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Spatial and temporal disturbances in the zone of mining of ferruginous quartzites of the Kostomuksha cluster, NW Russia

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A B S T R A C T

The research presents new methods for analyzing spatial and temporal disturbances, focusing on landscape ecology. The study covers the period from the beginning of the development of the field to the present stage. The Land Use and Land Cover (LULC) change analysis is based on processing of Landsat satellite imagery. The method uses landscape metrics, SDI calculation, and mapping to describe the mechanisms of transformation and self-regulation of the system. Landscape metrics include three groups: areas and edges, shape metrics, and diversity metrics. An increase in landscape fragmentation over time is shown. All LULC classes have been changed. The area of the "mining" class has been increased in 7.7% (from 0 to 55.5 thousand km^2). The increase in the area of quarries occurs evenly at the expense of all other land use classes. The data obtained confirm several stages of anthropogenic impact. An approach has been developed for mapping disturbances and assessing the impact on geosystemsIt was revealed that in the cell size range from 1500 to 2500 m, the landscape parameters are the most stable. The calculation of the spatial disturbance index is based on principal component analysis data. Factors were identified that indicate external load and the adaptation and self-regulation of the geosystem. Three degrees of disturbance of the territory are defined: low, medium, and high. In 2006, the maximum level of spatial disturbance was found, with the area of heavily disturbed areas being 68%. The results of this study indicate the importance of taking the necessary measures to reduce environmental risks.

1. Introduction

The basis for optimal development of territories is the conduct of economic activities, taking into account the ecological carrying capacity of the geosystem (Osipov, 2019). The ecological carrying capacity of the geosystem is determined by the indicator of sustainability (Fang et al., 2021). The stability of a geosystem is understood as the ability of natural components to resist anthropogenic impact and return to a state of equilibrium after the cessation of this impact (Armand, 1988; Wu, 2021). The ability of landscapes to self-regulate and self-develop leads to the restoration of internal properties and structure after a natural or anthropogenic impact that has changed these properties (Glazovskaya, 1999; Goleusov, 2015).

Geosystem research and monitoring are mainly focused on local measurements of environmental components, including analysis of the state of soil, water, and vegetation. However, most of the dynamics occur at landscape scales (Turner et al., 2001). To assess and manage environmental sustainability, managers need tools that can measure attributes of ecosystems at scales beyond local measurements (Cushman and McGarigal, 2019).

The mining industry is an industry where a comprehensive understanding of environmental impact is critical. Although mining brings enormous economic benefits, it is one of the human activities that directly alters landscapes (Toy, 1984; Malaviya et al., 2010; Bexeitova et al., 2021) and affects the quality of soil, water, vegetation, and the atmosphere (Luckeneder et al., 2021; Wang et al., 2021). Mining has direct and indirect impacts on forests, from deforestation during development and high quality timber to pressure on forests due to population pull (Mwitwa et al., 2012). Assessing the transformation of land cover associated with mining is very important in terms of taking appropriate measures to protect the ecosystem (Goparaju et al., 2017).

The environmental impact varies at different stages of mining. The assessment of this impact at each stage involves specialized continuous and long-term monitoring methods. Remote sensing methods are often used to analyze environmental parameters and monitor ecosystems in mining areas (Yu et al., 2018; Kayet et al., 2019; Orimoloye and Ololade, 2020; Rudke et al., 2020; Song et al., 2020). Satellite sensing data is very important and suitable for assessing land use and land cover (LULC)

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transformations (Cao et al., 2016; Garai and Narayana, 2018; Mohajane et al., 2018; Lu et al., 2004). It is noted that due to long-term availability, satellite data of the Landsat series are most preferable (Yang et al., 2018). Estimation of land-use change in mining areas is possible with various land image classification methods using machine learning algorithms, e.g. support vector machine (Demirel et al., 2011; Lamine et al., 2018), random forest, naive bayes analysis (Vasuki et al., 2019), homogeneity distance classification (Firozjaei et al., 2021). Choosing the most efficient classifier is a complex task that depends on the goals of the researcher.

Landscape metrics are used to quantify changes in the landscape and its structure from classified data (Cushman and McGarigal, 2019). Landscapes consist of a mosaic of natural or anthropogenically modified areas (Singh et al., 2017). The landscape pattern is determined by the spatial arrangement of these patches (Cushman et al., 2008; Kumar et al., 2018). An increase in anthropogenic load leads to a strong fragmentation of the landscape (Tian et al., 2011; Pyngrope et al., 2021), a decrease in the average and largest sizes of spots, and an increase in their density (Ololade and Annegarn, 2015). When assessing landscape sustainability, it is useful to recognize the adaptive capacity of the landscape to cope with external impacts (Wu, 2012). Fractal land use characteristics are used to analyze the spatial and temporal evolution of the landscape pattern (Zhang et al., 2020).

The boreal ecosystem has a special status and is an important global reservoir of stored carbon (Bradshaw and Warkentin, 2015). At the same time, the ecosystem is subject to multiple natural and anthropogenic impact factors that cause its disturbances. (Kuuluvainen and Gauthier 2018; Hofgaard et al., 2010). In the boreal zone, remote sensing has been used to map forests with particular attention to degradation (Saich, 2001), to assess environmental pollution from mining and enrichment (Rigina, 2002; Tutubalina and Rees, 2001).

The further development of land cover change assessment research should be closely integrated with landscape sustainability science and play a leading role in spatial planning (He et al., 2022). The degree of change in LULC as well as the restoration of ecosystems during and after mining is very important in terms of assessing the ecological carrying capacity of a geosystem. In this regard, the study is aimed at understanding the response of the geosystem to anthropogenic impact at different stages of the operation of a mining enterprise. The main objectives of our study are: (i) to examine the change in LULC under the influence of mining and other factors; (ii) obtain a quantitative assessment of the spatial disturbance of the landscape during different periods of time.

The novelty of the study lies in the possibility of assessing the ecological resources of the geosystem in the zone of influence of the mining cluster based on landscape indicators using remote sensing.

2. Materials and methods

2.1. Study area

The study area is located in the Republic of Karelia, Russian Federation, in the eastern part of the Fennoscandian Shield (64°41′44″N 30°39′50″E) (Fig. 1). The area includes the Kostomuksha and Korpang iron ore deposits. The city of Kostomuksha is located 7.5 km southwest of the industrial site. The climate of the area is temperate continental with cold, long winters and short, cool summers. The warmest month is July, the average temperature is +15 °C, the maximum temperature is +30 °C. The coldest month is January, the average temperature is −11 °C, the minimum winter temperature is −30 °C. The average annual precipitation is 614–680 mm/year. Snow cover forms in late October–early November and melts in May (Development of …, 2018).

The relief of the area is characterized by alternating ridged hills and gentle depressions, oriented predominantly in the northwestern and northern directions. The highest height is 257.9 m; relative elevations reach 50. The hydrographic network is well developed here. There are many small lakes fed by swamp waters. Significant areas are occupied by marshes and swamp forests. The study area is located on the border of the subzones of the middle and northern taiga. The vegetation cover is mainly represented by light coniferous forests, in the structure of which small areas of meadow and marsh vegetation are wedged.

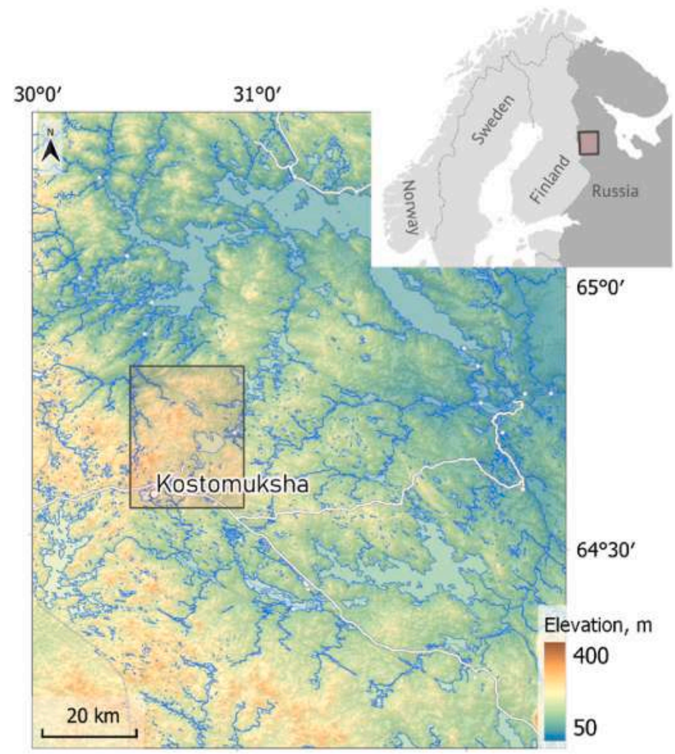

Fig. 1. Study area.

2.2. Research methodology

The workflow of this study includes: satellite data acquisition, image preprocessing, image classification, accuracy assessment, change detection analysis, landscape metrics calculation, principal component analysis, spatial disturbance index calculation, and mapping. The algorithm to perform the work is shown in the flow chart (Fig. 2).

2.2.1. Datasets

Landsat images, collection 1 and 2 were used. Images sourced from the United States Geological Survey (USGS) Earth Resources Observation Data Center database. For the analysis, images from collection 2 were mainly used. Collection 2 has a significant improvement in the absolute accuracy of geolocation of the global set of ground reference data used in the Landsat Level-1 processing flow. In addition, Collection 2 includes updated global digital elevation sources, calibration and verification updates (Landsat Collections). Atmospheric correction for the L2SP processing level was performed using the ground reflection code (LaSRC) (version 1.5.0) (Vermote et al., 2016). The study used images of the processing level L2SP 25/07/2019, 11/07/2014 (Landsat 8); Landsat 7 07/28/2000 (Landsat 7); 06/19/2006, 08/10/1996, 06/23/1990 (Landsat 5); processing level L1TP 06/29/1978 (Landsat 2). Images were taken during the peak growing season. The difficulty of choosing was that there are frequent periods of heavy cloudiness in this area. Details of the images are shown in Table 1.

2.2.2. Land use and land cover classification

Classification of multispectral images is carried out using the semi-automatic classification plugin for QGIS (Congedo, 2021; Semi-Automatic …). This module performs classification using different

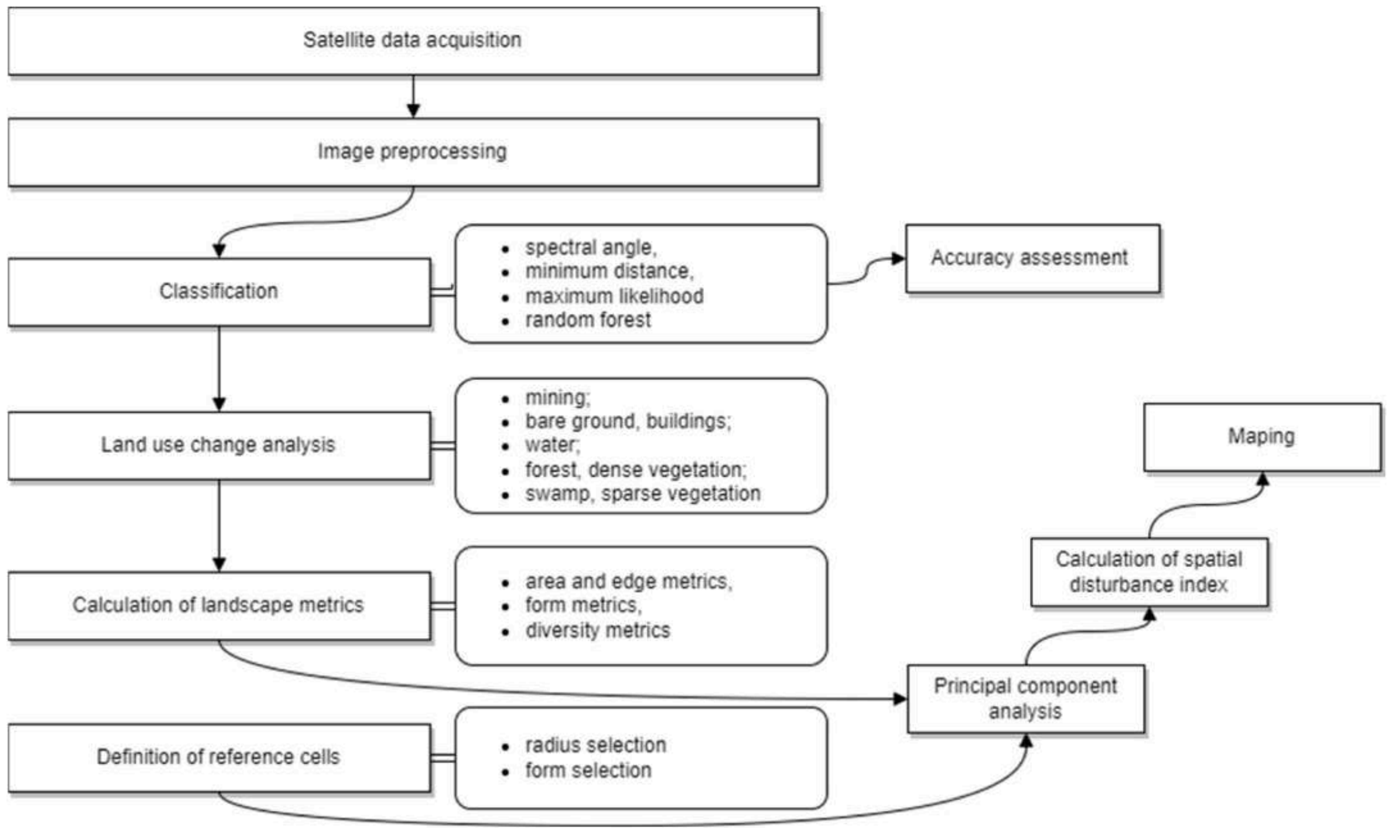

Fig. 2. Study workflow diagram.

Table 1
Satellite images used in this study.

Date of image acquisition	Satellite (Sensor)	Processing level	Path/Row	Bands used	Spatial Resolution (m)	Cloud cover (%)
2019-07-25	Landsat 8 (OLI)	L2SP	186/015	B2, B3, B4, B5, B6, B7	30	6.70
2014-07-11	Landsat 8 (OLI)	L2SP	186/015	B2, B3, B4, B5, B6, B7	30	0.97
2006-06-19	Landsat 5 (TM)	L2SP	186/015	B1, B2, B3, B5, B7	30	3.00
2000-07-28	Landsat 7 (ETM+)	L2SP	186/015	B1, B2, B3, B5, B7	30	0.00
10.08.1996	Landsat 5 (TM)	L2SP	186/015	B1, B2, B3, B5, B7	30	8.00
23.06.1990	Landsat 5 (TM)	L2SP	186/015	B1, B2, B3, B5, B7	30	0.00
29.06.1978	Landsat 2 (MSS)	L1TP	201/015	B4, B5, B6, B7	60	0.00

algorithms: spectral angle, minimum distance, maximum likelihood, and random forest. The minimum distance algorithm determines the Euclidean distance d(x,y) between the spectral signatures of the image pixels and the training spectral signatures. The maximum likelihood algorithm computes probability distributions for classes associated with Bayes' theorem, assessing whether a pixel belongs to a land cover class. The spectral angle algorithm calculates the spectral angle between the spectral signatures of the image pixels and the training spectral signatures. Random forest is a special machine learning technique based on the iterative and random generation of decision trees (i.e., a set of rules and conditions that define a class). The classification is carried out with the allocation of five classes of land use and land cover: 1 - mining; 2 - bare ground, buildings; 3 - water; 4 - forest, dense vegetation; 5 - swamp, sparse vegetation.

Accuracy assessment is performed with the calculation of the error matrix. Reports, high-resolution images, and field data were used to evaluate accuracy. Based on the error matrix, the overall accuracy (OA), users accuracy (UA), producers accuracy (PA), and Kappa coefficient were calculated. Overall accuracy is the ratio between the number of correctly classified samples and the total number of sample units (Congalton and Green, 2019).

2.2.3. *Landscape metrics*

Landscape metrics are measured at the level of a class and the landscape as a whole. Most of the metrics are strongly correlated with each other (McGarigal and Marks, 1995). Therefore, we chose the metrics that best represented the spatial and temporal variability of the landscapes. The study used metrics from three main groups: area and edge metrics, and shape metrics, diversity metrics. The class area (CA) and the percentage of the landscape (PLAND) are fundamental indicators of the composition of the landscape, showing which classes the landscape consists of. The number of patches (NP) is a simple measure of the degree of subdivision or fragmentation of classes. The number of patches in a class can be fundamental to ecological processes (Zamfir et al., 2022). Edge Density (ED) describes the configuration of the landscape. Pooling the same class will result in low edge density. Landscapes can be compared by ED because this measure is standardized by landscape area. To compare class fragmentation, it is useful to use the class patch density (PD), which indicates the number of class patches per unit area of the class. The interaction of patch shape and size can influence a number of important ecological processes. The contagion index (CONTAG) describes landscape fragmentation by the probability of two random cells belonging to the same class. CONTAG shows how aggregated or grouped landscapes are. Splitting Index (SPLIT) evaluates the degree of fragmentation of the landscape into patches. The fractal dimension is the base type of the shape index. It is based on a perimeter-area relationship. Fractal analysis can be applied to spatial parameters on a variety of scales. The perimeter-area fractal dimension method (PAFRAC) has been proposed to calculate the fractal dimension of natural flat shapes (Mandelbrot, 1982). The fractal dimension for simple Euclidean shapes is close to 1 (line size). As the polygons become more complex, the perimeter becomes more flat-filling, and PAFRAC approaches 2.

The Shannon Diversity Index (SHDI) is used to measure landscape diversity. It is a measure of diversity borrowed from ecology. SHDI reflects the probability that two random pixels belong to different classes. The Shannon Evenness Index (SHEI) is the normalization of the observed Shannon diversity index in terms of the maximum diversity index for that number of site types. This value is a more accurate guide to distinguishing landscape diversity. It allows estimating the deviation from randomness and the equiprobability of real landscapes.

Analysis of changes in landscape metrics provides important information on the transformation of the composition and structure of the system (Uuemaa et al., 2009). All metrics used in the study are given in Table 2.

2.2.4. Definition of operational-territorial units

To study the spatial and temporal variability of the landscape, its properties are measured within a sliding operational-territorial unit (OTU). OTUs are conditionally indivisible cells for which information is collected for subsequent analysis and mapping. The size and shape of the OTU is determined by the definition of individual elements (types) of the landscape and their variability. Toosi et al. (2022) showed that the most optimal shape is hexagonal cells. The nature of the change in landscape metrics determines the scale. Cell sizing is based on several principles. On the one hand, the cell should recognize the main types of landscape, on the other hand, the cell diameter should allow detecting changes between data within different OTUs. To select the size, four metrics were calculated at the landscape level (ED, CONTAG, SHEI, SPLIT) on 8 plots of different sizes. Cells with a diameter of 500–3500 m were studied. It was revealed that in the range of diameters of 1500–2500 m the landscape parameters are the most constant (Fig. 3). In this regard, a study was made of landscape metrics for a hexagonal OTU with a diameter of 2000 m, which corresponds to an area of 346 ha.

2.2.5. Principal component analysis

Principal component analysis (PCA) was carried out to assess the regularities of the dynamics of the landscape structure. PCA is a multivariate statistical analysis method. The method reduces the dimensions of a data set containing numerous interrelated variables. For better interpretation, the rotation of factor loadings by the varimax method was carried out. This factor rotation method minimizes the number of variables with high load values. As a result of orthogonal rotation, uncorrelated factors are obtained. PCA was carried out based on the values of NP, ED, PAFRAC, CONTAG, SPLIT, SHEI, PLAND1, PD1, ED1, PAFRAC1, PLAND2, PD2, ED2, PAFRAC2, PLAND3, PD3, ED3, PAFRAC3, PLAND4, PD4, ED4, PAFRAC4, PLAND5, PD5, ED5, PAFRAC5. Numeric indices denote LULC classes for 1990, 1996, 2006 and 2019 (1 – mining, 2 – bare ground, 3 – water, 4 – forest, 5 – swamp, sparse vegetation).

Table 2
Landscape metrics.

Metrics	Level	Index*	Unit of measurement
CA	Class	CA1, CA2, CA3, CA4, CA5	km^2
PLAND	Class	PLAND1, PLAND2, PLAND3, PLAND4, PLAND5	%
NP	Landscape	NP	unit
ED	Landscape	ED	m/ha
	Class	ED1, ED2, ED3, ED4, ED5	
PD	Class	PD1, PD2, PD3, PD4, PD5	Number per 100 ha
CONTAG	Landscape	CONTAG	%
SPLIT	Landscape	SPLIT	
PAFRAC	Landscape	PAFRAC	
	Class	PAFRAC1, PAFRAC2, PAFRAC3, PAFRAC4, PAFRAC5	
SHDI	Landscape	SHDI	
SHEI	Landscape	SHEI	

*1 – class mining, 2 – class bare ground, 3 – class water, 4 - class forest, 5 - class swamp, sparse vegetation

2.2.6. Calculation of spatial disturbance index

The spatial disturbance index (SDI) is calculated for each OTU based on the results of the PCA. Based on the PCA results, we obtain the loads matrix of each metric into the component and the eigenvalue of the factor. The spatial disturbance index for each cell is the sum of the factor scores, taking into account the value of each factor.

$$SDI = \sum E_i * S_i$$

Ei – eigenvalue factor *i*, Si – factor scores for i-th factor.

The calculation takes into account the factors that make a significant contribution to the distribution of landscape metrics over the entire industrial history of the development of the territory.

Based on the obtained values, an interpolated model of the SDI spatial distribution is created. With many existing interpolation algorithms, the Natural Neighbor method was used in the work. Natural neighbor interpolation finds the closest subset of input samples to the requested point, and applies weights to them based on proportional areas to interpolate a value (Sibson, 1981).

3. Results

3.1. Land use and land cover classification

Several algorithms have been tested to use the most optimal classification. The results show different accuracy for the method and for the image. The most accurate are the spectral angle classification algorithm for Landsat 8 and 7 images (accuracy is 88–89%, Kappa 0.82–0.84), for Landsat 5 images (accuracy is 70–77%, Kappa 0.62–0.65). Classifications using the random forest and minimum distance algorithms have an accuracy of 70–80%, Kappa 0.52–0.71. The maximum likelihood algorithm shows low accuracy values for Landast 8 images. More complete information on the accuracy assessment of classification algorithms is presented in the supplementary material (Fig. 1S and Table 1S).

The 'water' and 'forest' classes are determined most correctly. The accuracy is more than 90%, Kappa is more than 0,92, except for the maximum likelihood algorithm. Pixels belonging to the 'mining' class are determined more accurately using the spectral angle and random forest method. For the 'bare ground' and 'sparse vegetation' classes, the highest percentage of errors was revealed. This is due to the transition state of these classes and similar spectral characteristics. The need to separate these classes is due to the importance of understanding the scale of anthropogenic activities not related to mining.

Therefore, the most appropriate classification algorithms for the study area are random forest and spectral angle. The spectral angle algorithm is better at classifying objects that have similar brightness values in all spectral ranges. This algorithm is better to separate the classes of 'bare ground' and 'sparse vegetation'. Therefore, the spectral angle method was used to study the dynamics of land use and land cover in the area of ferruginous quartzite mining in the period from 1978 to 2019.

On Fig. 4 shows the spatial distribution of different LULC classes. Table 3 presents data on the spatial distribution of the classes.

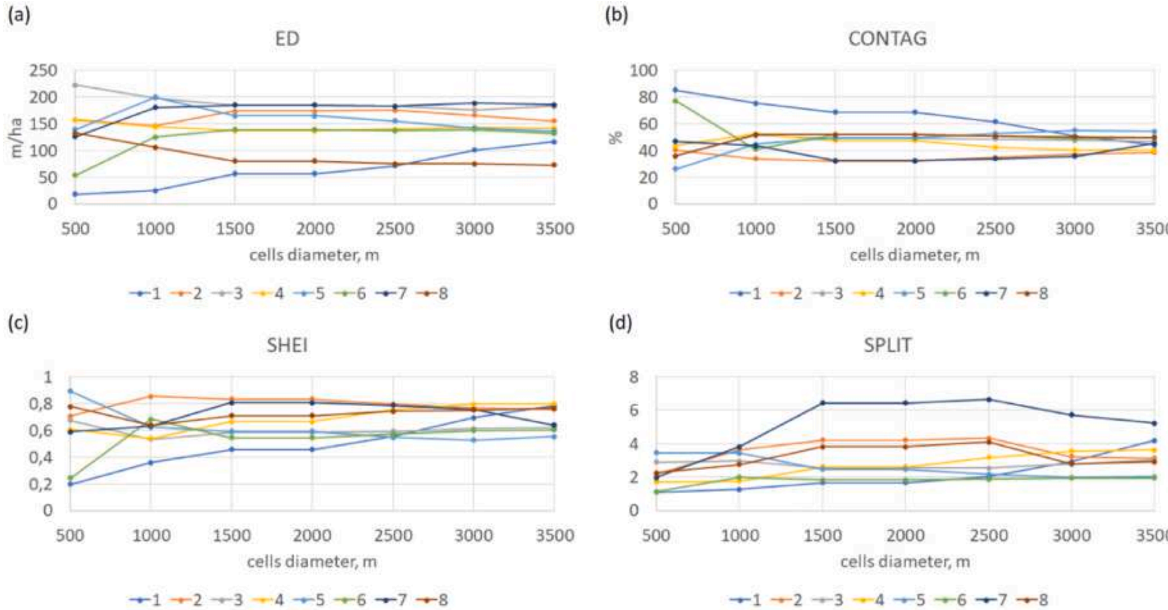

Fig. 3. Values of landscape metrics in cells of different sizes.

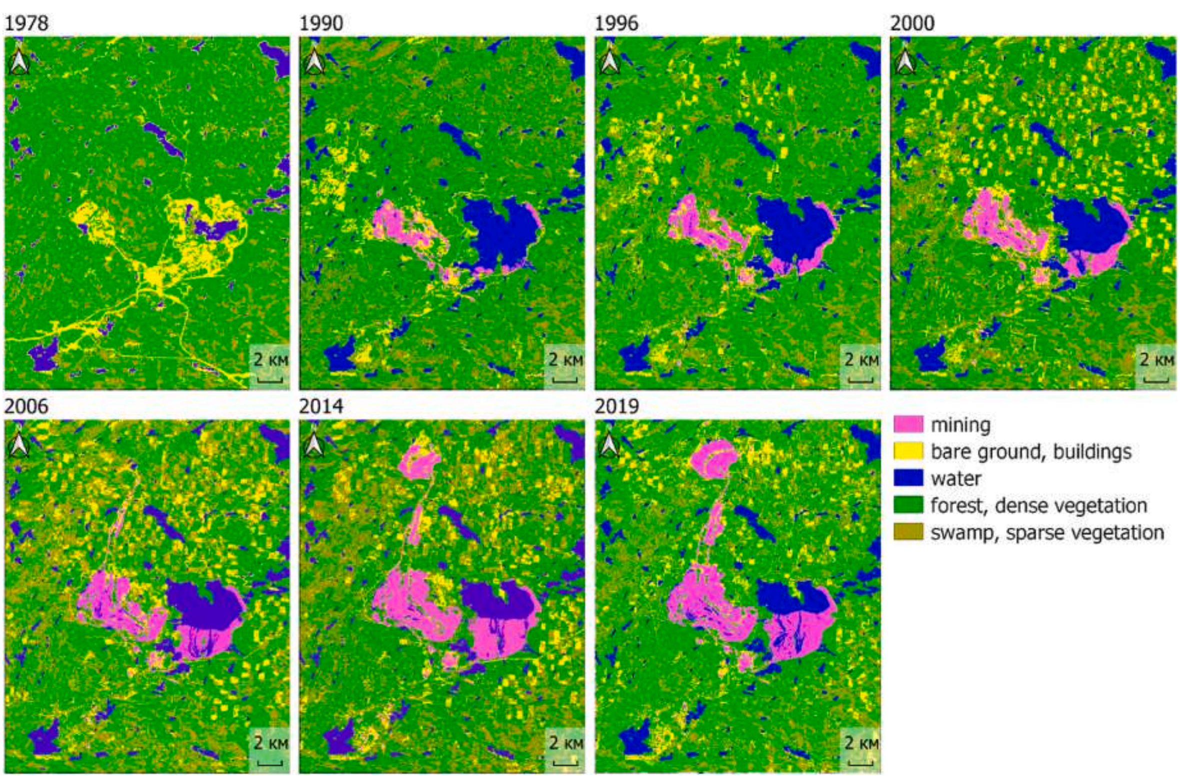

Fig. 4. LULC distribution from 1978 to 2019.

3.2. *Dynamics of landscape metrics*

The development of mining activities within the study area began in the 1970s of the twentieth century. Until the 1980s, the deposit was being prepared for development. By 1990, the mining class occupies an area of 17.4 thousand km^2, and by 2019 the area is 55.5 thousand km^2. This class includes both the quarry itself and the tailings-occupied territory. The area of quarries increases most intensively in the period from 2006 to 2014, the area increment rate is 2.2 km^2/year (Fig. 5.). The least development of the mining class occurred in the period 1990–1996. On average, the increase in class over 41 years is 1.9 km^2/year. The increase in the area of quarries occurs evenly at the expense of all other classes of land use (Fig. IIs).

The area occupied by the 'bare ground, buildings' class varies throughout the study period. In the first time interval under study, the area is reduced due to the transition to the 'mining' class and the 'water' class. In 1978, the deposit territory was intensively developed, and significant clearing was carried out for a quarry and a tailing dump. The area of the class is significant and is 70.8 km^2. Furthermore, there is a passing development of the territory, the development of logging. This

Table 3
Distribution of land use and land cover classes by area.

LULC classes	Metrics		1978	1990	1996	2000	2006	2014	2019
Mining	*CA1*	кМ^2	0,0	17,4	19,3	25,9	32,6	49,8	55,5
	PLAND1	%		2,4	2,7	3,6	4,5	6,9	7,7
Bare ground, buildings	*CA2*	кМ^2	70,8	41,2	43,2	77,6	66,3	59,7	64,8
	PLAND2	%	9,8	5,7	6,0	10,7	9,2	8,2	8,9
Water	*CA3*	кМ^2	29,3	62,6	62,8	58,6	61,2	54,5	53,8
	PLAND3	%	4,0	8,6	8,7	8,1	8,5	7,5	7,4
Forest, dense vegetation	*CA4*	кМ^2	500,4	435,7	437,8	399,0	340,9	346,5	398,3
	PLAND4	%	69,2	60,2	60,4	55,1	47,1	47,8	55,0
Swamp, sparse vegetation.	*CA5*	кМ^2	123,2	167,3	161,1	163,1	223,2	213,7	151,7
	PLAND5	%	17,0	23,1	22,2	22,5	30,8	29,5	20,9

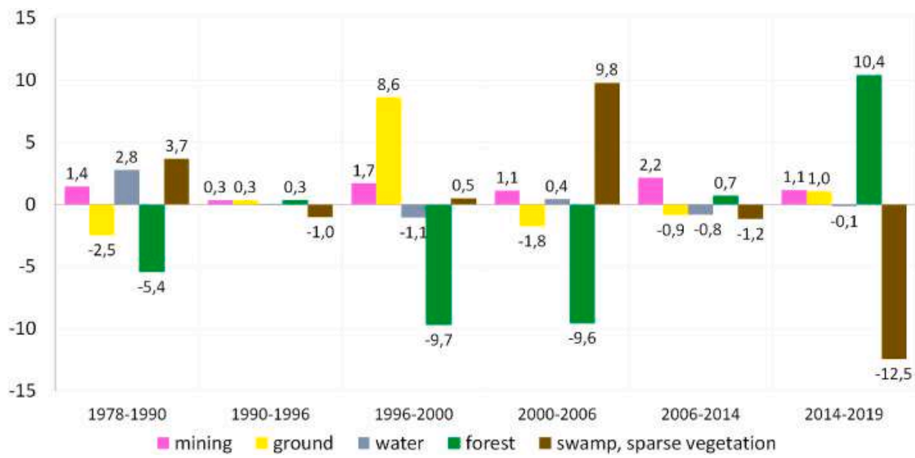

Fig. 5. Dynamics of changes in the area of LULC (km^2/year).

leads to an increase in the area of the 'bare ground' class due to forestry activities. The maximum growth of this class can be traced in the period 1996–2000 and is 8.6 km^2/year (Fig. 5), while in 2000 the area of the class is 77.6 km^2. The increase in the 'bare ground' class occurs mainly due to the forest (Fig. IIs).

The area of the class of water bodies varies over different periods. At the initial stage of development, due to the formation of a reservoir on Lake Kostomukshskoe, there is an increase in the area of water bodies from 29.3 km^2 in 1978 to 62.6 km^2 in 1990. Then the lake is used as a tailing dump. The tailings pond consists of an elevated beach, embankment dams, and a settling pond. Due to the constant washing of tails, the share of the "water" class is decreasing; in 2019 the area is 53.8 km^2.

More than 50% of the study area is forest cover. The maximum area covered by forest is fixed in the initial period. As of 1978, forest tracts occupy an area of 500.4 km^2, and by 2006 there is a decrease to 340.9 km^2. The decrease in forest area is associated both with its deforestation for mining, and with intensive logging activities in the region. A

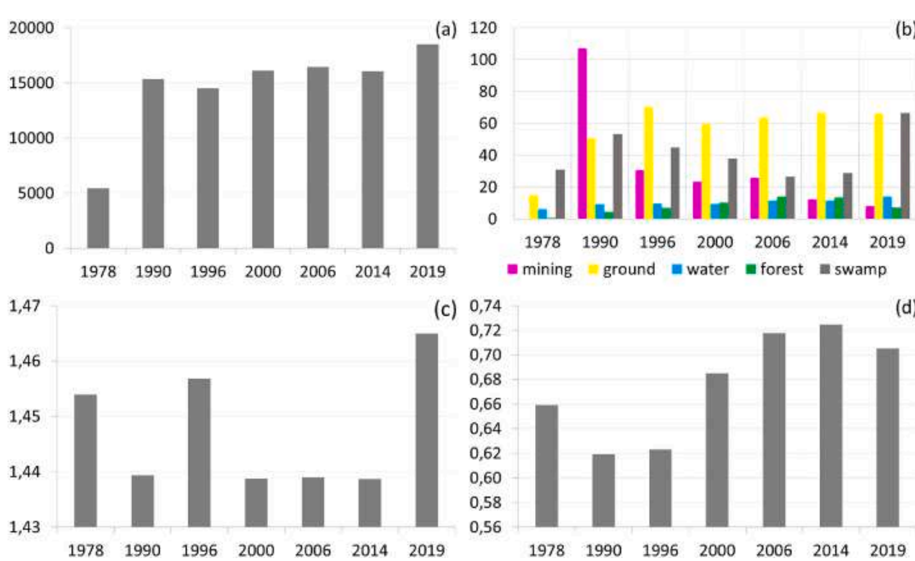

Fig. 6. Dynamics of changes in the number of patches (units) (NP) in the landscape (a), the density of patches (units/km^2) (PD) (b), fractal dimension of the perimeter area (PAFRAC) (c) and the Shannon Evenness Index (SHEI) (d).

significant reduction in forest areas was revealed from 1996 to 2006. The intensity of forest area decrease in these years averages 9.6 km^2/year (Fig. 5).

An analysis of landscape metrics showed that intensive development of the site leads to greater fragmentation of the landscape. The number of patches increases with time (Fig. 6a). The fragmentation of different landscape classes can be traced by the density of patches in each class (Fig. 6b). Anthropogenic landscape classes (mining) at the beginning of the study period are the most fragmented. As they grow, small patches unite and enlarged patches are formed, occupying large territories. Fragmentation of the 'bare ground' class reflects the anthropogenic impact associated with development, clearing and logging. An increase in the number of patches in the initial period was revealed, and then a relatively constant density of patches is traced. Natural landscape classes are characterized by the largest patch areas and, therefore, their patch density is noticeably lower. The intensity of logging activities in the 2000s leads to an increase in the fragmentation of the forest cover, which is subsequently reduced due to the restoration of territories.

Any system in violation of equilibrium tends to self-regulation. Fractality is the most flexible mechanism that ensures the efficient distribution of matter and energy in complex systems (Nasonov et al., 2018). The system is forced to select a more advantageous configuration when interacting with the external environment. However, the extreme case is the degeneration of the interaction contour and the transition to a straight line. The fractal dimension demonstrates the integral properties of an object and its parameters. An analysis of the dynamics of the fractal dimension in time gives a vision of the adaptation of the system under the influence of anthropogenic impact. This is demonstrated by the graph of the dynamics of the fractal dimension for the study area (Fig. 6c). Intense anthropogenic impact leads to a smoothing of the system contours and a decrease in the fractal dimension. However, when the impact decreases, the system exhibits its elastic properties and returns to its original position. This is associated with the adaptation of the ecosystem to constant anthropogenic impact and its self-regulation.

The diversity of the structure of the geosystem has a significant impact on its stability. On the one hand, the more diverse the landscape, the more adaptive resources it includes. On the other hand, the involvement of the anthropogenic component creates a specific landscape structure. It is determined that in the initial development period, SHEI is reduced, since the 'mining' class is not widely distributed (Fig. 6d). The growth of SHEI occurs with an increase in the impact and development of technogenic classes.

The studied periods are grouped using cluster analysis. The tree diagram (Fig. 7) highlights the stages of territory development based on landscape metrics. Several stages of territory development are interpreted: 1–1978; 2 - 1990–1996; 3 - 2000–2014; 4–2019.

3.3. Modeling of spatial disturbance

The results of the PCA of the standardized values of the selected metrics showed that the first four components have eigenvalues above one and explain in total 71,5% (36,1%, 18,8%, 9,5% and 7,0%) of the information distribution dispersion. On Fig. 8 shows the distribution of factor loads on the plane of the first and second factors; second and third factors. The highest positive load in the first component is exerted by ED5, PLAND5, PD4, ED, ED4, PAFRAC4, NP. This factor indicates the general fragmentation of the landscape. The second factor has positive loads for ED1, PLAND1, PD3, PD1, PAFRAC1, ED3, and negative loads PLAND4. The factor shows the impact of mining activities on the structure of the landscape. The third factor combines the positive loads of SHEI, PLAND2, ED2, SPLIT, and the negative load CONTAG. The factor reflects the transformation of landscapes due to deforestation. Factor 4 includes PLAND3 and negative PAFRAC, PAFRAC5, PLAND4. This factor shows the ability of the system to recover.

The first three factors form the spatial disturbance of the territory, and the fourth factor indicates the restoration of the system. The total value of the factors, taking into account their weight, indicates the stress experienced by the territory.

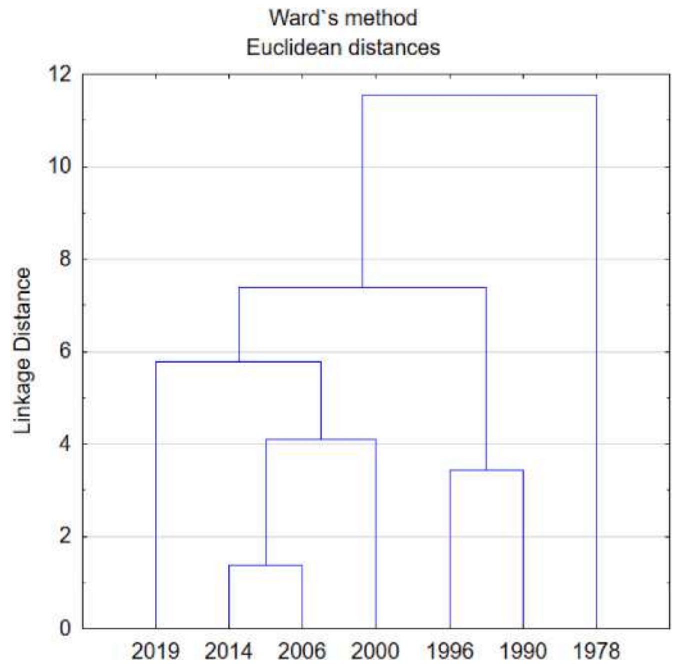

Fig. 7. Tree diagram for 7 years based on landscape metrics.

The maps of spatial disturbance (Fig. 9) show the destabilization of the geosystem from the impact of economic activity in different years. According to the degree of landscape disturbance, the territory is divided into three classes: low, medium, high. Additionally, examples of the distribution of LULC classes in some OTUs are shown.

The percentage of zones of disturbance is shown in Fig. 10. In the pre-industrial period (1978), mostly undisturbed territories are observed, the zone of low spatial disturbance occupies 93% of the total area. The minimum percentage of the total area of the low disturbance was recorded in 2006. 2006 is characterized by an increase in the area of highly disturbed territories (68%). By 2019, due to the restoration of landscapes, including the overgrowth of clearcuts, the reduction of overall fragmentation, the area of territories with high SDI is reduced to (28%)

4. Discussion

4.1. General characteristics of LULC

The analysis of changes in landscape indicators is based on LULC. The quality of classification is greatly influenced by a number of factors. On the one hand, classification accuracy is highly dependent on the method. On the other hand, the training set strongly determines the resulting classes. In order to improve the quality of classification and avoid spectral shift across sensors, it is recommended to train models separately for each period (Vasuki et al., 2019). Also, the quality of classification is sensitive to the set of training samples. It is important to maintain a balance between undertraining and overtraining the model. We used these principles in the study. Unfortunately, the 1978 model is inconclusive because only 4 spectral bands were used. To train and test model, we used visual interpretation of Landsat composites and archive data. Future research should focus on improving classification accuracy for early satellite imagery.

An imbalance in the classification is caused by the lack of a clear boundary between the classes "forest, dense vegetation" and "swamp, sparse vegetation". The important fact is that classes migrate and interpenetrate over time. Forest cutting can lead to both overgrowth and

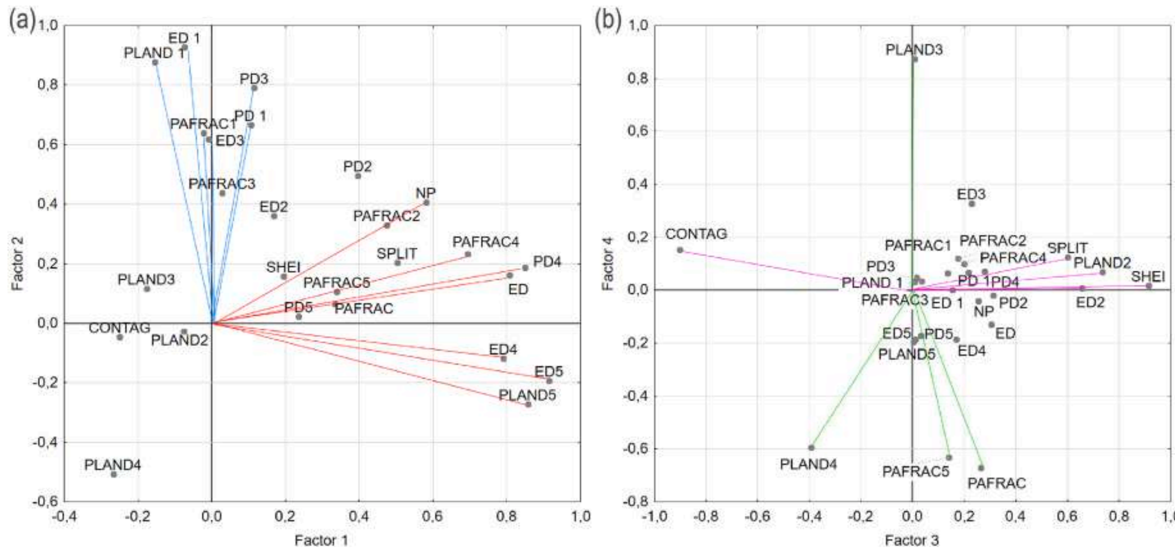

Fig. 8. Factor loadings in the planes of the first and second factors (a); second and third factors (b).

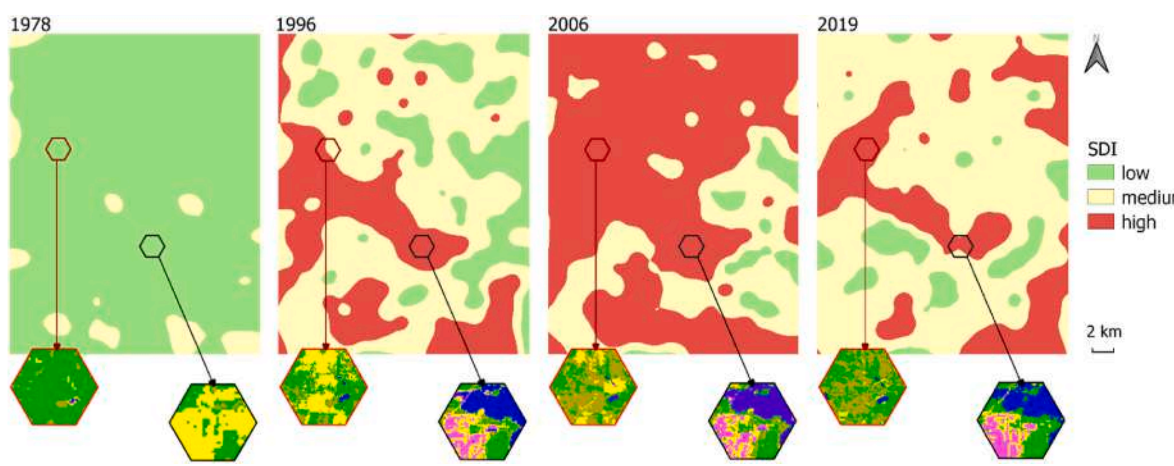

Fig. 9. Spatial disturbance of the territory of the Kostomuksha mining cluster from 1978 to 2019.

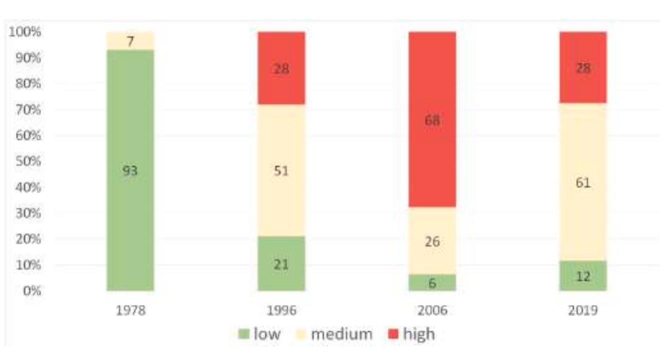

Fig. 10. Zones of spatial disturbance of the Kostomuksha mining cluster.

waterlogging of the area. Since two differently directed processes occur, it is necessary to divide this class into the classes "swamp" and "sparse vegetation". On the other hand, the study aims to analyze the impact of mining activities on the disturbance of the area.

4.2. Modeling spatial disturbance

Multiple studies show that landscape metrics reflect landscape features very well (Peng et al., 2010; Singh et al., 2017; Khoroshev and Dyakonov, 2020; Toosi et al., 2022; Zamfir et al., 2022). In our study, the four PCA factors accurately showed the characteristics of landscape spatial structure. The number of patches, the area of patches, the density of patches, and the density of edges determine the importance of landscape disturbance. The greatest disruption was detected in cells with a large number of separated patches, with a dense edge.

Using the mapping method, it was established that the maximum area with highly disturbed landscape was observed in 2006 and amounted to 40 thousand hectares. Spatial disturbance is reduced by half and by 2019 the area with high SDI values will be 20 thousand hectares. The SDI method has worked well in this area. The method is based on the main indicators of the load on landscapes and their rehabilitation, therefore it is used for an integral assessment of the area. If necessary, it is possible to separately map the territory by load factors based on PCA data.

Under the influence of such intensive anthropogenic activities as mining, changes are noticeable even in a shorter time segment (Hendrychová and Kabrna, 2016). Our study indicates a rapid change in the spatial heterogeneity of the mining area. When analyzing the change in LULC and landscape characteristics, several stages of the development of the territory were determined (Fig. 7). The initial stage of field development is separately identified. At this time, spatial disturbance is minimized. By 1990, there is an increase in impact due to the development of a mining enterprise. The period of the 1990s was determined by containing the growth of the anthropogenic load associated with the general economic recession in the country. At this time, the system is adapting to stress. In early 2000, the geosystem is experiencing new stress. There is an imposition of multidirectional processes of influence. Open-pit mining results in partial destruction of the original ecosystems (Hendrychová and Kabrna, 2016). At the same time, maximum stress manifested in 2006 and is maintained until 2014. Subsequently, self-regulation mechanisms and the search for a new equilibrium state are turned on. By 2019, there is a decrease in the spatial disturbance of the geosystem. This is consistent with studies that also find a reduction in impact intensity, typically as a result of gentle technological developments in mining and mineral processing (Iwatsuki et al., 2018).

4.3. Importance of research for sustainable development

An analysis of changes in landscape characteristics shows that spatiotemporal perturbation is associated with various properties of the geosystem and its individual components. When planning preventative measures to reduce human impacts, it is important to understand which activities have the greatest impact and which have the potential for reduction. There are several principal factors for the development of the territory. The first factor is associated with an increased anthropogenic impact. This is evidenced by the increased fragmentation of landscapes. During the period under review, there is a constant increase in the anthropogenic load. This pressure is due not only to the ever-expanding impact of mining activities, but also to the accompanying activity - logging. Constant logging has a negative impact on ecosystems, and full restoration of forest structure takes a long time. The species composition of vegetation changes in fellings (Qijing et al., 1998). First, the fellings are overgrown with deciduous tree species. The coniferous species inherent in the boreal forests have been recovering for a long time.

An increase in load leads to a decrease in adaptive resources of the system (Khoroshev and Dyakonov, 2020). However, removing or reducing the load allows the system to re-enable its elastic properties (Stanturf, 2015). The rate of self-regulation of the system depends on the intensity of the load and its type. In the 2000s, there was an imposition of impacts on natural systems and, naturally, the loss of the equilibrium state. Removing the impact, introducing environmentally friendly technologies leads to self-regulation of the system (Burton and Macdonald, 2011; Jennings et al., 2020). By 2019, the processes of self-regulation lead to a partial restoration of the spatial disturbance of the system and its adaptation to existing conditions. Partial restoration of disturbed landscapes in the study area is observed throughout the entire time. This is mainly due to the overgrowth of logging sites. The self-healing landscape is dynamic (Fig. IIIs). It reproduces and regenerates itself during disturbances. The maximum recovery period falls on 2014–2019. The area of transition to the 'forest and dense vegetation' classes is 128,4 км$^{2.}$ More than 90% of transitions are found for the 'bare ground' and 'swamp' classes. However, pixels associated with the recovery of the mining class have been identified. Basically, they are confined to the sides of the quarry. The landscape strives to maintain a constant composition among the changing surrounding material flows (Ferguson, 1996). The landscape reacts to moderate disturbance by secondary restoration. Extreme stress destroys the functional structures of the landscape. At the same time, its ability to respond to further loading is significantly reduced.

Our studies confirm that the modern landscape shows a higher degree of landscape diversity and fragmentation than before intensive anthropogenic activities (Malaviya et al., 2010; Hendrychová and Kabrna 2016).

This study is being conducted at a small regional site. However, this demonstrates the behavior of geosystems located in similar natural conditions. Forest ecosystems are the most stable, but any system experiences stress under external impact. Then, the adaptive mechanisms to find a new equilibrium position. The results of this study indicate the importance of taking the necessary measures to reduce environmental risks in the study area. Restoring the geosystem to its original level in mining areas is impractical. The main efforts must be made to restore the structure, processes and functions of the geosystem and create harmonious relations between nature and man (Lei et al., 2016).

It is important to continue research in the future to understand the reaction of environmental components to the impact of multidirectional economic activities. Remote sensing can quickly and continuously identify drivers of environmental change, is a powerful tool for environmental monitoring, and provides technical support for management decisions (Song et al., 2020).

5. Limitations

The study is based on the LULC classification. In this case, errors occur in the LULC data, which can lead to uncertainty in the assessment of the spatiotemporal disturbance of the geosystem. The overall accuracy of LULC data in our study was >72%, allowing reliable assessment of spatiotemporal disturbance. However, errors in LULC maps were inevitable. In future studies, classification accuracy should be increased for more accurate results.

Another limitation of the study is that landscape metrics were mainly used for the analysis of spatiotemporal disturbance. Continuation of the study of transformation dynamics will include characteristics of various landscape classes, showing their qualitative state.

6. Conclusions

The study shows the main trends in the changes in LULC over the period from the start of development (1978) to the current stage (2019). There is a direct impact of mining on forest cover, along with other factors. The paper uses a new method to analyze spatial and temporal disturbances with an emphasis on landscape ecology. The PCA method using landscape metrics, SDI calculation and mapping is an effective approach to describing the mechanisms of adaptation and self-regulation of the system. A retrospective analysis of the state of the system allows you to see and evaluate its properties, better understand the adaptive mechanisms that allow the system to show stability under the influence of continuous or increasing external loads. The use of multispectral remote sensing data ensures the continuity of the study due to the full temporal coverage of the anthropogenic impact on the territory.

CRediT authorship contribution statement

Natalya Krutskikh: Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pce.2024.103544.

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