Harmony in Extraction: A Variable Weight Theory Approach to Unraveling the Ecological Security Veins in China's Rare Earth Mining Under Variable Pressures

Jianying Zhang, Hengkai Li, Beiping Long, and Duan Huang

***Abstract*—The unique mining process of China's ion-adsorption rare earth (RE) mines has changed the structure of the mine ecosystem, and the interplay between the natural red soil characteristics and economic and social activities has exacerbated environmental problems such as the degradation of regional vegetation cover and soil erosion. These issues have had a profound and detrimental impact on the ecological security (ES) of the mining areas. The existing static evaluation study cannot comprehensively assess the ES status and dynamic evolution trend of the mining area, and cannot meet the needs of the complex ecosystem in the mining area. Therefore, this article constructs an ES evaluation index system based on the driver-pressure-state-impact-response-management causal framework model, and uses the variable weight (VW) theory to formulate a penalty-dominated state VW function to calculate the weight values of the indicators in different contexts of each year and evaluation unit. Finally, a dynamic evaluation of the spatial and temporal evolution trend of the ES of the Lingbei RE mining area is carried out during the period from 2000 to 2020. The geodetector model is then applied to reveal the driving factors impacting the ES of the mining area in different time periods. The results show that 1) Compared to the constant weight method, VW can provide a more detailed distribution of the ES level in the mining area, which has good application value in the small and dispersed ionic RE mining area. 2) The overall ES status of the Lingbei mining area shows a dynamic trend of deterioration followed by improvement and finally stabilization. 3) The vegetation health status is one of the most important driving factors of ES in the mine site, and the interaction between any two factors is greater than the explanatory power of the individual factors. This study provided insights into the ES and sustainable development of mining areas.**

***Index Terms*—Driver-pressure-state-impact-response-management (DPSIRM) model, driving factors, dynamic evolution, ecological security, rare earth ore, variable weight theory.**

I. Introduction

RARE earth elements (REE), as key raw materials for high-tech products, are widely used in high-tech industries such as smart manufacturing, high-end chips, and aerospace around the world [1]. As the largest producer, consumer, and supplier of REE, China already has the world's most complete REE industrial system, with exports accounting for over 80% of the global total [2]. Notably, the ionic RE mines in Ganzhou, Jiangxi Province account for more than 30% of China's total production and represent a crucial region for ionic RE mining in China [3]. While RE mining provides robust energy support for China's socioeconomic development, it also exerts significant adverse impacts on the ecological environment in mining regions.

Ionic RE ore is a unique RE deposit formed by the long-term weathering of surface rocks resulting in the migration and enrichment of REE in an ionic state adsorbed on clay minerals. Its mining process has gone through several technological stages, including barrel leaching, pool leaching, heap leaching, and in situ leaching. Despite continuous advances in process efficiency, the problems of heavy metal pollution and ecological damage remain unsolved [4], [5]. Most of the ionic RE mines are located in the southern red soil hilly and mountainous region, which is the second largest soil erosion area in China besides the Loess Plateau [6]. Therefore, in addition to the limitations of the process technology, the severe geographic conditions of the region have exacerbated the environmental problems of ionic rare earth mines, with ecological damage such as topsoil denudation, landslides, and destruction of vegetation, which have seriously affected the safety of the mines and the surrounding ecological system.

Ecological security (ES) refers to a state in which a composite ecosystem, comprised of natural, economic, and social components, retains its functionality to meet development needs and develop sustainably even when subjected to external pressures and disruptions [7]. Over the past three decades, ecological

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and environmental issues arising from RE mining have gradually gained international attention. For example, the United States has implemented stringent legislation to protect its domestic environment, including the enactment of laws such as the "Energy Policy Act." Similarly, countries like Japan and Australia have sought to outsource their rare earth production to mitigate the ecological and environmental pollution caused by their domestic rare earth industries [8]. In China, efforts to enhance ecological protection measures within the rare earth industry have been ongoing, including the establishment of a planned approval system for the RE sector [9]. In 2000, the United Nations convened the Conference on Ecological Change, Stable Social Order, and Culture, where it explicitly recognized ES as a vital component of national environmental governance. This marked the importance of ecological security worldwide [10].

ES assessment involves evaluating the impact of natural and social factors on a particular ecosystem within a defined time frame. It employs certain criteria to assess the condition of the ecosystem, thus analyzing its capacity to maintain health and sustainable development [11]. In 1993, the Organization for Economic Co-operation and Development proposed the "DSR (Driver-State-Response)" framework model. Since the research on ES evaluation has been carried out, it has evolved from simple single-factor assessments to progressively encompass more complex ecological process causal analysis assessments, and its connotation has been gradually enlarged and enriched. For example, Du et al. [12] used a Bayesian network model based on the driver-pressure-state-impact-response-management (DPSIRM) framework to simulate the risk of occurrence of ES warnings under different scenarios, which provided a new perspective for the study of watershed ES evaluation. Na et al. [13] assesses the ecological risk status of PAHs by integrating the risk quotient approach and the DPSIRM conceptual framework. These studies demonstrate the significant potential for the application of the DPSIRM model in ES assessment, as it can emphasize the interrelationships among evaluation indicators encompassing ecological, social, economic, resource, and policy dimensions. While this model can initially realize the selection and construction of evaluation indicators, indicator weighting remains a crucial aspect influencing the accuracy of the model. At present, the widely used methods for CW determination mainly include analytic hierarchy process (AHP) [14], least square method [15], principal component analysis [16], entropy weight information method [17], and so on. However, in practical applications, there are usually multiple evaluation indicators. The CW method may result in relatively low weights assigned to each indicator. If a lower-weighted indicator deteriorates, it may be offset by other indicators, leading to distortion and inaccuracy in the final evaluation results.

The dynamic development of the ecological environment in RE mining areas has stimulated the demand for dynamic evaluation methods. Traditional static ES assessment studies are no longer able to meet the needs of complex mining area ecosystems. Especially in the process of evaluating the ES of RE mining areas, the selection of evaluation index weights directly determines the accuracy of the comprehensive evaluation results. However, the current evaluation method usually adopts a constant weight evaluation method, which keeps the weight values unchanged even when the influencing factors in the mining area change, such as the sudden change of mining disturbance. This constant weight model with fixed weights only takes into account the relative importance of each factor in the evaluation, and is unable to accurately portray the impact of sudden changes in the indicator values of the factors on the ecology of the mining area due to various changes. The VW theory achieves a more reasonable allocation of weights for each evaluation indicator by constructing an equilibrium function that incorporates state-variable weighting and multiattribute decision-making [18]. For example, Li et al. [19] combined the VW theory and the DPSIRM causal framework to evaluate the ES status of forests in mainland China, providing valuable suggestions for forest ES management. Zhang et al. [20] derived an optimal hybrid model for assessing the risk of coal seam outbursts underground based on the VW theory and uncertainty analysis, aiming to accurately evaluate the risk of coal seam outbursts under different conditions. Ye et al. [21] constructed a Fuzzy-AHP method based on the VW theory to evaluate the safety of expansive soil slopes.

Remote sensing technology has become an effective tool for ecological environment protection and management in mining areas because of its advantages of low cost, high efficiency, and wide coverage. The continuously improving quality of remote sensing data has increasingly enhanced the significance of remote sensing data in the field of ecological monitoring in RE mining areas. RE mining areas are located in the red soil hilly mountainous areas, and the mine sites are small and dispersed, which makes timely and accurate monitoring of the mine environment difficult. Consequently, it becomes difficult to effectively capture the ecological changes occurring within the mining areas. With the advancement of spatio-temporal integrated remote sensing data, it is now feasible to acquire extensive and high-resolution surface information, including topography, vegetation cover, soil types, etc. This development provides solid data support for comprehensive monitoring of the ecological environment in RE mining areas. At present, the VW method has been continuously maturing in the system evaluation. However, it has not been well applied in the research of mining area ecosystems. Introducing the VW model into the evaluation of ES in mining areas is of great significance, both for the ES of the mining area and for the management and governance of relevant departments. Therefore, in this study, we proposed a dynamic evaluation method for ES in the Lingebei RE mining area, combining RS and GIS technologies with the DPSIRM framework and the VW theory. We explored the spatiotemporal variation characteristics of ES in the mining area from 2000 to 2020 under the influence of multiple factors. In addition, the GD model was used to analyze the synergistic effects among the driving factors influencing the changes in ES at the indicator level. This revealed the characteristics, evolutionary patterns, and driving mechanisms of ecological environmental changes in the southern ionic adsorption RE mining area. The main objective of this study is to provide a scientific basis for sustainable mining and ecological restoration in the mining area and to

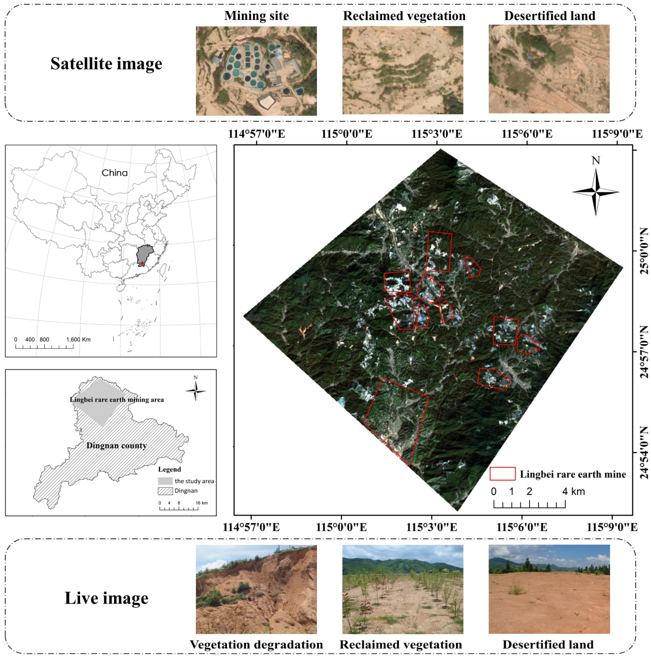

Fig. 1. Location map of the study area.

promote the harmonious development of the regional ecological environment, and social economy.

II. Materials and Methods

A. Study Area

The Lingbei RE mining area (24°51′24″∼25°02′56″N, 114°58′04″∼115°10′56″E) is located in the northern part of Dingnan County, Ganzhou City, Jiangxi Province, covering an area of about 200 km^2 (see Fig. 1), and is one of the most important production areas for ionic RE mining in southern China [22]. Mining methods in the area have been optimized since 1960 to the present, but this has not fundamentally changed the fact of ecological disruption in the mining area. The long-term heap leaching mining method has resulted in the accumulation of large amounts of nitrides in the surrounding water and soil. The changes in the physicochemical properties of the soil have led directly to vegetation degradation and soil erosion, posing a significant threat to the ES of the mining area. Starting in 2012, the mining area has gradually undertaken large-scale reclamation, but the reclaimed vegetation grows slowly and poorly under the stress of pollutants, and the reclamation effect is not satisfactory. The southern red soil hilly area is hot and rainy, and the soil is barren, which makes the ecological restoration of the mine area more difficult. How to scientifically and accurately monitor the ecological safety of mining areas dynamically is still the focus of mine environmental management.

B. Data Sources and Preprocessing

In order to evaluate its ecological restoration more comprehensively and accurately, and to ensure the integrity and reliability of the data, we analyze the spatial and temporal evolution of ecological resilience of the mining area in 2000, 2005, 2010, 2016, and 2020 from the perspective of historical mining in rare earth mining areas. Among them, both 2000 and 2005 belong to the rare earth mining expansion phase, 2000 to the pool leaching and heap leaching phase, and 2005 to the in situ leaching phase. The mine reclamation phase started in 2010 and 2016 is the later stage of reclamation, when mining completely stops. The year 2020 is the period of ecological improvement of the mine. These five years represent the typical stages of different mining and recovery of rare earth mining areas.

The data used in this study include remote sensing data, topographic data, meteorological data, socio-economic data, soil data, and other data of the study area in 2000, 2005, 2010, 2016, and 2020. Among them, this study takes the "T_OC: Real" field in the soil database attribute table as the evaluation indicator of soil organic matter content in the RE mining area. After loading and verifying the coordinates of this field data, the raster attribute table can be constructed directly, and finally, the data are exported and cropped. Second, to satisfy the construction requirements of the geodetector model, the driving factor data should be reclassified. Combining relevant literature and on-site investigation findings, the natural breakpoint method is employed to discretize 21 indicators, aiming to achieve the optimal classification with the maximum explanatory power (q value). Finally, to address the issue of differential information among various data types and break the boundaries of data mining patterns based on administrative units, statistical data interpolation is performed to convert it into raster data, which is then resampled to achieve consistent spatial and temporal resolution (30∗30 m). Data details are shown in Table I.

C. Research Method

In this study, we have proposed a dynamic method for assessing the ES of rare earth mining areas, focusing on the synergy between ecological environment and resource development. As shown in Fig. 2, the basic research framework is outlined as follows. First, we used remote sensing, meteorological, economic, atmospheric, soil, and other data sources, in conjunction with the DPSIRM framework, to extract assessment indicators tailored to the study area from six different dimensions: drivers, pressures, states, impacts, responses, and management. Then, based on the ecological evolution mechanism of the mining area, a VW function was constructed to calculate the weight value of each indicator. On the premise of determining the values and weights of each indicator in the RE mining area, an ES evaluation model of the RE mining area was established and used to assess the spatial and temporal evolution characteristics of the ES of the RE mining area. Finally, the geodetector model were used to analyze the driving factors and their interactions affecting the mining area during different periods.

1) ES Assessment Indicator System: The DPSIRM model is an emerging conceptual model formed by the gradual improvement of the PSR, DSR and PSIR models. It emphasizes the interconnected causal relationships between ecology, resources, policies and the economy [12]. The model allows a wide range

TABLE I
DATA TYPES AND SOURCES

Data type	Data Contents	Resolution	Data sources
Remote Sensing Data	Landsat dataset(TM/OLI)	30 m	USGS (https://www.usgs.gov/)
	Land use data	30 m	Zenodo (www.zenodo.org/), China's Land-Use/Cover Datasets (CLUD) [23]
	NPP data	500 m	USGS (https://www.usgs.gov/), MODIS MOD17A3HGF Products
Meteorological Data	Monthly precipitation, Monthly average temperature	Districts	National Eerth System Science Data Center (www.geoddata,cn)
Socio-economic Data	Population density, Number of students in school, GDP,	Districts	Jiangxi Statistical Yearbook, Dingnan County Statistical Yearbook
Soil Data	Soil organic matter content	Districts	National Tibetan Plateau Scientific Data Center (http://data.tpdc.ac.cn/), Harmonized World Soil Database
Terrain and other data	DEM data	30 m	Geospatial Data Cloud (https://www.gscloud.cn/)
	Vector boundary of the study area and mine sites	–	Obtained from field exploration
	Historical geohazard site data for the Lingbei mine area	–	Geological disaster prevention and control related maps

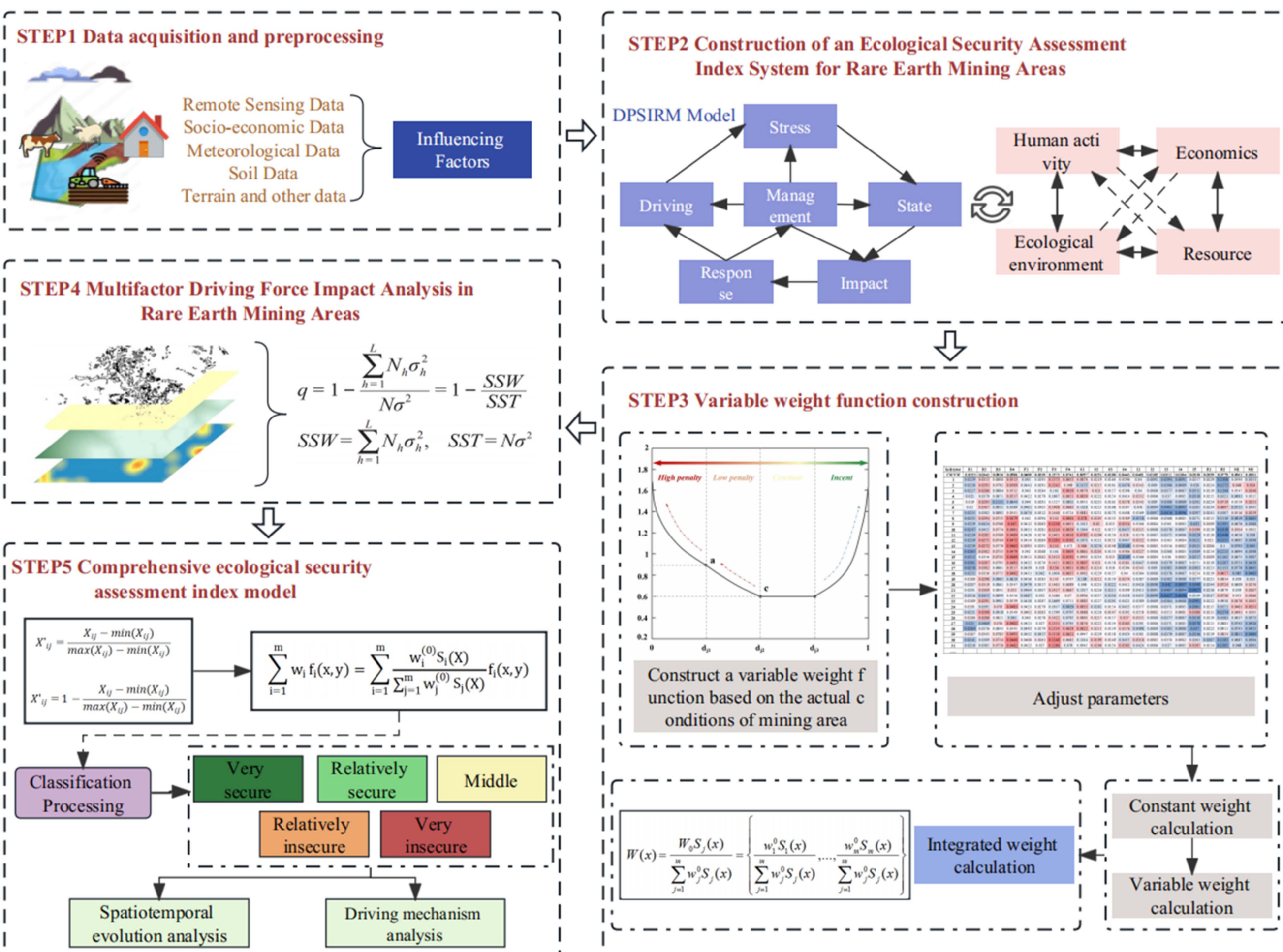

Fig. 2. Research framework.

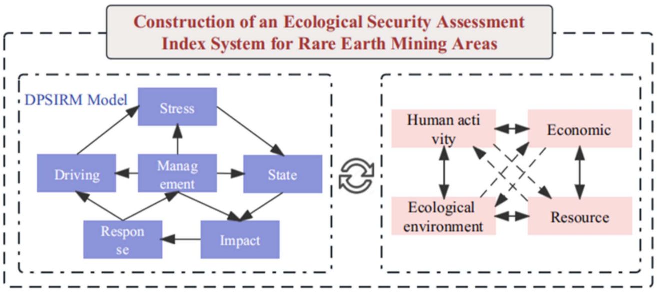

Fig. 3. DPSIRM framework.

of indicator factors to be selected, which can improve the assessment criteria.

The ecosystem of ion-adsorption RE mining area is a comprehensive multifactor and multi-indicator system, and the impact of human socio-economic activities on it is gradually increasing and complicating. Influenced by the supply and demand of REE, human exploitation of RE mines through various processes has led to the deterioration of the ecological environment in the mining areas, thus prompting the reverse feedback of socio-economic activities, and the adoption of certain treatment and regulatory measures to improve the ecological environment in the mining areas. Considering such a bidirectional role, we selected the DPSIRM model to construct the ES evaluation index system of the mining area in order to strengthen the sustainable development of the mining ecosystem and the integrated management of the impact factors, as shown in Fig. 3.

A scientific assessment index system is the basis for measuring the ES of mining areas. It is a prerequisite for evaluating the scientific, reliable, and accurate nature of the results. Different regions have varying natural conditions and economic development trends. On one hand, the Lingbei RE mining area is an integrated and complex ecosystem, with diverse biological species, abundant mineral resources and extremely fragile natural conditions. As human life and production gather and spread, the richness of the region's natural resources and the balance of its ecological landscape continue to suffer from impacts, leading to increasingly prominent conflicts between the local population and the land. The depletion of resources significantly impacts the socioeconomic development of human society, and if left unchecked, it is poised to generate a series of severe consequences. On the other hand, the feedback from ecological protection measures taken to prevent, alleviate, or eliminate negative impacts reflects the proactive response of human activities to the ecological security of RE mining areas. This response acts as a counterbalance to the adverse effects generated by human activities, thereby promoting the benign development of ecological security in rare earth mining areas. Therefore, taking into account the natural geographical conditions, ecological environmental status and socioeconomic conditions of the study area, combined with previous research, and following the principles of representativeness, accessibility and comparability of indicator selection, we have constructed a comprehensive ES assessment indicator system for mining areas. Using the DPSIRM model, we selected 21 indicators from 6 dimensions, as shown in Table V (Appendix).

TABLE II
CLASSIFICATION STANDARD OF ES VALUE OF RE MINING AREAS

Level	Comprehensive assessment value	ES Level
I	$0.00 < X \leq 0.26$	Very insecure
II	$0.26 < X \leq 0.40$	Relatively insecure
III	$0.40 < X \leq 0.47$	Middle
IV	$0.47 < X \leq 0.57$	Relatively secure
V	$0.57 < X \leq 1$	Very secure

2) Comprehensive Evaluation Method Based on VW Theory:

a) Determination of CW: Before calculating the VW, the constant weight (CW) should be determined first. In this paper, we use AHP to calculate CW, which is one of the most commonly used index weight calculation methods in ES evaluation. The basic steps include constructing the judgment matrix, calculating the weight vector, and the consistency test of the judgment matrix. The calculation results are shown in Table VI (Appendix).

b) VW theory: Ion-adsorption RE mining ecosystem is a complex and dynamic system with disturbance feedback lag effect and evident dynamics. In the comprehensive evaluation of ES in mining areas, conventional CW assignments are commonly used to represent the importance of different indicators. However, this method cannot reflect the actuality and dynamics of the development of mining areas. VW methods can effectively solve this problem. The particular principles and calculation process are as follows.

VW theory was first proposed by Wang [24], and then Li [25] proposed the axiomatic definition and calculation formula of three types of VW, namely penalty, incentive, and nonpenalty and nonincentive (1). Then different VW strategies were given according to the magnitude of the indicator state value, and Yao and Li [26] proposed the theory of local VW. The CW model reflects the relative importance of each factor on the target, but usually, the weight of the factors' influence on the target is also related to the magnitude of the factor state values and their combined states. For this reason, Wu et al. [27] introduced the local VW theory into the index method evaluation, pioneering the application of the local VW theory in index evaluation methods

$$
\begin{aligned}
W(x) &= \frac{W_0 S_j(x)}{\sum_{j=1}^{m} w_j^0 S_j(x)} \\
&= \left\{ \frac{w_1^0 S_1(x)}{\sum_{j=1}^{m} w_j^0 S_j(x)}, \ldots, \frac{w_m^0 S_m(x)}{\sum_{j=1}^{m} w_j^0 S_j(x)} \right\} \qquad (1)
\end{aligned}
$$

where w_j^0 is any constant weight vector, $S_j(x)$ is an m-dimensional partition state variable weight vector, $j = 1, 2, 3, \ldots, m$.

c) VW model construction and determination of tuning parameters: The development of a variable weight model that meets evaluation requirements is a crucial component of ecological security assessment in rare earth mining areas, closely tied to the accuracy of the final evaluation results. Given the disturbance

TABLE III
AREA STATISTICS OF THE EVALUATION RESULTS

VW	Area (m^2) and area ratio (%)				
Year	Very insecure	Relatively insecure	Middle	Relatively secure	Very secure
0 (0.00)	118 800 (8.08)	54 900 (3.74)	207 000 (14.08)	1089 000 (74.10)	0 (0.00)
81900 (5.57)	225 000 (15.31)	90 900 (6.18)	271 800 (18.49)	800 100 (54.44)	81 900 (5.57)
149400 (10.17)	459 900 (31.29)	117 000 (7.96)	135 900 (9.25)	607 500 (41.33)	149 400 (10.17)
36900 (2.51)	428 400 (29.15)	179 100 (12.19)	124 200 (8.45)	701 100 (47.70)	36 900 (2.51)
162000 (11.02)	339 300 (23.09)	142 200 (9.68)	100 800 (6.68)	725 400 (49.36)	162 000 (11.02)
CW	Area (m^2) and area ratio (%)				
Year	Very insecure	Relatively insecure	Middle	Relatively secure	Very secure
2000	0 (0.00)	76 500 (5.21)	60 300 (4.10)	117 900 (8.02)	1 215 000 (82.67)
2005	16 200 (1.10)	273 600 (18.62)	67 500 (4.59)	155 700 (10.59)	956 700 (65.09)
2010	3600 (0.24)	563 400 (38.33)	90 000 (6.12)	91 800 (6.25)	720 900 (49.05)
2016	3600 (0.24)	372 600 (25.35)	197 100 (13.41)	95 400 (6.49)	801 000 (54.50)
2020	56 700 (3.86)	365 400 (24.86)	141 300 (9.61)	100 800 (6.86)	805 500 (54.81)

and ecological evolution characteristics of rare earth mining areas, constructing a variable weight model necessitates accurately reflecting the impact of changes in each evaluation indicator on the assessment outcomes. Influenced by various factors, including mining processes and natural conditions, the mining area has limited self-restoration capacity. Following ecological damage, relying solely on natural recovery is challenging, and artificial vegetation reclamation is required. Therefore, if the constraint of various disturbances on the ES of the mine area accumulates exceeds the threshold of its own recovery, it may cause irreversible impacts. Guided by the VW method, and in an effort to better take into account the limitations imposed by natural conditions and the influence of human activities, while preventing negative indicators from being overshadowed by positive ones, this study, taking into account the changing trends in rare earth mining areas, adopts a model in which the magnitude of negative effects outweighs that of positive effects. We have constructed a hybrid VW function dominated by punitive measures, expressed as follows:

$$S(\mathrm{x}) = \begin{cases} \mathrm{e}^{\alpha(d_{j1}-x_j)} + \mathrm{e}^{\alpha(d_{j2}-d_{j1})} + C - 2, & 0 \leq x_j < d_{j1} \\ \mathrm{e}^{\alpha(d_{j2}-x_j)} + C - 1, & d_{j1} \leq x_j < d_{j2} \\ C, & d_{j2} \leq x_j < d_{j3} \\ \mathrm{e}^{\alpha(\mathrm{x_j}-d_{j3})} + C - 1, & d_{j3} \leq x_j < 1 \end{cases} \quad (2)$$

where x_j is the value of the original data after standardization, d_{j1}, d_{j2}, d_{j3}, respectively, for the threshold of the variation interval (calculated using the *K*-mean algorithm [28]), $e \approx 2.718$, α is the impact factor of the weight, indicating the degree of weight variation, a higher α value results in more significant weight changes, *C* is the adjustment level, reflecting the degree of total weight change, a smaller *C* corresponds to a greater degree of punishment (incentive).

As shown in Fig. 4, the exponential state VW vector constructed in this study is divided into four weight adjustment intervals. $d_{j3}\sim 1$ is the incentive interval, when the indicator state value lies in this interval, its weight value will increase with the state value. $d_{j2}\sim d_{j3}$ is the nonpenalty and nonincentive interval, and the weight value will not change with the indicator state value in this interval. $0\sim d_{j2}$ is the penalty interval, in which

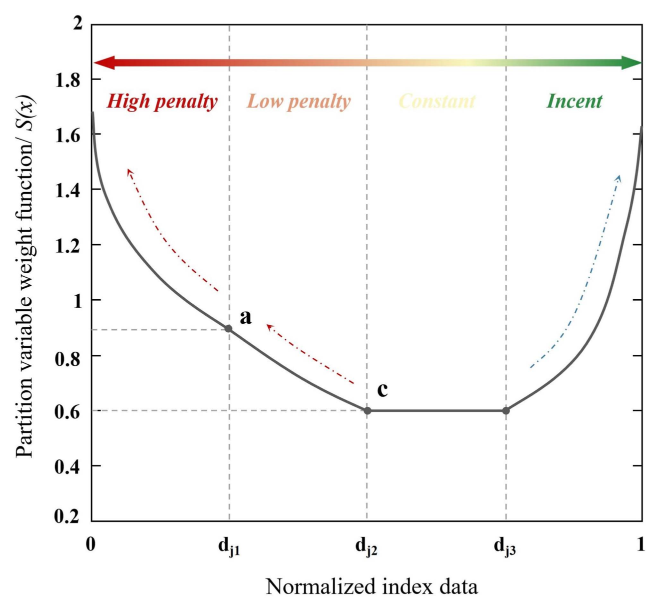

Fig. 4. Penalty and incentive variable weight function *S*(*X*).

the weight value increases as the indicator state value decreases, and the penalty intensity increases when the indicator value is in the range of $0\sim d_{j1}$.

After more than 200 assignment tests to ensure significant variable weighting effects and to avoid excessive weight reductions (increases), we found that the best results were achieved with $C = 0.6$ and $\alpha = 1.5$.

3) Comprehensive Evaluation of ES in RE Mining Areas: Before the comprehensive evaluation of the ES of RE mining areas, in order to eliminate the differences of indicators in different scales, units, and orders of magnitude. According to the role of each indicator in the ES of the mining area, the method of standardization of extreme differences was used to standardize the indicators. In this study, positive indicators (+) refer to those that have a positive impact on the ES of RE mining areas, with their increase promoting ES. Conversely, negative indicators (–) denote those that have a negative impact on ES, with their increase causing harm to ES. Positive indicators are calculated as in (4) and negative indicators are calculated as

TABLE IV
CRITERION INTERVAL OF DRIVING FORCE AND INTERACTION TYPE

Graphical representation	Description of the relationship	Interaction effect
	$q(X_1 \cap X_2) < \min(q(X_1), q(X_2))$	Nonlinear-weaken
	$\min(q(X_1), q(X_2)) < q(X_1 \cap X_2) < \max(q(X_1), q(X_2))$	Uni-weaken
	$q(X_1 \cap X_2) > \max(q(X_1), q(X_2))$	Bivariate-enhance
	$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	Independent
	$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	Nonlinear-enhance

in (5)

$$X_{ij} = \frac{x_{ij} - \min x_j}{\max x_j - \min x_i} \quad (3)$$

$$X_{ij} = \frac{\max x_j - x_{ij}}{\max x_j - \min x_i} \quad (4)$$

where X_{ij} is the standardized value of the i_{th} evaluation indicator in year j, x_{ij} is the original value of the i_{th} evaluation indicator in year j, max xj is the maximum value of the i_{th} evaluation indicator, and min x_i is the minimum value of the i_{th} evaluation indicator.

The comprehensive index model was used to calculate the integrated ES index of the mining area [29] with the following formula:

$$\text{ESI} = \sum_{j=1}^{n} X_j \times W_j \quad (5)$$

where ESI is the ecological security index of the mining area, X_{ij} is the normalized index, and W_j is the corresponding weight of the indicator.

In traditional ES evaluation research, many scholars use equidistant methods to classify evaluation result levels. However, we found that ES levels classified according to fixed distances did not capture the internal differences in regional ES well. Therefore, in this study, the ES evaluation index was reclassified using the natural breakpoint method and adjusted accordingly based on previous research [30]. The higher the ESI value, the better the regional ES status (see Table II).

4) Identification of Influencing Factors Based on Geographic Detector: Spatial heterogeneity is one of the fundamental characteristics of geographical phenomena, and the geographical detector is a novel statistical model that can examine the explanatory power of specific factors by measuring spatial heterogeneity. In recent years, it has been widely applied in fields such as ecological engineering and urban research [31], [32]. In this study, we used the factors and interaction detectors of the GD model to analyze the synergistic effects among the driving factors of ES in RE mining areas

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N \sigma_h^2} = 1 - \frac{\text{SSW}}{\text{SST}} \quad (6)$$

$$\text{SSW} = \sum_{\text{h}=1}^{L} N_h \sigma_h^2, \ \text{SST} = N\sigma^2 \quad (7)$$

where q is the degree of explanation of the ES status in the mining area by the indicator, L is the classification of X or Y, h is the number of the indicator grading, N_h and σ_h^2 are the number of samples and variance of a specific stratum, respectively, and N and σ^2 are the number of samples and variance of the whole region, respectively. The value of q is in the range of [0,1], the higher the value indicates the stronger the degree of explanation. $q = 0$ indicates that the driving factor has nothing to do with the ES status of the mining area, and $q = 1$ indicates that the driving factor completely controls the spatial differentiation of the ES status of the mining area. SSW and SST are the sum of the L-class variance and the total regional variance, respectively.

III. RESULTS

A. Dynamic Evaluation of ES in RE Mining Areas

Fig. 5 shows the results of ES index grading in 2000, 2005, 2010, 2016, and 2020 in Lingbei RE mining area. It can be seen that the spatial distribution of "very insecure" and "relatively insecure" regions with threats to ES has changed significantly over the last 20 years, while the spatial distribution of "very secure" regions with a stable state of ES has changed little. In 2000, the "very insecure" and "relatively insecure" regions expanded outward from the northwest and southwest, gradually transitioning into "middle," "relatively secure," and "very secure" regions. In 2005, the "very insecure" and "relatively insecure" areas were primarily concentrated around the mining sites, and this phenomenon became more pronounced in 2010. It was not until 2016 that the ES risk areas gradually dispersed throughout the study area away from the mining sites. In 2020, the size of the "very insecure" areas peaked, and the dispersal phenomenon became even more pronounced.

As can be seen from Fig. 5(f), the proportion of the total area of "very insecure" and "relatively insecure" areas in the study area showed a dynamic trend of first decreasing, then increasing and finally stabilizing from 2000 to 2020. This suggests that under the combined influence of various factors, ES in the mining area shows significant instability.

B. Dynamic Evolution of ES in Typical Mining Sites

In order to explore the process of ES change in the Lingebei RE mining area and to conduct an in-depth analysis of the impact of RE mining activities on ES, we selected two representative

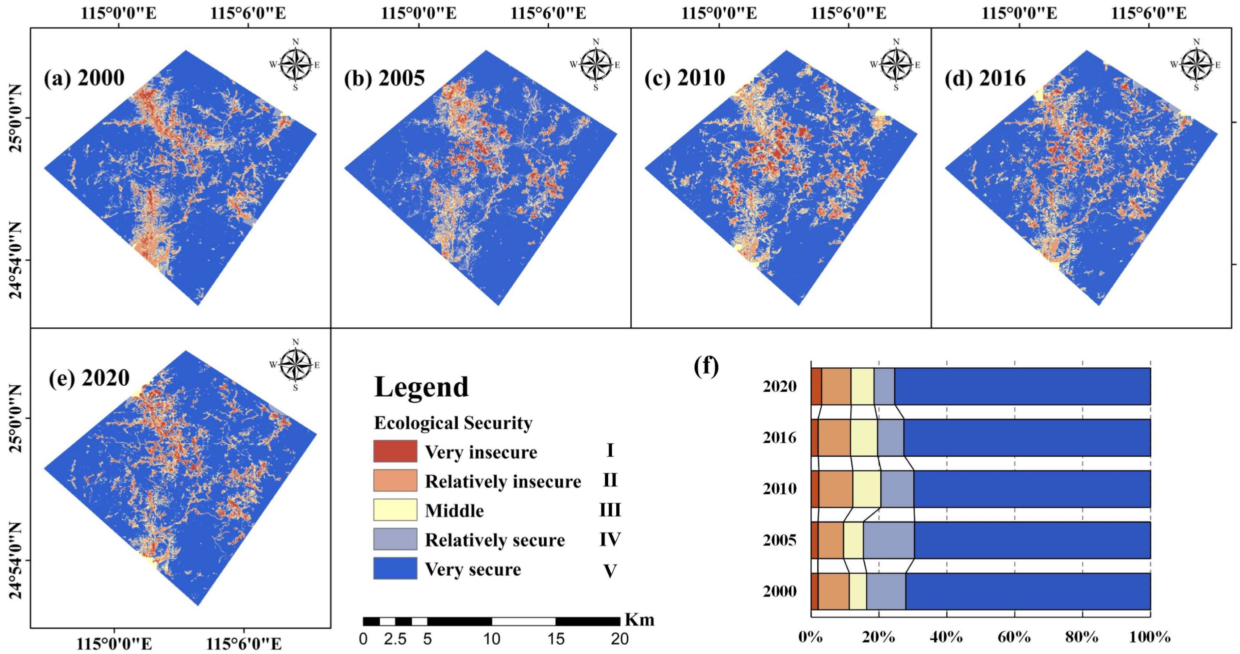

Fig. 5. Spatial distribution of ES values in the Lingbei RE mining areas (2000–2020).

mining sites within the Lingebei mining area, namely the Nongji and Qingjingtang mining sites. These two mining sites have gone through a complete process of rare-earth mining, cessation of mining, and ecological restoration, and are therefore representative of the Lingbei mining areas. Combining the 2000, 2005, 2010, 2016, and 2020 ES assessment results of the mining site with the 2005 high-resolution Google image, a comparative analysis of the ES status at critical stages of the mining process was conducted. The assessment results were compared with the high-resolution images as shown in Fig. 6.

As can be seen from Fig. 6, the spatial distribution of ES classification results in 2005 is very similar to the Google image of that year, with a good comparative relationship. In the first monitoring period in 2000, the damage to ES at the two mining sites had already developed in spots, and the size of the "very insecure" and "relatively insecure" areas increased rapidly over the five-year period. By 2010, the ES deterioration at the Nongji mining site had reached its peak, with the area of "very insecure" and "relatively insecure" areas growing to 504 000 m^2, accounting for 73.59% of the mining site area. In 2005, the ES of the Qingjingtang mine site was in the worst condition, with the area of "very insecure" and "relatively insecure" areas increasing to 342 000 m^2, accounting for 54.6% of the total area of the mine site. During the period from 2010 to 2020, there was a clear trend of ES recovery, marked by a significant reduction in the areas classified as "very insecure" and "relatively insecure" and the areas classified as "very secure" and "relatively secure" gradually increased. The ES restoration effect of the Nongji mine site is better compared with that of the Qingruntang mine site, which, due to the long duration of rare-earth mining, will still have a very low level of ecological safety up to 2020, and will need to be restored more vigorously.

C. Comparison of VW and CW Method

In order to clarify how the introduction of the VW method affects the ES evaluation of RE mining areas, this study compares the two evaluation results obtained by the VW and CW methods in a typical mining area. First, Fig. 7(a) shows the evaluation results obtained by the VW and CW methods at the Aobeitang mine site in 2010 compared with the high-resolution Google images of that year, and it can be seen that the spatial distribution of the different ES grades is generally consistent in both results and thus the results obtained by the VW method can be verified. Compared with the CW method, the VW method can obtain a more detailed ES classification and identify more es hazardous areas such as mining sites and tailing sites.

Considering the temporal ES assessment results for mining sites [see Fig. 7(b)] with Table III, it can be seen that the assessment results of different ES levels obtained using the two methods have changed to different degrees. The largest change is in the "very insecure" area, mainly due to the inclusion of the VW method, which results in a higher degree of penalty than incentive within the assessment. In CW evaluation, the weight of each indicator is the same in different years and does not change as the indicator values change. However, in VW evaluation, due to the higher degree of penalty compared to incentive, the weights of negative indicators such as desertification index and land surface temperature increase relatively in years with lower ES levels, leading to more accurate assessment results.

D. Driving Factors in ES Change

1) ES Driving Factors: Using the factor detector of the GD model, we analyzed the explanatory power of 21 indicator

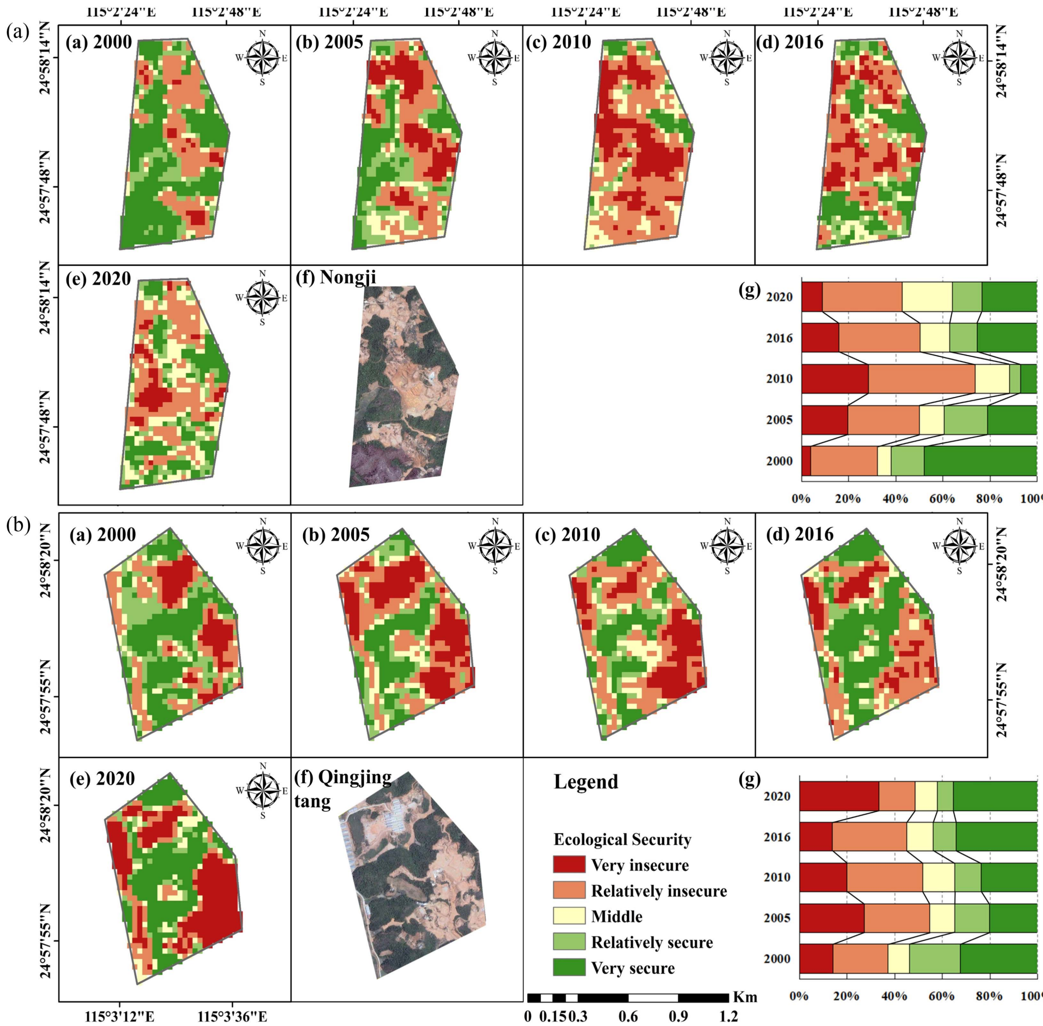

Fig. 6. ES evaluation of typical mining sites in Lingebei mining area (2000–2020).

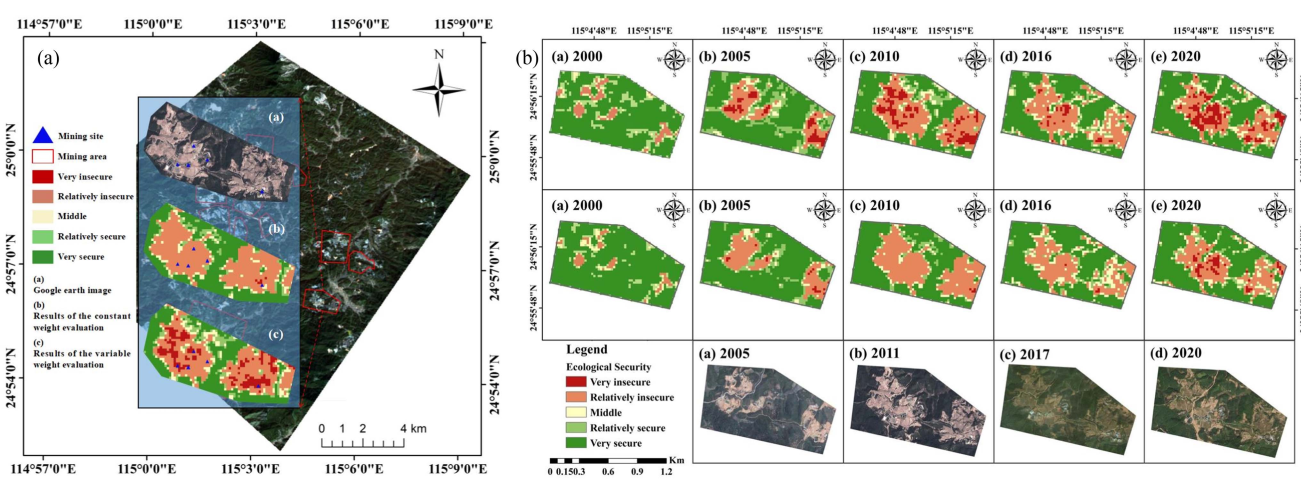

Fig. 7. (a) Comparison of results between VW and CW methods. (b) Temporal and spatial comparison of results between CW and VW methods.

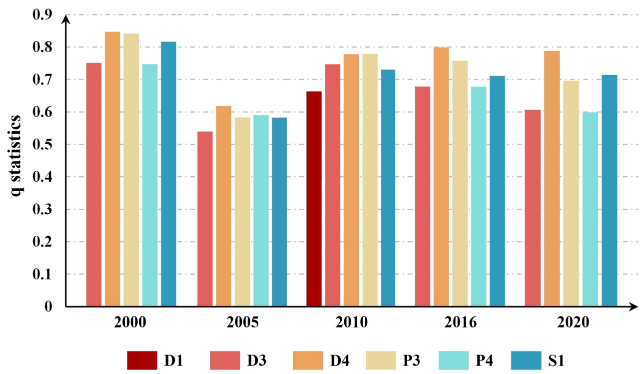

Fig. 8. Explanatory power of factors in RE mining areas (2000–2020)—ES Driving factors.

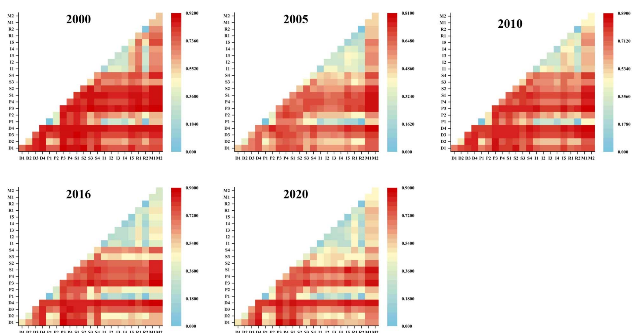

Fig. 9. Explanatory power of factors in RE mining areas (2000–2020)—Interacting explanatory power.

factors individually with respect to ES status and identified the top five driving factors (see Fig. 8). The results indicate that the ES status in the study area is primarily influenced by the three subsystems of drivers, pressures, and states. The explanatory power of each indicator on the ES status of the mining area is significant ($P < 0.001$), and there are differences in their influence at different time periods.

In terms of influencing factors VHI (D4), Desertification Index (P3), FVC (S1), LST (D3), DEM (D1), WET (S2), and NDBSI (P4) had a strong explanatory power for the ES status of the mining area. Among them, the VHI (D4) was always in a strong explanatory state during 2000–2020.

2) Detection of ES Interactions: The ES of RE mining areas is affected by a combination of influencing factors. In this article, we use the interactive analysis function of the GD model to analyze whether the explanatory power of the spatial distribution of ES indices in the mining area will be increased or decreased between two different driving factors when they act together. The interactions between driving factors are categorized into the following five situations (see Table IV).

An interaction analysis was conducted on the 21 driving factors, and the results are shown in Fig. 9. The interaction between any two factors is greater than the effect of a single factor. The results of factor interaction analysis consistently show either two-factor or nonlinear enhancement, with the two-factor enhancement pattern being the most prominent. The evolution of ES in mining areas is the result of the synergistic influence of many factors, and the different factors interact with each other. During the five monitoring years, the interaction of VHI (D4) with other factors was the most pronounced, consistently exceeding 60%. Considering the actual conditions of the mining area, it can be inferred that the vegetation health status serves as a crucial driving factor throughout the entire process of ES evolution in RE mining areas. It plays a significant role in the stability and resilience of the ecological system within the mining area. The interaction mechanisms of ES influencing factors in the mining area vary in different years, but the desertification index (P3), green space per capita (M1), VHI (D4), and educational attainment of residents (M2) always show a strong explanatory power.

IV. Discussion

A. Dynamic Evolution Characteristics of ES in RE Mining Areas

Combining the spatial and temporal changes in ES of the mining area as a whole with those of typical mining sites, further analysis shows that the process of ES change in the Lingbei RE mining area can be divided into the following three stages.

From 2000 to 2005, the ES status of the mining area changed significantly, with the areas of "very insecure" and "relatively insecure" expanding markedly, indicating that the ES status of the area is in a stage of slow deterioration. The reason for this phenomenon is that since the reform and opening up, the market demand for RE has increased, the price of REE has risen, and the REE industry has shown rapid development [33]. However, the early RE mining process is simple, coupled with the fact that most of the RE mining areas in Lingbei are located in remote mountainous areas, the mining sites are small and dispersed, the supervision is poor, and the phenomenon of indiscriminate mining and theft is serious. Frequent mining of RE, topsoil stripping to form dumps, and the expansion of industrial structures in the mining area, replacing the original vegetation, are the main reasons for the deterioration of regional ES. From 2005 to 2010, the area of "very insecure" and "relatively insecure" areas continued to expand, and the regional ecological security status entered a phase of rapid deterioration. While the in situ leaching method, upon its widespread adoption, may not directly lead to the devastating destruction of vegetation, the injection of substances like ammonium sulfate into the mountains through the leaching solution can have irreversible impacts on the root systems of vegetation. Simultaneously, the advancement in mining process technology has enabled large-scale mechanized production, resulting in profound land disturbance and a drastic decline in regional ES status.

From 2010 to 2020, the areas classified as "very secure" and "relatively secure" exhibited an expanding trend, indicating an improvement in the regional ecological environment. The ES status within the mining area reversed, entering a phase of stable development. On one hand, the concentration of mining rights and the continuous strengthening of government regulatory efforts, have to some extent curbed illegal mining activities. Another main reason is that since 2011, the RE mines in Ganzhou have become one of the first nationally planned RE mining areas in China. In addition, with the implementation of policies such as "Green Mining" since 2016, local government departments have invested significant funds in mine governance and remediation. As a result, most RE mining areas in southern Jiangxi have ceased mining operations, resulting in significant ecological restoration [34]. On the other hand, the cessation of RE mining has led to significant unemployment among the surrounding residents. In order to promote local economic development, ecological restoration measures in the mining area have transitioned from the previous singular focus on vegetation restoration to a vigorous promotion of various diverse models, such as orchards and vegetable cultivation. This transition in industrial focus has gradually alleviated the economic pressure on the local community [35].

B. Analysis of the ES Driving Factors in Mining Areas

From the perspective of the explanatory power of each factor, it can be observed that LST (D3), VHI (D4), desertification index (P3), and NDBSI (P4) consistently had the most significant influence on ES during the monitoring period. This indicates that anthropogenic activities have the most pronounced spatially differentiated impact on ES in mining areas. With the strengthening of environmental restoration efforts and the increased focus on reclamation in mining areas, the impact of detection factors on ES in 2020 has decreased compared to 2000. This reduction is particularly noticeable for LST (D3) and desertification index (P3), further confirming the significance of human activity changes in facilitating the restoration of ES in RE mining areas.

From the results of the interaction analysis of various factors, it is evident that the vegetation health status is one of the most important natural factors influencing ES in mining areas. The degree of desertification represents the change in the physical and chemical properties of the land due to human activities, and the significant interaction between these two factors indicates that natural factors have increased their influence on the spatial distribution of ES under the influence of human activities.

C. Application of VW Model in ES Evaluation of RE Mining Area

The establishment of a dynamic ES evaluation system for ion adsorption RE mining areas and the realization of dynamic spatial and temporal evolution research on the ES of mining areas. In essence, it involves an objective analysis of various influencing factors, including natural, economic, and human activities within the study area, followed by the construction of a comprehensive evaluation model that can effectively capture the multifaceted interactions of these factors. The results of the assessment should provide an objective and accurate representation of the ES status of the region. The commonly used CW evaluation model maintains fixed weight values regardless of variations in the indicator values of the evaluation units [18], [20]. Fixed and unvarying weight values fail to capture the impact of internal differences within indicators on the evaluation results, subsequently affecting the objectivity and accuracy of the evaluation results [36]. Compared to the mine area ES research conducted by Tian and Wang et al. [37], [38], the introduced VW model in this study has the capability to adjust and allocate weights of evaluation indicators for different years, evaluation units, as well as various mining and restoration patterns within the mining area. This allows for a more tailored and realistic assessment outcome that better aligns with the actual conditions of the study area. Therefore, this study has established a penalty-dominant hybrid VW function that aligns with the evaluation characteristics of RE mining areas. It can provide a more detailed reflection of ES levels and their degree of differentiation, particularly in small-scale typical mining sites, enabling the identification of a greater amount of ES risk information.

V. CONCLUSION

This study presents a dynamic ES assessment method tailored for RE mining areas. Combining the DPSIRM framework and the VW theory, and based on the mechanism of how various factors impact ES, an ES evaluation model for RE mining areas was established. This model was used to evaluate the spatiotemporal evolution characteristics of ES in the mining area. The results show the following.

1) Between 2000 and 2020, the spatial distribution of "very insecure" and "relatively insecure" areas in the mining area varied significantly, while the spatial distribution of "very secure" areas with stable ES status showed relatively minor variations. The overall ES status of the mining area showed a dynamic trend of deterioration followed by improvement and finally stabilization, indicating that the ES of the Lingbei mining area is extremely unstable due to the combined influence of various factors.
2) From the perspective of influencing factors, vegetation health status is one of the most important driving factors of ES in the mining area. Furthermore, the interaction between any two factors in the mining area is greater than the explanatory power of the individual factors, suggesting that natural factors under the influence of human activities have increased the degree of influence on ES.
3) The introduction of VW theory allows the results to obtain a more detailed distribution of ES levels, identifying ES hazardous areas such as mining sites and tailing sites. The VW model can effectively solve the problem of not failing to reflect the impact of internal differences of the indicators on the evaluation results in the CW evaluation, and it has a better application value in the small and dispersed ionic RE mining areas.

APPENDIX

See Tables V and VI.

TABLE V
DESCRIPTION OF ES EVALUATION INDEX SYSTEM AND DPSIRM MODEL IN THE RE MINE

Target layer	Criteria layer	Index layer	Calculation method	Attribute
ES of the RE mining area	Driver	D1: DEM	Direct access	(+)
		D2: Slope	DEM data extraction slope	(+)
		D3: Land surface temperature	Mono-Window algorithm calculation obtained [39]	(−)
		D4: Vegetation health index (VHI)	VHI=0.5VCI+0.5TCI [40]	(+)
	Pressure	P1: Soil Erosion Degree	RULSE algorithm calculation obtained [40]	(−)
		P2: Density of population	Direct access	(−)
		P3: Desertification difference index	Albedo-NDVI algorithm calculation obtained	(−)
		P4: Dryness index (NDBSI)	NDBSI=(IBI+SI)/2 [41]	(−)
	State	S1: Vegetation coverage (FVC)	$FVC = \frac{NDVI-NDVI_{soil}}{NDVI_{veg}-NDVI_{soil}}$ [42]	(+)
		S2: Wetness index	TM Tasseled Cap equivalent transformation method obtained [41]	(+)
		S3: Soil organic matter content	Direct access	(+)
		S4: Tasseled cap brightness (TCI)	Transformation coefficients method obtained [43]	(−)
	Impact	I1: Mine sites kernel density	Kernel density analysis obtained	(−)
		I2: Patch density	Fragstats moving window method obtained	(−)
		I3: Shannon's diversity index	Fragstats moving window method obtained	(+)
		I4: Area-Weighted Mean Patch Fractal Dimension	Fragstats moving window method obtained	(−)
		I5: NPP	Direct access	(+)
	Respond	R1: GDP	Statistical data	(+)
		R2: Distance from mine site	Distance analysis obtained	(+)
	Management	M1: Green space per capita	Statistical data	(+)
		M2: Educational attainment of residents	Statistical data	(+)

((+) is positive indicator, (-) is negative indicator)

TABLE VI
CW AND VW VALUE

Indicator	D1	D2	D3	D4	P1	P2	P3	P4	S1	S2	S3	S4	I1	I2	I3	I4	I5	R1	R2	M1	M2
CW/VW	**0.0223**	**0.0343**	**0.0926**	**0.0588**	**0.0499**	**0.0329**	**0.1573**	**0.0741**	**0.0957**	**0.0251**	**0.0188**	**0.0443**	**0.0401**	**0.0105**	**0.0211**	**0.0104**	**0.0238**	**0.0259**	**0.0779**	**0.0561**	**0.0281**
1	0.0229	0.0313	0.0808	0.0513	0.045	0.0293	0.1373	0.0653	0.0874	0.0219	0.0164	0.0396	0.04	0.0092	0.0394	0.0091	0.0257	0.0229	0.1306	0.0594	0.0353
2	0.0228	0.0293	0.0792	0.0509	0.0441	0.0291	0.1345	0.069	0.1155	0.0215	0.0161	0.0476	0.0343	0.009	0.0386	0.0089	0.028	0.0224	0.1273	0.048	0.024
3	0.0227	0.0286	0.0884	0.0532	0.043	0.0284	0.161	0.0619	0.0879	0.021	0.0157	0.0398	0.04	0.0088	0.0377	0.0087	0.0311	0.0219	0.1208	0.0547	0.0248
4	0.021	0.0379	0.0871	0.0517	0.0422	0.0279	0.1607	0.0653	0.0839	0.0222	0.0154	0.0414	0.0332	0.0086	0.037	0.0085	0.0318	0.0215	0.1021	0.0691	0.0315
5	0.019	0.0293	0.1131	0.0644	0.044	0.0291	0.1527	0.0802	0.0953	0.0235	0.0161	0.0378	0.0343	0.009	0.0386	0.0089	0.0292	0.0224	0.0719	0.0559	0.0253
6	0.02	0.0307	0.0931	0.0589	0.0461	0.0305	0.1408	0.0663	0.1028	0.0225	0.0168	0.0397	0.041	0.0094	0.0405	0.0093	0.0285	0.0234	0.0697	0.0755	0.0345
7	0.0235	0.0383	0.0892	0.0541	0.0474	0.0312	0.1448	0.0724	0.0881	0.0231	0.0173	0.0408	0.0369	0.0097	0.0416	0.0096	0.0297	0.0241	0.1007	0.0516	0.0259
8	0.0235	0.0294	0.0755	0.0479	0.042	0.0294	0.141	0.0604	0.078	0.0205	0.0153	0.0389	0.0558	0.0086	0.0368	0.0085	0.0271	0.0213	0.1116	0.0819	0.0465
9	0.0229	0.0434	0.0768	0.047	0.0412	0.0263	0.1256	0.0651	0.1013	0.02	0.015	0.0354	0.0366	0.0084	0.0361	0.0083	0.033	0.0209	0.1305	0.0676	0.0388
10	0.0247	0.0415	0.0774	0.0491	0.0431	0.0281	0.1314	0.0619	0.1044	0.022	0.0157	0.0477	0.0335	0.0088	0.0378	0.0087	0.0199	0.0219	0.1419	0.0504	0.0302
11	0.0239	0.0285	0.0769	0.0489	0.0428	0.0276	0.1401	0.0616	0.0795	0.0209	0.0156	0.038	0.0376	0.0087	0.0375	0.0086	0.0329	0.0218	0.1449	0.0656	0.038
12	0.0239	0.0275	0.0744	0.0472	0.0414	0.0264	0.1263	0.0595	0.1073	0.0232	0.0151	0.0447	0.0322	0.0084	0.0363	0.0084	0.0321	0.021	0.1355	0.0695	0.0398
13	0.0239	0.0272	0.0779	0.0463	0.0393	0.0291	0.135	0.072	0.086	0.0276	0.0148	0.0568	0.0346	0.0083	0.0356	0.0082	0.0325	0.0206	0.1	0.0793	0.045
14	0.0263	0.0302	0.0755	0.0479	0.042	0.0268	0.161	0.0604	0.0861	0.0205	0.0153	0.0386	0.0327	0.0086	0.0368	0.0085	0.0309	0.0214	0.1213	0.0694	0.0398
15	0.0252	0.0356	0.0745	0.0469	0.0411	0.0262	0.1413	0.0591	0.0903	0.0234	0.015	0.0569	0.0366	0.0084	0.036	0.0083	0.0317	0.0209	0.1162	0.0675	0.0387
16	0.0261	0.0287	0.0795	0.0493	0.0432	0.0276	0.1421	0.0621	0.0807	0.021	0.0158	0.0381	0.0447	0.0088	0.0379	0.0087	0.0251	0.0219	0.1207	0.0751	0.0429
17	0.0258	0.0302	0.0861	0.0517	0.0439	0.028	0.134	0.0631	0.0815	0.0214	0.016	0.0394	0.0343	0.009	0.0385	0.0089	0.0303	0.0223	0.1133	0.0778	0.0445
18	0.0235	0.0336	0.0775	0.0492	0.0431	0.042	0.1608	0.0637	0.0902	0.0229	0.0157	0.04	0.0384	0.0088	0.0378	0.0087	0.0234	0.0219	0.0657	0.085	0.0483
19	0.0188	0.0298	0.0965	0.0619	0.0436	0.0283	0.145	0.0707	0.109	0.0212	0.0159	0.0374	0.0387	0.0089	0.0382	0.0088	0.0277	0.0221	0.0834	0.059	0.035
20	0.0207	0.0319	0.0861	0.0547	0.0479	0.0317	0.1463	0.0689	0.096	0.0233	0.0222	0.0412	0.0426	0.0098	0.042	0.0097	0.0398	0.0244	0.0724	0.0609	0.0276
21	0.0201	0.0309	0.0841	0.053	0.0464	0.0307	0.1417	0.0667	0.1017	0.0226	0.0215	0.0399	0.0413	0.0095	0.0407	0.0094	0.0427	0.0236	0.0879	0.059	0.0267
22	0.0216	0.0455	0.0899	0.0556	0.0487	0.032	0.1486	0.07	0.0904	0.0237	0.0226	0.0428	0.0433	0.0099	0.0427	0.0098	0.0249	0.0247	0.0736	0.053	0.0266
23	0.0189	0.0291	0.0901	0.0539	0.0438	0.0287	0.1669	0.0711	0.0883	0.0227	0.0203	0.0421	0.0389	0.0089	0.0384	0.0088	0.0391	0.0222	0.0938	0.0476	0.0263
24	0.0191	0.0395	0.076	0.0483	0.0423	0.0279	0.1617	0.0929	0.0833	0.0262	0.0154	0.0435	0.0377	0.0086	0.0371	0.0085	0.0361	0.0215	0.1051	0.0461	0.0231
25	0.0221	0.0268	0.0918	0.0549	0.0402	0.0263	0.1599	0.0797	0.0888	0.0226	0.0147	0.0392	0.0358	0.0082	0.0353	0.0081	0.0186	0.0211	0.1274	0.0491	0.0293
26	0.0186	0.0286	0.0821	0.061	0.043	0.0278	0.1422	0.0795	0.0893	0.0217	0.0157	0.037	0.0335	0.0088	0.0377	0.0087	0.0336	0.0219	0.1083	0.0637	0.0373
27	0.025	0.0469	0.076	0.0482	0.0423	0.027	0.1355	0.0795	0.0876	0.0221	0.0154	0.0363	0.0391	0.0086	0.0371	0.0085	0.0378	0.0215	0.0883	0.0745	0.0426
28	0.0264	0.0376	0.0843	0.0545	0.0443	0.0279	0.1334	0.0628	0.0812	0.0213	0.0159	0.0376	0.0498	0.0089	0.0383	0.0088	0.037	0.0222	0.0911	0.0741	0.0425
29	0.0187	0.0343	0.0783	0.0493	0.0432	0.0417	0.1318	0.0621	0.0947	0.0229	0.0158	0.0424	0.0381	0.0088	0.0379	0.0087	0.0336	0.0219	0.0824	0.0851	0.0484
30	0.0241	0.0389	0.0734	0.0466	0.0408	0.0261	0.1246	0.0683	0.1014	0.0199	0.0149	0.0455	0.0318	0.0083	0.0358	0.0082	0.0263	0.0287	0.1283	0.0687	0.0394
31	0.0216	0.0385	0.0758	0.0482	0.0422	0.027	0.1288	0.076	0.0945	0.0206	0.0154	0.0363	0.0424	0.0086	0.037	0.0085	0.0195	0.0214	0.1305	0.068	0.0391
......																					

Note: (Due to the excessive number of evaluation units, only a portion of the weight value will be shown).

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