

Dem, Slope and Aspect Parameters in the Characterization of a Terrestrial Area through Remote Sensing

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Abstract. The study used remote sensing techniques to analyze and characterize a land area based on DEM, SLOPE and ASPECT parameters. An area of 5337,368 ha was considered, within the Surduc ATU, Timis County, Romania. Satellite scenes (Sentinel 2) were taken in the summer season, 2025. The territory was classified, considering nine classes within each parameter (DC1 to DC9 for DEM; SC1 to SC9 for SLOPE; AC1 to AC9 for ASPECT). Within the DEM parameter, two classes (DC1 and DC2) presented a larger area compared to the class average, with statistically significant differences ($p < 0.01$), and three classes presented smaller areas compared to the average ($p < 0.05$). Within the SLOPE parameter, one class (SC1) presented a value above the mean ($p < 0.001$), and two classes (SC8, and SC9) presented values below the mean ($p < 0.01$). Within the ASPECT parameter, one class (AC1) presented a value above the mean ($p < 0.001$), and three classes (AC4, AC5, and AC9) presented values below the mean ($p < 0.05$). According to PCA, three classes were positioned correlated with DEM, SLOPE, ASPECT parameters, and the other classes were positioned independently. DEM and SLOPE parameters showed positive action, of very strong intensity in PC1, and the ASPECT parameter showed positive action of moderate intensity in PC1 and PC2. According to Cluster Analysis, class C1 presented an independent position, and the other classes were grouped into two clusters based on similarity in the cluster dendrogram.

Keywords: algorithm, ASPECT, cluster, DEM, remote sensing, SLOPE, unsupervised classification

INTRODUCTION

Terrestrial areas are characterized by spatial and temporal variability in relation to natural and anthropogenic elements, with parameters and influencing factors (Zhang et al., 2022; Choi et al., 2025; Sun et al., 2025).

The geomorphology of the terrain is the result of natural processes of formation of the earth's crust, partially shaped by anthropogenic activities (Cunha et al., 2018; Xiong et al., 2022; He and Weng, 2025).

Remote sensing facilitates the analysis, description and modeling (imaging, mathematics) of the earth's surface based on satellite images, specific representation parameters and indices (Slaymaker, 2001; Tarolli et al., 2009; Herbei and Sala, 2014; Jin et al., 2022).

Remote sensing has been used to study terrestrial, coastal, marine and oceanic areas, in relation to various objectives of interest (Zhang and Fryirs, 2024; Evagorou et al., 2025).

DEM, SLOPE and ASPECT are important parameters in remote sensing studies, with variable dynamics in space in relation to the specifics of land surfaces (Maxwell and Shobe, 2022; Kandulna et al., 2025; Lima et al., 2024; Shitu and Tariq, 2025). Fifteen factors, including DEM, SLOPE and ASPECT, were used to assess the risks of land degradation (Shitu and Tariq, 2025).

Digital Elevation Model (DEM) is an important parameter in the analysis of information in the form of remote sensing data for land characterization (Saleem et al., 2019; Romshoo et al., 2021; Okolie and Smit, 2022; Ali et al., 2025). Based on the DEM, various important information with applications for land improvement works and agricultural land improvement results (Saleem et al., 2019; Asgari et al., 2020).

SLOPE is an important parameter in remote sensing studies for the characterization of natural and anthropogenic areas, for the assessment of land degradation risks, for the design of transport infrastructure, the development of urban and industrial areas (Deng et al., 2022; Shi et al., 2023; Shitu and Tariq, 2025). The analysis of landscape units was done based on SLOPE values, to improve soil prediction models (Zhu et al., 2024).

ASPECT is an important parameter, which expresses the direction in which a segment of a land surface is oriented (Jiao et al., 2012). It is of high importance in relation to the performance of ecosystems, with the efficient use of land through agricultural crops, fruit tree plantations, vineyards, but also urban areas, industrial parks, or other uses, as appropriate (Sigua and Coleman, 2010; Wang et al., 2019; Zou et al., 2024).

The present study used the remote sensing technique to evaluate the spatial variability of a terrestrial area based on the DEM, SLOPE and ASPECT parameters and to characterize the considered area through unsupervised classification in relation to the respective parameters.

MATERIAL AND METHODS

The study considered in the analysis a terrestrial area with a high level of complexity, within the Surduc ATU, Timis County, Romania, Figure 1. The area includes natural and anthropogenic areas, land and water areas, with variable levels of characterization parameters.

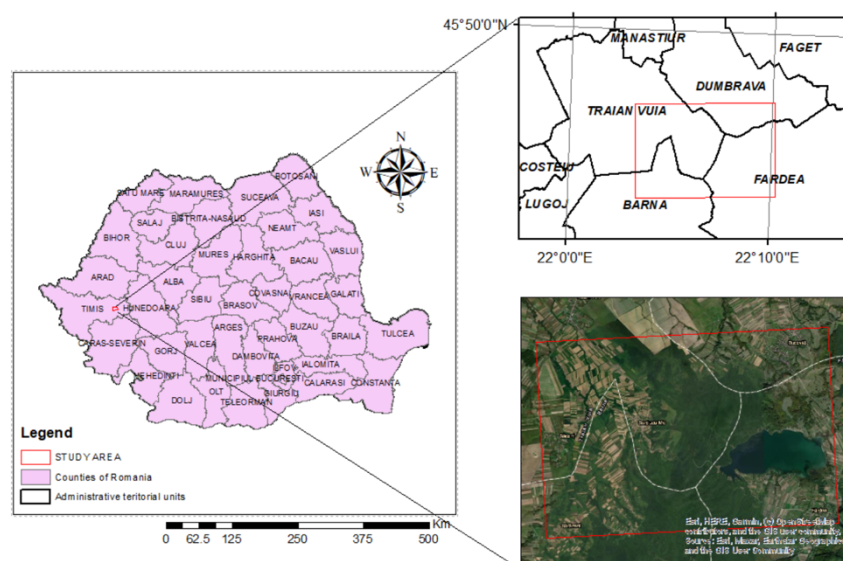


Figure 1. Study location, Surduc ATU, Timis County, Romania

The Sentinel 2 system was used to obtain the satellite image. The images were taken in the summer season, year 2025. Based on the spectral information, the classification of the considered area was made, by the unsupervised method, based on the K Means algorithm. DEM, SLOPE and ASPECT parameters were determined, to characterize the area in the study area, in relation to the recorded classes. Within each parameter, a comparative analysis of the area in each class in relation to the average area of the studied area was made (t Test). Standard thresholds were used for statistical significance of differences ($p < 0.05$, $p < 0.01$, $p < 0.001$). Multivariate analysis (PCA, CA) was used to find out the distribution of classes in relation to the principal components and the degree of similarity between classes. PAST software was used for data analysis and generation of graphical representations (Hammer et al., 2001).

RESULTS AND DISCUSSIONS

Based on satellite images (Sentinel 2) the area considered in the study, ATU Surduc, Timis County, Romania, was characterized based on the DEL, SLOPE, and ASPECT parameters. Within each parameter, a number of nine classes were considered, and the area values in each class (unsupervised classification) are presented in Table 1 and Figure 2.

Table 1. Values recorded by classes and morphological parameters, ATU Surduc, Timis County, Romania

Altitude	DEM Class	Area (ha)	Slope	Slope Class	Area (ha)	Aspect	Aspect Class	Area (ha)
0-171	DC1	1428.761	0-1.87	SC1	1828.271	N	AC1	1160.521
171-201	DC2	1257.134	1.87-4.45	SC2	816.064	NE	AC2	715.063
201-226	DC3	946.286	4.45-6.95	SC3	801.394	E	AC3	499.412
226-251	DC4	654.053	6.95-9.16	SC4	680.993	SE	AC4	369.617
251-280	DC5	474.079	9.16-12.60	SC5	512.578	S	AC5	311.587
280-315	DC6	245.499	12.60-16.28	SC6	335.065	SW	AC6	478.806
315-358	DC7	154.730	16.28 - 20.97	SC7	206.949	W	AC7	698.101
358-408	DC8	116.762	20.97-27.16	SC8	114.824	NW	AC8	807.964
408-493	DC9	60.063	27.16-44.33	SC9	41.230	N	AC9	296.296
	TOTAL	5337.368		TOTAL	5337.368		TOTAL	5337.368

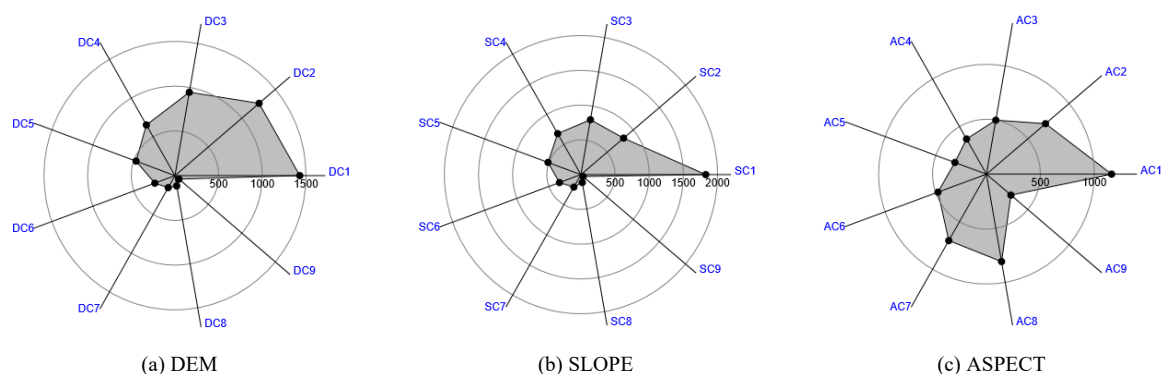


Figure 2. Graphical representation of the values of the studied parameters

Mann-Kendall trend test indicated the statistical certainty of the decreasing trend of the data series for the DEM parameter ($S = -36$, $p < 0.001$) and for the SLOPE parameter ($S = -36$, $p < 0.001$). In the case of the ASPECT parameter, the applied test showed that there was no statistically significant trend in the data series ($S = -12$, $p = 0.13$).

The comparative analysis of the land areas by class within each parameter of the studied territory was made in relation to the mean value (t Test). For the DEM parameter, the values in Table 2 resulted. The recorded results showed positive differences for classes DC1 and DC2 ($p < 0.01$, **) and negative differences for classes DC7, DC8, and DC9 ($p < 0.05$, ^o). In the case of four classes (DC3, DC4, DC5, and DC6) the differences did not present statistical certainty.

Table 2. Comparative analysis results for the DEM parameter

DEM Classes	Given mean	Sample mean	95% conf. interval	Difference	95% conf. interval	t	p (same mean)
DC1	1428.761			835.720 **	(441.35 1230.1)	-4.8866	0.0012
DC2	1257.134			664.090 **	(269.72 1058.5)	-3.8831	0.0047
DC3	946.286			353.250 ^{NS}	(-41.13 747.62)	-2.0655	0.0727
DC4	654.053			61.012 ^{NS}	(-333.36 455.39)	-0.3568	0.7305
DC5	474.079	593.040	(198.67 987.42)	-118.960 ^{NS}	(-275.41 513.34)	0.6956	0.5064
DC6	245.499			-347.540 ^{NS}	(-46.833 741.92)	2.0321	0.0766
DC7	154.730			-438.310 ^o	(43.936 832.69)	2.5629	0.0335
DC8	116.762			-476.280 ^o	(81.904 870.65)	2.7849	0.0237
DC9	60.063			-532.980 ^o	(138.6 927.35)	3.1164	0.0143

For the SLOPE parameter, the values in table 3 resulted. The recorded results showed a positive difference for class SC1 ($p < 0.001$, ***) and negative differences for classes SC8 and SC9 ($p < 0.05$, ^o).

Table 3. Results of the comparative analysis for the SLOPE parameter

SLOPE Classes	Given mean	Sample mean	95% conf. interval	Difference	95% conf. interval	t	p (same mean)
SC1	1828.271			1235.200 ***	(815.8 1654.7)	-6.7912	0.0001
SC2	816.064			223.020 ^{NS}	(-196.4 642.45)	-1.2262	0.2550
SC3	801.394			208.350 ^{NS}	(-211.07 627.78)	-1.1455	0.2851
SC4	680.993			87.952 ^{NS}	(-331.47 507.38)	-0.4836	0.6417
SC5	512.578	593.040	(173.61 1012.5)	-80.463 ^{NS}	(-338.96 499.89)	0.4424	0.6699
SC6	335.065			-257.980 ^{NS}	(-161.45 677.4)	1.4183	0.1939
SC7	206.949			-386.090 ^{NS}	(-33.335 805.52)	2.1227	0.0665
SC8	114.824			-478.220 ^o	(58.79 897.64)	2.6292	0.0302
SC9	41.230			-551.810 ^o	(132.38 971.24)	3.0338	0.0162

In the case of six classes (SC2, SC3, SC4, SC5, SC6 and SC7) the differences did not present statistical significance ($p > 0.05$), Table 3.

For the ASPECT parameter, the values in Table 4 resulted. The recorded results showed a positive difference for classes AC1 ($p < 0.001$, **) and negative differences for classes AC4, AC5, and AC9 ($p < 0.05$, ^o). In the case of five classes (AC2, AC3, AC6, AC7, and AC8) the differences did not present statistical certainty.

Table 4. Results of the comparative analysis for the ASPECT parameter

ASPECT Classes	Given mean	Sample mean	95% conf. interval	Difference	95% conf. interval	t	p (same mean)
AC1	1160.521			567.480 ***	(351.24 783.73)	-6.0515	0.0003
AC2	715.063			122.020 ^{NS}	(-94.223 338.27)	-1.3012	0.2294
AC3	499.412			-93.629 ^{NS}	(-122.62 309.87)	0.9984	0.3473
AC4	369.617			-223.420 ^o	(7.1787 439.67)	2.3825	0.0444
AC5	311.587	593.040	(376.8 809.29)	-281.450 ^o	(65.209 497.7)	3.0013	0.0170
AC6	478.806			-114.230 ^{NS}	(-102.01 330.48)	1.2182	0.2579
AC7	698.101			105.060 ^{NS}	(-111.18 321.31)	-1.1203	0.2951
AC8	807.964			214.920 ^{NS}	(-1.3218 431.17)	-2.2919	0.0511
AC9	296.296			-296.740 ^o	(80.5 512.99)	3.1644	0.0133

In the multivariate analysis, the principal components explained a high proportion of the total variance (PC1 = 79.349% of variance, PC2 = 18.16% of variance). The PCA diagram (Figure 3) showed the distribution of classes in relation to the three parameters, as biplot. Class C1 was positioned correlated and balanced with the three terrain parameters, DEM, SLOPE and ASPECT. Class C2 was positioned closely correlated with SLOPE, and class C3 was positioned correlated with DEM. The other classes were positioned independently of the parameters considered.

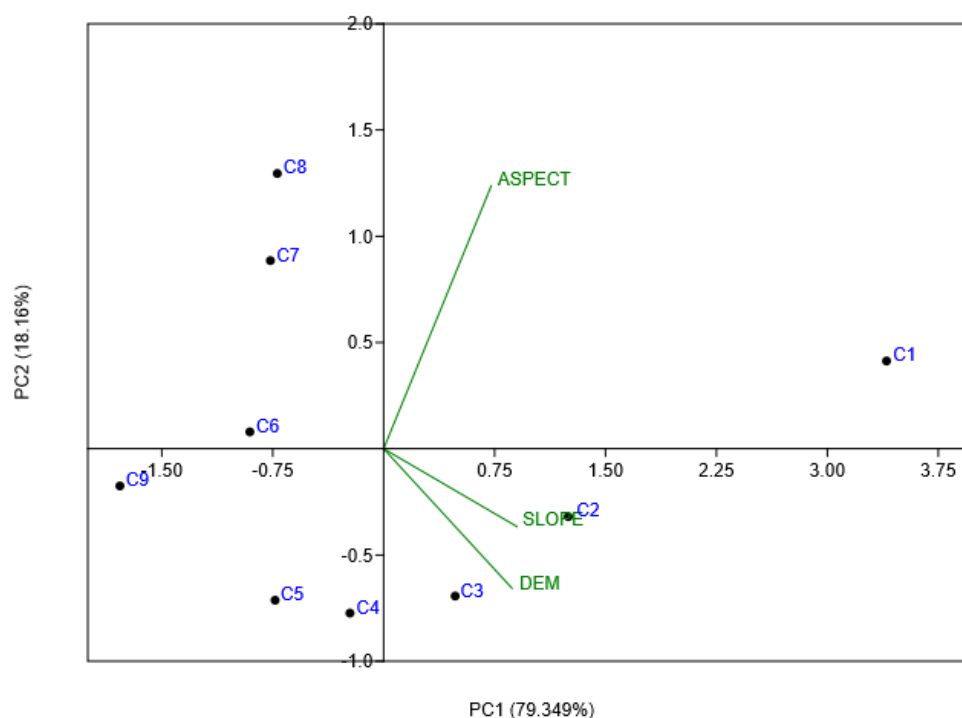


Figure 3. Diagrama PCA cu distributia claselor in raport cu cei trei parametri, as biplot

The parameter loadings in relation to the principal components are presented in Table 5. In PC1, all three parameters showed positive action, very strong in the case of the DEM parameter ($r = 0.925$) and the SLOPE parameter ($r = 0.961$). The ASPECT parameter showed moderate action ($r = 0.775$). In PC2, the ASPECT

parameter showed positive action, of weak intensity ($r = 0.631$), and the DEM and SLOPE parameters showed negative action, of very weak intensity. In PC3, DEM and ASPECT showed positive action, and SLOPE showed negative action.

Table 5. Parameter loadings in the principal components

Parameters	PC 1	PC 2	PC 3
DEM	0.925	-0.335	0.180
SLOPE	0.961	-0.187	-0.202
ASPECT	0.775	0.631	0.036

The cluster analysis generated the dendrogram in Figure 4, with the grouping of classes and parameters in clusters based on similarity (Coph.corr. = 0.866). In the case of parameters, the association of SLOPE with DEM and the independent positioning of the ASPECT parameter were observed. In the case of classes, the independent positioning of class C1 was observed, and the grouping of the other classes within two clusters, based on similarity. The highest level of similarity was recorded in the case of classes C7 and C8 (SDI = 148.32), followed by classes C4 and C5 (SDI = 253.22). The SDI data series are presented in Table 6.

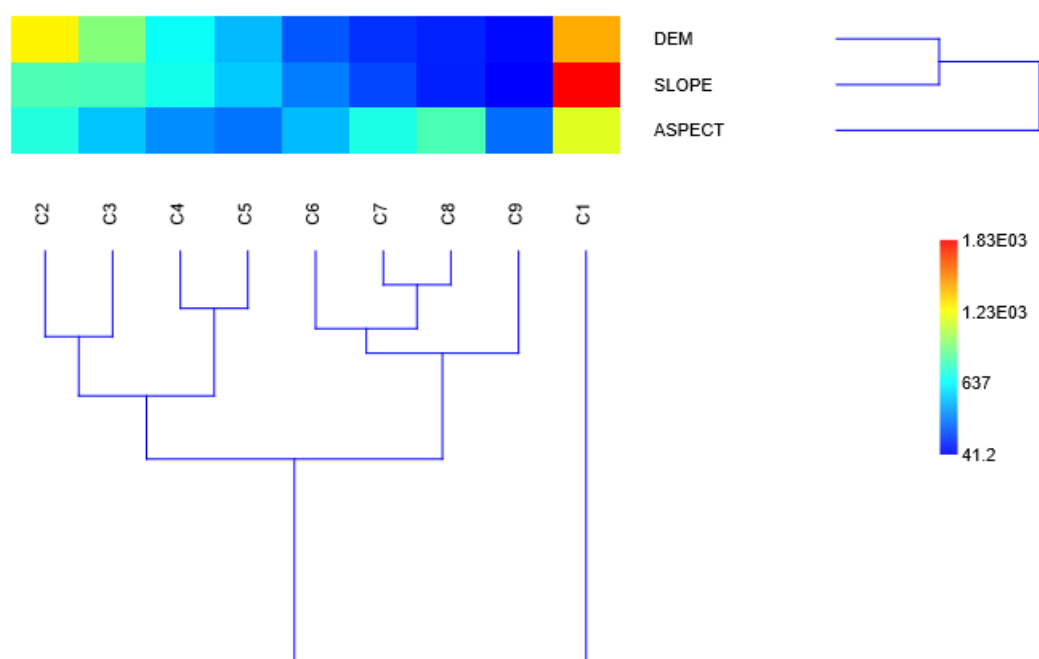


Figure 4. Cluster dendrogram for classes and parameters

Table 6. SDI values for determined classes

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1		1119.13	1313.14	1594.35	1833.89	2023.49	2113.21	2186.67	2411.17
C2	1119.13		378.61	708.01	931.70	1144.81	1259.60	1341.95	1486.17
C3	1313.14	378.61		341.68	584.53	842.02	1009.65	1120.13	1185.11
C4	1594.35	708.01	341.68		253.22	546.36	762.85	895.20	876.07
C5	1833.89	931.70	584.53	253.22		334.25	587.18	729.57	627.54
C6	2023.49	1144.81	842.02	546.36	334.25		269.71	416.44	392.47
C7	2113.21	1259.60	1009.65	762.85	587.18	269.71		148.32	444.83
C8	2186.67	1341.95	1120.13	895.20	729.57	416.44	148.32		520.03
C9	2411.17	1486.17	1185.11	876.07	627.54	392.47	444.83	520.03	

The graphical analysis of the classes in relation to the three parameters considered led to Figure 5, in ternary plot format. Based on the values of the classes in relation to the three parameters, analyzed simultaneously, it was observed that the classes were positioned in two areas in the ternary graph. Zone I included classes C1 – C5, which were positioned balanced between DEM and SLOPE. This showed that the two parameters had a high weight in the mixture composition of the respective classes. Zone II included classes C7 – C9, which were positioned close to the ASPECT parameter, which showed the high weight of this parameter in the composition of the respective classes. Intermediately, between the two zones, class C6 was positioned, with a high weight of the ASPECT and SLOPE parameters and a lower weight of the DEM parameter in its composition.

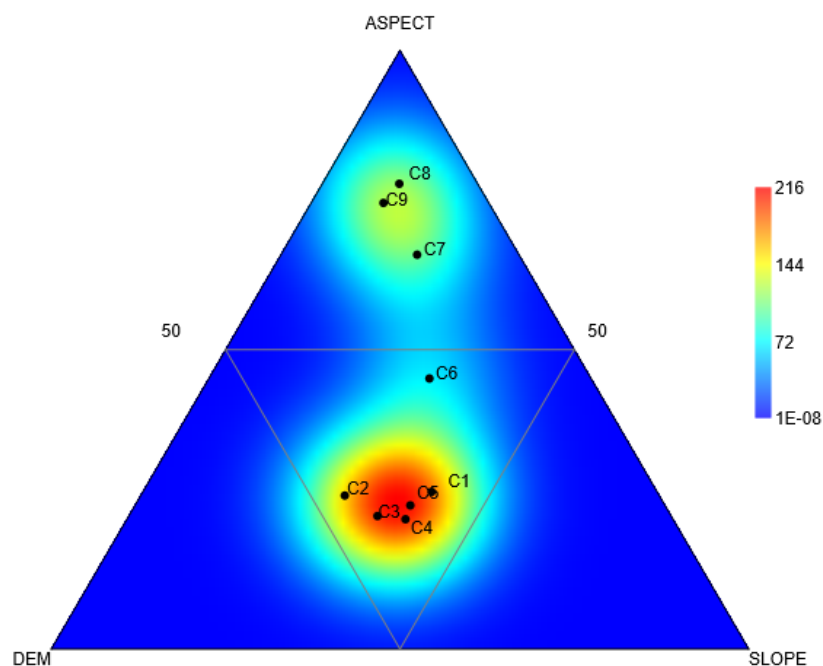


Figure 5. Distribution of classes in relation to the weight of parameters in their formation, ATU Surduc Timis County, Romania

DEM, SLOPE and ASPECT parameters are important for terrain characterization, and quantitative and qualitative methodologies were used to evaluate errors in determining SLOPE and ASPECT parameters from grid DEM (Zhou and Liu, 2004). DEM has been used in multicriteria modeling studies of environmental areas, under conditions of limited data available (Ebinne et al., 2022). Comparative analysis of DEMs in relation to resolution was done, to optimize slope units and associated natural phenomena (Ahmed et al., 2025).

According to the Mann-Kendall test, the data series by classes, for the DEM parameter and for the SLOPE parameter, presented a statistically significant decreasing trend ($S = -36$, $p < 0.001$), while the data series for the ASPECT parameter did not present a statistically significant trend ($S = -12$, $p = 0.13$). The test results showed the differentiated importance of the three parameters for the characterization of the area considered in the study.

Parameters such as SLOPE and ASPECT, derived from DEM, have presented certain limitations in relation to DEM quality, and in order to reduce the limitations, some studies have promoted quality control based on aspect and slope classes (Alba-Fernández et al., 2021). Studies to classify areas based on maps and specific indices (e.g. DEM, SLOPE, SLOPE gradient, ASPECT) were carried out in order to estimate possible ecosystem disturbances (Wang et al., 2023). The classification into mountain areas, in relation to tree species, was made based on DEM, and the degree of land cover was improved by using the DEM parameter resulting from Sentinel-2 data (Waśniewski et al., 2023).

In the case of the DEM parameter, five classes showed statistically significant differences in relation to the average value of the area, two classes with positive differences, and three classes with negative differences. In the case of the SLOPE parameter, three classes showed significant differences in relation to the average value of the area, one class with positive difference, and two classes with negative differences.

In the case of the ASPECT parameter, four classes presented significant differences from the average value of the surface, one class with a positive difference, and three classes with a negative difference. In all cases, class C1 presented a positive difference, and class C9 presented a negative difference. This showed that all three parameters (DEM, SLOPE, ASPECT) provided similar information regarding the specificity of the two classes (C1, and C9). The other classes presented variable surfaces, differentiated in relation to the parameter used in the analysis. In relation to the ASPECT parameter, modules can be arranged in the territory through fruit tree plantations or grapevine plantations, and local germplasm capitalizes on the zonal potential of the land (Dobrei et al., 2015).

DEM contains high-quality spatial data, useful for extracting terrain characterization parameters, such as SLOPE, ASPECT, curvature, etc., and multivariate analysis has been useful in studies on the surface properties of the terrain (Habib, 2021).

Principal component analysis (PCA) has found various applications in the evaluation of territory based on DEM, SLOPE, ASPECT parameters (but also other parameters), such as estimating slope stability, orientation of geological surfaces, and other aspects of interest (Quinn et al., 2019; Lei et al., 2024; Jing et al., 2025).

Based on the data series, multivariate analysis (PCA) showed the correlation of classes with parameters, so that class C1 was positioned balanced in relation to ASPECT, SLOPE and DEM. Class C2 was more strongly correlated with the SLOPE parameter, and class C3 was more strongly correlated with DEM. The other classes were positioned independently of the parameters considered.

CONCLUSIONS

The remote sensing technique facilitated the analysis of the area considered in ATU Surduc, Timis County, Romania, based on spectral data and the determined DEM, SLOPE and ASPECT parameters. The territory classification generated nine classes for each parameter, with variations in the size of the classes, as surface, in relation to each parameter.

Class C1, in relation to each parameter (DC1, SC1, and AC1) presented values above the average, in conditions of statistical safety ($p < 0.01$ in the case of DC1; $p < 0.001$ in the case of SC1 and AC1). Class C9, in relation to each parameter (DC9, SC9, and AC9) presented values below the average, in conditions of statistical safety ($p < 0.05$).

In relation to the principal components, DEM and SLOPE showed positive action in PC1, with very high intensity ($r = 0.925$ in the case of DEM, $r = 0.961$ in the case of SLOPE), and ASPECT showed positive action in PC1 ($r = 0.775$) and in PC2 ($r = 0.631$).

According to the Cluster analysis, class C1 was positioned independently, and the other classes were grouped into two clusters based on similarity ((C2,C3) (C4,C5)), respectively (C6 (C7,C8) C9)). The highest similarity was recorded in the case of classes C7 and C8 (SDI = 148.32), followed by classes C4 and C5 (SDI = 253.22).

The recorded results are useful for monitoring the area considered, for evaluating changes in the territory, and for management decisions at the ecosystem level.

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