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TEMPORAL VARIABILITY EVALUATION OF A MINE TAILINGS DUMP FROM SURFACE COAL MINING THROUGH REMOTE SENSING

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Abstract: *Through the remote sensing technique (Landsat), the study analyzed the temporal variability on the mine tailings dump located on Valea Motrului, Șteic – Valea Perilor, Gorj County, Romania. Satellite images were taken in ten years from 1988 – 2016. The NDVI and NBR indices were calculated in the ten years. An increasing, statistically significant trend was recorded in the data series for the NDVI index (S = 116115, Z = 18,394, p = 1.4786E-75), and a decreasing, statistically significant trend in the data series for the NBR index (S = -16043, Z = -2.5412, p = 0.011047). Statistically significant differences were recorded for the NDVI and NBR indices between most of the years considered in the study. In the multivariate analysis (PCA), independent positioning of the years 1988 and 1999 (primary area of the dump) and the years 2002, 2007 and 2014 was recorded, with reduced values of NDVI and NBR indices. The cluster analysis facilitated the association of years in clusters based on similarity, in relation to the NDVI and NBR indices values. The year 2011 was highlighted with the highest level for the NDVI and NBR indices. High level of similarity was recorded between 2010 and 2016, SDI = 0.0314.*
Keywords: *coal mining; miner tailings; natural restoration; remote sensing; temporal variability*

1. Introduction

Coal represented a widespread resource worldwide, a common and accessible resource for industries with high-energy consumption and for economic development at the global level [1, 2, 3].

Surface mining operations have variably influenced natural ecosystems [4]. Quality parameters were recorded in watercourses affected by surface coal mining in relation to the size of the coal mining, with its share in the hydrographic basin, with a negative impact on water quality indices, and on some intolerant species [4].

Negative effects on the health of workers (miners, operators) were recorded, generated by surface coal mining, through exposure to fine dust of coal dust and other minerals from the area of excavation and operation of excavated materials [5].

Differentiated variability in areas with surface carboniferous exploitation was recorded in relation to the categories of land use, with a tendency to increase empty and cultivated lands, a decreasing tendency of lands with natural vegetation and water bodies, and as a whole the reduction of ecosystem services [2].

In the specific conditions of Valea Jiului, the waste resulting from mining operations was transported and stored in different locations in the form of tailings dumps, with an impact on ecosystems, the environment and human communities [6].

Coal surface mining has generated negative effects on ecosystems and the environment, variable in relation to geomorphological and climatic conditions, with the specifics of land use and coverage, but also with the management of coal holdings [3, 7].

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Coal mining in surface mining was analyzed in relation to carbon storage [8]. In the interval 2002 – 2023, a downward trend in the carbon storage rate was recorded in the studied area, and the carbon sequestration capacity in the ecosystem affected by coal surface mining was decreased during the study period [8].

In order to evaluate the quality of the environment affected by the exploitation of coal on the surface, an index (SurMEI) with certain advantages over existing ecological indices, with automatic realization in Google Earth Engine, based on four work stages [7].

Geospatial data (Landsat, Google Earth Engine) were used to evaluate the environmental impact of surface coal holdings [9]. The historical production of coal with an active mining area was correlatively analyzed, and the recorded data presented interest and importance for economic, health and environmental studies [9].

The remote sensing technique (thermal remote sensing, microwaves) was used to evaluate the impact of coal mining combined with forest fires on the phenomenon of land subsidence, with strongly negative effects of an ecological, economic, and socio-human nature [10].

Classification and land use studies, to highlight the areas affected by coal mines, were done through remote sensing techniques (Landsat), algorithms and neural networks, with a classification accuracy of 95 - 98% of the affected surfaces [1].

The critical relationship between surface mining of coal and surface coverage and land use was evaluated, based on satellite images, in the form of trends and correlations, through appropriate statistical tools [11].

Remote sensing provides useful tools for the study and monitoring of surface mining operations and adjacent affected ecosystems [12]. Areas affected by the surface exploitation of coal were studied by remote sensing (ENVI) and the drilling of appropriate algorithms (random forest algorithm) over a period of 20 years (2000 – 2020) in order to evaluate land use, vegetation restoration and the value ecosystem services [2]. The remote sensing technique was used to monitor the surfaces affected by mining and the spatial and temporal evolution of the areas affected by the subsidence phenomenon, associated with coal mining [13].

High-resolution satellite images and specific indices have been used to identify surface coal mining areas and coal limits [3].

Remote sensing was used to monitor mining lands and areas affected by mining operations [14]. Techniques based on remote sensing associated with cloud computing were used to evaluate spatial and temporal dynamics in the recovery of vegetation on the area of a surface coal mine [15]. Vegetation installation and growth curves were recorded on land with coal mines on the surface, and the result was a time interval between 4.64 years and 6.50 years for land stabilization [15].

Imaging analysis (satellite images, UAV, Interferometric Radar) were used to study and evaluate the temporal variability of some areas with carboniferous exploitation [16].

This study used the technique based on remote sensing, Landsat, to characterize in dynamics the mine tailings dump in the area of Șteic – Valea Perilor, Gorj County, Romania, resulting from surface coal mining.

2. Materials and method

The study objective was represented by the mine tailings dump located in Valea Motrului, Șteic – Valea Perilor localities, Gorj County, Romania (Figure 1). An area of 5.72 ha was considered on the tailings dump as a study module.

The Landsat satellite system was used for the acquisition of satellite images. Satellite scenes were downloaded from the US Geological Survey [17] portal. They were considered ten years (1988, 1999, 2002, 2003, 2007, 2010, 2011, 2014, 2015, and 2016), during 1988 – 2016.

Based on spectral information, from satellite images, the NDVI index was calculated [18], Equation (1), and the NBR index [19], Equation (2).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{1}$$

$$\mathrm{NBR} = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}} \tag{2}$$

The NDVI identifier was used, along with other facilities specific to remote sensing, for the dynamic analysis of the surfaces affected by coal mining on the surface [12].

The classification of the images led to the identification of seven classes of coverage of the studied land, and showed the degree of disturbance of the landscape and the ecosystem in the coal mining area [12].

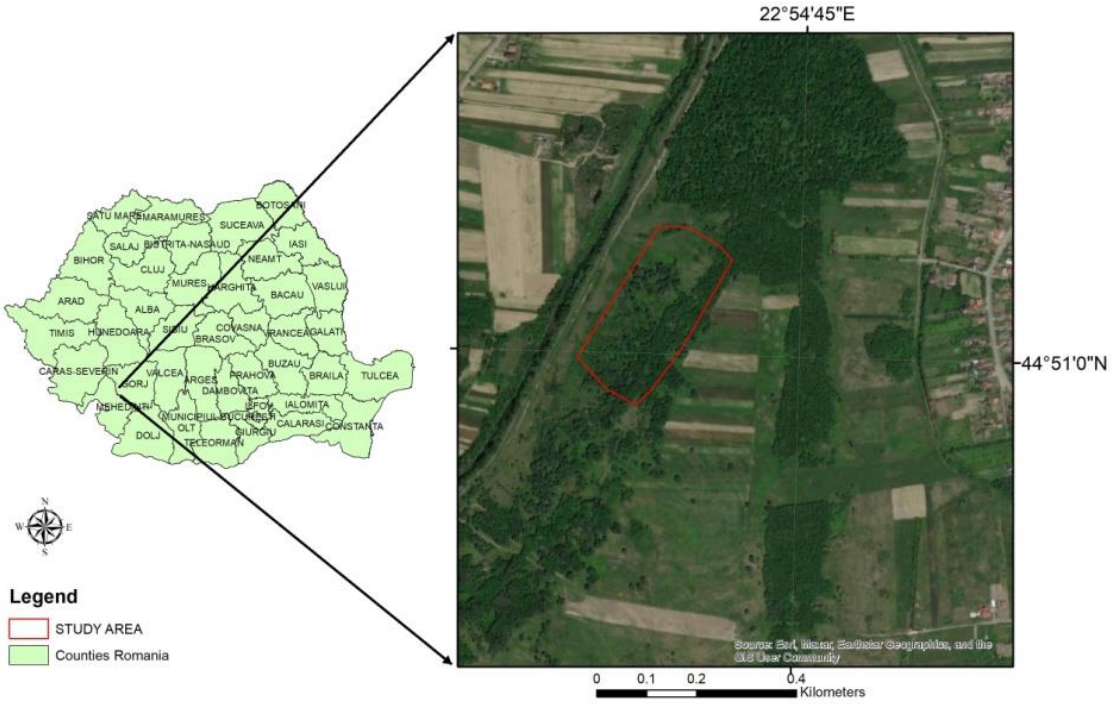

Fig.1. Study location, Steic – Valea Perilor, Gorj County, Romania

Based on the NDVI index, it was appreciated that the recovered areas presented higher NDVI values compared to the working areas [12].

The data of the NDVI and NBR indices were analyzed for general statistical characterization (Descriptive Statistical Analysis), for the evaluation of the differences between the data series by study years, within each index (t test, Wilcoxon test, Dunn's Post Hoc test). For mathematical and statistical analysis, the PAST v4.17 software was used [20].

3. Results and discussion

The values of the NDVI and NBR indices were determined in ten years, for the period 1988 – 2016, and the results of the descriptive statistical analysis for the characterization of the series of data are presented in Table 1 for the NDVI index, respectively in Table 2 for the NBR index.

The data series, considered during the entire study period, presented statistical safety, with r = 0.962 in the case of NDVI, and r = 0.919 in the case of NBR. The graphic representation of the studied area, based on the NDVI and NBR indices, is given in Figure 2, respectively in Figure 3.

Table 1. Statistic parameter values for NDVI data series

Statistical parameters	NDVI-1988	NDVI-1999	NDVI-2002	NDVI-2003	NDVI-2007	NDVI-2010	NDVI-2011	NDVI-2014	NDVI-2015	NDVI-2016
N	71	71	71	71	71	71	71	71	71	71
Min	-0.0526	0.0408	0.0588	-0.1099	0.0000	0.1194	0.1545	0.0909	0.1536	0.1530
Max	0.1613	0.1579	0.2364	0.4269	0.6054	0.6516	0.6643	0.2302	0.5482	0.6175
Sum	-0.2643	7.4295	10,5932	21.7111	9.4914	33,6715	37,5584	10,1749	30.2118	33,8292
Mean	-0.0037	0.1046	0.1492	0.3058	0.1337	0.4742	0.5290	0.1433	0.4255	0.4765
Std. error	0.0054	0.0033	0.0037	0.0148	0.0200	0.0102	0.0120	0.0042	0.0122	0.0123
Variance	0.0021	0.0008	0.0009	0.0155	0.0284	0.0074	0.0102	0.0013	0.0106	0.0108
Stand. dev	0.0458	0.0274	0.0308	0.1247	0.1686	0.0857	0.1010	0.0355	0.1031	0.1039
Median	-0.0189	0.1079	0.1481	0.3455	0.0435	0.4809	0.5591	0.1486	0.4571	0.5090
25 prcntil	-0.0345	0.0909	0.1321	0.2865	0.0213	0.4355	0.5041	0.1092	0.3775	0.4448
75 prcntil	0.0000	0.1254	0.1636	0.3855	0.1563	0.5194	0.6029	0.1674	0.4923	0.5503
Skewness	1,8093	-0.7138	0.1204	-1.7706	1.4158	-1.1223	-1.7092	0.3405	-1.2508	-1.1845
Kurtosis	3.2950	0.1549	1,4070	2.5024	0.7188	3.4659	3.0149	-0.6293	0.6538	0.6449

Table 2. Statistic parameter values for NBR data series

Statistical parameters	NBR-1988	NBR-1999	NBR-2002	NBR-2003	NBR-2007	NBR-2010	NBR-2011	NBR-2014	NBR-2015	NBR-2016
N	71	71	71	71	71	71	71	71	71	71
Min	-0.0465	0.3363	0.3810	-0.0795	-0.1166	0.1194	0.0923	-0.1034	0.0185	0.1201
Max	0.5775	0.4667	0.5814	0.4970	0.5455	0.6515	0.7000	-0.0248	0.5237	0.5764
Sum	31,1827	28,8163	34,2352	25.1347	1.3031	33,6116	36,1382	-3.7264	27.2597	31,3848
Mean	0.4392	0.4059	0.4822	0.3540	0.0184	0.4734	0.5090	-0.0525	0.3839	0.4420
Std. error	0.0196	0.0037	0.0054	0.0164	0.0192	0.0119	0.0174	0.0019	0.0152	0.0138
Variance	0.0274	0.0010	0.0021	0.0192	0.0263	0.0100	0.0215	0.0003	0.0164	0.0134
Stand. dev	0.1655	0.0313	0.0454	0.1385	0.1622	0.1001	0.1465	0.0159	0.1282	0.1159
Median	0.5152	0.4140	0.4762	0.4024	-0.0588	0.4880	0.5659	-0.0501	0.4336	0.4844
25 prcntil	0.4054	0.3913	0.4500	0.3210	-0.0769	0.4355	0.3985	-0.0598	0.3414	0.3921
75 prcntil	0.5429	0.4273	0.5122	0.4437	0.0137	0.5303	0.6154	-0.0430	0.4681	0.5231
Skewness	-1.6546	-0.7370	-0.2392	-1.7034	1,7242	-1.3456	-0.9103	-1.0750	-1.3134	-1.3280
Kurtosis	1,6699	-0.2114	-0.4548	2.0915	1,8623	2.6957	-0.0983	1,5367	0.7695	0.9238

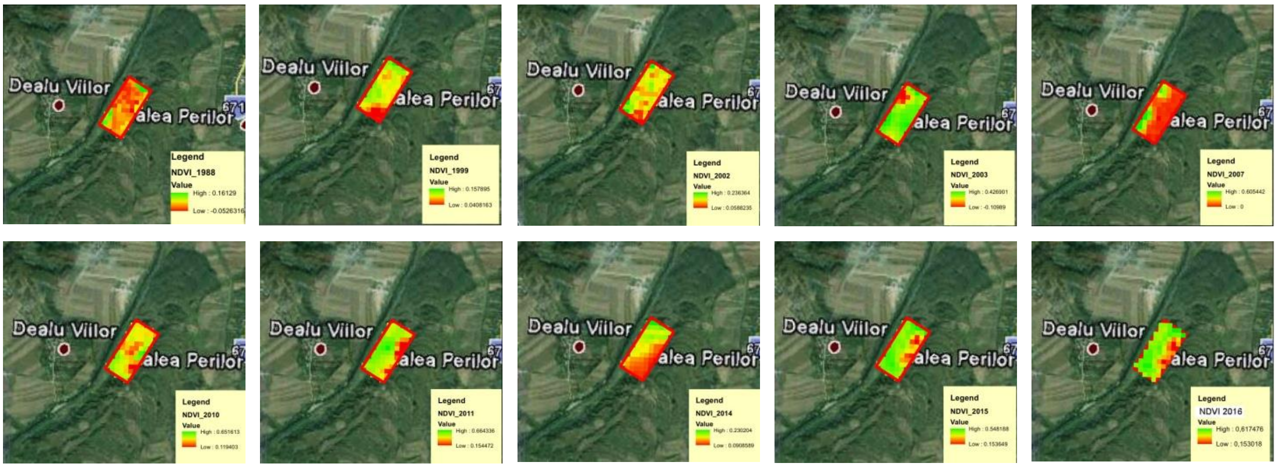

Fig. 2. Representation of the NDVI index in the map formed during the study period, Steic – Valea perilor miner tailings dump

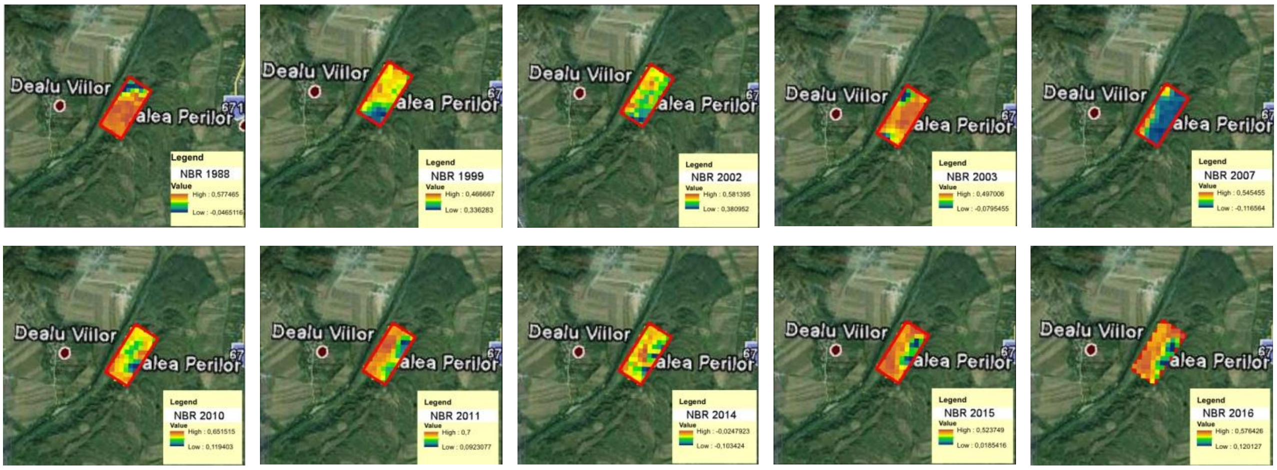

Fig. 3. Representation of the NBR index in the map formed during the study period, Steic – Valea Perilor miner tailings dump

The statistical analysis (Mann-Kendal test) confirmed an increasing, statistically significant trend in the data series for the NDVI index (S = 116115, Z = 18,394, p = 1.4786E-75), and a decreasing, statistically significant trend in the series of data for the NBR index (S = -16043, Z = -2.5412, p = 0.011047).

Based on the results of the Mann-Kendal test, the comparative analysis of the index data was made in the ten years considered during the study period. Thus, the Several-sample test (ANOVA, Kruskal-Wallis) led to the results in table 3. Both in the case of the NDVI index and in the case of the NBR index (Table 3), the safety of the test results was confirmed (p<0.001).

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Table 3. Several-sample tests results

Statistical parameters	Sum of square	df	Mean square	F	p (same)
			NDVI		
Between groups:	23.3049	9	2.5894	294.3	3.88E-231
Within groups:	6.1600	700	0.0088		
Total:	29.4649	709	1.00E-05		
Components of variance (only for random effects):					
Var(group):	0.0363	Var(error):	0.0088	ICC:	0.8051
omega2:	0.7880				
Levene´s test for homogeneity of variance, from means	p (same):	2.77E-39			
Levene´s test, from medians	p (same):	6.65E-16			
Welch F test in the case of unequal variants:	F=472.3, df=281.1, p=4.714E-164				
Bayes factor:	1.566E227 (decisive evidence for unequal means)				
			NBR		
Between groups:	24.8840	9	2.7649	201.1	1.85E-187
Within groups:	9.6251	700	0.0138		
Total:	34.5091	709	1.00E-05		
Components of variance (only for random effects):					
Var(group):	0.0387	Var(error):	0.0138	ICC:	0.7381
omega2:	0.7172				
Levene´s test for homogeneity of variance, from means	p (same):	1.29E-35			
Levene´s test, from medians	p (same):	7.11E-14			
Welch F test in the case of unequal variants:	F=2335, df=272, p=7.732E-252				
Bayes factor:	4.112E183 (decisive evidence for unequal means)				

Based on the statistical safety confirmed by the previous tests, the Dunn test was applied post hoc to evaluate the safety of the differences between the index values in the years of study. In the case of the NDVI index, Dunn's post hoc test led to the results in Table 4.

Table 4. Dunn's post hoc test results for NDVI indices

	NDVI-1988	NDVI-1999	NDVI-2002	NDVI-2003	NDVI-2007	NDVI-2010	NDVI-2011	NDVI-2014	NDVI-2015	NDVI-2016
NDVI-1988		0.00021	4.09E-10	3.18E-21	2.17E-05	3.88E-46	5.07E-59	4.85E-09	2.55E-38	3.97E-48
NDVI-1999	0.00021		0.01112	9.20E-09	0.59270	5.17E-26	8.68E-36	0.03230	2.65E-20	1.70E-27
NDVI-2002	4.09E-10	0.01112		0.00135	0.04507	1.15E-15	2.55E-23	0.69040	2.18E-11	8.39E-17
NDVI-2003	3.18E-21	9.20E-09	0.00135		1.89E-07	1.56E-06	1.55E-11	0.00031	0.00049	3.06E-07
NDVI-2007	2.17E-05	0.59270	0.04507	1.89E-07		1.33E-23	6.26E-33	0.10830	3.40E-18	5.17E-25
NDVI-2010	3.88E-46	5.17E-26	1.15E-15	1.56E-06	1.33E-23		0.05243	4.18E-17	0.18810	0.75180
NDVI-2011	5.07E-59	8.68E-36	2.55E-23	1.55E-11	6.26E-33	0.05243		4.30E-25	0.00113	0.104 50
NDVI-2014	4.85E-09	0.03230	0.69040	0.00031	0.10830	4.18E-17	4.30E-25		1.33E-12	2.69E-18
NDVI-2015	2.55E-38	2.65E-20	2.18E-11	0.00049	3.40E-18	0.18810	0.001131	1.33E-12		0.10260
NDVI-2016	3.97E-48	1.70E-27	8.39E-17	3.06E-07	5.17E-25	0.75180	0.104 50	2.69E-18	0.10260	

Notes: the values in yellow fields do not present statistical safety.

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The values presented in Table 4 confirmed the significant difference in the data series between the study years (marked in green in Table 4), for the NDVI index, with a few exceptions (marked in yellow in Table 4).

In the case of the NBR index, Dunn's post hoc test led to the results in Table 5. The values presented in table 5 confirmed the significant difference in the data series between most years of study, for the NBR index (marked in green in Table 5). Results without statistical certainty were also recorded in several cases (marked in yellow in Table 5).

Table 5. Dunn's post hoc test results for NBR indices

	NBR-1988	NBR-1999	NBR-2002	NBR-2003	NBR-2007	NBR-2010	NBR-2011	NBR-2014	NBR-2015	NBR-2016
NBR-1988		4.09E-06	0.75300	6.82E-07	3.26E-28	0.85300	0.13920	3.13E-31	0.00033	0.387 40
NBR-1999	4.09E-06		8.60E-07	0.71910	1.48E-10	1.65E-06	1.16E-09	2.27E-12	0.308 30	0.00018
NBR-2002	0.75300	8.60E-07		1.29E-07	9.44E-30	0.897 10	0.24430	7.49E-33	9.52E-05	0.23840
NBR-2003	6.82E-07	0.71910	1.29E-07		1.47E-09	2.58E-07	1.16E-10	2.79E-11	0.16810	4.10E-05
NBR-2007	3.26E-28	1.48E-10	9.44E-30	1.47E-09		4.10E-29	8.14E-36	0.54240	1.12E-13	3.32E-24
NBR-2010	0.85300	1.65E-06	0.897 10	2.58E-07	4.10E-29		0.19580	3.52E-32	0.00016	0.293 90
NBR-2011	0.13920	1.16E-09	0.24430	1.16E-10	8.14E-36	0.19580		3.19E-39	4.05E-07	0.01912
NBR-2014	3.13E-31	2.27E-12	7.49E-33	2.79E-11	0.54240	3.52E-32	3.19E-39		9.31E-16	5.37E-27
NBR-2015	0.00033	0.308 30	9.52E-05	0.16810	1.12E-13	0.00016	4.05E-07	9.31E-16		0.00646
NBR-2016	0.387 40	0.00018	0.23840	4.10E-05	3.32E-24	0.293 90	0.01912	5.37E-27	0.00646	

Notes: the values in yellow fields do not present statistical safety.

The multivariate analysis led to the PCA diagram (Figure 4), in which the years considered in the study were positioned differently in relation to the calculated NDVI and NBR indices (PC1 = 70.278% of variance; PC2 = 29.722% of variance). Independent position was registered for 1988 and 1999, with values low for NDVI.

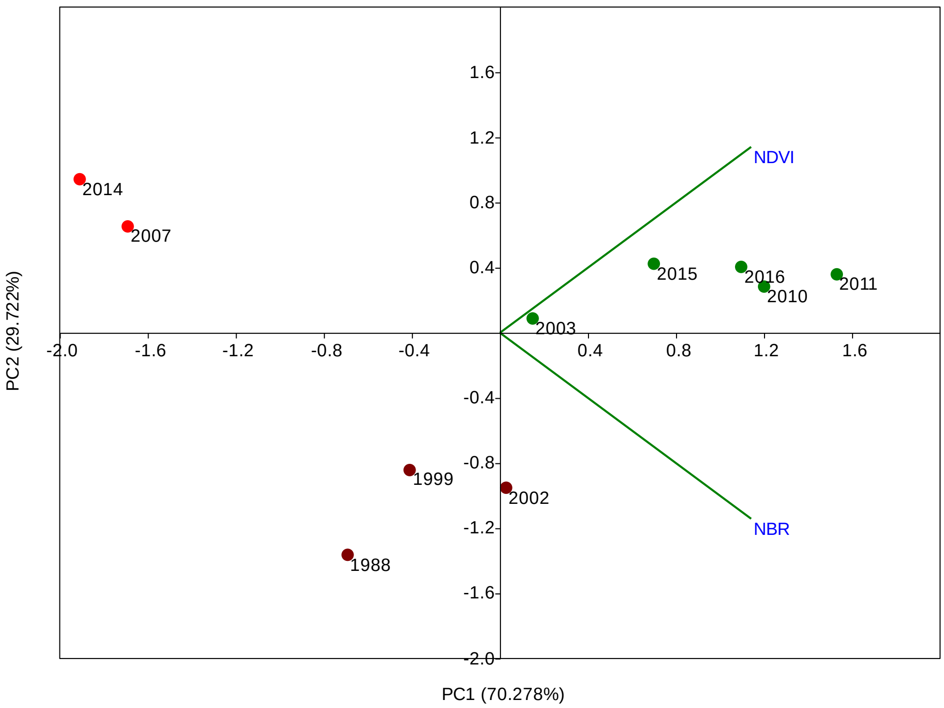

Fig. 4. PCA dendrogram with the distribution of years of study in relation to the NDVI and NBR indices

This was the beginning period of the construction of the tailings dump, when the vegetation was not yet installed on the surface of the dump. Also, an independent position was registered for 2002, 2007 and 2014, years with poor climatic conditions, conditions that affected the vegetation installed on the surface of the mine tailings dump. Instead, years were identified that were associated with calculated indices, with high values for NDBI (2003, 2010, 2011, 2015 and 2016).

The cluster analysis generated the cluster dendrogram (Figure 5) in which the years considered in the study were associated based on similarity in relation to the NDVI and NBR values (Coph.corr). = 0.905).

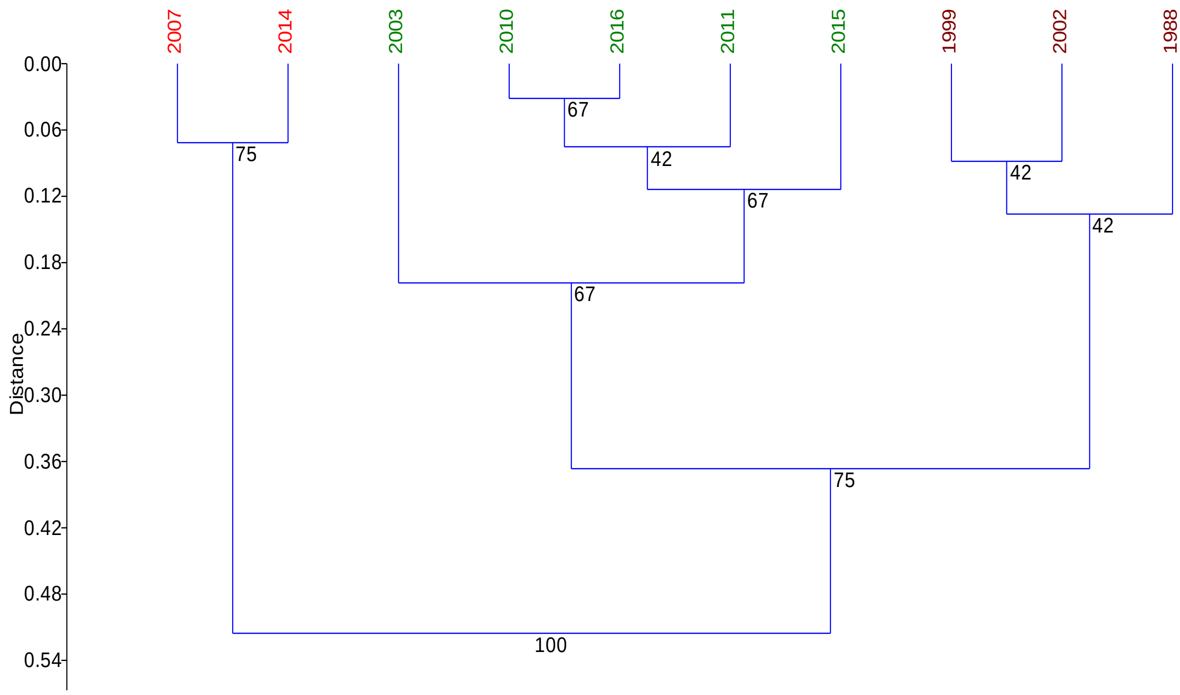

Fig. 5. Cluster dendrogram with the association of years in relation to NDVI and NBR indices

In the cluster to the left of the dendrogram, years were associated with climatic deviations (2007, 2014). In the cluster to the right of the dendrogram, three years from the beginning of the tailings dump were associated, with low values of NDVI and NBR indices, as a result of a reduced level of vegetation on the tailings dump.

In the central cluster, the years with high NDVI values of the NBR were associated, with the highest level of the NDVI index in 2011. High level of similarity was recorded between 2010 and 2016 (SDI = 0.0314).

The SDI (Similarity and Distance Indices) values resulting from the analysis are presented in matrix Table 6.

Table 6. SDI values between years, in relation to NDVI and NBR values

	1988	1999	2002	2003	2007	2010	2011	2014	2015	2016
1988		0.1134	0.1589	0.3210	0.4427	0.4792	0.5373	0.5132	0.4328	0.4802
1999	0.1134		0.0884	0.2077	0.3886	0.3757	0.4367	0.4600	0.3216	0.3736
2002	0.1589	0.0884		0.2024	0.4641	0.3252	0.3807	0.5347	0.2933	0.3297
2003	0.3210	0.2077	0.2024		0.3772	0.2065	0.2717	0.4378	0.1234	0.1920
2007	0.4427	0.3886	0.4641	0.3772		0.5684	0.6301	0.0715	0.4678	0.5450
2010	0.4792	0.3757	0.3252	0.2065	0.5684		0.0653	0.6214	0.1019	0.0314
2011	0.5373	0.4367	0.3807	0.2717	0.6301	0.0653		0.6812	0.1623	0.0851
2014	0.5132	0.4600	0.5347	0.4378	0.0715	0.6214	0.6812		0.5197	0.5963
2015	0.4328	0.3216	0.2933	0.1234	0.4678	0.1019	0.1623	0.5197		0.0773
2016	0.4802	0.3736	0.3297	0.1920	0.5450	0.0314	0.0851	0.5963	0.0773	

Monitoring the areas affected by coal mining is important to record changes in ecosystems, soil, vegetation, and an adequate management of the affected areas [21], [22], [23], [24].

The period 1988 – 2016 was currently considered a study for the evaluation of spatial variability in the case of the mine tailings dump from the surface exploitation of coal in the area of Valea Motrului. The ten years analyzed, within the study interval, presented variable values for the NDVI and NBR indices calculated based on satellite images, Landsat.

Comparative analyzes were made between surface active mining areas and waste storage areas, and the results showed strong correlation between “mineral extraction sites” with “non-irrigated arable land” and ”transition forests” [11]. The waste storage sites from the surface mines had a positive impact on the forest areas, which registered an expansion of approx. three times [11].

The NDVI identifier was used, along with other facilities specific to remote sensing, for the dynamic analysis of the surfaces affected by coal mining on the surface [12]. The classification of the images led to the identification of seven classes of coverage of the studied land, and showed the degree of disturbance of the landscape and the ecosystem in the coal mining area [12]. Based on the NDVI index, it was appreciated that the recovered areas presented higher NDVI values compared to the working areas [12].

The NDVI index registered an increasing trend for the study period, a fact that showed the development of natural vegetation in the study area on the surface of the dump.

The prevention of damage and the restoration of land surfaces affected by coal mines on the surface were studied in relation to the idea of mine governance [25].

Mining lands were studied and analyzed from the perspective of the opportunity for investments in order to capitalize on the potential of zonal development [26].

From the perspective of the energy transition, the closure of coal mines was forecast in the next period, with economic and social implications [27]. According to the legislation in force, and in accordance with the principles of the circular economy, the closure of mines involves certain stages that capitalize on certain categories of materials and reduce the economic, social and environmental impact [27].

The recovery and valorization of tailings dumps can be done by planting trees and shrubs, to consolidate and stabilize the material deposited in the dumps, especially the slopes, as well as by sowing grass species in order to cover the dump, retain water and support microbiological activity in the upper layer, and pedogenetic processes [28, 29].

Mining waste dumps can also represent areas for grapevine plantations, especially local germplasm, which makes good use of areas with coarse, sandy substrate, and the grapevine takes up mineral elements from the substrate for plant nutrition, canes ripening, and grape quality [30, 31].

The NDVI and NBR indices reflected the state of the vegetation naturally installed on the mine tailings dump, with variation over time in the values of the indices, reflected by the state of the vegetable carpet.

4. Conclusions

The remote sensing technique, Landsat, facilitated the dynamic evaluation of the mine tailings dump, generated by surface carboniferous exploitation, through the values of the NDVI and NBR indices calculated between 1988 and 2016.

The increasing trend was recorded in the series of NDVI values under statistical safety conditions ($p<0.001$), a pomp that indicated the positive dynamics of the vegetation installed on the tailings dump, in the study area. The comparative analysis showed the differences between the years and confirmed the level of statistical safety.

The multivariate analysis identified five years (2003, 2010, 2011, 2015, and 2016) that were associated with the NDVI and NBR indices, as biplot in the PCA diagram. The cluster analysis grouped the respective years in the central cluster of the dendrogram, highlighting the year 2011 in which the highest value for the NDVI and NBR indices was recorded.

In general, the years with a high level of similarity in the multivariate analysis (PCA, CA) did not present statistical certainty regarding the differences between the NDVI and NBR values.

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