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Assessment of Environmental Impacts of Mining Using Remote Sensing (Case Study: Eastern Alborz Coal Mines, Iran)

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Abstract

This study aims to assess the environmental impacts of coal mining in the Eastern Alborz region, focusing on coal mines from 2013 to 2021, using remote sensing techniques. Landsat 8 satellite images were digitized based on key environmental indices, including NDVI, NDWI, NDSI, and NDBI, and subsequent statistical analyses and evaluations were conducted for the study areas. To distinguish the effects of mining from those of climate change, the results were compared with a reference area located within a natural resource block (baseline area), and the outcomes were thoroughly analyzed. The findings indicate that the combined impacts of mining and climate change have caused significant environmental degradation in the region. In particular, vegetation cover has experienced a sharp decline in recent years, while soil erosion has increased at a slower rate. Projections of mining impacts on vegetation and soil were made by calculating the average NDVI and NDSI indices for 2030 and 2050 in the studied areas. These projections suggest that NDVI is expected to decrease by 0.25 by 2030 and by 0.72 by 2050, indicating further vegetation loss in the coming decades. In contrast, analysis of the NDWI index reveals no clear trend in soil moisture changes over the study period. Given the climatic conditions of the selected areas, it is essential to monitor, manage, and mitigate environmental risk factors to prevent the expansion of drought into northern forests, highlighting the need for appropriate intervention measures.

1. Introduction

The use of remote sensing tools in assessing the environmental impacts of mining can provide valuable information about the environment. Through remote sensing imagery, various forms of pollution, such as water and soil contamination, can be identified and their extent determined. Additionally, environmental changes caused by mining, such as alterations in vegetation cover, water levels, and air quality, can be analyzed and assessed. Remote sensing data can also be used to identify biodiversity hotspots, facilitating the planning and implementation of conservation strategies. Furthermore, environmental assessments of mining operations can be conducted to evaluate their impacts on the surrounding environment [1–5]. Remote sensing is commonly used to monitor environmental pollution caused by mining activities. To assess the environmental risks of mining, the following indices can be employed:

Pollution Indices: These indices are used to measure and evaluate various types of environmental pollution caused by mining activities. Examples include pollutant concentrations in water and soil, levels of airborne particulate matter, and more [6].

Environmental Change Indices: These indices help monitor changes in vegetation cover, water levels, air quality, and other environmental factors. They allow for the observation and evaluation of environmental changes induced by mining activities [6,7]. The environmental change indices for mining areas can be used to assess the environmental impacts caused by mining activities. Some of these indices include [8]:

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Vegetation Cover Changes: This index is used to monitor changes in the type and density of vegetation in mining areas. Remote sensing imagery and data can track vegetation cover changes over time and evaluate the impacts of mining activities on it [9]. To assess changes in the type and density of vegetation in mining areas, the Normalized Difference Vegetation Index (NDVI) is commonly used. By analyzing satellite images and remote sensing data, changes in NDVI over time can be observed, and the impact of mining activities on vegetation can be evaluated [10]. Statistical analyses, such as the Mann-Kendall test, can also be used to assess changes in vegetation cover in mining areas, helping to evaluate the environmental impacts of mining activities [7].

Water Level Changes: This index assesses changes in surface and groundwater levels in mining areas. Remote sensing data and hydrological systems can monitor water level changes over time and evaluate the impacts of mining activities on water resources [10,11]. To analyze water level changes in mining areas, the Normalized Difference Water Index (NDWI) can be utilized [12]. This index, derived from satellite imagery and remote sensing data, provides insights into water behavior in the region and tracks water level changes over time. The analysis of this index enables the evaluation of groundwater and surface water level changes in mining areas and their connection to mining activities [13]. NDWI is based on the differences in the reflectance of red and near-infrared light by water in the electromagnetic spectrum. When water levels are high, near-infrared (NIR) reflectance increases, resulting in a larger NDWI value. Conversely, when water levels decrease, NIR reflectance declines, leading to a smaller NDWI value [14]. Analyzing changes in NDWI over time allows for the observation of water level fluctuations in mining areas and the evaluation of the impact of mining activities on water resources [15]. Utilizing this index in the analysis of water level changes in mining areas helps in assessing the environmental changes caused by mining and the necessary steps for optimal environmental management and protection [16].

Air Quality Changes [17–20]: This index evaluates changes in air quality in mining areas. Remote sensing data and air quality monitoring systems can track changes in pollutant concentrations and particulate matter, allowing for the assessment of the impact of mining activities on air quality [21,22]. Remote sensing data and air pollutant measurements can also be used to analyze air pollution indices, such as the concentrations of airborne gases and particulate matter, and assess changes in air quality in mining areas. Changes in the concentration and distribution of airborne pollutants, including dust, toxic gases, and chemical contaminants, can also be monitored. The analysis of climatic and air quality changes in mining areas, including variations in water and soil parameters (e.g., heavy metal concentrations, nitrates, phosphates, pH levels, and dissolved oxygen content), is a practical application of satellite imagery. The Normalized Difference Soil Index (NDSI) is used to examine soil quality changes using remote sensing data. This index analyzes changes in soil moisture content and various elements, enabling the assessment of the impact of mining activities on soil quality [23]. It is important to note that each index and method for evaluating changes in water and soil quality in mining areas requires comprehensive analysis of remote sensing data and ground sampling [24].

Noise and Vibration Changes: This index monitors changes in noise levels and vibrations caused by mining activities. Acoustic and vibration monitoring systems can track changes in noise and vibration levels and assess their impacts [25,26].

Musetsho et al. used remote sensing and Geographic Information System (GIS) techniques to study land use changes in a biodiversity-rich area in northern Limpopo Province, South Africa, from 1990 to 2018, using data from the South African National Land Cover project. In 1990, the dominant land cover consisted of grasslands and dense shrublands, accounting for 40% and 24% of the total area, respectively. Forested areas and built-up areas comprised 18% and 4% of the total land cover, respectively. At this time, barren areas and forest lands were among the least prevalent land cover classes. By 2018, forests became the dominant land cover, accounting for 71% of the total area, with built-up areas making up 20% [27]. Satellite remote sensing data have been widely used for mapping, detecting, and monitoring land use/land cover changes at global, regional, and local scales [1]. Landsat is one of the most commonly used satellite datasets for monitoring land use over the past three decades due to its availability, coverage, and spatial and temporal resolution. Traditional data collection methods can be challenging and time-consuming; however, various environmental components and human activities can be easily monitored and assessed using remote sensing data. For instance, processing Landsat ETM+ images can provide soil salinity maps, and the Normalized Difference Vegetation

Index (NDVI) can be used to monitor vegetation cover [28]. Recent advances in remote sensing and GIS techniques have significantly improved mineral exploration, structural and lithological mapping, and environmental monitoring. Several studies have demonstrated the integration of geological, geochemical, geophysical, and multispectral data for porphyry copper deposit exploration [29–31]. Remote sensing and GIS have also been widely applied in landslide susceptibility assessment, infrastructure projects, geological hazard and coal mine monitoring [1,32–35]. In addition, modern approaches such as neural network–based classification of ASTER data have been successfully employed to map hydrothermal alterations and mineralization zones [36], while sub-pixel and hyperspectral methods provide high-resolution detection of alteration patterns [37]. Furthermore, remote sensing techniques have been used in structural and facies mapping in diverse geological settings [38–40] and for monitoring land subsidence [41]. These studies highlight the growing importance of integrating geospatial technologies with geological and geochemical data to enhance the efficiency and accuracy of exploration and environmental assessments. Research focusing on coal mining subsidence areas in China employed remote sensing and geographic information systems (GIS) to analyze surface environmental changes over decades. The study utilized multi-source remote sensing data to classify images and assess the spatial and temporal evolution of environmental elements, demonstrating the advantages of these technologies over traditional field methods due to their efficiency and cost-effectiveness [4].

Madasa et al. evaluated the adverse environmental impacts of mining activities in a region of South Africa. Remote sensing was used to quantify land use/cover changes in Welkom, Virginia (Goldfields), by analyzing Landsat images over five-year intervals from 1988 to 2018 using spatial indices. Global Environmental Monitoring Index (GEMI), Normalized Difference Built-up Index (NDBI), NDVI, Normalized Difference Soil Index (NDSI), and Normalized Difference Water Index (NDWI) were employed to detect different land cover types. Supervised classification using the Maximum Likelihood method was used to classify the images into appropriate classes. The findings revealed that land use changes were associated with fluctuations in the values of each index, with overall classification accuracy ranging from 88% to 96%. Mining activities caused the degradation of arable land and natural vegetation, significantly impacting the environment. Therefore, monitoring land use/cover changes in mining areas and their effects on ecology, the environment, and socio-economic conditions is critical for sustainable development [42]. Previous studies have also highlighted the importance of assessing the environmental impacts of coal mining and processing plants using systematic methods. For instance, Ghader Rahmati and Dolati-Ardejani (2012) emphasized that the evaluation of mining-related environmental effects, similar to other industrial projects, is essential for effective environmental management. They employed the modified Folchi matrix method, which allows for a rapid and comprehensive estimation of environmental impacts by considering a wide range of influencing factors such as climate, topography, geological formations, coal washing methods, and preventive measures against spontaneous combustion in coal tailings dumps. Their findings, based on the Eastern Alborz coal washing plant, demonstrated how quantitative environmental impact assessment can provide valuable insights into the interactions between mining operations and environmental components, thereby supporting better decision making for sustainable mining practices [43]. Similarly, Ataei et al. investigated the environmental and human impacts of coal mines operated by the Eastern Alborz Company and proposed a new quantitative model for environmental impact assessment (EIA) using the matrix method. Their results highlighted that the most significant adverse effects were associated with air quality, human health and safety, ecological balance, and soil quality. Based on these findings, they emphasized the need to prioritize these components when allocating resources and implementing mitigation measures, particularly under time and financial constraints. Moreover, they employed the Phillips mathematical model to evaluate the sustainability of mining projects, which revealed a weak sustainability status for the Eastern Alborz coal mines. This study underscores the importance of adopting systematic and prioritized approaches for environmental management in coal mining regions [44].

Among underground projects, the environmental effects of coal mines, both in terms of extraction difficulties and mining consequences, are more significant than those of other mines. The environmental pollution caused by coal mines has made them a serious threat to the environment. Therefore, in coal mining, all the socio-economic benefits and adverse effects, as well as environmental impacts, must be identified and

considered. Evaluating all these effects can be highly effective in preventing the destruction of the region's ecosystem and mitigating the negative impacts on it [45]. This study aims to evaluate the environmental impacts of coal mining in the Eastern Alborz region (2013–2021) using remote sensing indices (NDVI, NDWI, NDSI, NDBI) to differentiate between mining-induced effects and climatic variability. By integrating comparative analysis with a reference area and projecting future scenarios for 2030 and 2050, the research provides insights into long-term risks of vegetation loss, soil erosion, and land degradation. The findings are intended to support sustainable land-use planning and inform adaptive environmental management strategies.

2. Environmental indices in remote sensing

The analysis of vegetation cover using remote sensing involves various indices such as the Normalized Difference Vegetation Index (NDVI), the Multispectral Vegetation Index, and the Normalized Difference Soil Index (NDSI). These indices are used to assess the health and density of vegetation in different areas. Remote sensing technology is highly beneficial for systematic and long-term monitoring of vegetation cover and can be used to compare ground-based and satellite-based vegetation estimation methods. The application of remote sensing in environmental studies of mining operations can help in identifying and assessing the impacts of mining on the environment. Monitoring vegetation changes, identifying groundwater alterations, analyzing air quality changes, and tracking geological shifts are some of the key applications of remote sensing in mining related environmental studies [3,4,42,45]. Given the accuracy and capabilities of remote sensing in environmental studies of mining, the use of these techniques can assist researchers and mining managers in assessing the environmental impacts of mining activities and implementing appropriate measures to protect the environment and natural resources. Furthermore, through the comparison of remote sensing data over time, environmental changes can be tracked, and the effectiveness of conservation efforts can be evaluated.

2.1. NDVI Index

NDVI, which stands for "Normalized Difference Vegetation Index", is a remote sensing index commonly used to assess the health and vigor of vegetation. NDVI is derived from satellite or aerial imagery and is calculated using the reflectance values of near-infrared (NIR) and red light. The formula for calculating NDVI is as follows:

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

In this formula, NIR represents the reflectance in the near-infrared spectrum, and Red represents the reflectance in the red spectrum. Both values are typically obtained from remote sensing data, such as satellite images. NDVI values range from -1 to +1, with positive values indicating denser and healthier vegetation, while lower values suggest minimal vegetation or plants in critical conditions. NDVI has various applications, including monitoring plant health, estimating agricultural crop yield, assessing drought conditions, mapping land cover changes, and monitoring deforestation. It is a valuable tool for studying and managing agricultural, ecological, and environmental systems [42,45,46].

2.2. NDWI Index

The NDWI Index is another remote sensing index used to detect and analyze water and moisture areas on the Earth's surface. Introduced by McFeeters in 1996, it has been widely used in fields such as earth sciences, environmental studies, water resources, and irrigation monitoring [47,48]. NDWI, or the Normalized Difference Water Index, is a remote sensing index used to estimate water content on the Earth's surface. It is based on the difference in spectral reflectance between the red (R) and near-infrared (NIR) bands.

To compute NDWI values in a satellite or sensor image, the following steps can be followed:

1) Selecting appropriate bands: Depending on the sensor or system being used, the relevant bands for calculating NDWI should be selected. Typically, the red (R) band and the near-infrared (NIR) band are used.

2) Image preprocessing: Before calculating NDWI, image preprocessing may be necessary, including operations like noise reduction, geometric correction, and radiometric calibration.

3) Calculation of NDWI: The NDWI is calculated using the following formula:

$$NDWI = (NIR - Green) / (NIR + Green) \quad (2)$$

Where NIR represents the near-infrared band, and Green refers to the green band.

4) Interpreting NDWI values: NDWI values typically range from -1 to +1. Positive values

near +1 indicate the presence of water, while negative values close to -1 indicate the absence of water. Zero values suggest no distinction between water and dry land.

5) Image interpretation: By overlaying the NDWI image on a map or image, patterns and areas with higher water content can be identified. For example, water bodies such as rivers, lakes, and wetlands appear bright, while dry areas appear dark.

The use of the NDWI index in various fields such as water resources, the environment, and agriculture provides opportunities for better analysis, management, and monitoring of water areas. By combining the NDWI index with other indices and remote sensing data, more comprehensive analyses of water and moisture in the environment can be conducted [47,49–51].

2.3. NDSI Index

The Normalized Difference Soil Index (NDSI) is a remote sensing index used to evaluate and analyze soil information in satellite images. This index measures the difference in light reflection between two different bands of the electromagnetic spectrum, typically near-infrared (NIR) and shortwave infrared (SWIR). The NDSI is calculated using the following formula:

$$NDSI = (NIR - SWIR) / (NIR + SWIR) \quad (3)$$

In this formula, NIR represents the reflection of light in the near-infrared band, and SWIR represents the reflection of light in the shortwave infrared band. By using the light reflection values in these two spectral bands, the soil erosion index (NDSI) can be calculated. The values of this index range from -1 to +1, where values greater than zero indicate erosion, and values less than zero indicate no erosion. Additionally, positive values indicate soils with eroded surfaces, while negative values indicate soils that are wet and waterlogged. The NDSI index is particularly sensitive to changes in soil moisture content. Wet soils tend to reflect more light in the near-infrared band and less in the shortwave infrared band, resulting in higher NDSI values. Conversely, dry soils reflect less near infrared light and more shortwave infrared light, leading to lower NDSI values [52,53].

2.4. NDBI Index

The Normalized Difference Built-up Index (NDBI) is a remote sensing index specifically focused on built-up or urban areas. This index is used to assess the extent and density of built structures in a given region. The NDBI is calculated using the reflection values of near infrared (NIR) and shortwave infrared (SWIR) bands. The formula for calculating NDBI is as follows [54,55]:

$$NDBI= (SWIR+NIR)/(SWIR-NIR) \quad (4)$$

In this formula, SWIR represents the reflection in the shortwave infrared spectrum, and NIR represents the reflection in the near-infrared spectrum. NDBI values range from -1 to +1. Positive NDBI values indicate the presence of built-up areas, while negative values indicate non-built areas such as vegetation or water. A value of -1 indicates water or barren land with no reflectance, while a value of +1 indicates densely built urban areas. NDBI is commonly used in urban planning, land use mapping, and environmental studies to analyze the expansion of urban areas, monitor urban growth, assess the concentration of urban activities, and study the relationship between urban development and the surrounding environment.

NDBI is just one of several indices used to analyze urban areas and, for a comprehensive understanding of urban dynamics, it should be interpreted alongside other data and indices [56–59].

2. Eastern Alborz region (Coal Mine's Area)

In this study, satellite imagery processing was used to evaluate and monitor the environment in the Eastern Alborz region (coal mines), located in the northern part of Semnan province within the Eastern Alborz structural zone (Figure 1).

The region discussed in this study includes three mining areas. A reference area (RA) in the natural resource block and Coal Mine's Area (CMA) in the northwest of Semnan province were selected for validation purposes and were analyzed in detail.

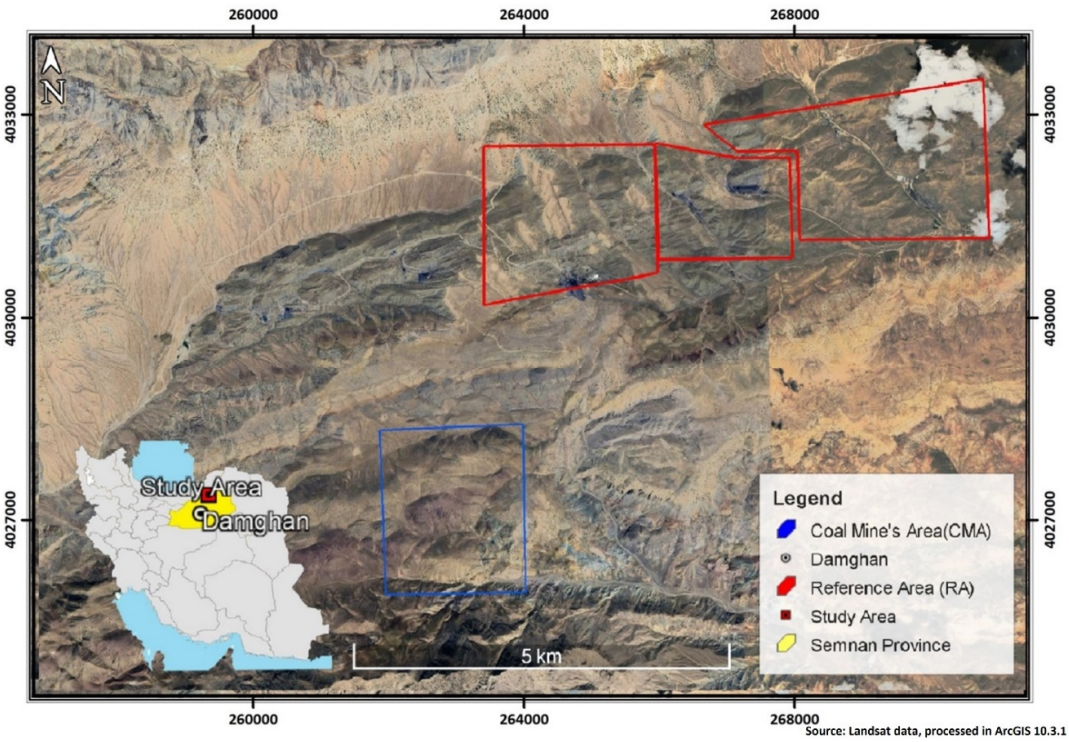

Figure 1. The location of the Coal Mine's Area and Reference Area

3. Methodology and Analyses

In this study, Landsat 8 satellite images were utilized to assess the environmental impacts in the Eastern Alborz region. Landsat imagery from the LANDSAT/LC08/T1_TOA sensor was acquired and processed over an eight-year period (2013–2021) at two-year intervals using the Google Earth Engine (GEE) platform. The 30 m spatial resolution of Landsat imagery provides detailed information over broad areas but limits the detection of fine-scale or short-term vegetation changes. Seasonal variations in vegetation cover often occur at sub-pixel scales or within small patches that cannot be reliably resolved at 30 m resolution. As a result, using annual or higher-frequency data could introduce noise or misinterpretation of subtle seasonal dynamics. Therefore, we selected a biennial temporal scale, which balances the spatial resolution of the imagery with the ability to capture long-term trends in vegetation change, while minimizing errors arising from sub-pixel variability and short-term seasonal fluctuations. Raw remote sensing data were analyzed through coding, and atmospheric effects were corrected using the LEDAPS (Landsat Ecosystem Disturbance Adaptive Processing System) algorithm to enhance surface reflectance reliability. Geometric corrections (orthorectification) and radiometric calibration were automatically applied based on sensor metadata. To reduce noise, cloud-free images from the early growing season (March–June) were selected, and QA band masking was applied to remove residual clouds, snow, and shadows. These preprocessing steps ensured consistent and high-quality datasets for environmental change assessment.

Key environmental indices, including NDVI, NDWI, NDSI, and NDBI, were then employed to quantify and interpret spatio-temporal patterns of vegetation decline, soil erosion, moisture fluctuations, and anthropogenic land-use changes in coal mining areas using ArcGIS 10.3.1. To ensure analytical robustness, a baseline reference area was selected, enabling differentiation between climatic influences and mining activities. Beyond retrospective analysis, the study projected future trajectories of vegetation cover and soil erosion under continued mining scenarios for 2030 and 2050, providing insights into long-term ecological risks. Additionally, the study incorporated climatic factors, such as precipitation, temperature, and wind speed, highlighting the complex interactions between natural processes and human-induced disturbances in shaping regional environmental dynamics. Figure 2 summarizes the research methodology.

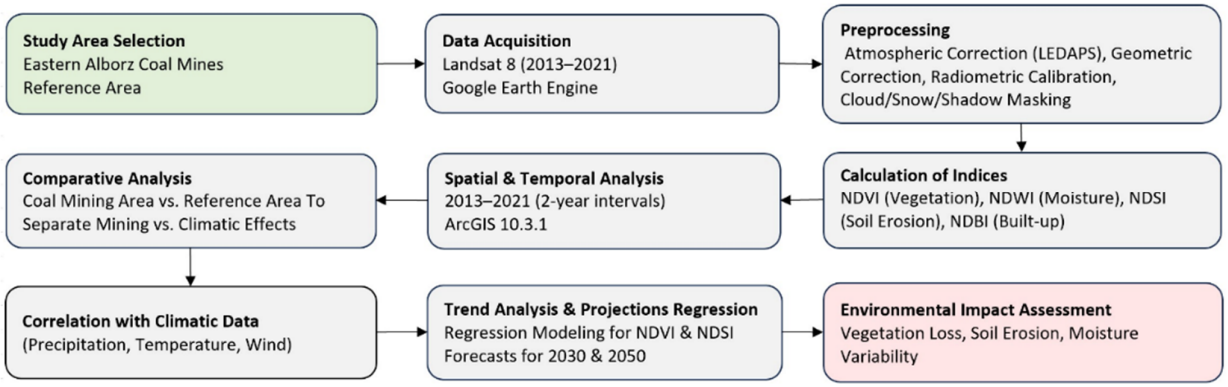

Figure 2. Methodology flowchart for the study

3.1. NDVI Index

Vegetation changes, measured using the NDVI index, over the years 2013 to 2021 at two-year intervals, are presented in Figure 3. As observed, vegetation cover has gradually decreased over time. Coal mining areas in the southwestern part of Eastern Alborz are shown in red borders. Additionally, in the center of the image, linear green regions represent vegetation in the lowland areas (Figure 4). Since, in addition to visual analysis, quantitative analysis is also required, an attempt was made to conduct a more comprehensive analysis using both positive and negative values of the index and their frequency distribution. Figure 5 displays the frequency distribution chart, mean, standard deviation, and the extent of changes in the positive values (indicating high vegetation density) and negative values (indicating low vegetation density) of the NDVI index. As shown in this Figure, over time, the NDVI values have shifted towards negative values, indicating a decrease in vegetation cover and an increase in barren lands. Meanwhile, in 2013 and 2015, the intensity of these changes was lower, but from 2017 to 2021, these changes became more noticeable, which could also be indicative of climatic changes in the region. Furthermore, the topographical conditions of this area differ from Area 1, as it has more variation in elevation, which warrants further investigation. It is noteworthy that the distribution of the frequency charts is normal, supporting the validation of the index calculations. Table 1 provides the statistical description of the NDVI index (minimum and maximum values, mean, variance, standard deviation, and mean deviation) for the various years.

Table 1. Statistical description of the NDVI index for various years

Year Min – Max (-0.23: 0.37)	2013	2015	2017	2019	2021
Mean	0.1276	0.1285	0.0801	0.0109	-0.0486
Variance	0.0006	0.0004	0.0005	0.0005	0.0014
STDEV	0.0240	0.0203	0.0227	0.0233	0.0379
Average deviation from the mean	0.0182	0.0150	0.0180	0.0178	0.0326

3.2. NDSI Index

The changes in soil erosion over the years 2013 to 2021, at two-year intervals, are shown in Figure 6 using the NDSI index. As observed in these images, soil erosion has gradually increased over time. The blue region in the southwest of the area corresponds to the coal mines of the Eastern Alborz region. Furthermore, the advance of the blue-colored areas, which represent soil erosion, is clearly visible towards the north of the image, where vegetative cover exists (as shown in Figure 7).

In addition to visual analysis, quantitative analysis was also performed by utilizing the positive and negative values of the NDSI index and their frequency distribution. Figure 8 illustrates the frequency distribution, mean, standard deviation, and the changes in positive (indicating the intensity of soil erosion) and negative (indicating the lack of soil erosion) values of the NDSI index. As shown in this Figure, over time, the NDSI values have shifted towards positive values, with more uniform changes observed between 2013 and 2017. However, in the years 2019 and 2021, the magnitude of these changes has increased

significantly, generally indicating an increase in soil erosion in the region.

Moreover, the analysis of the trend and change patterns suggests that although the intensity of changes is low, the overall trend is upward, which indicates the region's drought conditions and climatic conditions. Mining activities could also contribute to this phenomenon. It is worth noting that the distribution of the frequency charts is normal, which supports the reliability of the index calculations. Table 2 presents the statistical description of the NDSI index (minimum and maximum values, mean, variance, standard deviation, and mean deviation) for different years.

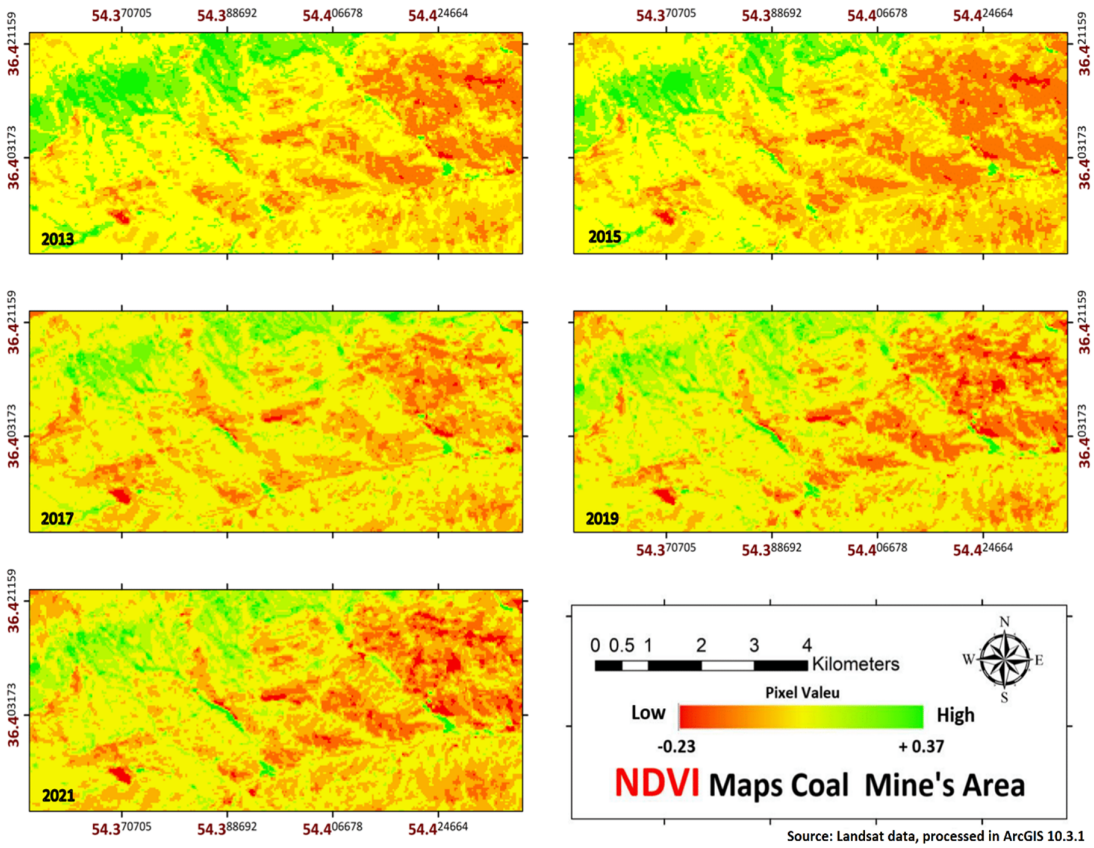

Figure 3. Normalized Difference Vegetation Index (NDVI) of the coal mine area over different years

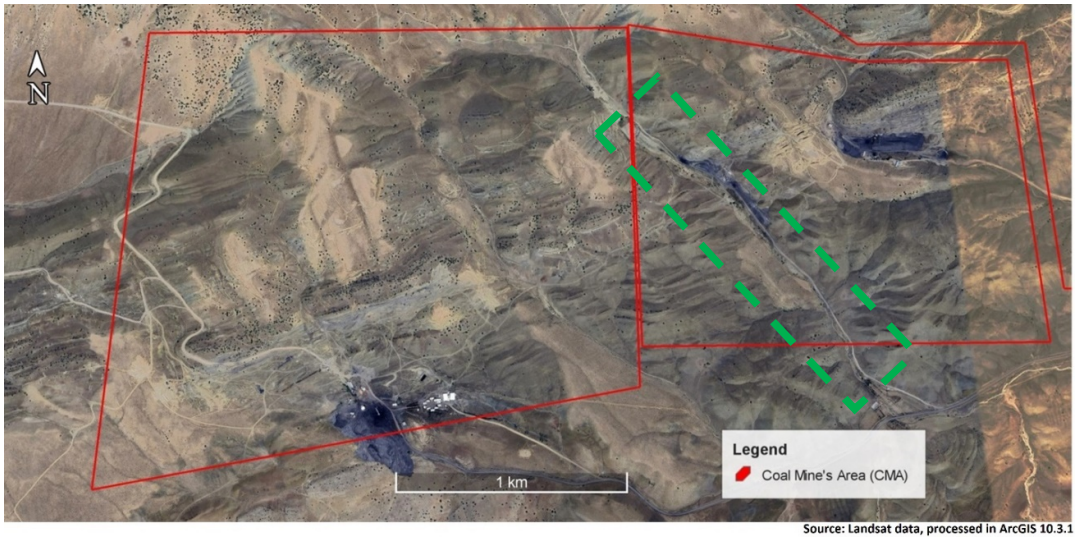

Figure 4. Aerial image showing the existing vegetation cover

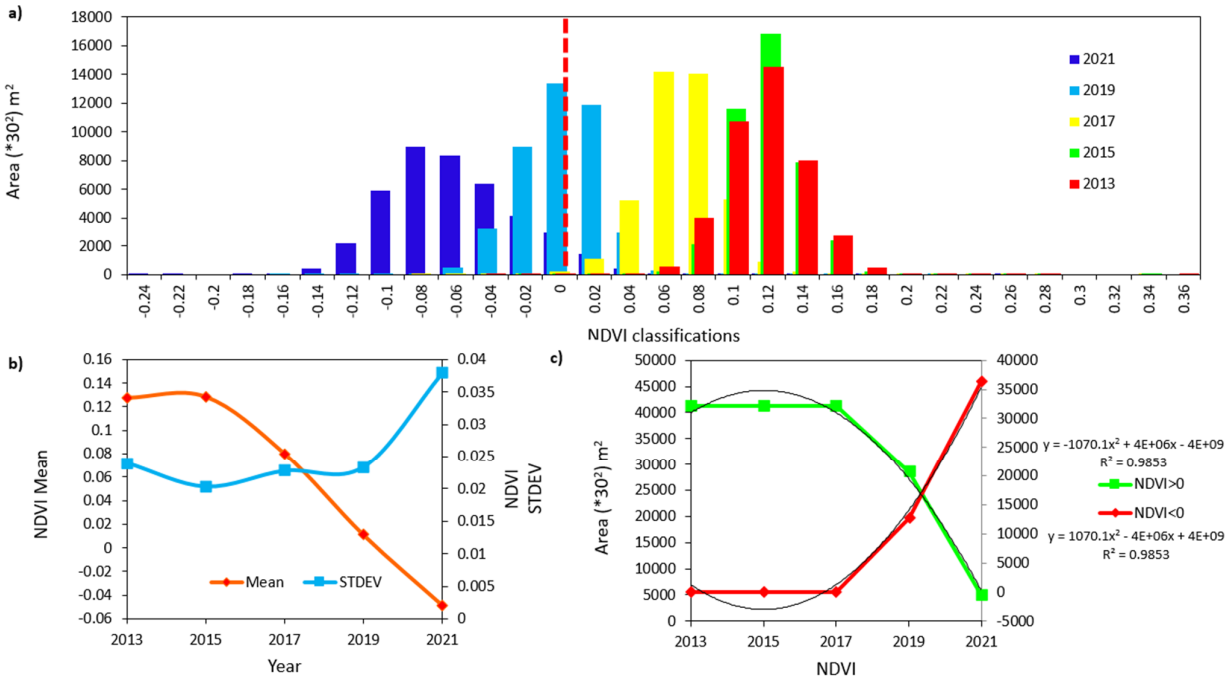

Figure 5. a) Frequency distribution of NDVI values, b) Trend of mean and standard deviation, c) Trend of positive and negative NDVI value changes (Coal mines)

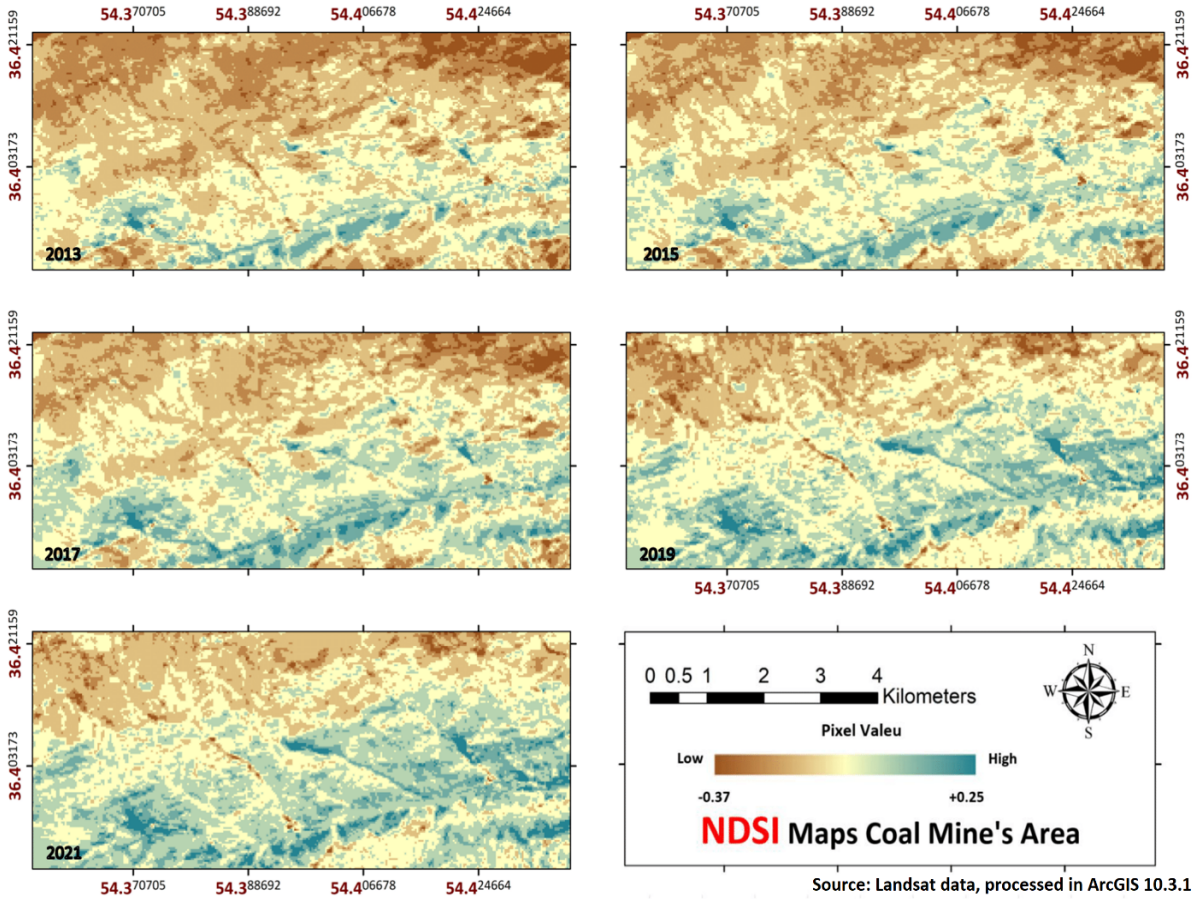

Figure 6. Normalized Difference Soil Erosion Index (NDSI) for the coal mine area in different years

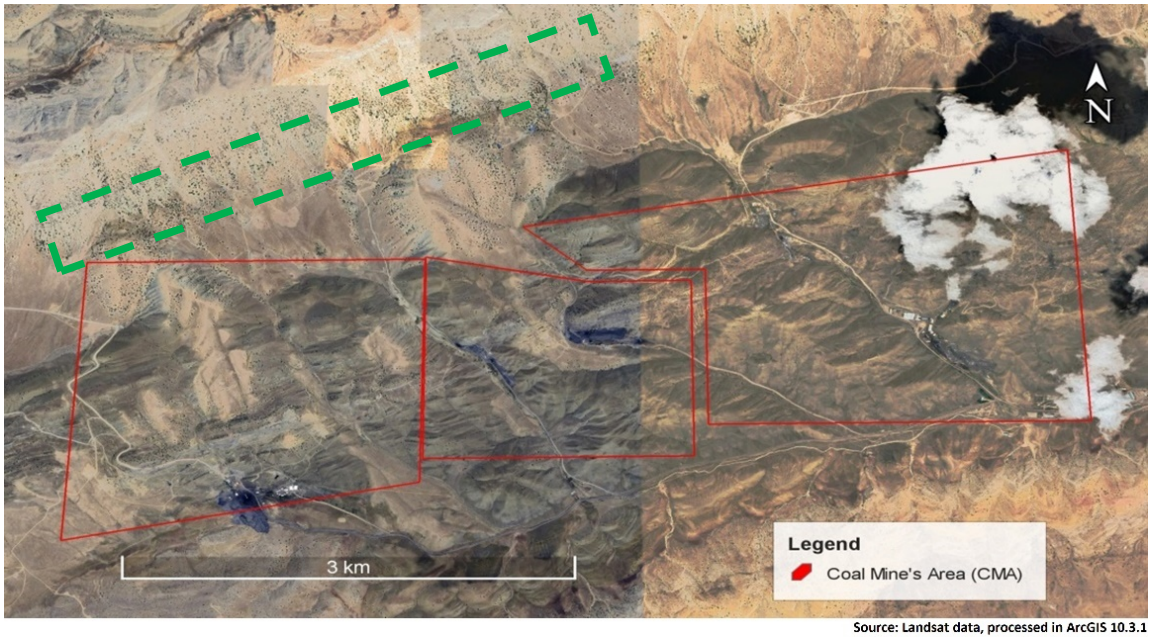

Figure 7. Aerial image of the northern part of the coal mine's region with relatively sparse vegetation

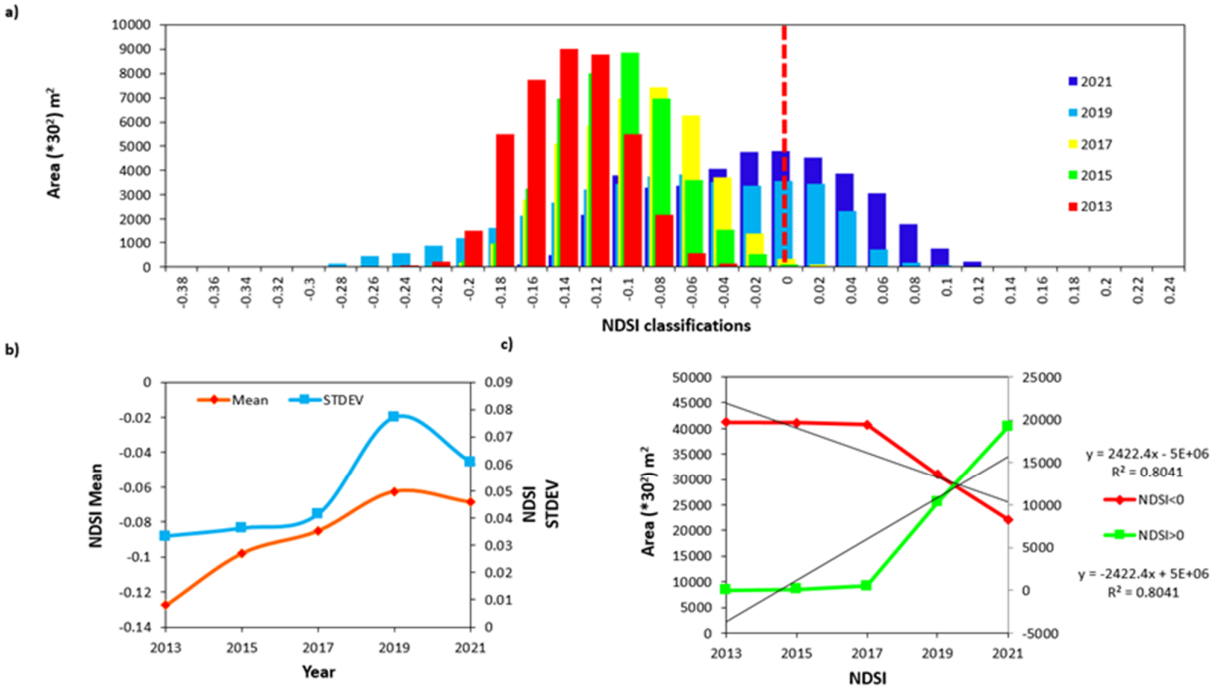

Figure 8. a) Frequency distribution of NDSI values, b) Trend graph of mean and standard deviation, c) Trend of changes in positive and negative NDSI values (Coal mines)

Table 2. Statistical description of the NDSI index for different years

Year / Min – Max (-0.37 : 0.25)	2013	2015	2017	2019	2021
Mean	-0.12744	-0.09780	-0.08498	-0.06245	-0.06852
Variance	0.00110	0.00131	0.00170	0.00593	0.00370
STDEV	0.03328	0.03620	0.04133	0.07706	0.06082
Average deviation from the mean	0.02670	0.02924	0.03384	0.06372	0.05132

3.3. NDWI Index

Changes in moisture levels using the NDWI index from 2013 to 2021 at two-year intervals are shown in Figure 9. As observed in these images, moisture levels have gradually decreased over time at a slow rate. The lighter areas correspond to regions with lower moisture values. In addition to visual analysis, a quantitative analysis has also been conducted by utilizing the positive and negative values of this index and their frequency distribution. Figure 10 shows the frequency distribution, mean, standard deviation, and the changes in positive (high moisture) and negative (moisture deficiency and drought conditions) values of the NDWI index. As seen in this Figure, over time, NDWI values have shifted towards negative values, indicating a reduction in moisture in the region. Furthermore, based on the chart and the trend of changes, it can be noted that the intensity of changes has been relatively low.

It should be considered that given the climatic conditions of the region (a dry and semi-arid area), this index reflects the range of values in terms of the frequency of water and moisture, and the scarcity of these values in the region, which suggests low accuracy. Moreover, as seen in Figure 10, most of the values in the image are positioned in the negative range, which further supports these findings. It is also worth noting that the distribution of the frequency charts is normal, confirming the accuracy of the index calculations. Table 3 presents the statistical description of the NDWI index (minimum and maximum values, mean, variance, standard deviation, and mean deviation) for different years.

3.4. NDBI Index

The changes in construction activities using the NDBI index for the years 2013 to 2021 at two-year intervals are shown in Figure 11. As observed in these images, the extent of construction activities has fluctuated with an overall undesirable trend. The dark areas in the southern part of the region correspond to coal stockpiles in Eastern Alborz. Since, in addition to visual analysis, a quantitative analysis is also required, an attempt has been made to provide a more comprehensive analysis by using both positive and negative values of the index and their frequency distribution. Figure 12 shows the frequency distribution, mean, standard deviation, and changes in positive values (high construction) and negative values (lack of construction) of the NDBI index. As seen in the Figure, over time, the changes in NDBI values were not uniform, which indicates the low accuracy of this index in the region. At the same time, based on the graph and the trend of value changes, it can be noted that the intensity of the changes is low. It is important to note that the role of building and asphalt spectral returns in the sensor is critical in this index, but due to the limited presence of these features in the images and the large area selected, the results are not sufficiently accurate. Generally, the use of this index is more applicable in urban areas with relatively smaller spatial scales. It should also be noted that the frequency distribution of the charts is normal, which supports the validation of the index calculations. Table 4 presents the statistical description of the NDBI index (minimum and maximum values, mean, variance, standard deviation, and deviation from the mean values) for the different years.

4. Results and Discussion

To achieve a more optimal analysis and comparison of remote sensing indices, data visualization is considered one of the most important factors. To determine the correlation relationships between indices, scatter plots were used. It is worth noting that the relationships between variables can be described in various ways: positive or negative, strong or weak. When two sets of data are strongly related or dependent, it can be stated that they have a high correlation. Positive correlation occurs when values increase in relation to each other (the slope of the line is upward), while negative correlation occurs when one data set increases as the other decreases (the slope of the line is downward).

In the areas under investigation, the mean indices for different years were plotted against each other in pairs. Figure 13 presents scatter plots comparing the indices pairwise for the regions. In this Figure, the NDVI and NDSI plot shows an inverse relationship, the NDVI and NDWI plot demonstrates a strong direct relationship, and the NDVI and NDBI plot shows a neutral relationship. In other words, it can be stated that as the rate of change in vegetation cover decreases, the rate of soil erosion increases, while the changes in moisture levels in the region have also decreased intermittently. On the other hand, the NDBI, which corresponds to the built-up area changes in the region, does not show a precise relationship with the other indices and is scattered in the plot across different years.

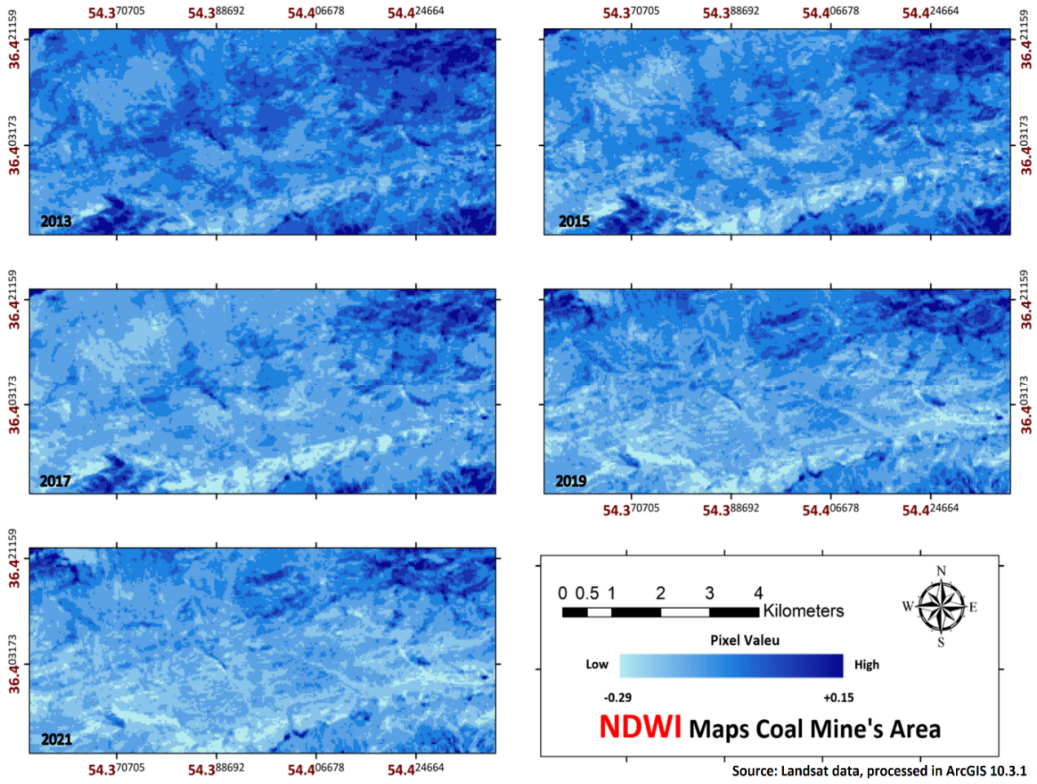

Figure 9. Normalized Difference Water Index (NDWI) for the coal mine area in different years

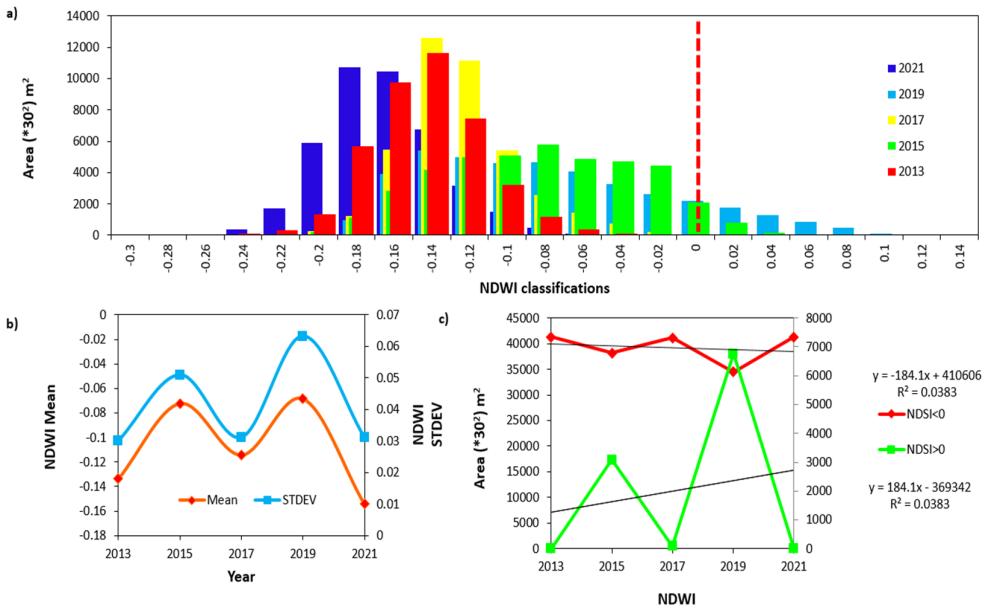

Figure 10. a) Frequency distribution of NDWI values, b) Trend chart of mean and standard deviation, c) Trend of changes in positive and negative NDWI values (coal mines)

Table 3. Statistical description of the NDWI index in different years

Year / Min – Max (-0.29 : 0.15)	2013	2015	2017	2019	2021
Mean	-0.13375	-0.07215	-0.11431	-0.06830	-0.15442
Variance	0.00090	0.00259	0.00096	0.00399	0.00096
STDEV	0.03002	0.05094	0.03111	0.06322	0.03108
Average deviation from the mean	0.02332	0.04235	0.02358	0.05198	0.02639

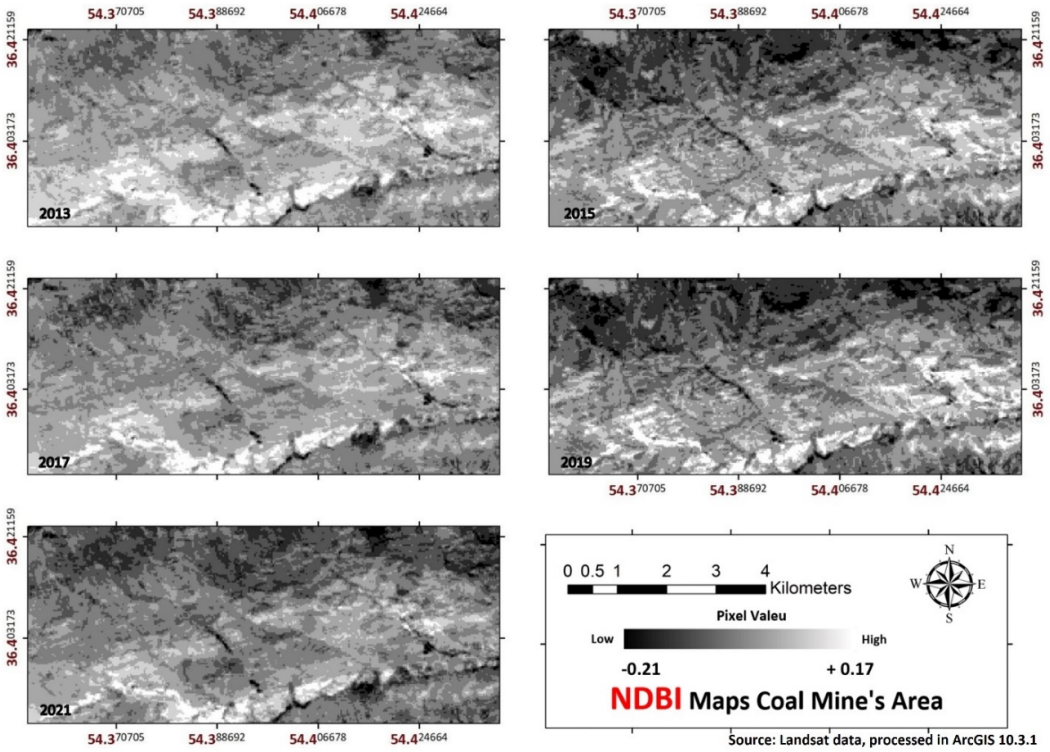

Figure 11. Normalized Difference Built-up Index (NDBI) for the coal mines region in various years

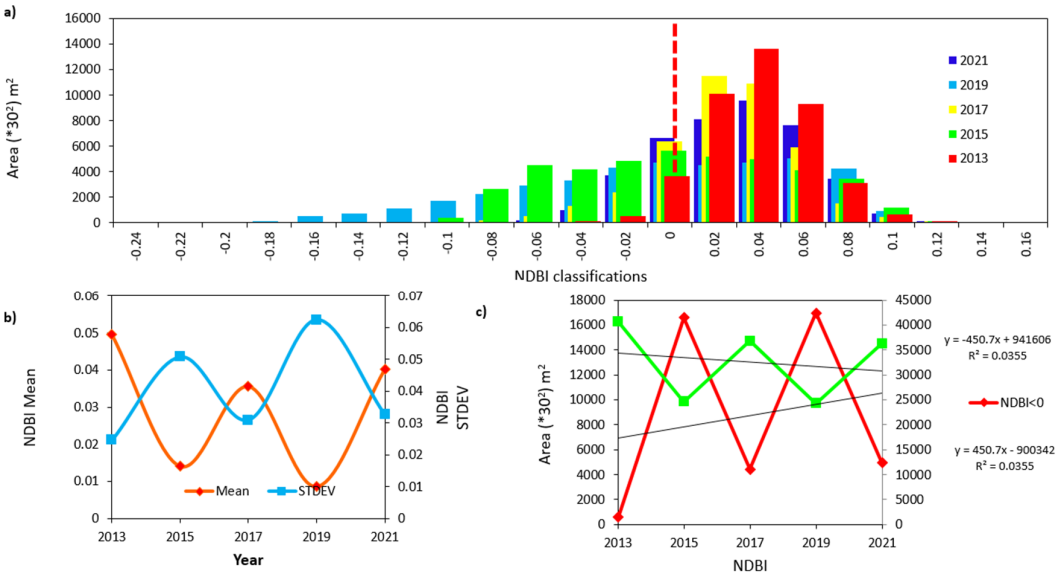

Figure 12. a) Frequency distribution of NDBI values, b) Graph of mean and standard deviation trends, c) Trend of positive and negative NDBI value changes (Coal mines)

Table 4. Statistical description of the NDBI index in various years

Year / Min – Max (-0.21: 0.17)	2013	2015	2017	2019	2021
Mean	0.04951	0.01403	0.03558	0.00857	0.04020
Variance	0.00060	0.00258	0.00096	0.00390	0.00107
STDEV	0.02468	0.05080	0.03100	0.06248	0.03275
Average deviation from the mean	0.01844	0.04271	0.02385	0.05132	0.02677

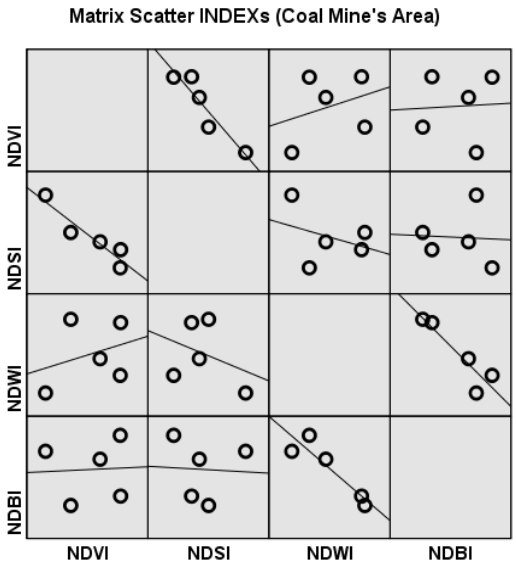

Figure 13. Scatter Plot of Various Indices for Regions of Coal Mines

Considering the characteristics of the study area and the nature of the available satellite data, it is acknowledged that the NDBI index did not provide a comprehensive or accurate representation of changes in the coal mining sites. Since no new construction activities have taken place in the region during the study period, and given that the minimum spatial resolution of the Landsat images is 30 meters, detailed analysis of built-up area changes using the NDBI is not feasible. Similarly, while the NDWI index was examined to assess moisture variations, the results did not reveal a consistent trend across the years from 2013 to 2021, which included both wet and dry periods. Therefore, NDWI also showed high temporal variability without a stable pattern, making precise analysis based on this index challenging. In contrast, the NDVI and NDSI indices exhibited more consistent and interpretable trends, thus forming the primary basis for the detailed analysis in this study.

To predict the impacts of mining activities on vegetation cover and soil erosion, regression models were used based on the NDVI and NDSI indices observed between 2013 and 2021 for the study area (Figure 14 and Table 5). The linear trend (R^2 = 0.9968) allowed for forecasting the expected NDVI values for 2030 and 2050. As shown in Figure 14a, the projected vegetation change rates are -0.25 and -0.72, respectively, indicating a substantial decrease correlated with the extension of the projection period. These projections indicate a significant decline in vegetation cover over time, which is consistent with ongoing environmental degradation due to mining activities. In addition to the NDVI projections, the NDSI values were forecasted using a logarithmic regression model based on the observed data from 2013 to 2021 (Figure 14b). The logarithmic trend demonstrated a very strong correlation (R^2 = 0.9869), indicating a good fit for modeling the gradual increase in soil erosion over time. According to this model, the predicted soil erosion change rates (based on mean NDSI values) for the years 2030 and 2050 are -0.04 and -0.01, respectively, suggesting a relatively low but steady increase in soil erosion, with a slow growth trend. To quantify the difference between the rates of vegetation loss and soil erosion, the mean annual change rates of the NDVI and NDSI indices were calculated based on linear and logarithmic regression models, respectively. The slope of the linear regression line for NDVI (-0.023 per year) indicates a much steeper decline compared to the slope of the logarithmic trend line for NDSI (+0.0032 per year) which shows a relatively slower but consistent increase in soil erosion over time.

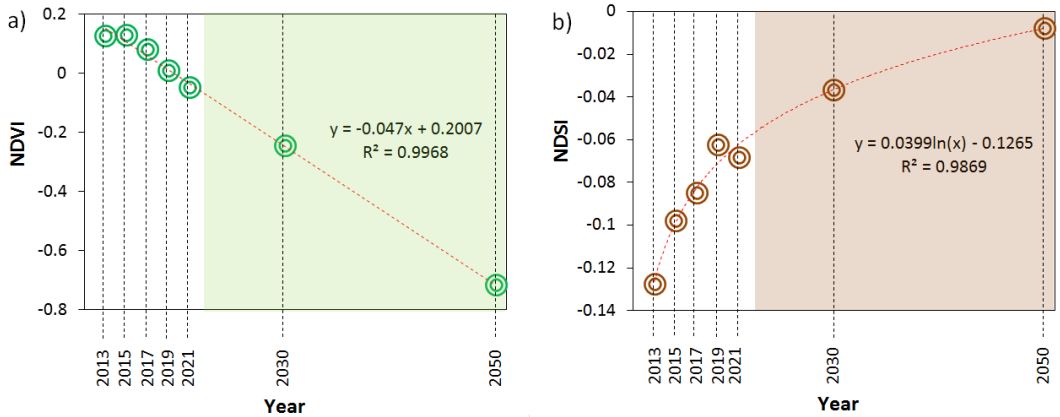

Figure 14. Forecast of Mean (a) NDVI and (b) NDSI Indices Based on Regression Relationships for the Years 2030 and 2050

Table 5. Mean NDVI and NDSI Indices for the Different Years

Year	2013	2015	2017	2019	2021	2030	2050
NDVI- Coal Mine's Area	0.13	0.13	0.08	0.01	-0.05	-0.25	-0.72
NDSI- Coal Mine's Area	-0.13	-0.10	-0.08	-0.06	-0.07	-0.04	-0.01

It should be noted that the projections presented in this study are based on linear and logarithmic extrapolations of past trends, assuming stable conditions and the continuation of mining activities. These projections do not account for potential external drivers such as climate policy interventions, technological innovations, or extreme climate events, which could significantly alter the trajectory of environmental impacts. Future research should therefore aim to incorporate climate change projections and scenario-based modeling approaches to improve the robustness and accuracy of long-term forecasts. Also, as explained in Table 5, the projected NDVI value of –0.72 by 2050 approaches the theoretical minimum of the NDVI range (–1 to +1), implying near-total vegetation loss in the affected areas. Such an extreme decline would indicate severe ecological degradation, including the collapse of vegetative cover, loss of biodiversity, and increased vulnerability to soil erosion and desertification.

In order to better compare the results and gain a clearer understanding of the mining impacts on the region, an area not affected by mining operations was selected as a reference region. This reference area is located within the Natural Resources Block, with parts of it in higher elevations and other sections in barren land (Figure 1). The trends of the indices examined in the reference area (Natural Resources Block) from 2013 to 2021, with two-year intervals, show fewer changes compared to the studied areas (Figure 15). To enhance understanding and provide a clearer visual representation, the average values of these indicators over the years are presented alongside the contour chart in Figure 16.

To assess the impacts of mining, the annual mean of each index was calculated, and the coal mining areas were compared with the reference area to distinguish the climatic and weather-related effects in addition to the mining impacts in the region (Figure 16). As observed in the Figure 16a, vegetation changes in this period were also affected by climatic changes, and the slope of the curve has become steeper in recent years. However, soil erosion changes are growing at a milder slope. On the other hand, climatic changes and annual rainfall have been intermittent in different years, with a decreasing trend at a low rate. As for the NDBI index, it can be stated that this index is not valuable in mountainous and desert environments, as the high variability of this index in different years suggests that it is not suitable for use in such environments.

Based on Figures 10 and 16a, the changes in the NDWI index in 2015 and 2019 show higher rates compared to other years. Other important factors such as surface water sources (precipitation), ambient temperature, wind speed in the region, and more can significantly influence the performance of this index and the accuracy of the images, in addition to mining activities.

To better assess the impact of mining in the study area, the effects of coal mining zones were compared with a reference area using correlation analysis. As shown in Figure 16b, the slope of the NDSI index is notably higher than those of the other indices (NDVI, NDWI, and NDBI). This indicates that, assuming stable and similar climatic and environmental conditions between the mining and reference areas, soil erosion induced by coal mining has had the greatest impact, followed by the reduction of vegetation cover in the study area. Subsequently, a decrease in moisture content is observed, although this index is highly dependent on prevailing climatic conditions. In contrast, due to the relatively low slope observed in the NDBI, the effect of mining on this index cannot be reliably assessed.

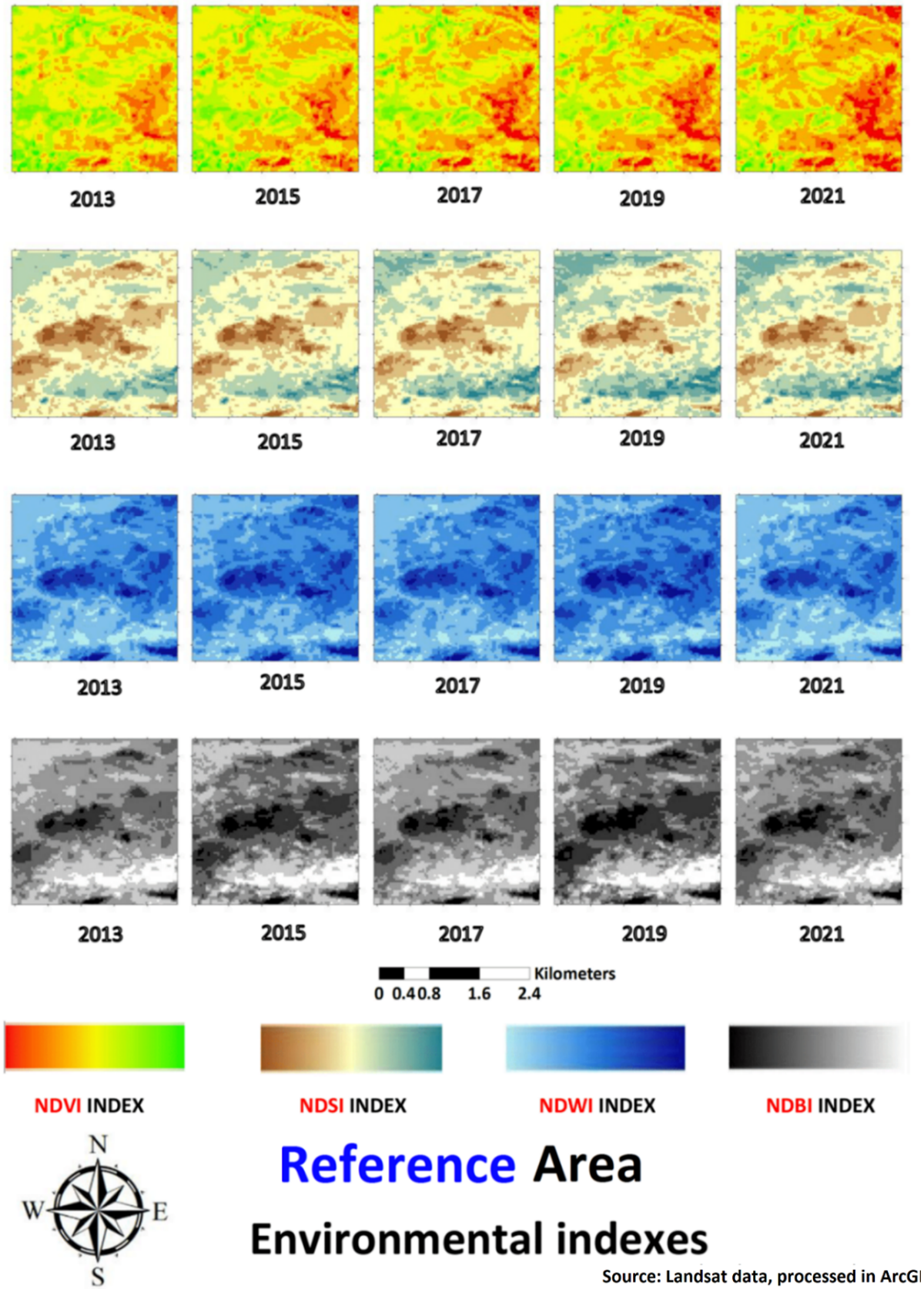

Figure 15. Trend of changes in the indices examined in the reference area (Natural Resources Block)

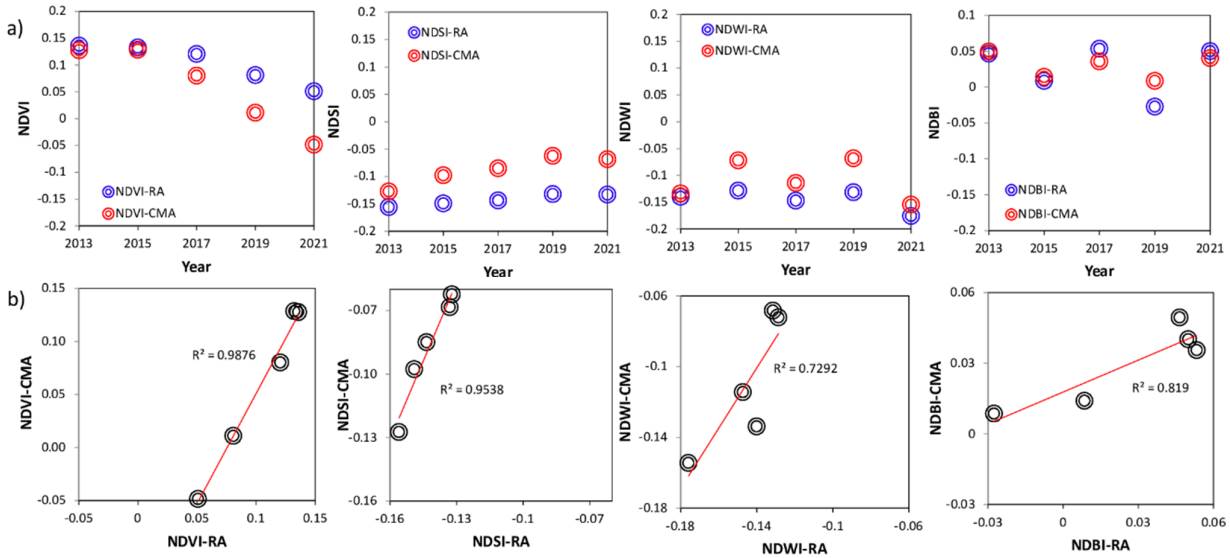

Figure 16. a) Comparison of various indices in different years between the Coal Mine Area (CMA) and the Reference Area (RA) for assessing mining impacts; b) Correlation of different indices between the Coal Mine Area (CMA) and the Reference Area (RA)

It should be mentioned that the information of weather monitoring system of Damghan (Figure 17a), Semnan province, indicate that in 2015, the precipitation (mm) and average wind speed (m/s) in the Damghan city station were high and low, respectively, while the average temperature (C°) showed an increasing trend that year. Figure 17a illustrates the trend of changes in these factors. Although a reference area unaffected by mining was analyzed to help distinguish the impacts of mining activities from climatic factors, the projections themselves were not adjusted for future climate scenarios. Future work should aim to incorporate climate change projections (e.g., variations in precipitation, temperature) and explore alternative predictive models to enhance the robustness and accuracy of long-term forecasts.

Also, Figure 17b demonstrates that climatic variables exert different levels of influence on the remote sensing indices. The NDVI shows a strong positive correlation with both precipitation and temperature, indicating that favorable moisture and thermal conditions enhance vegetation cover, while higher wind speeds tend to suppress vegetation growth. The NDWI also exhibits a high sensitivity to precipitation and temperature, reflecting its strong dependence on surface moisture availability. In contrast, the NDSI is most strongly correlated with wind speed, suggesting that higher wind activity exposes more bare soil surfaces and reduces vegetation protection. The NDBI, however, does not reveal a clear or consistent relationship with climatic variables, as it is predominantly controlled by anthropogenic activities such as land use changes and mining operations rather than short-term climatic fluctuations.

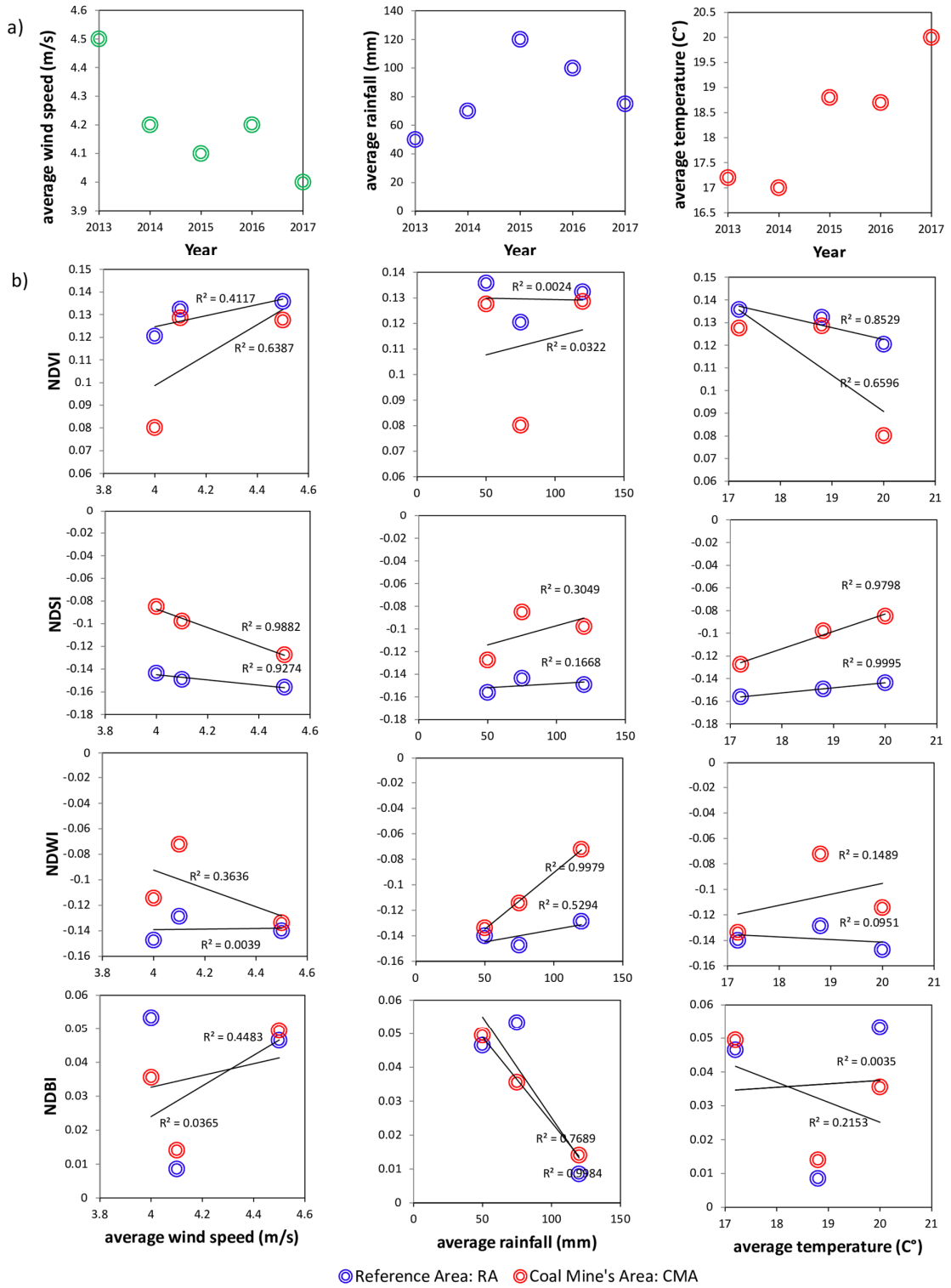

Figure 17. a) Variations in wind speed, precipitation, and temperature from the Damghan weather station (Semnan Province); b) Correlation of CMA and RA indices with climatic variables

5. Conclusions

The analysis of environmental indices in the coal mining areas indicates a negative trend in NDVI values, reflecting a decline in vegetation cover and an increase in barren lands. In 2013, the average value of NDVI was 0.13, and by 2021, it had decreased to -0.05. The average NDSI values for the region suggest a positive trend from 2013 to

2021, indicating an increase in soil erosion. Specifically, in 2013, the NDSI value was -0.13, and by 2021, it had risen to -0.07. The changes in moisture, indicated by the NDWI index, show an increase in values during 2015 and 2019, although the overall trend across the study years is not substantial. The NDBI index, which is generally used for urban analysis and understanding urban dynamics, did not provide a comprehensive or accurate analysis of the studied coal mining areas. The changes in this index over the years showed no significant trend within the studied regions.

In order to better understand the results and compare the various remote sensing indices for the coal mining regions, data visualization techniques, including scatter plots, were employed. The results show an inverse relationship between the NDVI and NDSI indices in both regions, while the NDVI and NDWI indices exhibit a strong positive correlation. Conversely, the NDVI and NDBI indices show a neutral relationship. A decrease in the rate of vegetation growth has been linked to an increase in soil erosion, while changes in moisture levels have shown an alternating pattern. The NDBI index, which reflects changes in construction and urbanization, did not have a significant effect on the other indices. To predict the effects of mining activities on vegetation and soil erosion, the average values of the NDVI and NDSI indices for the years 2030 and 2050 were calculated for the studied regions. The results suggest that the rate of NDVI (vegetation cover) will decrease by 0.25 in 2030 and by 0.72 in 2050 for the coal mining regions, indicating a significant loss of vegetation in the coming years. Additionally, soil erosion is predicted to increase slightly but at a relatively low rate over the same periods in both regions. The projections in this study were made under the assumption of stable conditions and recurring mining activities, while disregarding the potential influence of external drivers such as policy interventions, technological innovations, or extreme climate events. Naturally, many other factors could affect the long-term environmental impacts of mining. To facilitate a better comparison and understand the impact of mining, a baseline region was chosen. The results indicate that the changes in the indices within this baseline region were lower compared to the coal mining regions. However, over time (from 2013 to 2021), the average values of these indices have been influenced by climatic changes, resulting in some variations in their rates. The increased NDWI values in both the baseline region and the coal mining areas in 2015 and 2019 suggest that factors other than mining, such as surface water availability, annual rainfall, ambient temperature, and wind speed, may influence the changes in this index.

The analysis indicates that climatic variables exert significant but differential impacts on remote sensing indices: NDVI and NDWI are strongly influenced by precipitation and temperature, while NDSI responds most sensitively to wind speed. By contrast, NDBI does not display a clear climatic dependence, underscoring its stronger association with anthropogenic activities such as mining and land-use changes. To mitigate the negative impacts of mining and enhance ecosystem resilience, adaptive management strategies are essential. Practical measures include reforestation, land reclamation, stricter mining regulations, the adoption of cleaner technologies, and continuous monitoring of ecological and climatic indicators. Implementing these interventions can help maintain a sustainable balance between resource extraction and environmental protection.

Data Availability Statement

The datasets analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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چکیده

این پژوهش با هدف ارزیابی پیامدهای زیست‌محیطی فعالیت‌های معدنکاری زغال‌سنگ در ناحیه البرز شرقی، طی دوره ۲۰۱۳ تا ۲۰۲۱، و با استفاده از تکنیک‌های سنجش‌ازدور انجام شده است. تصاویر ماهواره‌ای Landsat 8 بر اساس شاخص‌های کلیدی زیست‌محیطی شامل NDVI، NDWI، NDSI و NDBI پردازش و سپس تحلیل‌های آماری و ارزیابی‌های لازم در محدوده‌های مورد مطالعه صورت گرفت. به‌منظور تفکیک اثرات ناشی از معدنکاری از تغییرات اقلیمی، نتایج با یک محدوده مرجع واقع در عرصه منابع طبیعی (ناحیه مبنا) مقایسه و به‌طور جامع تحلیل شدند. یافته‌ها نشان می‌دهد که اثرات ترکیبی معدنکاری و تغییرات اقلیمی، موجب بروز تخریب زیست‌محیطی قابل‌توجهی در منطقه شده است. به‌ویژه، پوشش گیاهی طی سال‌های اخیر با کاهش چشمگیری مواجه بوده، در حالی‌که فرسایش خاک با آهنگ کمتری افزایش یافته است. برای پیش‌بینی پیامدهای معدنکاری بر پوشش گیاهی و خاک، میانگین شاخص‌های NDVI و NDSI برای سال‌های ۲۰۳۰ و ۲۰۵۰ محاسبه شد. نتایج پیش‌بینی‌ها بیانگر آن است که مقدار NDVI تا سال ۲۰۳۰ حدود ۰٫۲۵ و تا سال ۲۰۵۰ حدود ۰٫۷۲ کاهش خواهد یافت که نشان‌دهنده کاهش بیشتر پوشش گیاهی در دهه‌های آتی است. در مقابل، تحلیل شاخص NDWI روند مشخصی در تغییرات رطوبت خاک طی دوره مطالعه نشان نمی‌دهد. با توجه به شرایط اقلیمی مناطق انتخابی، پایش، مدیریت و کاهش عوامل خطر زیست‌محیطی برای جلوگیری از گسترش خشکسالی به جنگل‌های شمالی ضروری بوده و بر اهمیت اتخاذ اقدامات مداخله‌ای مناسب تأکید دارد.

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