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Landscape Analysis and Ecological Risk Assessment during 1995–2020 Based on Land Utilization/Land Coverage (LULC) and Random Forest: A Case Study of the Fushun Open-Pit Coal Area in Liaoning, China

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Abstract: China's Fushun open-pit mine is the largest century-old coal mine in Asia. Large-scale mining and the use of coal has caused dramatic changes in the regional urban landscape pattern, seriously affecting the ecological function and ecosystem stability of its surrounding landscape. Evaluating the ecological risks of the landscape in the urban areas of open-pit mines contributes to the risk management of regional ecosystems and the sustainable development of society. This study selected six-phase Landsat ETM/OLI remote sensing images from 1995 to 2020 and combined them with the random forest model to carry out an LULC classification of the open-pit mine and its surrounding areas and, on this basis, discusses the evolution of its landscape pattern and evaluates the ecological risks. It fills the gap in the research on the evolution of regional landscape patterns and ecological risks in the study area and improves the automatic classification efficiency of LULC for use in open-pit mines. The results show that the classification accuracy of LULC regarding open-pit mines based on image pixels and the random forest model can reach 30 m, and the rate of accuracy can reach 92–97%. From 1995 to 2020, the coverage area of forest land and building land in the study area has increased and is mainly composed of grassland and undeveloped land. The use of land was transferred to the mining area, the water body area maintained a relative dynamic balance, and the overall vegetation coverage of the mining area was greatly improved; the forest land began to expand from the surrounding area to the mining area in 2010, and the construction land began to move from the areas surrounding the mining area to the surrounding valleys in 2015. The landforms have extended radially, and the landscape sprawl index has increased, indicating the optimization of the ecological environment; the high- and medium-risk areas decreased by 75.51 km², the low-risk areas expanded by 461.48 km², and the overall ecological risk index decreased. From this, it is possible to conclude that the landscape restoration project adopted in the study area has achieved great results, and the improvement of the ecological environment also directly affects the increase of construction land. These research results can provide scientific guidance for the rational utilization and sustainable development of land resources in urban areas of open-pit mines.

Keywords: Liaoning Fushun open-pit coal mine; random forest; LULC; landscape index; landscape ecological risk assessment



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1. Introduction

With the rapid development of global industrialization and economic levels, the demand for mineral resources is rising, and the large-scale exploitation of mineral resources

has a large impact on the use of land resources and the ecological environment [1]. Studies have shown that ecosystem stability and ecological risk assessment are more significantly affected by land use change [2,3]. Therefore, in recent years, exploring landscape patterns and ecological risks in a region based on changes in land use types has gradually become a research hotspot. Due to the unqualifiable nature of land use types and the diversity of factors influencing their changes, a true and accurate classification of land use types must be the basis for landscape pattern analysis and ecological risk evaluation [4]. Remote sensing images have been gradually applied in land object classification research because of their high temporal and spatial resolution characteristics. At present, the classification methods of mine features based on satellite remote sensing images mainly include visual interpretation and supervised classification [5]. There are two main problems: (1) Visual interpretation has a high level of accuracy, but the workload is large, and the interpretations by personnel are subjective. Knowledge has a greater impact. (2) The supervised classification method is fast and efficient, but the accuracy is relatively low. After years of continuous development of machine learning technology and deep learning methods, the automatic extraction and classification of features has become a new direction for artificial intelligence [6–9]. Random forest belongs to supervised classification and is representative of the Bagging model of integrated learning in machine learning technology [10]. It is characterized by efficient, stable, and accurate results [11], and it has been confirmed to have a high accuracy rate in some feature classification studies [12,13], but it is less applied in the field of open-pit mine feature classification studies [14–18]. Visual interpretation is still the main method of land use classification in open-pit mines. Therefore, the automatic classification of features in the urban areas of surface coal mines using the random forest method is an area urgently requiring a breakthrough.

At present, many experts and scholars have proposed the use of landscape ecological risk assessment to provide a decision-making basis for regional comprehensive risk prevention, which can effectively guide the optimization and management of regional landscape patterns [16]. Ecological risk assessment studies have been conducted by scholars in urban, rural, watershed, forest, mountain, and highland areas [2,19]. For example, the evaluation of the ecological risk level of resource-based cities explores the time-series evolution and ecological risk changes of landscapes such as forests, oceans, glaciers, and rivers [20,21]. Within the Jinghe County region, Zhang et al. [22] used the CLUE-S model to predict land use under different scenarios and assessed the spatial and temporal evolution of ecological risk characteristics under different land use conditions. Deng et al. [1] analyzed the evolution of the landscape pattern of the urban agglomeration in central Yunnan based on changes in land use types and systematically evaluated the landscape ecological risk of this urban agglomeration. Lin et al. [23] assessed the landscape ecological risk of Guiyang, a typical mountainous city with a karst landscape, and modeled the landscape ecological risk under different scenarios in the future, which is an important guide for the maintenance and management of local ecological safety. However, in ecological risk studies of open-pit mines, ecosystem stability studies have been conducted mainly by evaluating the dynamic changes of coal mine expansion and retreat [4,24] and monitoring the changes of vegetation in mining areas [25–28]. There is a lack of research in the analysis of land cover and utilization type changes, as well as landscape pattern evolution of open-pit mines in a regional scale [29]. Therefore, this study addresses this issue to classify land use types and analyze the landscape pattern within the mining area, with an aim of filling the gap in the research in the field of landscape ecological risk in open-pit mines.

China's Fushun open-pit mine is located in the southwest of Fushun City, Liaoning Province, China. It is the largest century-old coal mine in Asia. Mining activities in the past 100 years have caused serious soil erosion, accompanied by secondary geological and soil hazards. The groundwater is polluted, and ecological structure components are destroyed. This seriously affects the landscape structure and ecosystem of the mining area, destroys the ecological function of the landscape, and increases the ecological risks [30–32]. At the same time, due to the special location of "mines in the city", the dramatic changes in the

landscape structure and ecological risk changes in the mining area and its surrounding areas seriously affect the daily life of residents in urban areas near the mining area [33]. However, current research on the ecological environment of the study area mainly focuses on mine geological hazards [32–34], vegetation and soil effects [31], and the monitoring of the mine geoenvironment [35]. There are few related studies on landscape pattern changes [31]. The mining activities and restoration of the Fushun open-pit mine will change the landscape structure of the mine land. At the same time, because of the scale and location of the study area, pattern changes are closely related to the lives of the surrounding residents, and changes in ecological risks will greatly affect the surrounding residents' living conditions. Therefore, it is of great scientific significance to explore the landscape pattern evolution and ecological risk changes of the Fushun open-pit mine in order to improve its landscape pattern [27,36], reduce its ranking on the ecological risk index, and protect the lives of the surrounding residents and the surrounding urban environment.

In this paper, we utilize China's Fushun mine (which has a large open-pit mining area and is relatively ecologically fragile) as a study site with the following goals: (1) develop a random forest classification method based on equidistant sampling points to achieve efficient land use for pixel-based remote sensing using six-phase Landsat ETM/OLI remote sensing images from 1995 to 2020; (2) evaluate and analyze the evolution of landscape patterns and ecological risks in the Fushun mine based on our classification results to provide a quantitative basis for future land use planning at Fu-shun and other open-pit coal mines in China. The results of this study are intended to provide a scientific basis for ecological risk prevention and sustainable development in the urban area of the Fushun open-pit coal mine.

2. Materials and Methods

2.1. Study Area

The Fushun open-pit mine is in the southwest of Fushun City, Liaoning Province, China (Figure 1). The study area is 1865.61 km², and the area of Fushun East–West Open-pit Mine is 13.2 km². Its mining scale is very large, and it is known as “the largest open-pit mine in Asia” [35]. Data for a digital elevation model (DEM) were downloaded from the Geospatial Data Cloud Platform (<https://www.gscloud.cn/>, accessed on 19 May 2023). The study area has a semi-humid continental monsoon climate, with an uneven distribution of precipitation during the year, which is mainly concentrated in July–September. The annual average temperature is 6.6 °C, and the annual average annual precipitation is 800.00 mm. The hilly landform in the study area is formed by the combined action of crustal uplift and weathering and denudation. Its major bedrock types are Paleogene basalts and Archean granite gneiss complexes [31,34]. The mine products are coal and kerogen shale. The coal products include long-flame and gas coal, the average calorific value is 7500–8000 kcal/kg, and the oil content of the kerogen shale is 6–14% [29,31–33,35].

2.2. Data Sources

This study relied on quantitative remote sensing parameters [37] to extract features such as vegetation, water bodies, and land use types in the mining area. Because the vegetation growth state has obvious differences in response to seasonal changes, and vegetation growth is an important indicator for ecological risk assessment in mining areas [38–40], a selection of remote sensing images with good vegetation growth and low cloud coverage was important for extracting vegetation information within the mining area [41–43]. In this study, on the USGS platform (<https://earthexplorer.usgs.gov/>, accessed on 20 May 2023), six Landsat images with a low cloud cover and lush vegetation were selected in the study area from June to August. This study was conducted using Landsat-TM/ETM satellite imagery from 1995 to 2010 and Landsat 8 OLI satellite imagery from 2015 and 2020 [44]. To calculate the corresponding quantitative remote sensing index based on the reflectance of the relevant bands of the satellite image, it was necessary to use ENVI5.6 software to perform data preprocessing such as radiometric calibration, atmospheric cor-

rection, geometric correction, and image enhancement on the Landsat image to reduce the influence of the atmosphere on surface reflectance [45]. The 6 images covered the changes in land use types, landscape pattern evolution, and ecological risk changes from 1995 to 2020. The same research area was cut according to the mask range in ArcGIS 10.2. This provided a data basis for the calculation of quantitative remote sensing parameters and the classification of land use types in the study area based on random forest (RF).

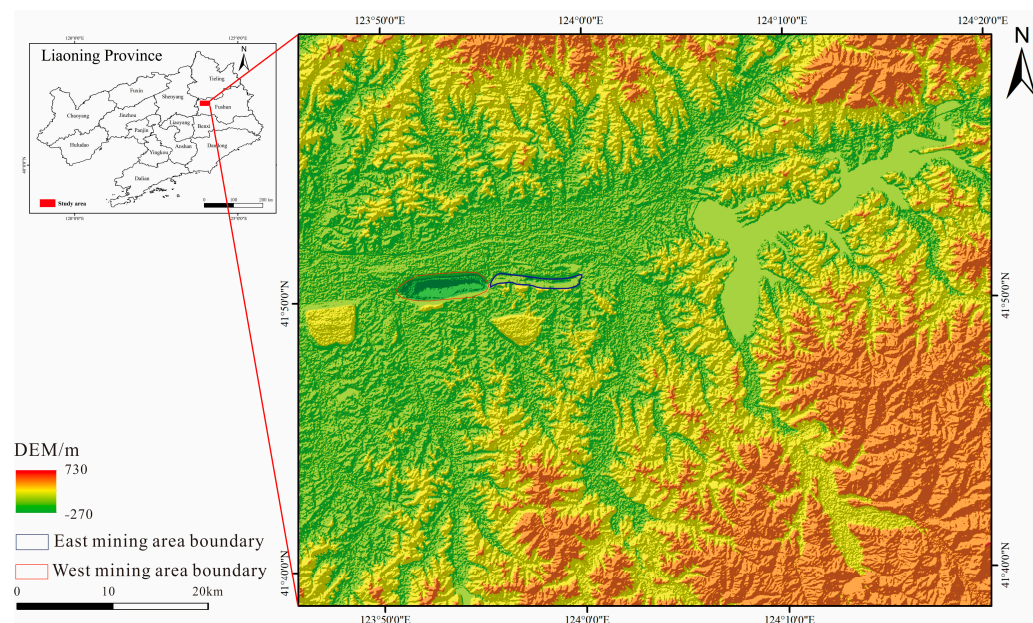


Figure 1. Study area.

2.3. Research Methods

Based on the present conditions at the Fushun mine, we divided the ground features into six types: grassland, forest land, water, construction land, mining area, and unused land. According to the spectral characteristics of different ground objects, NDVI, NDISI/NDBI/NDWI, visible light RGB bands, and red bands were selected as evaluation parameters, and 10,000 training points in each period were established to classify images in each period. Based on the classification results, Fragstate4.2 was used to calculate the main landscape pattern index within the study area, and the landscape pattern and ecological characteristics were analyzed to comprehensively evaluate the landscape pattern evolution and ecological risk index evaluation from 1995 to 2020 [7,46] (Figure 2).

2.3.1. Random Forest Classification Method

(1) RF algorithm

The random forest algorithm is based on the Bagging ensemble learning theory published by Professor Leo Breiman of the University of California in 1996 [47] and the random subspace method proposed by Tinkam in 1998 [48,49] as algorithms for the combinatorial classification models of trees. It forms an integrated classifier from a variety of weak classifiers, and the mode of the output category of the decision tree determines the output classification. RF is robust for feature selection and is an efficient supervised ML algorithm [50].

RF consists of three parts: bootstrap resampling, generating decision trees, and forming random forests. Bootstrap resampling is used to perform a random sampling of the data sample set N times with a replacement and obtain a subset of the training set as a new training set; the generation of the decision tree is to randomly select m from the feature variable attribute set in the new training set, with equal probability. Each attribute is used as an attribute subset, and an optimal attribute selected for node splitting comes from this

subset and is used to generate the decision tree; the composition of the random forest is based on the generation of k decision trees, and the classification results are voted by the k decision trees.

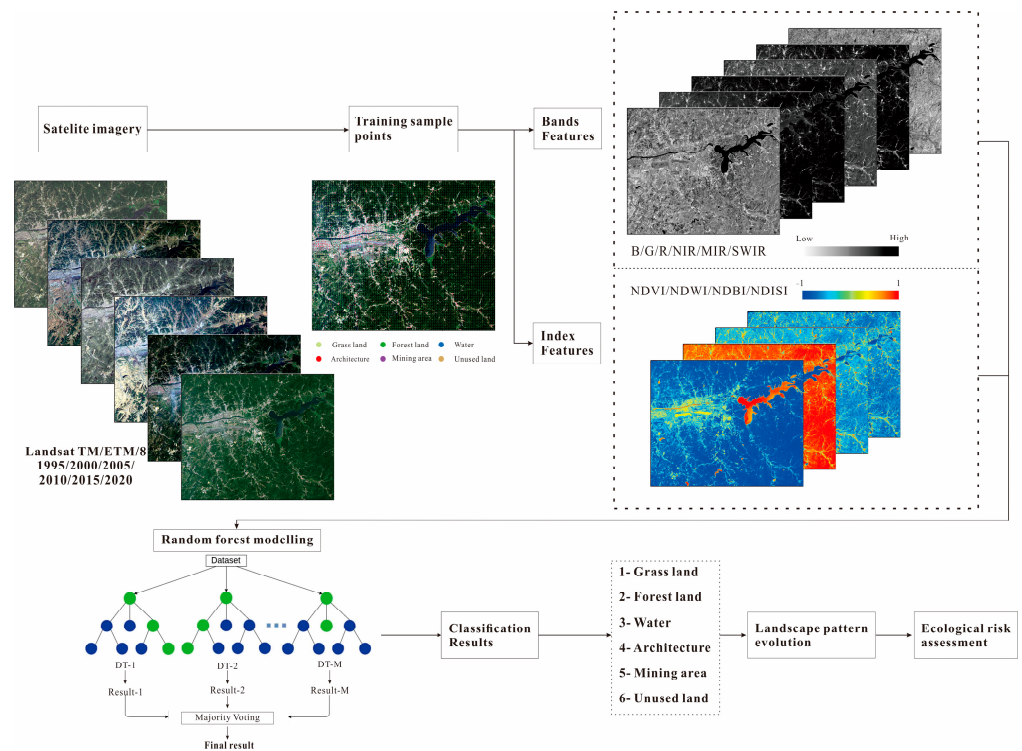


Figure 2. Workflow.

After the random forest is generated, the RF model can be used to classify and discriminate the training set samples. The process is to let each decision tree vote separately and finally use the category with the most output categories among all the decision trees as the classification result. The discriminant of the final classification is as follows [13,49,50]:

$$H(x) = \text{voting} \sum_{i=1}^k I(h_i(x) = Y) \quad (1)$$

In the formula, $H(x)$ is the classification combination model; h_i is the decision tree classification model; $I()$ is the indicative function (1 when this value is present in its parameter set and 0 when there is no such value in the set); and Y represents the target variable (or output variable) [50].

According to the training process of the random forest model and the present understanding of random forest, the tree (k) of the decision tree and the number of elements (m) randomly selected by each tree in each split are the factors that determine the prediction result, which is an important parameter of the degree of accuracy (Figure 3). During the model training process, two-thirds of the samples are used as the training set, and the remaining one-third of the samples is used to verify the accuracy of the prediction results (OOB). The RF model was established on Pycharm by using the sklearn package, which consists of three parts: training data selection, model training, and classification result output.

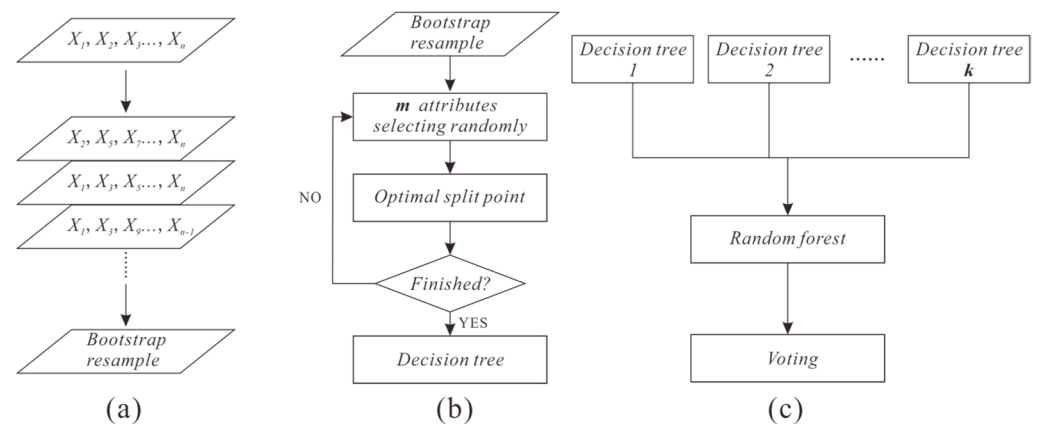


Figure 3. Random forest model composition: (a) bootstrap resample; (b) decision tree; (c) random forest establishment.

(2) Predictor establishment

There are six main types of land use in the Fushun open-pit mining area. According to the spectral curve characteristics of the different types of ground objects, we select the normalized vegetation index (NDVI) to quantitatively extract the vegetation range and determine whether the covered vegetation is forest or grassland according to the NDVI and its identification characteristics in visible light [37,51]; the normalized water body index (NDWI) is selected to extract the characteristics of water bodies within the mining area [52]; and the normalized bare soil index (NDBI) is selected to distinguish the non-vegetation and bare soil areas [53]. The open-pit mine is not sensitive to the NDBI index between construction land and bare soil; therefore, the normalized impervious surface index (NDISI) [54] is selected to further distinguish them. In order to realize the classification of land types more intuitively and accurately, the RGB, NIR, MIR, and TIR bands provided by the Landsat multispectral sensor are added to the prediction elements to realize the distinction between the types of land objects in the study area [54]. The main parameter formulas include, as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (2)$$

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \quad (3)$$

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \quad (4)$$

$$NDISI = \frac{TIR - (GREEN + NIR + MIR)/3}{TIR + (GREEN + NIR + MIR)/3} \quad (5)$$

(3) Training data

The training sample points are selected year by year for the six images of 1995/2000/2005/2010/2015/2020, 10,000 training sample points are evenly selected on each image, and the ground object types are extracted by visual interpretation [54]. Prediction feature extraction is performed on the training sample points to provide training samples for the construction of the random forest model. The spatial location of the training samples and some of the training samples are shown in Figure 4 and Table 1.

The optimal parameter adjustment refers to the accuracy of OBB, carried out based on the GridSearchCV, a sub-module of the sklearn module in Python [55]. It traverses all the parameters to determine the optimal values.

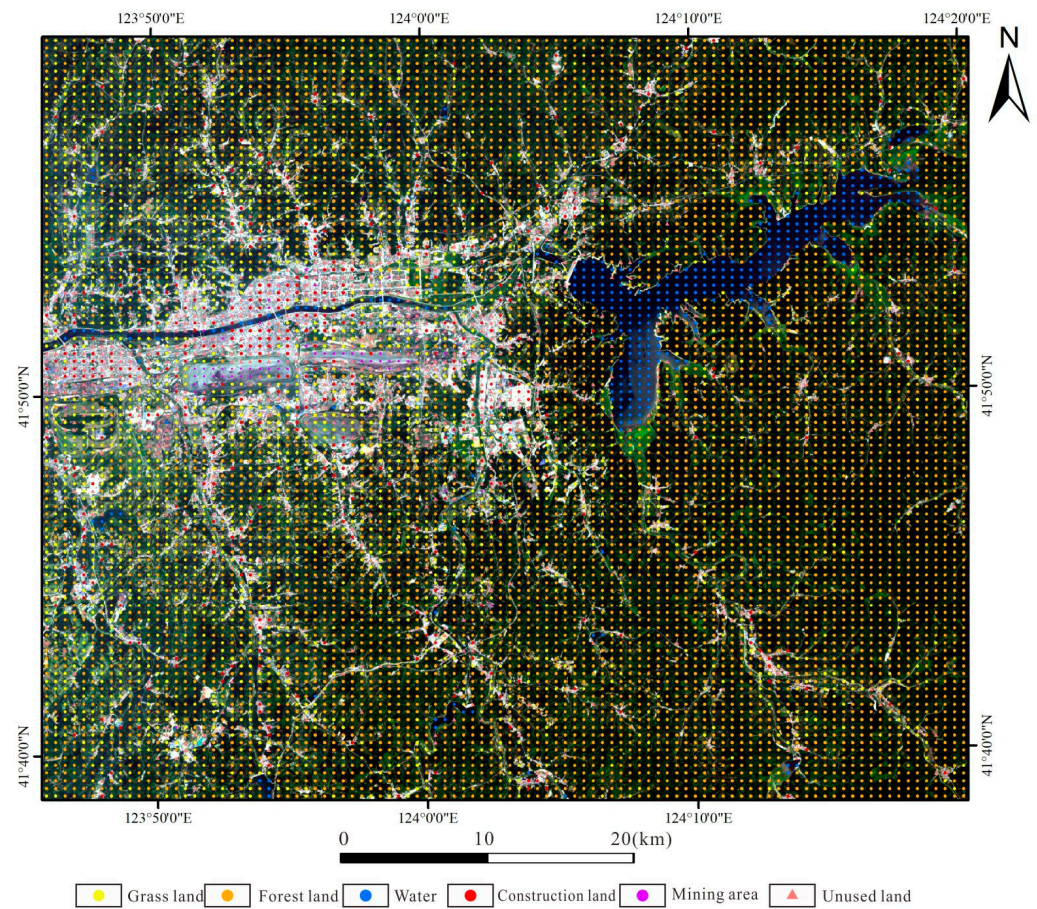


Figure 4. Location selection of the training samples.

Table 1. Part of training data.

Type	NDVI	NDWI	NDISI	NDBI	b1	b2	b3	b4	b5	b6
1	0.584135	−0.64032	−0.29876	−0.22434	381	578	692	2636	1670	879
1	0.542924	−0.60207	−0.1671	−0.11805	454	654	780	2633	2077	1276
2	0.722332	−0.68164	−0.51319	−0.44637	305	411	350	2171	831	366
2	0.716343	−0.68729	−0.41997	−0.30992	337	508	453	2741	1444	639
3	−0.05752	0.159763	−0.28824	−0.31077	207	294	239	213	112	114
3	−0.07042	0.106767	−0.43947	−0.53488	204	368	342	297	90	98
4	0.139021	−0.3472	0.056139	0.07168	692	957	1213	1975	2280	1944
4	0.118249	−0.48795	−0.03852	−0.04796	599	797	950	2316	2104	1610
5	0.196325	−0.36039	−0.00138	0.052072	523	796	919	1693	1879	1452
5	0.176895	−0.24164	0.056169	0.02004	657	896	1026	1467	1527	1451
6	0.047214	−0.52	−0.05496	−0.03754	446	816	987	2584	2397	1731
6	0.189973	−0.53352	−0.10072	−0.04629	526	856	1235	2814	2565	1698
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Instrument: 1—Grass land, 2—Forest land, 3—Water, 4—Architecture, 5—Mining area, 6—Unused land, b1—Blue, b2—Green, b3—Red, b4—NIR, b5—MIR, b6—TIR.

2.3.2. Landscape Analysis Method

Mining activities have reduced vegetation cover and patch connectivity in mining areas, have accelerated fragmentation, and have altered landscape patterns in mining areas [56]. Therefore, calculating the landscape pattern index of the study area and quantitatively analyzing the changes in the landscape pattern of the mining area are very important for the ecological risk assessment of the mining area [8]. Based on the characteristics of the distribution of land use types in the study area, this study calculated

the landscape pattern index at the land type level and the landscape level to analyze the evolution characteristics of the mining area's landscape pattern.

Selecting the patch area (PA) from the land type level to measure the components of the landscape [55] and selecting the patch density (PD) is conducive to the comparison of landscape types of different sizes between landscapes [56]. The proportion of landscape area occupied by patches (PLAND) is an important factor in determining ecosystem indicators such as biodiversity and quantity in the landscape [57]. The largest patch index (LPI) is extracted to determine the type of landscape dominance, and the change in its value can reflect the direction and strength of human activities [41]. The Shannon Diversity Index (SHDI) is selected from the landscape level to reflect landscape heterogeneity, as this index is especially sensitive to the uneven distribution of each patch type in the landscape [58]. The landscape isolation index (DIV) can characterize the intensity of anthropogenic disturbance to some extent. The Shannon Evenness Index (SHEI) is calculated to compare the diversity of different landscapes or the same landscape in different periods [54,59]. The degree of aggregation or dispersion of different types of plaques is analyzed using the contagion index (CONTAG) [60]. The indices above are calculated based on the Fragstats4.2 moving window method.

2.3.3. Landscape Ecological Risk Index

In order to spatialize the ecological risk index of the mining area on the basis of considering the scope of the study area, the spatial heterogeneity of the landscape, and the size of the patch, and according to the principle of 2–5 times the average area of the landscape patch in the study area [61], this study adopts the sampling method at equal intervals [62]. Using the fishing net sampling method, the study area was divided into $1.5 \text{ km} \times 1.5 \text{ km}$ risk areas, and a total of 829 landscape ecological risk areas. The value of each grid is assigned to the center point of this grid, and finally, the value of the center point is spatially interpolated using the Cree interpolation method to obtain the spatial distribution map of ecological risk.

Ecological risk refers to the possible adverse consequences of the interaction between landscape patterns and ecological processes under the influence of natural or human factors [8]. The landscape ecological risk index refers to the risk value of different landscapes to the ecological environment and is used to characterize the contribution of ecological risks caused by different landscapes [63–66]. This study constructed a landscape ecological risk index (ERI) based on the proportion of land use type area, landscape pattern index, and landscape loss index (R_i) [67]. The calculation formula and meaning are shown in Table 2.

The final landscape loss index (R_i) and landscape ecological risk index (ERI) models are as follows:

$$R_i = U_i \times E_i \quad (6)$$

$$ERI = \sum_{i=1}^N \frac{A_i}{A} R_i \quad (7)$$

In order to discuss and analyze the spatial and temporal distribution and evolution trend of landscape ecological risks in this mining area, the ecological risk index was divided into 5 landscape ecological risk levels by the natural discontinuity method combined with the actual situation of the research area [62]. The ecological risk level of each landscape and its area proportion in different periods were calculated separately.

Table 2. Ecological risk assessment index and calculation method [60,63].

Landscape Pattern Index	Calculation Formula	Formula Description
Landscape fragmentation index (C_i)	$C_i = \frac{n_i}{A_i}$	n_i is the number of patches of landscape i ; A_i is the total area of landscape i
Landscape separation index (S_i)	$S_i = \frac{A}{2A_i} \sqrt{\frac{n_i}{A}}$	A is the total landscape area
Landscape dominance index (K_i)	$K_i = \frac{1}{4} \left(\frac{n_i}{N} + \frac{m_i}{M} \right) + \frac{A_i}{2A}$	m_i is the quadrat number of landscape type i patches, m_i is the total quadrat number, and i is the total number of patches
Landscape disturbance index (U_i)	$U_i = aC_i + bS_i + cK_i$	Indicates the impact of each index on the value of landscape ecological services, $a + b + c = 1$, and here, $a = 0.5$, $b = 0.3$, $c = 0.2$
Landscape vulnerability index (V_i)	Drawing on relevant research in mining areas and combining the characteristics of risk sources, the land type and vulnerability are linked, and the vulnerability is divided into 6 levels	Unused land = 6, Grass land = 5, Water = 4, Forest land = 3, Mining area = 2, Architecture = 1
Landscape loss index (R_i)	$R_i = U_i \times E_i$	U_i and E_i are the disturbance index and vulnerability index of landscape i , respectively

3. Results

3.1. RF-Based Classification Results

3.1.1. Optimal Model Parameter Training

We perform RF classification on the Pycharm platform by using the sklearn package. According to existing research, the main parameters set by random forest are the main tree k and the number of attributes m participating in the establishment of each tree (Figure 5 and Table 3). We use GridsearchCV to adjust the optimal parameters. According to the suggestion of Breiman [48], we choose the square root of the total number of predictors as a reference to adjust the optimal m and value, and then, on the basis of determining the m value, we traverse and analyze the optimal tree k , and, according to OBB_error, the best parameter selection is performed with the lowest value of OBB_error (high accuracy).

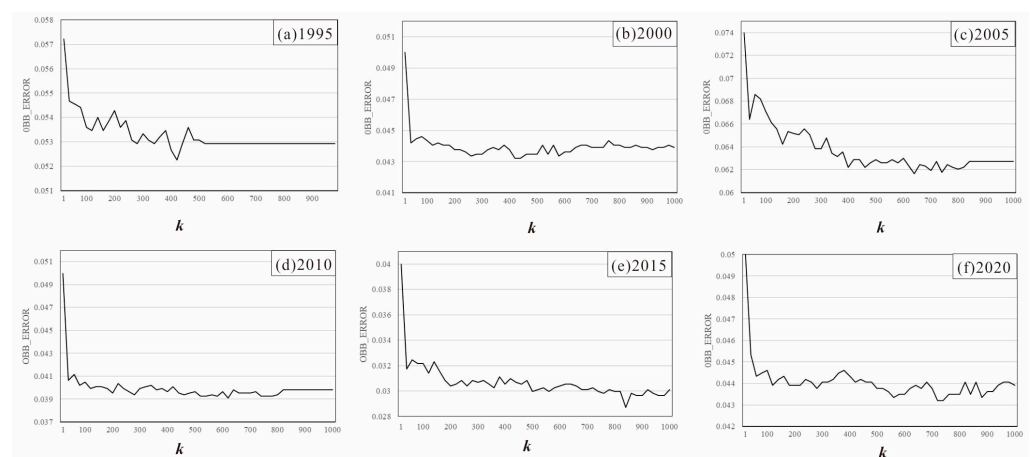
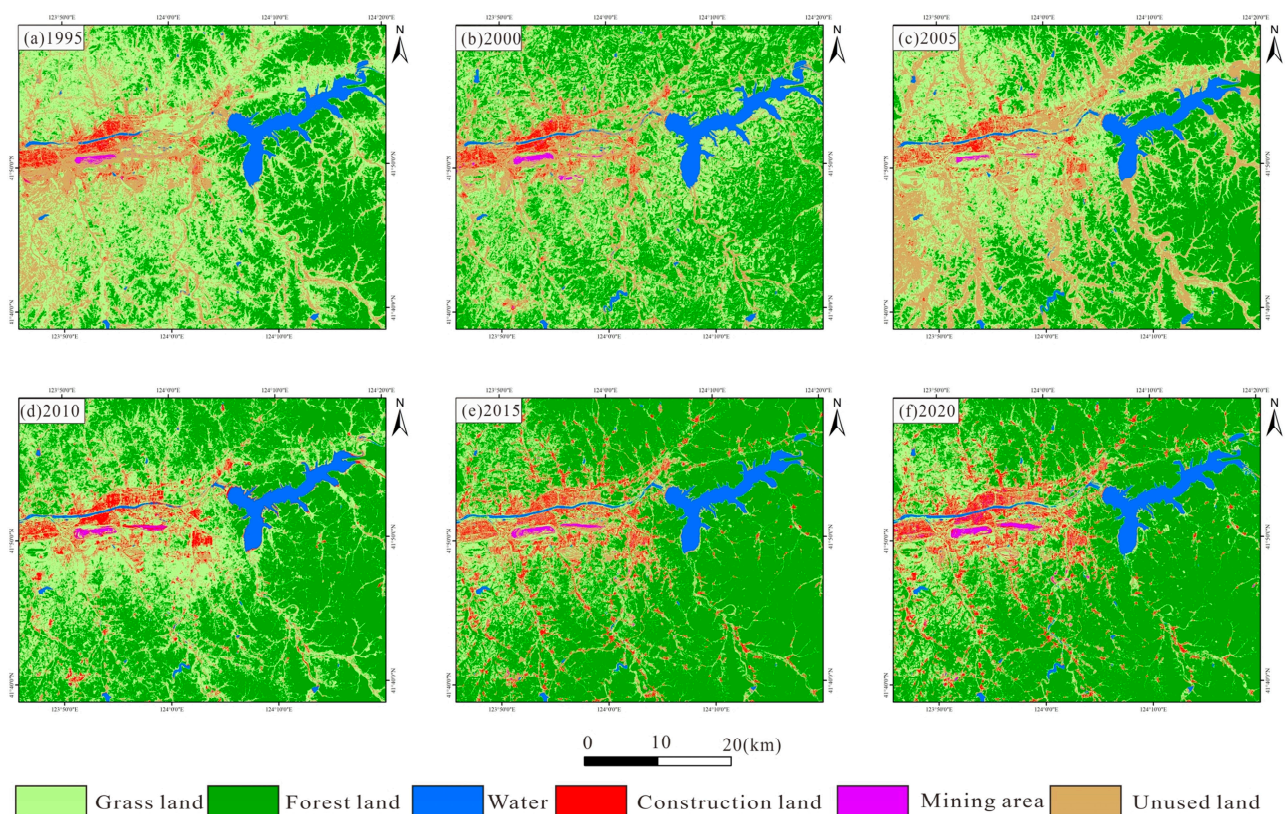
**Figure 5.** Calculation results of various trees (k): (a) 1995; (b) 2000; (c) 2005; (d) 2010; (e) 2015; (f) 2020.

Table 3. Optimized parameters of random forest during 2002–2020.

Year	max_features (m)	n_estimators (k)	Obb_error	Overall_accuracy
2020	4	720	0.043209008	0.956790992
2018	3	840	0.028688777	0.971311223
2015	8	610	0.039110745	0.960889255
2011	4	450	0.043209008	0.956790992
2007	3	650	0.061650552	0.938349448
2002	3	425	0.052264808	0.947735192

3.1.2. Classification Results of Ground Objects

With the support of the optimal parameters in the study area for each year, we complete the classification of ground object types within the mining area (Figure 6). It can be clearly seen from the figure that the overall vegetation coverage (green) from 1995 to 2020 is characterized by an increase, of which the forest land coverage (dark green) is very obvious, showing a trend from the east of the study area to the west of the study area. It is characterized by the gradual expansion of coverage around the mining area, and the grassland coverage gradually decreases with the expansion of forest land. The coverage of construction land (storage land, residential areas, etc.) increases significantly over time, showing the characteristics of radial diffusion from around the mining area to the surrounding area, which gradually expanded from 1995 to 2005 and then decreased rapidly from 2005 to 2020.

**Figure 6.** LULC from 1995–2020.

3.2. Temporal and Spatial Changes of Land Use Cover

The study area vegetation coverage increased significantly from 1995 (1420.73 km², 76.15%) to 2020 (1577.79 km², 84.57%) (Figure 7 and Table 4). Unused land was greatly reduced from 1995 to 2020, with values of 350.64 km², 18.79% and 128.37 km², 6.88%, respectively. As exhibited in the classification results and statistical results, the land use

change includes two stages: 1995–2005 and 2010–2020. In the first stage, the vegetation coverage decreased relatively (1995: 76.15%, 71.85% in 2005), and the unused land (bare soil) area increased with a peak in 2005 (1995: 18.79%, 23.32% in 2005). The second stage is characterized by a significant increase in vegetation coverage (2010: 71.85%; 2020: 84.57%) and a significant reduction in bare soil area (2010: 23.32%; 2020: 6.88%). Due to the influence of human activities such as mining, governance, and restoration, the mining area within the study site presents a relatively dynamic and stable change. The construction land (storage land, residence, etc.) was relatively stable from 1995 to 2005, remaining at 26.5 km², accounting for about 1.45%. It then increased to 26.8 km² in 2020, accounting for 1.45%, and increased to 85.78 km² in 2020, accounting for 4.60%.

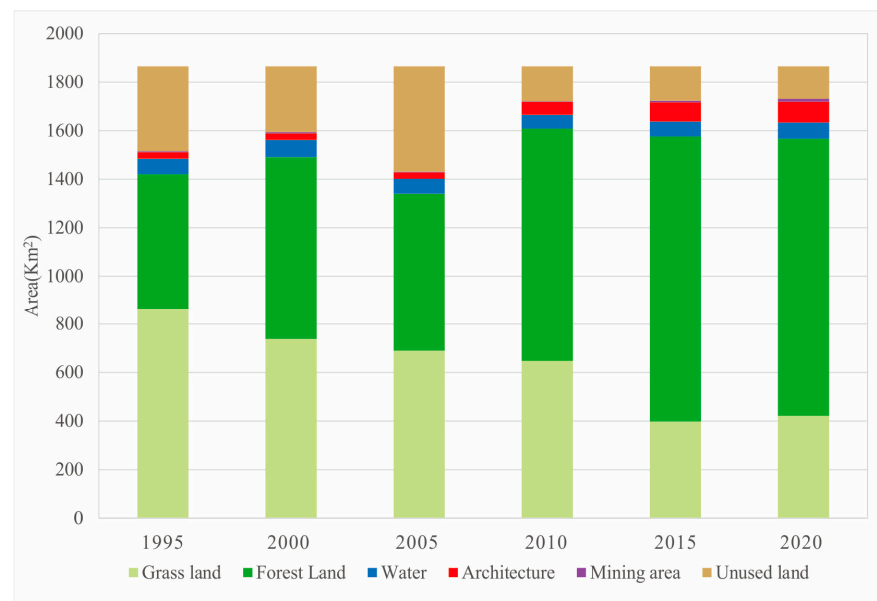


Figure 7. Percentage statistics of different land use in the study area.

Table 4. Land use change in the study area.

Land Use	1995		2000		2005		2010		2015		2020	
	Area/km ²	%	Area/km ²	%	Area/km ²	%	Area/km ²	%	Area/km ²	%	Area/km ²	%
Grass land	862.1	46.2	738.1	39.6	689.5	37.0	643.5	34.5	398.3	21.4	398.1	22.1
Forest land	558.6	29.9	753.2	40.4	650.8	34.9	961.1	51.5	1178.1	63.2	1179.7	62.5
Water	63.6	3.4	70.2	3.8	59.3	3.2	56.7	3.0	61.3	3.3	67.2	3.6
Construction land	26.8	1.4	27.0	1.4	26.9	1.4	50.2	2.7	79.9	4.3	85.8	4.6
Mining area	4.0	0.2	5.7	0.3	4.0	0.2	5.1	0.3	5.8	0.3	6.5	0.4
Unused land	350.6	18.8	271.4	14.6	435.0	23.3	149.0	8.0	142.1	7.6	128.4	6.9

The land use types (vegetation, construction land) that are mainly changed are comprehensively displayed and displayed year by year (Figure 8a,b). From 1995 to 2020, the vegetation coverage increased by 157 km², the construction land increased by 59.12 km², and the bare soil area decreased by 222.26 km². The vegetation coverage increased most widely in 2010 (Figure 8c, yellow part), compared with 2005. The annual increase was 264.24 km²; the construction land coverage increased most widely in 2015 (Figure 8d, pink part)—an increase of 29.70 km² compared with 2010.

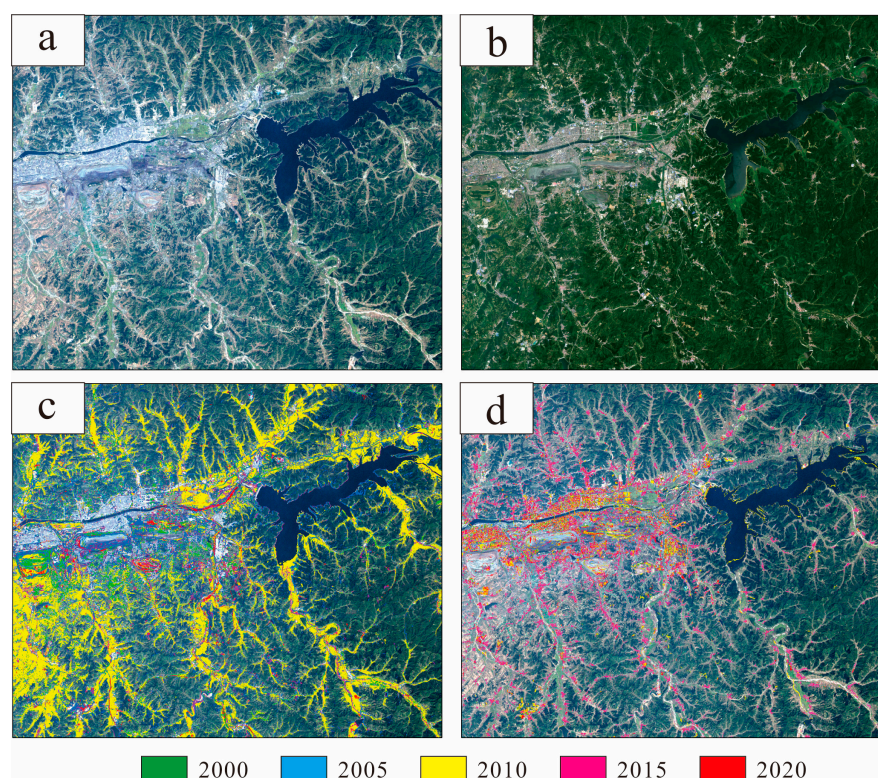


Figure 8. Temporal and spatial dynamic changes of vegetation cover and construction land from 1995 to 2020: (a) Remote sensing image in 1995; (b) remote sensing image in 2020; (c) the range of vegetation coverage increasing year by year; (d) the range of construction land increasing year by year.

3.3. Landscape Pattern Evolution Analysis

3.3.1. Type Level

It can be seen that the PD of grassland increases and LPI decreases, indicating that the fragmentation degree of grassland increases, and the maximum patch area is relatively reduced, while the PD of woodland decreases and LPI increases, indicating that the fragmentation degree of grass land cover decreases and the maximum patch area increases (Table 5). At the same time, its PSI also decreases correspondingly, and the shape of the patches is simplifying, indicating that the coverage of forest land is increasing and gradually connecting into patches, and coverage is becoming more extensive. The PD and LPI of construction land increased, and its PSI value also increased, indicating that the fragmentation degree, maximum patch area, and patch shape of construction land were becoming more and more complex, implying that the scope of construction land was gradually expanding in the study area. The PD value and PSI value of the unused land increased, while the LPI value decreased, indicating that the fragmentation degree increased, and the plaque shape was complex, but the maximum plaque area decreased, which correspondingly showed that the unused land showed a strong trend for reduction. This is due to the introduction of the overall urban planning of Fushun City in 2005, the implementation of unified planning and management of urban and rural areas, and the strengthening of planning and construction management of urban villages and urban–rural fringe areas.

Table 5. Changes in landscape pattern indices for various solid types in the study area during different time periods.

Landscape Index	Year	Grass Land	Forest Land	Water	Construction Land	Mining Area	Unused Land
Patch area (PA)/km ²	1995	862.0758	558.5715	63.6219	26.6598	4.0428	350.64
	2000	738.0702	753.1947	70.2153	26.9748	5.7024	271.4544
	2005	689.5719	650.8053	59.3145	26.8758	4.0176	435.0267
	2010	643.5234	961.0929	56.6694	50.247	5.0859	148.9932
	2015	398.3229	1178.1477	61.2765	79.9452	5.8437	142.0758
	2020	398.1393	1179.6534	67.1652	85.7817	6.4944	128.3778
Patch density (PD)	1995	5.3178	6.1444	0.1072	2.419	0.3452	6.221
	2000	7.7996	6.571	0.1528	1.7565	0.2074	5.7965
	2005	5.2621	3.066	0.1463	3.0167	0.1303	4.911
	2010	6.6954	4.5406	0.1844	2.8773	0.1801	5.0043
	2015	7.7631	3.2413	0.3259	5.4352	0.9107	7.0695
	2020	9.0308	3.6369	0.2321	6.1358	0.4176	7.009
Largest patch index (LPI)	1995	16.6371	7.4525	3.0135	0.1751	0.1559	10.7358
	2000	4.5866	5.9877	3.1722	0.1897	0.1809	8.5946
	2005	14.8271	7.9614	2.6333	0.1899	0.0769	5.5252
	2010	17.7092	12.7109	2.4737	0.211	0.1514	1.6487
	2015	5.9317	23.7637	2.6377	0.3212	0.1274	1.4199
	2020	4.533	24.9531	2.8278	0.3216	0.2008	0.6174
Patch shape index (PSI)	1995	180.4106	127.191	12.0808	82.1652	21.6444	150.9367
	2000	232.1645	170.6306	13.4687	73.9914	16.5562	140.2393
	2005	190.1148	92.7431	13.1954	89.4538	15.43	146.4098
	2010	197.4249	117.0503	12.0757	87.3467	18.2318	158.0393
	2015	234.3494	96.0826	13.2778	146.5678	22.5247	168.3258
	2020	215.0102	89.856	15.3949	138.5405	36.8243	169.4496

3.3.2. Landscape Level

From the perspective of the CONTAG, the overall increase is increasing year by year, indicating that the landscape has shifted to a multi-element decentralized layout (Table 6). In 1995–2005, the Shannon Diversity Index (SHDI) increased, indicating a balanced distribution of patch types in the landscape, while in 2010–2020, the Shannon Diversity Index (SHDI) increased. The decrease in 2020 indicates that some patch types have been reduced and transformed into another type of patches, mainly due to the transformation of some grassland and unused land into forest land and construction land, resulting in a relative reduction in diversity. The Shannon Meanness Index (SHEI) also showed a trend of increase from 1995 to 2005 and decrease from 2010 to 2020, indicating that after 2005, after a series of work, the land use type of the study area underwent a certain transformation. It also proves that after 2005, the land use types disturbed by human factors have been changed to a certain extent. Diversity has a significant varying effect.

Table 6. Changes in landscape level indices in the study area during 2002–2020.

Year	CONTAG	DIVISION	SHDI	SHEI
1995	48.1628	99.6718	0.9274	1.2212
2000	48.8063	99.3558	0.975	1.2159
2005	49.7651	99.5941	0.9531	1.2558
2010	53.5956	99.619	0.9359	1.1303
2015	54.1648	99.1954	0.9283	1.1169
2020	54.9521	99.2635	0.9223	1.0813

3.4. Ecological Risk Analysis

Ecological risk analysis was carried out on the basis of determining the minimum risk area, $C_i, S_i, K_i, U_i, E_i, R_i$ of each area were calculated, respectively, and the ESI index was calculated. Then, supported by the Kriging interpolation method, the ecological risk of the whole area was completed (Figure 9). Under the support of the Jenks method in ARCGIS 10.2, the ecological risk of each year was divided into five levels: HESI, SHESI, MESI, SLEI, and LEI. The change trend of the overall risk pattern from 1995 to 2020 was similar. The high-risk area and the sub-high-risk area were mainly distributed along the east and west of mining area and showed a weakening rate of expansion to the northeast, east and southeast. From 1995 to 2005, the high-risk region and the second high-risk region showed a trend of expansion to the southeast, east, and northeast, while the two low risk regions decreased correspondingly. This was mainly caused by the degradation of grassland and the relative expansion of unused land. It is worth mentioning that in 2005, the new high-risk areas and sub-high-risk areas in the southwest of the open-pit mining area were mainly due to the reduction of grassland, forest land, and unused land. In 2010, the high-risk area and the sub-high-risk area decreased significantly, and the high-risk area was gradually scaled to the east–west open-pit mine in 2020. The medium-risk area gradually moved closer to the open-pit mine, and the sub-low risk and low-risk areas showed an obvious trend of expanding to the open-pit mine area and the surrounding construction land. From 1995 to 2020, the overall ecological stability of the Fushun open-pit mine and its surrounding areas showed a trend of expanding low-risk areas and decreasing high-risk areas.

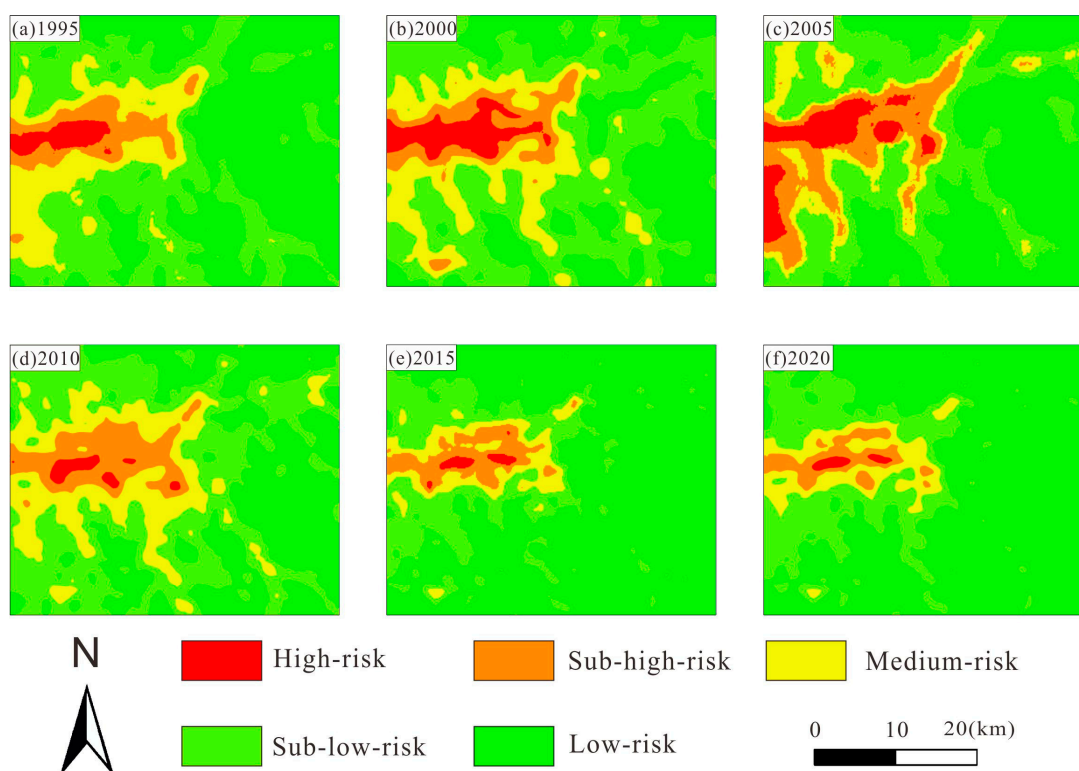


Figure 9. Changes in ecological risk from 1995 to 2020.

Comparing the changes in ecological risk levels in the five stages from 1995 to 2020 (Figure 10), it can be said that on the whole, the low-risk areas increased significantly in 2015. The number of sub-low-risk areas, medium-risk areas, sub-high-risk areas, and high-risk areas decreased significantly, and all of them all changed significantly in 2015. The high-risk areas and sub-high-risk areas increased first and then decreased, of which 152.17 km² increased from 1995 to 2005, and 227.68 km² decreased from 2010 to 2020. The medium-risk area shows a relatively continuous decrease, with a decrease of 126.7 km² in

2020 compared with 1995. The sub-low-risk area shows a fluctuation from 1995 to 2010 and a downward trend in 2020, with a total decrease of 259.628 km² in 2020 compared with 1995. The low-risk area shows a trend of fluctuation before 2010 and a significant increase in 2020, with a total increase of 486.74 km² in 2020 compared with 1995.

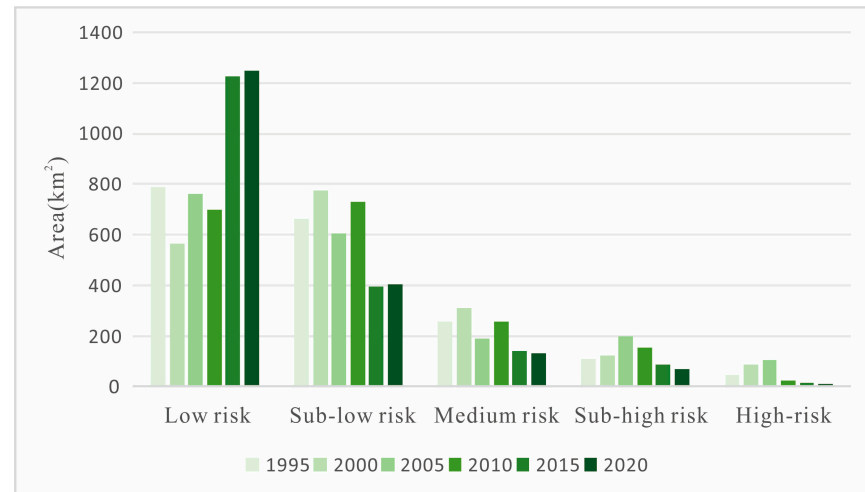


Figure 10. Area of different ecological risk grades from 1995 to 2020.

The establishment of the conversion matrix for each level of risk area is shown in Table 7. It can be seen that since 1995, a total of 28.13 km² of high-risk areas have been converted to sub-high-risk areas, and 62.74 km² of high-risk areas and sub-high-risk areas have been converted to medium-risk. The 178.04 km² high-risk, sub-high-risk, and medium-risk areas are turned into sub-low-risk areas, and the 496.12 km² high-, sub-high-, medium-, and sub-low-risk areas are turned into low-risk areas, and the study areas are judged in turn. The ERI of the Fushun open-pit coal mine has been significantly reduced, and the ecological environment has been greatly improved from 1995 to 2020.

Table 7. Transition matrixes of ecological risks from 1995 to 2020 (km²).

Ecological Risk	Low Risk	Sub-Low Risk	Mediumrisk	Sub-High Risk	High Risk	2020
Low risk	752.87	467.19	28.82	0.11	0.00	1249.00
Sub-low risk	34.29	192.85	154.64	20.81	2.59	405.18
Medium risk	0.00	4.73	64.04	56.44	6.30	131.49
Sub-high risk	0.00	0.05	10.69	30.62	28.13	69.48
High risk	0.00	0.00	0.00	3.80	6.66	10.46
1995	787.16	664.81	258.19	111.78	43.67	

4. Discussion

4.1. Exploration of Methods and Results of Land-Use Type Classification

This study quantitatively monitors land cover, land use type changes, and the evolution of landscape patterns in the Fushun open-pit coal mining area, China, from 1995 to 2020. At the same time, an ecological risk assessment was conducted to explore the dynamic changes of ecological environment recovery in the study area. Land use type classification is the basis of ecological risk assessment. Previous studies have used a combination of indoor image interpretation and field survey validation to classify land use types through supervised classification and human–computer interaction as well as visual interpretation with 85–90% accuracy rates [15,16]. Different from previous studies, this study adopts the random forest method to classify land use types of open-pit mines, which has good robustness in feature selection. After adjusting the optimal parameters, the accuracy of predictive classification for selected time points increased to between 93.8% and 97.1%.

Truong et al. [68] used random forest in machine learning and the maximum likelihood algorithm, respectively, to classify and extract land cover in the Pham Ngan District, An Phuy Province, Vietnam. Their results showed that the OA and Kappa coefficients of the random forest algorithm were significantly higher than those of the maximum likelihood method, and, in particular, the results were more accurate for all land use types except the building class. Mao et al. [69] compared the classification accuracies of the three machine learning methods, namely, the random forest, the support vector machine, and the artificial neural network model for the classification of land use types, using the city of Hangzhou as the study area. The results show that the random forest model has the highest classification accuracy, followed by support vector machine, and finally artificial neural network, and the random forest model has more than 80% classification accuracy in education and medical land use. The land types within the study area are relatively simple; therefore, in this study, NDVI for extracting vegetation information, NDBI for extracting building information, NDISI for distinguishing the relationship between soil and buildings, and NDWI for extracting water body information were selected as the main classification elements to improve the accuracy of the classification results. In addition, visible and infrared bands were added to the prediction elements, which proved to markedly improve classification accuracy.

4.2. Exploration of Ecological Risk Assessment Results and Applicability

According to this study, it can be seen that the ecological risk in the north and south of the mining area has been greatly reduced after environmental treatment, indicating that the treatment has been very effective. At present, based on the existing location of the risk area, it is believed that the next key treatment direction should be focused on the open-pit mine area and the surrounding residential areas. The aim of this study is to quantitatively monitor the evolution of landscape pattern and dynamic changes in ecological restoration of open-pit mines using the landscape ecological risk index ERI. Comparison of the results of this study with those of the Pingshuo Leaktian coal mine area on the Loess Plateau shows that the landscape ecological risk index can be used to evaluate the spatial and temporal changes of ecological risk within the coal mine area [70]. According to the study of Wang et al. [71], the ecological risk evaluation results also provide a prediction for the areas that need ecological restoration in the open-pit coal mine area, so as to carry out land reclamation and other work in a more planned manner. This paper not only analyzes the Fushun open-pit mine but also systematically describes the land cover of the open-pit mine and its utilization type change, landscape pattern, and its ecological risk assessment research method, hoping to be helpful to other researchers and mining areas with ecological risks, in order to provide data support for local ecological environment monitoring and mine mining regulation. In addition, this study can also provide reference for mine environment monitoring in other countries and regions with complex geological conditions and difficult mine environment investigation.

4.3. Limitations of this Study and Future Work

In this paper, land use change, landscape pattern evolution, and the ecological risks of the Fushun open-pit mine over a period of 25 years are investigated. Compared with the existing results in the study area, it is more in-depth in landscape ecology. However, this study also has some limitations. In land use type classification, more training samples and quantitative parameters should be introduced based on the characteristics of ground objects, so as to improve the reliability and accuracy of the classification results, and this should be accomplished by integrating socioeconomic data into the random forest model to obtain higher classification accuracy [5]. In subsequent studies, socioeconomic factors should be included in the analysis, which can provide a more comprehensive understanding of the drivers behind land use change and its ecological impacts. The resolution of the Landsat satellite used in the study was 30 m. In future studies, satellite images with higher resolution, such as Sentinel-2 and China's Gaofen series, can be used, thus improving the interpretation accuracy of land use types. In the construction of the landscape ecological risk

assessment model, some ecological function variables (e.g., supply, supervision, support, and cultural services, etc.), which are mainly concerned with the ecological service functions provided by open-pit mining areas for human beings) can be introduced, so as to further improve the landscape ecological risk assessment model and enhance the accuracy of the ecological risk assessment.

5. Conclusions

In this study, based on the six-period remote sensing images from 1995 to 2020, combined with multiple remote sensing quantitative parameters (NDVI, NDISI, NDBI, NDWI, visible lights and infrared bands), we used random forest technology to evaluate land use and ecological change in the open-pit mine and surrounding land in Fushun, China. We used type classification and quantitative analysis of the landscape pattern and the temporal and spatial evolution characteristics of ecological risks in the study area to make up for the lack of related research on ecological risks in the study area, and we derived the following conclusions:

- (1) The method of the equidistant establishment of interpretation sampling points to construct a training set combined with the random forest model and multi-quantitative remote sensing index method proposed in this paper can accurately and efficiently achieve the classification of LULC in open-pit mining areas. This approach has high precision and accuracy (the accuracy in this study is 92–97%), which can provide technical reference for dynamic monitoring of other open-pit mines.
- (2) The land cover changes in the study area encompass two main trends. During the period from 1995 to 2005, changes in vegetation, buildings, bare soil, and other land types were relatively stable. From 2010 to 2020, the vegetation coverage and building land coverage increased significantly. By 2010, the degree of vegetation coverage increased significantly, mainly from a decrease in unused land. In 2015, construction land expanded radially from the mining area to the surrounding area, mainly from unused land. Our results shows that the land use around the study area has been greatly improved, which is closely related to a series of ecological and environmental protection plans by the Chinese government.
- (3) The overall ecological risk index of the study area is characterized by an increase from 1995 to 2005 and a decrease from 2010 to 2020. In 2015, the high-risk area and the low-risk area showed a cliff-like increase and decrease, respectively. In 2020, mid-year, the high ecological risk areas were lower than in 1995. It is generally believed that the landscape pattern and ecological environment of the study area have been greatly improved. The ecological risk in the study area is generally reduced, and the next governance direction should focus on the open-pit mining area and surrounding construction land.

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