

Characterization of the Jiu Valley Mining Basin, Romania, using Remote Sensing Techniques in Relation to Land Use Categories and Relief Parameters

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Abstract. The study aimed to analyze and characterize the mining basin of the Jiu Valley, Romania, through remote sensing techniques. The land use categories and morphological parameters of the area, represented by DEM and SLOPE, were considered. Twenty-one land use categories were identified, with areas ranging from 27.83 ha (Water bodies, 512 Code) to 33543 ha (Broad-leaved forest, 311 Code). Five land use categories were included in the lower quartile (63.055 quartile threshold), with a total area of 204.71 ha. Eleven land use categories were included in the middle quartile (63.055 – 4650.855, interquartile range), with a total area of 18651.42 ha. In the upper quartile (4650.855, quartile threshold) five categories were included, with a total area of 76501.70 ha. In the agricultural domain, five categories (211, 231, 242, 243, and 321 Codes) were found with a total area of 23093.18 ha, which represents 24.22% of the total area of the study area. In the case of DEM parameters, 21 classes (DC1 to DC21) were generated, with values ranging from 435.59 ha (DC21) to 7080.98 ha (DC5). The decreasing trend of DEM values was confirmed (Mann-Kendall test), and the linear model described the decreasing trend of DEM values, with slope = -326.8, in conditions of statistical safety ($p < 0.001$). Within the SLOPE parameter, 21 classes (SC1 to SC21) were generated with values ranging from 17.22 ha (SC21) to 9960.56 ha (SC8). The Mann-Kendall test confirmed the decreasing trend of the data series, and a linear model described the data layout, with slope = -405.96, in statistical safety conditions ($p < 0.001$). Cluster analysis grouped the DEM classes (Coph.corr. = 0.833), and the SLOPE classes (Coph.corr. = 0.804) based on similarity into clusters with several subclusters.

Keywords: clustering, DEM, land use categories, monoindustrial area, remote sensing, SLOPE

INTRODUCTION

The evaluation and monitoring of natural resources based on remote sensing presents multiple advantages through accessibility to areas of interest, scale of coverage, image databases, high image resolution, details provided by images, spatial and temporal dynamics of aspects on the earth's surface (Panda et al., 2024; Sharma et al., 2024; Admas et al., 2025; Ramachandra and Negi, 2025).

Within terrestrial areas, coal resources are of high importance from an ecological, economic and social perspective (Vielvoye, 1976; Wu, 2019; Li et al., 2022).

The mono-industrial development of coal (mining) areas presented certain particularities, with advantages and disadvantages in the medium and long term, in relation to the respective industry (Makarov and Perov, 2022; Missbach et al., 2024; Greenberg et al., 2025).

Coal areas were studied in relation to the potential presented for other economic sectors (e.g. agriculture, agroforestry, tourism, energy, etc.) from the perspective of the sustainability of the respective areas (Gao et al., 2024; Leuner and Hirschl, 2024; Pous de la Flor, 2024; Sui et al., 2025).

Coal mining areas were studied and analyzed in terms of the degree of vegetation coverage, land use categories, and the remote sensing technique facilitated the obtaining of information in spatial and temporal dynamics (Karan and Samadder, 2018; Zhang et al., 2022; Hong et al., 2023; Xu et al., 2024). Mining areas were analyzed based on DEM (Digital Elevation Model) in order to obtain information on changing landscape topography (Jeiner Yobany Buitrago and Luis Joel Martínez, 2016; Jaskulski and Nowak, 2019).

The slope parameter has been used to evaluate the deformations of land slopes in coal mining operations in mountainous areas (Tian et al., 2025), in mining areas from which the ore was extracted, partially or fully (Han et al., 2022), or in other mining areas with a certain specificity (Li et al., 2024). Various models and simulations have analyzed slopes to evaluate characterization and stability parameters of mines and mining areas (Zhou et al., 2024). Slope and aspect parameters have also been used to characterize the dynamics and geomorphology of mining waste heaps (Hyssen and Vermeersch, 2010) and to predict the stability of heaps in coal mines (Sahoo et al., 2025).

This study used remote sensing techniques to characterize the Jiu Valley mining area, Romania, in terms of land use categories and land morphology based on DEM and SLOPE parameters.

MATERIAL AND METHODS

The geomorphological characterization of mining areas where subsidence occurs is essentially based on the analysis of digital terrain models (Digital Elevation Model – DEM) and the parameters derived from them, such as slope (Slope) and slope exposure (Aspect). These parameters allow highlighting topographic changes, assessing terrain instability and identifying the relationships between microrelief and geomechanical processes determined by underground mining.

The DEM is the primary source of altimetry data used in the analysis of the behavior of the surface affected by mining activity. It can detect and quantify surface changes associated with subsidence, by comparing elevation models from different periods (multi-temporal analyses). Therefore, the DEM is the fundamental element in mining subsidence monitoring studies and in the assessment of associated risks (Burrough et al., 2015).

The slope of the terrain, calculated as the first-order derivative of the DEM, is a critical indicator of geomorphological stability. In a mining context, slope contributes to the interpretation of how subsurface deformations are transmitted to the surface. Areas with low slopes tend to accumulate uniform deformations and exhibit diffuse subsidence, while areas with steep slopes are prone to ruptures, cracks and secondary landslides (Evans, 1980). Slope analysis is essential for: identifying sectors with high potential for instability; assessing the impact on infrastructure and surface constructions; calibrating geomechanical models that describe the behavior of rocks and soils subject to subsidence.

The study characterized the area in the Jiu Valley mining basin, Romania, Figure 1, in relation to land use categories, and DEM and SLOPE parameters.

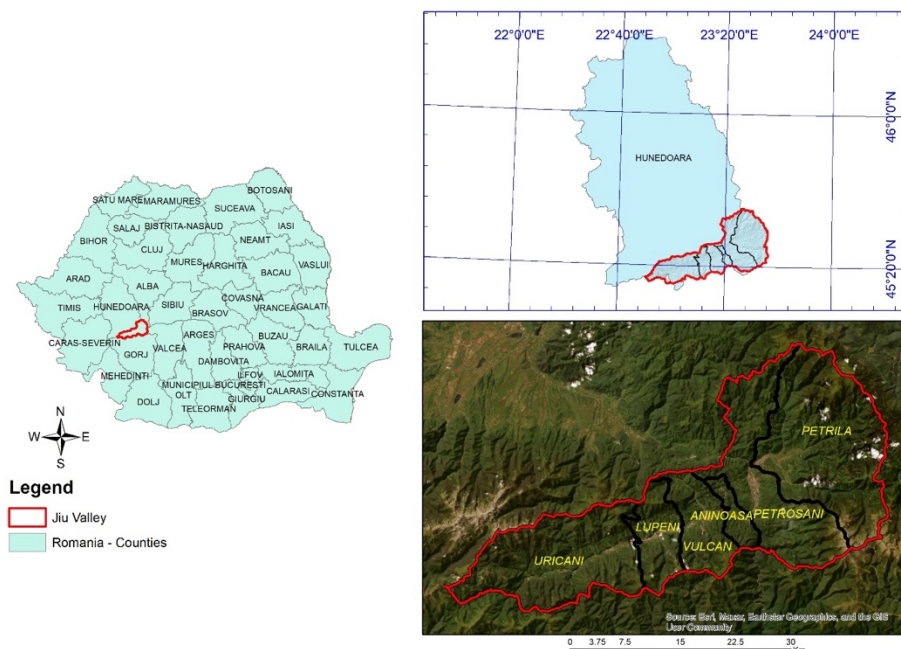


Figure 1. Study area, Jiu Valley, Romania (figure generated based on ESRI, 2011)

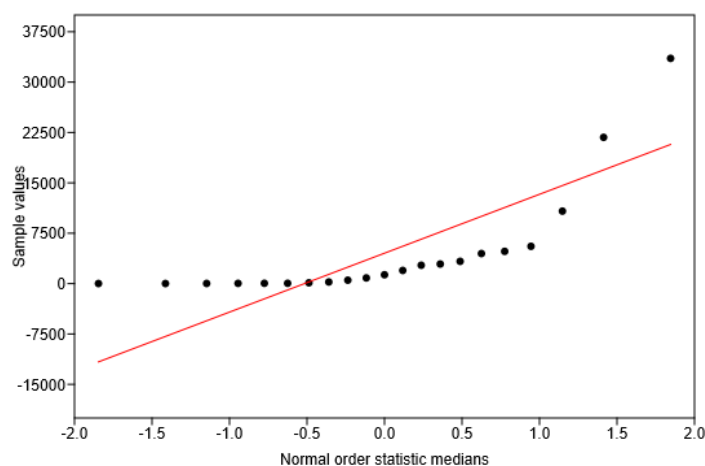
The use categories were classified into different size categories, based on the related land areas. The distribution of DEM and SLOPE values for the study area was analyzed and described, through statistical parameters and linear models. The DEM and SLOPE classes were grouped based on similarity, through cluster analysis. The calculated SDI values (Similarity and Distance Indices) showed the level of similarity between the classes of the two parameters (DEM, SLOPE). The PAST software was used to analyze the experimental data and generate graphs (Hammer et al., 2001).

RESULTS AND DISCUSSIONS

The study area included different land use categories, Table 1, in relation to the relief, the level of land suitability, the development and management plan of the area, the economic potential, but also to factors that directly and indirectly affected the study area. Twenty-one land use categories were recorded, with values ranging between 27.83 ha (512 code) and 33543.00 ha (311 code). The data presented a normal distribution, with $r = 0.755$.

Table 1. Land categories in the study area, Jiu Valley, Romania

OID	Value	Land categories	CODE_18	CLASS	Area	
					(ha)	(%)
0	2	Discontinuous urban fabric	112	2	1974.32	2.07
1	3	Industrial or commercial units	121	3	521.93	0.55
2	4	Road and rail networks and associated land	122	4	31.93	0.03
3	7	Mineral extraction sites	131	7	132.87	0.14
4	8	Dump sites	132	8	259.24	0.27
5	10	Green urban areas	141	10	32.61	0.03
6	11	Sport and leisure facilities	142	11	67.91	0.07
7	12	Non-irrigated arable land	211	12	58.2	0.06
8	18	Pastures	231	18	4812.17	5.05
9	20	Complex cultivation patterns	242	20	2934.01	3.08
10	21	Land principally occupied by agriculture, with significant areas of natural vegetation	243	21	4489.54	4.71
11	23	Broad-leaved forest	311	23	33543	35.18
12	24	Coniferous forest	312	24	21784.49	22.84
13	25	Mixed forest	313	25	5562.79	5.83
14	26	Natural grasslands	321	26	10799.25	11.32
15	27	Moors and heathland	322	27	2750.57	2.88
16	29	Transitional woodland-shrub	324	29	3332.05	3.49
17	31	Bare rocks	332	31	1332.11	1.40
18	32	Sparsely vegetated areas	333	32	856.87	0.90
19	40	Water courses	511	40	54.14	0.06
20	41	Water bodies	512	41	27.83	0.03
TOTAL					95357.83	100.00

**Figure 2.** Distribution of the data series for the surface of the use categories (Area) in the study area

Descriptive statistical analysis generated the quartile delimitation thresholds for the solodin categories in relation to the area, and resulted in the value 25 percentile = 63.055, respectively 75 percentile = 4650.855, with the Median value = 1332.11. In relation to the respective thresholds and the real values of the use categories identified in the study area (Table 1), the lower quartile (Q1) included five categories (512, 122, 141, 511, 211), with a total area of 204.71 ha. The median quartile Q2 included five categories (142, 131, 132, 121, 333), with a total area of 1838.71 ha. Six categories (332, 112, 322, 242, 324, 243) with a total area of 16812.60 ha were included in the median quartile Q3. Five categories (231, 313, 321, 312, 311) were included in the upper quartile Q4, with a total area of 76501.70 ha. The distribution of the categories by quartile is presented in Figure 3.

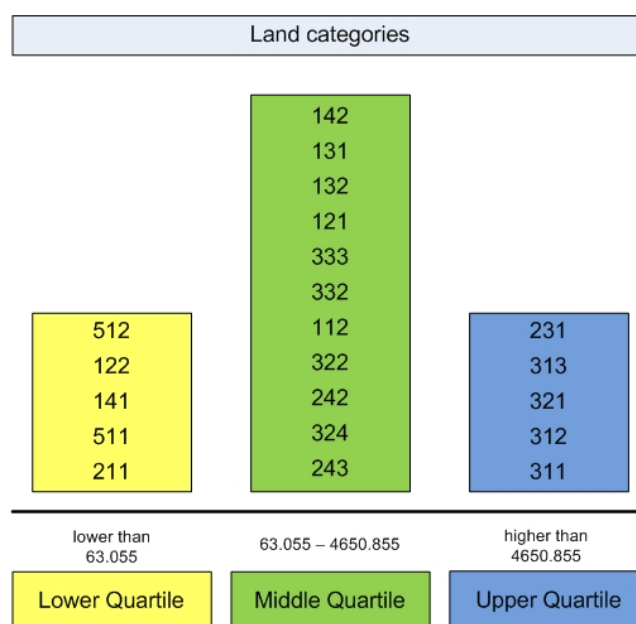


Figure 3. Quartile distribution of land use categories in the study area

In the case of the DEM parameter, values between 435.59 ha (DC21) and 7080.98 ha (DC5) were recorded. The series of values, by DEM classes, identified in the study area, is presented in Table 2. The DEM data series presented a normal distribution, with $r = 0.955$, Figure 4. According to the Outlier test, no outlier values were recorded for the DEM data series, $G = 1.817$, $p = 1$, $Q = 0.1124$, $p = 0.937$.

Table 2. DEM Class in the study area, Jiu Valley, Romania

DEM Interval	DEM Class	Area (ha)
530 - 662	DC1	4570.07
662 - 743	DC2	6940.78
743 - 820	DC3	6661.73
820 - 894	DC4	7054.77
894 - 966	DC5	7080.98
966 - 1040	DC6	6642.86
1040 - 1113	DC7	6550.4
1113 - 1184	DC8	6304.8
1184 - 1254	DC9	6220.47
1254 - 1323	DC10	5974.3
1323 - 1392	DC11	5579.24
1392 - 1462	DC12	5270.83
1462 - 1535	DC13	4516.68
1535 - 1612	DC14	3721.49
1612 - 1693	DC15	3221.15
1693 - 1779	DC16	2665.96
1779 - 1870	DC17	2306.79
1870 - 1971	DC18	1669.77
1971 - 2093	DC19	1166.81
2093 - 2245	DC20	837.43
2245 - 2500	DC21	435.59

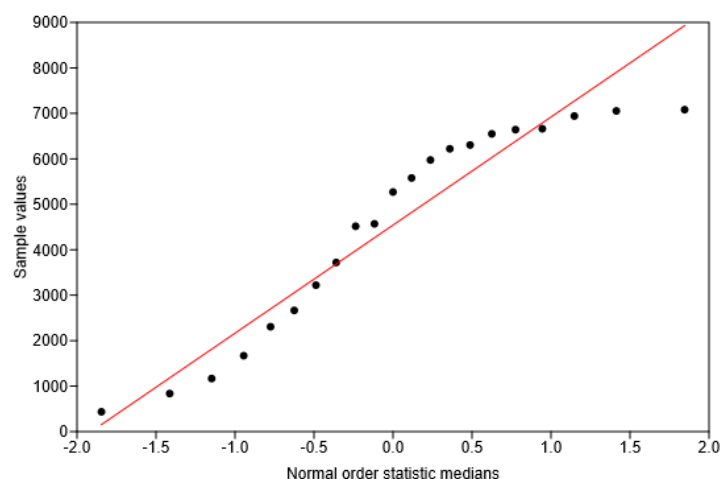


Figure 4. Distribution of the data series for the DEM parameter in the study area

A statistically significant decreasing trend of DEM values in the data series was recorded (Mann-Kendall test), with $S = -178$, $Z = -5.3449$, $p < 0.001$. Regression analysis indicated statistical reliability in the distribution of DEM data, with the values of statistical reliability parameters in Table 3. The graphical distribution model of the data is presented in Figure 5, with Slope = -326.8, Intercept = 8137.30.

Table 3. The values of the statistical parameters related to the regression analysis for the DEM parameter

Statistical parameters		Statistical parameter values		
Slope a		-326.8	Std. error a	36.9420
t		8.8462	p (slope)	3.65E-08
Intercept b		8137.3	Std. error b	463.8700
95% bootstrapped confidence intervals (N=1999)				
Slope a		(-429.5, -226.97)		
Intercept b		(6622.1, 9400.4)		
Correlation				
r		-0.8970		
r²		0.8046		
t		-8.8462		
p (uncorr.)		3.65E-08		
Permutation p		0.0001		

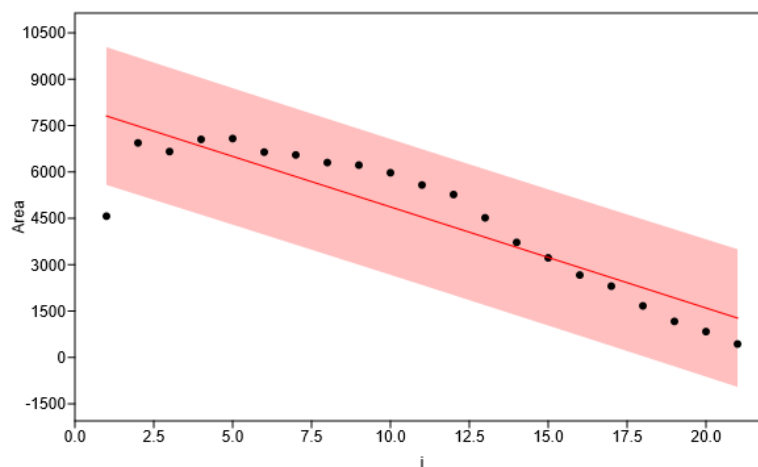


Figure 5. Linear fit model for DEM data

Based on the recorded values, Cluster Analysis grouped the DEM classes based on similarity into two distinct clusters (Coph.corr. = 0.833), Figure 6. A cluster C1 included 8 DEM classes, and cluster C2 included 13 DEM classes. Within cluster C1, the highest level of similarity was recorded between classes DC19 and DC20 (SDI = 329.38). Within cluster C2, a high level of similarity was recorded between classes DC3 and DC6 (SDI = 18.87).

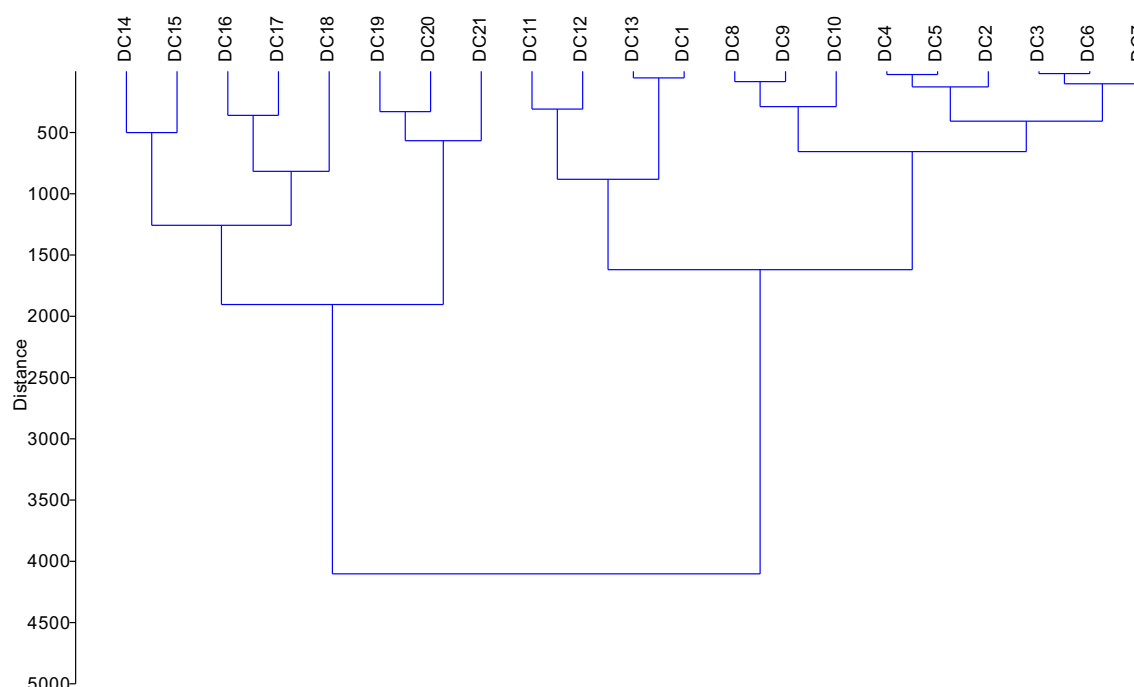


Figure 6. Cluster diagram for DEM classes in the study area

In the case of the SLOPE parameter, values ranging from 17.22 ha (SC21) to 9960.56 ha (SC8) were recorded. The series of values, by SLOPE classes, identified in the study area, is presented in Table 4. The SLOPE data series presented a normal distribution, with $r = 0.956$, Figure 7. According to the Outlier test, no outlier values were recorded for the SLOPE data series, $G = 1.477$, $p = 1$, $Q = 0.0295$, $p = 0.9985$.

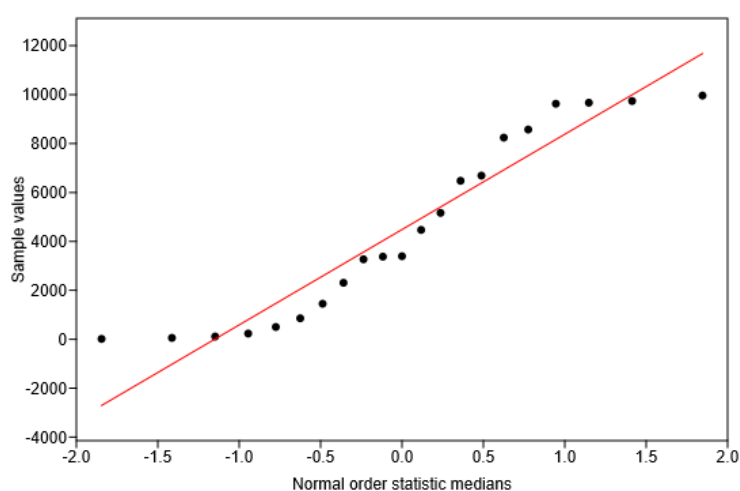


Figure 7. Distribution of the data series for the SLOPE parameter in the study area

In the data series, a statistically significant decreasing trend in SLOPE values (Mann-Kendall test) was observed, with $S = -124$, $Z = -3.7142$, $p < 0.001$. Regression analysis indicated statistical reliability in the

distribution of SLOPE data, the values of the statistical reliability parameters being presented in Table 4. The graphical model of data distribution is presented in Figure 8, with Slope = -405.96, Intercept with Order = 8952.10.

Table 4. SLOPE Class in the study area, Jiu Valley, Romania

SLOPE Interval	SLOPE Class	Area (ha)
0 - 2.817178	SC1	3397.28
2.817178 - 6.146571	SC2	3378.13
6.146571 - 9.475963	SC3	5168.17
9.475963 - 12.549248	SC4	6689.64
12.549248 - 15.622533	SC5	8244.07
15.622533 - 18.695819	SC6	9628.28
18.695819 - 21.512997	SC7	9740.88
21.512997 - 24.330175	SC8	9960.56
24.330175 - 27.147353	SC9	9670.27
27.147353 - 29.964531	SC10	8572.15
29.964531 - 32.525602	SC11	6477.67
32.525602 - 34.830566	SC12	4470.24
34.830566 - 37.13553	SC13	3270.32
37.13553 - 39.440494	SC14	2310.85
39.440494 - 41.745458	SC15	1453.59
41.745458 - 44.050422	SC16	857.31
44.050422 - 46.611493	SC17	503.25
46.611493 - 49.428671	SC18	236.61
49.428671 - 52.758064	SC19	114.36
52.758064 - 57.367992	SC20	57.26
57.367992 - 65.307312	SC21	17.22

Table 5. The values of the statistical parameters related to the regression analysis for the SLOPE parameter

Statistical parameters	Statistical parameter values		
Slope a	-405.96	Std. error a	100.48
t	4.0402	p (slope)	0.0007
Intercept b	8952.10	Std. error b	1261.70
95% bootstrapped confidence intervals (N=1999)			
Slope a	(-587.16, -125.82)		
Intercept b	(4587.2, 11638)		
Correlation			
r	-0.6798		
r ²	0.4621		
t	-4.0402		
p (uncorr.)	0.0007		
Permutation p	0.0015		

Based on the recorded values, Cluster Analysis grouped the SLOPE classes in relation to the level of similarity into two distinct clusters (Coph.corr. = 0.804), Figure 9. A cluster C1 (left side of the dendrogram) included 11 SLOPE classes, and cluster C2 (right side of the dendrogram) included 10 SLOPE classes. Within cluster C1, the highest level of similarity was recorded between classes SC1 and SC2 (SDI = 19.15). Within cluster C2, the highest level of similarity was recorded between classes SC6 and SC9 (SDI = 41.99).

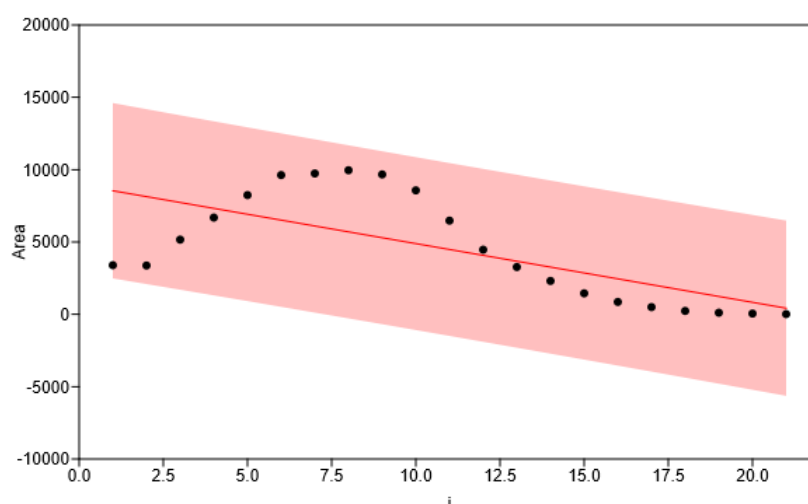


Figure 8. Linear fit model for SLOPE data

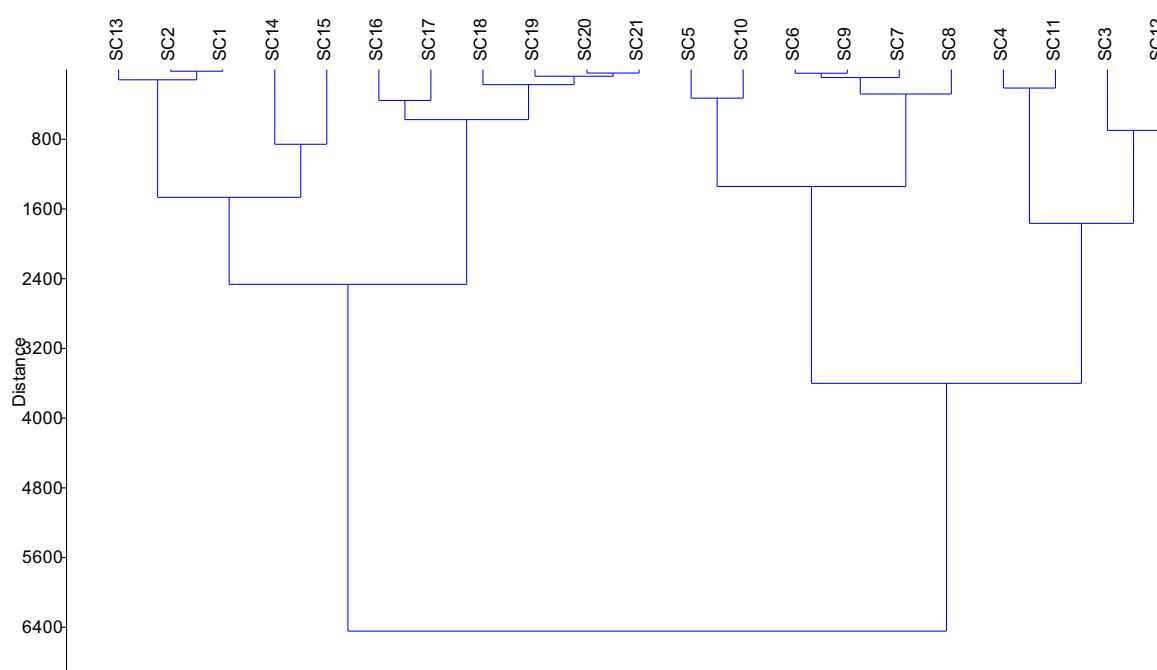


Figure 9. Cluster diagram for SLOPE classes in the study area

Spatial and temporal variability in the study of terrestrial areas was recorded with great precision through remote sensing techniques, and important information was provided for appropriate management in relation to specific ecological, economic and social objectives (Herbei and Sala, 2014; Sharma et al., 2024; Ramachandra and Negi, 2025).

The classification of land use in coal mining basins has been studied and evaluated through complex analysis methods. (Xu et al., 2024). Interactions and influences of coal mining activities and other land use categories, including agricultural and agroforestry categories, were studied (Song et al., 2024; Xu et al., 2024). Associated with mining activities (ongoing or after closure), effects on natural ecosystems, landscape fragmentation, land degradation, pollution (soil, water), effects on agricultural lands, human habitats have been reported (Bridge et al., 2004; Maus et al., 2022). The importance of mapping and monitoring areas affected by mining operations was communicated, in order to evaluate the associated effects on ecosystems, biodiversity, sustainable use of natural resources, estimate potential risks, as well as for management decisions in the affected

areas (Kobayashi et al., 2014; Moran et al., 2020; Bringezu, 2019; Silva Rotta et al., 2020).

Twenty-one land use categories were identified in the study area, with surface values ranging between 27.83 ha (Water bodies, 512 Code) and 33543.00 ha (Broad-leaved forest, 311 Code). Knowledge of the use categories is important in relation to the development potential of the area, given that the industry based on coal mining is no longer sustainable. Five categories were found in the agricultural field (211, 231, 242, 243, and 321 Codes). The evaluation of local germplasm in some plant species, of culture technologies, and complementary methods based on the activity of microorganisms, led to recommendations for differentiated use of genetic resources, and promoted technologies with high potential for capitalization in the reconstruction of some mining areas (Dobrei et al., 2009, 2015; Chen et al., 2023; Gigena et al., 2025).

The studied area was described by DEM parameter values ranging from 435.59 ha (DC21) to 7080.98 ha (DC5) and SLOPE parameter values ranging from 17.22 ha (SC21) to 9960.56 ha (SC8). The clustering of DEM and SLOPE classes provides information on the degree of similarity of the classes in the study area, useful information for the management of the area in a development perspective.

CONCLUSIONS

The study area, represented by the Jiu Valley mining basin, Romania, was characterized by twenty-one land use categories, with values ranging from 27.83 ha (Water bodies, 512 Code) to 33543.00 ha (Broad-leaved forest, 311 Code). The large number of land use categories shows, on the one hand, high spatial variability of the area, and on the other hand, it shows diverse potential of natural resources and multiple development perspectives.

Five agricultural land use categories (211, 231, 242, 243, and 321 Codes) were identified with a total area of 23093.18 ha, which represents 24.22% of the total area of the study area. This confirms the agricultural potential of the study area, as a partial alternative to mining activities, which have been reduced in recent times.

Also, land use categories with high potential for natural ecosystem resources, for tourism, but also other socio-economic activities were identified.

DEM and SLOPE parameters provided valuable information for the study area, and their classification based on similarity provides the basis for management decisions for sustainable development projects in the reference area.

ACKNOWLEDGMENTS

The authors thank the GEOMATICS Research Laboratory, ULS "King Mihai I" from Timisoara, for the facility of the software used for this study.

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