

Article

Study on the Eco-Environmental Index and Its Application: A Case Study of the Surablak Coal Fire Area, Xinjiang, China

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Abstract: Coal fires are disasters that occur when underground coal seams are subjected to combustion conditions induced by natural or human factors. This study attempts to investigate the impact of coal fires on the surrounding environment by assessing the eco-environmental quality and its dynamic changes in the Surablak coal fire area. To achieve this, an improved remote sensing ecological index (termed RSEIs) is introduced to assess and track the quality and dynamics of eco-environmental conditions in the Surablak coal fire area from 1990 to 2022. Subsequently, this index is combined with a geographic detector (GeoDetector) model to identify potential factors influencing eco-environmental quality. The findings indicate that (1) compared with the established Remote Sensing Ecological Index (RSEI), the RSEIs provides a high degree of precision in reflecting the eco-environmental conditions within the regions affected by coal fires, (2) the eco-environmental quality within the Surablak coal fire area underwent a continuous deterioration from 1990 to 2022, with the area of ecological degradation constituting 53.41% of the study region, (3) regions with excellent and good RSEIs values are mainly found in the forested mountainous regions located in the northern section of the coal fire area, whereas regions with poor and fair RSEIs values largely coincide with the coal fire locations, and (4) since 2006, the distance to the coal fire has become the key factor influencing eco-environmental quality in the Surablak area, while temperature and precipitation remained important factors. The outcomes of this study will provide essential references for guiding ecological restoration and promoting sustainable development in coal fire areas.



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Keywords: remote sensing ecological index; eco-environmental quality; geographic detector; Surablak coal fire area

1. Introduction

Coal fires are disasters that occur when underground coal seams are subjected to combustion conditions induced by natural or human factors [1,2]. The combustible constituents within coal are a complex mixture of various high-molecular-weight organic compounds. When reacting with oxygen, coal seams spontaneously combust and release considerable heat and gases, as well as suspended particles, which directly and indirectly affect the eco-environmental conditions surrounding the coal mining area [3]. Coal fire disasters lead to not only persistent resource wastage and endanger the mining safety, but also trigger numerous environmental challenges, including the deterioration of water quality, atmospheric impacts, and landscape degradation [4]. The eco-environmental deterioration in coal fire areas affects surrounding towns especially negatively, resulting in a decline in soil fertility and posing health risks to local residents [5,6]. Therefore, a detailed investigation

of the current status, spatiotemporal changes, and influencing factors of eco-environmental quality in coal fire areas is essential for formulating effective restoration strategies that promote regional sustainable development.

In recent years, methods based on remote sensing have been widely adopted for eco-environmental monitoring and assessment due to their extensive spatial coverage and high precision [7–9]. Certain studies employ a single remote sensing indicator to represent a specific aspect of the ecological conditions. For instance, Jiang et al. [10] conducted a systematic assessment of China's eco-environmental quality over the past two decades using the normalized difference vegetation index (NDVI). However, while a single indicator can reflect one aspect of the eco-environment, the diverse and complex nature of eco-environmental systems requires a comprehensive evaluation from multiple perspectives. The remote sensing ecological index (RSEI), initially proposed by Xu [11], integrated four remote-sensing-based indicators to represent the four major aspects of ecological conditions: soil, air, vegetation, and temperature. Specifically, soil moisture is reflected by WET, air dryness is reflected by NDBSI, vegetation coverage is reflected by NDVI, and temperature is reflected by LST. In recent years, the RSEI has become one of the most widely applied models due to its extensive coverage and high applicability [12–14]. For instance, the RSEI index has been applied in assessing the eco-environmental quality in the Loess Plateau [15], the Yangtze River Basin [16], and Pingshuo open-cast mine area [17].

However, due to differences in geographic backgrounds and anthropogenic factors across different study regions, there is still potential to improve the RSEI index for assessing regional eco-environmental quality. Numerous studies have improved this index to enhance its precision in discerning the regional eco-environmental status. For instance, Liu et al. [18] applied the TDRSEI index to assess the eco-environmental quality in forests, while Ma et al. [19] utilized the IRSEI index to evaluate the eco-environmental status of river basins. Consequently, based on the regional characteristics of the coal fire areas, this study also extended and improved the RSEI index. In assessing the eco-environmental quality of these areas, two key aspects were considered: (1) during the process of coal spontaneous combustion, organic and inorganic materials in the coal burn, generating a large amount of particulate matter, including PM_{2.5}—these particulates are emitted into the atmosphere surrounding and above the combustion area, constituting a major source of air pollution [3,20]; (2) during coal seam spontaneous combustion, the thermal energy generated not only accelerates the dissolution and release of salt compounds in the soil but also the evaporation of soil moisture, leading to an increase in the soil salinity content [21].

Generally, the research on eco-environmental quality focuses on two primary aspects. The first is eco-environmental quality monitoring, which employs optical images and various remote sensing data sources to monitor the regional eco-environmental status [22]. Through a comprehensive analysis of ecological components, the dynamic changes and overall conditions of the ecological environment can be revealed [23]. The second aspect is eco-environmental evaluation, in which the improved RSEI is used to assess the ecological quality and environmental risk [24]. By examining the potential factors affecting the eco-environmental quality, such as the geographic features, climate change, and anthropogenic activities, this method identifies potential eco-environmental problems and risks, thereby providing scientific support for the eco-environmental management and policy-making [25,26]. To investigate and analyze the influencing factors, various statistical models have been employed, including a partial least squares structural equation model, a multiple regression model, and a stepwise regression model [27,28]. However, these models are mainly based on the correlation between the eco-environmental quality and single factors, revealing only the average effects under the assumption of constant coefficients and failing to explain the interactions among various influencing factors, which

may result in biased outcomes [29]. Therefore, the Geodetector spatial regression model is applied in this study to investigate the natural and anthropogenic factors influencing the eco-environmental quality within coal fire areas.

The aim of this study is to propose a more effective index for assessing the eco-environmental quality of coal fire areas, analyze the spatiotemporal changes over the past thirty-two years, and determine the potential interactions among environmental influencing factors. First, an improved remote sensing ecological index (termed RSEIDs) is introduced by integrating the salinization monitoring index (SMI) for salinization assessment, and the difference index (DI) for PM_{2.5} pollution assessment into the RSEI model. Second, the continuous spatiotemporal dynamics of the eco-environmental quality in the Surablak coal fire area from 1990 to 2022 are examined. Third, the GeoDetector model's univariate and interactive modules are applied to identify the natural and anthropogenic factors driving changes in eco-environmental quality. Finally, the applicability and effectiveness of the RSEIDs model are discussed.

2. Materials and Methods

2.1. Study Area

The Surablak coal fire area is located in the central part of the Southern Junggar Coalfield. (Figure 1). Specifically, this fire area is situated in a valley of the northern Tianshan Mountains. The topography generally slopes from south to north and from west to east, with elevations ranging from 1995–2211 m and with the relative height differences between 50 and 110 m. The region is characterized by a continental temperate arid climate, with severe winters, warm summers, highly variable spring weather, and rapidly declining temperatures in autumn. The lowest annual temperatures occur in January and February, and annual precipitation ranges from 170.4–201.1 mm. The prevailing wind direction is from the southwest, with typical wind speeds of 1.2 to 2.0 m/s and maximum wind speeds reaching up to 2.9 m/s. In this study, fire areas 1 and 3 were triggered by the exposure of shallow coal seams during excavation processes, leading to the spontaneous combustion of coal seam outcrops. Fire area 2 resulted from incomplete underground mining, causing residual coal in the goaf to ignite spontaneously.

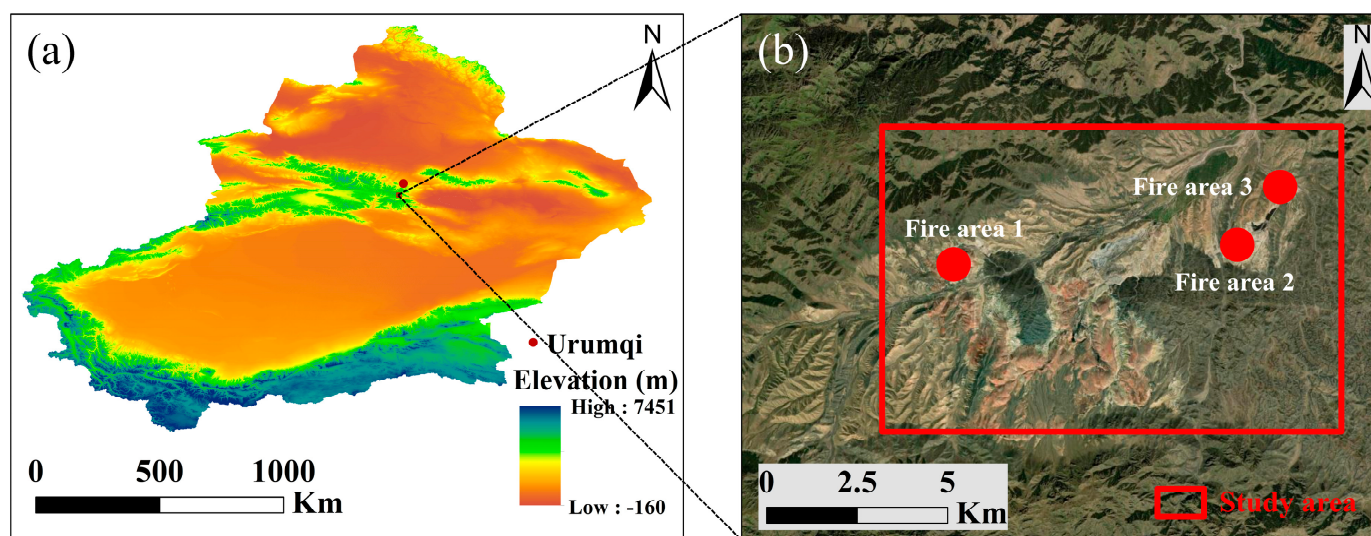


Figure 1. The geographical location of the study area. (a) DEM. (b) Study area.

2.2. Data Sources and Processing

Routinely accessible Landsat imagery is extensively utilized to detect and evaluate the eco-environmental conditions (e.g., NDVI of vegetation, temperature, air dryness, soil

moisture) at high resolutions and fine scales on a periodic basis. This study collected Landsat 5 (MSS/TM) and Landsat 8 (OLI/TIRS) imagery, acquired from June to September, covering the period from 1990 to 2022. The RSEIds indices were computed directly on the Google Earth Engine (GEE) platform, with preprocessing steps including radiometric calibration, atmospheric correction, outlier removal, and normalization. To avoid the effects of water bodies on the calculations, the modified normalized difference water index (MNDWI) was employed to mask the water areas [30,31].

Based on prior research experience and available data, we selected seven influencing factors, both natural and anthropogenic, to determine potential influences on eco-environmental quality in the study area. These factors included temperature, precipitation, elevation, slope, slope aspect, population density, and distance to the Surablak coal fire area [32]. The data mentioned above are thoroughly detailed in Table 1.

Table 1. Details of research data.

Data	Spatial Resolution (m)	Temporal Resolution	Source
Landsat5	30	16 days	http://www.usgs.gov/
Landsat8	30	16 days	http://www.usgs.gov/
Temperature	1000	monthly	https://www.resdc.cn/
precipitation	1000	monthly	https://www.resdc.cn/
Elevation	30	2020	https://www.gscloud.cn/
Slope	30	2020	Calculated in ArcGIS Pro based on DEM https://www.gscloud.cn/
Slope aspect	30	2020	Calculated in ArcGIS Pro Based on DEM https://www.gscloud.cn/
Population density	1000	yearly	https://landscan.ornl.gov/
The distance to the Surablak coal fire area	-	2020	Calculated using Euclidean distance from fire point locations http://www.usgs.gov/

2.3. Methods

2.3.1. Establishment of RSEIds Index

The RSEIds index model developed in this study comprises six remote-sensing-based indicators to comprehensively assess the eco-environmental status of the coal fire areas, focusing on four key aspects: vegetation, soil, air, and temperature. Specifically, vegetation coverage is indicated by NDVI, soil moisture is indicated by WET, air dryness is indicated by NDBSI, land surface temperature is indicated by LST, atmospheric particle concentration is indicated by DI, and soil degradation is indicated by SMI. Among them, NDBSI and NDVI capture the eco-environmental responses of RSEIds to land-use changes induced by human economic activities (particularly mining); WET and LST capture the eco-environmental responses of RSEIds to surface temperature changes caused by the self-ignition of coal seams; DI captures the eco-environmental responses of RSEIds to air pollution resulting from coal mining and spontaneous coal combustion; and SMI captures the ecological responses of RSEIds to soil salinization in coal fire areas. These indicators are often used in studies evaluating eco-environmental conditions [24,33].

The following provides a more comprehensive explanation of the equations used for each of the indicators in this study.

- (1) Vegetation coverage: the normalized difference vegetation index (NDVI) is a key indicator for monitoring vegetation growth and coverage, as it is closely related to

the leaf area index, green biomass, and the percentage of green vegetation cover [34]. NDVI is calculated using the normalized difference algorithm, as shown below:

$$\text{NDVI} = (\rho_{\text{NIR}} - \rho_{\text{Red}}) / (\rho_{\text{NIR}} + \rho_{\text{Red}}) \quad (1)$$

where ρ_{NIR} and ρ_{Red} are the reflectance of the near-infrared and red bands, respectively.

- (2) Soil moisture: the wet indicator (WET) is intently connected to the moisture content of soil, vegetation, and surface water. WET is calculated using the wetness component of the Tasseled Cap Transformation [35]. The equation is as follows:

$$\begin{aligned} \text{WET}_{\text{OLI}} = & 0.1511\rho_{\text{Blue}} + 0.1973\rho_{\text{Green}} + 0.3283\rho_{\text{Red}} \\ & + 0.3407\rho_{\text{NIR}} - 0.7117\rho_{\text{SWIR1}} - 0.4559\rho_{\text{SWIR2}} \end{aligned} \quad (2)$$

$$\begin{aligned} \text{WET}_{\text{TM}} = & 0.0315\rho_{\text{Blue}} + 0.2021\rho_{\text{Green}} + 0.3102\rho_{\text{Red}} \\ & + 0.1594\rho_{\text{NIR}} - 0.6806\rho_{\text{SWIR1}} - 0.6109\rho_{\text{SWIR2}} \end{aligned} \quad (3)$$

where ρ_{Blue} , ρ_{Green} , ρ_{Red} , ρ_{NIR} , ρ_{SWIR1} , ρ_{SWIR2} are the reflectance of the blue, green, red, near-infrared, short-wavelength infrared 1 (SWIR1), and SWIR2 bands, respectively.

- (3) Air dryness: dryness is initially indicated by the soil index (SI), which reflects the scarcity of vegetated land in a given area. However, a large amount of construction land also contributes to regional dryness, increasing the significance of the index-based built-up index (IBI). Therefore, according to Hu and Xu [36], the normalized difference built-up soil index (NDBSI) is formulated by combining the IBI and SI, thereby providing a more precise representation of regional dryness. The equation is as follows:

$$\text{SI} = [(\rho_{\text{SWIR1}} + \rho_{\text{Red}}) - (\rho_{\text{NIR}} + \rho_{\text{Blue}})] / [(\rho_{\text{SWIR1}} + \rho_{\text{Red}}) + (\rho_{\text{NIR}} + \rho_{\text{Blue}})] \quad (4)$$

$$\begin{aligned} \text{IBI} = & \{2\rho_{\text{SWIR1}} / (\rho_{\text{SWIR1}} + \rho_{\text{NIR}}) - \rho_{\text{NIR}} / (\rho_{\text{NIR}} + \rho_{\text{Red}}) - \rho_{\text{Green}} / (\rho_{\text{Green}} + \rho_{\text{SWIR1}})\} \\ & / \{2\rho_{\text{SWIR1}} / (\rho_{\text{SWIR1}} + \rho_{\text{NIR}}) + \rho_{\text{NIR}} / (\rho_{\text{NIR}} + \rho_{\text{Red}}) + \rho_{\text{Green}} / (\rho_{\text{Green}} + \rho_{\text{SWIR1}})\} \end{aligned} \quad (5)$$

$$\text{NDBSI} = (\text{IBI} + \text{SI}) / 2 \quad (6)$$

where ρ_{Red} , ρ_{Blue} , ρ_{Green} , ρ_{NIR} , ρ_{SWIR1} are the reflectance of the red, blue, green, near-infrared, and short-wavelength infrared 1 (SWIR1) bands, respectively.

- (4) Land surface temperature: the land surface temperature (LST) reflects the surface temperature of the region and is closely related to the regional eco-environment (particularly in coal fire areas) [37]. The equation is as follows:

$$\text{LST}_{\text{TM}} = T_{\text{sen}} / [1 + (\lambda T_{\text{sen}} / \rho) \ln \beta] - 273.15 \quad (7)$$

$$\text{LST}_{\text{OLI}} = \gamma [(\phi_1 L_{\text{senor}} + \phi_2) / \varepsilon + \phi_3] + \delta \quad (8)$$

$$\gamma \approx T_{\text{sen}}^2 / b_{\gamma} L_{\text{senor}}, \delta = T_{\text{sen}} - T_{\text{sen}}^2 / b_{\gamma} \quad (9)$$

where b_{γ} is a constant, T_{sen} is the brightness temperature detected by the sensor, L_{senor} is the radiance brightness measured by the sensor, ϕ_1 – ϕ_3 are constants, ε is the surface emissivity, λ is the wavelength of the thermal infrared band, ρ is a constant.

- (5) Atmospheric particle concentration: the difference index (DI) establishes a strong correlation between light reflectivity and atmospheric particle concentration, effectively reflecting variations in air quality within the eco-environment [24]. According to previous research analyzing the spectral characteristics sensitive to PM_{2.5} particles, these particles distinctly influence light reflectivity across different parts of the spectrum, enhancing it in the infrared band while reducing it in the near-infrared band. Building

on these findings, Hai-ying et al. [38] developed a difference index (DI) that leverages the disparity in reflectivity between these two spectral bands to indicate changes in PM2.5 concentrations. The equation is as follows:

$$DI = \rho_{\text{Red}} - \rho_{\text{NIR}} \quad (10)$$

where ρ_{Red} and ρ_{NIR} are the reflectance of the near-infrared and red bands, respectively.

- (6) Soil degradation: soil degradation has been demonstrated to have a significant correlation with vegetation cover. This relationship can be visualized through remote sensing technology, particularly by observing how the modified soil-adjusted vegetation index (MSAVI) decreases as soil salinity index (SSI) increases. Therefore, Zongfan, Ling, Huiqun, Xuhai and Liangzhi [33] developed the salinization monitoring index (SMI) by integrating MSAVI and SI to monitor soil salinization. The equation is as follows:

$$\text{MSAVI} = \frac{2\rho_{\text{NIR}} + 1 - \sqrt{(2\rho_{\text{NIR}} + 1)^2 - 8(\rho_{\text{NIR}} - \rho_{\text{red}})}}{2} \quad (11)$$

$$\text{SSI} = \sqrt{\rho_{\text{Blue}} \times \rho_{\text{Red}}} \quad (12)$$

$$\text{SMI} = \sqrt{(\text{MSAVI} - 1)^2 + \text{SSI}^2} \quad (13)$$

where ρ_{Blue} , ρ_{Red} , ρ_{NIR} are the reflectance of the blue, red, near-infrared bands, respectively.

2.3.2. Calculation of RSEIds Index

To eliminate dimensional and unit discrepancies among various indicators, the six indicators (NDVI, WET, NDBSI, LST, DI, and SMI) were normalized prior to constructing RSEIds. Subsequently, principal component analysis (PCA) was utilized on the Google Earth Engine (GEE) platform to compute the initial RSEIds (termed RSEIds₀) for the six normalized indicators. PCA, a robust technique for dimensionality reduction, effectively addresses multicollinearity among multiple variables, thereby enhancing a more objective measurement of changes in ecological conditions [24]. The equation for calculating RSEIds₀ is as follows:

$$\text{RSEIds}_0 = \text{PC}_1[f(\text{NDVI}_n, \text{WET}_n, \text{NDBSI}_n, \text{LST}_n, \text{DI}_n, \text{SMI}_n)] \quad (14)$$

To ensure that higher RSEIds values accurately reflect better ecological status, as expected, it was essential to validate RSEIds₀ values against prior knowledge before normalization. If superior ecological conditions are incorrectly reflected by lower RSEIds₀ values, contrary to expectations, the RSEIds₀ values should first be corrected using Equation (15) and then normalized using Equation (16).

$$\text{RSEIds}_0 = 1 - \text{PC}_1[f(\text{NDVI}_n, \text{WET}_n, \text{NDBSI}_n, \text{LST}_n, \text{DI}_n, \text{SMI}_n)] \quad (15)$$

$$\text{RSEIds}_n = (\text{RSEIds}_0 - \text{RSEIds}_{0_min}) / (\text{RSEIds}_{0_max} - \text{RSEIds}_{0_min}) \quad (16)$$

where RSEIds₀ represents the unnormalized raw RSEIds, RSEIds_{0_max} and RSEIds_{0_min} denote the maximum and minimum values in RSEIds₀, respectively. RSEIds_n represents the normalized RSEIds.

The normalized RSEIds were reclassified into five levels at equal intervals of 0.2: poor (0–0.2), fair (0.2–0.4), moderate (0.4–0.6), good (0.6–0.8), and excellent (0.8–1) [12,34].

2.4. Spatiotemporal Change Analysis of RSEIds

Change vector analysis (CVA) enables the identification and quantification of diverse change types between multitemporal datasets by computing change vectors, but it cannot reveal the specific states before and after the changes on its own [39,40]. The introduction of “From-to” change analysis significantly enriches this process by providing precise insights into the states and extents of changes across multitemporal datasets [41]. Based on previous research [12], this study combined the strengths of both methods to evaluate the eco-environmental changes in the Surablak coal fire area from 1990 to 2022 (Figure 2). First, CVA was applied to determine the changes in RSEIds levels, mapping the areas and spatial distributions of different change types (sharp decline, slight decline, relative stability, slight increase, drastic increase) and the change grades of RSEIds levels (Δ RSEIds, i.e., decrease: $-4, -3, -2, -1$; stability: 0 ; increase: $1, 2, 3, 4$). Secondly, the “From-to” change analysis was used to elucidate the change directions in RSEIds levels.

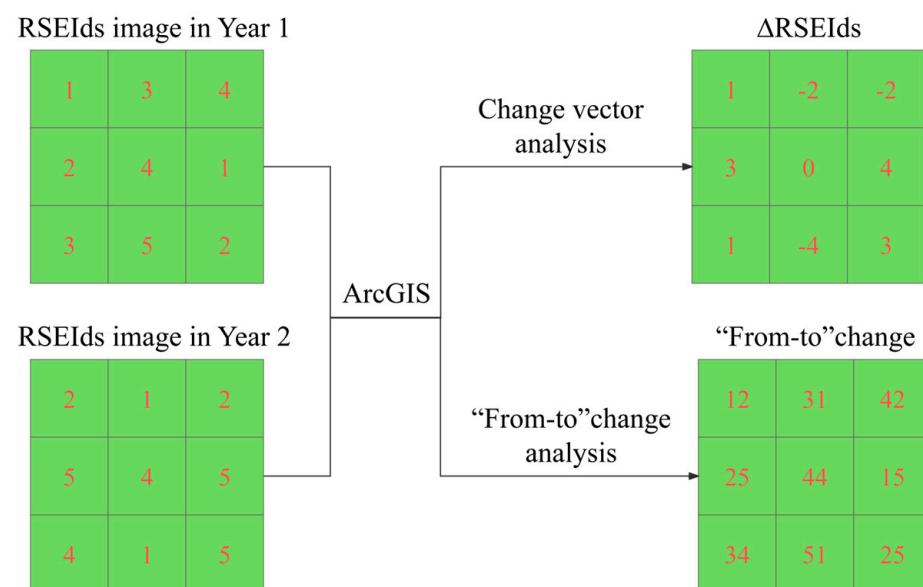


Figure 2. Flowchart of Spatiotemporal Change Analysis of RSEIds.

In the results of the CVA analysis, the indicated values quantified the degree of change in RSEIds levels (Δ RSEIds) from Year 1 to Year 2 (Figure 2). In the results of “From-to” change analysis, the indicated values detailed the transition in RSEIds levels between Year 1 and Year 2 (Figure 2). For instance, the notation “12” signifies that the RSEIds level changed from 1 (Poor) in Year 1 to 2 (Fair) in Year 2.

2.5. Detection of Factors Influencing RSEIds

The GeoDetector model is a multivariate statistical method for geospatial data analysis that includes four components: factor detection, interaction detection, ecological detection, and risk zone detection [42]. The factor detector quantifies the influence of individual factors on a specific outcome or a dependent variable, while the interaction detector examines the combined effects of two factors on the dependent variable. In this study, we utilized the factor detector to quantify the impact of natural and human factors on the RSEIds of the coal fire area. We selected the annual mean temperature (X1), annual mean precipitation (X2), elevation (X3), slope (X4), slope aspect (X5), population density (X6), and distance to the coal fire area (X7) as the independent variables for the subsequent analysis. Temperature, precipitation, and topography constitute key abiotic factors limiting vegetation growth. The elevation is an important determinant of plant photosynthesis [43], the slope influences the change of soil moisture [44], and the slope aspect can induce

microenvironmental variations by influencing precipitation redistribution, solar radiation, near-surface temperatures, and evapotranspiration [45]. Population density represents the extent of human activities. The geographical distance to the coal fire area indicates the degree of environmental influence exerted by the Surablak coal fire areas.

The calculation formula of factor detector can be expressed as follows:

$$q = 1 - \frac{1}{n\sigma^2} \sum_{h=1}^L n_h \sigma_h^2 = 1 - \frac{SSW}{SST} \quad (17)$$

$$SSW = \sum_{h=1}^L n_h \sigma_h^2, SST = n\sigma^2 \quad (18)$$

where the detection power of the influencing factor on the dependent variable is denoted by q , ranging from 0 to 1; the strata of the influencing factor are represented by L . Sample sizes for the whole area and stratum h are denoted by n and n_h , respectively; the variance of strata h and whole area are represented by σ_h^2 and σ^2 , respectively.

Interaction detection is employed to detect the influences of variable interactions on a dependent variable, testing whether these interactions increase, decrease, or independently influence the dependent variable. This process helps to better elucidate the driving mechanisms of the dependent variable. Based on the q value of the two factors and their interactive value, the effects of the interaction are classified into five distinct categories (Table 2).

Table 2. The interaction types of two factors.

Types of the Interaction	Criteria for Judgment
Nonlinear weakening	$q(X1 \cap X2) < \min[q(X1), q(X2)]$
Univariate nonlinear weakening	$\max[q(X1), q(X2)] > q(X1 \cap X2) > \min[q(X1), q(X2)]$
Bivariate enhancement	$q(X1) + q(X2) > q(X1 \cap X2) > \max[q(X1), q(X2)]$
Independence	$q(X1 \cap X2) = q(X1) + q(X2)$
Nonlinear enhancement	$q(X1 \cap X2) > q(X1) + q(X2)$

3. Results

3.1. Comparative Analysis of RSEIDs and RSEI Results

In this research, the RSEIDs index model for the Surablak coal fire area was computed and contrasted with the established RSEI index model (see Figure 3). The analysis demonstrated a statistically robust linear correlation between the RSEI indices and the RSEIDs, with a coefficient of determination (R^2) of 0.76 and a Pearson's correlation coefficient (r) of 0.87, indicating that the RSEIDs index developed in this study more accurately captures the dynamic changes in the eco-environmental quality across the Surablak coal fire area. However, considering the difference between the fitted regression line and the 1:1 line, the RSEI index was significantly overestimated. A comparison of the frequency distribution diagrams for the two indices showed that the RSEIDs index results magnified the disparities in the eco-environmental quality, whereas the RSEI values were mostly distributed across the interval of 0.4 to 0.8. Simultaneously, according to the results of PCA, the Principal Component 1 (PC1) contribution rate of the RSEIDs reached 70.12%, indicating that PC1 reflected the majority of the index's characteristic information. Furthermore, the loading values of NDVI and WET on PC1 were inverse to those of DI, SMI, NDBSI, and LST, illustrating that the eco-environmental quality within the Surablak coal fire area was influenced in opposite ways by these two groups of indicators. More specifically, NDVI and WET had positive impacts, whereas DI, SMI, NDBSI, and LST had negative impacts.

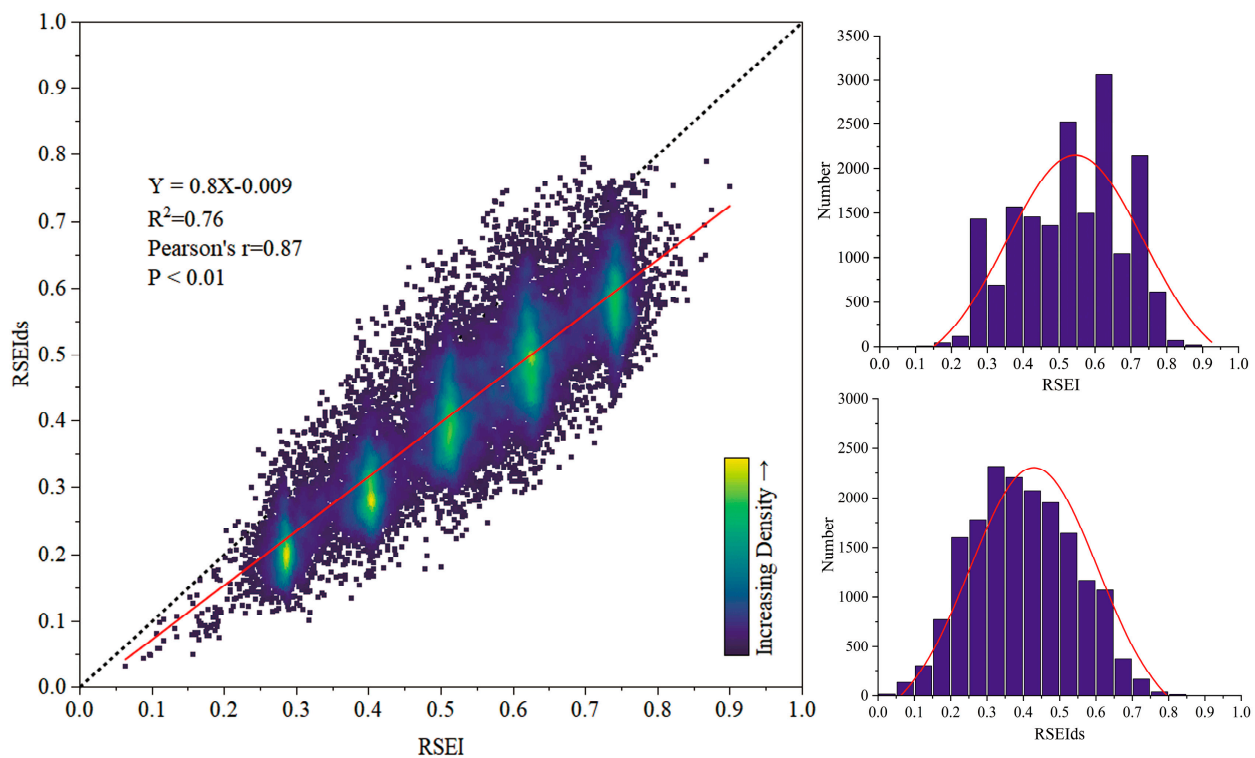


Figure 3. Comparative results of eco-environmental quality within Surablak coal fire area in 2022 under RSEIds and RSEI models.

3.2. Ecological Quality Status

The geographic distribution of the RSEIds levels in the Surablak coal fire area from 1990 to 2022 is presented in Figure 4. Overall, the RSEIds exhibits apparent spatial differences. Among these areas, those with excellent ecological status are mainly situated in the northwestern part of the Surablak coal fire area. Characterized by forested hills and mountains, these areas are subject to minimal human interference, sustain high vegetation coverage, and play an important role in the conservation of soil and water, as well as in the maintenance of the ecosystem stability. Nevertheless, the lowlands in the central part of the Surablak region have been intensively mined for coal and exhibit fair to poor ecological conditions, which substantially overlap with the three coal fire areas. Although coal mining activities promoted economic development in the region, the geological disturbances from the extraction process have led to the self-ignition of coal seams in certain regions, causing substantial natural resource wastage and severe environmental pollution.

The average RSEIds values revealed an overall declining trend, ranging from 0.45 in 1990 to 0.33 in 2022 (mean $\pm$ standard deviation: 0.367 ± 0.056). The index value reached its lowest point in 2014 at 0.39, significantly below the values observed in other years. Figure 4 provides a detailed analysis of the variations in the areas corresponding to the five levels of RSEIds. These distributions displayed apparent differences across the five levels in the Surablak coal fire area from 1990 to 2006 and 2022 (Figure 4). RSEIds of fair level has the largest area ($39.62 \pm 5.35 \text{ km}^2$), followed by moderate ($21.64 \pm 6.64 \text{ km}^2$) and poor levels ($11.35 \pm 7.86 \text{ km}^2$), then the good level ($9.55 \pm 4.47 \text{ km}^2$), and excellent level has the smallest area ($1.71 \pm 2.06 \text{ km}^2$) (Figure 5). Notably, after 2006, upwards of 61% of the eco-environment within the Surablak coal fire area was classified as fair (level 2) and poor (level 1) levels, whereas only about 1% was rated as excellent (level 5). The above findings suggest that the eco-environmental quality within the Surablak coal fire area fluctuated markedly between 1990 and 2022.

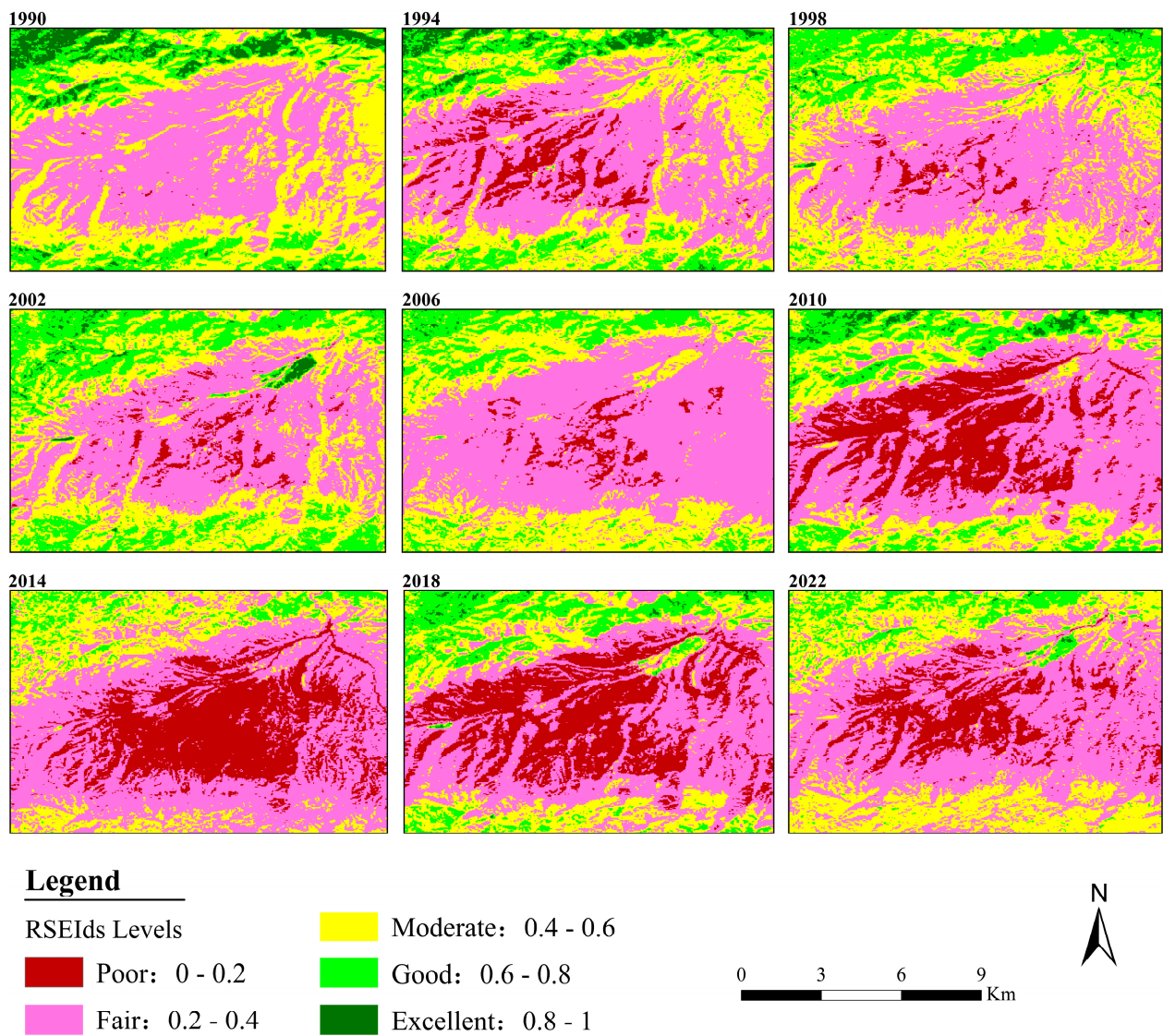


Figure 4. Spatiotemporal distribution of RSEIDs quality levels within the Surablak coal fire area, 1990–2022.

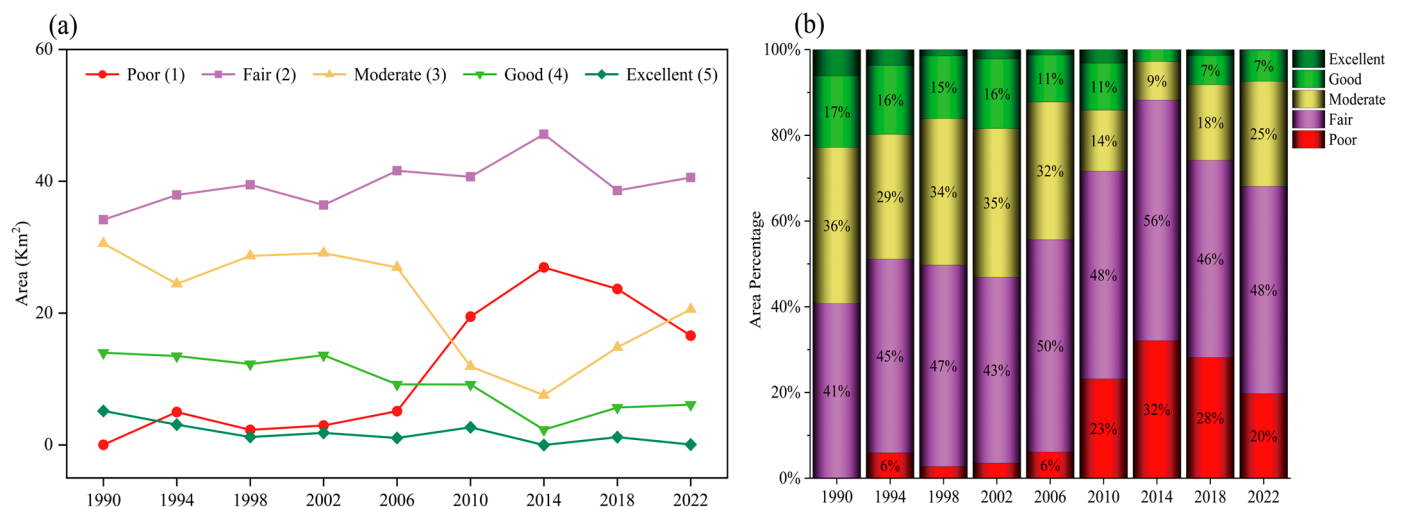


Figure 5. Distribution of area (a) and percentage (b) across different RSEIDs levels within Surablak coal fire area, 1990–2022.

3.3. Spatiotemporal Changes in Ecological Quality

To conduct a more detailed analysis of the dynamic changes in the eco-environmental quality within the Surablak coal fire area between 1990 and 2022, the changes in RSEIs levels were categorized into five types: sharp decline (RSEIs change levels of -4 and -3), slight decline (RSEIs change levels of -2 and -1), relative stability (RSEIs change level of 0), slight increase (RSEIs change levels of 1 and 2), and drastic increase (RSEIs change levels of 3 and 4) (Figure 6). Specifically, between 1990 and 2022, the eco-environmental degradation rate reached 53.41%, mainly exhibiting a slight decline. This degradation occurred mainly in the northwestern and southeastern mountainous belts and in the central region of the Surablak coal fire area (Table 3 and Figure 6). Conversely, the proportion of eco-environmental improvement was merely 2.66%, exhibiting a slight increase, distributed in the northern pastureland (Table 3 and Figure 6).

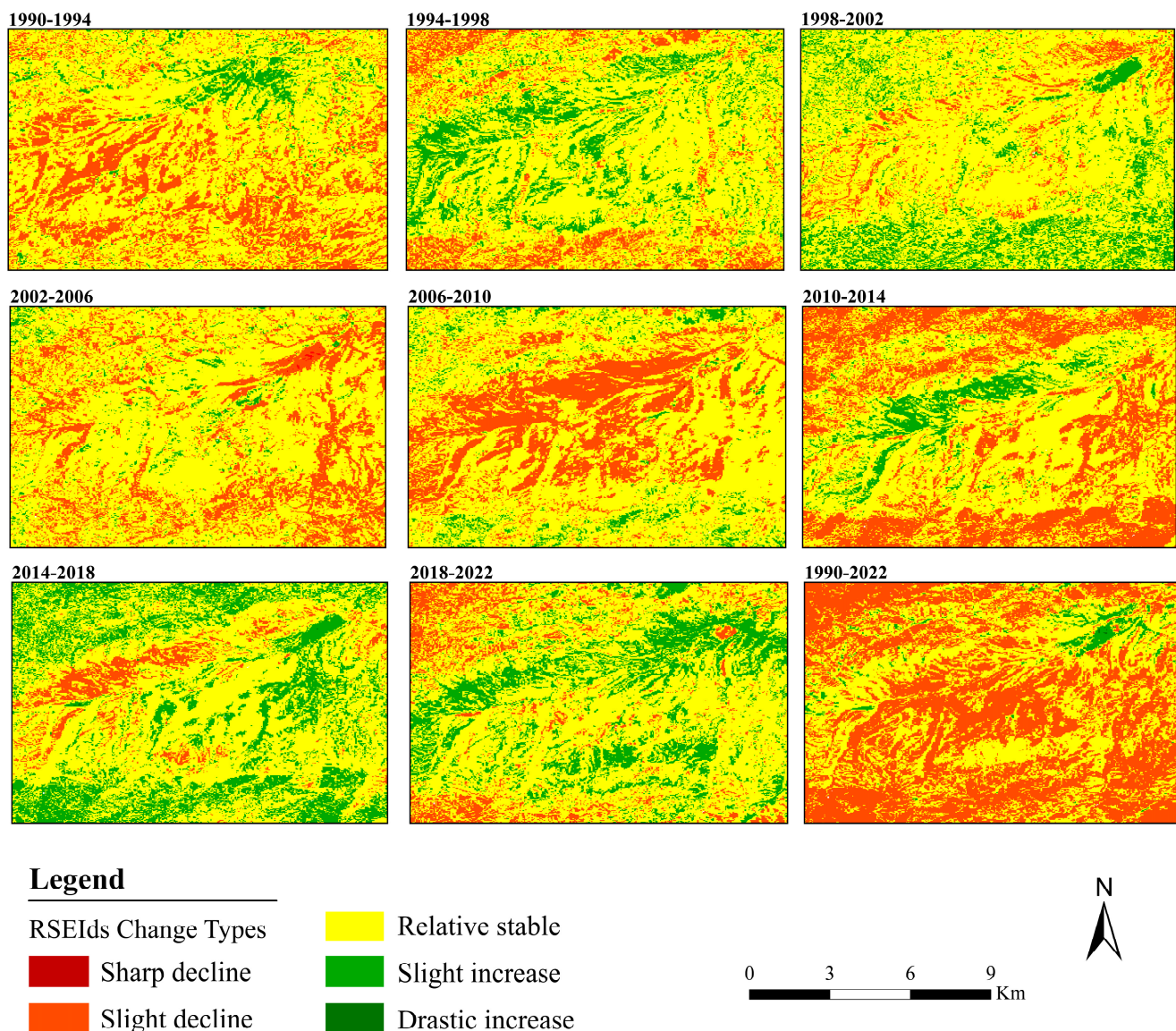


Figure 6. Spatiotemporal distribution of RSEIs change types in the Surablak fire area, 1990–2022.

Based on the distribution and the area statistics of RSEIs change types in the Surablak coal fire area, the eco-environmental quality exhibited periodic fluctuations (Table 3 and Figure 6). The study revealed that from 2006 to 2010, approximately 72.47% of the area maintained a relatively stable eco-environmental quality, while 24.18% showed a slight

degradation, mainly located in the core region of the Surablak coal fire area. From 2010 to 2014, the percentage of regions with relatively stable ecological conditions decreased to 65.18%, and the areas with a slight degradation increased to 29.54%, mainly in the southern and northern mountain belts of the coal fire area. During this period, a slight improvement in eco-environmental quality was found around Surablak coal fire area 1, accounting for 5.28%. Between 2014 and 2018, the proportion of relatively stable areas rose again to 73.16%, while the areas of slight degradation decreased to 8.97%, focused near the Surablak coal fire area 1. The areas experiencing slight improvement significantly increased to 17.87%, primarily distributed in the northern and southern mountain belts. Finally, during the observation period from 2018 to 2022 stable areas accounted for 71.07%; slightly improved areas increased to 21.71%, extending from the edge of the Surablak coal fire area to the northern pastures; and areas of slight degradation constituted 7.22%, primarily concentrated in the northern mountainous belt. More specifically, during the four periods, the study area exhibited intermittent periods of minor recovery in eco-environmental quality, despite an overall trend of gradual decline.

Table 3. Area statistics of RSEIds change type in Surablak coal fire area during 1990–2022.

Year	Index	RSEIds Change Type				
		Sharp Decline	Slight Decline	Relative Stability	Slight Increase	Drastic Increase
1990–1994	Area (km ²)	0	13.37	65.61	4.98	0
	Ratio (%)	0%	15.92%	78.15%	5.93%	0%
1994–1998	Area (km ²)	0	7.70	62.73	13.53	0
	Ratio (%)	0%	9.17%	74.71%	16.12%	0%
1998–2002	Area (km ²)	0	7.81	66.40	9.75	0.001
	Ratio (%)	0%	9.30%	79.10%	11.60%	0%
2002–2006	Area (km ²)	0.049	21.73	60.10	2.08	0
	Ratio (%)	0.05%	25.88%	71.59%	2.48%	0%
2006–2010	Area (km ²)	0.002	20.30	60.85	2.81	0
	Ratio (%)	0%	24.18%	72.47%	3.35%	0%
2010–2014	Area (km ²)	0	24.80	54.73	4.43	0.004
	Ratio (%)	0%	29.54%	65.18%	5.28%	0%
2014–2018	Area (km ²)	0	7.53	61.42	15.00	0.012
	Ratio (%)	0%	8.97%	73.16%	17.87%	0%
2018–2022	Area (km ²)	0.003	6.05	59.67	18.23	0.003
	Ratio (%)	0%	7.22%	71.07%	21.71%	0%
1990–2022	Area (km ²)	0.013	44.83	36.89	2.21	0.021
	Ratio (%)	0.015%	53.39%	43.94%	2.63%	0.025%

Due to significant variations in the eco-environmental quality within the Surablak coal fire area after 2006, it is necessary to compare the spatial distributions of RSEIds changes across five levels during the periods 1990–2006, 2006–2022, and 1990–2022 (Figure 7). The results of the eco-environmental grade change matrix calculations are presented in Table 4.

The areas of five RSEIds change categories (sharp decline, slight decline, relative stability, slight increase, and drastic increase) demonstrated notable differences over three periods (1990–2006, 2006–2022, 1990–2022; Figure 7 and Table 4). Specifically, during 1990–2006 and 2006–2022, the areas of the types of relative stability and slight decline were the highest (relative stability: 53.07 km² during 1990–2006 and 61.09 km² during 2006–2022; slight decline: 29.74 km² during 1990–2006 and 19 km² during 2006–2022), followed by the type of slight increase (1.16 km² during 1990–2006; 3.87 km² during 2006–2022), and the types of drastic increase and sharp decline were the smallest, nearly negligible; however,

during the period from 1990 to 2022, the areas with the slight decline (44.83 km²) were the highest, followed by relative stability (36.89 km²) and slight increase (2.63 km²), and the drastic increase and sharp decline areas were the smallest and nearly negligible. Although the change intensity in the five levels of RSEIDs from 1990 to 2022 were not dramatic, the change areas were very extensive, accounting for approximately 70% of the study area (Table 4). More specifically, the regions categorized as the slight decline type primarily derived from RSEIDs change level −1 (35.33% during 1990–2006; 22.62% during 2006–2022; 51.88% during 1990–2022; Table 4).

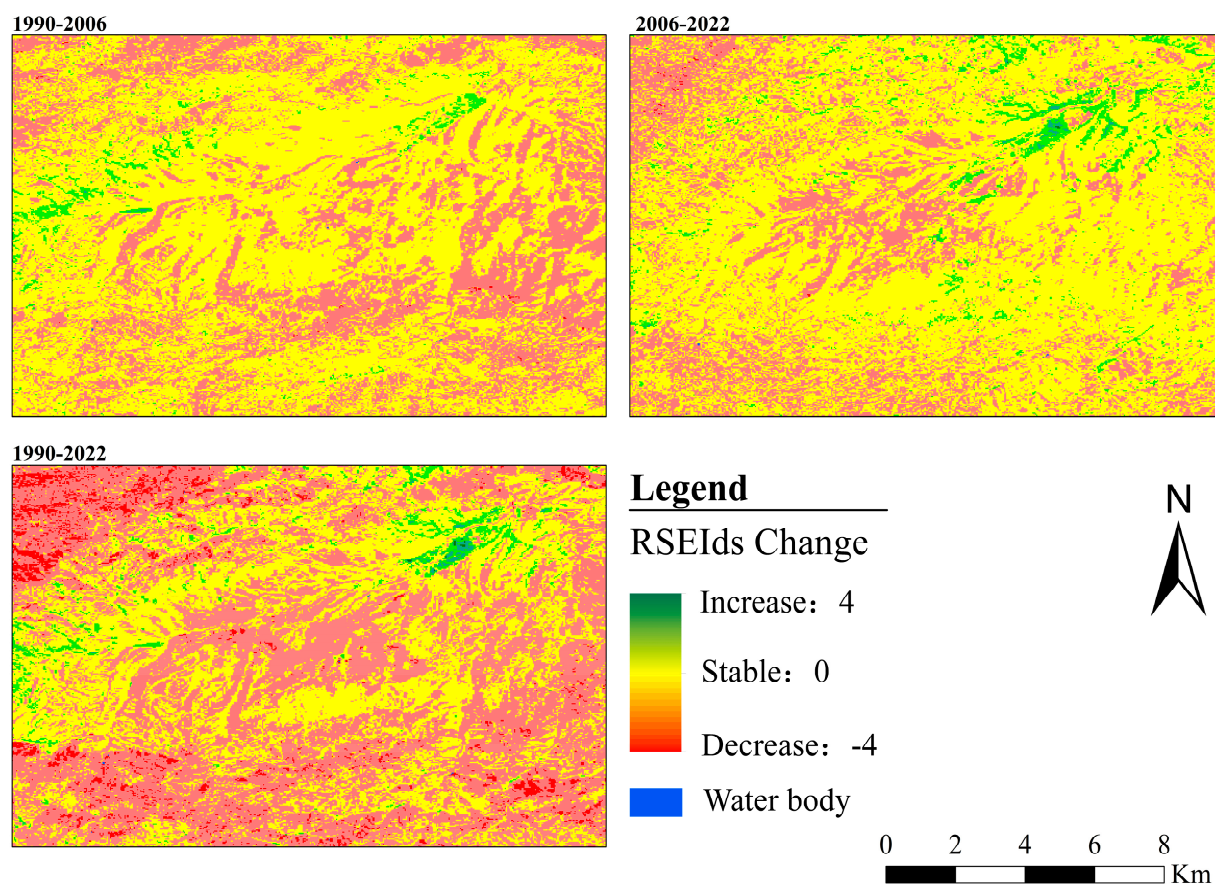


Figure 7. Distribution of RSEIDs level changes in Surablak fire area, 1990–2006, 2006–2022, and 1990–2022.

Table 4. Area statistics of changes in the RSEIDs levels in the Surablak coal fire area during 1990–2022.

RSEIDs Change Type	RSEIDs Change Grade	1990–2006			2006–2022			1990–2022		
		Area (km ²)	Total Area (km ²)	Ratio (%)	Area (km ²)	Total Area (km ²)	Ratio (%)	Area (km ²)	Total Area (km ²)	Ratio (%)
Drastic increase	4	0	0	0	0	0.005	0	0	0.021	0.025
	3	0			0.005			0.021		
Slight increase	2	0.03	1.16	1.38	0.19	3.87	4.61	0.27	2.21	2.63
	1	1.13			3.68			1.94		
Relative stability	0	53.07	53.07	63.20	61.09	61.09	72.75	36.89	36.89	43.94
Slight decline	−1	29.67	29.74	35.42	18.99	19.00	22.63	43.56	44.83	53.39
	−2	0.07			0.015			1.27		
Sharp decline	−3	0	0	0	0.005	0.005	0	0.013	0.013	0.015
	−4	0			0			0		

To deeply detect the changes in the RSEIDs within the Surablak coal fire area, a chord diagram was used to show the mutual transformation of areas across various RSEIDs levels (Figure 8). The findings revealed that the transitions predominantly occurred between adjacent RSEIDs levels, with relatively smaller areas transforming across multiple levels. This suggests that the degradation and improvement of the eco-environmental quality are gradual processes, with a low probability of abrupt changes. During the 1990–2022 period, the changes in the RSEIDs primarily shifted to a lower quality level. For instance, an area of 21.2 km² shifted from moderate to fair, whereas merely 1.2 km² shifted from fair to moderate; most notably, an area of 13.27 km² shifted from fair to poor. This also provides robust evidence of the persistent deterioration in the eco-environmental quality within the Surablak coal fire area.

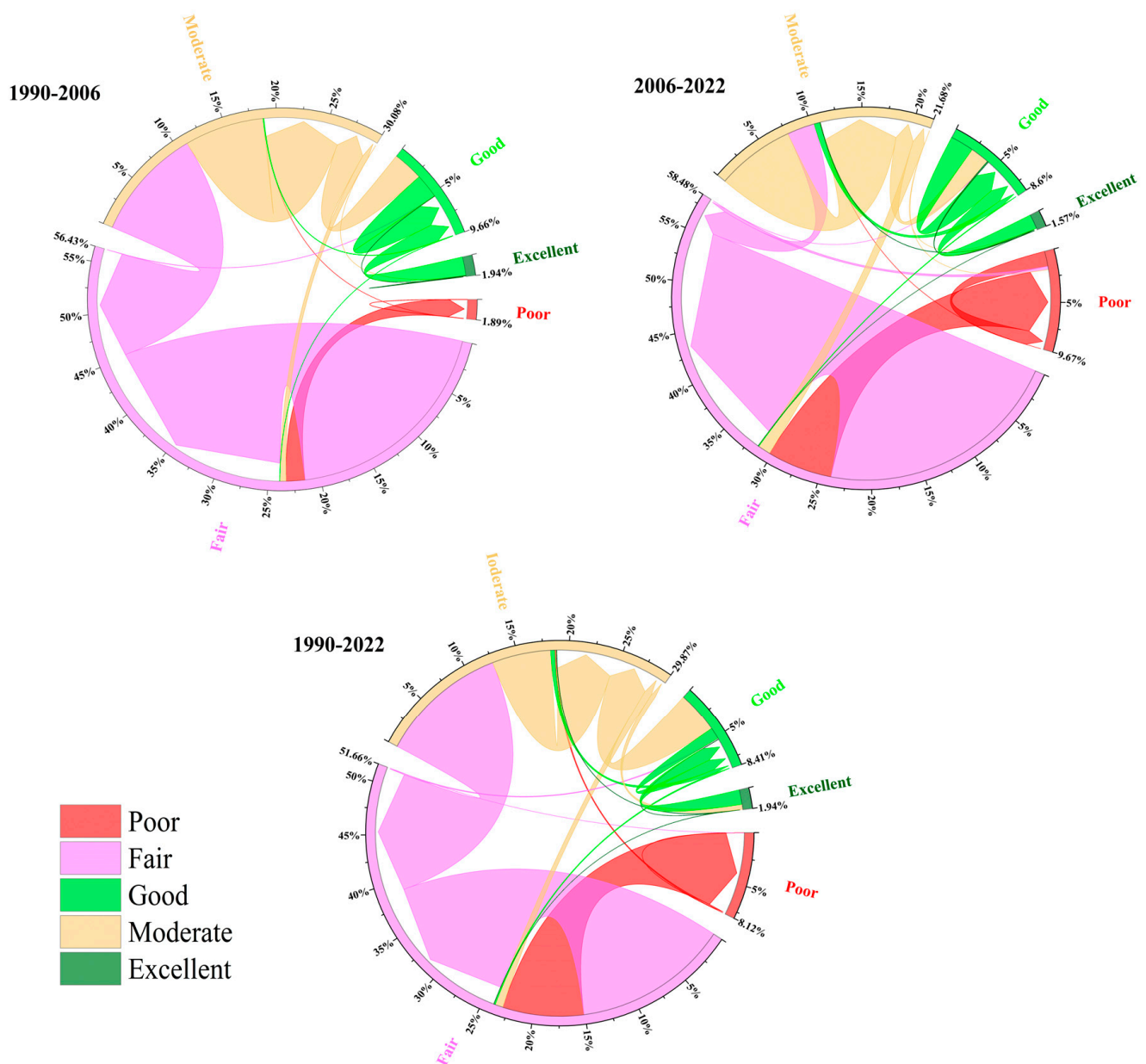


Figure 8. Chord diagram of “From-to” changes in RSEIDs levels, 1990–2022.

3.4. Influencing Factors

Each factor’s force on the eco-environmental quality changes between 1990 and 2022 was calculated through the GeoDetector (Table 5). Among these factors, the annual mean

temperature (X1) and annual mean precipitation (X2) demonstrated the highest explanatory power throughout the study period, with the average q values exceeding 0.2, followed closely by the distance to the coal fire area (X7; mean $q = 0.18$).

The contributions of these influencing factors to the eco-environmental quality varied in different periods (Table 5). From 1990 to 2006, the annual mean temperature (X1; mean $q = 0.21$) and annual mean precipitation (X2; mean $q = 0.23$) showed significantly higher mean q values compared to other factors, primarily explaining the significant impact of climate factors on the dynamic changes in eco-environmental quality during this period. However, from 2006 to 2022, the distance to the coal fire area (X7; mean $q = 0.30$) recorded the highest mean q value, followed closely by the annual mean temperature (X1; mean $q = 0.23$) and annual mean precipitation (X2; mean $q = 0.24$), indicating that the distance to the coal fire area became a major influencing factor on the eco-environmental quality changes during this period. Although the eco-environmental quality of the study area from 1990 to 2022 was dominated by climate factors, the impact of the Surablak coal fire area on the surrounding environment became increasingly significant, especially after 2006.

Table 5. q -Statistics of factors influencing eco-environmental quality.

Influencing Factor	Year								
	1990	1994	1998	2002	2006	2010	2014	2018	2022
X1	0.23	0.22	0.14	0.18	0.3	0.21	0.24	0.25	0.25
X2	0.2	0.31	0.17	0.2	0.3	0.25	0.18	0.28	0.26
X3	0.2	0.19	0.11	0.17	0.02	0.2	0.21	0.2	0.22
X4	0.02	0.19	0.01	0.16	0.25	0.23	0.01	0.02	0.22
X5	0.04	0.07	0.02	0.07	0.02	0.06	0.01	0.01	0.05
X6	0.09	0.35	0.03	0.05	0.03	0.05	0.02	0.01	0.04
X7	0.11	0.07	0.04	0.1	0.15	0.24	0.36	0.29	0.3

Note: denote the statistical results based on pixels that passed the significance test ($p < 0.001$).

The interactive relationships between each pair of influencing factors indicated that the synergistic effects of these paired factors on eco-environmental quality changes were larger than those of any single factor (Figure 9). The explanatory power of each factor was amplified when combined with other factors. Specifically, during the period from 1990 to 2006, the primary factors influencing the study area were precipitation, temperature, and elevation; from 2006 to 2022, the main influential factors were the distance to the coal fire area, precipitation, and temperature.

Throughout the study period, $X1 \cap X7$ (temperature and distance to the coal fire area; the symbol “ $\cap$ ” represents the interaction of two factors) and $X2 \cap X7$ (precipitation and distance to the coal fire area) demonstrated the highest explanatory power concerning eco-environmental quality, with mean q values of 0.4121 and 0.4105, respectively, contributing to 41.21% and 41.05% of the effect on eco-environmental quality. Moreover, $X3 \cap X7$ (elevation and distance to the coal fire area) also had obvious explanatory significance, with a q value of 0.3504, while the explanatory power of $X5 \cap X6$ (slope aspect and population density) was the least significant.

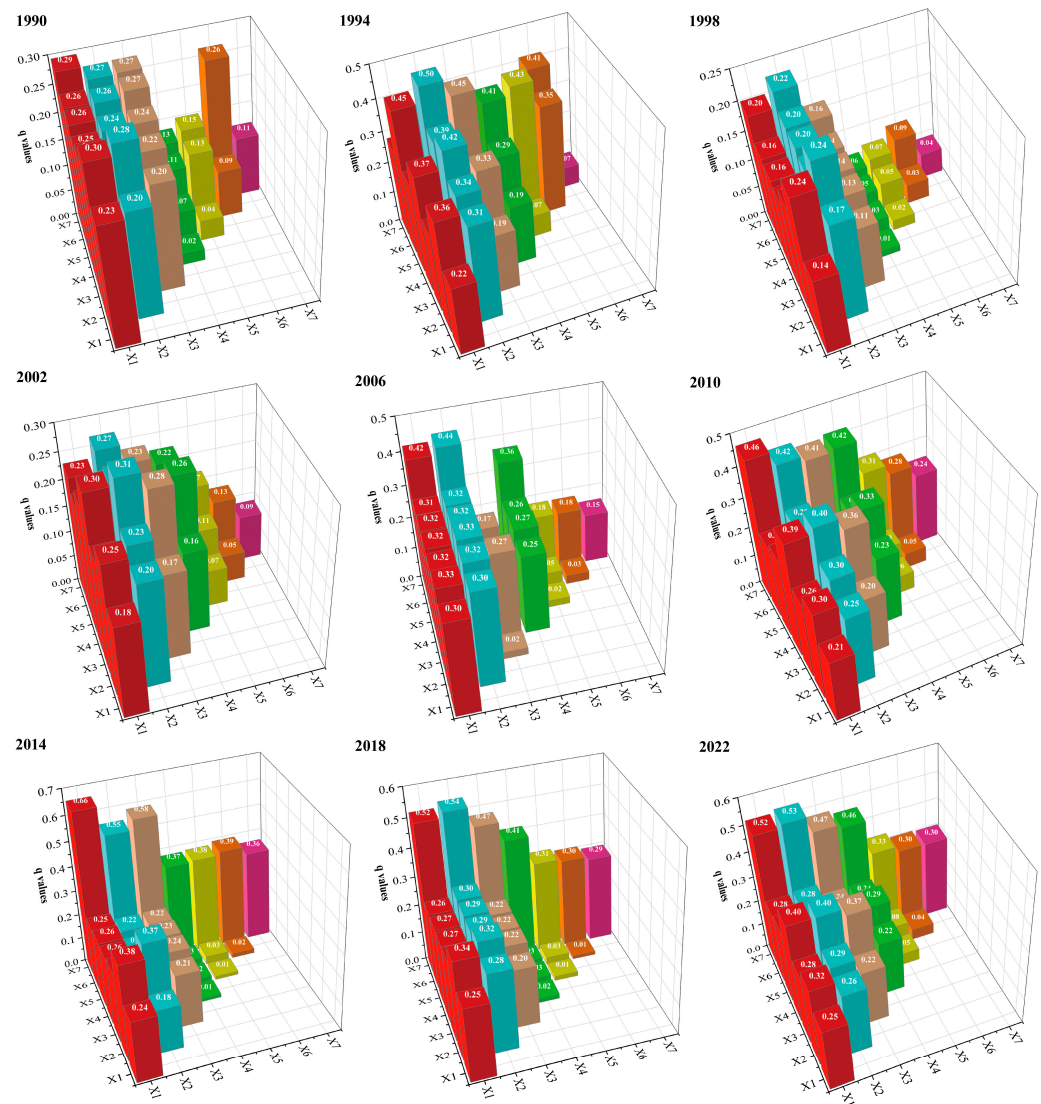


Figure 9. Interactive effects of paired factors on eco-environmental quality within the Surablak coal fire area, 1990–2022.

4. Discussion

4.1. Effectiveness of RSEIDs

By summarizing previous studies, the RSEI values exhibit a discernible regularity: from excellent to poor eco-environment quality, the RSEI values progressively decline [14,29,46,47], e.g., greater than 0.8 in good farmland [29], greater than 0.63 in forest or densely vegetated regions [48], 0.49–0.69 in large river floodplains or basins [49], 0.41–0.50 in oasis region [50], 0.29–0.54 in opencast mine areas [17,51], and even as low as 0.24 in desert regions [52]. In this study, the Surablak coal fire area displayed varying RSEIDs values across different subregions: the core fire area, the fire edge zone, and the adjacent mountain belts (Figure 4). As the primary focus of analysis, the RSEIDs values in the core zone fluctuated around 0.2 due to mining activities and spontaneous coal combustion. The edge zone, being proximate to the fire area and thus highly susceptible to its impacts, showed RSEIDs values around 0.4. However, the mountainous belts, benefiting from partial forest cover, exhibited the highest RSEIDs values, peaking at 0.92. These results were similar to the regularity of previous studies, suggesting that RSEIDs can effectively identify the eco-environmental quality, particularly in coal fire areas with complex environmental issues.

By using areas with ecological improvement as examples, we validated the RSEIds index model. The results indicated that regions exhibiting slight improvement in eco-environmental quality were mainly located near the northern pasture adjacent to the Surablak coal fire area. These areas, benefiting from their proximity to water bodies and the implementation of artificial ecological protection measures, exhibited good and excellent RSEIds values (Figure 10). Conversely, other parts of the study area primarily demonstrated a trend of slight ecological degradation, mainly caused by the negative effects of natural factors and anthropogenic activities. These findings affirm the precision of the RSEIds index in evaluating the regional eco-environmental quality [29].

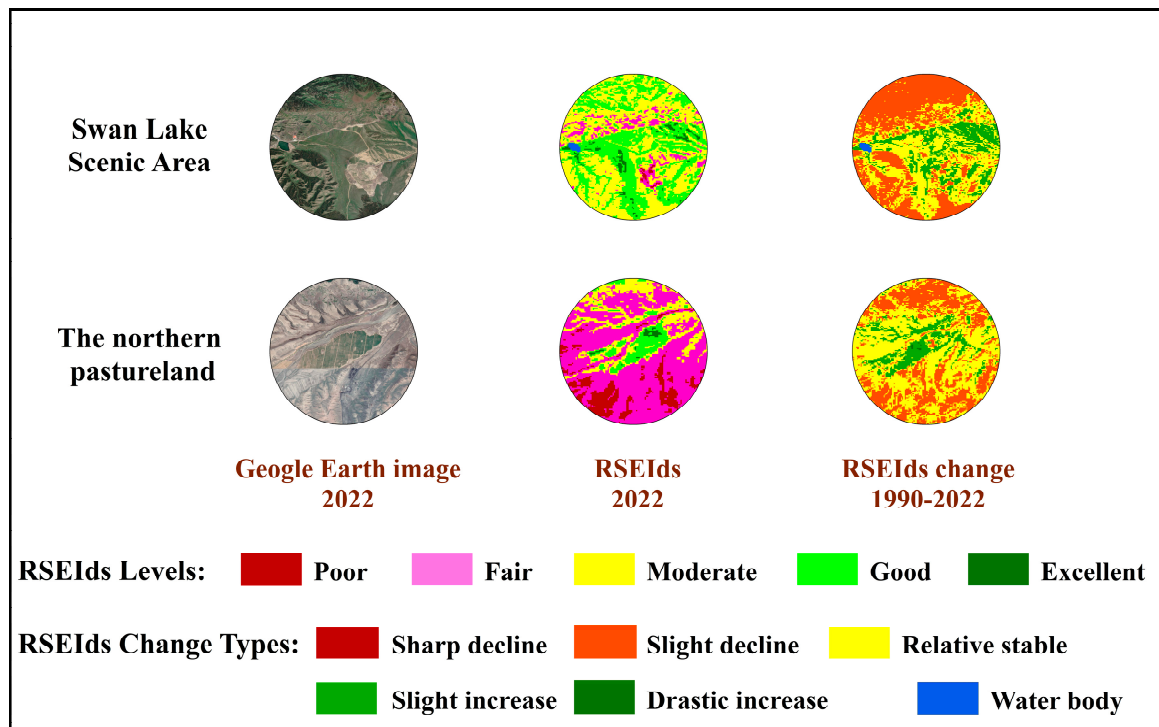


Figure 10. Examination of the accuracy of the RSEIds index based on the 2022 RSEIds, the 1990–2022 RSEIds change types, and Google Earth images.

4.2. Analysis of Eco-Environment

Between 1990 and 2022, the eco-environment of the Surablak coal fire area underwent significant changes. This change is primarily reflected in the mean RSEIds values, which gradually declined from 0.45 in 1990 to 0.33 in 2022. Notably, after 2006, the eco-environmental quality deteriorated more rapidly, reaching its lowest point in 2014. By reviewing the relevant literature [53,54], this ecological degradation may be mainly attributed to the ecological damage caused by the spontaneous combustion of exposed shallow coal seams or residual coal in the mined-out areas during this period. The eco-environmental quality within the study area fluctuated across different years, exhibiting slight periodic recovery. However, the overall trend shows a gradual decline, with most changes occurring at adjacent eco-environmental levels (Figure 8).

There are spatial variations in the eco-environmental quality between the core fire area and the adjacent mountain belts in Surablak (Figure 5). Areas with higher RSEIds values are primarily concentrated in the forest-covered mountainous belts, while regions with lower RSEIds values are mainly found in the mountain valleys, which coincide with the coal fire areas and mining zones. Possible reasons include environmental disturbances resulting from historical mining operations, spontaneous coal combustion triggered by changes in underground conditions and coal storage [55,56]. Moreover, the variations in RSEIds not

only map out the regions subjected to ecological degradation but also identify potential zones for ecological recovery. Specifically, areas such as the northern pastureland, while showing only slight improvements in ecological quality, demonstrate a discernible potential for ecological improvement. This trend is likely associated with the implementation of grassland protection law and measures [57]. These findings provide critical insights for formulating precise and effective ecological protection strategies.

4.3. Analysis of RSEIds-Influencing Factors

The factors influencing eco-environmental quality exhibit significant spatial and temporal variability, attributed to the complex interaction of the region-specific factors, with the most direct influences being anthropogenic activities and alterations in natural conditions [29]. According to Fang et al. [58], this variability is attributed to the complex interaction of region-specific factors, with the most direct influences being human activities and alterations in natural conditions. In this study, precipitation and temperature exerted the strongest explanatory power on ecological quality between 1990 and 2006, which can be attributed to the study area's location in a continental arid climate zone. Natural factors such as precipitation and temperature dominate in stabilizing the ecosystems of arid regions [59,60]. However, since 2006, the distance to the coal fire has emerged as the most important factor influencing the eco-environmental quality within the Surablak area. This transformation may result from the extensive spontaneous combustion of coal seams within the study area, which gradually spreads to adjacent regions, thereby impairing the local ecological environment.

Eco-environmental quality is also affected by topography, which can alter the conditions of direct influencing factors. Hawthorne and Miniati [61] found that topography can mitigate the effects of drought on vegetation through differential soil-moisture redistribution along a hillslope gradient in the southern Appalachian mountains. This study revealed that elevation and slope are important factors influencing eco-environmental quality, which may be attributed to the fact that the Surablak area is a mid to low mountain and hilly region with a topographical gradient inclining downward from south to north and from west to east. Consequently, influenced by elevation and slope, significant vertical variation exists in soil moisture and vegetation distribution. Different terrain features exert long-term impacts on the structure, distribution, growth, and succession of plant communities, ultimately impacting the eco-environmental quality [62].

5. Conclusions

To conduct an effective evaluation of the eco-environmental quality within the Surablak coal fire area, this study constructed the RSEIds model, which considers the regional characteristics specific to the eco-environmental context of coal fire areas. The eco-environmental quality and the spatiotemporal variations in the Surablak coal fire area from 1990 to 2022 were examined, and the GeoDetector model was applied to quantify the explanatory power of the influencing factors on the RSEIds. The results show that the RSEIds model accurately reflects the complex environmental conditions in coal fire areas, demonstrating high accuracy in identifying regions of both ecological degradation and improvement.

The Surablak coal fire region's overall ecological environment exhibited a continuous deterioration from 1990 to 2022, with the area of ecological degradation constituting 53.41% of the study region. The eco-environmental quality index decreased from 0.45 in 1990 to 0.33 in 2022, with a notable decline starting after 2006, reaching its lowest point at 0.28 in 2014. The areas with excellent and good RSEIds values are primarily found in the forested mountainous zones located north of the coal fire area, whereas areas with poor

and fair RSEIs values largely coincide with the coal fire areas. Furthermore, signs of ecological recovery have been identified in the northern pastures, adjacent to the edge of the Surablak fire zone. Precipitation (mean $q = 0.24$, 1990–2022) and temperature (mean $q = 0.22$, 1990–2022) are the important factors influencing the eco-environmental quality of the Surablak coal fire area. However, since 2006, the distance to the coal fire area (mean $q = 0.30$, 2006–2022) has emerged as the key factor, indicating that changes in the distance from the coal fire area could better explain the dynamic changes in the eco-environmental quality observed within the Surablak coal fire area.

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