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Disturbance Study and Analysis of Vegetation Cover Dynamics in Jiaozuo Mining Area Based on Remote Sensing Monitoring

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Highlights:

- High-resolution remote sensing data were analyzed to reveal vegetation cover patterns and change trends
- Correlation coefficients and t-tests were used to accurately delineate vegetation disturbance ranges
- Interannual standard deviation was applied to quantify vegetation disturbance in the mining area

Keywords:

Fractional Vegetation Cover (FVC)

Remote Sensing Monitoring

Vegetation Disturbance

Spatiotemporal Dynamics

Jiaozuo Mining Area

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Abstract Vegetation disturbance induced by coal resource development represents a critical issue in ecological management and restoration in mining areas. This study has chosen the buffer zone surrounding the Jiaozuo mining area as the research region. Based on Landsat imagery, an improved modified three-band gradient difference model was employed to extract fractional vegetation cover (FVC). Spatiotemporal vegetation trends were revealed using Mann-Kendall and Theil-Sen slope analyses, while disturbance extent was identified by integrating the correlation coefficient method with the t-tests. Disturbance intensity was assessed using the interannual standard deviation of FVC. The results showed that: (1) During the study period, FVC exhibited significant fluctuations, with annual mean values ranging between 46.36% and 73.03%, displaying a slight overall degradation trend. A notable decline occurred between 2009 and 2010. (2) The identified high-intensity disturbance areas showed strong spatial correspondence with active mining sites, exhibiting outward expansion correlating with mining intensity. (3) Regarding the disturbance intensity, high and extremely high disturbance levels covered 35.82% of the mining area, significantly exceeding 19.90% observed in the buffer zone. Spatially, the disturbance displayed a "strong-weak" gradient distribution radiating southeastward from the mining cores. This study developed an integrated remote sensing framework for FVC extraction and disturbance assessment in mining areas, enhancing the precision and spatial explicitness of ecological monitoring. The findings provided a quantitative basis for zonal ecological restoration management in mining areas, carrying significant theoretical and practical implications for promoting sustainable development in resource-based regions.

1. Introduction

The exploitation of coal resources, while generating substantial economic benefits, induces complex land degradation issues such as subsidence, excavation, and occupation, causing severe disturbance and damage to ecosystems. This triggers a cascade of environmental problems, including vegetation degradation and surface desertification. As mining activities persist, regional ecological degradation intensifies, and the cumulative effects of ecological damage become increasingly pronounced (Li et al., 2022; Wu et al., 2014). Therefore, when studying the ecological impacts of mining disturbances, it is crucial not only to focus on the direct impact zone within the mining area itself but, more importantly, to investigate and analyze the effects of coal mining on the ecological conditions of the surrounding regions (Wu et al., 2021). Understanding how these impacts attenuate with increasing distance and scientifically delineating the ecological influence range of mining areas are essential for evaluating and mitigating ecological issues. Vegetation serves as a key indicator for assessing the ecological and environmental quality of mining areas (Bi and Liu, 2022). Investigating vegetation disturbance around opencast coal mines and evaluating the degree of damage to plant communities are of paramount importance for promoting orderly and rational exploitation of local mineral resources and maintaining regional ecological security (Yao et al., 2013). Remote sensing technology, as an efficient means of acquiring regional surface information, is widely applied in vegetation dynamic monitoring (Zhang et al., 2010; Zhang and Wu, 2015). Remote sensing-based vegetation indices and fractional vegetation coverage (FVC) can effectively characterize the state and quality changes of vegetation in mining areas, revealing vegetation response patterns to mining activities and providing data support for assessing vegetation ecological risks (Li et al., 2020). The spatiotemporal dynamics of FVC directly reflect the state and processes of regional ecosystems and serve as a critical parameter for evaluating ecological environmental quality and resource management effectiveness (Hou et al., 2024). Vegetation in mining areas suffers severe damage from anthropogenic activities like mining, leading to ecosystem degradation and reduced FVC (Liu et al., 2021;Zhang, 2022). Previous studies indicate that the spatiotemporal variation of FVC in mining areas is significantly correlated with mining intensity and distance (Li et al., 2022). Consequently, monitoring and assessing the dynamic changes of FVC in mining areas, identifying the spatial extent of vegetation disturbance, and analyzing the degree of disturbance hold significant scientific value for elucidating vegetation degradation mechanisms and informing ecosystem protection and restoration strategies.

Environmental changes in mining areas reflect the cumulative disturbance effects of human activities on the local ecology over extended periods and are directly related to different mining methods (Sun et al., 2015). Traditional monitoring of the mining ecological environment involves field surveys, sample collection, and subsequent qualitative or quantitative analysis using various physical, chemical, and biological indicators. This process is time-consuming, labor-intensive, costly, and challenging in regions with complex or unique geographical settings (Wang, 2017). Remote sensing technology successfully overcomes these limitations. Satellite remote sensing offers broad coverage, long-term time series, and diverse, extensive data, making it a rapid, comprehensive, and dynamic technical means for monitoring the ecological environment of mining areas (Chen et al., 2020; Gao et al., 2020). Utilizing multi-temporal remote sensing satellite data for long-term tracking and assessment of surface environmental changes in mining areas enables the analysis of response patterns and ecological disturbance effects of different mining methods on the surface environment, which is crucial for environmental management and ecological restoration (Li et al., 2022). Research on ecological environmental elements primarily focuses on four categories: water, atmosphere, soil, and vegetation. Different mining methods exert distinct disturbance effects on these elements. Opencast mining primarily causes surface soil and vegetation damage and dust pollution through areas like excavation and stripping zones, open pits, industrial sites, unreclaimed dump sites, and reclaimed dump sites. For instance, the EU-funded MINEO project (Reinhaeckel et al., 1998), undertaken by the University of Hanover and the Clausthal University of Technology, primarily employed airborne hyperspectral remote sensing to extract spectral variation parameters of contaminated vegetation in Germany's Ruhr mining area. Bi and Bai (2007) selected environmental factors such as stripped and piled areas, coal mining and transportation areas, slope areas, and vegetation coverage within a mining area to assess surface disturbance caused by opencast mining, deriving cumulative contribution rates via principal component analysis; the framework and methodology from this study have been widely applied and promoted in remote sensing monitoring of spatiotemporal dynamics of surface features in opencast mining areas. Lei (2010) integrated multiple monitoring methods (remote sensing, ground-penetrating radar, field observation) to reveal the coupling relationships among environmental factors like soil water, groundwater, and the NDVI vegetation index in Shendong mining area. Li et al. (2015) used 28 years of Landsat time-series imagery to detect mining locations and quantify mining disturbance in a coal mining area, revealing continuously expanding disturbance throughout the study period; the information obtained can further be used to study the impacts of mining on ecology and other environmental characteristics. In summary, remote sensing has become a vital tool for monitoring ecological disturbances from mining and is increasingly enabling quantitative assessment.

The impacts of mining activities often extend beyond the mining area itself, affecting the surrounding environment. Researching and defining the spatial extent of ecological influence is fundamental for analyzing and elucidating the pathways and mechanisms of regional ecological impacts. Domestic and international studies have addressed various ecological impacts, such as vegetation changes under ecological stress (Lechner et al., 2016), effects of mining activities on the potential geographical ranges of different species communities (de Castro Pena et al., 2017; Weir et al., 2007), monitoring surface subsidence induced by large transportation projects (Hejmanowski and Malinowska, 2016), studying the impact of inhalable particulates like atmospheric dust from mining areas (Sahu et al., 2018), and patents analyzing the ecological impact boundaries of mining from engineering or geological perspectives (Li et al., 2016). These delineations often focus on visually apparent boundaries like subsidence ranges or atmospheric influence, while studies on the boundaries of indirect ecological impacts, such as vegetation growth disturbance, which are not readily observable, are relatively scarce. Research in China on the impact boundaries of mining areas primarily focuses on small-scale extraction of subsidence ranges (Li and Zhou, 2020), vegetation growth at collapse fissures (Qiao et al., 2018), or soil conditions (Liu et al., 2019), employing methods mainly involving field sampling (Wang et al., 2016) or microwave remote sensing (Lyu et al., 2017; Zhang et al., 2019). Research on the boundary of vegetation condition impacts at the mining area scale is limited, and methodologies vary. For example, Liao et al. (2010) used vegetation indices derived from remote sensing imagery and GIS spatial analysis to study the influence range of mining activities on regional vegetation growth using the Yangquan opencast coal mine in Shanxi Province as a case study. Results indicated that vegetation indices around the mining area were affected by mining activities, with the degree of influence decreasing with distance from the mine and stabilizing beyond 500 meters. Bai et al. (2016) after field surveys in the Bayan Obo mining area in Baotou, Inner Mongolia, acquired high spatial resolution Landsat and Quickbird imagery and DEM data. Utilizing GIS spatial analysis, they established a frequency ratio analysis system, calculated three indicator factors (vegetation degradation, land destruction, soil erosion), and studied the disturbance of mining activities on the regional ecological environment. Li et al. (2018) studied the Yanzhou coalfield, establishing a soil moisture spatial distribution model for inferring subsidence water accumulation areas by calculating the Temperature Vegetation Dryness Index (TVDI) and using MATLAB for linear fitting of TVDI trends to identify the influence boundary of mining on regional habitats.

The aforementioned research highlights the growing attention from domestic and international experts to environmental issues in mining areas, particularly the monitoring of vegetation coverage and mining-induced vegetation disturbance. While most vegetation studies leverage the advantages of remote sensing data, they often overlook the issue of low monitoring accuracy in areas with sparse vegetation cover within mining areas. Employing traditional FVC calculation methods can lead to significant uncertainty in the analysis results. Furthermore, research specifically targeting the spatial extent and degree of vegetation disturbance in mining areas remains scarce. There is an urgent need to integrate high-resolution remote sensing data and localized model parameters for further analysis and research on FVC, vegetation disturbance extent, and disturbance intensity in and around mining areas.

This study aims to utilize high-resolution remote sensing data to monitor and extract multi-temporal FVC data for the Jiaozuo mining area and its surrounding region (a 10 km buffer). Using statistical analysis, modeling, and field investigations, it seeks to assess the spatial extent and degree of vegetation disturbance caused by mining activities, while considering the influence of various natural conditions. The goal is to achieve quantitative identification and assessment of the vegetation degradation process induced by mining. The findings will enhance the scientific understanding of vegetation dynamics under mining impacts and provide technical support for ecological environment management and ecological civilization construction in mining areas, holding significant scientific research value and practical application importance.

2. Materials and Methods

2.1. Study area

The Jiaozuo mining area (Figure 1) is located in northern Henan Province, China, with geographical coordinates 35°15'N–35°26'N, 113°07'E–113°28'E. The region experiences a temperate continental monsoon climate and is situated in the transitional zone between the southern foothills of the Taihang Mountains and the North China Plain. This study focuses on the Jiaozuo mining area core and extends to a 10-kilometer buffer to comprehensively encompass the potential ecological impact range of mining activities.

The Jiaozuo coalfield holds an extremely important position in the history of China's coal industry development. Its modern coal mining activities date back to 1894, making it one of the earliest four modern mines established in China with foreign capital, renowned as the cradle of China's coal industry (Zhang et al., 2020). After the founding of the People's Republic of China, the Jiaozuo coal mine contributed significantly to national economic construction, producing hundreds of millions of tons of coal cumulatively. At its peak production period, it set national records for safety, cost, and efficiency for consecutive years, with an annual output reaching approximately 7 million tons (Lu et al.,2018).

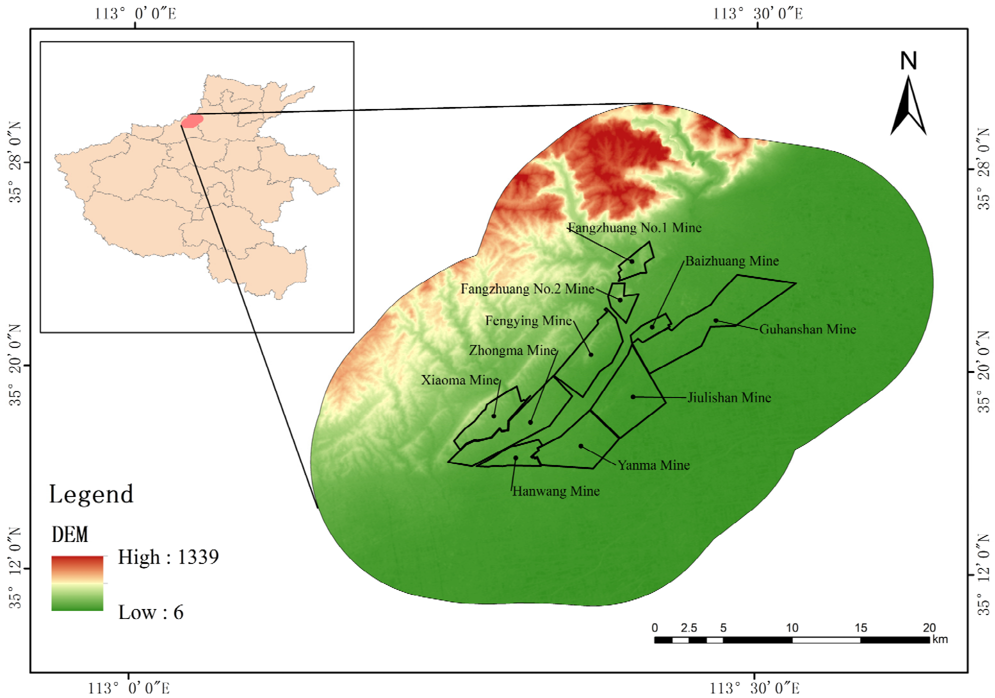

Fig. 1 Overview Map of the Jiaozuo Mining Area and the 10km Buffer Zone

The prolonged mining history and continuous production activities have shaped a dense mining landscape in the region. The study area contains over ten major coal mines, including the Jiulishan Mine, Guhanshan Mine, Zhongmacun Mine, Zhaogu No.1 Mine, and Zhaogu No.2 Mine (Si and Wang, 2021). In recent years, to enhance production capacity, the region has actively promoted the expansion, renovation, and resource integration of existing mines. Specific measures include increasing the annual output of Guhanshan Mine from 0.7 million tons to 1.8 million tons, raising Zhongmacun Mine's annual output from 0.6 million tons to 1.2 million tons, and achieving an annual increase of 4.05 million tons of raw coal through resource integration. Furthermore, the Jiaozuo Coal Group invested in constructing the Zhaogu No.1 Mine (starting its operation in 2008, with an annual capacity 2.4 million tons) and Zhaogu No.2 Mine (starting its operation in 2009, with an annual capacity 1.8 million tons) in the eastern part of the Jiaozuo coalfield, further expanding the production scale (Zhang et al., 2020).

However, such intense and sustained mining activities inevitably exert tremendous pressure and cause significant damage to the ecological environment of the mining area and its surroundings, with vegetation damage being particularly prominent (Lu et al., 2018). Therefore, selecting the Jiaozuo mining area as a case study for investigating FVC dynamic changes, disturbance extent identification, and degree assessment holds typical representativeness and urgent practical significance for understanding ecological response patterns in high-intensity mining areas, guiding regional ecological restoration, and achieving sustainable development goals.

2.2. Data collection processing

This study utilized the Google Earth Engine (GEE) cloud platform for remote sensing data processing and analysis. A long-term time-series dataset covering the period 2000–2024 was constructed using Landsat series imagery with a spatial resolution of 30 meters. Specifically, Landsat 7 ETM+ data were employed for 2000–2012, and Landsat 8

OLI/TIRS data for 2013–2024. To accurately capture vegetation conditions during the growing season, all images were acquired between June 1 and September 30 of each year.

To address the data gaps caused by the Scan Line Corrector (SLC-off) failure of the Landsat 7 ETM+ sensor after May 2003, this study applied the GapFill algorithm sourced from the Geospatial Data Cloud platform (www.gis5g.com) for restoration. This algorithm predicts and fills the missing strips by leveraging information from surrounding valid pixels, significantly enhancing data quality and temporal continuity.

The administrative boundary vector data for the study area were obtained from the National Platform for Common Geospatial Information Services. All preprocessing of the original imagery—including radiometric calibration, atmospheric correction, cloud removal, and final clipping based on the study area boundary—was efficiently and batch-processed on the GEE platform. This workflow provided a high-quality, cloud-free, and standardized data foundation for subsequent analysis.

2.3. Methodology

2.3.1 Extraction of Fractional Vegetation Coverage

Fractional Vegetation Coverage (FVC) is a key indicator for assessing surface vegetation conditions and fundamental data for describing ecosystems. Considering the prevalence of low vegetation cover in the study area due to anthropogenic and natural disturbances, and recognizing the limited accuracy of conventional FVC extraction methods, this study adopts an improved approach. Guli et al. (2017) enhanced the original Three-Band Gradient Difference method, proposing the Modified Three-Band Gradient Difference method. This method ensures positive gradient difference values (*d*) for vegetation pixels and negative values for bare soil pixels, thereby amplifying the gradient difference between vegetation and non-vegetated areas. Experimental validation confirms that the Modified Three-Band method yields FVC information consistent with measured values across different scales, effectively extracting vegetation information in low-coverage areas and producing more accurate results. The method is expressed by Formula (1):

$$FVC = \frac{d}{d_{veg}}, d = \frac{R_{ir} - R_r}{\lambda_{ir} - \lambda_r} - \frac{R_{swir} - R_{ir}}{\lambda_{swir} - \lambda_{ir}} \quad (1)$$
$$FVC = 0 \quad if \quad FVC < 0$$

Where R_{ir}, R_r, and R_{swir} represent the reflectance of ground objects in the near-infrared, red, and shortwave infrared bands, respectively; λ_{ir}, λ_r, and λ_{swir} are the central wavelengths of the near-infrared, red, and shortwave infrared bands, respectively; *d* is the pixel gradient difference; d_{veg} is the maximum pixel gradient difference; and FVC is the Fractional Vegetation Coverage. The Normalized Difference Vegetation Index (NDVI), derived from remote sensing spectral data, is a quantitative measure of surface vegetation status and serves as an optimal indicator of vegetation growth state and coverage. Fully vegetated surfaces typically exhibit NDVI values greater than 0.6. Therefore, determining d_{veg} involves first calculating the NDVI of the image (see Formula 2), then mapping ground sampling points with NDVI = 0.6 onto the image, and obtaining d_{veg} by identifying the corresponding row and column numbers. This approach effectively mitigates errors arising from inconsistent calculation scales due to human factors.

$$NDVI = \frac{R_{ir} - R_r}{R_{ir} + R_r} \quad (2)$$

2.3.2. Spatiotemporal Variation Characteristics Analysis

Based on the calculated key vegetation parameters for the study area, this study analyzes the spatiotemporal variation characteristics of different FVC grades. We employ the Mann-Kendall (MK) trend test and Theil-Sen's slope estimator, which are non-parametric statistical tests widely used for analyzing trends in non-normally distributed data. The MK test does not require the sample data to follow a specific distribution and is less sensitive to outliers. Assuming the sample dataset consists of a time series set X with n sample data, the test statistic S can be calculated using Formula (3):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \tag{3}$$

where S is a statistic following a normal distribution. Its standard normal distribution statistic Z can be obtained by Formula (4):

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, S < 0 \end{cases} \tag{4}$$

where, at a given confidence level α=0.05, if $|Z| > 1.96$, the time series data exhibits a significant trend. The Theil-Sen method is a robust non-parametric statistical technique for trend calculation. This method is computationally efficient and, unlike linear regression, does not require the time series data to follow a normal distribution. It is insensitive to measurement errors and outliers, effectively mitigating the impact of anomalous values. It is commonly used for trend analysis in long-term time series data. The method can be represented by Formula (5):

$$\beta = median[x_j - x_i] \tag{5}$$

where median denotes the median value. A positive β indicates an upward trend, while a negative β indicates a downward trend.

To systematically evaluate the spatiotemporal evolution characteristics of FVC in the mining area, this study establishes a comprehensive vegetation change trend classification system based on the results of Theil-Sen slope estimation and Mann-Kendall trend testing. Considering that slope absolute values of zero are rare in natural vegetation changes, and referencing relevant studies and the specific context of the mining area (Yuan et al.,2013), the threshold for distinguishing between FVC improvement and degradation is set at β = 0.0005.

The specific classification criteria are shown in Table 1. This system effectively differentiates vegetation change patterns of varying intensities and significance, providing a quantitative basis for assessing the mining area's ecological environment.

Table 1. Classification of FVC Change Trends

Β Value	*|Z| Value*	*Vegetation coverage change trend*
β≥0.0005	|Z|>1.96	Significant Improvemen
	|Z|≤1.96	Slight Improvement
-0.0005≤β<0.0005	|Z|>1.96	Stable
	|Z|≤1.96	
β<-0.0005	|Z|>1.96	Severe Degradation
	|Z|≤1.96	Slight Degradation

2.3.3. Vegetation Disturbance Ranges Identifying

Coal mining is a significant factor causing vegetation damage in the study area, and the degree of disturbance is related to the distance from the mining zone. Vegetation closer to the mining area likely experiences more intense disturbance, leading to more severe damage. Furthermore, the decrease in FVC is primarily associated with the continuous expansion of mining scale and the consequent intensification of human activities, such as dust dispersion during mining and screening, increases in the area and scale of mining zones and dump sites, impacts of coal transportation on surrounding vegetation, and disposal of domestic waste. Based on this premise, this study calculates the correlation coefficient of FVC over recent decades across the spatial domain. Using a t-test, areas where the correlation coefficient is statistically significant at the 0.01, 0.05, and 0.1 levels are identified to determine the vegetation disturbance extent.

When the spatial correlation coefficient *r* of FVC passes the significance test, it indicates a significant impact of mining activities on vegetation. A positive (negative) *r* signifies a linear increasing (decreasing) trend of FVC over time. Since *r* follows a t-distribution with degrees of freedom n-2, the t-distribution can be used to test the significance level of the correlation between the two variables. Therefore, this study defines areas passing the significance test as the vegetation disturbance range. The correlation coefficient can be expressed by Formulas (6) and (7):

$$b = \frac{\sum_{i=1}^{n} x_i t_i - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} t_i\right)}{\sum_{i=1}^{n} t_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} t_i\right)^2} \tag{6}$$

$$r = \frac{\sum_{i=1}^{n} t_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} t_i\right)^2}{\sum_{i=1}^{n} x_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} x\right)^2} \cdot b \tag{7}$$

Where *b* is the slope of the linear fit; x_i is the FVC in the i-th year; t_i is the year; and *n* is the total number of years.

2.3.4. Vegetation Disturbance Degree Assessing

Under natural conditions, barring abnormal extreme climate variations, the inter-annual standard deviation of FVC typically exhibits little change. However, in areas disturbed by human activities like the Jiaozuo mining area, the inter-annual standard deviation of FVC may be significantly influenced by external factors, reflecting the instability of vegetation distribution. This study utilizes the inter-annual standard deviation of FVC as a key indicator to quantitatively assess the degree of disturbance experienced by vegetation within the mining area, reveal the spatiotemporal variability of FVC, and evaluate the impact of disturbance on vegetation. Analyzing the standard deviation of FVC across the study area helps determine the disturbance degree inflicted by mining activities on vegetation at different locations, providing a scientific basis for assessing and managing the effectiveness of vegetation restoration and ecological protection measures in the mining area.

3. Results

3.1. Spatiotemporal Variation Characteristics of Fractional Vegetation Cover

Based on Landsat time-series imagery from 2000 to 2024, the vegetation coverage map of the Jiaozuo mining area during the study period was retrieved using the Modified Three-band Gradient Difference Method (Figure 2), with the statistical results of its interannual variation presented in Table 2. Spatially, the natural forest areas in the foothills of the Taihang Mountains in the northwest and the farmland areas in the east consistently maintained high vegetation coverage, forming the ecological baseline of the region. In contrast, the mining operation areas, industrial sites, and urban built-up areas in the central and southeastern parts exhibited significantly low vegetation coverage. Major transportation arteries and river corridors also formed belt-shaped or linear low vegetation coverage corridors due to frequent human activities. During the study period, the mean annual FVC in the Jiaozuo mining area ranged between 46.36% and 73.03%, demonstrating significant interannual fluctuations. The lowest mean FVC (46.36%) occurred in 2010, while the highest (73.03%) was recorded in 2006. Notably, a sharp decline in FVC was observed between 2009 and 2010, which coincided with the operational commencement of the Zhaogu No.1 (commissioned in 2008) and Zhaogu No.2 (commissioned in 2009). This temporal correlation indicates that the concentrated launch of new mining operations exerted a significant impact on regional vegetation.

The standard deviation (SD) of FVC effectively reflects the level of spatial heterogeneity in regional vegetation, with higher values indicating greater spatial disparity. The SD of FVC in the Jiaozuo mining area from 2000 to 2024 ranged from 0.1823 to 0.2538. The minimum SD (0.1823) was observed in 2000, and the maximum (0.2538) in 2018. The overall increasing trend in SD throughout the study period suggests an enhancement in the spatial heterogeneity of FVC within the mining area, indicating a progressively more distinct spatial differentiation pattern in vegetation conditions.

A univariate linear regression analysis performed on the annual mean FVC values from 2000 to 2024 yielded a change slope of -0.000414 units/year and a correlation coefficient of -0.0454 (p = 0.829). Although this decreasing trend was not statistically significant, the overall fluctuation pattern shows that after the sharp decline in 2009-2010, the FVC exhibited a trend of fluctuating recovery. This recovery pattern may be associated with a series of ecological restoration measures implemented after 2008, including land reclamation and vegetation rehabilitation projects in the mining areas. Particularly after 2015, with the advancement of green mine construction, FVC was maintained at a relatively stable level, reflecting the positive effects of ecological restoration measures. However, the persistent increasing trend in SD indicates that while the overall vegetation condition improved, vegetation degradation in localized areas remained an issue. This polarization phenomenon highlights the complexity of the mining area ecosystem and the long-term nature of ecological restoration work.

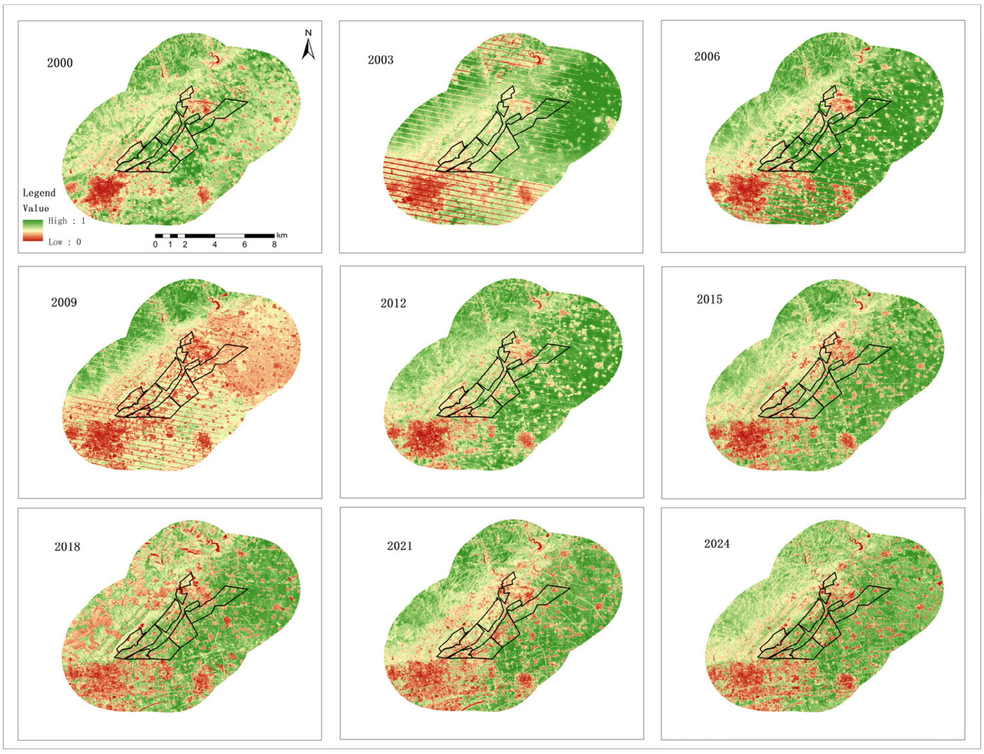

Fig. 2 Vegetation Cover Map of the Jiaozuo Mining Area and the 10km Buffer Zone from Selected Years between 2000 and 2024.

Table 2. Statistics of mean and standard deviation of vegetation coverage from 2000 to 2024

（a）Statistics of mean and standard deviation of vegetation coverage from 2000 to 2008

Year	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*
FVC	66.14%	56.62%	68.85%	64.55%	64.15%	67.66%	73.03%	67.17%	66.81%
SD	0.1823	0.2230	0.2087	0.2410	0.1946	0.2000	0.2344	0.2260	0.2357

（b）Statistics of mean and standard deviation of vegetation coverage from 2009 to 2017

Year	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
FVC	48.11%	46.36%	71.70%	70.59%	71.91%	64.81%	69.90%	64.24%	57.85%
SD	0.2011	0.2275	0.2011	0.2100	0.2341	0.2369	0.2038	0.2179	0.2193

(c) Statistics of mean and standard deviation of vegetation coverage from 2018 to 2024

Year	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*	*2024*
FVC	62.03%	55.88%	64.75%	65.37%	67.56%	62.85%	64.57%
SD	0.2538	0.2504	0.2199	0.2299	0.2222	0.2310	0.2343

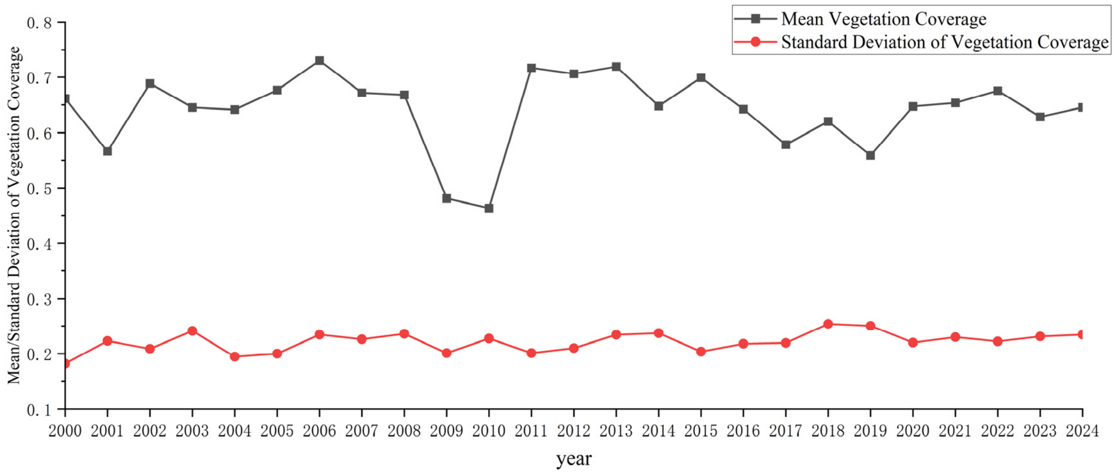

Fig. 3 Annual average change trend of vegetation coverage and interannual variability from 2000 to 2024

3.2 Interannual Variation Trend and Significance of Fractional Vegetation Cover

The spatial distribution of FVC change trends from 2000 to 2024 in the Jiaozuo mining area and its 10 km buffer zone, based on the MK-TS comprehensive analysis method, is shown in Figure 4, with detailed change statistics presented in Tables 3 and 4. The results exhibit distinct spatial heterogeneity. According to the classification system, vegetation change trends were divided into five types, and statistical results show significant differences in the areal distribution of each type within the study area.

Within the 10 km buffer zone of the Jiaozuo mining area, areas with vegetation improvement (including significant and slight improvement) accounted for 45.14% of the total area. Specifically, the area of significant improvement was 173.32 km² (9.60%), and the area of slight improvement was 641.83 km² (35.54%). Improvement areas were primarily distributed in the peripheral edges of the mining area and scattered zones where ecological restoration projects were implemented. Their spatially dispersed distribution likely reflects the positive effects of natural recovery and ecological restoration efforts. Areas with vegetation degradation (including slight and severe degradation) accounted for 44.50% of the total area. The area of severe degradation was 257.62 km² (14.26%) and exhibited strong spatial aggregation, predominantly concentrated immediately around large mines such as the Guhanshan Mine and Zhaogu No.1 Mine, as well as along main transport corridors and waste dump areas, forming distinct ecological disturbance corridors. The area of slight degradation was 546.12 km² (30.24%), mainly located in the transitional zones between the core mining areas and the peripheral regions, reflecting the spatial diffusion effect of mining impacts. Stable areas accounted for 187.14 km² (10.36%), primarily situated in regions relatively less disturbed by mining activities, potentially representing vegetation communities maintaining natural succession processes.

Spatial analysis further revealed a close correlation between vegetation change trends and the intensity of human activities. Although the overall proportions of improvement and degradation are similar between the core mining area and the buffer zone, their spatial composition and driving mechanisms are fundamentally different. The core mining area contains large mines such as Guhanshan and Zhaogu No.1. Its severe degradation areas (16.61%) are highly aggregated around the operational zones, waste dumps, and transport corridors of these mines, clearly identifying intensive mining activity as the direct driver of sharp vegetation decline.

In contrast, the extensive 10 km buffer zone's vegetation degradation pattern (44.50%) results from the combined effect of multiple factors. On one hand, it is influenced by the diffusion of mining impacts from the core area, manifesting as a degrading transitional belt surrounding the mining zone. On the other hand, the buffer zone itself contains substantial urban built-up areas, towns, villages, and transportation networks, where human activities such as urbanization and infrastructure development independently cause vegetation degradation, thereby elevating the overall degradation percentage for the buffer zone. This is the key reason why the quantitative proportions are similar but their intrinsic meanings differ.

Consequently, the attenuation pattern of vegetation degradation from the core mining area outwards remains clearly discernible in space. The most severe degradation hotspots align highly with locations of intensive mining activity, particularly around mines like Jiulishan and Zhongmacun, and their supporting infrastructure. This spatial correspondence provides strong evidence for a direct link between mining intensity and the degree of vegetation degradation.

Overall, the study area exhibits coexisting and proportionally comparable trends of vegetation improvement and degradation, reflecting that despite the advancement of ecological restoration policies, the pressure from human-induced disturbances remains substantial. Degradation in the core mining area is primarily driven by mining, whereas degradation in the buffer zone results from the combined effects of mining influence and urban expansion, among other factors.

Table 3. Statistics on vegetation change trends in the 10km buffer zone of Jiaozuo mining area from 2000 to 2024

Change trend of vegetation	*Area/ km²*	*Area proportion*
Significant Improvemen	173.32	9.6%
Slight Improvement	641.83	35.54%
Stable	187.14	10.36%
Slight Degradation	546.12	30.24%
Severe Degradation	257.62	14.26%

Table 4. Statistics on vegetation change trends in Jiaozuo mining area from 2000 to 2024

Disturbance Degree	*Area/ km²*	*Area Proportion*
Significant Improvemen	17.91	9.9%
Slight Improvement	70.66	39.06%
Stable	11.06	6.12%
Slight Degradation	51.24	28.32%
Severe Degradation	30.05	16.61%

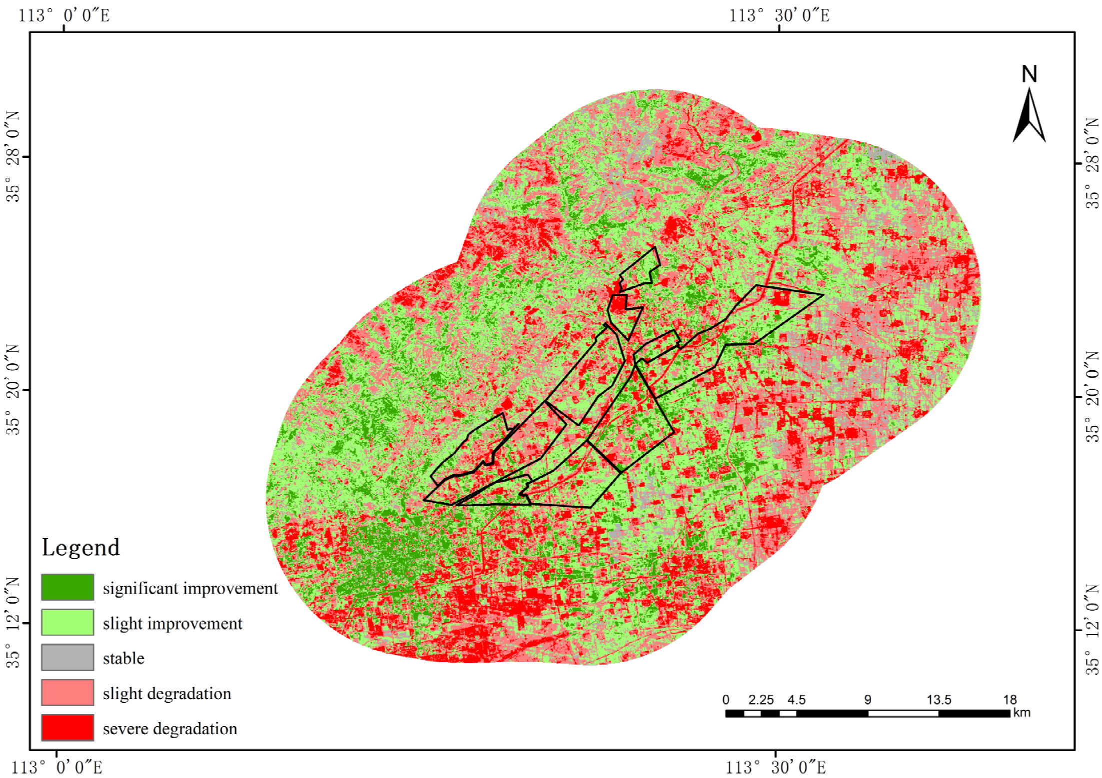

Fig. 4 Spatio-emporal variation of vegetation coverage in Jiaozuo mining area and 10km buffer zone

3.3. Identification Results of Vegetation Disturbance Extent

To scientifically delineate the extent of vegetation disturbance caused by mining activities, this study calculated the correlation coefficient between the Fractional Vegetation Cover (FVC) and time for each pixel based on data from 2000 to 2024. Statistical tests were conducted at three significance levels ($p < 0.01$, $p < 0.05$, $p < 0.1$). Areas showing a significant negative correlation were identified as vegetation zones disturbed by mining activities.

The spatial distribution of the identified vegetation disturbance extents at different significance levels is shown in Figure 5. Overall, the identified disturbance areas exhibit a clustered distribution pattern centered around major mining facilities. Under the stringent significance level of $p < 0.01$, the vegetation disturbance extent was primarily concentrated immediately adjacent to direct operation sites such as mine shafts, open pits, waste dumps, and industrial yards. As the significance level was relaxed (from $p < 0.05$ to $p < 0.1$), the disturbance extent progressively expanded from the core areas towards the periphery, demonstrating a distinct gradient diffusion characteristic. Particularly at the $p < 0.1$ level, the disturbance extent not only covered the main direct destruction zones but also extended along major transport routes and areas downwind of the dominant wind direction, reflecting the indirect impacts of dust settlement and human activity intensity on vegetation.

Spatial overlay analysis further revealed a high consistency between the vegetation disturbance extent and the spatial pattern of mining activities. The most severe disturbance core ($p < 0.01$) highly coincided with the boundaries of the industrial sites of high-intensity mining operations, such as the Guhanshan Mine and Zhaogu No.1 Mine. Moderate disturbance areas ($p < 0.05$) often corresponded to the coverage areas of waste dumps and zones affected by land subsidence. The slight disturbance boundaries ($p < 0.1$) roughly outlined the maximum spatial extent of mining impact, effectively encompassing the composite mining landscape formed by point-source mines, linear roads, and areal waste dumps.

In summary, by integrating the correlation coefficient method with statistical testing, this study successfully identified the extent of vegetation disturbance caused by mining activities in the Jiaozuo mining area. The results indicate that vegetation disturbance occurs not only in direct destruction zones but also diffuses its influence to the surrounding landscape through various pathways, exhibiting a concentric structure that attenuates from the core outward. This provides a direct decision-making basis for precisely defining the ecological impact boundaries of the mining area and implementing zonal management strategies.

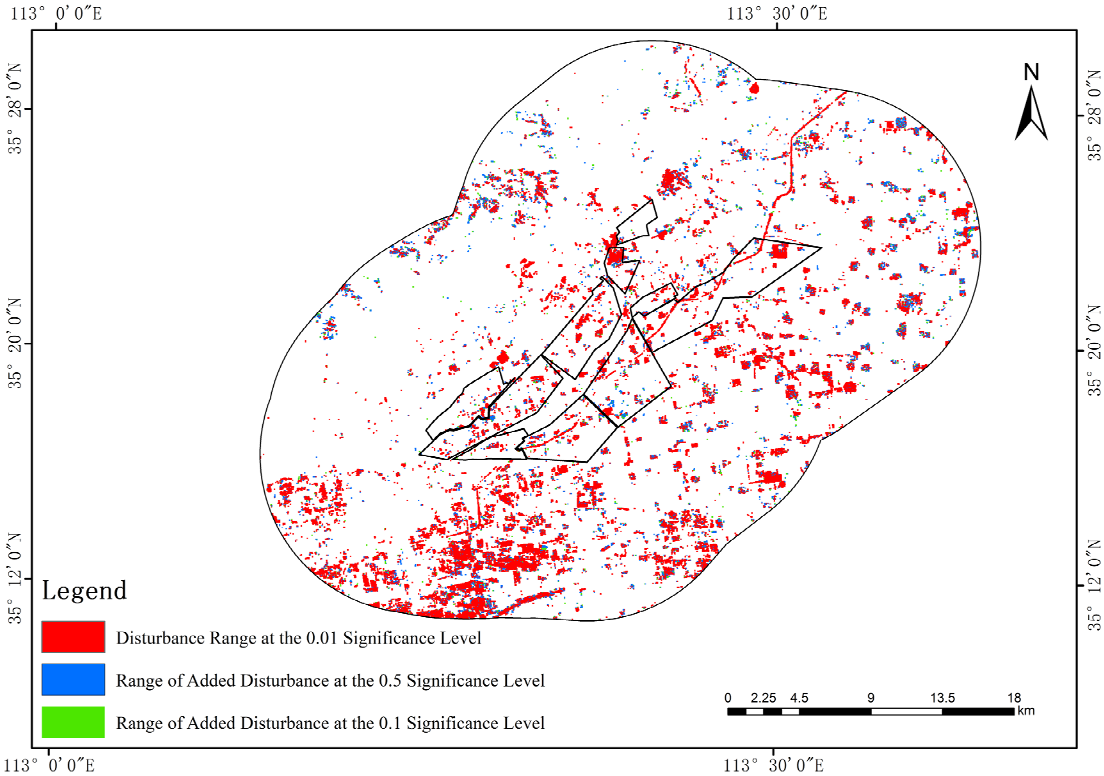

Fig. 5 Vegetation disturbance range identification in the Jiaozuo mining area and 10km buffer zone

3.4. Assessment Results of Vegetation Disturbance Intensity

To quantitatively evaluate the intensity of vegetation disturbance in the mining area, this study employed the inter-annual standard deviation of Fractional Vegetation Cover (FVC) as a key indicator, aiming to reveal the stability of vegetation growth and the degree of disturbance. Under natural conditions, inter-annual fluctuations in FVC are typically confined to a small range, whereas significant external disturbances disrupt this stability, leading to an increased standard deviation.

The analysis results (Figure 6) show that the coefficient of variation of FVC within the 10 km buffer zone of the Jiaozuo mining area exhibits significant spatial heterogeneity, with a value range from 0 to 0.429 and a mean value of 0.1407. To more intuitively reveal the degree of vegetation disturbance over the 25-year period in the mining area, and with reference to relevant literature (Bai , 2022.) and the value range of the inter-annual standard deviation, the standard deviation values were classified into five levels from low to high: Extremely Low Disturbance (inter-annual standard deviation < 0.06), Low Disturbance (0.06 ≤ inter-annual standard deviation < 0.12), Moderate Disturbance (0.12 ≤ inter-annual standard deviation < 0.18), High Disturbance (0.18 ≤ inter-annual standard deviation < 0.24), and Extremely High Disturbance (inter-annual standard deviation ≥ 0.24). The spatial distribution of vegetation disturbance intensity in the study area, classified according to the above criteria, is shown in Figure 3-5. The areas and percentages for each disturbance intensity level within the buffer zone and the core mining area are presented in Tables 5 and 6, respectively.

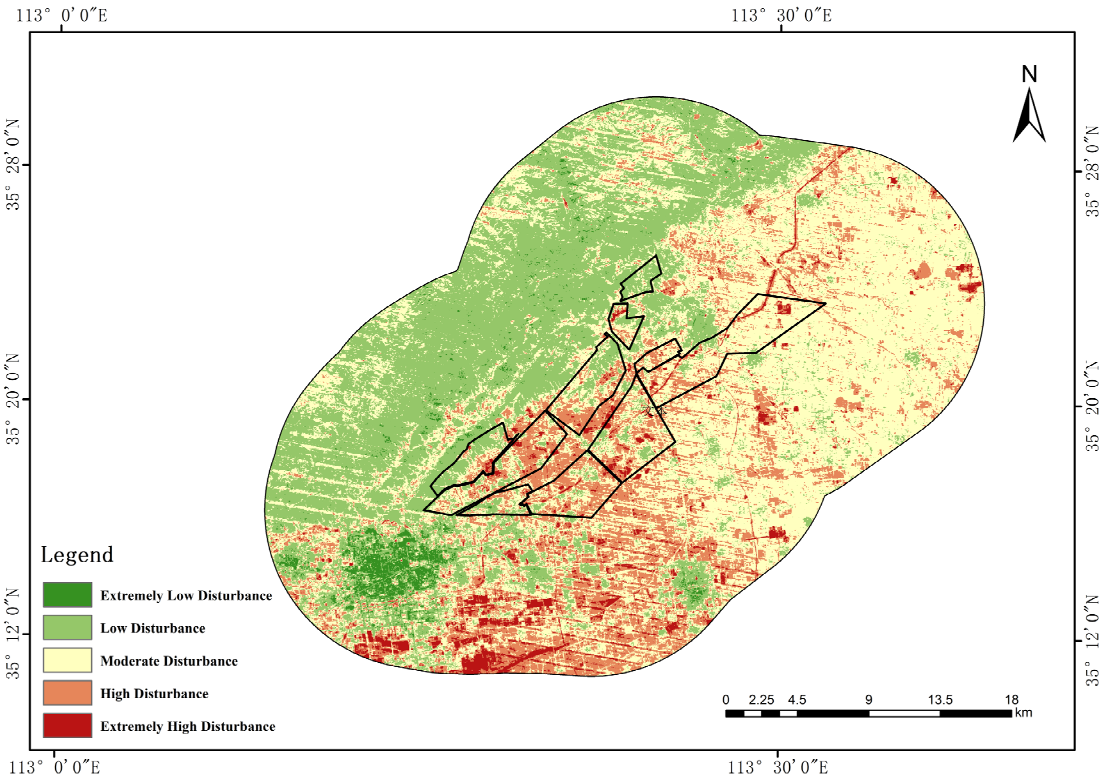

Fig. 6 Spatial distribution of vegetation disturbance degree in Jiaozuo mining area and 10km buffer zone

Table 5. Vegetation disturbance statistics in the 10km buffer zone of Jiaozuo mining area from 2000 to 2024

Annual Standard Deviation	*Disturbance Degree*	*Area/ km²*	*Area Proportion*
Interpolation<0.06	Extremely Low Disturbance	31.62	1.75%
0.06≤Interpolation<0.12	Low Disturbance	591.8	32.77%
0.12≤Interpolation<0.18	Moderate Disturbance	823.14	45.58%
0.18≤Interpolation<0.24	High Disturbance	308.52	17.08%
0.24≤Interpolation	Extremely High Disturbance	50.95	2.82%

Table 6. Statistics on vegetation disturbance degree in Jiaozuo mining area from 2000 to 2024

Annual Standard Deviation	*Disturbance Degree*	*Area/ km²*	*Area Proportion*
Interpolation<0.06	Extremely Low Disturbance	0.08	0.05%
0.06≤Interpolation<0.12	Low Disturbance	33.63	18.59%
0.12≤Interpolation<0.18	Moderate Disturbance	82.41	45.55%
0.18≤Interpolation<0.24	High Disturbance	57.09	31.56%
0.24≤Interpolation	Extremely High Disturbance	7.7	4.26%

Within the 10 km buffer zone of the Jiaozuo mining area, the Extremely High Disturbance areas accounted for 2.82% (50.95 km²) of the total area, while within the core Jiaozuo mining area boundary, they constituted 4.26% (7.7 km²). Spatially, these areas exhibited a highly aggregated distribution pattern, predominantly concentrated around the operational zones of large mines such as Guhanshan, Zhaogu No.1, and Jiulishan, as well as in the immediate vicinity of major transport arteries and waste dump sites. In these locations, persistent and intense anthropogenic disturbances — including continuous excavation, mechanical compaction, and dust settlement — create a highly unstable environment for vegetation growth, resulting in the most dramatic inter-annual fluctuations in FVC.

Of the total area studied, Moderate Disturbance was the most widespread category, forming the fundamental background pattern of vegetation disturbance and constituting 45.58% (823.14 km²) of the buffer zone and 45.55% (82.41 km²) of the core mining area, illustrating the interaction between human activities and natural processes. In contrast, High Disturbance areas accounted for a substantially larger proportion of the core mining area (31.56%, 57.09 km²) compared to the buffer zone (17.08%, 308.52 km²); these areas primarily form a distinct gradient transition zone that encircles the periphery of the Extremely High Disturbance cores, reflecting the diffusion effect of mining impacts along transportation routes. Conversely, Low and Extremely Low Disturbance areas, which together accounted for 34.52% of the buffer zone and 18.64% of the core mining area, were primarily located in the outer buffer zone and areas far removed from mining activities, representing the least disturbed vegetation types with relatively stable ecosystems and minor inter-annual fluctuations.

A further comparative analysis of the distribution of vegetation disturbance intensity levels between the 10 km buffer zone and the core mining area reveals distinct spatial heterogeneity. Within the core mining area, the combined area percentage of High and Extremely High Disturbance levels reached 35.82% (31.56% High + 4.26% Extremely High), significantly higher than the 19.90% (17.08% High + 2.82% Extremely High) observed in the 10 km buffer zone. Conversely, the combined percentage of Low and Extremely Low Disturbance levels was only 18.64% within the core mining area, compared to 34.52% in the buffer zone. This contrast indicates that vegetation within the core mining area is subject to direct and intense disturbance from mining activities, leading to more violent inter-annual fluctuations in FVC and poorer ecosystem stability. In contrast, as the distance from the core mining zones increases, the degree of vegetation disturbance gradually diminishes, and the ecosystem tends towards greater stability. The Moderate Disturbance level constituted the highest proportion in both zones (45.55% in the core area, 45.58% in the buffer zone), forming the fundamental background pattern of vegetation disturbance in the study area and reflecting the widespread spatial interweaving of human activities and natural processes.

Spatial overlay analysis clearly demonstrates a high consistency between the vegetation disturbance intensity and the spatial pattern of mining activities. A distinct "core-periphery" differentiation pattern is evident around individual mines, characterized by a sequential decrease in vegetation disturbance intensity from the mine center outwards. Notably, significant Extremely High Disturbance hotspots formed around expansion areas of existing mines like Guhanshan and newly developed mines like Zhaogu No.1, providing direct evidence of a dose-response relationship between mining intensity and the degree of vegetation disturbance.

Regarding the overall spatial distribution, the vegetation disturbance intensity exhibits a pattern of being higher in the southeastern part and lower in the northwestern part. The southeastern area concentrates large mines (e.g., Guhanshan, Zhaogu No.1) and major transport corridors, resulting in high anthropogenic disturbance intensity and poor vegetation stability. The northwestern part, predominantly comprising mountainous terrain and natural vegetation cover farther from the core mining zones, experiences relatively less direct impact from mining activities. This spatial heterogeneity pattern is likely influenced by the region's prevailing wind direction (predominantly southeasterly in summer), which can transport pollutants like dust generated by mining activities towards the northwest, exacerbating physiological stress on vegetation in the downwind areas and consequently leading to significantly higher disturbance levels in the southeast compared to the northwest.

This spatial correspondence not only confirms the significant impact of mining activities on the stability of the vegetation ecosystem but also provides a scientific basis for identifying key areas for ecological restoration and formulating differentiated management strategies. The precise identification of Extremely High and High Disturbance zones facilitates the prioritized implementation of vegetation restoration projects, thereby enhancing the targeting and effectiveness of ecological remediation efforts in the mining area.

4. Discussion

4.1. Comparison and Validation of Methodologies

The Modified Three-band Gradient Difference Model employed in this study demonstrated significant advantages in the low-vegetation-coverage environment of the mining area. Compared to traditional vegetation indices like the NDVI, this method effectively enhances the spectral contrast between vegetation and bare soil background, thereby improving the accuracy of vegetation information extraction in areas with sparse cover. This finding aligns with the conclusions of Guli Jiapaer, confirming the model's applicability in arid and semi-arid regions. However, compared to the multi-index frequency ratio method used by Bai et al. (2016) in the Baiyun'ebo mining area, the approach herein still has limitations regarding the comprehensive assessment of ecological degradation. Future research should consider integrating more environmental factors to enhance the comprehensiveness of the evaluation.

Regarding the identification of vegetation disturbance extent, the method based on correlation coefficients and statistical testing used in this study, compared to the simple distance-decay model applied by Liao et al. (2010), more precisely characterizes the non-linear diffusion pattern of mining impacts. Specifically, the core disturbance zones identified under the stringent significance level ($p < 0.01$) show a high degree of consistency with the ecological impact boundaries determined by Li et al. (2018) using the Temperature Vegetation Dryness Index, validating the reliability of our method. Nevertheless, compared to the multi-source monitoring techniques proposed by Lei (2010), relying solely on optical remote sensing data still struggles to fully capture the effects of latent factors such as groundwater level changes.

4.2. Analysis of Vegetation Dynamics Driving Mechanisms

This study identifies mining activities as the dominant factor leading to vegetation degradation, a conclusion consistent with the findings of Li et al. (2022) in similar mining areas. However, compared to the Pingshuo mining area studied by Wu et al. (2021), the Jiaozuo mining area exhibits a more pronounced improvement trend, potentially stemming from differences in the intensity and duration of ecological restoration policy implementation between the two regions. Specifically, the sharp vegetation degradation during the initial operational phases of the Zhaogu No.1 and Zhaogu No.2 Mines aligns closely with the ecological impact patterns of new mines reported by Li et al. (2020), confirming a clear dose-response relationship between mining intensity and ecological disturbance.

Notably, the vegetation improvement trend observed in this study differs from the results reported by Liu et al. (2019) in the Shendong mining area. This discrepancy may originate from the following factors: Firstly, the Green Mine Construction policies implemented earlier in the Jiaozuo mining area have likely played a positive role. Secondly, the relatively humid climatic conditions in the study area provide a more favorable basis for natural vegetation recovery. These finding highlights that assessing the ecological impacts of mining requires comprehensive consideration of the interactions between regional climatic background and management policies.

4.3. Implications and Optimization for Ecological Restoration

The "core-transition-periphery" disturbance pattern revealed in this study provides a scientific basis for zonal management in mining area ecological restoration. Compared to the collaborative restoration concept proposed by Bi et al. (2022), the spatially explicit assessment in this study supports a more precise layout of restoration measures. Particularly, the identified Extremely High Disturbance hotspots should be closely integrated with mine lifecycle management for implementing prioritized remediation strategies.

However, this study has certain limitations. Firstly, the use of 30-meter resolution remote sensing data makes it difficult to capture the impact of micro-topographic changes on vegetation within the mining area, which somewhat affects the accuracy of delineating disturbance boundaries. Secondly, although the primary influence of mining activities was considered, interference from natural factors such as climatic fluctuations and soil heterogeneity has not been fully isolated. Future research should integrate multi-source data to establish a more comprehensive framework for analyzing driving mechanisms.

5. Conclusion

This study systematically revealed the spatiotemporal evolution of vegetation cover in the Jiaozuo mining area from 2000 to 2024 by developing an integrated remote sensing monitoring methodology. The research demonstrates that vegetation degradation caused by mining activities exhibits significant spatial aggregation, primarily distributed around mines, along transport corridors, and near waste dump sites. Although the study area overall showed a slight degradation trend, localized improvement indicates that ecological restoration measures have yielded positive effects.

Methodologically, the improved Fractional Vegetation Cover extraction model and the spatially explicit disturbance assessment framework provide a new technical pathway for ecological monitoring in mining areas. Specifically, the method for identifying disturbance extent based on statistical significance and the vegetation stability evaluation indicator enable a refined quantification of the ecological impacts of mining.

However, the evolution of the mining area ecosystem results from the interaction of multiple driving factors. Future research should focus on the following aspects: Firstly, developing multi-scale integrated monitoring technologies to enhance the understanding of typical ecological processes in mining areas. Secondly, constructing comprehensive assessment models that incorporate both natural factors and human interventions to clarify the relative contributions of various drivers. Finally, strengthening the long-term efficacy evaluation of ecological restoration in mining areas to provide a more solid scientific foundation for green mine construction. Through continuous methodological innovation and systematic research, ecological management in mining areas can be advanced from passive remediation towards proactive regulation.

Author Contributions

Conceptualization, J.L.; methodology, K.L., J.L., M.L.; formal analysis, K.L., W.W., J.Y.; investigation, K.L., J.L., M.L.; resources. and W.W.; writing-original draft preparation, K.L., M.L., W.W. and J.Y.; writing-review and editing, J.L., M.L., W.W., J.Y.; visualization, K.L.; supervision, J.L.; All authors have read and agreed to the published version of the manuscript.

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Conflict of Interests

The authors declare no conflicts of interest.

Data Availability

The data supporting the findings of this study are available upon request from the corresponding author.

Reference

Bai, S.Y., Zhu, Q.W., Shen, W.S., et al., 2016. Study on Ecological Degradation in the Bayan Obo Mining Area. Journal of Ecology and Rural Environment, 32(03): 367-373.

Bai, X., 2022. Analysis of Spatiotemporal Changes and Influencing Factors of Vegetation Coverage in Yulin City. Chang'an University, https://doi.org/10.26976/d.cnki.gchau.2022.000450.

Bi, R., Bai Zhongke, 2007. Study on Land Characteristic Information and Classification in Opencast Coal Mine Area Based on Remote Sensing Image. Transactions of the Chinese Society of Agricultural Engineering, (02): 77-82+291.

Bi, Y.L., Liu, T., 2022. Multi-source Data Time Series Analysis of Vegetation Co-evolution in Open-pit Mining Area——Taking the Zhungeer Mining Area as an Example. Coal Science and Technology, 50(01): 293-302.

Chen, J., Gao, Z.H., Wang, S.S., et al., 2020. Review on the Development of Aerial Remote Sensing Geological Survey Technology in the Three Gorges Reservoir Area. Remote Sensing for Land & Resources, 32(02): 1-10.

de Castro, Pena, J.C. et al., 2017. Impacts of mining activities on the potential geographic distribution of eastern Brazil mountaintop endemic species. Perspectives in Ecology and Conservation, 15(3): 172-178, https://doi.org/10.1016/j.pecon.2017.07.005.

Gao, J.X., Zhao, S.H., 2020. Forty Years of Remote Sensing of Ecological Environment in China. Journal of Geo-information Science, 22(04): 705-719.

Guli, J., Yi, Q.X., Yao, F., et al., 2017. Comparison of non-destructive LAI determination methods and optimization of sampling schemes in an open Populus euphratica ecosystem. Urban Forestry & Urban Greening, 26: 114-123, https://doi.org/10.1016/j.ufug.2017.06.010.

Hejmanowski, R., Malinowska, A.A., 2016. Significance of the uncertainty level for the modeling of ground deformation ranges. International Journal of Rock Mechanics and Mining Sciences, 83: 140-148, https://doi.org/10.1016/j.ijrmms.2015.12.019.

Hou, J., Hou, P., Gao, H.F., et al., 2024. Spatiotemporal Changes of Vegetation in Chinese Forest Nature Reserves and Their Response to Climate Change. Chinese Journal of Ecology: 1-9.

Lechner, A.M., Kassulke, O., Unger, C., 2016. Spatial assessment of open cut coal mining progressive rehabilitation to support the monitoring of rehabilitation liabilities. Resources Policy, 50: 234-243, https://doi.org/10.1016/j.resourpol.2016.10.009.

Lei, S.G., 2010. Monitoring of Key Environmental Elements and Study on Mining-induced Influence Patterns in Desert Mining Areas. Journal of China Coal Society, 35(09): 1587-1588, https://doi.org/10.1016/j.resourpol.2016.10.009.

Li, H.C., Liu, L., X, Z.L., et al., 2022. Analysis of Spatiotemporal Changes in Ecological Environment Quality in the Zhongliangshan Mining Area, Chongqing. Environmental Science & Technology, 45(S1): 220-226, https://doi.org/10.19672/j.cnki.10036504.2375.21.338.

Li, J., Han, Y., Yang, Z., Miao, H., Yin, S.Q., 2018. Remote Sensing Extraction of Coal Mining Impact Boundary in Yanzhou Coalfield Based on Temperature Vegetation Dryness Index. Transactions of the Chinese Society of Agricultural Engineering, 34(19): 258-265.

Li, J., Peng, S.P., Zhang, C.Y., et al., 2022. Technical Framework and Application of Quantitative Remote Sensing Monitoring and Evaluation for Ecological Environment in Mining Areas. Journal of Mining Science and Technology, 7(01): 9-25+88, https://doi.org/10.19606/j.cnki.jmst.2022.01.002.

Li, J.W., Li, X.T., Liu, C.Y., et al., 2020. Dynamic changes in surface damage induced by high-intensity mining of shallow, thick coal seams in gully areas. Advances in Civil Engineering, 2020: 1-16, https://doi.org/10.1155/2020/5151246.

Li, J., Zipper, C.E., Donovan, P.F., et al., 2015. Reconstructing disturbance history for an intensively mined region by time-series analysis of Landsat imagery. Environmental monitoring and assessment, 187: 1-17.

Li, Q.S., Xu, Y.L., Li, J., et al., 2022. Extraction of Mining Impacts on Vegetation Change and Quantitative Analysis of Ecological Cumulative Effects. Journal of China Coal Society, 47(06): 2420-2434, https://doi.org/10.13225/j.cnki.jccs.2021.1296.

Li, R.J., Yang, Z.W., Wu, S.W., et al., 2020. Study on the Impact of Coal Mining on Spatiotemporal Variation of Surface Vegetation Coverage Based on Landsat Images. Journal of North China University of Water Resources and Electric Power (Natural Science Edition), 41(04): 52-60, https://doi.org/10.19760/j.ncwu.zk.20200049.

Li, X.J., Zhou, J.J., 2020. Research on Extraction Method of Surface Subsidence Information in Coal Mining Areas with High Groundwater Level. Coal Science and Technology, 48(04): 105-112, https://doi.org/10.13199/j.cnki.cst.2020.04.010.

Liao, C.H., Liu, X.H., 2010. 3S-based Identification of the Influence Scope of Coal Mining on Regional Vegetation in Yangquan. Journal of Natural Resources, 25(02): 185-191.

Liu, Y., Lei, S.G., Chen, X.Y., et al., 2021. Analysis of Temporal Variation of Vegetation Coverage and Driving Factors in Shendong Mining Area and Guided Restoration Strategies. Journal of China Coal Society, 46(10): 3319-3331, https://doi.org/10.13225/j.cnki.jccs.2020.1387.

Liu, Y., Lei, S.G., Gong, C.G., et al., 2019. Response of Chlorophyll Content in Caragana Leaves to Soil Water Content Changes in Coal Mining Subsidence Fissure Areas. Acta Ecologica Sinica, 39(09): 3267-3276.

Lu, F., Wang, X., Zhang, H., et al., 2018. Analysis on landscape pattern evolution and driving forces in Jiaozuo mining area from 1980 to 2015. Research of Soil and Water Conservation, 25(4), 237-243, https://doi.org/10.13869/j.cnki.rswc.2018.04.035.

Lü, G.P., Liao, C.R., Gao, Y.Y., et al., 2017. Application of LiDAR Technology in Mnitoring Mine Ecological Environment. Journal of Ecology and Rural Environment, 33(07): 577-585.

Qiao, G., Xü, Y.N., Chen, H.Q., et al., 2018. Impact of Ground Fissures on Vegetation Ecology in the Ningdong Coal Mining Area. Geological Bulletin of China, 37(12): 2176-2183.

Reinhaeckel, G., Zhukov, B., Oertel, D., et al., 1998. Unmixing of simulated ASTER data with applications for the assessment of mining impacts in central Germany, Imaging Spectrometry IV. SPIE, pp. 345-354, https://doi.org/10.1117/12.328115.

Sahu, S.P., Yadav, M., Pradhan, D.S., et al., 2018. Spatio-temporal variations of respirable particles at residential areas located in the vicinity of opencast coal projects, India: a case study. Arabian Journal of Geosciences, 11: 1-15, https://doi.org/10.1007/s12517-018-3551-1.

Si, J., Wang, S., 2021. Ecological security evaluation and spatiotemporal differentiation of Jiaozuo mining area based on combination weighting method. Research of Soil and Water Conservation, 28(3), 348-354, https://doi.org/10.13869/j.cnki.rswc.2021.03.038.

Sun, Q. Bai, Z.K., Cao, Y.G.,et al., 2015. Ecological Risk Assessment of Land Damage in Extra-large Open-pit Coal Mine. Transactions of the Chinese Society of Agricultural Engineering, 31(17): 278-288.

Wang, R., Ma, S.C., Zhang, H.B., et al., 2016. Effects of Surface Fissures Induced by High-intensity Mining in Arid Areas on Soil Microbiological Properties and Plant Communities. Research of Environmental Sciences, 29(09): 1249-1255, https://doi.org/10.13198/j.issn.1001-6929.2016.09.01.

Wang, Y.J., 2017. Progress and Prospects of Ecological Disturbance Monitoring in Mining Areas. Acta Geodaetica et Cartographica Sinica, 46(10): 1705-1716.

Weir, J.N., Mahoney, S.P., McLaren, B., et al., 2007. Effects of mine development on woodland caribou Rangifer tarandus distribution. Wildlife Biology, 13(1): 66-74.

Wu, G., Wei, D., Zhou, Z.D., et al., 2014. A Review of Ecological Restoration Technologies for Large Coal Base Construction in China. Acta Ecologica Sinica, 34(11): 2812-2820.

Wu, J.S., Zhu, Q.L., Qiao, N., et al., 2021. Ecological risk assessment of coal mine area based on "source-sink" landscape theory – A case study of Pingshuo mining area. Journal of Cleaner Production, 295: 126371, https://doi.org/10.1016/J.JCLEPRO.2021.126371.

Yao, F., Guli, J., Bao, A.M., et al., 2013. Assessment of Vegetation Community Damage in Open-pit Coal Mines in Arid Desert Areas Based on Remote Sensing Technology. China Environmental Science, 33(04): 707-713.

Yuan, L.H., Jiang, W.G., Shen, W.M., et al., 2013. Spatiotemporal Variation of Vegetation Coverage over the Yellow River Basin during 2000–2010. Acta Ecologica Sinica, 33(24): 7798-7806.

Zhang, F., Wang, Q., Li, Y., 2010. A Quantitative Method for Monitoring Spatiotemporal Dynamic Changes of Vegetation Coverage in Hulun Buir Grassland. Journal of Natural Resources, 25(10): 1698-1708.

Zhang, H., Zhang, K., Liu, P., et al., 2020. Extraction of ecological indicators and security evaluation in mining area based on RS and GIS: A case study of Jiaozuo mining area. Coal Science and Technology, 48(4), 80-88, https://doi.org/10.13199/j.cnki.cst.2020.04.007.

Zhang, M., 2022. Study on Spatiotemporal Evolution Characteristics of Land Use and Ecological Impacts in Large Open-pit Coal Mines. PhD Thesis, China University of Geosciences (Beijing), https://doi.org/10.27493/d.cnki.gzdzy.2021.000031.

Zhang, X.H., Zhu, B., Wang, W., et al., 2019. Research and Application of Stepwise Extraction Method for Ground Fissures Based on Objects. Remote Sensing for Land & Resources, 31(01): 87-94.

Zhang, X.W., Wu, B.F., 2015. A Method for Temporal Phase Transformation of Fractional Vegetation Cover Based on Medium and High Resolution Remote Sensing. Acta Ecologica Sinica, 35(04): 1155-1164.