



Research Article

Monitoring of Open-pit Mining Disturbance and Restoration Using GEE-LandTrendr: A Case Study of Huolinhe Coalfield in Inner Mongolia, China

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Abstract

Increasing open-pit mining is considered to have a remarkable impact on the regional ecological environments due to drastic surface excavation and vegetation damage, therefore there is an urgent need for large-scale disturbance monitoring and restoration effect evaluation. Taking the Huolinhe Mining Coalfield as an example, this study employed the LandTrendr algorithm integrated with the Google Earth Engine (GEE) platform to detect mining disturbances and vegetation recovery using the Normalized Difference Vegetation Index (NDVI) calculated from long-term Landsat images. The results show that: (1) the extent of mining disturbance expanded before 2010 and remained broadly stable until 2017, after which it decreased following the implementation of the restoration project from 2018 onwards. (2) Breakpoints were identified in all years within the study period, and the detection rate for mining-disturbed areas exceeded 96% in the validation years of 2000, 2010, 2017, and 2021. (3) Vegetation recovery started in two periods, 2010–2012 and 2017–2019, the earlier period followed the severe drought of 2010 and is attributed to natural recovery, whereas the larger latter period coincided with the implementation of artificial restoration projects. (4) A lag of approximately one growing season was found between the implementation of reclamation engineering and the first detectable vegetation recovery, so that detection in the implementation year identified only 14.9% to 30.0% of the implemented restoration area, whereas a one year lag adjustment increased the value to 70.0% to 85.1%. (5) NDVI increased in the mining area between 2017 and 2022, and the increase was spatially concentrated in the restoration project area, which is consistent with a positive vegetation-cover response associated with the restoration projects. The results indicate that LandTrendr is an effective tool in change detection and can support rapid identification of large-scale disturbance in mining areas. The results provide a basis for subsequent monitoring of vegetation cover and for the sustainable development of a typical mining area, and they define the conditions under which annual mining-disturbance monitoring can be interpreted at face value.

Keywords

LandTrendr, Google Earth Engine, Open-pit Mining, Ecological Disturbance, Vegetation Recovery

1. Introduction

With the continuous development of the global economy, mining activities, particularly open-pit mining, have become

increasingly frequent, providing vital energy support for socio-economic development. However, the conflict between

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the exploitation of mining resources and the ecological environment continues to deteriorate, which often endangers the stability of ecosystems and the sustainable development of society [1-3]. Mining disturbance refers to the damage and land occupation caused by mining activities, leading to environmental problems such as vegetation degradation, soil erosion, air and water pollution, and loss of biodiversity [1, 4, 5]. Whereas mine restoration refers to the technical means employed after mining operations have ceased to repair and restore the damaged mine, returning it to its natural state or endowing it with new ecological functions [6]. Long-term mining or post evaluation of restoration both require continuous monitoring of these changes to identify the dynamic impacts on the environment and land cover [1, 5, 7, 8], which may provide scientific basis for the subsequent ecological restoration and sustainable development of the mining area. Therefore, effective monitoring of ecological disturbances and their restoration processes in open-pit mining areas has become a crucial issue in current mine environmental management.

Traditional monitoring strategy primarily relies on field surveys and sampling methods, which can provide a foundational and reliable datasets for specific research, but such methods have limited spatio-temporal scale and high time and labor costs, making large-scale implementation infeasible and hindering quantitative analysis of land disturbance [3, 9]. Additionally, due to the historical legacy of past mining, field surveys and sampling cannot determine historical quantitative changes. With advancements in satellite observation technology, remote sensing has been widely applied in mine environmental monitoring due to its advantages of large coverage, rapidness, and non-contact nature [7, 10]. Besides, the emergence of the cloud computing platform, e.g. Google Earth Engine (GEE), has significantly enhanced the processing and analysis capabilities of remote sensing big data [9-11].

The identification of mining disturbances and restoration is part of change detection research. There are various change detection algorithms for different research subjects and purposes, including deep learning-based methods, object-based methods, algebra-based methods, statistics-based methods, and transformation-based methods that integrate two or more of these approaches [12, 13]. The LandTrendr algorithm, a key spectral-temporal segmentation algorithm integrated into the GEE platform (GEE-LandTrendr), deeply analyzes time-series remote sensing data to accurately identify trends and disturbance events in land surface changes [14]. Compared to traditional supervised and unsupervised classification methods, the GEE-LandTrendr algorithm boasts higher classification accuracy and stronger anti-interference capabilities, making it ideally suited for dynamic monitoring of mine ecological environments [1, 9]. Due to its powerful capabilities, the algorithm has been widely applied in various fields, including land use and cover change, vegetation monitoring and ecosystem change, forest monitoring and land cover change, and natural disaster assessment [4, 9, 15]. This provides strong support for

decision-makers and researchers, helping them better understand and respond to surface cover changes. The Shengli Coalfield study [9] has demonstrated that GEE-LandTrendr can identify surface-mining disturbance and reclamation in a surface coal mine. A question that remains open, and that directly determines how such results are interpreted, is how the date of engineering reclamation relates to the date at which a vegetation signal becomes detectable in a Landsat time series.

Huolinhe Open-Pit Coalfield is one of the five largest open-pit coal mines in China. Since the 1980s, rapid exploitation of coal resources brought significant ecological issues, such as the destruction of grassland vegetation and air pollution [16]. To address these problems, the central government established a special supervision team in 2018 to initiate a comprehensive ecological restoration effort, ranging from soil and water management to vegetation coverage. However, the ecological restoration process still faces challenges such as the failure of enterprises to fulfill their primary responsibilities, inadequate rectification, and weak supervision [16, 17]. Therefore, this study uses the GEE-LandTrendr algorithm to detect surface disturbances and vegetation recovery in the mining area, focusing on three questions that determine how the results should be interpreted. First, the lag between the implementation of reclamation engineering and the first detectable vegetation recovery, and how this lag should be handled when the detected restoration area is compared with engineering records. Second, the separation of climate-driven natural greening from engineering-driven restoration by normalizing the mining-area Normalized Difference Vegetation Index (NDVI) series against a non-mining reference area. Third, the disturbance and recovery baseline of a semi-arid steppe coalfield under a national restoration programme. By quantifying the extent of ecological disturbance caused by mining and the subsequent vegetation-cover change, this study aims to provide a scientific basis for mine environmental management and ecological restoration, and to serve as a reference for monitoring in other similar mining areas.

2. Materials and Methods

2.1. Study Area

Huolinhe Open-Pit Coalfield is located within Hologol City in the northwest of Tongliao City of Inner Mongolia, covering an area of approximately 9605.9 hectares (Figure 1). It is situated at the center of the Horqin Grassland, on the ridge at the southern end of the Greater Khingan Mountains. The area belongs to a temperate arid continental grassland climate, characterized by short-cool summers and long-cold winters, with frequent strong winds throughout the year, significant diurnal temperature variation, and abundant solar and wind energy resources [16]. The annual total precipitation is 363.2 mm, mostly concentrated in the summer. The vegetation is predominantly desert and grassland. Hologol City is rich in

mineral resources, primarily including coal, silica, and limestone. Among these, the coal mines, especially the Huolinhe Coal Mine, one of China's five largest open-pit coal mines, are particularly renowned.

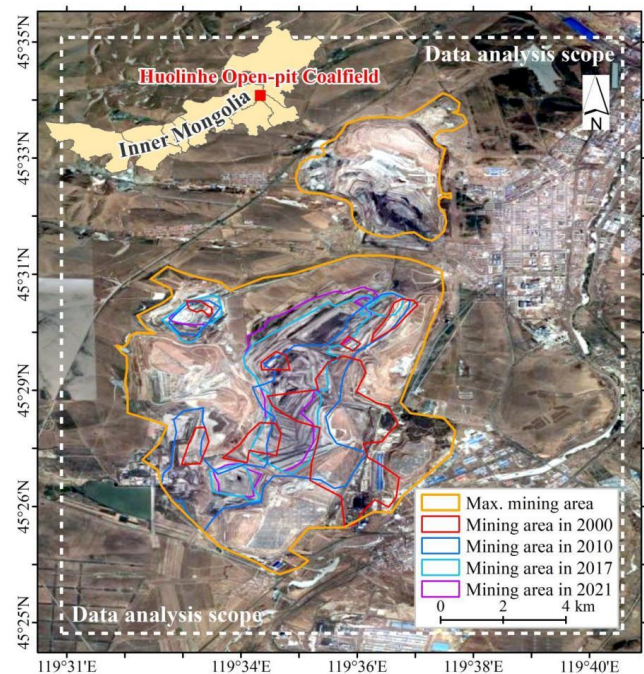


Figure 1. The location of the Huolinhe Open-pit Coalfield. The coalfield boundary is shown as a solid line. The white dashed rectangle indicates the data analysis scope used for this study. The maximum mining extent is the union of all mining boundaries over the analysis period.

The coalfield has shallow overburden, simple geological structure, and high-quality lignite reserves totaling 13.1 billion tons. During the 1980s and 1990s, the exploitation of these resources played a crucial role in alleviating the energy shortage in Northeast China. In recent years, as mining activities have intensified, ecological environmental issues in the mining area have become increasingly prominent. To achieve sustainable development of the mining area, the government

has initiated systematic ecological restoration activities. However, challenges remain, such as the indistinct boundaries between the extraction and restoration zones and significant changes in ecological recovery disturbances. Four spatial extents are used in this study and are distinguished throughout. The coalfield boundary encloses approximately 9,605.9 ha (Figure 1). The data analysis scope is the extent delimited by the white dashed rectangle in Figure 1 and was used for the comparison between mining and non-mining areas. The maximum mining extent is the union of all mining boundaries over the analysis period. The restoration project area is the union of the engineering polygons for the restoration projects implemented between 2018 and 2020 and is a subset of the maximum mining extent.

2.2. Data Sources and Processing

High spatial resolution remote sensing data should be selected for monitoring disturbances and recovery in open-pit mining areas. The Landsat images are freely available and have relatively high resolution, which meets the research objectives considering the conditions of image availability and the spatial extent of the study area. Therefore, surface-reflectance images were obtained from the Collection 2 Level 2 collections of Landsat 5 Thematic Mapper, Landsat 7 Enhanced Thematic Mapper Plus and Landsat 8 Operational Land Imager in the GEE platform, namely "LANDSAT/LT05/C02/T1_L2", "LANDSAT/LE07/C02/T1_L2", and "LANDSAT/LC08/C02/T1_L2". These collections provide surface-reflectance products that have undergone atmospheric, radiometric and geometric correction [18]. Reflectance was converted to physical surface reflectance using the scaling factors and offsets distributed with these collections. Clouds (bit 3), dilated cloud (bit 1), cirrus (bit 2), cloud shadow (bit 4), snow (bit 5) and water (bit 7) were masked using the QA_PIXEL band. Only images acquired between April and October were retained from 1998 to 2022. Because the three sensors have different spectral response functions, the analysis was arranged so that each calendar year is represented by a single sensor wherever possible, as shown in Table 1, and NDVI was used as a normalized index, which limits systematic differences between sensors.

Table 1. Selected bands and number of Landsat images used per year:

Sensor	Chosen Bands	Year (number of used images)
Landsat-5	R, NIR (30 m)	1998 (43), 1999 (51), 2000 (57), 2001 (64), 2002 (50), 2003 (51), 2004 (48), 2005 (53), 2006 (50), 2007 (37), 2008 (34), 2009 (51), 2010 (46), 2011 (35)
Landsat-7	R, NIR (30 m)	2012 (44)
Landsat-8	R, NIR (30 m)	2013 (44), 2014 (58), 2015 (58), 2016 (60), 2017 (66), 2018 (63), 2019 (58), 2020 (56), 2021 (59), 2022 (60)

Generally, several spectral indices can be used as an analyzing proxy, among which vegetation indices are more effective, such as the NDVI, the Difference Vegetation Index (DVI), and the Enhanced Vegetation Index (EVI) [10, 15]. For mining areas, studies have shown that NDVI, calculated using the reflectance of near-infrared band (NIR) and red band (R), can effectively reflect changes in surface vegetation [9]. Therefore, this study selects NDVI as the spectral index for detecting disturbance and restoration in mining areas.

To calculate NDVI values for the Landsat images at different periods, a percentile composite method is used to extract the 95th percentile NDVI values within the year. The 95th percentile was chosen because it removes residual low-value outliers, reduces seasonal fluctuation, and characterizes the near-optimal vegetation condition of the growing season, which is the quantity relevant to detecting a recovery signal, as in [19]. By analyzing temporal NDVI changes, it is possible to determine vegetation disturbances during specific periods, indirectly identifying mining areas and restoration zones.

In addition, part of the mining and restoration area data were obtained from Huolinhe Opencut Coal Industry Corporation Limited of Inner Mongolia, including the mining boundaries for the years of 2000, 2010, 2017, and 2021 (in Figure 1), as well as the engineering area boundaries for mining ecological restoration efforts during 2018–2020, used for validation of the detection results.

2.3. Methods

2.3.1. Overview of LandTrendr Algorithm

The LandTrendr (Land Trends Detection and Recovery) algorithm is a set of spectral-temporal segmentation algorithms used for change detection in time series of moderate-resolution satellite images, primarily Landsat. It generates trajectory-based spectral time series data largely free from interannual signal noise [14, 19]. This algorithm requires long time series of remote sensing images as input. Its core technique involves temporal segmentation, analyzing extensive pixel spectral parameter data obtained from long time series remote sensing images. It removes disturbances and outliers, performs linear fitting, and segments the spectral parameters over time into line segments corresponding to different phases of disturbance and recovery events in the study [14]. The basic principle of the algorithm is illustrated in Figure 2. For each pixel, the algorithm generates a spectral parameter curve (such as NDVI) over time. Through segmentation and linear fitting, observations from different time periods are segmented into distinct segments based on nodes, providing information on the magnitude and duration of disturbances in the region's events.

In 2018, developers of the LandTrendr algorithm collaborated with GEE engineers to port LandTrendr into the GEE [14]. Users can now access a vast repository of image data products stored in GEE platform. By simply setting the start

and end detection years, selecting appropriate spectral indices, and configuring key parameters, researchers can apply the LandTrendr algorithm to their study areas. This integration allows for rapid generation of detection results, significantly improving algorithm efficiency while reducing costs and barriers to use [14]. This study employs three parameters, slope, magnitude, and duration, to quantitatively describe and analyze change trends and patterns. Using the LandTrendr algorithm allows for capturing abrupt changes in NDVI time series, characterized by breakpoints defined by years and spectral indices, forming vertices that represent the spectral history of each pixel as a series of line segments (Figure 2). This approach helps in identifying stable areas, disturbance areas, and recovery areas. Finally, the detection rate of the results is validated using mining area boundaries for 2000, 2010, 2017, and 2021, along with restoration area boundaries for each year.

The LandTrendr run used the following settings, with parameter names as defined in the GEE implementation of the algorithm [14]. The maximum number of segments in a sequence (*maxSegments*) was 6. The spike threshold (*spikeThreshold*) was 0.9. The recovery threshold used to prevent one year recovery (*recoveryThreshold*) was 0.25. The *p* value threshold for model selection (*pvalThreshold*) was 0.1. The minimum number of observations required for a pixel to be fitted (*minObservationsNeeded*) was 5. Besides, the parameters *vertexCountOvershoot*, *preventOneYearRecovery*, and *bestModelProportion* were set to 3, false, and 0.75, respectively. The technical roadmap of this study is illustrated in Figure 2.

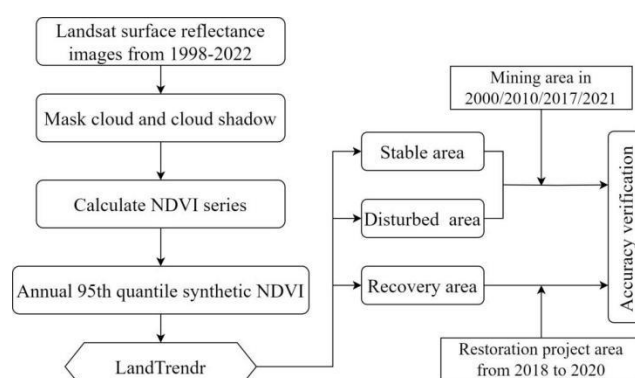


Figure 2. Workflow of the methodology used in this study.

2.3.2. Classification and Detection Rate

When using NDVI values as a remote sensing indicator to represent vegetation change, the NDVI change magnitude can be calculated by computing the difference in NDVI values between segment endpoints. Dividing this magnitude by the duration gives the change rate $\beta = (\text{NDVI}_{\text{end}} - \text{NDVI}_{\text{start}}) / (t_{\text{end}} - t_{\text{start}})$. The segment used for the classification of a given year is the segment whose time span contains that year, and a change event is assigned to the year of the vertex that begins

the segment, following the standard LandTrendr convention [14, 19]. Therefore, the disturbance and recovery status of a pixel was determined from three independent layers. The spatial reference layer defines the coalfield boundary, the maximum mining extent over the analysis period, and the restoration project area, which is the union of the engineering polygons for the restoration projects implemented between 2018 and 2020. The vegetation trajectory layer is obtained from the fitted NDVI segments and assigns each segment to one of three mutually exclusive classes according to the sign of β (with no non-zero tolerance applied), namely greening when $\beta > 0$, browning when $\beta < 0$, and stable when $\beta = 0$. The event layer records whether a breakpoint begins in the year of interest. The combination of the three layers defines the classes

used in this study and is given in Table 2.

Based on the above rules, recovery and restoration are distinguished as follows. Vegetation recovery refers to a greening trajectory and therefore to a vegetation response. Reclamation engineering refers to the implementation of engineering works inside a restoration project polygon, irrespective of the sign of β , and a browning trajectory inside such a polygon in the year of implementation indicates engineering activity whose vegetation has not yet established. Established restoration refers to stable or greening trajectories inside a restoration project polygon that follow an earlier breakpoint, and these pixels form the cumulative restored area. Mining disturbance refers to a browning trajectory inside the maximum mining extent and outside a restoration project polygon.

Table 2. Classification rules used in this study. The three layers are the spatial reference layer, the NDVI trajectory layer defined by the sign of β , and the breakpoint layer.

Spatial reference layer	NDVI trajectory class	Breakpoint in year Y	Class assigned in this study
Inside maximum mining extent, outside restoration project area	$\beta > 0$, greening	Yes	Vegetation recovery starting in year Y
Inside maximum mining extent, outside restoration project area	$\beta < 0$, browning	Yes	Mining disturbance starting in year Y
Inside restoration project area	$\beta < 0$, browning	Yes	Reclamation engineering implemented in year Y, vegetation not yet established
Inside restoration project area	$\beta > 0$, greening	Yes	Vegetation recovery starting in year Y, counted as newly restored area
Inside restoration project area	$\beta = 0$, stable	No, with an earlier breakpoint	Established restoration, counted as cumulative restored area
Inside maximum mining extent, bare surface	$\beta = 0$, stable	No	Ongoing mining, no significant vegetation change
Inside maximum mining extent, vegetated	$\beta = 0$, stable	No	Stable vegetated area, no disturbance
Outside maximum mining extent	Any	Any	Not classified

For a given year, detected area is defined as the area of the spatial intersection between the pixels assigned to the class of interest and the reference polygon for that class in that year, and is denoted A_m . The reference area for that class in that year, taken from the mining boundaries or restoration engineering polygons provided by the mining company, is denoted A_r . The detection rate (DR) is then

$$DR = A_m / A_r \times 100\% \quad (1)$$

The same formulation is used for the mining class and for the restoration class. The statistic is a detection rate, or recall, with respect to the reference polygons. It is not an overall clas-

sification accuracy, because it does not include the area of incorrectly detected pixels that lie outside the reference polygons, and it therefore does not quantify commission error.

3. Results

3.1. Temporal Change of NDVI in the Mining Area

Based on a stack of NDVI sequences for the study period (1998–2022) (Figure 3a–k), the average NDVI were computed separately for mining and non-mining areas (Figure 3l). From the distribution range of low NDVI values, it can be observed

that the mining area gradually expanded around 2010, maintained this scale between 2010–2017, and decreased after 2018, coinciding with the implementation of the restoration projects. These spatial changes are also reflected in the temporal changes of NDVI averages. The temporal variation characteristics of NDVI averages in mining areas are highly similar to those in non-mining areas (correlation coefficient of 0.68,

$p < 0.05$). The average NDVI in non-mining areas over the period was 0.58, while in mining areas it was 0.37 (considering the maximum mining area extent during the analysis period, with some areas undergoing natural recovery after mining cessation), indicating a clear difference in mean NDVI between the two regions. Due to the impact of mining activities, the NDVI average in mining areas shows relatively minor fluctuations but significant trends.

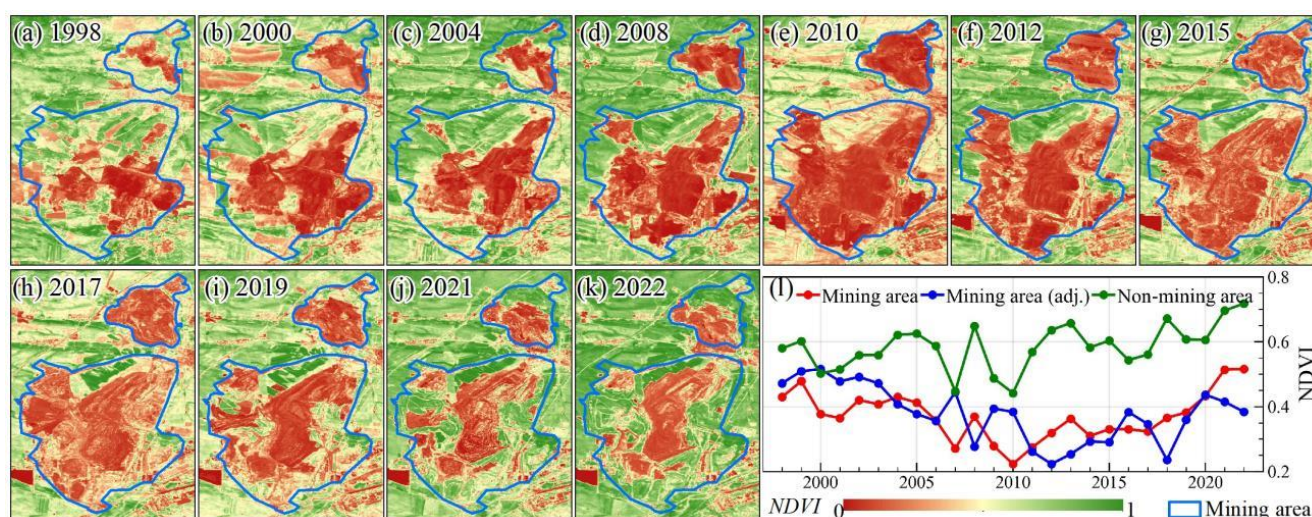


Figure 3. The stack of NDVI sequences (a–k) and temporal change (l). In (l), the maximum mining extent refers to the union of all mining boundaries over the analysis period, and the mining area refers to the area of low NDVI within it; non-mining area refer to the data analysis scope (Figure 1) excluding mining areas, construction land and water bodies.

To eliminate the influence of natural factors, adjustments were made to the NDVI sequence in mining areas. This involved subtracting the sequence signals from the non-mining area (representing natural changes) from the mining area NDVI sequence. The adjusted results were then linearly scaled to fit within the original range of the mining area NDVI sequence, facilitating precise analysis of temporal change characteristics. From the adjusted mining area values (Figure 3l), the changes closely resemble the original sequence, but specific periods of mining disturbance signals are significantly enhanced. For instance, disturbances are notably observed around 2000, 2009, 2016, and 2020. These periods of change slightly deviate from the validation years provided, as the validation range represents stable mining areas of that year, with time points possibly slightly delayed.

3.2. Detection of Disturbed Areas

The LandTrendr algorithm initiates segmentation from the starting year, necessitating filtering of detection results to include segments starting from the initial year (1998), where

disturbance starting year back to at least 1998. Results from the algorithm indicate that throughout the study period, initial mining disturbances occurred in various years, with notable concentrations in 1999, 2008, 2013, and 2018–2020 (Figure 4a and Figure 4c). The mining area described in Section 3.1 is the area of low NDVI within the maximum mining extent and is therefore a net extent for each year, whereas Figure 4a reports the starting year of the disturbance segment of each pixel and is an event layer rather than a net extent. The two quantities are not directly comparable. Disturbance started in some pixels in 2018, 2019 and 2020 because excavation continued within the maximum mining extent while previously excavated surfaces were being reclaimed, and because earthworks associated with the reclamation projects temporarily exposed bare substrate, which the segmentation identifies as disturbance (Figure 6a). New disturbance events therefore appear within the maximum mining extent in the same years in which the net low-NDVI extent decreases. Figure 4c and Figure 4d report area by starting year and are consistent with this interpretation.

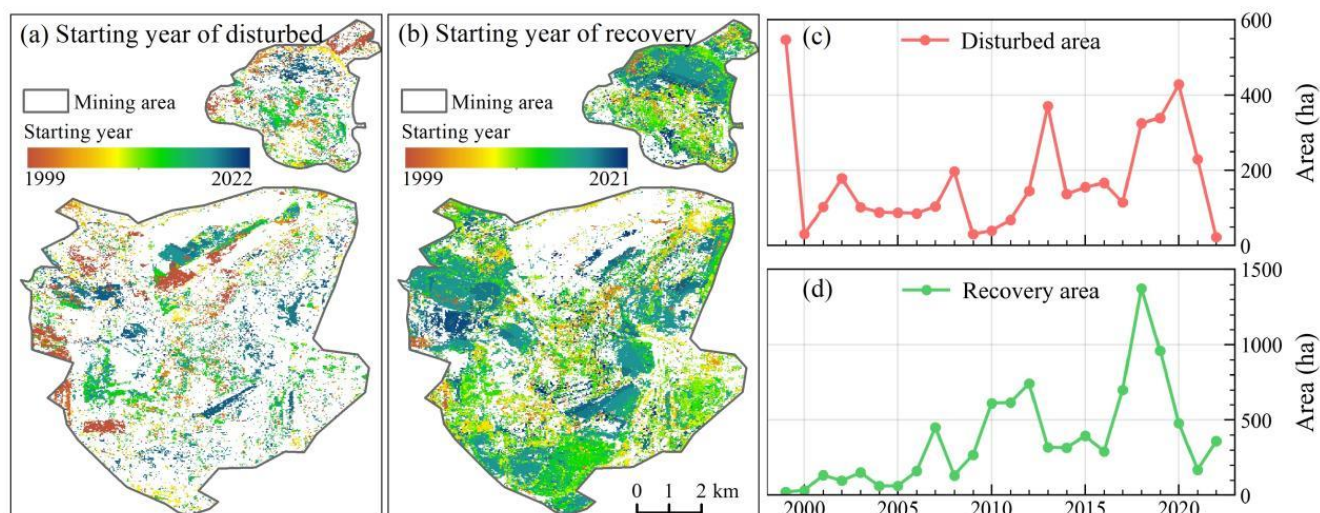


Figure 4. The starting year of mining disturbance (a) and vegetation recovery (b), and the corresponding area by starting year (c, d), within the maximum mining extent during the monitoring period. The blank areas within the maximum mining extent are pixels whose detection start year was filtered out.

According to the algorithm, identifying disturbance, recovery, or stable states within segments involves discriminating based on the rate of NDVI change within each segment. Following the criteria established in previous section, Figure 5 illustrates the surface conditions within mining areas for each validation year (2000, 2010, 2017, and 2021), along with area statistics and *DR* as shown in Table 3. It is evident that the *DR* for each year is above 96%, with the highest *DR* reaching up

to 99.9% and the lowest at 96.1%. Notably, the year 2010 shows a significant absolute error of approximately -110.6 ha. The incorrectly identified areas generally exhibit spatially dispersed distributions, yet with some clustering or strip-like patterns (Figure 5). The latter patterns may relate to newly excavated steps and slopes within mining pits, where spectral characteristics change due to manual compaction of work platforms whose edges exhibit strong spectral features.

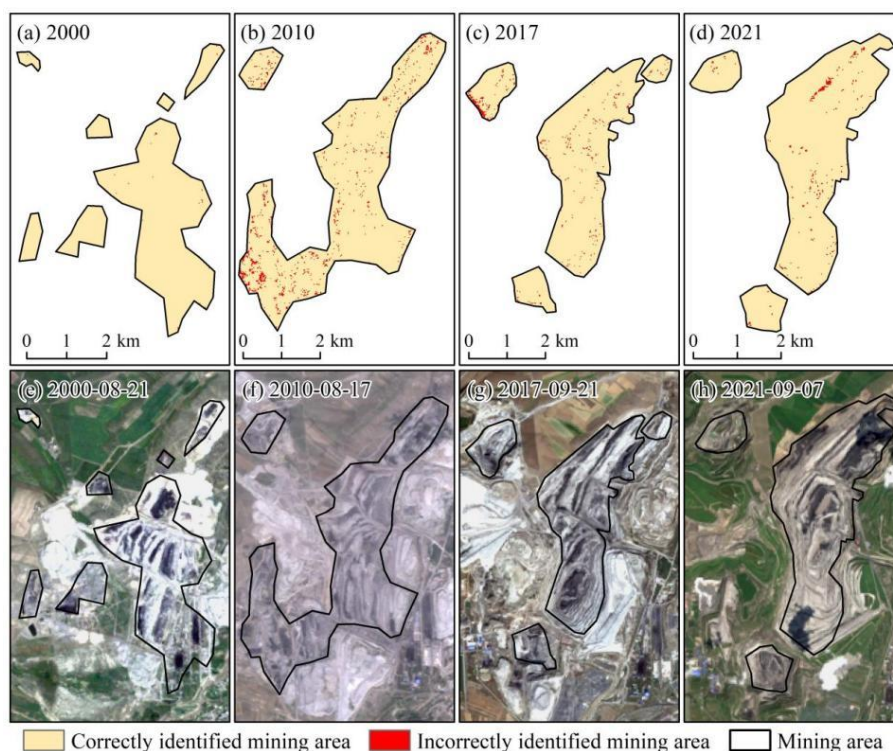


Figure 5. Detection results for the mining area in the validation years. The yellow area is the correctly detected mining area within the reference mining boundary of that year, and the red area is the incorrectly detected area. The lower panels are Landsat true-colour composites for the corresponding years.

Table 3. Detection of the mining area in the validation years.

Year	2000	2010	2017	2021
Reference mining area/ha	1976.4	2832.5	2060.1	2027.4
Detected mining area/ha	1973.9	2721.9	2011.0	1998.7
Absolute error/ha	-2.5	-110.6	-49.1	-28.7
Detection rate (DR)/%	99.9	96.1	97.6	98.6

Note: The reference mining area is the mining boundary for the corresponding year provided by the mining company. The detected mining area is the area of the spatial intersection between the pixels classified as mining-disturbed and the reference boundary.

3.3. Detection of Restoration Areas

The reclamation implementation date and the first detectable vegetation recovery are distinguished throughout this section. The reclamation implementation date is the year in which engineering works were recorded as implemented in the company polygons, and the first detectable vegetation recovery is the year of the first greening breakpoint identified at the same location. The interval between the two is the reclamation and recovery lag. The starting years of vegetation recovery within

the mining zone ranged from 1999 to 2022, with most occurring after 2010 and especially after 2017 (Figure 4b). Besides, the starting years of large-scale vegetation recovery within the mining area were concentrated mainly during two periods: 2010–2012 and 2017–2019, with the latter period showing a significantly larger extent (Figure 4d). It is evident that vegetation conditions were generally poor around 2010 (Figure 3e, Figure 5f), which correlates with severe drought conditions occurring that year [20]. In the years following the drought, vegetation began to recover as the precipitation increased. Therefore, the vegetation recovery during 2010–2012 is attributed to natural changes, whereas the adjusted NDVI trends within the mining area still indicate intensified mining activities during this period (Figure 3l).

Since 2018, the Inner Mongolia subsidiary of the National Energy Investment Group has undertaken ecological restoration and management of the mining areas, and vegetation cover increased in previously damaged areas over the same period. The LandTrendr results indicate that the area whose recovery started in 2018 reached 1375 ha (Figure 4d). Restoration projects were implemented in several phases between 2018 and 2020. Based on the company restoration polygons, the detected restoration area in the implementation year corresponded to 14.9%, 23.4% and 30.0% of the implemented area in 2018, 2019 and 2020, respectively (Table 4).

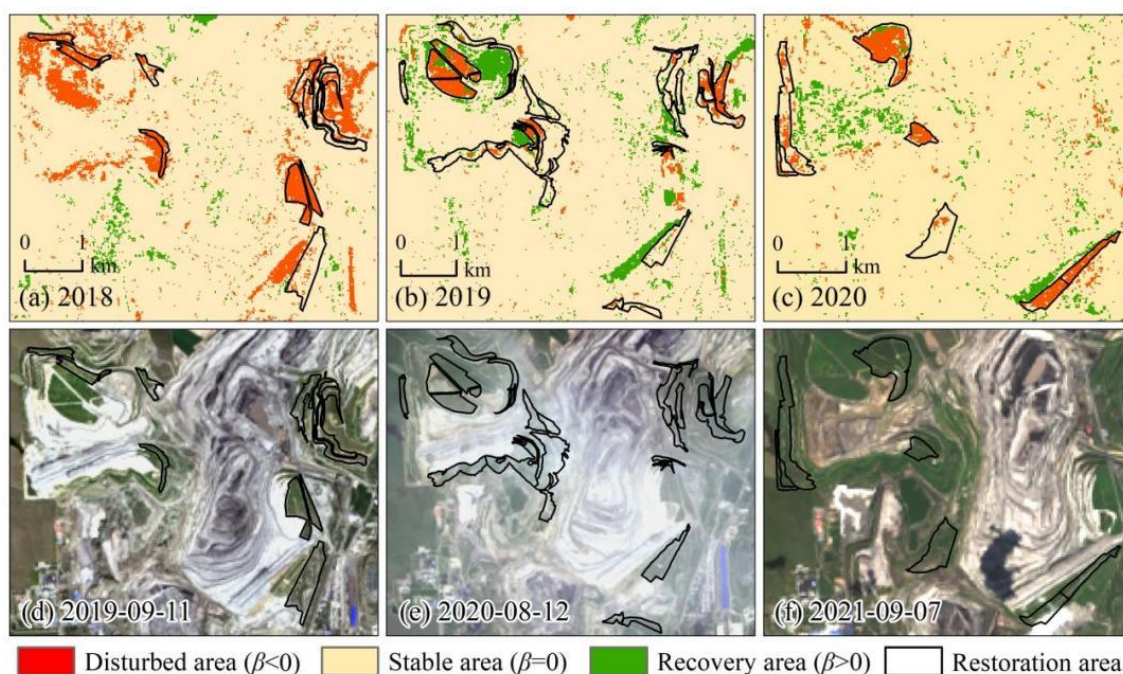


Figure 6. Detection results within the restoration project area from 2018 to 2020. In a to c, red indicates disturbance, yellow indicates stable surface and green indicates recovery; d to f are the Landsat true-colour composites of the following year.

Field survey revealed that in the year when ecological restoration projects were implemented, surface cover changes occurred, but vegetation did not immediately recover that same

year. For example, in 2018 when restoration projects were initiated, there was no vegetation visible on the surface; instead, it exhibited disturbed conditions. This disturbance change was

also identified by the LandTrendr algorithm (Figure 6a). However, one year after project implementation, vegetation began to recover on the surface (Figure 6d-f). Since vegetation cannot be detected before it is present, the low values in the implementation year are consistent with a lag of approximately one growing season between engineering works and a detectable canopy signal, rather than with a failure of the segmentation.

When the detection of year Y+1 was used as an exploratory adjustment for the restoration implemented in year Y, the adjusted values corresponded to 85.1%, 76.6% and 70.0% of the implemented area in 2018, 2019 and 2020, and the area that had been restored before each year corresponded to 49.6%,

90.9% and 97.9% of the corresponding reference area, for the areas restored before 2018, before 2019 and before 2020, respectively (Table 4). This adjustment was calibrated against the same company restoration records that were used for its evaluation, and it is therefore reported as an exploratory adjustment and not as an independent validation of implementation-year detection. Independent validation of implementation-year detection is not feasible with the data available for this site, because no independent record of reclamation timing exists. Testing the adjustment would require an independent source of implementation dates, for example engineering records from additional mines, or field plots established at the time of reclamation.

Table 4. Detection of implemented, lag-adjusted and cumulative restoration area.

Category		2018	2019	2020
Implemented restoration area	Reference area/ha	143.2	466.1	136.4
	Detected area/ha	21.3	109.2	40.9
	Detection rate (DR)/%	14.9	23.4	30.0
Lag-adjusted restoration area	Reference area/ha	143.2	466.1	136.4
	Detected area/ha	121.9	356.9	95.5
	Detection rate (DR)/%	85.1	76.6	70.0
Cumulative restoration area	Reference area/ha	115.1	258.3	724.4
	Detected area/ha	57.1	234.8	709.3
	Detection rate (DR)/%	49.6	90.9	97.9

Note. Implemented restoration area is the area of the engineering polygons for the projects implemented in that single year. Lag-adjusted restoration area is the area detected in the following year and used as an exploratory adjustment for the year of implementation. Cumulative restoration area is the total area recorded as restored before the column year, that is, before the projects of that year were implemented.

3.4. Vegetation Cover Change Associated with the Restoration Projects

The restoration project lasted from 2018 to 2021, which allows the NDVI values before the project, in 2017, to be compared with those after it, in 2022, for the restoration project area. After the implementation of the restoration project, the mining area decreased while the greening area expanded (Figure 3a-k), and the NDVI time series within the restoration project area showed an increasing trend with larger amplitude than before the project (Figure 3l). This result is consistent with the spatial distribution of NDVI and its changes in the

mining area before and after the implementation of the restoration project, as shown in Figure 7a-c.

The spatial pattern of change in NDVI (Δ NDVI, Figure 7d) is consistent with a positive vegetation-cover response associated with the restoration projects (Figure 7a-c), and the change is concentrated in the restoration project area. Within that area, the proportion of pixels with Δ NDVI less than 0 is 2.8%, compared with 20.5% within the mining area, and the proportion of pixels with Δ NDVI greater than 0.4 is 40.6%, compared with 20.4% within the mining area (Table 5). The data therefore show a vegetation-cover change that is spatially and temporally associated with the restoration projects, and they do not by themselves establish a causal effect of the projects, nor do they measure soil recovery, biodiversity, erosion control or ecosystem function.

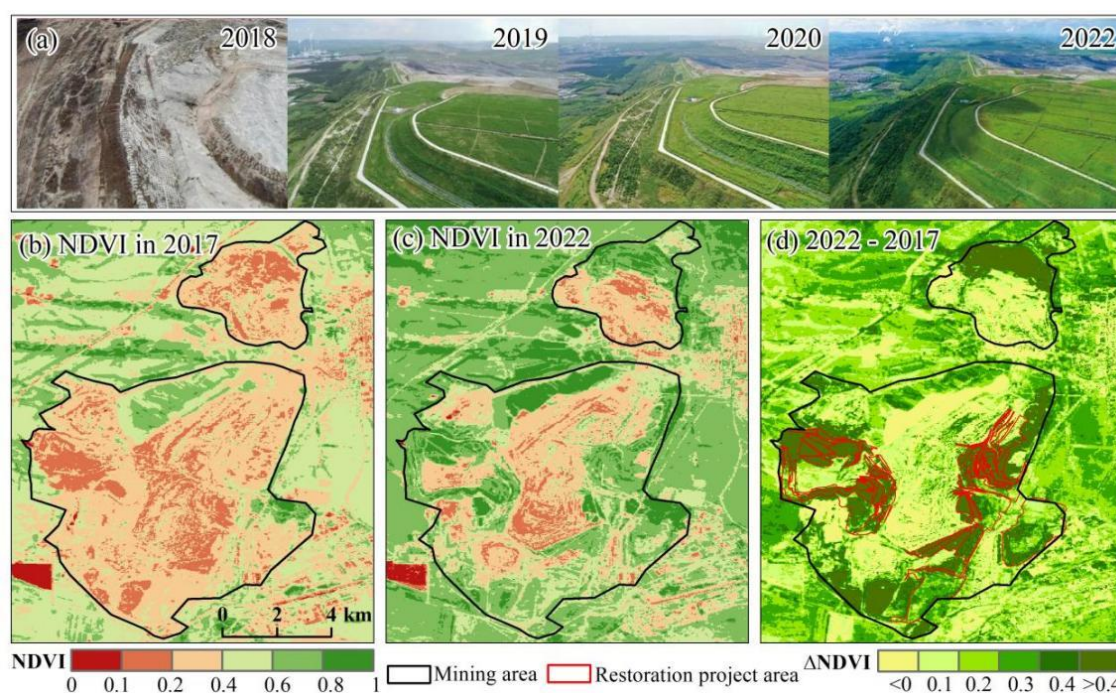


Figure 7. Spatial distribution of NDVI in the mining area before (2017) and after (2022) the implementation of the restoration projects, and the difference (Δ NDVI) between them. Panel a shows field photographs of the same mining area.

Regional ecological restoration is a long-term process, and the greening identified here from remote sensing represents a change in vegetation cover rather than a complete ecological recovery. A comprehensive evaluation of ecological restoration would require long-term observation combined with on-

site physical and chemical monitoring, and a design that can separate the effect of the projects from concurrent climatic variation.

Table 5. Area and its proportion of Δ NDVI classes between 2017 and 2022 within the maximum mining extent and within the restoration project area.

Δ NDVI class	Within the maximum mining extent		Within the restoration project area	
	Area/ha	Proportion/%	Area/ha	Proportion/%
<0	1833.9	20.5	57.2	2.8
0-0.1	1712.7	19.1	159.9	7.9
0.1-0.2	1514.5	16.9	327.9	16.2
0.2-0.3	1230.3	13.8	371.2	18.3
0.3-0.4	824.4	9.2	284.9	14.1
>0.4	1829.1	20.4	822.4	40.6

Note. Both columns are tabulated over the maximum mining extent, defined as the union of all mining boundaries over the analysis period. The restoration project area is a subset of the maximum mining extent, so the two columns are nested. Within each column, proportions are expressed relative to the column total. The coalfield boundary encloses approximately 9,605.9 ha, of which 8,944.9 ha is assigned to one of the six classes within the maximum mining extent and the remaining 661.0 ha lies outside that extent. The maximum mining extent is contained within the coalfield boundary.

4. Discussion

4.1. Uncertainties of LandTrendr Algorithm

The parameter settings of the LandTrendr algorithm may introduce some uncertainties to the results. Due to the involvement of various data processing and parameter settings in the algorithm, such as the maximum number of segments in a sequence, the segment recovery threshold, minimum observation values, etc., these parameters directly affect the sensitivity of monitoring and the accuracy of results. Different parameter settings can lead to different monitoring effects of vegetation disturbance/recovery [19], thus introducing certain errors that require manual calibration based on actual conditions.

This study employs NDVI as vegetation indicator proxy, but in certain situations, it may not be suitable. NDVI can distort in areas with low vegetation cover, such as built-up areas, roads, bare soil, snow-covered areas, and water bodies [10]. In mining areas, sparse vegetation cover may cause large uncertainties. In future studies, integrating multiple remote sensing indicators that characterize changes in land surface cover could improve the accuracy of results.

Although cloud-free images were used, issues related to data quality, such as weather, clouds and noise, are inevitable. This is especially true in long time-series analyses where imagery data quality may degrade, particularly in sequences longer than five years, which limits the reliability of long-term trend detection. Additionally, this study utilized multiple satellites from the Landsat series, and there may be discontinuities in sensor parameters and generated data, which could introduce errors into the results.

A further limitation is that independent reference samples are not available for this study. The reference data are the mining boundaries and the restoration engineering polygons provided by the mining company, and the reported statistic is therefore an area-based detection rate against those polygons rather than an accuracy of the full spatial classification. A spatially independent accuracy assessment based on field observations or photo-interpreted samples would be a valuable extension of this work.

4.2. Reclamation and Recovery Lag

The lag identified here has a direct consequence for monitoring. A comparison of detected restoration against engineering records within the administrative year of implementation under-reports implemented restoration by a factor of between three and seven in this study, and a monitoring programme that reports only within year values could conclude that a restoration project had largely failed. We therefore recommend that evaluation windows be placed at least one growing season after implementation, and that cumulative restored area be evaluated on a rolling basis rather than at a single reporting date.

The lag is also a testable expectation rather than an established constant. It is derived from one coalfield and one restoration campaign, it is calibrated against the same records used for evaluation, and its length is expected to depend on climate, on the type of reclamation engineering, on whether seeding or irrigation was used, and on species composition. Applying the same analysis to other mining areas with independent implementation records is the appropriate next step.

4.3. Implications for Ecological Monitoring

Mining activities can disrupt existing land cover, leading to exposed soil, accumulation of mine tailings and residues, among other disturbances, which can result in negative impacts such as soil erosion and sedimentation [1, 2]. Restoration activities help in improving soil structure and quality and restore vegetation cover as well as ecosystem functions in mining areas. Both mining disturbances and surface restoration need just-in-time monitoring to evaluate potential effects of such actions.

Traditional on-the-ground monitoring is costly in terms of time and manpower. In contrast, the GEE-LandTrendr algorithm offers advantages such as large-scale, continuous, and high-precision dynamic monitoring. In monitoring mining disturbances, it analyzes and monitors the impact of mining activities on land cover, identifies patterns and trends in mining area changes, and provides strong support for mining activity management and environmental protection. In the monitoring of restoration processes, it can detect vegetation changes associated with restoration activities, offering robust decision-making support for mining area ecological restoration planning.

The attribution of the 2017-2022 greening to the restoration projects rests on the spatial concentration of the change within the restoration project area and on the normalized series (Figure 3). Climate confounding cannot be fully removed by this approach, because the non-mining reference area does not reproduce all climatic and hydrological conditions of the reclaimed surfaces, and because other management changes occurred over the same period. A causal attribution would require a counterfactual design, for example a matched unreclaimed area with comparable substrate, slope and climate. The findings reported here are therefore associations between vegetation-cover change and restoration activity.

5. Conclusions

Increasing open-pit mining activity affects regional ecological environments, which requires large-scale disturbance monitoring and evaluation of restoration effects. Using long-term Landsat surface-reflectance imagery in the Google Earth Engine platform, this study used the LandTrendr algorithm to monitor surface disturbances and subsequent vegetation-cover changes in the Huolinhe open-pit mining area over the period 1998 to 2022. The algorithm identified mining disturbance

with a detection rate exceeding 96% in the validation years. For the identification of reclamation project effects, the results require an adjustment for the lag between engineering implementation and detectable vegetation recovery. The monitored vegetation-cover change was spatially concentrated in the restoration project area and is consistent with a positive response associated with the reclamation projects, although the data do not establish a causal effect and do not measure soil recovery, biodiversity, erosion or ecosystem function. Future work should include parameter sensitivity testing, the comparison of multiple spectral indices, and independent validation of the lag using independent implementation records. Overall, the LandTrendr algorithm provides rapid identification of surface disturbance and can support the formulation of strategies for large-scale monitoring of ecological disturbance.

Abbreviations

LandTrendr	Land Trends Detection and Recovery Algorithm
GEE	Google Earth Engine
GEE-	LandTrendr Algorithm on the Google
LandTrendr	Earth Engine Platform
NDVI	Normalized Difference Vegetation Index
DVI	Difference Vegetation Index
EVI	Enhanced Vegetation Index
NIR	Near-Infrared Band of Landsat Image
R	Red Band of Landsat Image
Δ NDVI	Change in Normalized Difference Vegetation Index
DR	Detection Rate
β	Rate of NDVI Change Per Year

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Data Availability Statement

The Landsat surface-reflectance collections used in this study are available from the Google Earth Engine data catalog

(LANDSAT/LT05/C02/T1_L2, LANDSAT/LE07/C02/T1_L2, LANDSAT/LC08/C02/T1_L2). The mining and restoration boundaries were provided by Huolinhe Opencut Coal Industry Corporation Limited of Inner Mongolia.

Conflicts of Interest

The authors declare no conflicts of interest.

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