



MULTITEMPORAL ANALYSIS OF LAND SURFACE DYNAMICS IN PETROȘANI MUNICIPALITY USING NDVI, NDWI, NBR AND SAVI SPECTRAL INDICES DURING THE 2020–2025 PERIOD

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DOI: 10.2478/minrv-2026-0054

received – 10.08.2026 / revised – 17.08.2026

accepted – 10.09.2026 / published – 25.09.2026

Abstract: *Monitoring changes in the land surface is an essential element for assessing the transformation processes of the urban and peri-urban environment, especially in regions with a long history of mining activities. The development of Earth observation programs and the availability of freely accessible satellite images allow for detailed multi-temporal analyses of the evolution of vegetation, humidity and the general condition of the land. In this context, spectral indices calculated from satellite images provide objective information on spatial and temporal changes of the analyzed surface. The paper presents a multitemporal analysis of the Petroșani municipality using four of the most widely used spectral indices in remote sensing: Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Burn Ratio (NBR), and Soil Adjusted Vegetation Index (SAVI). The analysis was carried out for the period 2020–2025 based on a set of 20,000 points uniformly distributed in the study area, for each year analyzed. The working methodology included processing the time series of spectral indices, calculating descriptive statistical parameters, comparing annual distributions, analyzing correlations between indicators and interpreting the spatio-temporal trends highlighted during the analyzed period. The integrated approach allows for the simultaneous assessment of vegetation changes, moisture conditions and land surface transformations. The results obtained highlight the existence of interannual variations in all analyzed indices, reflecting both the influence of climatic conditions and the effects of anthropogenic transformations specific to a city in a continuous process of economic restructuring and urban regeneration. The comparative analysis demonstrates the complementarity of the four indices and the usefulness of their integrated use in assessing the evolution of the urban environment. The study confirms that multitemporal analysis based on satellite images is an effective method for environmental monitoring in mining regions and can provide useful information for territorial planning, green space management and the substantiation of sustainable development strategies.*

Keywords: *environmental monitoring; GIS; multitemporal analysis; NBR; NDVI; NDWI; Petroșani; remote sensing; SAVI; Sentinel-2*

1. Introduction

Changes in the land surface represent one of the most important consequences of urban development, the intensification of anthropogenic activities and climate variability, directly influencing the functioning of ecosystems, environmental quality and the use of natural resources. In recent decades, monitoring these transformations has become a priority in geospatial research, as it provides essential information for assessing processes of urbanization, ecological regeneration, land degradation and sustainable territorial planning [1], [2], [3].

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Classical methods based on field measurements provide accurate information at a local scale, but are limited in terms of spatial coverage and update frequency. In contrast, modern Earth observation technologies allow continuous monitoring of the Earth's surface through the use of multispectral satellite images, providing objective, repetitive and comparable data for long time intervals. The development of the Landsat and Copernicus programs has fundamentally changed the way environmental changes are investigated, facilitating multitemporal analyses at local, regional and global scales [4], [5].

The European Copernicus program, through the Sentinel-2 mission, represents one of the most important sources of data for environmental monitoring. The MultiSpectral Instrument (MSI) sensor provides images in 13 spectral bands, with spatial resolutions of 10, 20 and 60 m and a revisit frequency of approximately five days, features that allow tracking of changes in vegetation, soil and water resources in a systematic and reproducible way [4]. Compared to previous generations of satellites, Sentinel-2 offers superior spectral resolution, in particular by introducing bands in the red-edge region, which improves the estimation of biophysical parameters of vegetation and the accuracy of multitemporal analyses [6], [7].

One of the most used methods for interpreting multispectral images is the calculation of spectral indices. They synthesize the spectral response of the land surface and allow the characterization of the state of vegetation, water content, the degree of disturbance of ecosystems and the changes produced on the land. Due to their computational simplicity and robustness, spectral indices have become standard tools in agriculture, forestry, environmental monitoring, ecology, and land use change analysis [8].

The most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI), introduced by Rouse et al. (1974) [9] and later substantiated by Tucker (1979) [10]. NDVI uses the contrast between red and near-infrared reflectance to estimate vegetation vigor and photosynthetic activity, and is applied in a very wide range of studies regarding agricultural crop monitoring, biomass assessment, drought analysis and mapping of natural ecosystems [9], [10], [11].

In areas with sparse vegetation or where soil reflectance significantly influences the spectral response, the exclusive use of NDVI may lead to less accurate estimates. To reduce this effect, Huete (1988) [12] proposed the Soil Adjusted Vegetation Index (SAVI), which introduces a correction factor designed to reduce the influence of the soil background. SAVI is particularly recommended for degraded lands, urban areas and former industrial areas, where vegetation cover is discontinuous and soil reflectance can affect the interpretation of NDVI values [12].

In addition to vegetation monitoring, assessing the water regime and identifying changes in the structure of the land surface are important components of remote sensing studies. The Normalized Difference Water Index (NDWI) is used to delimit aquatic surfaces and estimate water content variations, having been initially proposed by McFeeters (1996) [13] and subsequently adapted for the assessment of vegetation water by Gao (1996) [14]. At the same time, the Normalized Burn Ratio (NBR) uses spectral information from the NIR and SWIR bands to identify changes in vegetation and to assess the degree of disturbance to the land surface, being used not only in the analysis of forest fires, but also in monitoring the regeneration of ecosystems and lands affected by anthropogenic activities [15].

Recent studies have highlighted that the simultaneous use of multiple spectral indices provides a more complete characterization of the land surface than the individual interpretation of each. While NDVI and SAVI describe the response of vegetation, NDWI provides information on water distribution and dynamics, and NBR is sensitive to structural changes in vegetation and disturbed surfaces. The integration of these indicators allows the simultaneous evaluation of several biophysical processes and improves the interpretation of transformations produced in the urban and peri-urban environment [8], [16], [17].

The transformations produced in mining regions represent some of the most complex processes of land surface modification, as they involve simultaneous changes in land use, vegetation structure, soil properties and water regime. The closure of mining operations is typically followed by processes of natural vegetation regeneration, ecological reconstruction, functional land conversion and urban development, all of which influence the spectral response of the land surface. Monitoring these transformations is essential both for assessing the environmental impact and for underpinning sustainable development strategies and regeneration projects for former industrial areas [18], [19], [20].

In this context, the analysis of time series of satellite images offers the possibility of objective quantification of changes over time and allows the identification of evolutionary trends of different components of the environment. Unlike analyses based on a single satellite image, multitemporal approaches reduce the influence of atmospheric conditions, seasonal variability and phenological particularities, providing more stable and representative results for the characterization of territorial processes [21] [22].

In recent years, the use of Sentinel-2 time series has experienced accelerated development due to the free availability of data and advances in geospatial processing. Platforms such as Google Earth Engine allow the rapid processing of very large volumes of satellite images and the development of reproducible workflows, facilitating the analysis of changes in the earth's surface at different spatial and temporal scales [23]. In parallel, the development of harmonized Landsat–Sentinel databases has contributed to the expansion of multitemporal analyses and to the improvement of the comparability of results obtained in different geographical regions [24].

Although the applications of spectral indices are very numerous, most research is oriented towards monitoring agricultural crops, assessing vegetation productivity, analyzing forest ecosystems, or identifying the effects of drought and fires. In contrast, studies dedicated to the urban environment in mining regions are considerably fewer, and those that simultaneously use the NDVI, NDWI, NBR and SAVI indices to characterize land surface changes are still limited. In most cases, research analyzes each index separately, without highlighting the relationships between them and without integrating the information provided by each indicator into a unitary interpretation of territorial transformations [8], [25].

The Jiu Valley represents one of the most important coal mining regions in Romania, its economic, social and territorial development being closely linked, for over a century, to the exploitation of hard coal. Mining activities have produced important transformations of the landscape, through the development of industrial infrastructure, the appearance of tailings dumps and other anthropogenic landforms, as well as through the modification of land structure and use [26], [27]. Petroșani Municipality, the main urban center of the Jiu Valley, preserves in the structure of its current landscape numerous elements associated with this industrial evolution, including former mining and industrial areas, degraded or abandoned lands and areas in various stages of reconversion and regeneration [28], [29].

The progressive reduction of mining activities and the closure of some exploitations have determined a new stage in the evolution of the territory, characterized by changes in land use, spontaneous or assisted regeneration of vegetation and the need to reintegrate former mining areas into the urban and peri-urban landscape. Multitemporal analyses conducted for the Jiu Valley demonstrated the existence of important changes in built-up areas, mining lands, dumps, forests and other land cover categories and confirmed the usefulness of satellite images for quantifying these processes [30], [31]. In particular, the use of vegetation indices, including NDVI and SAVI, has proven useful in differentiating active mining areas from lands in different stages of regeneration [30].

From a remote sensing perspective, Petroșani municipality thus represents a relevant area for evaluating the specific transformations of post-mining urban environments. The diversity of land use and cover categories – built-up areas, industrial and post-industrial areas, forests, grasslands, watercourses and lands undergoing regeneration – generates high spectral heterogeneity. Recent research conducted in the Jiu Valley mining basin has confirmed this diversity of land use and the opportunity to use remote sensing techniques for its characterization [32]. In this context, the integrated analysis of NDVI, NDWI, NBR and SAVI indices can provide complementary information on the state of vegetation, moisture conditions and structural changes of the land surface.

In the literature consulted, no study dedicated to the municipality of Petroșani was identified that would simultaneously track the multitemporal evolution of the four indices NDVI, NDWI, NBR and SAVI during the period 2020–2025, based on the same extensive spatial network of observation points. Therefore, the proposed approach complements previous research conducted on the dynamics of the mining landscape in the Jiu Valley by integrating multiple spectral indicators into a common temporal analysis framework.

Therefore, the purpose of this study is to evaluate land surface changes in Petroșani municipality during the period 2020–2025 through integrated analysis of the NDVI, NDWI, NBR and SAVI spectral indices calculated based on Sentinel-2 images. The present study aimed to: (i) the statistical characterization of each spectral index, (ii) the comparison of interannual distributions, (iii) the analysis of the relationships between spectral indices and (iv) the identification of spatio-temporal trends associated with the transformations of the post-mining urban environment. The results obtained contribute to the development of a reproducible methodology for environmental monitoring and can support the decision-making process regarding urban regeneration and sustainable land management.

2. Materials and method

2.1. Study area

The analyzed area is represented by the Petroșani municipality, located in the central part of the Petroșani Depression, Hunedoara County, Romania, Figure 1. The municipality represents the main urban center of the Jiu Valley and developed around coal mining activities, carried out for over a century. The progressive reduction of mining activities after 1990 led to important changes in land use, the expansion of natural vegetation regeneration processes and the transformation of industrial areas into areas with other functions. From a land use perspective, Petroșani municipality includes built-up areas, residential areas, industrial lands, forests, meadows, watercourses and lands in various stages of regeneration, which recommends it as a study area for analyzing land surface changes through satellite images.

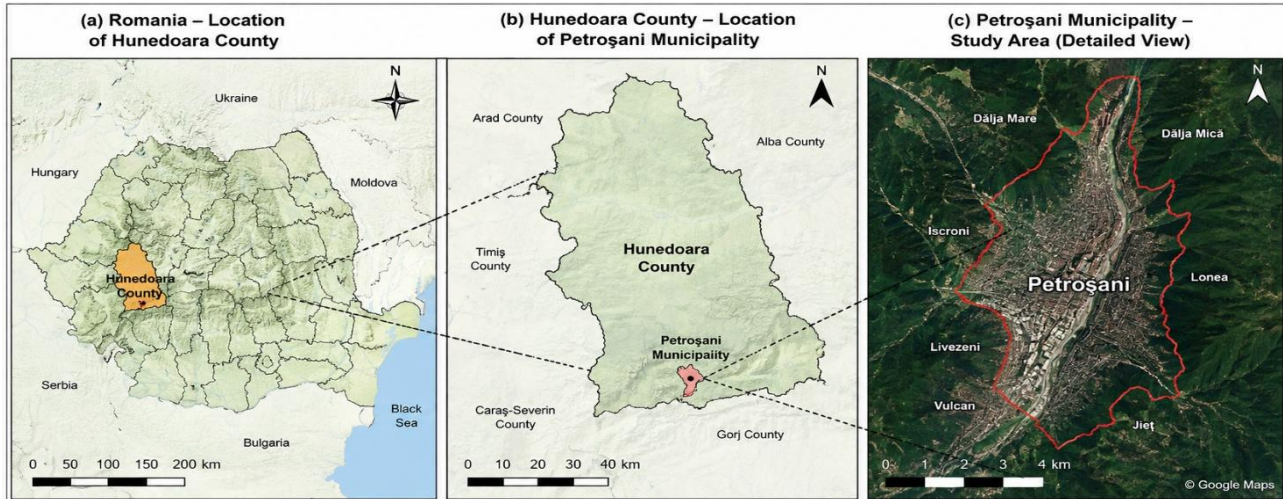


Fig. 1. Geographic location of the study area: (a) location of Hunedoara County within Romania; (b) location of Petroșani Municipality within Hunedoara County; (c) detailed view of the study area. Source: [33], [34]

2.2. Data used

The analysis was based on the use of Sentinel-2 multispectral images, processed for the period 2020–2025. Four spectral indices frequently used in environmental monitoring were calculated from the satellite images: Normalized Difference Vegetation Index (NDVI); Normalized Difference Water Index (NDWI); Normalized Burn Ratio (NBR); Soil Adjusted Vegetation Index (SAVI).

For each spectral index, the values corresponding to a set of 20,000 observation points uniformly distributed in the study area were extracted. The same grid of points was used for all six years analyzed, which allowed for direct comparison of index values and assessment of changes over time. The database used in the analysis included: 20,000 points; 4 spectral indices; 6 years (2020–2025), resulting in a total of 480,000 spectral values used in the statistical analyses.

2.3. Spectral indices used

Four spectral indices established in the specialized literature were used to characterize land surface changes.

Normalized Difference Vegetation Index (NDVI), equation (1), is one of the most used indicators for assessing the state of vegetation.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where: NIR - represents near infrared reflectance; Red - represents reflectance in the red band

NDVI values are in the range (−1, +1), with high positive values indicating healthy and dense vegetation.

The Normalized Difference Water Index (NDWI), equation (2), was used to assess the distribution of water and surface moisture in the study area.

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (2)$$

where: Green - represents the green band; NIR - represents near infrared

The Normalized Burn Ratio (NBR), equation (3), was used to highlight structural changes in the land surface in the study area.

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \quad (3)$$

where: NIR - stands for near infrared; SWIR - stands for short wavelength infrared band

The Soil Adjusted Vegetation Index (SAVI), equation (4), was used to reduce the influence of soil reflectance on the vegetation assessment.

$$SAVI = \frac{NIR - Red}{NIR + Red + L} \times (1 + L) \quad (4)$$

where: NIR - represents near infrared; Red - represents reflectance in the red band; L - is the soil correction factor, for which the value 0.5 was used, recommended for areas with medium vegetation cover

2.4. Statistical analysis

The data series for the determined indices were statistically analyzed to find the following statistical indicators: arithmetic mean; median; minimum value; maximum value; standard deviation; coefficient of variation.

The relationships between spectral indices were evaluated using the Pearson correlation coefficient. The interdependence between indices was assessed using quadratic regression analysis (R^2 , $p < 0.05$). The multivariate structure of the database was investigated by Principal Component Analysis (PCA). This method allows to reduce the dimensionality of the data set and to identify the main directions of variation of the analyzed indices. Cluster analysis (CA) was used to describe the bidirectional association of indices and years in the study period, based on the recorded values.

For data analysis and generation of graphical representations, PAST software v.4.17 [35], JASP software v.0.16.2 (2022) [36], and Mathematica software v.14.2 (2024) [37] were used.

3. Results and discussion

3.1. Descriptive statistics of spectral indices

In the first stage, the statistical characteristics of the data series for the NDVI, NDWI, NBR and SAVI indices were evaluated for the period 2020–2025. To highlight these changes, descriptive statistics were calculated for each spectral index, and the results are summarized in Table 1.

Table 1. Statistical parameters of the NDVI, NDWI, NBR and SAVI indices in the period 2020–2025

Index	Year	Mean	Median	Minimum	Maximum	SD	CV (%)
NDVI	NDVI 2020	0.3524009	0.3726915	0	0.5729300	0.086937392	24.67
	NDVI 2021	0.3978413	0.4222925	0	0.5692950	0.087615019	22.02
	NDVI 2022	0.3792034	0.3978985	0	0.5631370	0.088193726	23.26
	NDVI 2023	0.3231088	0.3624760	-0.0069905	0.9005960	0.125932566	38.98
	NDVI 2024	0.3476667	0.3717635	0	0.5540910	0.103788278	29.85
	NDVI 2025	0.3548880	0.3674020	0	0.5413710	0.075444149	21.26
NDWI	NDWI 2020	-0.3333239	-0.3511540	-0.5153670	0	0.079371385	-23.81
	NDWI 2021	-0.3733188	-0.3942385	-0.5421520	0	0.078964297	-21.15
	NDWI 2022	-0.3631338	-0.3785205	-0.5594310	0	0.079262115	-21.83
	NDWI 2023	-0.3076991	-0.3443280	-0.7257770	0.0075429	0.115899807	-37.67
	NDWI 2024	-0.3353035	-0.3569055	-0.5264970	0	0.095720791	-28.55
	NDWI 2025	-0.3393097	-0.3515395	-0.5176790	0	0.068523772	-20.20
NBR	NBR 2020	-0.0690246	-0.0744987	-0.5336560	0.2966290	0.034589352	-50.11
	NBR 2021	-0.0808257	-0.0846732	-0.3195230	0.3983390	0.028754611	-35.58
	NBR 2022	-0.0912217	-0.0965869	-0.2091510	0.0404810	0.029068544	-31.87
	NBR 2023	-0.0546610	-0.0756036	-0.7884870	0.4010770	0.076133888	-139.28
	NBR 2024	-0.0751572	-0.0822107	-0.6736670	0.1642990	0.03775306	-50.23
	NBR 2025	-0.0829019	-0.0865729	-0.3823800	0.0377608	0.028603735	-34.50
SAVI	SAVI 2020	0.5274982	0.5590420	0	0.8262500	0.131691488	24.97
	SAVI 2021	0.5950424	0.6340425	-0.0000592	0.8401580	0.133927845	22.51
	SAVI 2022	0.5709375	0.5979305	0	0.8413680	0.130111661	22.79
	SAVI 2023	0.4829221	0.5440515	-0.0096551	1.0039800	0.190890126	39.53
	SAVI 2024	0.5205253	0.5557875	0	0.8658570	0.155570167	29.89
	SAVI 2025	0.5334847	0.5526355	0	0.8113210	0.113330304	21.24

The recorded variations reflected both the influence of climatic conditions during the study period and the changes in land cover resulting from natural and anthropogenic processes. In the case of an anthropic territory, with a post-mining specific, these variations are determined by the regeneration of vegetation on

former industrial areas, the expansion of green spaces, the modification of built surfaces and the evolution of humidity conditions. The values of the coefficients of variation (CV) indicated moderate and high variability in the data series of the studied indices, according to Table 1.

3.2. Multitemporal evolution of spectral indices in the period 2020–2025

The analysis of the data series highlighted the existence of interannual variations in the analyzed indices, reflecting the dynamics of biophysical and anthropogenic processes that characterize the municipality of Petroșani. The average values calculated for each year allowed the evaluation of general trends in vegetation, humidity conditions and changes in the land surface, while the dispersion analysis provided information on the spatial heterogeneity of the investigated areas, Figure 2.

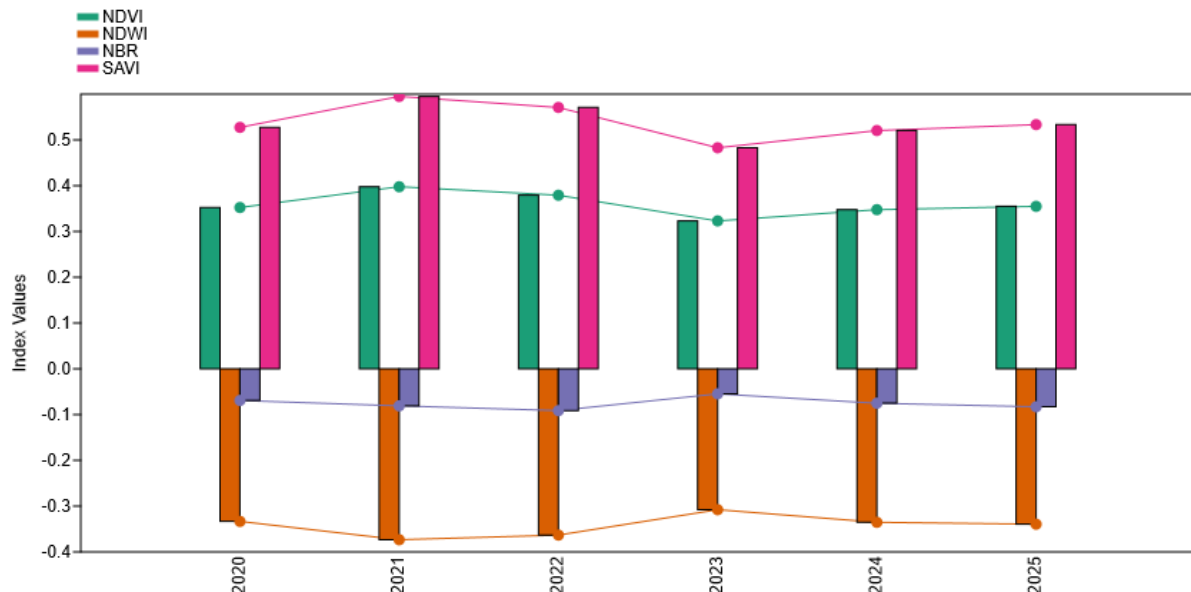


Fig. 2. Evolution of the average values of the NDVI, NDWI, NBR and SAVI spectral indices during the period 2020–2025

The average values of the NDVI index showed moderate variations during the analyzed period. In 2021, the highest average value was observed, which indicated a favorable state of vegetation and a more intense photosynthetic activity compared to other years. Subsequently, in 2022 and especially in 2023, the average NDVI recorded a decrease, suggesting the influence of less favorable climatic conditions or local changes in land cover. In 2024 and 2025, a slight recovery of NDVI values was observed, without however reaching the maximum level observed in 2021. At the same time, the standard deviation and the coefficient of variation indicated an increase in the heterogeneity of the distribution of NDVI values in 2023. This result suggested the existence of more pronounced differences between the different land use categories, a phenomenon characteristic of urban environments in which built surfaces, forest vegetation, green spaces and lands in different stages of regeneration coexist.

The NDWI index highlighted interannual variations associated with changes in water content and humidity conditions of the studied area. The observed fluctuations were lower than in the case of NDVI, which indicated a relative stability of the spatial distribution of humidity at the level of Petroșani municipality. However, the differences between the analyzed years may reflect the influence of the precipitation regime and the meteorological conditions specific to each vegetation season.

NBR values showed moderate variability during the analyzed period. The lack of sudden changes in the average values suggests that, at the scale of the entire municipality, there were no major disturbances in the vegetation structure or land surface. Local differences highlighted by the dispersion of values can be associated with the transformations produced on former industrial sites and natural regeneration processes.

The SAVI index showed a similar evolution to NDVI, but with smaller variations, confirming the role of the soil correction factor in reducing the influence of the reflectance of bare surfaces. This behavior is particularly important in a post-mining urban territory, where the alternation between built-up areas, degraded lands and vegetation, can affect the interpretation of classical vegetation indices.

The comparative analysis of the four spectral indices highlighted the fact that no index can fully characterize the dynamics of the land surface when analyzed individually. The NDVI and SAVI indices

mainly described vegetation changes, the NDWI index provided information on the moisture distribution, and the NBR index reflected the structural changes of the surface. Their integrated use allows a more robust assessment of the transformations produced in the Petroșani municipality and reduces the risk of interpretations based on a single spectral indicator.

An important result is the position of 2023, which appears as a distinct year in the time series: NDVI and SAVI reached the minimums of the period, while NDWI and NBR moved towards higher values (negative values), Figure 3. This simultaneous change justified a more in-depth analysis of 2023 in the discussions, including by reference to climatic conditions and possible land cover changes.

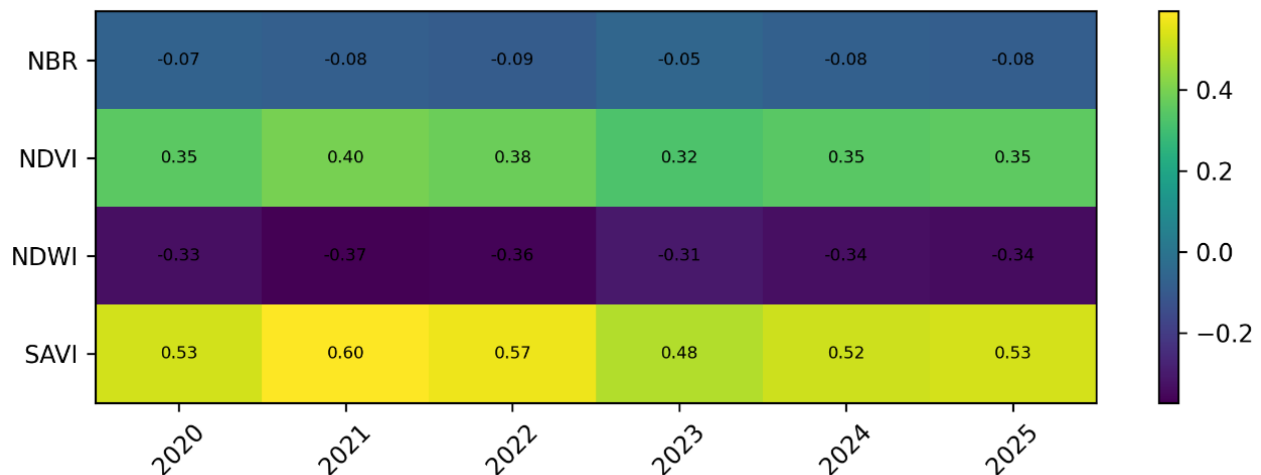


Fig. 3. Matrix representation of the average values of the indices by years of study

The standardized representation of the index values (Figure 4) is useful because standardization eliminates the differences in scale between the four indices and allows for a direct comparison of their temporal behavior. The favorable character of 2021 for NDVI and SAVI, as well as the distinct position of 2023, was very well observed.

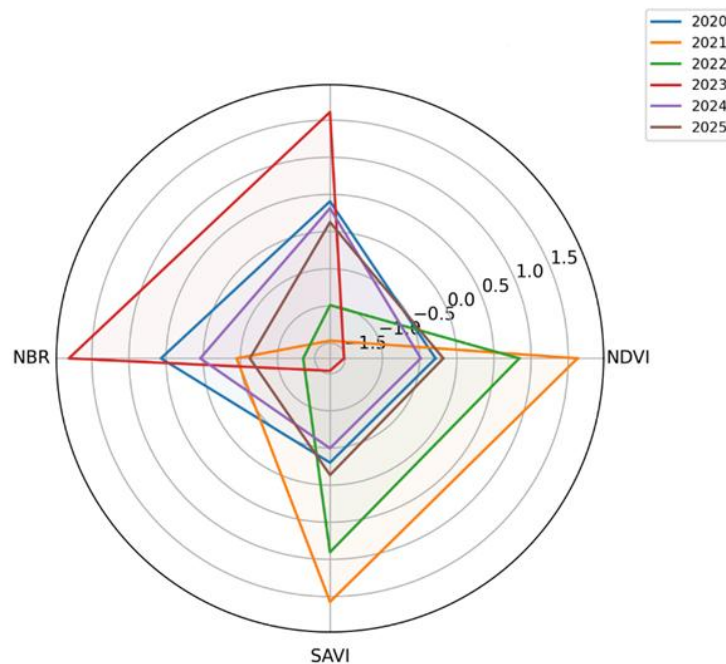


Fig. 4. Standardized profile of annual mean values for NDVI, NDWI, NBR and SAVI indices in the period 2020–2025

3.3. Relationships between spectral indices

Pearson correlation analysis showed variable levels of correlation between indices, within statistical safety conditions, Table 2.

Table 2. Correlation matrix table

Variable	Statistical parameters	NDVI	NDWI	NBR	SAVI
NDVI	Pearson's r	—			
	p-value	—			
	Upper 95% CI	—			
	Lower 95% CI	—			
NDWI	Pearson's r	-0.992***	—		
	p-value	< .001	—		
	Upper 95% CI	-0.921	—		
	Lower 95% CI	-0.999	—		
NBR	Pearson's r	-0.779	0.844*	—	
	p-value	0.068	0.035	—	
	Upper 95% CI	0.089	0.983	—	
	Lower 95% CI	-0.974	0.102	—	
SAVI	Pearson's r	0.999***	-0.994***	-0.801	—
	p-value	< .001	< .001	0.056	—
	Upper 95% CI	1.000	-0.947	0.031	—
	Lower 95% CI	0.992	-0.999	-0.977	—

Note: * p < .05, ** p < .01, *** p < .001

The NDVI index showed a very strong positive correlation with SAVI ($r = 0.999^{***}$, $p < 0.001$), and a very strong negative correlation with NDWI ($r = -0.992^{***}$, $p < 0.001$). The NDWI index showed a very strong negative correlation with SAVI ($r = -0.994^{***}$, $p < 0.001$), and a strong positive correlation with NBR ($r = 0.844^*$, $p < 0.05$). The NBR index showed a moderate negative correlation with NDVI ($r = -0.779$) and with SAVI ($r = -0.801$) and a positive correlation with NDWI ($r = 0.844^{**}$, $p < 0.01$). These results supported the complementary use of the four indices instead of interpreting them as redundant indicators.

In the context of Petroșani municipality, the relative independence between the spectral indices can be explained by the high heterogeneity of the land cover. Built-up areas, forest and grassy vegetation, open lands, former industrial areas and areas with different humidity, generated distinct spectral responses, so that the variation of one index is not necessarily accompanied by a proportional variation of the others.

3.4. Interdependence between spectral indices

The interdependence between the spectral indices was evaluated by quadratic regression analysis. The NBR index was considered as the dependent variable, eloquently highlighting the structural changes of the land surface in the study area, whose variation was evaluated in relation to the other indices (independent variables) in different combinations.

The resulting model is given by equation (5), with the values of the variables, the coefficients of the equation, and the statistical safety parameters in Table 3. The graphical expression of the function and the distribution of NBR values in relation to the variables considered are given in Figures 4 – 6.

$$NBR = ax^2 + by^2 + cx + dy + exy + f \quad (5)$$

where: NBR – Normalized Burn Ratio; x, and y – variables of equation (5), Table 3; a, b, c, d, e, f – values of coefficients of equation (5), Table 3.

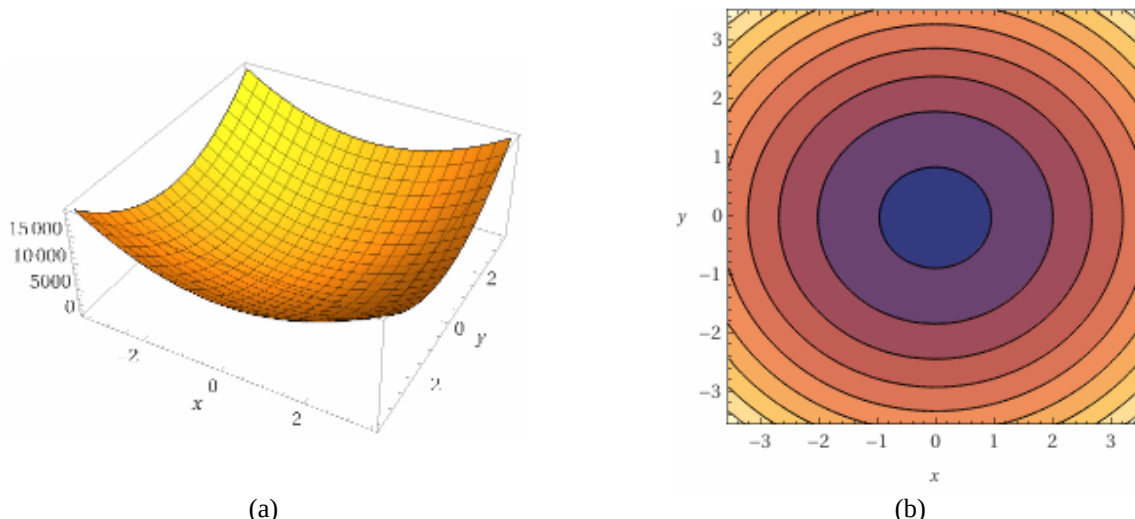


Fig. 4. Graphical distribution of NBR values in relation to NDVI (x – axis) and NDWI (y – axis);
(a) – 3D model; (b) – model in isoquants format

Based on the values of the coefficients of equation (5), and the graphic distribution in Figure 4, the active convergence of the NDVI and NDWI indices in the formation and variation of NBR values was observed for the area evaluated during the study period.

Table 3. Values of the coefficients and statistical safety parameters related to Eq (5)

Index	Variables	Eq (5) coefficients						Statistical safety parameters	
		a	b	c	d	e	f	R ²	p
NBR	x = NDVI, y = NDWI	638.4627	787.3775	26.6200	32.7490	1414.4700	0.8451	0.999	<0.001
	x = NDVI, y = SAVI	-30.5970	14.9835	28.2817	-20.5283	0.0000	0.4204	0.965	<0.001
	x = SAVI, y = NDWI	341.4704	981.4418	28.3469	52.9971	1153.7886	1.4528	0.999	<0.001

In the case of the NDVI and SAVI indices, as variables in equation (5), based on the coefficient values (Table 3) and the graphical distribution (Figure 5), a divergent contribution to the formation and variation of the NBR index values was observed.

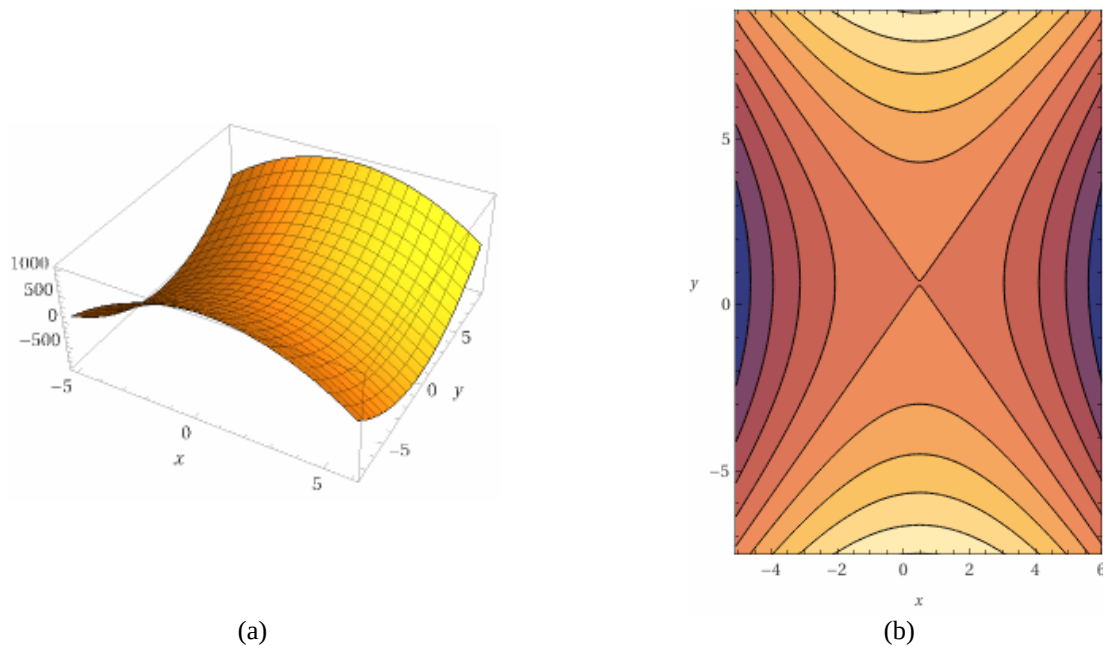


Fig. 5. Graphical distribution of NBR values in relation to NDVI (x – axis) and SAVI (y – axis);
(a) – 3D model; (b) – model in isoquants format

In the case of the SAVI and NDWI indices, as variables in equation (5), based on the coefficient values (Table 3) and the graphical distribution (Figure 6), a convergent contribution to the formation and variation of the NBR index values was observed.

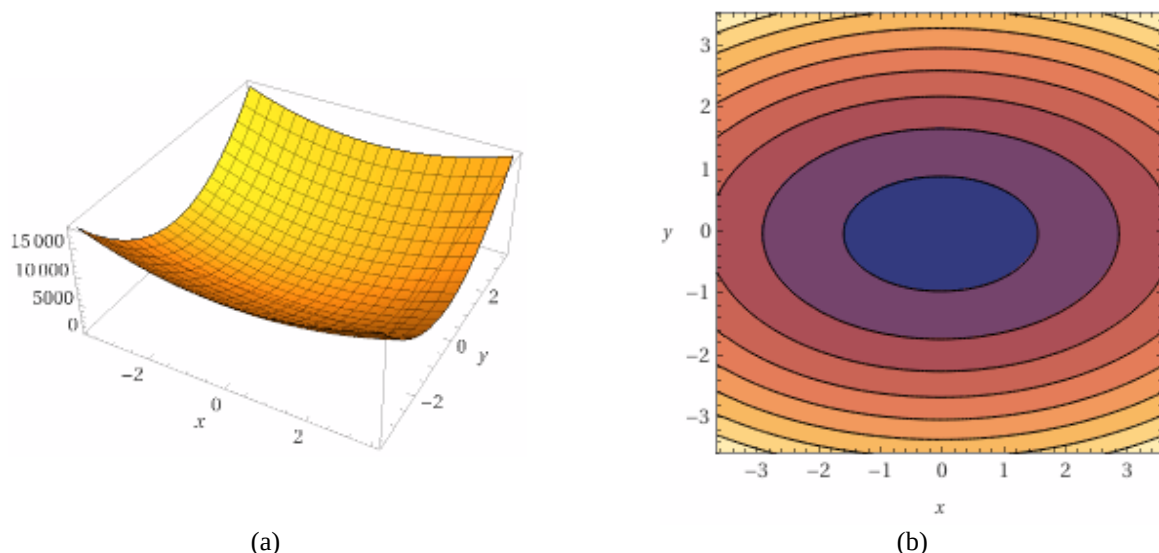


Fig. 6. Graphical distribution of NBR values in relation to SAVI (x – axis) and NDWI (y – axis);
(a) – 3D model; (b) – model in isoquants format

3.5. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) was applied to evaluate multivariate relationships between spectral indices and identify the main directions of variation of the database. This method reduced the dimensionality of the data set and allowed the general structure of the observations to be highlighted by transforming the original variables into a reduced number of orthogonal components, Figure 7. PC1 explained 92.80% of the total variance, and PC2 explained 7.12% of the total variance.

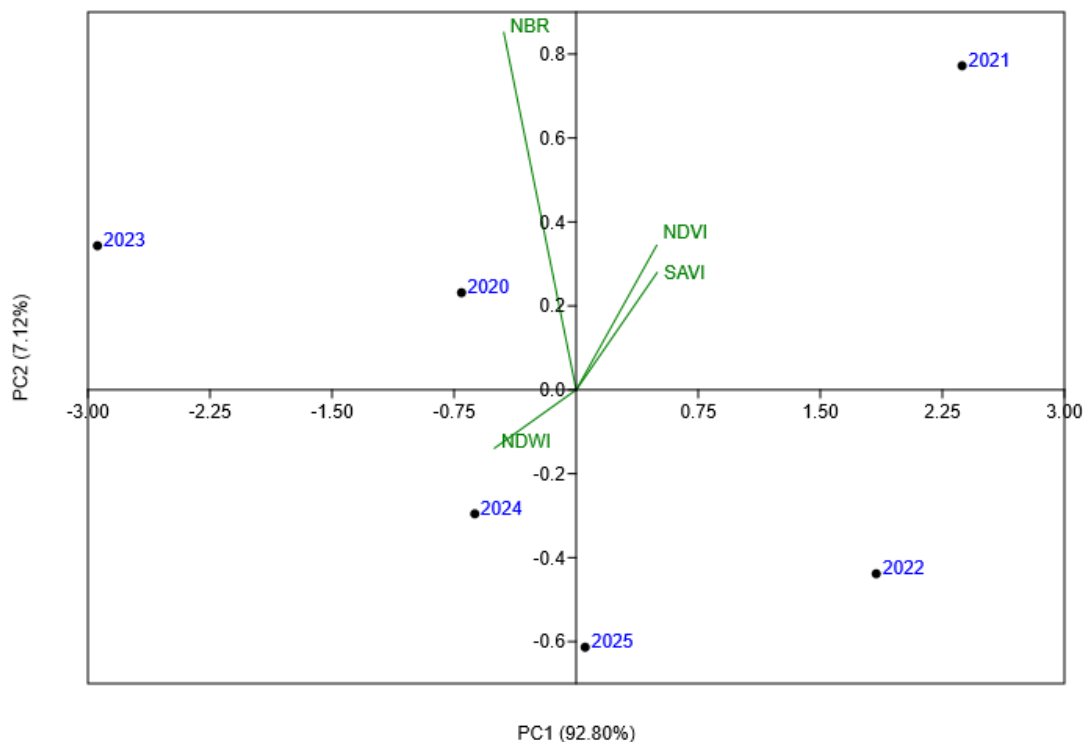


Fig. 7. PCA diagram with the distribution of years in relation to the calculated indices

Multivariate analysis (PCA) generated the years' score values in relation to the principal components, presented in Table 4, and the index loading values in the principal components, presented in Table 5. In PC1, the years 2021 and 2022 were positioned with positive values, and the years 2020, 2023, 2024 and 2025 with negative values. In PC2, the years 2020, 2021, and 2023 were positioned with positive values, and the years 2022, 2024, and 2025 were positioned with negative values.

Table 4. Score values of years in the principal components

	PC 1	PC 2	PC 3	PC 4
2020	-0.7049	0.2315	0.0480	0.0037
2021	2.3708	0.7723	-0.0042	0.0040
2022	1.8436	-0.4383	-0.0140	-0.0157
2023	-2.9416	0.3434	-0.0027	-0.0095
2024	-0.6228	-0.2955	-0.0932	0.0098
2025	0.0548	-0.6134	0.0662	0.0077

Table 5. Index loading values in the principal components

	PC 1	PC 2	PC 3	PC 4
NDVI	0.5096	0.3548	0.2905	0.7281
NDWI	-0.5169	-0.1432	0.8384	0.0971
NBR	-0.4586	0.8778	-0.1262	-0.0565
SAVI	0.5127	0.2881	0.4437	-0.6763

Regarding the loading of indices in the principal components, in PC1 the NDVI and SAVI indices were loaded with positive action, and the NDWI and NBR indices were loaded with negative values. In PC2 the NDVI, NBR and SAVI indices were loaded with positive action, and the NDWI index was loaded with negative action.

3.6. Summary of results

The integrated analysis of the four spectral indices highlighted the existence of moderate temporal variations during the period 2020–2025, without sudden changes at the scale of the entire municipality. The evolution of the average values indicated that the year 2021 was characterized by the highest values of the

vegetation indices (NDVI and SAVI), suggesting favorable conditions for vegetation development. In contrast, the year 2023 was distinguished by the minimum values of these indices, indicating a temporary reduction in vegetation vigor or changes in land cover.

Pearson correlation coefficients revealed linear relationships varying in intensity and direction of manifestation (positive, negative), confirming that each of them described a distinct component of the spectral response of the studied land surface. This relative independence justifies the simultaneous use of NDVI, NDWI, NBR and SAVI indices in studies dedicated to urban environment monitoring.

The PCA analysis confirms the existence of significant spatial variability and highlights the heterogeneous character of Petroșani municipality in terms of surface spectral properties. The diversity of land use types and transformation processes associated with the post-mining environment contribute to the high dispersion of observations and support the need to use multivariate approaches in the interpretation of satellite images.

Overall, the results demonstrate that multitemporal analysis based on Sentinel-2 images and the integrated use of NDVI, NDWI, NBR and SAVI indices, represents an efficient method for monitoring land surface transformations in Petroșani municipality. The applied methodology can be extended to other anthropized areas with an industrial or post-mining profile, contributing to the development of modern environmental monitoring systems and to the substantiation of decisions regarding territorial planning and urban regeneration.

4. Discussions

The multitemporal analysis of the NDVI, NDWI, NBR and SAVI indices highlighted the fact that the changes produced in the Petroșani municipality during the period 2020–2025 were gradual, without sudden changes at the scale of the entire investigated area. This behavior is characteristic of regions in a post-mining transition stage, where landscape transformations are mainly generated by progressive vegetation regeneration, industrial land conversion and land use changes, processes that take place over long time intervals. Recent studies show that Sentinel-2 time series represent one of the most efficient data sources for monitoring these processes due to their high spatial resolution and high acquisition frequency, which allow the identification of evolutionary trends in ecosystems and anthropized landscapes [4], [25].

The similar evolution of the NDVI and SAVI indices confirms that both indicators describe changes in the state of vegetation, but SAVI reduces the influence of soil reflectance and provides more stable results in areas with discontinuous vegetation cover. This aspect is particularly important in the municipality of Petroșani, where the alternation between built-up areas, uncovered lands and vegetation in different stages of development determines important variations in the spectral background. The results obtained are consistent with the observations of Huete (1988) [12], who demonstrated that SAVI improves vegetation estimation in areas where soil influence is significant, as well as with the syntheses made by Xue and Su (2017) [8], who recommend the simultaneous use of multiple vegetation indices to characterize complex ecosystems.

The maximum values of NDVI and SAVI recorded in 2021, followed by the decrease observed in 2023 and the partial recovery in 2024–2025, suggest the existence of a temporal vegetation dynamics influenced by both annual climatic conditions and local land use transformations. Since the present study did not include meteorological variables or information on land cover changes, these results should be interpreted with caution. The literature emphasizes that interannual variations in vegetation indices are simultaneously controlled by precipitation, temperature, phenology and anthropogenic interventions, and the integration of these information leads to more robust interpretations of satellite time series [11], [8].

The NDWI index showed lower variations than the vegetation indices, indicating a relative stability of the general humidity conditions at the scale of the entire municipality. This result is in agreement with studies showing that the NDWI is sensitive to changes in water content and the distribution of aquatic surfaces, but its interpretation must be made together with other spectral indices, since the response is influenced by the type of land cover and local surface characteristics [13], [14].

In the case of the NBR index, the moderate variations observed during the analyzed period suggest the absence of major disturbances in the vegetation structure at the level of the entire municipality. Although NBR was initially developed to assess the severity of forest fires, subsequent research has also demonstrated its usefulness in monitoring vegetation regeneration, land degradation and ecological restoration processes. In this context, the use of NBR together with NDVI, NDWI and SAVI provides a more complete picture of the transformations produced in the post-industrial urban environment.

The variable correlation coefficients identified between spectral indices confirm that they describe different components of the environment and are not redundant. In urban ecosystems characterized by high land cover heterogeneity, it is expected that the relationships between spectral indices will be differentiated compared to homogeneous agricultural or forest ecosystems. For this reason, the literature recommends the use of complementary sets of indicators and multivariate methods for the interpretation of complex territorial processes [8].

The results of the PCA analysis support the same conclusion. The dispersion of observations in the principal component space reflects the high variability of the spectral properties of the investigated surface and confirms the heterogeneous character of the Petroșani municipality. In mining regions undergoing restructuring, this variability is determined by the coexistence of built-up areas, regeneration lands, forests and former industrial sites. Thus, the use of multivariate techniques complements the information provided by individual index analysis and leads to a more realistic interpretation of the transformations produced on the land surface [8], [25].

From a practical point of view, the proposed methodology can be used for periodic monitoring of urban environmental transformations in the Jiu Valley and can be extended to other cities with an industrial or post-mining profile. The integration of Sentinel-2 series with climate data, digital terrain models and classification algorithms based on artificial intelligence can significantly improve the ability to detect and interpret changes on the land surface, contributing to the substantiation of urban regeneration and sustainable development strategies.

5. Conclusions

The multitemporal analysis carried out for the municipality of Petroșani demonstrated the usefulness of integrating the NDVI, NDWI, NBR and SAVI spectral indices for characterizing the dynamics of the land surface in an urban environment with a post-mining specific. The evaluation of the 480,000 spectral values corresponding to the period 2020–2025 highlighted clear interannual variations, but generally gradual, indicating a complex evolution of the vegetation, humidity conditions and spectral characteristics of the analyzed surfaces.

The NDVI and SAVI indices showed a very close temporal evolution and an extremely strong positive correlation ($r = 0.999$, $p < 0.001$), confirming their common response to vegetation dynamics. Their highest average values were recorded in 2021, while 2023 stood out for its lowest values and the highest spatial variability. This particularity indicates the year 2023 as the moment with the most pronounced spectral differentiation in the analyzed series. At the same time, the relationships between NDWI, NBR and vegetation indices demonstrated the complementary nature of the information provided by the four indicators.

Regression models revealed very strong statistical relationships between NBR and the NDVI–NDWI and SAVI–NDWI combinations ($R^2 = 0.999$, $p < 0.001$), indicating the existence of important interdependencies between vegetation response, moisture conditions and surface structural characteristics. PCA analysis efficiently synthesized these relationships, with the first two principal components explaining 99.92% of the total variation and distinctly highlighting the position of the analyzed years.

The results confirm that the use of a single spectral index is not sufficient for the complete description of a heterogeneous urban territory, especially in the case of a post-mining area like Petroșani. The integration of NDVI, NDWI, NBR and SAVI provides a more robust interpretation and allows the simultaneous highlighting of several components of the surface spectral response.

The proposed methodology is reproducible and can be used for periodic monitoring of Petroșani municipality, as well as other industrial and post-mining territories. Future integration of Sentinel-2 time series with meteorological data, land use change information and automatic classification methods would allow for a more precise differentiation of climatic effects from those caused by anthropogenic transformations and could constitute a useful tool for monitoring ecological regeneration and for sustainable territorial planning.

Acknowledgements

The authors thank to the GEOMATICS Research Laboratory, University of Life Sciences "King Michael I" from Timisoara, for the facility of the software use for this study.

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