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SPATIAL VARIABILITY OF WHEAT CROP ASSOCIATED WITH SOME TECHNOLOGICAL PRACTICES DESCRIBED BASED ON REMOTE SENSING

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Abstract

The study analyzed the spatial variability of the autumn wheat crop, based on remote sensing techniques. The RapidEye satellite system was used to retrieve images of the wheat crop. The images were taken during May, when the vegetation was already well represented in relation to the vegetation conditions. Based on the images, the NDVI index was calculated. The map of the NDVI index was reclassified and six classes resulted (C1 to C6). The NDVI raster image was transformed into vector format and the area (Area, ha) was calculated for each class. The area per class varied between 1.873 ha (3.81%) in the case of C1, and 12.659 ha (25.78%) in the case of C4. There were significant differences between sample medians of NDVI on the six identified classes, H (chi^2) = 1.877E04, H_c (tie corrected) = 1.877E04, p = 0. According to the t Test and the Wilcoxon Test, there were significant differences (sig. diff.) between the data series C1 to C6 of the NDVI index, and the mean value, respectively the median, at the wheat crop level. The Area variation in relation to NDVI was described by a 3rd degree polynomial model (R^2 = 0.999, p = 0.00104). The spatial distribution of NDVI values was most likely associated with fertilization works, which generated certain non-uniformity in the distribution of fertilizers.

Key words: *agricultural practices, farm management, field spatial variability, geostatistics, RapidEye, wheat*

INTRODUCTION

Agricultural crops can express spatial and temporal variability in relation to soil conditions (soil genesis, and soil types and quality), with climatic factors, but also with certain agricultural practices, a fact that affects the yield and quality of agricultural production [17, 27]. Agricultural practices can induce variability in the quality of the soil, can alter the ecosystems, and can have a variable impact on the environment [3, 6, 10, 26].

Fanelli (2020) [10] evaluated how certain agricultural practices influenced the variability of agricultural land, and the environment in EU countries. Based on the study, a classification of the considered countries into four classes resulted, in relation to certain considered parameters.

Popescu et al. (2024) [20] carried out an extensive study on land use during the last two decades, globally and at the level of EU countries, which shows the very high importance of agricultural land and soil resources in safety and food security.

In order to achieve an adequate management of nutrients and some technical approaches in relation to the specifics of the location, the spatial variability of the content of nutrients in agricultural lands was analyzed, on a large scale, as well as on a small scale [14]. The authors identified significant spatial variability, in relation to the surface of the plots, and the history of agricultural practices, especially in relation to the applied fertilizers. The yields were in close correlation with the degree of variability recorded, and based on the results, recommendations were formulated for sustainable agricultural practices, in relation to the specifics of the study area.

Kihara et al. (2016) [15] found different sensitivities of corn crops to the application of mineral and organic fertilizers, in relation to soil fertility.

The land of a farm has variable areas in terms of yield, some with better potential and others with lower production potential, in relation to various influencing factors, such as the soil, topography of the land, climatic conditions, and management practices [16]. The authors conducted an extensive study (338 crop fields) of different crops (wheat, soybeans, corn, cotton) in conditions specific to the US Midwest, and evaluated how the stability of production is affected by environmental factors.

Studies and experiments at the farm level represent appropriate tools for evaluating variability, in order to improve management decisions and agricultural practices [27]. The authors of the study evaluated the spatial variability of the corn crop in relation to nitrogen and variable seed rates, under the aspect of technological costs.

Spatial variability was analyzed for different agricultural crops through remote sensing techniques (Landsat), and specific indices (e,g, NDVI, EVI, SAVI, GNDVI), in specific Mediterranean climate conditions [2]. The authors recorded variable levels of yield correlation in relation to the indices used, and the location within the crops.

Agroecosystem models are important to estimate crop variability, yields and management of agricultural production systems. Brogi et al. (2020) [5] used simulations to analyze the spatial variability of soil water content and crop dynamics in relation to soil properties. Data from the RapidEye system were used to calculate indices for the purpose of the study. The authors recorded the variation of the LAI index in relation to the water stress in the soil, as well as to the analyzed agricultural soils.

In the context of precision agriculture, the variation of soil properties at the small scale of agricultural land surfaces is important for agricultural practices and crop yields [11]. The authors found a 45-46% explanation of the variation in autumn wheat production in relation to certain soil properties. Significant differences in the yield variation were given by soil organic carbon.

The combined influence of fertilizers with relief on production was studied in different crops [1]. The authors recorded variable yields depending on the relief, and the interaction of the relief with the application of fertilizers to wheat (*Triticum aestivum*) and teff (*Eragrostis tef*).

Crop productivity was analyzed through the appropriate management of nutrients in relation to the spatial variability of soil quality indices [23]. The authors considered certain areas of differentiated soil management necessary in relation to quality indices. The heterogeneity of the soil was assessed based on the values of the coefficient of variation, calculated in relation to the soil quality indices. Based on appropriate methods of analysis, the authors formulated recom-mendations for nutrient management for sustainable yields in the sugar beet and barley crops they studied.

Based on the remote sensing technique, the RapidEye satellite system, the study analyzed the spatial variability of the autumn wheat crop, as a possible effect of some agricultural practices through fertilization, and generated a classification based on NDVI values.

MATERIALS AND METHODS

The study analyzed a wheat crop, to characterize the spatial variability based on satellite images. The field research and the study took place within the DER (Didactic and Experimental Resort), University of Life Scisnces “King Mihai I” from Timisoara (ULST), Figure 1.

The wheat crop was carried out on a plot of 50 ha, with chernozem type soil, medium fertility, and non-irrigated crops system. For the analysis and characterization of the wheat crop, the satellite images were taken in May. The RapidEye satellite system was used to retrieve the images, at a resolution of 5m [19]. Based on the spectral values, the NDVI index was calculated, equation (1) [21].

$$NDVI = ((NIR - Red)/(NIR + Red)) \quad (1)$$

In relation to the purpose of the study, the map of the NDVI index was analyzed for reclassification [9]. To determine the area on the identified classes, the NDVI raster image was transformed into vector format, and the area of each class was calculated.

For the general characterization of the

recorded data, descriptive statistical analysis was applied. The comparative analysis of the NDVI data series between classes, as well as against the mean value of NDVI at the plot level, was done by specific tests, Several-sample tests (Kruskal-Wallis), and One sample test (t Test, Wilcoxon) [12, 13].

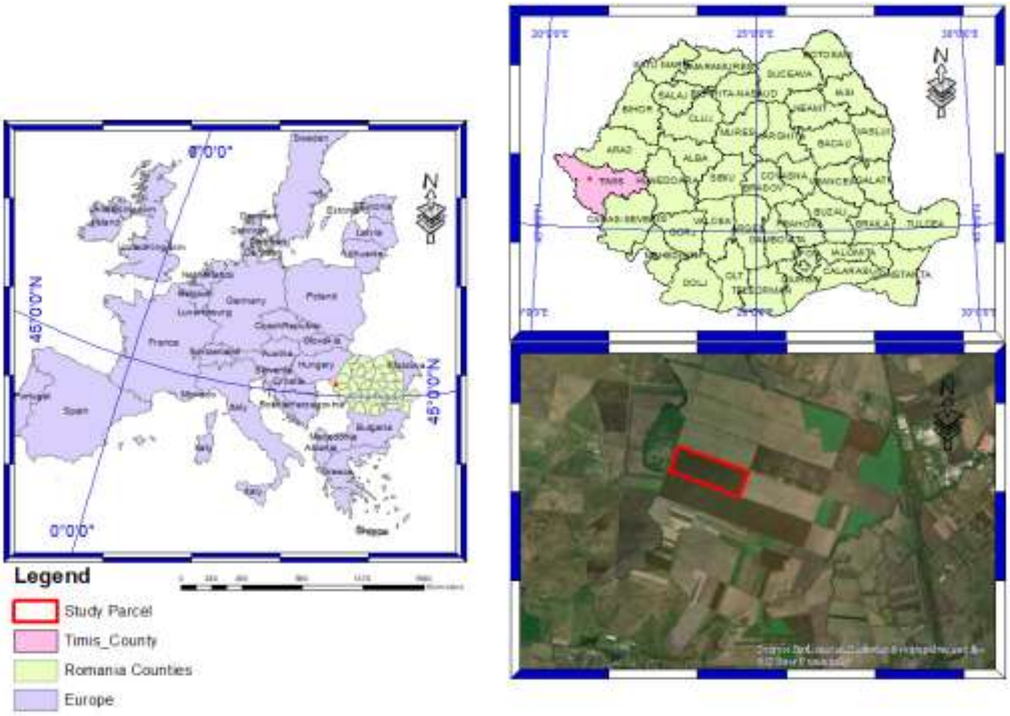


Fig. 1. Study location
Source: Original figure.

RESULTS AND DISCUSSIONS

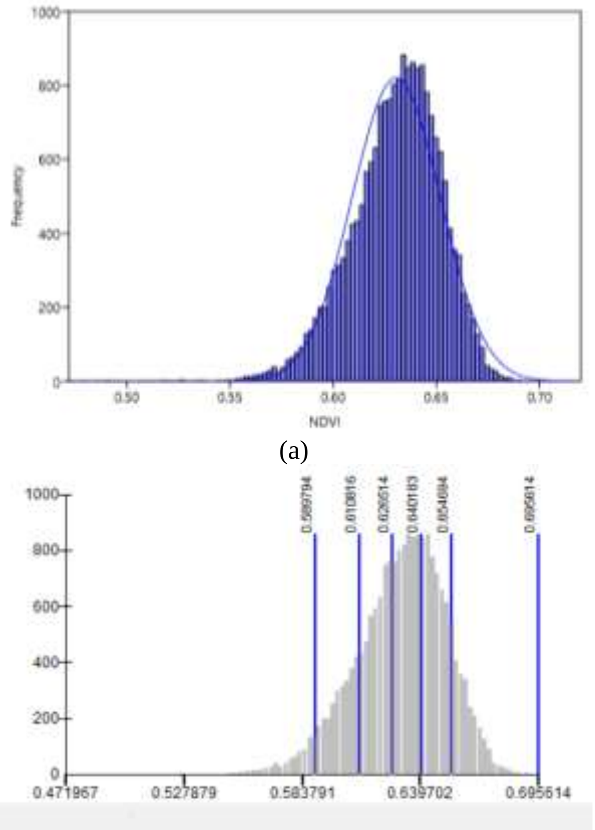
The satellite images (RapidEye) were analyzed and the spectral values were obtained. Based on the spectral values, and equation (1), the values of the NDVI index were calculated. A series of 19,650 values resulted, which described the wheat crop in the study plot. The NDVI raster image was reclassified and resulted in 6 classes (C1 to C6), depending on the intensity of the pixels. The number of values within the classes was unequal, according to the descriptive statistical analysis presented in Table 1.

Table 1. The statistical data characterizing the NDVI values by class in the wheat crop analysis

Statistical Parameters	C1	C2	C3	C4	C5	C6
Valid	771	2642	4254	5073	4674	2236
Median	0.582	0.603	0.620	0.634	0.647	0.661
Mean	0.578	0.602	0.620	0.634	0.647	0.663
Std. Error of Mean	5.279×10^{-4}	1.131×10^{-4}	6.821×10^{-5}	5.497×10^{-5}	6.050×10^{-5}	1.334×10^{-4}
Coefficient of variation	0.025	0.010	0.007	0.006	0.006	0.010
Variance	2.149×10^{-4}	3.379×10^{-5}	1.979×10^{-5}	1.533×10^{-5}	1.711×10^{-5}	3.981×10^{-5}
Minimum	0.472	0.590	0.611	0.627	0.640	0.655
Maximum	0.590	0.611	0.627	0.640	0.655	0.696
25th percentile	0.573	0.598	0.616	0.630	0.643	0.658
50th percentile	0.582	0.603	0.62	0.634	0.647	0.661
75th percentile	0.587	0.607	0.623	0.637	0.650	0.666

Source: Original data.

The data series presented a normal distribution, Figure 2. Based on spatial analysis, the raster image of NDVI was transformed into vector format, and it was possible to calculate the area of each class (C1 to C6). The NDVI mean values, and the values areas per class, are presented in table 2. The NDVI values in map format are presented in Figure 3, and the graphic representation of the classes is presented in Figure 4.



(a)

(b)

Fig. 2. Graphic distribution of NDVI values; (a) distribution histogram; (b) the class intervals associated with the histogram
Source: Original figure.

Table 2. Mean values of the NDVI index and of the area per class

Class	NDVI	Area	
		(ha)	(%)
C1	0.5775013	1.873	3.81
C2	0.6021298	6.656	13.55
C3	0.6195131	10.593	21.57
C4	0.6335167	12.659	25.78
C5	0.6468586	11.815	24.06
C6	0.6625326	5.513	11.23
Total		49.109	100.00

Source: Original data.

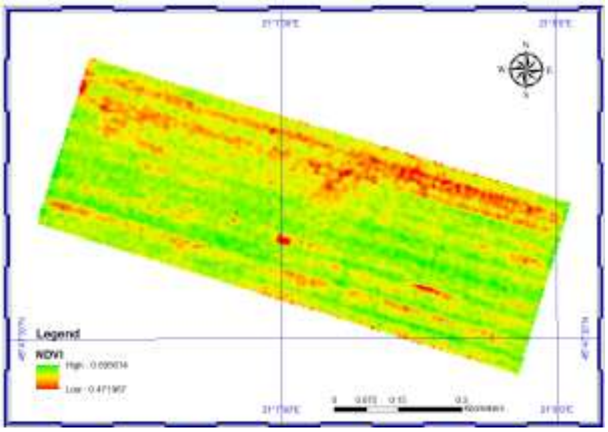


Fig. 3. Map of the NDVI index in the characterization of the wheat crop
Source: Original figure.

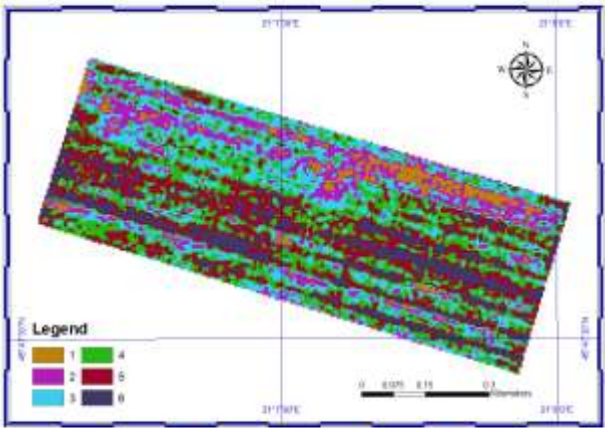


Fig. 4. Map of the resulting classes for the characterization of the wheat crop
Source: Original figure.

According to Several-sample tests, Kruskal-Wallis test for equal medians, it resulted that there are significant differences between sample medians of NDVI on the six identified classes (C1 to C6), H (chi^2) = 1.877E04, H_c (tie corrected) = 1.877E04, p = 0.

The NDVI values expressed the condition of the wheat plants on the crop plot. The distribution of the values was random, depending on the condition of the land, but also with technological works, especially with fertilization.

The comparative analysis was made between each series of NDVI values according to the classification (C1 to C6), with the mean and median value, at the wheat crop level (complete series of data). The results obtained are presented in table 3.

According to the t Test and the Wilcoxon Test, it turned out that there were significant differences (sig. diff.) between the data series

C1 to C6 of the NDVI index and the mean value, respectively the median, at the level of the wheat crop. The results of the applied tests are presented in Table 3.

Table 3. Test values for NDVI data series by class

Statistical parameter	C1	C2	C3	C4	C5	C6
	t Test					
Given mean:	0.62367535	0.62367535	0.62367535	0.6236753	0.62367535	0.62367535
Sample mean:	0.5775	0.60213	0.61951	0.63352	0.64686	0.66253
95% conf. interval:	(0.57646 0.57854)	(0.60191 0.60235)	(0.61938 0.61965)	(0.63341 0.63362)	(0.64674 0.64698)	(0.66227 0.66279)
Difference:	0.046174	0.021546	0.0041622	0.0098414	0.023183	0.038857
95% conf. interval:	(0.045138 0.04721)	(0.021324 0.021767)	(0.0040285 0.0042959)	(0.0097336 0.0099492)	(0.023065 0.023302)	(0.038596 0.039119)
t :	-87.464	-190.53	-61.02	179.02	383.2	291.21
p (same mean):	0	0	0	0	0	0
Significance of differences for mean	sig. diff.	sig. diff.	sig. diff.	sig. diff.	sig. diff.	sig. diff.
	Wilcoxon Test					
Given median:	0.624285667	0.624285667	0.624285667	0.624285667	0.624285667	0.624285667
Sample median:	0.58181	0.6028	0.61996	0.63352	0.64656	0.66106
W :	2.98E+05	3.49E+06	8.47E+06	1.29E+07	1.09E+07	2.50E+06
Normal appr. z :	24.055	44.518	49.258	61.686	59.21	40.956
p (same median):	7.47E-128	0	0	0	0	0
Significance of differences for median	sig. diff.	sig. diff.	sig. diff.	sig. diff.	sig. diff.	sig. diff.

Source: Original data.

The Area variation in relation to the NDVI values was described by equation (2), R^2 = 0.999, p = 0.00104, figure 5.

$$\text{Area} = -0.693\text{E}04x^3 + 1.577\text{E}05x^2 - 9.515\text{E}04x + 1.909\text{E}04 \quad (2)$$

where: x – NDVI values

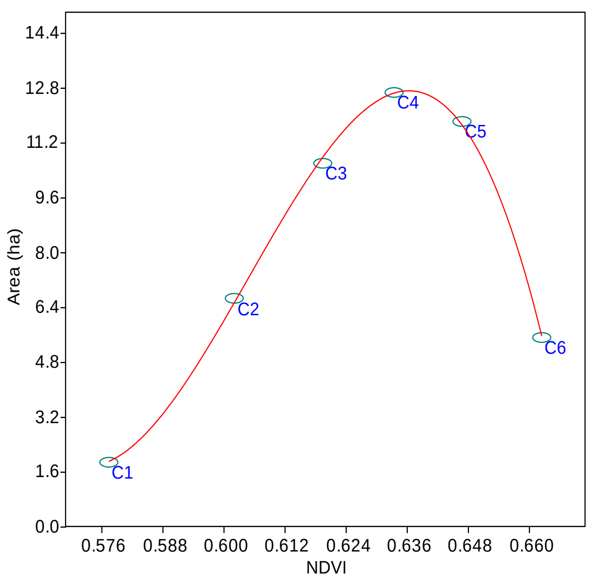


Fig. 5. Graphic distribution of Area in relation to NDVI
Source: Original figure.

The Ranking analysis led to the ranking of the classes identified in the wheat crop, by reclassifying the NDVI raster image, diagram in Figure 6.

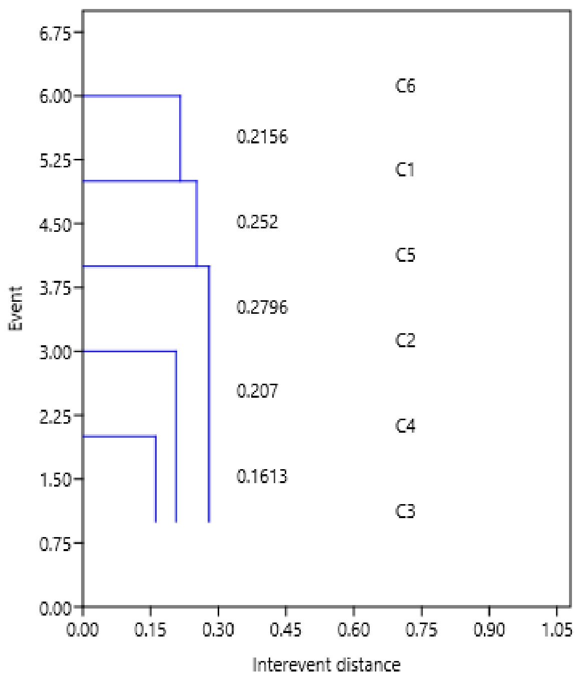


Fig. 6. Hierarchy of wheat crop classes, in relation to mean values
Source: Original figure.

From the analysis of the spatial distribution of the NDVI values (Figure 3), as well as of the resulting classes Ffigure 4), a certain tendency of predominantly longitudinal arrangement of the NDVI values and classes (according to the maps, Figure 3 and Figure 4) was found within the plot of wheat crop.

This layout can be associated with a certain work of agricultural technology, especially with fertilization.

Through the cross-sectional analysis of the values within the study plot, a sinusoidal graphic distribution resulted (Figure 7). In the fertilization work, the administration of fertilizers is done on a variable width of 12m, 24m or 36m. The distribution width of the fertilizers varies depending on the working width of the fertilizer application machine, but also depending on the quality indicators of the mineral fertilizers (e.g. granulometry).

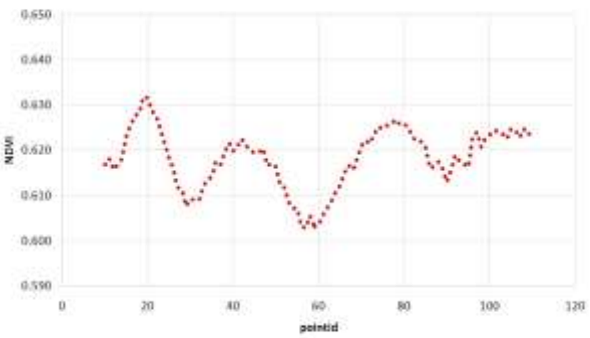


Fig. 7. Transversal distribution profile of NDVI values
Source: Original figure.

The spatial variability of agricultural lands was recorded in relation to natural and anthropogenic factors. The variability of the land induced by agricultural practices was also communicated in different studies [3, 8, 10].

Some studies have recommended certain fertilization systems to control the yield and quality of plant production, for the purpose of sustainable agricultural practices, sustainable agrosystems, and environmental sustainability [7, 18, 24, 28].

The variability of crops in relation to fertilizers was also analyzed in other studies, in order to understand the causes and formulate solutions [15, 22].

The methods based on the remote sensing technique and imaging analysis are very effective in assessing the variability of crops in relation to fertilization, and soil fertility [4, 25], and facilitate yield and quality estimates of agricultural production.

In the present study, certain variability was identified in the winter wheat crop, associated with the land and fertilizer application practices. The non-uniformity of the crop, based on the NDVI values, presented a pronounced longitudinal distribution, expressed by a sinusoidal graphic representation.

This overlaps with the routes of application of mineral fertilizers. Through the partial covering of the fertilization strips, during the mechanized application of fertilizers, associated with the granulometric quality of the fertilizers, it led to an uneven distribution of the fertilizers, and to the generation of spatial non-uniformity in the vegetation state of the plants.

CONCLUSIONS

The analysis based on remote sensing, the RapidEye satellite system, facilitated the analysis and highlighting of the spatial variability of the autumn wheat crop, in an area of 49.109 ha, and the understanding of the significance of the differences.

Through the reclassification analysis of the NDVI map and the transformation of the NDVI raster image into vector format, the classification was made into six classes (C1 to C6) and the land surface was calculated for each class.

The differences between the classes, regarding the mean and median values, calculated on the basis of the NDVI values, showed statistical certainty ($p = 0$), which confirmed the certainty of the classification and the significant difference in the spatial variability of the wheat crop.

The surface of the classes (Area, ha) varied in relation to the NDVI index according to a 3rd degree polynomial model ($R^2 = 0.999$, $p = 0.00104$).

The transversal analysis of the cultivated surface of wheat, based on the NDVI values, led to a sinusoidal graphic distribution, which suggested the association of the recorded variability with the fertilizer application practice.

The recorded results recommend the evaluation of soil quality indices and the adaptation of fertilization works in order to normalize the current situation of the land, sustainable yields of agricultural crops under the study conditions.

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