

Using Sentinel-2 Images and Unsupervised Classification to Characterize Saline Soil Areas in the Banat Plain

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Abstract. Soils affected by salinization represent an important limitation for the sustainable agricultural use of land in lowland areas, where reduced natural drainage and a water table close to the surface favor the accumulation of soluble salts. The purpose of the research was to identify and spatially delimit areas affected by salinization in the Ciacova–Jebel–Voiteg area, Timiș County, using Sentinel-2 multispectral images, false color compositions, vegetation indices and unsupervised K-Means classification. The analyzed area was 1046584.70 m², or 104.66 ha. The classification separated ten spectral classes, of which class 5 was interpreted as being associated with areas with pronounced salinization, having 25660.76 m², or 2.45% of the total. The values of NDVI, SAVI and MSAVI2 indices differed significantly between classes, according to the analysis of variance ANOVA ($p < 0.001$). The results confirm the usefulness of integrating Sentinel-2 images with statistical analysis and digital classification for rapid mapping of salinities and for supporting agricultural land management decisions.

Keywords: ANOVA, Banat Plain, K-Means, MSAVI2, NDVI, salty soils, SAVI, Sentinel-2

INTRODUCTION

Soil salinization is one of the most important processes of agricultural land degradation, as it directly affects germination, water and nutrient absorption, vegetation development and crop productivity (Shrivastava and Kumar, 2015; Tarolli et al., 2024; Aryal et al., 2025). Saline and alkaline soils require specific diagnosis and management, and classic specialized literature emphasizes the importance of evaluating salt content and soil reaction to establish improvement measures (Richards, 1954; Aboelsoud et al., 2022; Meng et al., 2026). Globally, interest in mapping salt-affected soils has increased significantly in recent decades, amid climate change, agricultural intensification and pressure on water resources (FAO & ITPS, 2021).

In lowland areas, salinization processes are favored by poor drainage, high evapotranspiration, fine soil texture, and a water table relatively close to the surface (Daba and Qureshi, 2021; Sarupria et al., 2026). Under such conditions, soluble salts can migrate upward through capillarity and accumulate in the superficial horizons, reducing the soil's ability to support uniform vegetation (Wagenet and Jury, 1984; Li et al., 2020). In agricultural systems, the effect of salinity often appears in the form of sparse vegetation patches, color differences, reduced biomass, and the appearance of surfaces with increased reflectance (Ahmed et al., 2024; Tarolli et al., 2024).

Classical methods for assessing salinity are based on soil sampling and laboratory determinations, but these can be expensive and difficult to apply over large areas. Remote sensing offers a rapid and repeatable alternative, as it allows the identification of spectral variations associated with soil, vegetation and moisture. have shown that multispectral, hyperspectral sensors and geophysical methods can contribute to the detection and mapping of lands affected by salinity, but also underline the need for careful interpretation of spectral signatures, as soil, vegetation, moisture and surface roughness can produce spectral confusions (Kilic et al., 2022; Salem and Jia, 2024; Luo et al., 2025; Zhang et al., 2025). Metternicht și Zinck (2003). Image analysis has been promoted for the study and characterization of natural vegetation and crop plants in relation to different influencing factors, methods and study models, with importance for the improvement of agricultural technologies (Herbei and Sala, 2014; Li et al., 2014; Sala et al., 2020; Yu et al., 2024; Sankaramaddi et al., 2026).

The development of the Sentinel-2 mission has considerably expanded the possibilities for monitoring agricultural land. The Sentinel-2 system provides multispectral data with spatial resolutions of 10, 20 and 60 m and a high revisit frequency, making it suitable for assessing vegetation and agricultural land degradation (Drusch et al., 2012). The red and near-infrared bands are particularly important for calculating vegetation indices and for highlighting differences between active vegetation, stressed vegetation and bare soil.

One of the most widely used vegetation indices is NDVI, introduced in vegetation dynamics monitoring studies using ERTS/Landsat data (Rouse et al., 1974). NDVI uses the contrast between the high reflectance of vegetation in the near infrared and absorption in the red band. In the case of lands affected by salinization, NDVI values tend to decrease as a result of reduced biomass and physiological stress. For areas with low vegetation cover, Huete (1988) proposed the SAVI index, which reduces the influence of the soil background, and Qi et al. (1994) developed the MSAVI, useful in situations where vegetation is sparse and the soil has a strong spectral

contribution.

Digital classification of satellite images is an important step in transforming spectral information into thematic maps. Unsupervised K-Means classification groups pixels into spectral classes based on the similarity of reflectance values, without the need for predefined training sets. This approach is useful in exploratory salt mapping studies because it allows for the rapid identification of spectral units that can be subsequently interpreted by comparison with vegetation indices, natural color images, and field observations (Lillesand et al., 2015).

The objective of this study was to identify and delimit the areas affected by salinization in the Ciacova–Jebel–Voiteg area, Timiș County, Romania, using Sentinel-2 data, vegetation indices and unsupervised classification. The specific objectives were: calculating and interpreting the NDVI, SAVI and MSAVI2 indices; applying K-Means classification; calculating the areas occupied by spectral classes; verifying statistical differences between classes by ANOVA; and developing a thematic interpretation regarding the areas potentially affected by salinization.

MATERIAL AND METHODS

Study area

The research was carried out in the southern part of Timiș County, in the Banat Plain, in the area between the localities of Ciacova, Ghilad, Voiteg and Jebel. The area is characterized by low plain relief, low slopes, poor natural drainage and the presence of agricultural areas with uneven vegetation. The experimental perimeter was delimited by digitizing an analysis polygon, with a total area of 1046584.70 m², equivalent to 104.66 ha.



Figure 1. Investigated plot in the Ciacova–Jebel–Voiteg area, Timiș County, Romania; the red polygon marks the analyzed perimeter

Satellite data and analyzed indices

The analysis used Sentinel-2 imagery and raster data derived from the red, green, blue and near-infrared spectral bands, Table 1.

Table 1. Spectral indices used for assessing vegetation and salt stress

Index	Equation	Eq. No	Interpretation
NDVI	$NDVI = (NIR - RED) / (NIR + RED)$	(1)	vegetation vigor and photosynthetic activity
SAVI	$SAVI = ((NIR - RED) / (NIR + RED + L)) \times (1 + L)$; $L = 0.5$	(2)	correction of the influence of the soil background
MSAVI2	$MSAVI2 = \frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 9 \times (NIR - Red)}}{2}$	(3)	reducing the influence of soil in sparse vegetation

Unsupervised classification was used to classify land surfaces in relation to specific features captured in spectral information.

Statistical processing included descriptive statistics for each spectral class and one-way analysis of

variance (ANOVA). The factor analyzed was the K-Means spectral class, and the dependent variables were NDVI, SAVI, MSAVI2 and the NIR, RED, GREEN and BLUE spectral bands. The significance of the differences between classes was assessed at the $p < 0.05$ threshold. In relation to the purpose of the study, the PAST software v.4.14 was used (Hammer et al., 2001).

RESULTS AND DISCUSSIONS

To highlight the differences between vegetation and salt-affected surfaces, the false color composition B8-B4-B3 was created, Figure 2. Active vegetation appears in intense shades of pink-magenta, Figure 2, and surfaces with sparse, stressed vegetation or bare soil present lighter tones or reduced contrasts, Figure 3.

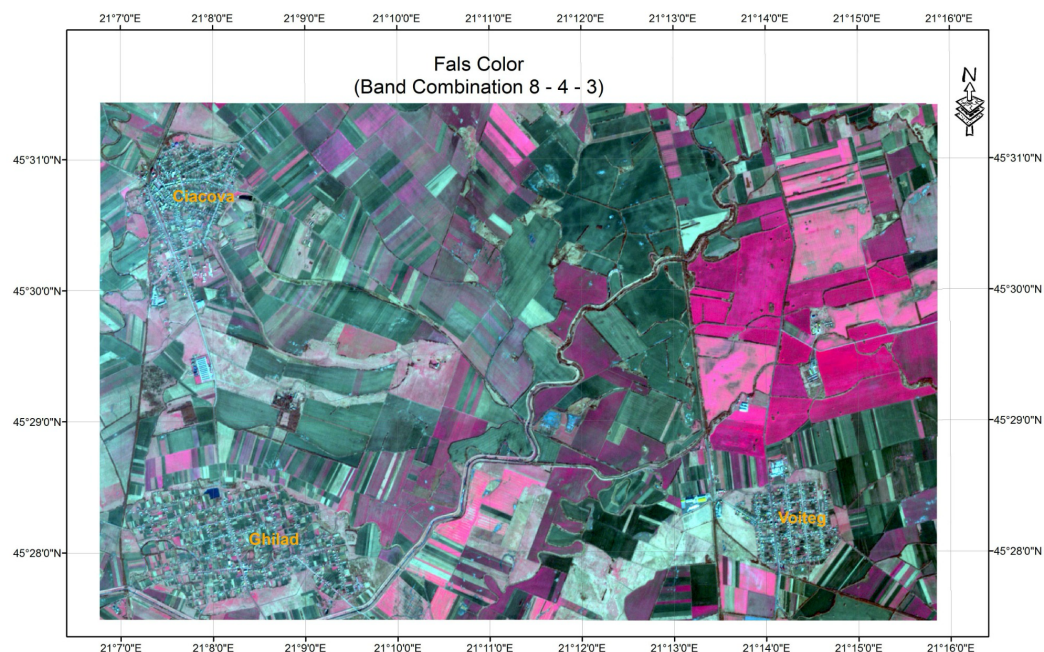


Figure 2. Sentinel-2 B8-B4-B3 false color composite to highlight spectral variations of vegetation and soil

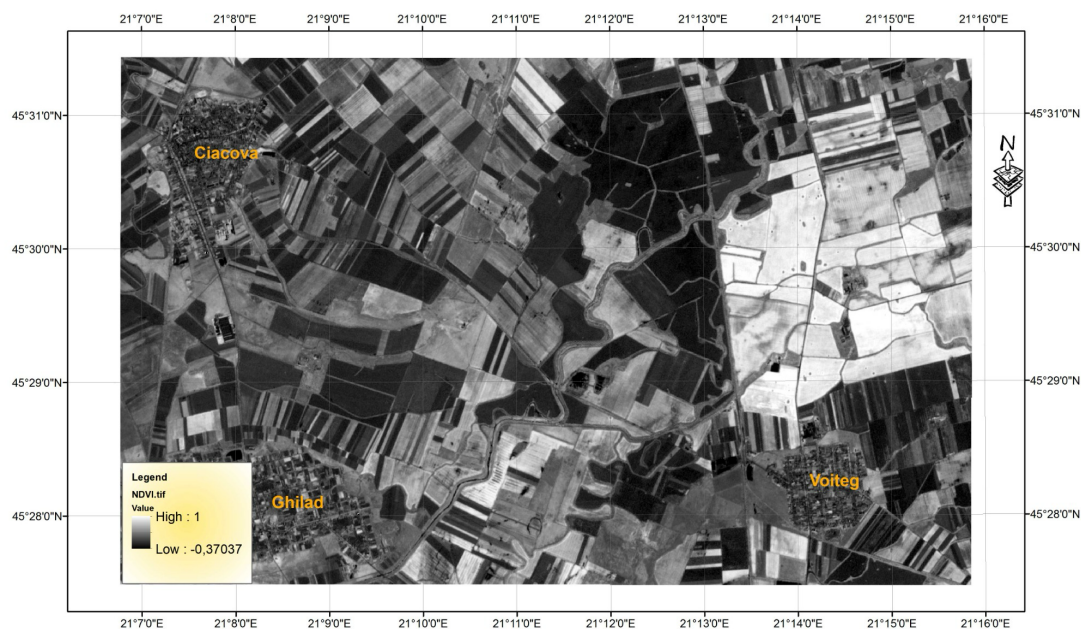


Figure 3. NDVI index map for the analyzed area; (low values indicate poor vegetation or areas with vegetative stress)

Unsupervised classification was performed using the K-Means algorithm, with the surface separated into ten spectral classes, Table 2. Each class was subsequently analyzed by calculating the surface area and extracting the mean values of the NDVI, SAVI and MSAVI2 indices. The class associated with the salts was established by integrated interpretation of the natural color image, the false color composition, the NDVI map and the classification results, Figure 4.

Table 2. Distribution of surfaces resulting from unsupervised K-Means classification

Class	Poygons number (No)	Area (m ²)	Area (ha)	Percentage weight (%)
1	16	73202.46	7.32	6.99
2	46	107722.91	10.77	10.29
3	124	151319.94	15.13	14.46
4	159	162599.26	16.26	15.54
5	22	25660.76	2.57	2.45
6	184	146444.90	14.64	13.99
7	106	134442.80	13.44	12.85
8	131	163863.31	16.39	15.66
9	80	60441.05	6.04	5.78
10	10	20887.30	2.09	2.00

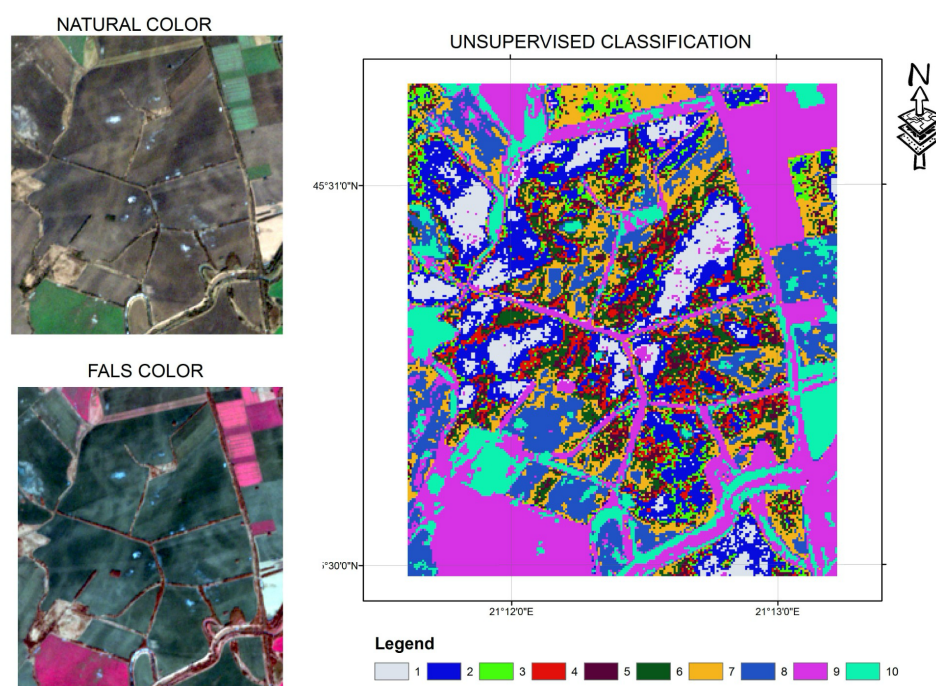


Figure 4. Unsupervised K-Means classification of the analyzed surface, with the delimitation of the ten spectral classes

The total investigated area was 104.66 ha. The highest shares were recorded by class 8 (15.66%), class 4 (15.54%) and class 3 (14.46%), which indicated a high heterogeneity of the agricultural area. Class 5, interpreted as being associated with areas affected by salinization, occupied 2.57 ha, respectively 2.45% of the total. This proportion showed that salinization is not uniformly distributed, but appeared in the form of concentrated areas, with important relevance for local land management.

The analysis of vegetation indices revealed clear differences between spectral classes, Table 3. The highest mean NDVI values were observed in class 9 (0.3430) and class 10 (0.1912), indicating areas with more active vegetation. Classes 1–6 had low NDVI values, ranging approximately between 0.0301 and 0.0716, which suggested poor vegetation, exposed soil, areas affected by moisture or stress. Class 5, associated with salinity, had a mean NDVI of 0.0593, a mean SAVI of 0.0955 and a mean MSAVI2 of 0.1195. These values support the interpretation of this class as an area with sparse vegetation and potentially affected by salt accumulations.

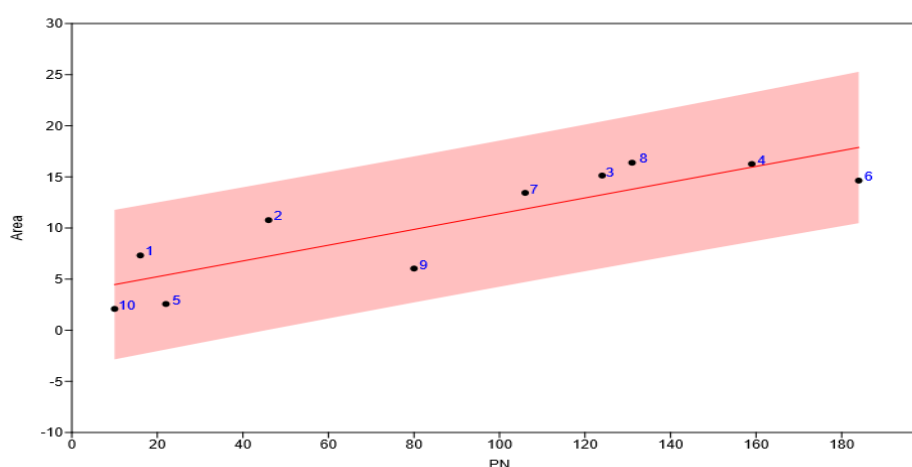
Table 3. Descriptive statistical parameters of vegetation indices by spectral classes

Clasa	n	NDVI	s.d.	SAVI	s.d.	MSAVI2	s.d.
1	3613	0.0301	0.0353	0.0493	0.0177	0.0633	0.0221
2	6776	0.0484	0.0418	0.0731	0.0212	0.0926	0.0255
3	2246	0.0716	0.0516	0.1061	0.0215	0.1317	0.0247
4	2349	0.0488	0.0303	0.0715	0.0127	0.0908	0.0156
5	2687	0.0593	0.0331	0.0955	0.0170	0.1195	0.0201
6	3087	0.0575	0.0290	0.0908	0.0168	0.1139	0.0202
7	5627	0.0871	0.0508	0.1268	0.0271	0.1553	0.0304
8	6542	0.0850	0.0471	0.1321	0.0330	0.1611	0.0372
9	12289	0.3430	0.1589	0.4526	0.1842	0.4498	0.1470
10	5184	0.1912	0.0894	0.2928	0.1034	0.3209	0.0998

ANOVA indicated highly significant differences between spectral classes for all analyzed variables. For NDVI, the F value was 9862.22, and $p < 0.001$. For SAVI and MSAVI2, the F values were 13729.20 and 17438.76, with $p < 0.001$. The results demonstrate that the K-Means clustering did not separate arbitrary classes, but classes with distinct spectral response. The high significance of the differences for NIR, RED, GREEN and BLUE confirms the spectral separability of the analyzed surfaces. Regression analysis described the relationship between Area (ha) and number of polygons (PN) in relation to spectral classes, with statistical safety ($p < 0.01$), Table 4, Figure 5.

Table 4. Statistical safety parameters related to regression analysis

Statistical Parameters		Statistical parameters values	
Slope a		0.0771	Std. error a: 0.0157
t		4.8982	p (slope): 0.0012
Intercept b		3.6965	Std. error b: 1.6676
95% bootstrapped confidence intervals (N=1999)			
Slope a		(0.043974, 0.10633)	
Intercept b		(0.092545, 6.6987)	
Correlation			
r		0.8660	
r ²		0.7499	
t		4.8982	
p (uncorr.)		0.0012	
Permutation p		0.0022	

**Figure 5.** Graphical expression of the relationship between Area and PN, and the positioning of the classes in relation to the regression line

The multivariate analysis described the distribution of classes in relation to the NDVI, SAVI, MSAVI2 indices and in relation to the polygon number (PN) and area parameters. The PCA diagram, Figure 6, showed the positioning of the classes in relation to the indices and parameters considered, as biplot.

Class 9 was correlated with NDVI, SAVI, and MSAVI2 indices. Five classes (3, 4, 6, 7, and 8) were correlated with PN and Area parameters. The other four classes (1, 2, 5, and 10) were independently ranked. The two principal components explained 97.945% of the total variance. The scores of the classes in relation to the principal components are presented in Table 5.

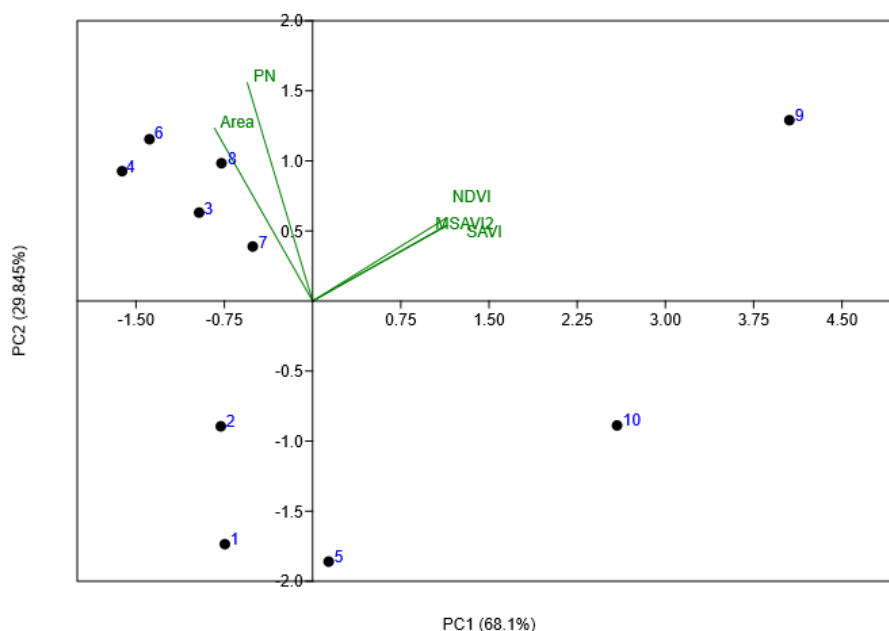


Figure 6. PCA diagram of class distribution in relation to the indices and parameters considered

Table 5. Class score in relation to the principal components

Class	PC 1	PC 2	PC 3	PC 4	PC 5
1	-0.7455	-1.7350	0.1695	-0.1056	0.0162
2	-0.7801	-0.8941	0.3538	-0.0521	0.0013
3	-0.9641	0.6312	0.1647	0.0215	-0.0078
4	-1.6193	0.9268	-0.1157	-0.0500	0.0083
5	0.1370	-1.8594	-0.4449	-0.0204	-0.0176
6	-1.3862	1.1548	-0.5661	0.0087	0.0093
7	-0.5090	0.3893	0.1684	0.0384	-0.0245
8	-0.7745	0.9835	0.2979	0.1037	0.0042
9	4.0534	1.2906	0.0262	-0.1433	-0.0011
10	2.5883	-0.8877	-0.0539	0.1993	0.0114

The cluster analysis grouped the classes based on similarity, in relation to the values of the NDVI, SAVI and MSAVI2 indices (Coph.corr. = 0.912). The cluster dendrogram, Figure 7, shows the grouping of the classes resulting from the unsupervised analysis. Two distinct clusters resulted; one cluster included classes 9 and 10, with the highest values of the SAVI and MSAVI2 indices, and the other classes were included in the second cluster, in several subclusters. The highest level of similarity was recorded between classes 2 and 4 (SDI = 0.0024; SDI – Similarity and Distance Indices), and the SDI dataset is presented in Table 6.

The multiannual series of indices showed significant variations between years, Table 7. The mean NDVI value was negative in 2012 (-0.0395), increased in 2013 (0.0684), reached a maximum in 2014 (0.3802), then decreased in 2015 (0.2125), 2016 (0.1131) and 2017 (-0.0354). This variation indicated strong differences in vegetation status between years, probably determined by crop phenology, climatic conditions and the degree of

vegetation cover at the time of the images. Salinity index values also had interannual variations, which supports the need for multitemporal monitoring and not just a single image.

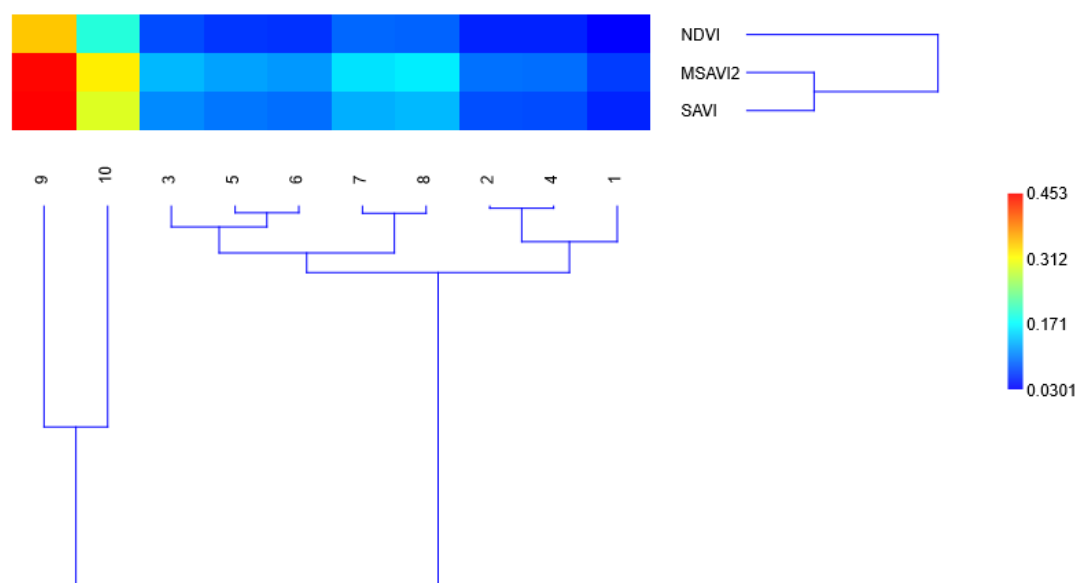


Figure 7. Cluster dendrogram with grouping of classes and characterization indices

Table 6. SDI values for the resulting classes in unsupervised analysis

	1	2	3	4	5	6	7	8	9	10
1		0.0420	0.0981	0.0400	0.0784	0.0709	0.1331	0.1394	0.6403	0.3894
2	0.0420		0.0562	0.0024	0.0367	0.0292	0.0912	0.0975	0.5987	0.3475
3	0.0981	0.0562		0.0582	0.0203	0.0274	0.0350	0.0415	0.5431	0.2915
4	0.0400	0.0024	0.0582		0.0389	0.0313	0.0932	0.0996	0.6006	0.3496
5	0.0784	0.0367	0.0203	0.0389		0.0075	0.0551	0.0611	0.5631	0.3113
6	0.0709	0.0292	0.0274	0.0313	0.0075		0.0623	0.0685	0.5703	0.3186
7	0.1331	0.0912	0.0350	0.0932	0.0551	0.0623		0.0081	0.5083	0.2565
8	0.1394	0.0975	0.0415	0.0996	0.0611	0.0685	0.0081		0.5026	0.2503
9	0.6403	0.5987	0.5431	0.6006	0.5631	0.5703	0.5083	0.5026		0.2553
10	0.3894	0.3475	0.2915	0.3496	0.3113	0.3186	0.2565	0.2503	0.2553	

Table 7. Multiannual average values of the indices calculated for the period 2012–2017

An	NDVI	SAVI	SI_1	SI_2
2012	-0.0395	-0.0592	4125.23	3376.64
2013	0.0684	0.1026	4766.61	4394.99
2014	0.3802	0.5703	3339.24	4573.82
2015	0.2125	0.3187	3247.51	3147.73
2016	0.1131	0.1696	3812.90	3951.99
2017	-0.0354	-0.0531	3930.91	3134.83

The cluster analysis showed the grouping of years based on similarity, in relation to the values of the NDVI, SAVI and SI indices (SI 1, SI2), in conditions of statistical safety (Coph.corr. – 0.811). The dendrogram in Figure 8 showed the independent positioning of the year 2013, based on the high NDVI values that highlighted it. The other years were grouped in the second cluster, based on similarity, Figure 8. The highest

level of similarity was recorded between the years 2012 and 2017 (SDI = 310.21), followed by the years 2012 and 2016 (SDI = 654.66), and respectively by the years 2015 and 2017 (SDI = 683.52). The SDI dataset is presented in Table 8.

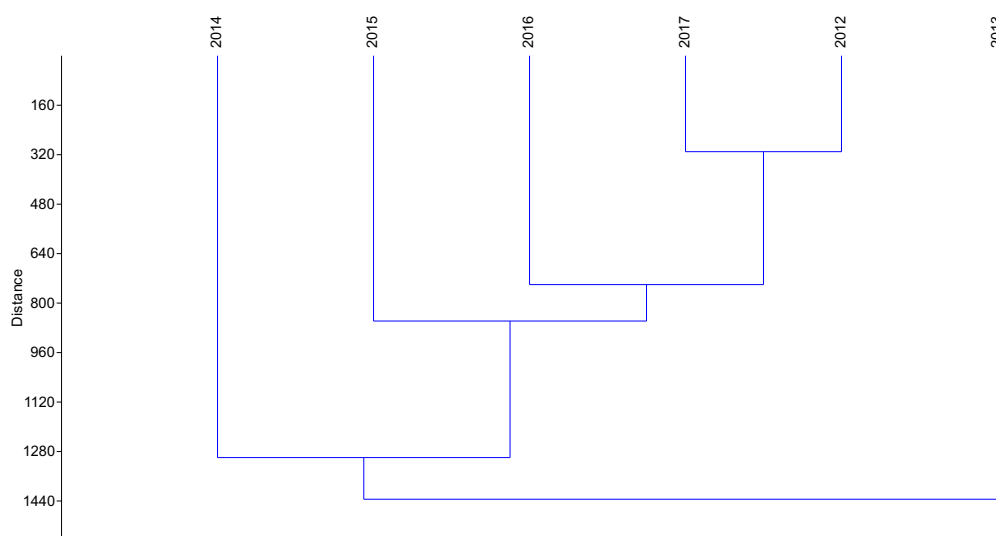


Figure 8. Cluster dendrogram with grouping of years and indices considered

Table 8. SDI values for the years of the study period

	2012	2013	2014	2015	2016	2017
2012		1203.50	1432.10	907.08	654.66	310.21
2013	1203.50		1438.50	1965.50	1051.60	1512.10
2014	1432.10	1438.50		1429.00	781.68	1555.90
2015	907.08	1965.50	1429.00		983.11	683.52
2016	654.66	1051.60	781.68	983.11		825.64
2017	310.21	1512.10	1555.90	683.52	825.64	

From the analysis of the distribution of years in the cluster diagram (Figure 8) and of the SDI values (Table 8), a level of similarity was observed between the years 2015, 2016, 2017.

By superimposing information from the false color composition, the NDVI map and the K-Means classification, class 5 was interpreted as a spectral unit associated with salts. It has an area of 25660.76 m² and occurs in areas where vegetation is poorly developed or discontinuous. The low values of NDVI and the statistical differentiation compared to the classes with active vegetation support this interpretation. However, for a complete pedological validation, the obtained map must be correlated with field analyses regarding electrical conductivity, pH, soluble salt content and ionic composition of the soil solution.

CONCLUSIONS

The total area analyzed in the Ciacova–Jebel–Voiteg area was 104.66 ha, and the K-Means classification delimited ten distinct spectral classes.

Class 5 was associated with areas affected by salinization, occupying 25660.76 m², respectively 2.45% of the total area.

The NDVI, SAVI and MSAVI2 indices highlighted clear differences between the spectral classes, the highest values being associated with classes with more vigorous vegetation.

ANOVA analysis confirmed highly statistically significant differences between classes for NDVI, SAVI, MSAVI2 and the analyzed spectral bands ($p < 0.001$).

The integration of Sentinel-2 images, vegetation indices and unsupervised classification represents an efficient method for the rapid identification of areas potentially affected by salinization.

For the final publication of the study, it is recommended to validate the satellite results through soil samples and laboratory determinations of electrical conductivity, pH and soluble salt content.

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