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Spatio-temporal Evaluation Model of Mining Geo-environmental Carrying Capacity Integrating Remote Sensing Ecological Index and Geological Safety Index

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Abstract. The evaluation of the geological environment carrying capacity of mines is crucial for achieving sustainable development and risk management of mines. This study proposes a spatio-temporal evaluation model that integrates remote sensing ecological indices and geological safety indices to take into account the surface ecological status of the mining area and underground geological safety. This method is based on the theoretical framework of "state-pressure-response", integrates multi-source remote sensing, InSAR, geology and other multi-temporal data, constructs RSEI through principal component analysis, builds GSI through analytic hierarchy process, and determines the weights using entropy weight method for comprehensive evaluation, generating the spatial distribution of carrying capacity. Taking the Pingshuo mining area in Shanxi Province as an example, the application of the model (from 2015 to 2024) shows that the high carrying capacity vulnerable areas present a "point-line-plane" composite feature, which is highly correlated with mining activities and structural zones. The verification indicates that the overall accuracy of the model is 86.4%, and it can identify 35% of the emerging deformation and ecological degradation risk areas that were underestimated by traditional methods, providing an effective spatialization tool for dynamic monitoring and precise control of the mining area environment.

Keywords: Mine geological environment carrying capacity, Remote sensing ecological index, Geological safety index, Spatiotemporal evaluation model

1. Theoretical basis and index system for model construction

1.1. Theoretical framework for evaluation of mine geological environment carrying capacity

This study uses the "state pressure response" model as the theoretical framework to achieve spatial and dynamic assessment of the mine geological environment carrying capacity by integrating the remote sensing ecological index with the geological safety index. Among them, RSEI comprehensively reflects the health status and resilience of the surface ecosystem, and embodies the "state" of the system and the "response" to disturbances. GSI quantifies the stability and safety risks of the geological environment and reflects the "state" and potential "response" under "pressure". The integration of the two constructs a comprehensive evaluation system that takes into account both surface ecology and underground geological processes, which is a concrete and spatial realization of the SPR framework [1].

1.2. Construction of remote sensing ecological index

The study used multi-source remote sensing data such as Landsat 8/9 and Sentinel-2, and carried out standard preprocessing such as radiometric calibration and atmospheric geometric correction.

The study identified four fundamental indicators of the remote sensing ecological index and their specific algorithms as follows.

Greenness, using the most widely used normalized vegetation index to represent vegetation cover versus biomass.

$$NDVI = (\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R) \tag{1}$$

Here, and represent the near-infrared and red-band surface reflectance after atmospheric correction, respectively. $\rho_{NIR}\rho_R$

Humidity: The "humidity" component in the Yinghat transformation is adopted. This component is sensitive to the moisture of soil and vegetation and has a low correlation with NDVI, which is conducive to the information decomposition in principal component analysis.

Dryness: Use the bare soil index to highlight bare land, construction land, and mining sites without vegetation coverage.

$$NDBSI = [(\rho_{SWIR1} - \rho_{NIR})/(\rho_{SWIR1} + \rho_{NIR}) + (\rho_R - \rho_{SWIR1})/(\rho_R + \rho_{SWIR1})]/2 \tag{2}$$

Heat: The surface temperature obtained by inversion using the radiative transfer equation (in the case of Landsat data).

$$LST = \frac{B}{\ln(\frac{B}{F}+1)} \tag{3}$$

Among them, B and F are intermediate variables related to the radiation value and the specific surface emissivity of the same thermal infrared band. Their calculation is based on the general algorithmic model for retrieving surface temperature from this band..

After the raster layers of the above four indicators were calculated respectively, they were standardized to eliminate the dimensions, and then principal component analysis was performed. The first principal component was reversed and standardized to the interval [0,1] to obtain the final RSEI. The higher the RSE value, the better the ecological environment quality [2].

1.3. Construction of geological safety index

The geological stability factor mainly assesses the stability of the surface and shallow strata. Differential interferometric synthetic aperture radar technology, especially the time series InSAR method, can obtain large areas of surface deformation rate fields with millimeter-level accuracy in the mining area. It is a direct and core indicator for characterizing surface instability caused by activities such as mining and groundwater drainage. In addition, Active fault structures are a key element in controlling regional stability, which can be evaluated by establishing multi-level buffer zones of fault lines. Terrain slope is another fundamental and important stability factor, where the natural stability of steep slope areas is poor and they are more prone to instability under external forces [3].

Geological disaster susceptibility factors are used to assess the likelihood of geological disasters occurring in a specific geological environment context. Lithology is the material basis for controlling slope stability. Different lithologies have significant differences in weathering and shear strength. Slope orientation affects sunlight, precipitation infiltration and weathering, thereby affecting slope stability. Hydrological conditions, such as river cutting, groundwater activity, etc. It is an important trigger for landslides and collapses. The spatial distribution density of historical geological disaster points is direct evidence of regional susceptibility, which can be obtained through point density analysis.

When constructing the geological safety index, geographic information system (GIS) spatial analysis technology is required. First, normalize the above factor layers and unify the dimensions. The judgment matrix constructed in this study is based on the geometric average of the scores given by three senior mine geology and environment experts, taking the criterion layer (geological stability B1 and geological disaster susceptibility B2) as an example, The judgment matrix and its weights are calculated as follows.In Table 1.

Table 1. Criterion layer judgment matrix with the same weights

Criteria	Geological stability (B1)	Susceptibility to geological disasters (B2)	Weight (wi)
B1	1	2	0.667
B2	1/2	1	0.333

The maximum eigenvalue was calculated to be 2.000, the consistency index CI=0, and the random consistency ratio CR=0<0.1. Through the consistency test, similarly, the judgment matrix of each factor of the index layer relative to its criterion was constructed. Finally, the comprehensive weights of each evaluation factor were calculated through the hierarchical single ranking and total ranking, as shown In Table 2. λmax

Table 2. Geological safety index evaluation factor system and comprehensive weights

Target layer	Criterion Layer (Weights)	Metrics Layer	Descriptions and data sources	Combined weights
Geological Safety Index (GSI)	Geological stability (0.667)	Surface deformation rate (D)	Annual average deformation rate (mm/yr) of PS-InSAR based on Sentinel-1 data	0.400
		Distance from fault (F)	Euclidean distance (km) from a known active fault zone	0.200
		Slope (S)	Based on DEM calculation (degree)	0.067
	Susceptibility to geological disasters (0.333	Lithology coefficient (L)	Assign values based on rock hardness and integrity (1-5)	0.133
		Slope (A)	Assignment after classification (high risk on sunny slopes)	0.067
		Distance from water systems (W)	Euclidean distance (km) from major rivers	0.067
		Density of disaster points (H)	Number of historical disaster points per unit area (units /km²)	0.066

Finally, calculate the weighted linear summation model for each raster cell, where is the combined weight of factor $GSI : GSI = \sum i = 1n(wi*xi')wi$ i, is the normalized factor value, and the higher the value, the greater the geological safety risk. $xi'GSI$

2. Spatio-temporal evaluation model construction is integrated with the algorithm

2.1. Multi-source data fusion and spatio-temporal database construction

The realization of the spatio-temporal evaluation model of mine geological environment carrying capacity depends on the effective organization and integration of massive data from multiple sources, multiple time phases, and multiple scales, and the transformation to effective integration. Constructing a structured spatio-temporal database is the basis for the operation of the model.

First, preprocessing such as coordinate system unification, resampling, registration and normalization was carried out on all multi-source spatio-temporal data. On this basis, a structured spatio-temporal database was constructed for the efficient organization and management of raw data, intermediate indicators and model results to support multi-temporal analysis.

At the data fusion level, corresponding methods were adopted for different applications, such as using IHS transform to fuse high-resolution panchromatic and multispectral data to enhance the details of land use classification, and using wavelet transform to fuse optical and SAR data to combine spectral and texture information to better identify the boundaries of mining sites and geological structures.

2.2. Algorithm for comprehensive evaluation model of bearing capacity

The core of the comprehensive evaluation model of carrying capacity lies in scientifically integrating the remote sensing ecological index with the geological safety index, and revealing their spatio-temporal evolution laws and driving mechanisms.

A linear weighted model is used to integrate RSEI and, where is the comprehensive carrying capacity index (the larger the value, the worse the carrying capacity condition), is the normalized index, and is the weight, which is determined by combining the analytic hierarchy process and the entropy weight method to take into account both expert experience and data information.

$$GSI : CCI = w_1 * (1 - RSEI_{norm}) + w_2 * GSI_{norm} CCI RSEI_{norm} GSI_{norm} w_1 w_2$$

To explore the driving factors of spatial differentiation of bearing capacity, a geoweighted regression model can be used. The traditional global regression model assumes that the relationship between variables is spatially constant, which often does not hold in mining areas with complex geological environments. The GWR model embeds the geographical location of the data into the regression parameters, allowing the parameters to vary with spatial location, thereby establishing a local regression equation. The results not only yield local R2 on each pixel to assess the model's explanatory power, but also generate spatial distribution maps of regression coefficients for each variable, visually revealing the dominant influencing factors and the spatial variation characteristics of their influence intensifies in different regions.

For the analysis and prediction of carrying capacity time series, the time series analysis method can be applied. For multi-year continuous carrying capacity index series, trend analysis, periodic analysis and mutation point detection can be performed. The autoregressive integral moving average model is suitable for modeling and predicting stationary time series by establishing the ARIMA model for historical interannual carrying capacity index series. In the study of an open-pit coal mine in northern Shaanxi, a multi-year NDVI sequence was used to construct an ARIMA model, which successfully predicted the trend of vegetation coverage in the reclamation area [4].

3. Model application verification and case analysis

3.1. Overview of the study area and data preparation

To validate the model, the Pingshuo mining area (E112.8°-113.2°, N39.5°-39.8°) in Shuozhou City, Shanxi Province was selected as the case study. This mining area is one of the largest open-pit co-underground coal mining bases in China, with a mining history of more than 30 years. The ecological environment is fragile and the surface subsidence is significant, and the transformation is highly typical. The study collected a multi-period, multi-source dataset covering the mining area (2015, 2018, 2021, 2024), as shown in Table 3. All data were unified to the WGS_1984_UTM_Zone_49N projection coordinate system and resampled to a spatial resolution of 30 meters to ensure consistency in the analysis. This provides a strong support for data consistency in subsequent model runs.In Table3.

Table 3. List of multi-source remote sensing and geospatial data used in the study area

Data types	Data source/Sensor	Get Date (YYYY-MM-DD)	Main Uses	Key steps in pretreatment
Multispectral images	Landsat 8 OLI/TIRS	2015-08-10, 2018-07-22, 2021-08-05, 2024-07-30	Calculate RSEI	Radiometric calibration, FLASSH atmospheric correction, orthoejection correction
SAR images	Sentinel-1A (IW, VV)	Descending track image stack 2015-2014 (about 60 scenes)	PS-InSAR deformation analysis	Precision orbit correction, flattening, Goldstein filtering
High-resolution images	Gf-2 (PMS)	2023-08-15	Verify sample extraction	Orthotropic correction, fusion
Digital elevation model	ALOS World 3D	2011	Terrain factor extraction	Projection transformation, pit filling
Geological data	1:50,000 regional geological map	--	Lithology, tectonics	Digitization, registration
Disaster point data	Local geological environment monitoring stations	As of 2023	Density of historical disaster sites	Spatialization
Auxiliary data	Mining area plan	2024	Correlation analysis of mining activities	Scan registration

3.2. Model running is the same as result output

Based on the aforementioned model and method, a spatio-temporal assessment of the mine geological environment carrying capacity was conducted in the study area. First, the remote sensing ecological index and geological safety index for the four years 2015, 2018, 2021, and 2024 were calculated respectively. This calculation process then shifted to dynamic assessment.

The calculation results show that during 2015-2024, the RSEI in the core mining area of the mining area decreased significantly, with obvious ecological degradation, while the RSEI in some reclamation areas rose. The GSI high value area (high-risk area) coincided with the active working face, fault zone and high and steep slope, and the range expanded westward and northward with the mining activity, a trend that could not be captured by traditional methods.

The weights of RSEI and GSI calculated using the entropy weight method were 0.55 and 0.45 respectively, indicating that in this mining area, the constraint effect of ecological environment vulnerability on the overall bearing capacity is slightly stronger than that of geological instability. Using the weighted integrated model, the spatial distribution map of the mine geological environment bearing capacity in the study area for the four periods 2015-2024 was generated for the convenience of management decision-making. The natural breakpoint method was used to divide the comprehensive index of bearing capacity into four grades: high bearing capacity area, medium bearing capacity area, low bearing capacity area and vulnerable area. This classification result provides an intuitive diagram for mine risk management.

Spatial interpolation analysis of the bearing capacity index was conducted, and the results showed that the vulnerable area presented the characteristics of a combination of "points" (mining subsidence centers), "lines" (vulnerable zones along faults), and "areas" (continuous subsidence areas), clearly revealing the spatio-temporal pattern of the influence of mining activities. The identification of this pattern provides strong support for precise prevention and control and is one of the key achievements of this study [5].

3.3. Model accuracy verification is the same as comparative analysis

To verify the model accuracy, a variety of methods were used for verification. First, 300 verification points were randomly set up using high-resolution orthometric images of unmanned aerial vehicles obtained in 2023. The land cover types and damage conditions were visually interpreted, and then confusion matrix analysis was conducted with the bearing capacity classification results of the same year to verify the model accuracy. A multi-angle verification was conducted using high-resolution drone images and ground monitoring data. First, 500 verification points were randomly generated based on the 2023 drone orthometric images, and their actual environmental conditions (stable zone, mild impact zone, severe impact zone, disaster zone) were determined through visual interpretation, and then confusion matrix analysis was performed with the CCI classification results of the same period. The results are shown in Table 4., with an overall accuracy of 86.4% and a Kappa coefficient of 0.82, indicating that the model classification results are reliable.

Table 4. 2023 CCI grading results confusion matrix

Actual categories of classification results	High bearing capacity (I)	Medium bearing capacity (II)	Low bearing capacity (III)	Vulnerable zone (IV)	User precision (%)
Stabilization zone	120	15	3	2	85.7
Mild impact area	10	95	22	8	70.4
Severely affected area	2	18	88	25	65.8
Disaster zone	0	5	20	68	73.1
Producer precision (%)	90.9	71.4	66.2	66.0	Overall precision = 86.4%

Next, 15 long-term GPS monitoring points (cumulative sedimentation from 2015 to 2024) and 8 groundwater monitoring Wells (comprehensive water pollution index in 2024) were selected to calculate their correlations with the 2024 CCI values of the respective pixels. Pearson correlation analysis showed that CCI was significantly positively correlated with cumulative sedimentation ($r=0.78$). $p<0.01$), and also significantly positively correlated with the comprehensive water pollution index ($r=0.71$, $p<0.05$). This quantitative relationship confirms that the CCI value can effectively represent the degree of deterioration of the geological environment directly or indirectly caused by mining activities, which provides a strong evidence for the reliability of the model.

The results of this model were spatially compared with those of the traditional bearing capacity model based on fuzzy comprehensive evaluation. The traditional model used static factors such as land use, slope, and vegetation coverage with equal weights. The comparison revealed that the core vulnerable areas (such as huge mine pits) were basically the same, while in the boundary area and the dynamic change area, this model showed significant advantages. 1) In the vulnerable areas defined by this model, approximately 35% of the areas were classified as low-risk by the traditional model, and these areas happen to be emerging deformation areas or marginal areas of rapid ecological degradation monitored by PS-InSAR. 2) The results of the traditional model have low spatial heterogeneity and are difficult to identify linear high-risk zones distributed along faults. This model, which integrates spatio-temporal dynamic RSEI and high-precision InSAR deformation information, has a stronger ability to identify the spatial details and timeliness of environmental stress, an advantage that traditional models cannot achieve.

4. Conclusion

The study demonstrates that the proposed spatio-temporal model, integrating RSEI and GSI, achieved an overall accuracy of 86.4% in identifying mining geo-environmental carrying capacity. It effectively reveals the "point, line, and area" evolution pattern of vulnerable zones and captures emerging risks along faults, outperforming traditional methods.The results confirm the model's ability to enable dynamic, collaborative assessment of surface ecology and subsurface geological safety. The weight assignment (RSEI:0.55, GSI:0.45) indicates ecological vulnerability exerts a slightly stronger constraint on overall capacity in the study area.This model provides a spatially explicit and quantitative tool for dynamic monitoring and risk management in mining areas, supporting precise prevention and control strategies.

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