CHARACTERIZATION OF SOME VARIETIES OF CEREAL GRASSES ON THE BASIS OF SPECTRAL INFORMATION FROM AERIAL IMAGES

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***Abstract**. This study aimed at assessing and classification of some grain varieties, on the basis of spectral data and indices calculated from aerial images. Were studied 18 varieties of cereals as follows: barley - Jallon, Tektoo, Saphira; wheat - Moison, Lukullus, Antonius, Linus, Atoupic, Illico, Sosthene, Avenue, G.K. Bekes, Akteur, Alex, Exotic, Messino, Patras; triticale - Trismart. The images were taken with the drone, model DJI Phantom series, in principal growth stage 3, and stem elongation, 30 – 31 BBCH code. By analyzing the images, they were obtained of primary spectral values in RGB system. Based on their values were calculated normalized rgb values, and also equivalent values were determined in HSB system. Based on primary spectral values (RGB), of the normalized values (rgb), and of the values in HSB system, specific indices were calculated for the characterization of vegetation: NDI (normalized difference index), INT (Intensity) and DGCI (dark green color index). ANOVA, revealed the source of variance and degree of statistical certainty of results (F>F crit; p<< 0.001). Through Cluster analysis (based on Euclidean distances) was performed classification of the varieties studied, based on the values of indices determined, and in relation to the degree of their values similarity. The 18 varieties studied were grouped into two clusters, with 5 in clusters and three independent positions, safely statistics (Cophenetic coefficient = 0.801).*

Keywords: *aerial images, cereal grasses, classification, imaging, physiological indices*

INTRODUCTION

Study of grain crops grasses (wheat, barley, rye, triticale) and other crops, based on satellite images, aerial or terrestrial images have been developed more and more as a result of the need to control quickly and efficiently to these crops with high share and high importance in human and animal nutrition (SHEWRY, 2009; EUROSTAT DATABASE), and secondly due to the development, and increase of the usefulness and accuracy of imaging technique for agriculture (ISHIMWE et al., 2014; LUKAS et al., 2016). Imaging techniques based on satellite images are very useful to study large areas of land and crops being harnessed relationships between satellite indices for phenological characterization of crops, but also in production estimating (KRYVOBOK, 2000; SAKAMOTO et al., 2005; LOPRESTI et al., 2015).

A particular interest are the studies by imaging technique for classifying land use categories, and also for the identification and classification of crop species, or even varieties and hybrids (YANG et al., 2011; SCHMEDTMANN and CAMPAGNOLO, 2015). Based on satellite imagery and specific techniques, numerous studies have been conducted for monitoring the quality of crops, assessing issues concerning the health of crops, or for predicting grain production or the biomass production of forage crops (LAMB and BROWN, 2001; REMBOLDT et al., 2013; HERBEI and SALA, 2015, 2016).

Some studies used Unmanned Aerial Vehicles based techniques for evaluating crop of wheat in small experimental plots (LELONG et al., 2008), for evaluating crops status and the quality of sugar beet (LUNA and LOBO, 2016), developing and perfecting models to increase the accuracy of data interpretation.

A number of indicators characterizing the various elements on the land, or vegetation cover, were developed based on interdependencies between the spectral information and realities on the ground that needed to be characterized, captured on digital images, and expressed by different mathematical formulas (MYNENI et al., 1995; SILLEOS et al., 2006). In the case of techniques based on satellite images to characterize vegetation, were proposed a series of dedicated indices, grouped based on slope (CTVI, NDVI, NRVI, RATIO, RVI, TVI, TTVI), based on the distance (AVI, DVI, PVI, TSAVI, WDVI) or based on orthogonal transformation.

Assessment of land areas, vegetation cover as a whole, and agricultural crops by imaging methods are based on the close relationship between the spectral information captured by digital images, and specific indexes of characterizing, being communicated close correlation at their level (HERBEI et al., 2015).

In the case of imaging analysis based on aerial images were also proposed specific indices to characterize the vegetation, on the basis of colors in RGB spectrum, namely NDI, INT, DGCI (AHMAD and REID, 1996; KARCHER and RICHARDSON, 2003; MAO et al., 2003; RORIE et al., 2011; LEE and LEE, 2013).

This study aimed to evaluate and classify the varieties of cereal grasses on the basis of spectral data and specific indices obtained from aerial images.

MATERIAL AND METHOD

The study was conducted in Didactic and Experimental Station of BUSAMV Timisoara, Romania, in an experimental plot that included several varieties of cereals (barley, winter wheat and triticale). The collection of varieties of grain grass was placed in the experimental plot A519/1, topo coordinates 45°47'N 21°12'E. Soil and technology conditions were uniform, represented by chernosem soil type, fertilized with 75 kg P ha^{-1} a.s. (active substance), 75 kg K ha^{-1} a.s. and 150 kg a.s. N ha^{-1} a.s. The study was conducted between 2015-2016 periods.

The biological material was represented by 18 varieties of cereal grasses as follows: barley - Jallon (hybrid), Tektoo (hybrid), Saphira; wheat - Moisson (hybrid), Lukullus, Antonius, Linus, Atoupic (hybrid), Illico, Sosthene, Avenue, G.K. Bekes, Akteur, Alex, Exotic, Messino, Patras; triticale - Trismart, figure 1. The study was conducted in early elongation stage, principal growth stage 3: stem elongation, 30 – 31 BBCH code (MEIER, 2001).

The images were taken in the time slot 11.30 – 11.45, with drone model DJI Phantom series, at a resolution of 12 MP. Flight altitude was 6 m. The images were downloaded to a computer and analyzed with the software ImageJ (RASBAND, 1997). They were extracted spectral information, related to the color channel RGB. Starting from the primary spectral values of the channels RGB normalized values rgb were calculated (LEE and LEE, 2013) on the basis of the relations (1) – (3).

$$r = \frac{R}{R+G+B} \tag{1}$$

$$g = \frac{G}{R+G+B} \tag{2}$$

$$b = \frac{B}{R+G+B} \tag{3}$$

where: r, g, b – normalized values; R – spectral values in red channel; G – spectral values in green channel; B – spectral values in blue channel.

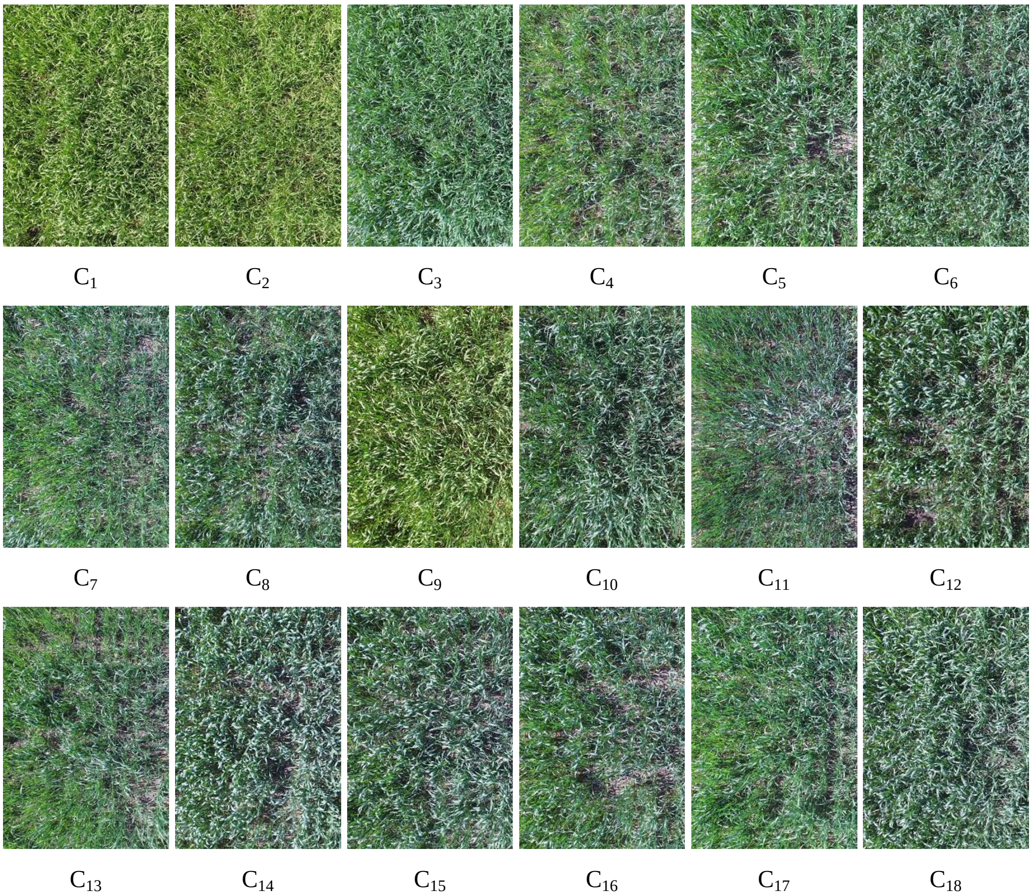


Figure 1. Images of cereal grasses varieties studied
(C_1 – Jallon, C_2 – Tektoo, C_3 – Saphaira, C_4 – Moisson, C_5 – Lukullus, C_6 – Antonius, C_7 – Linus, C_8 – Atopic, C_9 – Illico, C_{10} – Sosthene, C_{11} – Avenue, C_{12}- G.K.Bekes, C_{13} – Akteur, C_{14} – Alex, C_{15} – Exotic, C_{16} – Messino, C_{17} – Patras, C_{18} - Trismart)

On the basis of the color parameter values in RGB and HSB systems, and on the normalized values r,g,b, NDI index were calculated (normalized difference index), the relationship that facilitates color distinction based on plant (MAO et al., 2003), and also INT index (Intensity) which helps to better differentiate color in terms of brightness (AHMAD and REID, 1996). NDI and INT synthetic indices were calculated using relations (4) and (5), (LEE & LEE, 2013).

$$NDI = \frac{(r-g)}{(r+g+0.01)} \tag{4}$$

$$INT = \frac{(R+G+B)}{3} \tag{5}$$

where: R – spectral values in red channel; G – spectral values in green channel; B – spectral values in blue channel.

DGCI index (dark green color index), commonly used to estimate nitrogen supplement at cereals (KARCHER and RICHARDSON, 2003) was calculated by the relation (6) based on the values of the HSB system (RORIE et al., 2011).

$$DGCI = \left[\frac{(H-60)}{60} + (1-S) + (1-B)\right]/3 \quad (6)$$

where: H – Hue; S – Saturation; B – Brightness HSB system.

Statistical analysis of experimental data. Experimental data were analyzed in terms of variance by ANOVA. The interdependence of the primary spectral bands, normalized values (r, g, b) and calculated indices INT, NDI and DGCI was assessed by correlation analysis. Classification of varieties studied, based on normalized spectral information (rgb) and indices calculated was done by cluster analysis method based on Euclidean distances. Safety parameters used were: correlation coefficients r and R^2, and Cophenetic coefficient. For the analysis of experimental data were used Excel 2007, calculation module, and software PAST (HAMMER et al., 2001).

RESULTS AND DISCUSSIONS

From the analysis of the digital images, resulting in the primary spectral data channels (RGB), on which were calculated normalized values (rgb). Spectral values from RGB system have been converted into HSB system, transformation necessary for the calculation of some indices. Based on the color parameters were calculated indices NDI, INT and DGCI. Spectral values from RGB and HSB systems, and also normalized values (rgb), are presented in Table 1. Statistical data resulting from the ANOVA test, about the source of variance and the statistical reliability of the results are shown in Table 2.

In the state of vegetation analyzed, stem elongation, 30-31 BBCH code, and uniform conditions for growing, varieties showed phenotypic differences in terms of color intensity of the leaves, and leaf mass development. These differences were highlighted by color spectrum, both in RGB system and in the normalized values rgb, and based on specific indices (NDI, INT, and DGCI).

Analyzing the coefficient of variation (CV) was found a wider spectral variation in primary values compared to normalized values.

Thus, for red color channel (CV_R = 6.49 compared to CVr = 2.53) and green color channel (CV_G = 5.63 compared to CV_g = 2.18) the differences between the coefficient of variation was much higher than in the case of the blue color channel (CV_B = 4.61 compared to CV_b = 4.08), to which differences of variation coefficient were smaller.

Calculated indices showed specific values: NDI = -0.106 ÷ - 0.150, INT = 93.18 ÷ 110.65, DGCI = 0.6456 ÷ 0.9022. Normal probability plot of indices such values represented in figure 2 – 4, safely statistics.

In the case of calculated indices, two indices presented values of the coefficient of variation (CV_{INT} = 4.72, respectively CV_{DGCI} = 10.20), which contributed to the differentiation of varieties within a specific analysis.

Through on Cluster analysis, varieties of cereals studied were grouped based on

Euclidean distances, in concordance to normalized spectral values and determined indices, the statistical safe (Cophenetic coefficient = 0.801).

Table 1

Color parameters in RGB and HSB systems, and corrected values (rgb) to characterize varieties of cereals studied

Cereal cultivar	Color parameters								
	R	G	B	r	g	b	H	S	B
Jallon	101.28	129.99	93.85	0.313	0.399	0.289	107	0.28	0.50
Tektoo	100.08	127.61	92.42	0.318	0.394	0.288	103	0.27	0.51
Saphira	105.45	130.93	95.56	0.297	0.403	0.300	122	0.26	0.48
Moison	89.74	121.96	90.82	0.312	0.400	0.289	107	0.28	0.51
Lukullus	94.63	127.15	93.27	0.300	0.404	0.296	116	0.27	0.50
Antonius	90.81	119.92	96.76	0.295	0.390	0.315	132	0.24	0.47
Linus	91.81	124.6	96.94	0.293	0.398	0.309	129	0.26	0.49
Atoupic	85.91	113.26	92.65	0.294	0.388	0.317	136	0.24	0.44
Illico	99.4	123.55	97.41	0.310	0.386	0.304	116	0.22	0.49
Sosthene	83.14	109.37	87.87	0.297	0.390	0.313	132	0.24	0.43
Avenue	89	114.18	95.97	0.298	0.382	0.321	137	0.22	0.45
G.K. Bekes	85.2	107.63	86.71	0.305	0.385	0.310	125	0.21	0.42
Akteur	89.63	119.69	89.8	0.300	0.400	0.300	120	0.25	0.47
Alex	93.52	119.25	103.38	0.296	0.377	0.327	143	0.22	0.47
Exotic	87.77	112.73	96.55	0.295	0.379	0.325	142	0.22	0.44
Messino	89.78	116.61	94.83	0.298	0.387	0.315	131	0.23	0.46
Patras	89.47	119.9	93.26	0.296	0.396	0.308	126	0.25	0.47
Trismart	93.13	120.6	102.54	0.294	0.381	0.324	141	0.23	0.47
SE	±1.41	±1.59	±1.03	±0.002	±0.002	±0.003	±2.91	±0.005	±0.006

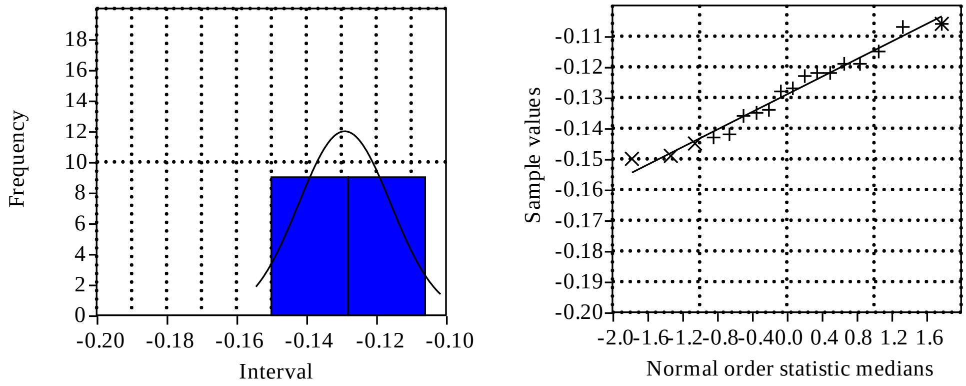
R – red color channel; G – green color channel; B - blue color channel; r – normalized red channel; g – normalized green channel; b – normalized blue channel; H – Hue; S – Saturation; B – Brightness.

Table 2

ANOVA test, single factor

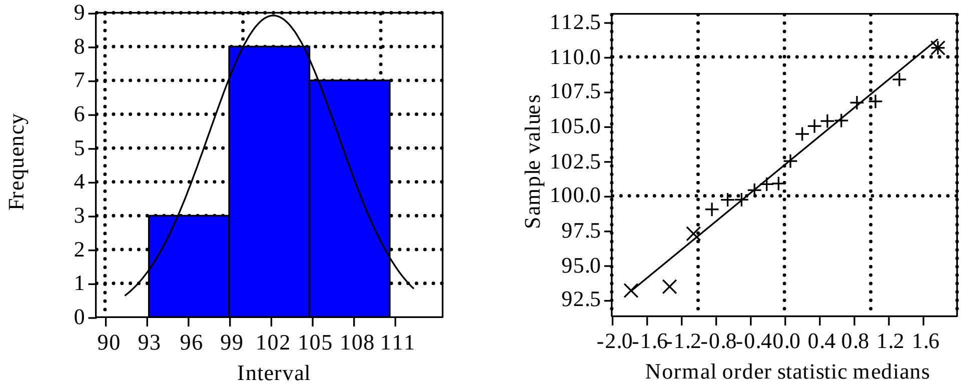
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	807829.8	13	62140.75	810.8567	8E-189	2.790242
Within Groups	18239.35	238	76.63592			
Total	826069.1	251				

Alpha = 0.001



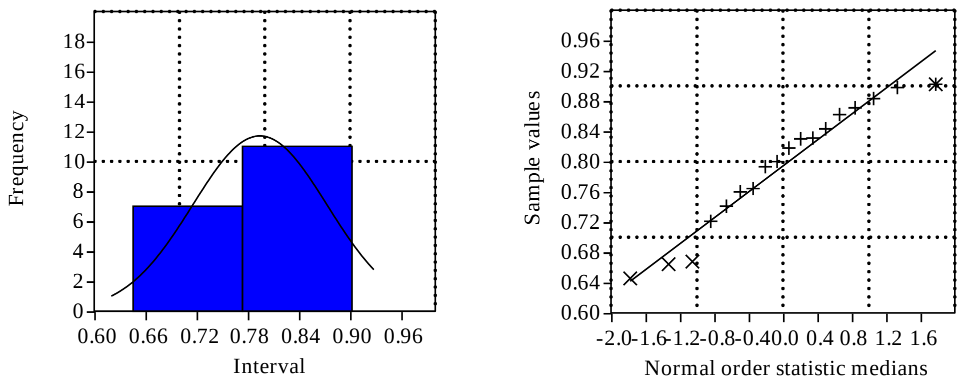
(a) (b)

Figure 2. The histogram of NDI values (a) and normal probability plot for NDI values (b);
(× - barley varieties; + wheat varieties; * - triticale variety).



(a) (b)

Figure 3. The histogram of INT values and normal probability plot for INT values (b);
(× - barley varieties; + wheat varieties; * - triticale variety).



(a) (b)

Figure 4. The histogram of DGCI values (a) and normal probability plot for DGCI values (b);
(× - barley varieties; + wheat varieties; * - triticale variety).

From the analysis that was done, have resulted two distinct clusters: cluster I (CI), which includes two varieties C_{10} and C_{12} and the cluster II (CII), which comprises the other 16 varieties studied, figure 5.

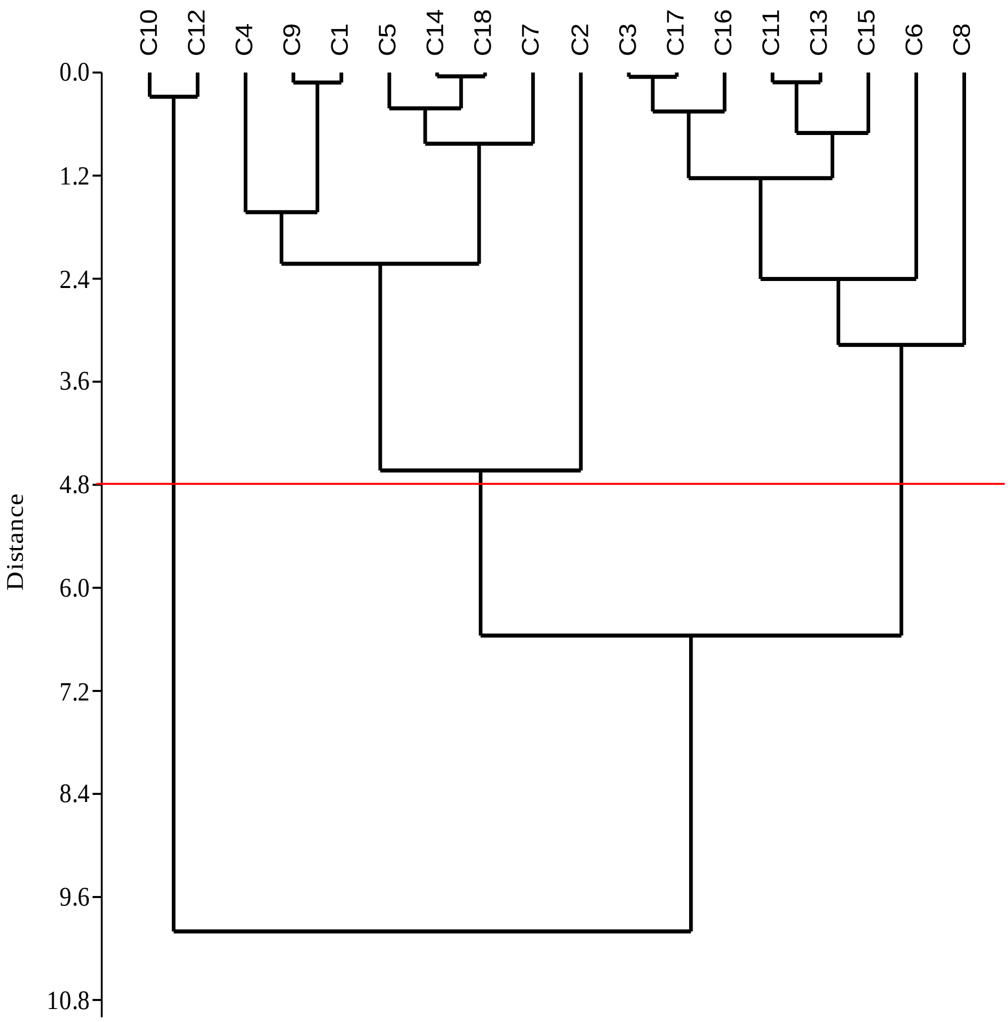


Figure 5. Grouping varieties of cereals studied, based on Euclidean distances, in relation to values of determined indices

Within the cluster CII, are found two major in clusters (CII/1 and CII/2) with more in clusters each. Within in the case of the in cluster CII/1, were grouped with similar characteristics: varieties C_4, C_9, and C_1 (in cluster CII/1/1); varieties C_5, C_{14}, C_{18} and C_7 (in cluster CII/1/2), respectively, at a distinct position, variety C_2 (in cluster CII/1/3). Within in the case of the in cluster CII/2 was identified: varieties C_3, C_{17} and C_{16} (in cluster CII/2/1); varieties C_{11}, C_{13} and C_{15} (in cluster CII/2/2), and at s distinct position variety C_6 (in cluster CII/2/3), and variety C8 (in cluster CII/2/4).

Benchmarking studies, with different variants of fertilization on wheat were conducted in order to formulate multiple solutions with comparable results to choose the most suitable solution, in technical or economical aspect (MEYER-AURICH et al., 2008; SALA and BOLDEA, 2011; KOONDHAR et al., 2016; SALA et al., 2015, 2016). Most of these studies have quantified the effect of treatments at endpoint, harvesting, little too late to be possible to make corrections. But such analysis, based on spectral properties of varieties or crops, in combination with the technological level, and crops status, prove to be very useful for early identification of different situations, and to be possible efficient corrections (BASSO et al., 2016; SCHIRRMANN et al., 2016; WANG et al., 2017).

In other species, they were studied the influence of factors, most often fertilizer at the crops or some physiological indices such as foliar distribution, leaf area or the state of nutrition, which are found in interdependence with production and quality (Jivan and Sala, 2014; RAWASHDEH and SALA, 2013, 2015, 2016). Various studies and computer simulation models concerning the production of wheat in relation to environmental and technological factors, in particular fertilization, were carried out for different climatic conditions (BRENTRUP et al., 2004; BAKHSH et al., 2013; RONG et al., 2013).

Image analysis based on spectral information associated with physiological indexes of leaves and subsequent production and quality would be more efficient to conduct quantitative and qualitative prediction models of agricultural production (JIN et al., 2016).

The results of this study falls within the context and trend of the research on crop monitoring by imaging methods, and managed to characterize a number of varieties of cereal grasses based on spectral information from aerial images.

CONCLUSIONS

From the analysis of the aerial images, taken with the drone, the spectral values were obtained in RGB system, from which the RGB normalized values were calculated (rgb), and also the values in the HSB system, were calculated. Based on their values, specific indices were calculated (NDI, INT and DGCI) and were found different situations of the coefficient of variation (CV) compared with the specific phonological properties of varieties studied.

Based on normalized values (rgb) and NDI, INT and DGCI indices, has been possible to group the 18 varieties studied in clusters, safely statistical, confirmed by the Cophenetic coefficient.

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BIBLIOGRAPHY

AHMAD I.S., REID, J.F., 1996. Evaluation of color representations for maize images. Journal of Agricultural Engineering Research 63: 185–196.

BAKHSH A., BASHIR I., FARID H.U., WAJID S.A. 2013. Using ceres-wheat model to simulate grain yield production function for Faisalabad, Pakistan, conditions. Experimental Agriculture 49(3): 461-475.

BASSO B., FIORENTINO C., CAMMARANO D., SCHULTHESS U. 2016. Variable rate nitrogen fertilizer response in wheat using remote sensing. Precision Agriculture 17(2): 168-182.

BRENTRUP F., KÜSTERS J., LAMMEL J., BARRACLOUGH P., KUHLMANN H. 2004. Environmental impact assessment of agricultural production systems using the life cycle assessment (LCA) methodology II. The application to N fertilizer use in winter wheat production

systems. European Journal of Agronomy 20(3): 265-279.
HAMMER Ø., HARPER D.A.T., RYAN P.D., 2001. PAST: Paleontological statistics software package for education and data analysis. Palaeontologia Electronica 4(1): 1-9.
HERBEI M.V., SALA F. 2015. Use Landsat image to evaluate vegetation stage in sunflower crops. AgroLife Scientific Journal 4(1): 79-86.
HERBEI M. SALA F., BOLDEA M. 2015. Relation of normalized difference vegetation index with some spectral bands of satellite images. AIP Conference Proceedings 1648: 670003-1 – 670003-4.
HERBEI M., SALA F. 2016. Biomass prediction model in maize based on satellite images. AIP Conference Proceedings 1738: 350009-1 – 350009-4.
ISHIMWE R., ABUTALEB K., AHMED F. 2014. Applications of thermal imaging in agriculture—A Review. Advances in Remote Sensing 3: 128-140.
JIN X., KUMAR L., LI Z., XU X., YANG G., WANG J. 2016. Estimation of winter wheat biomass and yield by combining the aquacrop model and field hyperspectral data. Remote Sensing 8: 972.
JIVAN C., SALA F. 2014. Relationship between tree nutritional status and apple quality. Horticultural Science 41(1): 1-9 pp.
KARCHER, D.E., RICHARDSON, M.D., 2003. Quantifying turfgrass color using digital image analysis. Crop Science 43 943–951.
KRYVOBOK O., 2000. Estimation of the productivity parameters of wheat crops using high resolution satellite data. International Archives of Photogrammetry and Remote Sensing. XXXIII(B7): 717-722.
KOONDHAR M.A., QIU L., MAGSI H., CHANDIO A.A., HE G., 2016. Comparing economic efficiency of wheat productivity in different cropping systems of Sindh Province, Pakistan. Journal of the Saudi Society of Agricultural Sciences, 1-10.
LAMB D.W., BROWN R.B. 2001. PA—Precision Agriculture: Remote-Sensing and Mapping of Weeds in Crops. Journal of Agricultural Engineering Research 78(2): 117-125.
LEE K.-J., LEE B.-W. 2013. Estimation of rice growth and nitrogen nutrition status using color digital camera image analysis. Europ. J. Agronomy 48: 57– 65.
.LELONG C.C.D., BURGER P., JUBELIN G., ROUX B., LABBÉ S., BARET F. 2008. Assessment of unmanned aerial vehicles imagery for quantitative monitoring of wheat crop in small plots. Sensors (Basel) 8(5): 3557-3585.
LOPRESTI M.F., DI BELLA C.M., DEGIOANNI A.J. 2015. Relationship between MODIS-NDVI data and wheat yield: A case study in Northern Buenos Aires province, Argentina. Information Processing in Agriculture 2(2): 73-84.
LUKAS V., NOVÁK J., NEUDERT L., SVOBODOVA I., RODRIGUEZ-MORENO F., EDREES M., KREN J. 2016. The combination of uav survey and landsat imagery for monitoring of crop vigor in precision agriculture. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLI-B8: 953-957.
LUNA I., LOBO A. 2016. Mapping crop planting quality in sugarcane from UAV imagery: A pilot study in Nicaragua. Remote Sensing 8: 500.
MAO W., WANG Y., WANG Y. 2003. Real-time detection of between – row weeds using machine vision. Paper number 031004, ASAE, St Joseph, MI, USA.
MEIER U. 2001. Growth stages of mono-and dicotyledonous plants. BBCH Monograph, pp.14-19.
MEYER-AURICH A., GANDORFER M., WEERSINK A., WAGNER P. 2008. Economic analysis of site-specific wheat management with respect to grain quality and separation of the different quality fractions. 12th Congress of the European Association of Agricultural Economists – EAAE 2008, 1-7.
MYNENI R.B., HALL F.G., SELLERS P.J., MARSHAK A.L. 1995. The interpretation of spectral vegetation index, IEEE Transactions on Geoscience and Remote Sensing 33(2), 481-486.
RASBAND W.S. 1997. ImageJ. U. S. National Institutes of Health, Bethesda,Maryland, USA, pp. 1997–2014.
.RAWASHDEH H.M., SALA F. 2013. The effect of foliar application of iron and boron on early growth parameters of wheat (*Triticum aestivum* L.). Research Journal of Agricultural

Sciences, 45(1): 21-26.
RAWASHDEH H.M., SALA F. 2015. Foliar application with iron as a vital factor of wheat crop growth, yield quantity and quality : A Review. International Journal of Agricultural Policy and Research 3(9): 368-376.
RAWASHDEH H., SALA F. 2016. The effect of iron and boron foliar fertilization on yield and yield components of wheat. Romanian Agricultural Research 33: 1-9.
REMBOLD F., ATZBERGER C., SAVIN I., ROJAS O. 2013. Using low resolution satellite imagery for yield prediction and yield anomaly detection. Remote Sensing 5: 1704-1733.
RORIE R.L., PURCELL L.C., KARCHER D.E., KING A.C., 2011. The assessment of leaf nitrogen in corn from digital images. Crop Science 51: 2174–2180.
RONG L., ZHANG C., ZHANG X., WU S., WANG Z. 2013. Wheat production simulation based on the ALMANAC model of North China region. Sustainable Agriculture Research 2(3): 148-159.
SAKAMOTO T., YOKOZAWA M., TORITANI H., SHIBAYAMA M., ISHITSUKA N., OHNO H. 2005. A crop phenology detection method using time-series MODIS data. Remote Sensing of Environment 96(3-4): 366-374.
SALA F., BOLDEA M. 2011. On the optimization of the doses of chemical fertilizers for crops. AIP Conference Proceedings 1389: 1297-1300.
SALA F., BOLDEA M., RAWASHDEH H., NEMET I. 2015. Mathematical model for determining the optimal doses of mineral fertilizers for wheat crops. Pakistan Journal of Agricultural Sciences 52(3): 609-617.
SALA F., RUJESCU C., CONSTANTINESCU C. 2016. Causes and solutions for the remediation of the poor allocation of P and K to wheat crops in Romania. AgroLife Scientific Journal 5(1): 184-193.
SCHIRRMANN M., GIEBEL A., GLEINIGER F., PFLANZ M., LENTSCHKE J., KARL-HEINZ D. 2016. Monitoring agronomic parameters of winter wheat crops with low-cost UAV imagery. Remote Sensing 8(9): 706.
.SCHMEDTMANN J., CAMPAGNOLO M.L. 2015. Reliable crop identification with satellite imagery in the context of common agriculture policy subsidy control. Remote Sensing 7: 9325-9346.
SHEWRY PR. 2009. Wheat, Darwin review. Journal of Experimental Botany 60(6): 1537-1553.
SILLEOS N.G., ALEXANDRIDIS T.K., GITAS I.Z., PERAKIS K. 2006. Vegetation indices: Advances made in biomass estimation and vegetation monitoring in the last 30 years, Geocarto International 21(4): 21-28.
WANG C., FENG M., YANG W., DING G., XIAO L., LI G., LIU T. 2017. Extraction of sensitive bands for monitoring the winter wheat (*Triticum aestivum*) growth status and yields based on the spectral reflectance. PLoS ONE 12(1): e0167679.
YANG C., EVERITT J.H., MURDEN D. 2011. Evaluating high resolution SPOT 5 satellite imagery for crop identification. Computers and Electronics in Agriculture 75(2): 347-354.
***.ec.europa.eu/eurostat (acces date: 15.06.2015)