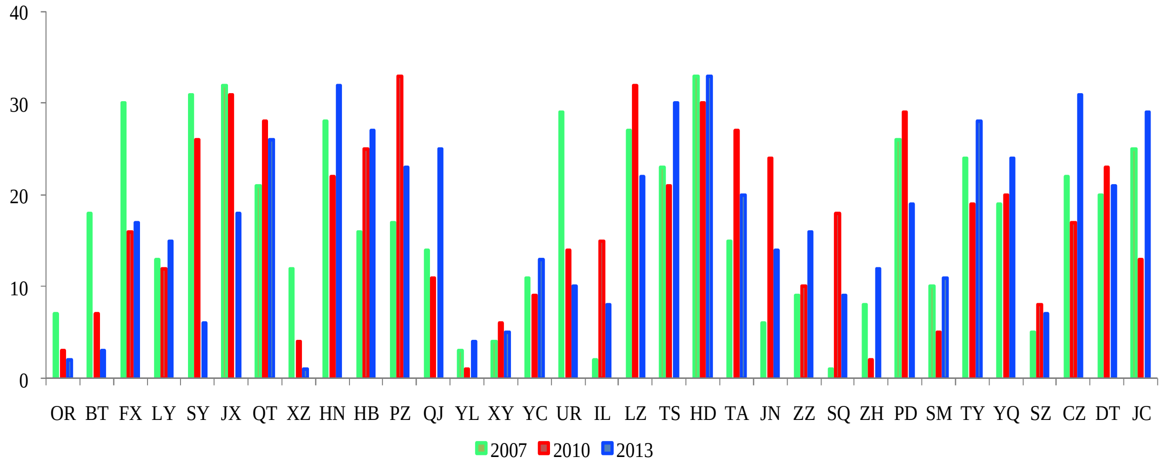

Fig.7. Rankings of coal mining areas based on SEI score

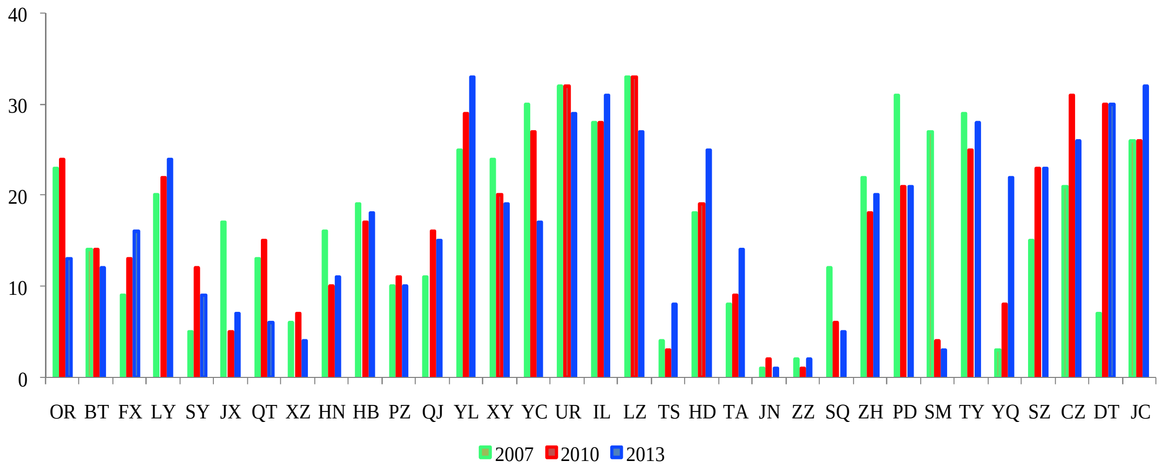

Fig.8. Rankings coal mining areas based on RI score

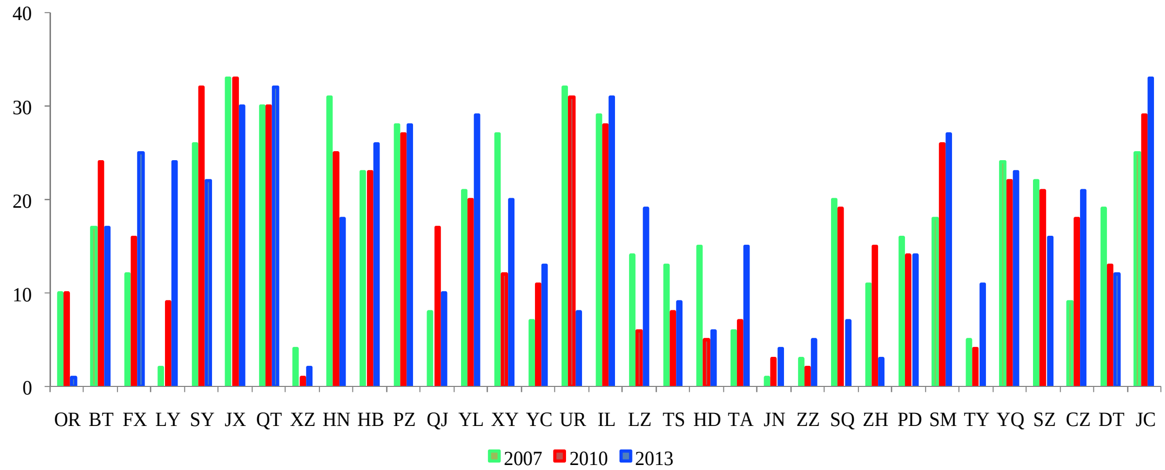

Fig.9. Rankings of coal mining areas based on STI score

6.2. Identification of groups of coal mining areas

The proposed model grouped mining areas based on their CVI score, with inherent statistically similarity. To test the statistical significance of the grouping, the descriptive statistics and the analysis of variance of 14 variables after grouping were conducted in SPSS 19.0. This step is crucial, as the results provided determine whether or not the grouping of coal mining areas is meaningful and acceptable for business managers and policymakers. The results are shown in Table 4. The statistics shows that each variable in the different group had significant differences (p<0.05). This implies that the grouping is reasonable.

Table 4 Descriptive statistics and variance analysis of the variables after grouping

	Group	2007				2010				2013			
		N	Mean	Std. Dev.	Sig.(P)	N	Mean	Std. Dev.	Sig.(P)	N	Mean	Std. Dev.	Sig.(P)
X_{11}	I	4	12.546	4.521	0.002	5	43.002	24.305	0.009	4	60.703	19.594	0.003
	II	24	19.828	14.164		21	54.219	30.588		24	68.238	39.503	
	III	5	31.017	10.943		7	85.093	48.709		5	102.069	24.334	
X_{22}	I	4	2.000	0.951	0.009	5	1.031	0.968	0.002	4	-0.452	0.232	0.008
	II	24	2.187	1.464		21	1.779	2.405		24	0.166	3.956	
	III	5	1.248	1.024		7	1.386	1.442		5	-1.528	4.596	
X_{23}	I	4	2.834	1.360	0.002	5	1.395	1.552	0.001	4	1.400	1.073	0.002
	II	24	2.352	1.327		21	2.849	1.588		24	1.557	3.891	
	III	5	3.422	2.419		7	2.010	0.604		5	-0.402	2.837	
X_{27}	I	4	8.261	3.677	0.000	5	16.740	6.432	0.000	4	12.611	2.781	0.000
	II	24	7.235	4.674		21	7.426	4.896		24	5.671	4.334	
	III	5	3.675	2.531		7	7.586	3.699		5	2.308	2.657	
X_{32}	I	4	0.141	0.005	0.000	5	0.153	0.016	0.000	4	0.166	0.025	0.000
	II	24	0.164	0.025		21	0.159	0.024		24	0.158	0.027	
	III	5	0.189	0.040		7	0.196	0.040		5	0.176	0.042	
X_{33}	I	4	85.000	37.833	0.000	5	64.400	44.881	0.006	4	73.750	52.265	0.002
	II	24	44.080	27.142		21	49.380	30.541		24	48.170	30.105	
	III	5	34.400	14.011		7	30.860	9.686		5	28.200	17.254	
X_{37}	I	4	6.570	1.367	0.000	5	7.974	1.438	0.000	4	8.695	2.195	0.000
	II	24	4.842	0.796		21	6.199	1.101		24	6.738	1.236	
	III	5	4.596	0.440		7	5.583	0.694		5	6.754	0.889	
X_{42}	I	4	0.429	0.115	0.000	5	0.723	0.480	0.000	4	0.585	0.299	0.000
	II	24	1.570	0.584		21	0.902	0.394		24	0.677	0.391	
	III	5	2.573	0.362		7	1.536	0.272		5	1.542	1.275	
X_{45}	I	4	54.515	3.866	0.007	5	60.356	17.578	0.008	4	71.018	2.125	0.005
	II	24	34.797	24.213		21	58.312	10.420		24	59.848	15.886	
	III	5	14.870	14.501		7	25.084	16.318		5	50.514	14.750	

X_{47}	I	4	0.283	0.301	0.001	5	0.326	0.086	0.006	4	0.291	0.052	0.005
	II	24	0.320	0.187		21	0.519	0.265		24	0.528	0.283	
	III	5	0.364	0.345		7	0.571	0.305		5	0.583	0.314	
X_{48}	I	4	69.160	17.925	0.000	5	71.673	14.438	0.002	4	69.622	21.832	0.000
	II	24	62.173	17.705		21	60.147	16.417		24	66.145	17.205	
	III	5	65.487	16.503		7	53.040	11.212		5	61.031	12.769	
X_{410}	I	4	2.208	0.561	0.000	5	2.059	0.258	0.003	4	3.224	1.536	0.006
	II	24	2.507	1.010		21	2.669	0.878		24	3.056	1.188	
	III	5	2.747	0.762		7	3.118	1.653		5	3.105	0.331	
X_{411}	I	4	1.101	0.790	0.000	5	2.834	1.005	0.000	4	3.809	1.909	0.000
	II	24	1.135	0.869		21	1.268	0.781		24	1.659	1.148	
	III	5	0.589	0.277		7	0.771	0.445		5	1.098	0.483	
X_{412}	I	4	58.160	20.595	0.002	5	72.080	11.736	0.001	4	63.414	24.994	0.001
	II	24	55.596	15.197		21	51.590	15.335		24	55.048	17.392	
	III	5	54.758	31.324		7	52.370	22.010		5	49.614	12.487	

Fundamentally, the essence of cooperation is learning from each other to which comparing can be a starting point. The next step is to benchmark the performance with other so-called ‘low vulnerability’ coal mining areas which have already obtained outstanding industrial ecosystem management. In terms of benchmarking, it is not only the final ranking or grouping that is of interest, but also the contribution of each indicator to them. This is crucial and will be a valuable asset for identifying the problems in the industrial ecosystem of a coal mining area.

For example, practices of CMIES governance of Xuzhou, whose vulnerability always remained at a low level, can provide the model and the reference for other coal mining areas with high vulnerability level. As a coal resource-based region and an old industrial base, Xuzhou has been committed to promoting industrial transformation and ecological environment construction in recent years. First, in order to override the dependence on coal industry, Xuzhou actively nurtures non-resource-based industries such as biomedical, iron and steel, engineering machinery, and so on. This improved the level of regional industrial diversification. As the geographical center of Huaihai Economic Zone and the transportation hub, Xuzhou vigorously develops the logistics, trade, and tourism industry. While driving the transformation of traditional energy enterprises, Xuzhou energetically develops the new energy industry such as photovoltaic, wind power, and so on. After nearly 10 years of development, Xuzhou has been one of the largest engineering machinery industry and the new energy industry base in China. Second, Xuzhou continuously strengthens the ecological restoration and environment protection, and strives to improve the level of ecological civilization construction. In 2008, Xuzhou established the Sino-German Center for Energy & Ecological Environment in Mining Areas through cooperation with the German government, universities, and research institutions. The center aims to promote ecological restoration, land reclamation, energy conservation, emission reduction, and the construction of ecological culture industry park in Xuzhou mining area. So far, Xuzhou has made significant achievements in ecological environment construction. The cumulative amount of controlled mining subsidence area in Xuzhou was more than 50, 000 acres, and its forest coverage rate reached 33.2%. Xuzhou has been successively evaluated as China’s top ten investment environment city, the National Sanitary City, and one of the first 7 national ecological garden cities in China.

6.3. Implication

Coal mining areas are special areas characterized by strong man-land interaction. Reducing the vulnerability of industrial ecosystem in coal mining areas has become an urgent task for the local government. In doing so, policymakers are required to assess the CMIES vulnerability situation from an overall perspective. They could compare it with other coal mining areas and learn from those that are superior performers, specifically in terms of action programmes formulation by means of benchmarking. In addition, the assessment results show that the vulnerability level of each CMIES changes continuously as time goes on. This requires policymakers to establish the dynamic evaluation and prediction mechanisms of the CMIES vulnerability, and identify its change rules and causes. Then they can develop the coping strategies pertinently in advance.

In order to gain a thorough understanding of the results of the ranking and grouping, it is necessary to take a closer look at the data behind each indicator. This will support the policymakers in making the appropriate decisions and taking necessary actions to reduce the industrial ecosystem vulnerability of these areas in the future. For the coal mining areas with high sensitivity or low resilience of living system, developing non-resource-based industries and increasing the investment in science and technology play an important role in reducing vulnerability. Most coal mining areas with low stability of life-support system in China are in the remote areas, their ability to attract external investment is inadequate. This urges the central government to provide the necessary financial support and favorable policies on one hand, on the other hand, requires the local government to improve investment environment by facilitating the construction of infrastructure and restoring the ecosystem.

7. Conclusions

7.1. Key conclusions

In this study, a set of indicators related to the CMIES vulnerability was selected to construct a hierarchical structure of the CMIES Vulnerability Index (CVI). Based on the primary vulnerability assessment indices, reducing the condition attributes by using a rough set theory, we obtained 14 valid vulnerability evaluation indices without the loss of information. Subsequently, the RS-TOPSIS–RSR methodology was structured in a systematic way to evaluate CMIES vulnerability from an overall perspective. The integration of three isolated models can exert each other’s advantages as well as overcome their disadvantages. Therefore, this method provides a promising decision support system for adaptive management of coal mining areas.

In application, the 33 coal mining areas of China were ranked and classified into three groups by CMIES vulnerability from low to high, based on the CVI score derived from the RS-TOPSIS–RSR method. In addition, by evaluating the CMIES’ sensitivity index, resilience index, and stability index, we showed the key problems and their causes, which led to higher degree of CMIES vulnerability. The results verified the feasibility of applying the method to solve performance evaluation problems containing multi-alternative and multi-criteria, as well as various decision-making activities in many other fields.

7.2. Outlook

Although initial results show the validity of the RS-TOPSIS-RSR method, there are still some critical factors which need to be further explored. First, a set of more comprehensive assessment indicators should be further investigated to provide a sound overall picture of industrial ecosystem vulnerability. Second, the results obtained from the RS-TOPSIS-RSR model might be sensitive to the priority weights of the decision attributes. Thus, a change in the set of industrial ecosystem vulnerability indicators may lead to a different conclusion. To ensure the robustness of the results to the utmost extent, uncertainty analysis and sensitivity analysis could be performed, by changing indicator weights, or inputting data in different ways. This would also enable policymakers to assess the effects on the evaluation process, in terms of the impact that a change in an indicator's weight restriction, or indicator's set could make.

Acknowledgments

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Appendix

Table A explains the reason for selecting each evaluating indictor as well as the related references. Tables B.1 and B.2 provide the necessary information for evaluation basis. Tables C.1, C.2, and C.3 reproduce the results in Subsection 5.3. Tables D.1, D.2, and D.3 reproduce the results in Subsection 6.1. These tables are detailed in the Supplement file.

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Highlights

Introducing a hierarchical structure of Coal Mining Industrial Ecosystem Vulnerability Index.

Obtaining fourteen evaluating indexes without losing information using rough sets.

Proposing a new method to compare the vulnerability of coal mining industrial ecosystem.

Providing with a promising decision support system for industrial ecosystem management.