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Evaluation Study of Ecological Resilience in Southern Red Soil Mining Areas Considering Rare Earth Mining Process

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Abstract: Ion-adsorption rare earth mining areas are located in southern China's ecologically fragile red soil hills region. For a long time, under the influence of multiple factors such as low mining technology and indiscriminate mining, this area has experienced serious environmental problems. Therefore, it is crucial for the ecological management and restoration of mining areas to accurately conduct a quantitative evaluation of ecological restoration status. We used remote sensing and geographic information data to establish an ecosystem resilience evaluation index system consisting of five criteria (land stress, vegetation conditions, surface conditions, biodiversity, and air pollution) and 17 evaluation factors. The Lingbei rare earth mining area in Dingnan County in the red soil hill region was used as a case study since it is a representative ion adsorption rare earth mining area. The restoration status of the mining area was evaluated from 2000 to 2020. The results showed the following: (1) From 2000 to 2020, the ecological resilience level of the mining area was 0.695, 0.685, 0.664, 0.651, and 0.657, exhibiting a decrease followed by an increase. (2) Spatially, the ecological resilience was low at the mine site and increased with increasing distance, indicating that rare earth mining adversely affected ecological resilience in the mining area. (3) The regional ecological resilience has improved over time due to the implementation of green development policies. However, the rate of improvement is slow and ecological restoration of mining areas will remain an ongoing challenge in the future. This study can provide a scientific basis and practical reference for the ecological protection and restoration of mining areas.

Keywords: rare earth mining area; ecological resilience; mining disturbance; multi-index evaluation; comprehensive evaluation model; combination weighting method; spatio-temporal evolution analysis

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1. Introduction

As a non-renewable strategic resource, rare earth deposits are crucial for high-tech and national economic development [1]. Ionic rare earth deposits are formed by the migration and enrichment of clay minerals during ion adsorption [2]. Whether it is the early pool leaching and heap leaching technology, or the improved in situ leaching process, it will change the original ecosystem structure of the mine, causing a series of environmental problems such as land desertification, ammonia and nitrogen enrichment in water bodies, excessive heavy metal contents in the soil, and vegetation degradation [3,4]. The contradiction between economic development and ecological environment in mining areas is becoming increasingly prominent. Lei's research suggests that in order to achieve sustainable development of mining areas and to solve the conflict between resource extraction and ecological environment, ecological restoration and the reconstruction of mining areas is the key [5]. Li's research found that ecological protection should be taken as fundamental to improve the sustainable development of mining areas according to the natural environment and socio-economic development of the region [6]. Therefore, exploring the ecological restoration process of mining areas and coordinating the relationship between rare earth mining and ecological protection are the keys to achieve the sustainable development of mining areas.

Ecological resilience is a fundamental aspect of restoration ecology, which focuses on the study of natural ecosystems destroyed or degraded by human activities and natural catastrophes and their restoration and reconstruction [7]. The concept of resilience was first introduced into the study of ecosystems by the American ecologist Holling in 1973 [8]. With the deepening of research in this field, the research on ecological resilience has also been enriched and developed. Wang's research shows that ecosystems have different structures and properties due to different natural conditions such as landscape, vegetation, climate, and soil, which determine the magnitude of ecological resilience [9]. Mining ecosystems are anthropocentric and holistic ecosystems, and the disturbances caused by human activities have changed the functional composition of mining ecosystems. Once the mining ecosystem is destroyed, it is difficult to restore its original state, so it is difficult to evaluate the resilience of the mining ecosystem. Therefore, by combining with 3S technology, a multi-level and multi-scale evaluation index model is established [10] which provides a new idea for the evaluation of ecological resilience in mining areas.

Remote sensing has been widely used for regional environmental monitoring and assessment due to its broad spatial coverage and multi-temporal monitoring ability [11,12]. At present, the use of remote sensing for ecological resilience assessment has become a key research question in ecological monitoring [13,14]. For example, Morey constructed an applicable urban ecological security evaluation framework based on a limited number of security indicators and dimensions from the perspective of ecological restoration and circulation [15]. Valente has developed a multi-indicator model for agricultural watersheds combining multi-criteria assessment (MCE) and participatory techniques to provide decision support for agricultural landscape ecosystem service under different forest ecological restoration states [16]. Wu assessed the ecosystem resilience of coal mining areas in the Yellow River Basin based on influencing factors such as soil, vegetation conditions, and biodiversity to provide scientific strategies for ecological conservation in the Yellow River Basin [17]. The unique metallogenic characteristics of the ionic rare earth mining area in the red soil region in southern China result in a complex ecosystem. Thus, the factors influencing ecological restoration differ significantly from that of other regions [18], thus targeted indicator establishment is required for ecological resilience assessment in mining areas. Ecological resilience is often influenced by biodiversity, ecological storage, habitat conditions, climate, human activities, and other factors [19]. Therefore, on the basis of the above criteria, this paper adjusts the appropriate parameters for the ecological destruction characteristics of the mining area, and reasonably reflects the process of rare earth mining and ecological restoration, while respecting the objective laws of the ecosystem. Finally, the index model was constructed from five aspects: land stress, vegetation conditions, surface environmental status, biodiversity, and air pollution load. In the process of index quantification, the correlation between indicators and the weight determination affect the results. These limitations can be solved by using a combined weighting [20] and a comprehensive index method [21] to develop a multi-perspective quantitative evaluation model for regional ecosystem restoration that incorporates subjective and objective methods.

In this context, we extract various relevant indicators in the mining area by using remote sensing, meteorological, topographic and economic statistics data for the special mining process, and red soil characteristics of the mining area combined with the comprehensive index method and combined weighting to build a mining ecological restoration evaluation index system model to quantitatively evaluate the ecological resilience of the mining area from 2000 to 2020. This study provides key basic data and quantitative monitoring methods for the ecological restoration of ion-adsorption rare earth mining areas. Combining this method with the mining process and policies at different stages, analyzing the reclamation effect and ecological restoration status is important for further implementation of ecological restoration planning and promoting the sustainable development of mining areas.

2. Study Area and Data Collection

2.1. Study Area

The Lingbei rare earth mining area is located in northern Dingnan County, Jiangxi Province, China, with geographical coordinates of 114.97°E~115.19°E, 24.85°N~25.05°N and a total area of 214 km^2. The terrain is complex and consists mainly of mountains and hills. Figure 1 shows the geographical location of the study area.

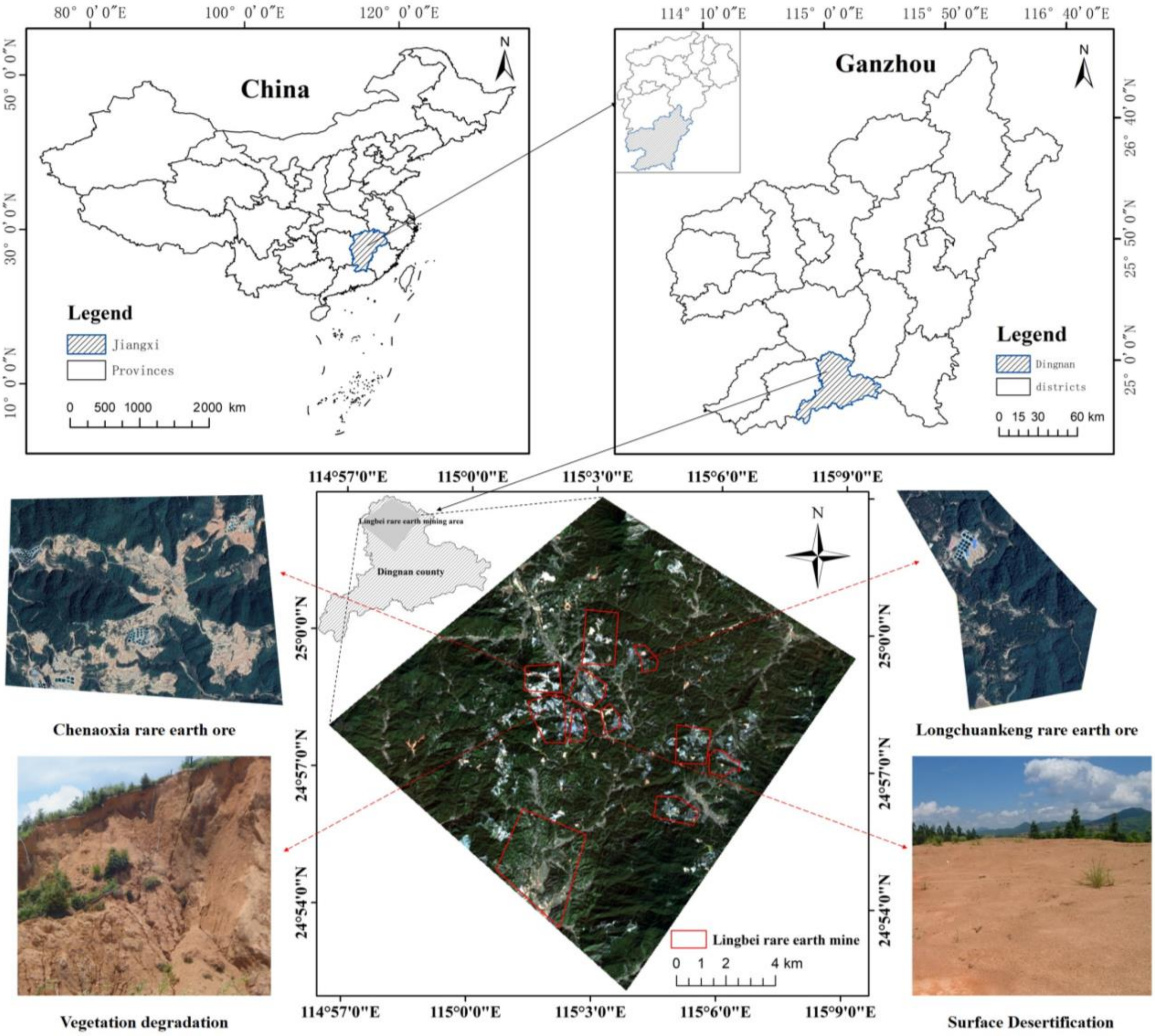


Figure 1. Location map of the study area.

Mining methods have undergone three technological stages since 1960: pond leaching, heap leaching, and in situ leaching [22]. Before 2001, rare earth mining was dominated by pond leaching and heap leaching, which stripped the topsoil in large areas, causing extensive damage to vegetation, massive tailing accumulation, soil erosion, and landslides that pose a serious threat to the ecological environment [23]. In situ leaching was used predominantly after 2002. Although this method was an improvement over the first two processes, its implementation was more difficult, and the leaching agent leaked into the soil. Thus, the water and soil around the mine accumulated large amounts of nitrogen compounds, causing water pollution and land desertification. As a result, the ecological damage was not reversed by this process [24]. Large-scale reclamation has been implemented in mining areas since 2012. However, areas of reclaimed vegetation increased slowly, the vegetation was stressed by the pollutants, and the reclamation performance was not satisfactory. The ecological restoration of mining areas in the red soil region with low soil quality and high soil erosion is difficult but remains a top priority.

2.2. Data Sources and Preprocessing

The data used for this study includes remote sensing, topographic, land use, meteorological, atmospheric, and statistical data from 2000 to 2020. The types, formats, sources, and descriptions of data are listed in Table 1. Among them, the study area was clear and cloudless during remote sensing image acquisition and all data are extracted, interpolated, and resampled into 30 m grid cells.

Table 1. Data types and descriptions.

Data Type	Data Formats	Data Sources	Data Descriptions
Remote sensing data during 2000–2020	Landsat5 TM/8 OLI image data	Geospatial Data Cloud (http://www.gscloud.cn/)	The remote sensing image data were used to invert vegetation, temperature, and other indicators.
Topographic Data	Raster data at 30 m resolution	Geospatial Data Cloud (http://www.gscloud.cn/)	The topographic data were used to calculate temperature and soil erosion indicators.
Land use data during 2000–2020	Grid cells at 30 m resolution	China Land Cover Dataset (CLCD) [25]	Land use data were used to calculate landscape metrics.
Meteorological data during 2000–2020	Monthly rainfall data	National Meteorological Information Center (SURF_CLI_CHN_MUL_MON)	The meteorological data were used to calculate RULSE model.
Atmospheric data during 2000–2020	Table format	Atmospheric Composition Analysis Group of Dalhousie University and China CO_2 county-level data [26]	The atmospheric data were used to calculate atmospheric pollution indicators.
Statistical data during 2000–2020	Table and text format	National Bureau of Statistics of China (http://www.stats.gov.cn/)	The statistical data were used to obtain the population, area, and so on.

Since the study area is located in the mountainous region of southern China and belongs to the subtropical monsoon humid climate, the rainy season in the first half of the year makes it difficult to obtain useful information from the optical images during this period. Although there is green vegetation coverage throughout the year, the different growth states of the vegetation make the index information extracted different. To ensure the consistency of the spectral information, the image acquisition time of this study was concentrated in August–December each year. In addition, the study area is a complex ecosystem that integrates natural, economic and social factors. Its natural factors include high temperature and rainfall climatic factors, topographic factors consisting of mountains and hills, and sensitive red soil characteristics, which make the bare soil easily eroded by rain leaching. Economic and social factors include long periods of mining and farming activities in which large amounts of waste rock and tailings left by mining directly lead to land degradation, and irrational farming creates conditions for vegetation degradation and soil erosion. 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.

3. Research Methods

3.1. Establishing an Index System to Evaluate Ecological Restoration in Mining Areas

Establishing a comprehensive and effective index evaluation system is crucial for the accurate and quantitative evaluation of ecological resilience. Therefore, the indicators were chosen to be applicable to the ecological characteristics of the rare earth mining area and the goals of ecological restoration. We focused on five aspects: land stress, vegetation conditions, surface conditions, biodiversity, and atmospheric pollution. The indicators are listed in Table 2.

Table 2. Evaluation index system for ecological resilience in ionic rare earth mining areas.

Target Layer A	Criteria Layer B	Index Layer C	Objective Weight	Subjective Weight	Combined Weight	Trend
Evaluation index system for ecological resilience A	Land stress B_1	Desertification index C_1	0.0554	0.1815	0.1185	−
		Soil erosion degree C_2	0.0566	0.0906	0.0736	−
	Vegetation condition B_2	FVC C_3	0.0573	0.2534	0.1554	+
		VHI C_4	0.0613	0.1269	0.0941	+
	Surface condition B_3	Population density C_5	0.0619	0.0075	0.0347	−
		HAI C_6	0.0543	0.0115	0.0329	−
		Wetness index C_7	0.0706	0.0552	0.0629	+
		Dryness index C_8	0.0597	0.0302	0.0450	−
		LST C_9	0.0577	0.0369	0.0473	−
		Surface albedo C_{10}	0.0564	0.0213	0.0389	−
		TCI C_{11}	0.0555	0.0175	0.0365	−
	Biodiversity B_4	BAI C_{12}	0.0562	0.0192	0.0377	+
		ECO C_{13}	0.0667	0.0122	0.0395	−
		SHDI C_{14}	0.0560	0.0271	0.0416	+
		FN C_{15}	0.0603	0.0421	0.0512	+
	Atmospheric pollution B_5	PM2.5 Emissions C_{16}	0.0567	0.0223	0.0391	−
		CO_2 Emissions C_{17}	0.0575	0.0446	0.0511	−

3.1.1. Land Stress Indicators

The study area is located in the red soil mountain region of southern China, with poor soils and high rainfall. Frequent mining activities coupled with continuous soil erosion have reduced the quality of the already poor land. Therefore, the desertification index and soil erosion degree can be used to represent the land stress in the mining area. The desertification index is calculated using the albedo-NDVI feature space [27] as follows:

$$DDI = k * N - A \quad (1)$$

$$A = a * N + b \quad (2)$$

where k is the negative inverse of a in Equation (2), N is the vegetation index after normalization, A is the surface albedo after normalization, a is the slope of the regression equation, and b is the intercept of the regression equation in the vertical coordinate.

Soil erosion was determined using the revised universal soil loss equation (RUSLE) [28]:

$$A = K * L * P * R * C \quad (3)$$

where A is the average annual soil loss, R is the rainfall erosivity factor, K is the soil erosion factor, L is the slope length factor, S is the slope factor, C is the vegetation cover factor, and P is the soil erosion control factor.

3.1.2. Vegetation Condition Indicators

Vegetation is a critical component of the ecological environment and ecological restoration. The fractional vegetation cover (FVC) and vegetation health index (VHI) were selected to reflect the vegetation cover and health of the mining area. The vegetation health index is calculated as follows [29]:

$$VHI = a * VCI + (1 - a) * TCI \tag{4}$$

where *VCI* is the vegetation condition index, *TCI* is the temperature condition index, *a* is the contribution of *VCI* and *TCI* to *VHI*, which depends on local conditions. Here it is assumed that the water demand during plant growth is the same as the temperature contribution, and *a* equals 0.5 [30].

The FCI was estimated using the normalized difference mountain vegetation index in the dimidiate pixel model [31], which minimizes the shadow effect in mountainous terrain:

$$NDMVI = \frac{(\rho_{nir} - \rho_{red}) + (R_{min} - NIR_{min})}{(\rho_{nir} + \rho_{red}) - (R_{min} + NIR_{min})} \tag{5}$$

$$FVC = (S - S_{soil}) / (S_{veg} - S_{soil}) \tag{6}$$

where ρ_{red} and ρ_{nir} represent the Landsat reflectance in the red and near-infrared bands, respectively, R_{min} and NIR_{min} represent the minimum reflectance values in the red and near-infrared bands, S represents the vegetation index of the pixel, S_{veg} is the vegetation index of a surface completely covered by vegetation, S_{soil} is the vegetation index of completely bare land.

3.1.3. Surface Condition Indicators

Rare earth mining activities have led to extensive vegetation degradation and contributed to surface changes in the study area, such as changes in the thermal characteristics of the regional subsurface, i.e., tailings appear white. The conflict between local people and the land has increased due to continued rare earth mining and population growth. Therefore, the surface conditions of the mine site can be monitored by the population density, human effect index (HAI) [32], land surface temperature (LST), tasseled cap brightness (TCI), surface albedo (albedo), wetness index and dryness index [14]. The HAI is calculated as follows:

$$HAI = \sum_{i-1}^{n} A_i P_i / TA \tag{7}$$

where n is the number of landscape component types, A_i is the area of the *ith* landscape type in the evaluation unit (hm^2), P_i is the human impact intensity parameter in the *ith* landscape type, *TA* is the total area of the landscape in the evaluation unit (hm^2).

The LST is calculated using the radiative transfer algorithm [33]:

$$L_\lambda = \left[\varepsilon * B(T_s) + (1 - \varepsilon) L_\downarrow\right] * \tau + L_\uparrow \tag{8}$$

where T_S is the surface temperature (K), τ is the atmospheric transmittance, ε is the surface radiance, $B(T_S)$ is the black body radiation brightness, $L_\uparrow$ and $L_\downarrow$ are the upwelling and downwelling thermal radiation, respectively.

The TCI was calculated using the following transformation coefficients [34]:

$$TCB_{TM} = 0.3037\rho_1 + 0.2793\rho_2 + 0.4743\rho_3 + 0.5585\rho_4 + 0.5082\rho_5 + 0.1863\rho_7 \tag{9}$$

$$TCB_{OLI} = 0.3029\rho_2 + 0.2786\rho_3 + 0.4733\rho_4 + 0.5599\rho_5 + 0.508\rho_6 + 0.1872\rho_7 \tag{10}$$

where ρ_1 to ρ_7 are different bands of the sensor.

The surface albedo is calculated by the narrow-band to wide-band conversion algorithm [35]:

$$\alpha_{short} = \frac{0.356\rho_1 + 0.130\rho_3 + 0.373\rho_4 + 0.085\rho_5 + 0.072\rho_7 - 0.0018}{0.356 + 0.130 + 0.373 + 0.085 + 0.072} \tag{11}$$

where ρ_1 to ρ_7 are different bands of the sensor.

3.1.4. Biodiversity Indicators

The destruction of landscape structure and reduction of biodiversity caused by rare earth mining has become a major hidden danger for ecological recovery in mining areas. Biodiversity makes possible the reorganization of ecosystems after disturbances and plays a vital role in restoring them to a stable state [36]. Related studies show a positive correlation between the growth of ecological resilience as ecological diversity increases [37]. Therefore, we selected the biological abundance index (BAI) [38], the Shannon diversity index (SHDI) [39], ecological resilience (ECO) [40], and landscape fragmentation (FN) [41] to reveal the regional ecological restoration status at the landscape level, combined with Fragstats software for calculation. The biological abundance index is calculated as follows:

$$\begin{aligned} A_{bio} \times (0.35 \times Woodland + 0.21 \times Grassland + 0.28 \times Wetland \\ +0.11 \times Cropland + 0.04 \times Construction\ Land \\ +0.01 \times Utilized\ land) \end{aligned} \tag{12}$$

where A_{bio} is the normalized coefficient of biological abundance index.

The landscape fragmentation index is calculated as follows:

$$FN = MPS\left(N_f - 1\right)/N_c \tag{13}$$

where FN is the landscape fragmentation, MPS is the ratio of the average area of all patches within the landscape to the minimum patch area, N_f is the total number of patches of the landscape type, N_C is the ratio of the total area of the landscape to the minimum patch area.

The Shannon diversity index is calculated as follows:

$$SHDI = -\sum_{i-1}^{m}(p_i \times lnp_i) \tag{14}$$

where p_i is the proportion of area occupied by landscape type i, m is the number of landscape types.

3.1.5. Atmospheric Pollution Indicators

The atmospheric environmental quality reflects the level of environmental pollution in a region and the environmental quality of the mining area [42]. Thus, carbon dioxide and particulate matter emissions were selected as indicators using the Ambient Air Quality Standard GB3095-2012.

3.2. Indicator Weighting Method

The subjective weighting method is somewhat arbitrary, whereas the objective weighting method is based on indicator values and statistical methods. The latter is not affected by human factors and is science-based, although the weights may not conform to actual conditions. Therefore, this study uses a combination of subjective and objective weighting to obtain a comprehensive weight value; the specific index weights are listed in Table 2.

3.2.1. Analytic Hierarchy Process to Calculate Subjective Weights

The analytic hierarchy process (AHP) [10] is commonly used for evaluating ecological restoration. It uses an evaluation matrix based on stratification, branching, and disassembly of complex problems. It performs two comparisons to calculate weights and provides a result for the target problem. Since we used many evaluation indices, the AHP method was chosen to determine the subjective weights:

$$w_{ai} = \overline{w}_i / \sum_{i=1}^{n} \overline{w}_i \tag{15}$$

where $\overline{w}_i$ is the *n-th* root vector after multiplying the elements of the evaluation matrix one by one in a single row, I = 1, 2, 3,..., n, w_{ai} is the index's subjective weight value.

3.2.2. Mean Square Error Weighted Decision Method to Calculate Objective Weights

The mean square error weighted decision (MSE) method [43] is an objective methods to determine indicator weights according to the relative dispersion of the indicator data. It is calculated as follows.

$$w_{bi} = \sigma_i / \sum_{i=1}^{n} \sigma \tag{16}$$

where σ_i is the mean square error of each indicator, I = 1, 2, 3,..., n, w_{bi} is the index's objective weight value.

We combined the empirical and scientific aspects of the two methods to integrate the weights of each index using subjective and objective methods; the formula is as follows:

$$w_i = (w_{ai} + w_{bi})/2 \tag{17}$$

where w_i is the combined weight value of the *ith* indicator, w_{ai} is the subjective weight value, w_{bi} is the objective weight value.

3.3. Ecological Restoration Evaluation Model

3.3.1. Standardization of Indicators

Since the ecological resilience evaluation uses multiple indicators, the units, magnitudes, and orders of the indicator differ, and they cannot be compared. The positive index can help the mine to maintain stability and recover itself when the mine is disturbed by the outside world. The negative index is the opposite. Thus, it is necessary to normalize the indicators as follows [44].

For a positive index:

$$X'_{ij} = \frac{X_{ij} - min(X_{ij})}{max(X_{ij}) - min(X_{ij})} \tag{18}$$

For a negative index:

$$X'_{ij} = 1 - \frac{X_{ij} - min(X_{ij})}{max(X_{ij}) - min(X_{ij})} \tag{19}$$

where $max(X_{ij})$ and $min(X_{ij})$ are the maximum and minimum values of the *j-th* index, respectively, X_{ij} is the initial value, and X'_{ij} is the normalized value of X_{ij}; I = 1, 2, 3,..., m, j = 1, 2, 3,..., n.

3.3.2. Calculation of Ecological Resilience

The ecological resilience evaluation model is defined as [13]:

$$P = \sum_{j=1}^{n} W_j * T_j \tag{20}$$

where P is the ecological resilience value, n is the number of evaluation factors, W_j is the weight of the evaluation factors, and T_j is the standardized score of the *j-th* evaluation factor.

3.3.3. Classification Criteria of Ecological Resilience

The ecological resilience level refers to the difference in the self-sustainability of an ecosystem that has been disturbed by external disturbances and deviated from its equilibrium state. High ecological resilience level means high resistance to external disturbances. The classification of ecological resilience levels can visually show the differences in the ecological resilience in each region so that areas requiring priority ecological protection can be identified. Since no unified standard existed for the classification of ecological resilience, we considered the natural, social, and economic status of the study area and the results of domestic and international studies [10,41]. Combining calculation results and natural breakpoint method, we classified the ecological resilience values of the Lingbei mining area into five classes: severe, poor, moderate, good, and excellent (Table 3).

Table 3. Classification criteria of ecological resilience.

Severe	Poor	Moderate	Good	Excellent
<0.38	0.38–0.41	0.41–0.63	0.63–0.73	>0.73

4. Results and Analysis

The classification results of the ecological resilience of the mining area in different years are shown in Figure 2. The dynamic changes in ecological resilience in the past two decades were analyzed by calculating the growth rate of ecological resilience in different years.

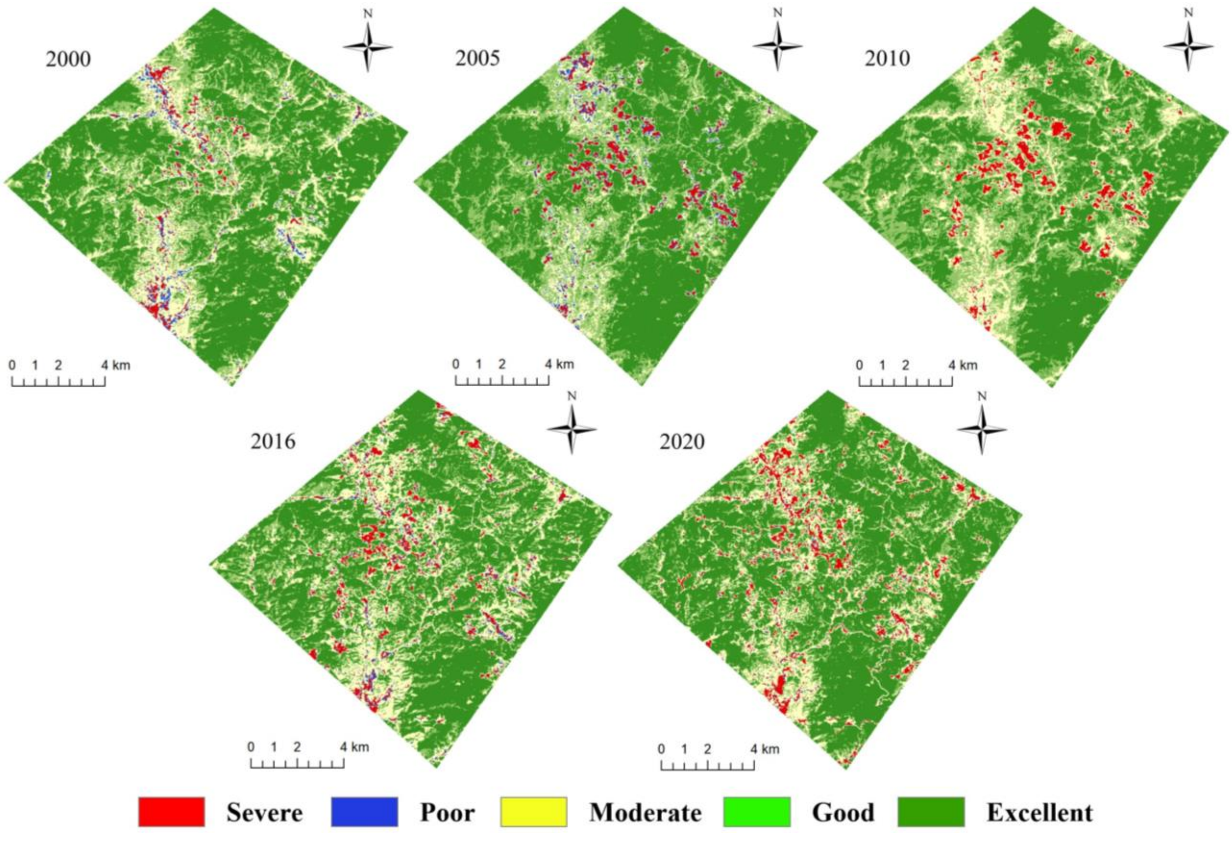


Figure 2. Ecological resilience of the mining area from 2000 to 2020.

4.1. Assessment of the Ecological Restoration Status of Mining Areas

The overall ecological resilience levels of the Lingbei mining area were 0.695, 0.685, 0.664, 0.651, and 0.657 in 2000, 2005, 2010, 2016, and 2020, respectively. The level of ecological restoration status was good, showing a decrease followed by an increasing trend. The spatial differences were significant, with low levels at the mine site and high levels in the surrounding area.

The areal proportions of the ecological resilience levels are shown in Figure 3. A higher ecological resilience level represents a greater potential for the ecosystem to return to its original state after a disturbance. The results indicate that the ecological resilience of the mining area was good in 2000. Areas with excellent and good levels accounted for 76.88% of the total area, and areas with poor resilience levels comprised 1.89% of the total area, mainly in the west and northwest of the mining area. In 2005, areas with excellent and good resilience levels accounted for 77.83% of the total area. Areas with a poor resilience level were located at the original and new mine sites, accounting for 3.06% of the total area, an increase of 61.9% compared with 2000. In 2010, areas with excellent and good resilience levels accounted for 79.11%, and areas with poor resilience levels accounted for 3.92% due to the expansion of mining sites to the surrounding areas. In 2015, areas with excellent and good ecological resilience levels accounted for 71.04%, and areas with poor ecological resilience levels accounted for 3.93%, indicating a negligible difference compared with 2010. The ecological resilience level of some mining sites changed from poor to medium and good due to a change to the in situ leaching method and reclamation. In 2020, areas with excellent and good ecological resilience levels accounted for 74.54% of the total area, and areas with a poor ecological resilience level accounted for 4.82%. These were located in the urban areas northwest of the mining area.

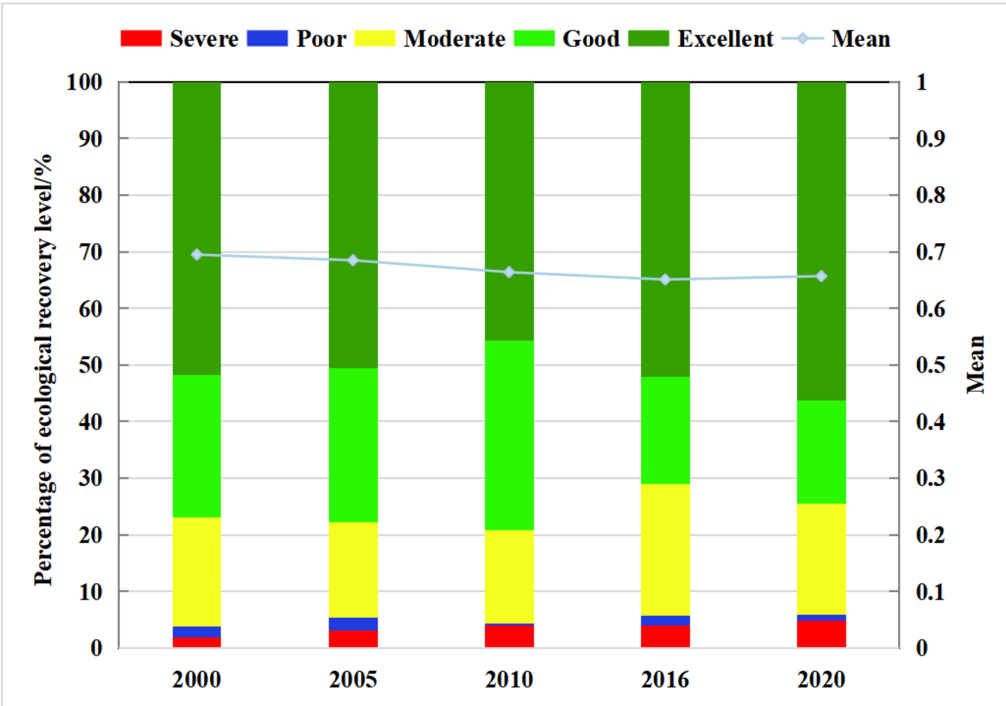


Figure 3. Percentage and mean values of ecological resilience levels in the study years.

4.2. Time-Series Analysis of the Ecological Restoration Status in Mining Areas

The ecological resilience of the Lingbei rare earth mining area showed significant change over time (Figure 4). The ecological resilience level decreased from 2000 to 2005, with a slight decline in most areas. Few areas with serious ecological degradation were observed. The scale of rare earth mining expanded sharply after 2000 due to an increased demand for rare earth metals. The initial use of strip mining damaged the vegetation and the soil structure, reducing the ecological resilience of the mining area. The level of ecological resilience in the mining area showed a downward trend from 2005 to 2010, and areas with low ecological resilience were located at the mine site and expanded to the surrounding area. The reason is that although the stripping of vegetation had slowed down after 2005 because of improvements in rare earth mining technology and the use of in situ leaching methods, the problems of rare earth mining had not been solved. The tailings area expanded continuously, and the ecological resilience of the mining area decreased. The overall ecological resilience of the mining area declined from 2010 to 2016, but the rate of decline slowed down, and some mining sites exhibited increases in the level of ecological resilience. The main reason is that the local government has issued green mining and other policies since 2010, increasing the supervision of rare earth mining. After the implementation of land reclamation, the vegetation cover gradually returned to the normal level, improving the mining area's ecological resilience. The overall resilience level of the mining area showed an upward trend from 2016 to 2020, and the ecological resilience of some mining sites increased. The ecological resilience level of the Lingbei mining area only decreased in some regions. The preliminary analysis shows that the increase in ecological resilience from 2016 to 2020 was affected by the people's continuous and active response to national ecological and environmental changes and conservation, indicating that human governance was critical in the ecological restoration of rare earth mining areas.

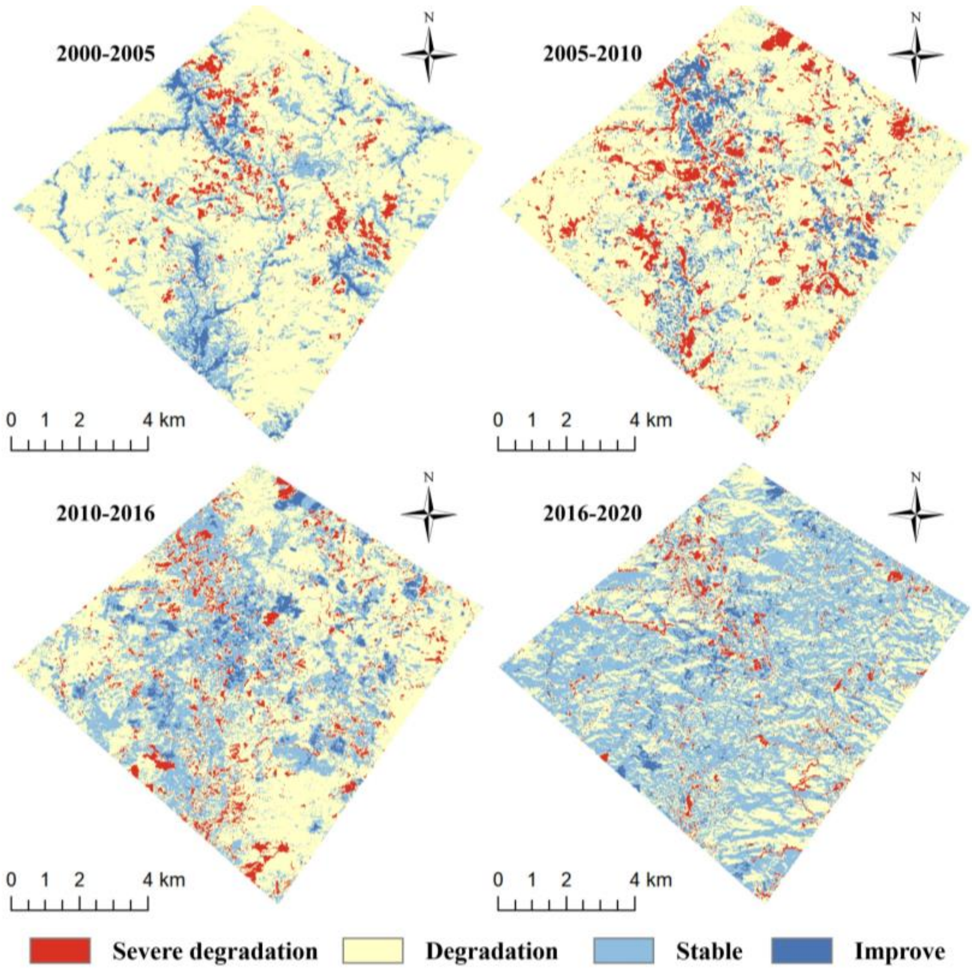
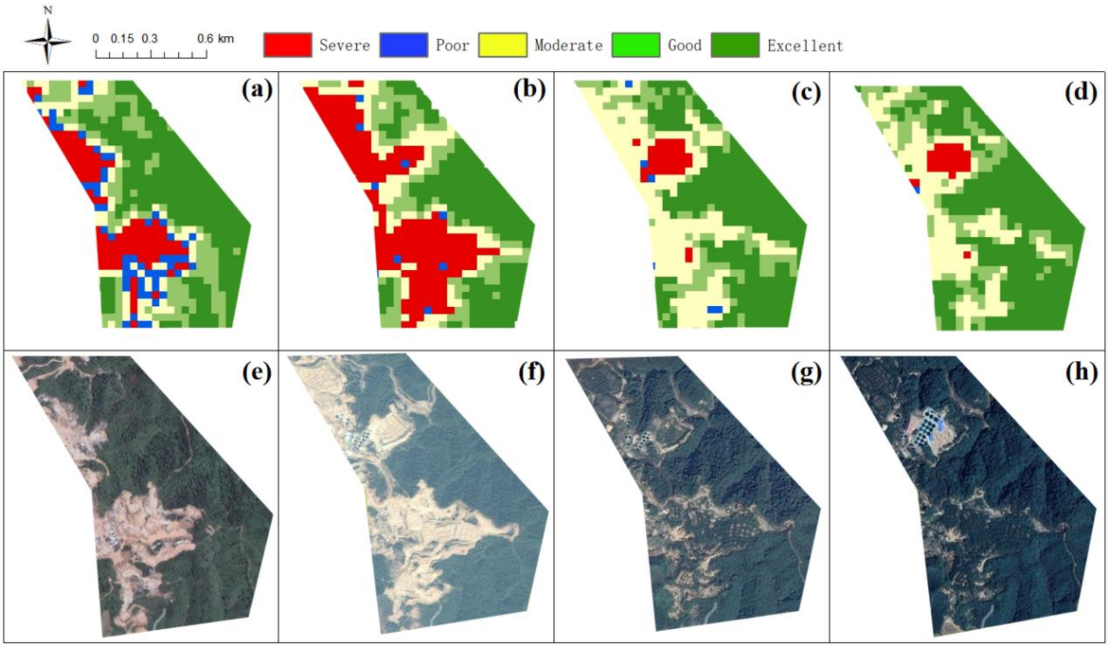


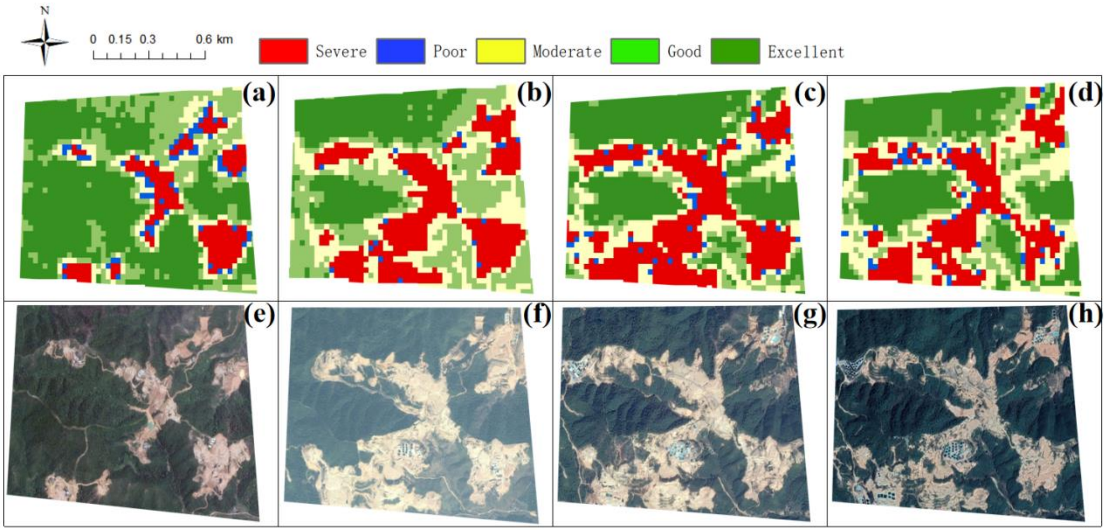
Figure 4. Spatial distribution ecological resilience change of the mining area in four time periods.

4.3. Ecological Resilience of a Typical Mining Site

To further explore the impact process of rare earth mining on the ecological resilience of the study area, we monitored and analyzed the evolutionary mechanisms of ecological restoration and the differences between different typical mining sites. The Chenaoxia and Longchuankeng mine sites were extracted as representative areas of the Lingbei mining area. These two mining sites are located in the main area of rare earth mining, and they have a more than 30-year mining history. These areas went through all three rare earth mining stages, and their mining areas are relatively large. The images of the ecological resilience levels of the mine site in 2005, 2010, 2016, and 2020 are shown in Figure 5a–d, and the Google images are shown in Figure 5e–h.



A. Google images and ecological resilience images in various periods of Longchuankeng mine.



B. Google images and ecological resilience images in various periods of Chenaoxia mine.

Figure 5. Comparison of Google images and ecological resilience levels at typical mining sites in the Lingbei Mining Area.

The Google images acquired in 2005, 2009, 2015, and 2018 are sufficiently close in time to the Landsat images acquired in 2005, 2010, 2016, and 2020 to compare them. The ecological resilience levels of the Chenaoxia and Longchuankeng mine sites were 0.669, 0.559, 0.560, 0.571 and 0.623, 0.549, 0.627, 0.652, from 2005 to 2020, respectively, showing a decreasing and increasing trend. However, the ecological restoration effect was better for the Longchuankeng mine than for the Chenaoxia mine. A comparison of the rare earth mining areas in the high-resolution image of the two mining sites showed that the spatial distribution of the severe and poor areas in the ecological resilience classification map was highly consistent, demonstrating that rare earth mining has adverse effects on the ecosystem health of the mining areas. Figure 5 shows extensive mining activities at the two mines in 2005 and before. Most of the area had been mined by 2009, and the ground remained bare from 2000 to 2010. After the in situ leaching process had been adopted, the bare surface area of the mine site did not expand significantly, and areas with severe and poor ecological resilience levels did not increase. The reclamation of the Longchuankeng mine site from 2005 to 2018 was successful, and some areas with severe ecological resilience levels improved to good levels. However, vegetation growth in the reclaimed areas was poor due to rare earth mining pollutants, and some areas still had low vegetation cover after more than 10 years. Thus, the area remained at a moderate ecological resilience level. From 2016 to 2020, in situ leaching at the Chenaoxia mine site caused vegetation degradation around the original mine site, and although the ecological resilience level did not decrease in a large area, it declined to a moderate level.

5. Discussion

This study is based on the complex surface environment of ion-adsorbed rare earth mining areas, and uses multi-source data support such as remote sensing, topography, and economic statistics to construct a mining ecological resilience evaluation model with 17 evaluation indicators in five sub-systems, in response to the long-term damage and recovery characteristics of rare earth mining areas. Moreover, on the basis of considering the influence mechanism of each indicator on the ecological resilience of the mining area, a combination of subjective and objective weighting and the comprehensive index method is used for weighted coupling to analyze its ecological resilience from multiple characteristic perspectives, providing a scientific basis for the sustainable development of mining resources. The results show that the current pattern of development in the surveyed mining areas is progressing towards ecological improvement, but that the ecological environment has not been restored to its optimum state. This is due to the reduction and degradation of forested green areas in mining areas as a result of long-term mining activities, making it impossible for the declining landscape structure and ecosystem functions of mining areas to recover in a short period of time. Looking at the local details of typical mining sites, the reclamation work is not progressing smoothly in some areas. Although the implementation of ecological restoration projects can improve the ecological condition of mining sites in the short term, there is still uncertainty as to whether the reclaimed vegetation can adapt to the local topography, climate, and growing environment in the long term.

Therefore, we quantified the process of change in the ecological resilience of rare earth mining areas and constructed an evaluation model that is better tailored for rare earth mining areas while following a scientific and comprehensive approach. Compared to previous ecological resilience evaluation studies, this method is no longer limited to the exploration of a single ecological problem, but effectively considers the ion-adsorbed rare earth mines which are integrated states between multiple variables of complex ecosystems with unknown internal mechanisms and establishes a multi-perspective understanding of regional ecological resilience that combines subjectivity and objectivity. Compared with Wu's study on the evaluation of the ecological resilience of mining areas, this method does not only consider the influence of natural factors in the selection of indicators, but selects evaluation indicators based on multiple levels of nature, human activities, and human-earth relations in the region, so as to accurately reflect the process of ecological restoration changes in rare earth mining areas [17]. The combined weighting method used in this study combines the subjective and objective conditions of the indicators, and compared with Morey's quantitative weighting of indicators, the evaluation results are more scientifically accurate and consistent with the actual situation of the study area [15]. Compared with Xiao's study, this study provides an in-depth analysis of the spatial and temporal evolution of ecological resilience in the study area as a whole and at typical mining sites based on higher resolution data and results, which can better reflect the way in which the transition between the changes in ecological resilience at mining sites and surrounding areas due to rare earth mining is articulated in order to reveal the mechanism of the impact of rare earth mining on ecological resilience [45]. The method combines a comprehensive indicator evaluation model with a combined weighting method, which can better avoid the influence of correlation between indicators and the determination of artificial weight on the results.

The data interval used in this paper is around five years due to data access constraints, making the quantitative assessment of ecological resilience in mining areas limited in scope. In future research, higher precision data will be selected to quantify the ecological restoration status of mining areas on a wider spatial and temporal scale, and taking into account the soil and vegetation growth conditions in mining areas to establish and improve a comprehensive ecological restoration evaluation model that is applicable to different mining areas.

6. Conclusions

In this study, we select the Lingbei rare earth mining area, which is located in the ecologically fragile area of southern red soil, as the research object, and uses remote sensing to trace the historical process of rare earth mining and ecological restoration in the area, and conducts scientific and accurate monitoring and quantitative assessment of the ecological resilience of the mining area from 2000 to 2020. The results show that:

(1) The ecological resilience of the Lingbei rare earth mining area showed a decreasing trend followed by an increasing trend in the past two decades. Spatially, the ecological resilience was low at the mine site and increased with increasing distance, indicating that rare earth mining reduced the level of ecological resilience of the mining area.

(2) Combined with the trend of overall ecological resilience, it is found that the areas with severe and poor levels of ecological resilience decreased, suggesting that the regional environment was stabilizing and ecological restoration measures had a positive effect. However, the level of recovery was not satisfactory, and the rate of change was slow. Currently, the ecological resilience level is predominantly good and moderate.

(3) Comparing the results of ecological resilience of typical mining sites, it can be seen that the ecological restoration processes and mechanisms vary among different sites, and most of the reclamation effects are not ideal. The strong reaction of rare earth mining to biological and ecological stresses in mining areas cannot be restored by common means, and requires targeted and differentiated ecological restoration of individual mining sites.

This study provides references for analyzing the factors influencing changes in the ecological restoration status in the Lingbei rare earth mine area and its coupling mechanism. Our results also provide a scientific basis for mine governance and ecological restoration policies, which is significant for environmental protection and high-quality development of mining areas.

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