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THE USE OF REMOTE SENSING IMAGES IN ORDER TO CHARACTERIZE THE SOIL AGROCHEMICAL INDEXES IN RELATION TO THE AGRICULTURAL CROPS

SUMMARY

The present study evaluated the interdependence relationship between agrochemical soil indexes, agricultural crops, NDVI and SAVI indices, respectively Red Edge band, based on RapidEye remote sensing images. The NDVI, SAVI, and Red Edge were used to characterize the crops. Agrochemical indices of pH, humus (H), saturation in bases (V), nitrogen index (NI), phosphorus (P) and potassium (K) content, were used for the soil characterization. Kendall's correlation analysis revealed a very strong correlation between P and Red Edge (r = -0.905), moderate correlations between P and NDVI respectively SAVI (r = 0.619), and weak correlations between K and Red Edge (r = -0.524). The regression analysis facilitated the achievement of 2nd degree polynomial equations for the P prediction based on NDVI under the conditions of R^2= 0.724, p <0.01, the P prediction based on SAVI under conditions of R^2= 0.718, p <0.01, respectively P prediction based on Red Edge, under conditions of R^2= 0.985, p <<0.001. Prediction of K was possible based on NDVI, under the conditions of R^2= 0.774, based on SAVI under the conditions of R^2= 0.768, and respectively based on Red Edge under condition of R^2= 0.889. For the other agrochemical indices, the predictive relations in condition of low statistical safety were obtained (e.g. for pH based on Red Edge, R^2= 0.696; for H based on Red Edge, R^2= 0.538). For all agrochemicals, the safety predictions achieved through regression analysis were higher based on the Red Edge band compared to NDVI or SAVI indices.

Keywords: agrochemical indices, NDVI, prediction model, Red Edge, SAVI, soil

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INTRODUCTION

Precision agriculture is growing ground due to the immense advantages it has in terms of practical, technically and economically, profitability at farm level, but also in terms of environmental protection and agricultural products (Wójtowicz *et al.*, 2016). The satellite techniques have already been used in the evaluation and characterization of the vegetal cover, the classification of the territory and the crops (Ustuner *et al.*, 2014; Gómez *et al.*, 2016; Dalmau *et al.*, 2017) on vegetative stages studies (Firoozi *et al.*, 2020), LAI and chlorophyll content evaluation (Delegido *et al.*, 2011; Frampton *et al.*, 2013), crop evapo-transpiration (Reyes-Gonźalez *et al.*, 2018), discrimination of subtle differences between C3 and C4 grasses (Shoko and Mutanga, 2017), estimation of grain and biomass production (Panda *et al.*, 2010; Prabhakara *et al.*, 2015; Kostić *et al.*, 2020).

The assessment of soil fertility by classical methods is no longer considered adequate due to the high workload, time consumed and lack of spatial exhaustiveness (Ge *et al.*, 2011). A very useful tool for precision farming is already remote sensing, which allows real-time, rapid, cost-effective information gathering and large spatial resolution to study and assess soil fertility (Kilic, 2021; Khaki *et al.*, 2017; Lense *et al.*, 2020). But this instrument, through the facilities they provide, can also be useful for farms that do not practice precision agriculture, for the more efficient management of soil and agricultural crops, sustainable agriculture (Popovici *et al.*, 2018). A wide range of soil-specific fertility properties and high agricultural importance such as moisture content, different textures, organic substances, carbon content, macro- and oligoelements, cation exchange capacity, pH, electrical conductivity and iron, can be successfully quantified with remote sensing (Kozar *et al.*, 2002; Wan *et al.*, 2004; Calina *et al.*, 2020). This already facilitates mapping of the soil in the field, with techniques based on satellite imagery and specific indices.

Techniques based on satellite imagery have been used to evaluate land with agricultural potential and to delimit land units and areas affected by certain limiting factors (Eldeiry and Garcia, 2010; Saleh *et al.*, 2015). Nutrient management also benefits from remote sensing and GIS facilities (Markoski *et al.*, 2015). Kim *et al.* (2014) conducted a survey of P and N soil based on remote sensing to characterize some water systems. Sharf *et al.* (2002) used remote sensing in nitrogen management studies, which have a very high impact on the increase in agricultural output but with high variability in the field. Similar studies have been conducted by Muñoz-Huerta *et al.* (2013).

The purpose of this study was to evaluate how certain agrochemical soil indices are reflected in the values of specific indices calculated on the basis of spectral information of agricultural crops based on satellite imagery.

MATERIAL AND METHODS

The purpose of the study was to evaluate the interdependence of the NDVI, SAVI and Red Edge indices based on spectral information from the satellite images and soil agrochemical indices, and to formulate remote sensing working models on the sustainable use of farmland.

The used satellite system. RapidEye is a satellite remote sensing system that allows you to have at any point on Terra, at least daily, a multispectral imaging capability. The Rapid Eye system consists of 5 spectral bands: Blue, Green, Red, Red Edge and NIR, with a 5-meter spatial resolution. The transition between Red Absorption and NIR (Near Infrared) reflecting the Red Edge band is able to provide additional information about the vegetation and its feature.

The studied area. The studied agricultural area is located within the Didactic and Experimental Resort of BUASVM Timisoara, Timis County, Romania. The study was conducted place during the agricultural year 2016 - 2017. In this study, a Rapid Eye satellite image was taken at the 5M resolution of 15.05.2017 from Planet portal (Planet Team, 2017) with the 3460215_2017-05-15_RE4_3A flag. The coordinate system of the Rapid Eye scene is the 34N UTM System, WGS 84. To view the studied area, two combinations of spectral bands were made, namely the RGB image combination 321 and the False Color image combination 532, Figure 1. The retrieved satellite data was processed with the ERDAS Image v. 11 and ArcGIS v. 10.5 software. Based on the satellite image, the Red Edge band numerical values were extracted and two vegetation indices, namely the NDVI (Normalized Difference Vegetation Index) introduced by Rouse *et al.* (1974), relationship (1) and SAVI (Soil Adjusted Vegetation Index), introduced by Huete (1988), relationship (2).

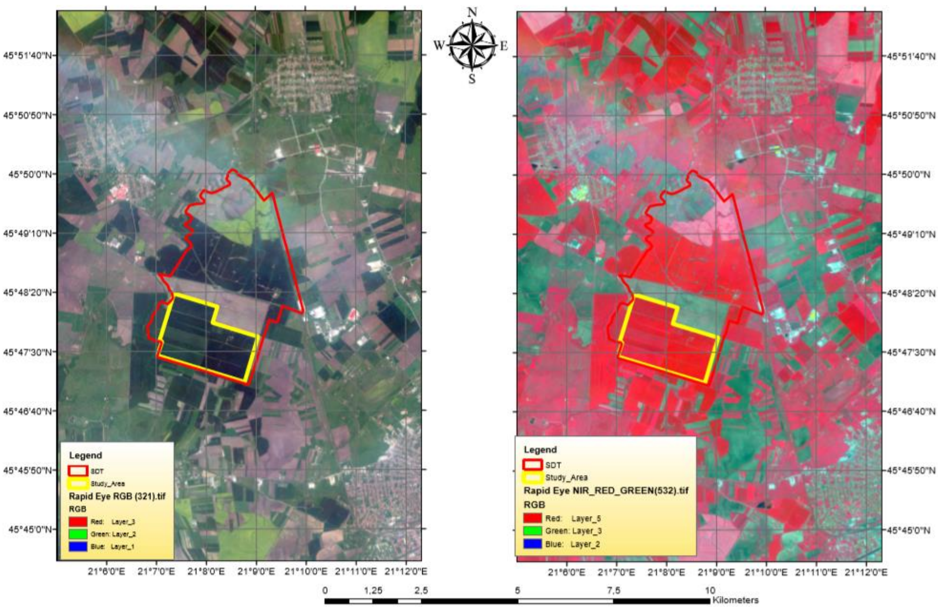

Figure 1. Studied area in Natural colors and False colors

$$NDVI = \frac{R_{800} - R_{670}}{R_{800} + R_{670}} = \frac{NIR - RED}{NIR + RED} = \frac{B5 - B3}{B5 + B3} \quad (1)$$

$$NSAVI = \frac{(R_{800} - R_{670}) \times (1 + L)}{(R_{800} + R_{670} + L)} = \frac{(NIR - RED) \times (1 + L)}{(NIR + RED + L)} = \frac{(B5 - B3) \times (1 + L)}{(B5 + B3 + L)} \quad (2)$$

where: R_i is reflectance at the band centered at a given wavelength i (in nm); L= 0.5 – Vegetation cover correction factor.

Soil and agricultural crops. The soil in the studied area is cambic chernozem, the land being divided into 7 parcels with the area between 52.22 and 54.49 ha. There were wheat, oats and barley in culture. The agrochemical indices studied were the humus content (H), soil pH, phosphorus (P), potassium (K), the degree of saturation in bases (V) and Nitrogen Index (NI) (OSPA).

Processing of experimental data. The experimental data obtained were analyzed by the Kendall correlation analysis, descriptive statistics and regression analysis, using the EXCEL statistical calculation module, the OFFICE 2007 suite, the PAST 3 software (Rujescu *et al.*, 2014; Hammer *et al.* 2017).

RESULTS AND DISCUSSION

The values of the agrochemical indices on the land plots studied had variable values in relation to the specificity of the agrochemical index and the real situation in the field. The pH was between 6.27 and 7.35, the soil reaction being slightly acidic on 71.44% of the studied area (373.6 ha) and neutral on 28.56% of the area. Phosphorus supply is poor on 28.56% of the surface, average supply is 28.73% and very good supply is 42.71% of the area. Supply with K was good at 14.56% and very good on 85.44% of the surface. The supply of humus (H) was of medium level on the whole surface, the degree of saturation in bases (V) ranged from 84.0-94.5%, and the Nitrogen Index (NI) was the average level on the whole surface according to the standards in force (Sala, 2011), the values being presented in Table 1.

Cultures have expressed phenotypical the state of supply of land with nutrients. As a result, the agricultural images were compared with their real state at the time of the study, and the values of the NDVI, SAVI and Red Edge indices reflected crop information in close connection with the soil fertility status, agrochemical index values and of those calculated are shown in Table 1. Testing the level of correlation between the data series corresponding to the above indicators using the Kendall correlation coefficient, the data in Table 2 was obtained. A strong and statistically correlation was observed between P and Red Edge, correlated inversely ($r = -0.905$, $p = 0.004$). Direct intensity correlations between P and SAVI respectively between P and NDVI ($r = 0.619$ with p values close to 0.05) were observed. And the values of K correlate, but only slightly, $r = 0.429$ with NDVI and SAVI, respectively with Red Edge, $r = - 0.524$.

It is to be noticed that the NI and V values do not differ greatly from one plot to the other, with the differences between the minimum and maximum being low. Also, their series are homogeneous, with a low coefficient of variation, Table 3.

Table 1. Agrochemical index values and calculated indices for crop characterization

Parcel	Area (ha)	NDVI	SAVI	Red Edge	pH	P (ppm)	K (ppm)	H	V (%)	NI
1 / A84	52.22	0.677674	1.016389	6085.572	6.62	78.66	241.17	4.42	87	3.85
2 / A80	54.49	0.627742	0.941212	6111.502	6.74	69.59	234.4	4.05	88	3.56
3 / A75	52.32	0.661968	0.993197	6126.947	7.12	55.64	238.59	4.12	92	3.79
4 / A68	54.38	0.613137	0.920047	6242.421	7.35	19.94	178.41	3.71	94.5	3.51
5 / A77	52.85	0.62897	0.943328	6177.625	6.27	48.64	210.54	4.58	84	3.85
6 / A82	53.96	0.677191	1.015643	6034.912	6.30	97.53	298.7	3.66	84.5	3.09
7 / A86	53.38	0.681264	1.021864	5999.694	6.65	95.01	217.95	4.05	87	3.52

Table 2. Matrix correlation table (Kendall) between calculated indices and agrochemical indices

	NDVI	SAVI	Red Edge	pH	P	K	H	V	NI
NDVI		0.002	0.024	0.453	0.051	0.176	0.758	0.356	0.758
SAVI	1.000		0.024	0.453	0.051	0.176	0.758	0.356	0.758
Red Edge	-0.714	-0.714		0.293	0.004	0.099	0.538	0.218	0.538
pH	-0.238	-0.238	0.333		0.176	0.453	0.356	0.002	0.538
P	0.619	0.619	-0.905	-0.429		0.051	0.356	0.124	0.356
K	0.429	0.429	-0.524	-0.238	0.619		1.000	0.538	0.758
H	0.098	0.098	0.195	-0.293	-0.293	0.000		0.430	0.003
V	-0.293	-0.293	0.390	0.976	-0.488	-0.195	-0.250		0.636
NI	0.098	0.098	0.195	-0.195	-0.293	0.098	0.950	-0.150	

Table 3. Statistical parameters describing the values of agrochemical indices

	pH	P	K	H	V	NI
Min	6.271	19.940	178.410	3.660	84.000	3.090
Max	7.348	97.530	298.700	4.580	94.500	3.850
Sum	47.055	465.010	1619.760	28.590	617.000	25.170
Mean	6.722	66.430	231.394	4.084	88.143	3.596
Stand. Dev	0.398	27.501	36.764	0.337	3.837	0.270
Median	6.651	69.590	234.400	4.050	87.000	3.560
Coeff. Var	5.919	41.398	15.888	8.256	4.354	7.507

It is possible, therefore, that this aspect does not reveal a possible correlation between them and the calculated indices. Furthermore, low NI values of less than 4 for these parcels can make potassium inefficient, as only the presence of potassium under low nitrogen levels cannot effectively support plant growth.

The phenomenon identified and highlighted in this case, demonstrates the functionality of the minimum, maximum and optimum law.

Considering the complexity of the agrochemical mapping work in terms of the time of realization, the workload on the field and in the laboratory, the human resource involved and the costs, and starting from the correlation between the indices calculated on the basis of the spectral information in the satellite images and certain agrochemical indices, a regression analysis was performed to assess the possibility of soil situation prediction based on remote sensing.

In the case of phosphorus, the best correlated element in the studied conditions with NDVI, SAVI and Red Edge, regression analysis facilitated the obtaining of some 2nd degree polynomial equations for the prediction of P in relation to NDVI, the relation (3) under conditions of R^2= 0.724, p <0.01, for P prediction in relation to SAVI, relation (4) under conditions of R^2= 0.718, p <0.01 respectively P prediction in relation to Red Edge, relation (5) under conditions of R^2= 0.985, p<<0.001. The graphical distribution of real and predicted P values in relation to NDVI and Red Edge are shown in Figure 2, respectively Figure 3.

$$P_{NDVI} = -5307.2x^2 + 7702.3x - 2696.1 \qquad (3)$$

$$P_{SAVI} = -2257.6x^2 + 4936.6x - 2599.1 \qquad (4)$$

$$P_{REDEDGE} = -0.0005x^2 + 6.0476x - 17439 \qquad (5)$$

where: x – NDVI in relation (3); x – SAVI in relation (4); x – Red Edge in relation (5)

In the case of potassium, from correlation analysis resulted lower correlation coefficients with both NDVI and SAVI (r = 0.429), and as well as with Red Edge (r = 0.524). Regression analysis facilitated prediction K based on NDVI, under conditions of R^2= 0.774, relation (6), based on SAVI, under conditions of R^2= 0.768, relation (7) and based on Red Edge under condition of R^2= 0.889, the relation (8). The graphical distribution of real and predicted K values in relation to NDVI and Red Edge are presented in Figure 4, respectively Figure 5.

Different studies have approached fertilization models with mineral or foliar fertilizers to restore soil fertility, especially with P and K, and direct sustaining agricultural production (Rawashdeh and Sala, 2016).

$$K_{NDVI} = -12818x^2 + 7478x - 5706.6 \qquad (6)$$

$$K_{SAVI} = -5735.7x^2 + 11726x - 5742 \qquad (7)$$

$$K_{REDEDGE} = -0.0014x^2 + 17.178x - 51419 \qquad (8)$$

where: x – NDVI in relation (6); x – SAVI in relation (7); x – Red Edge in relation (8)

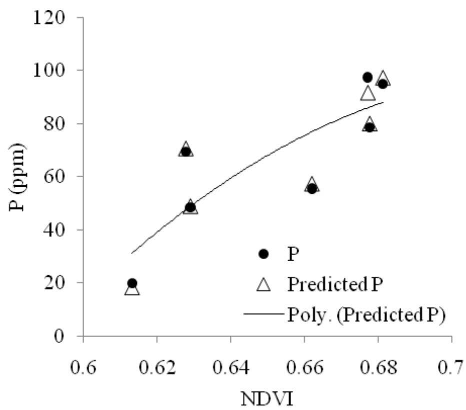

Figure 2. Graphical distribution of real and predicted P-values by NDVI

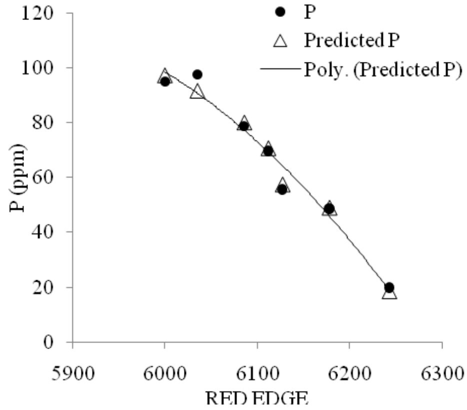

Figure 3. The graphical distribution of the real and predicted values of P by Red Edge

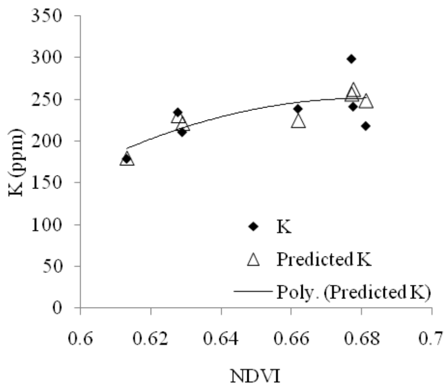

Figure 4. The graphical distribution of the real and predicted K values of the NDVI

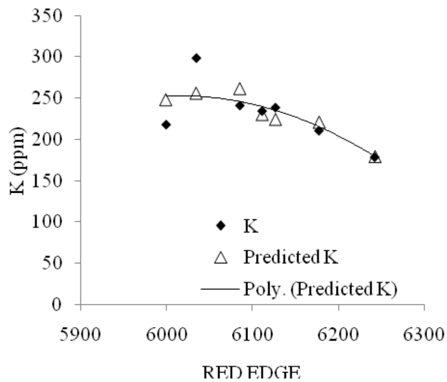

Figure 5. The graphical distribution of the real and predicted K by Red Edge

For the other agrochemical soil characterization indices, the correlation level was lower, according to the Kendall correlation analysis. As a result, regression analysis also facilitated the prediction of these indices with lower statistical safety. Thus, the soil pH was predicted by NDVI under condition of R^2= 0.324, depending on SAVI under conditions of R^2= 0.316, and depending on Red Edge under conditions of R^2= 0.696. The humus content (H) was predicted based on NDVI under conditions of R^2= 0.152, based on SAVI under conditions of R^2= 0.154, respectively based on Red Edge under conditions of R^2= 0.538. The degree of saturation in bases (V) was predicted based on NDVI under conditions of R^2= 0.325, under conditions of R^2= 0.317 based on SAVI, respectively under conditions of R^2= 0.703 based on Red Edge. The nitrogen index (NI) was predicted under conditions of R^2= 0.144 based on NDVI, under conditions of R^2=

0.147 based on SAVI, respectively under conditions of R^2= 0.623 based on Red Edge.

Red Edge band has proven to be particularly useful when studying crops health, nutrition and vegetation stress (Filella and Peñuelas, 1994; Li *et al.*, 2014), but it is also a tool for studies of astrobiology (Seager *et al.*, 2005). The Red Edge band is a unique feature that brings extra spectral information of RapidEye satellites to most multispectral satellites. The Red Edge band is located between the red band and the NIR band, without overlapping. The Red Edge band's sensitivity to the differences in leaf structure and chlorophyll content in relation to soil and nutrition factors, especially N, already has useful applications in the field of precision farming and resource monitoring and management (Clevers and Gitelson, 2013).

Vegetation indices are numerical indicators that reduce multispectral data (2 or more spectral bands) to a single variable for the prediction and evaluation of vegetation and vegetal carpet information.

The most widely used indicator of vegetation is the NDVI index, introduced in 1974 by Rouse and used to highlight vegetation health status, but also as an indicator of green biomass on the land surface or at the level farms, plots, agricultural crops. A series of scientific articles have been studied on the basis of remote sensing by means of dedicated indices of the state of the crops, the state of nutrition especially with nitrogen (Fitzgerald *et al.*, 2010). NDVI index values ranged from -1 to 1. In the case of normal and healthy vegetation, NDVI values are typically in the range of 0.1-0.75 and rarely reach 1, depending on its density, being one of the most use indices to characterize vegetation in relation to soil and growth conditions (Wu, 2014; Yang and Guo, 2014).

The SAVI index, introduced in 1988 by Huete, is a "hybrid" between the indices based on the ratio of spectral bands and perpendicular indices. The use of the SAVI index allows observation and monitoring of seasonal, annual and multi-annual vegetal cover, being used in various studies and underlying other vegetation indices, MSAVI, OSAVI (Hartfield and Prueger, 2010).

In the present study, for all soil agrochemical indices, the correlation coefficient with calculated indices (NDVI, SAVI and by Red Edge) and implicitly safety predictions made by regression analysis was higher based on the by Red Edge band compared to NDVI or SAVI indices.

CONCLUSIONS

Kendall's correlation analysis highlighted the high correlation between P and by Red Edge and weak average correlations between calculated indices and other agrochemical indices.

Regression analysis facilitated the acquisition of 2nd degree polynomial equations as predictive models of agrochemical indices based on NDVI, SAVI and by Red Edge, with high statistical safety for P and average statistical safety for K.

For all soil agrochemical indices considered, in the study agricultural area conditions (DER, BUASVM Timisoara, Timis County, Romania) the safety level of predictions made by regression analysis was higher based on the Red Edge band compared to NDVI or SAVI indices.

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