

IMAGING ANALYSIS IN CROP MANAGEMENT. CASE STUDY IN SOYBEAN

Andreea Lidia JURJESCU¹, Florin SALA^{1,2}

¹Agricultural Research and Development Station Lovrin, Lovrin, 307250, Romania, andreealidia19@gmail.com, florin_sala@usvt.ro

²University of Life Sciences "King Michael I" from Timisoara, Timișoara, 300645, Romania
Emails: florin_sala@usvt.ro

Corresponding author: florin_sala@usvt.ro

Abstract

The study used imaging analysis to describe and characterize a soybean crop, in terms of plant uniformity and the presence of weeds, with the formulation of intervention decisions for crop management. Images were taken in digital format (cell phone camera), which were analyzed for spectral information (RGB) and fractal geometry (D). Based on the obtained data, normalized values (rgb), different ratios (R/G, R/B, G/R, G/B, B/R, B/G), specific indices (NDI – normalized difference index, INT - intensity) and degree of vegetation cover (DVC, %), as green canopy cover. A flow diagram was developed for the study carried out in the assessment of soybean culture. From the correlation analysis, the values of the correlation coefficient (r) were obtained, in conditions of statistical safety. The regression analysis led to obtaining some equations that described the variation of DVC in relation to the considered parameters. Very high levels of precision and safety were recorded based on the R/G ratio, the corrected g value ($R^2=0.998$, $p<0.001$), followed immediately by the equations based on the G/R ratio and the NDI index ($R^2=0.997$, $p<0.001$). 3D models and in the form of isoquants described the variation of DVC in relation to the considered parameters. According to PCA, PC1 explained 95.997% of variance, and PC2 explained 3.9978% of variance. Cluster analysis led to the grouping of the variants based on similarity, highlighting the variants with a high degree of weeding (s8, s9), the variant with a normal state (s7) and the other experimental variants.

Key words: decision support, imaging analysis, models, soybean crop, weeds

INTRODUCTION

The management of agricultural crops, from sowing to harvesting, requires permanent knowledge of the vegetation state of the plants, the performance of the works foreseen by the culture technologies, and appropriate interventions, in real time, in relation to aspects identified during periods of vegetation [16, 27, 30]. Knowledge of the vegetation and the evolution of crops by growth stages require information in real time, regarding the status of plants in relation to biotic and abiotic factors and culture technologies [14, 19].

Obtaining information can be done through direct observation, based on satellite, aerial or terrestrial images, and different investigation systems, which capture the reality of plants and agricultural crops [1, 7, 36]. Satellite images have the advantage of large-scale coverage of terrestrial and agricultural areas, with variable image resolutions and related

costs [9, 35].

Aerial images (UAV) have a smaller scale coverage (plots) but at a better resolution, with very high dynamics for moving the work technique in the field, and the facility to work at different photographing heights for analysis and crop evaluation [3, 6, 25]. At the same time, images taken with cameras or mobile devices (at high resolutions) allow obtaining localized, punctual images in areas of a culture ascertained from observations on the ground to be normal areas, or areas with variable plant density (gaps in the row of plants), weedy areas (presence of different weed species), or affected by diseases, pests or nutrient deficiency [18, 24, 33, 34]. The images taken, accompanied by recorded observations (notes, data, measurements, etc.) represent an information base that needs to be analyzed, processed in order to obtain additional, more precise information and on the basis of which the culture can be

characterized, or maybe be generated intervention decisions / corrections on the crops [5, 21, 24]. These interventions can target the entire culture (plot, soil) or only certain areas of the culture depending on the identified problem. In this way, localized interventions have immediate, high efficiency and low costs, compared to a generalized intervention, on the scale of the entire crop plot [25]. Different types of image analysis can be used to analyze data in the form of images related to plants or agricultural crops. Some methods are based on spectral information and specific indices [9, 10, 19, 22], and others are based on fractal analysis [23, 29].

The present study used imaging analysis to study soybean culture in terms of plant growth, uniformity and development and the degree of weeding, in order to formulate characterization models and attention to some

intervention works.

MATERIALS AND METHODS

The study analyzed the soybean crop with imaging methods in relation to the uniformity of the plants in a row and the presence of weeds in the crop. Soybean crop was organized within SCDA Lovrin, under non-irrigated crop conditions. The soybean crop was analyzed in stage 5 BBCH code (Principal growth stage). In relation to the purpose of the study, images were taken in digital format (cell phone camera SM-N910C model, 2,988 x 5,312 pixels, 24 bit depth, jpg format) to capture areas with appropriate density, and areas with gaps (missing plants). Also, images were taken in areas of culture with weeds. Examples of images are shown in Photo 1.



Photo 1. Aspects of soybean crop considered in the study
Source: Original photos made by authors.

Imaging analysis was used to obtain information in the form of data [20, 29].

To describe the fractal geometry was determined for each image total pixels (TP),

foreground pixels (FP), fractal dimension (D, and Mean^D). For the fractal analysis, binarized images were used, Photo 1 (s7 binary). Based on the RGB color parameters, the normalized rgb values were calculated [12], equations (1), (2), (3). The ratios between the color parameters (R/G, R/B, G/R, G/B, B/R, B/G) were calculated. In addition, the NDI [15], equation (4) and INT [2], equation (5) indices were calculated.

$$r = \frac{R}{R+G+B} \quad (1)$$

$$g = \frac{G}{R+G+B} \quad (2)$$

$$b = \frac{B}{R+G+B} \quad (3)$$

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

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

The degree of vegetation cover (DVC, %), as green canopy cover, was determined [17]. Through the regression analysis, the DVC variation was evaluated in relation to the imaging analysis parameters considered.

The obtained data through imaging analysis and results through calculations were analyzed to evaluate the statistical safety (p, R², RMSEP), the level of interdependence between the considered parameters. Distribution and similarity of variants, PCA, Cluster Analysis were evaluated [8, 11, 31].

The study was conducted based on the designed flow diagram, represented in Figure 1.

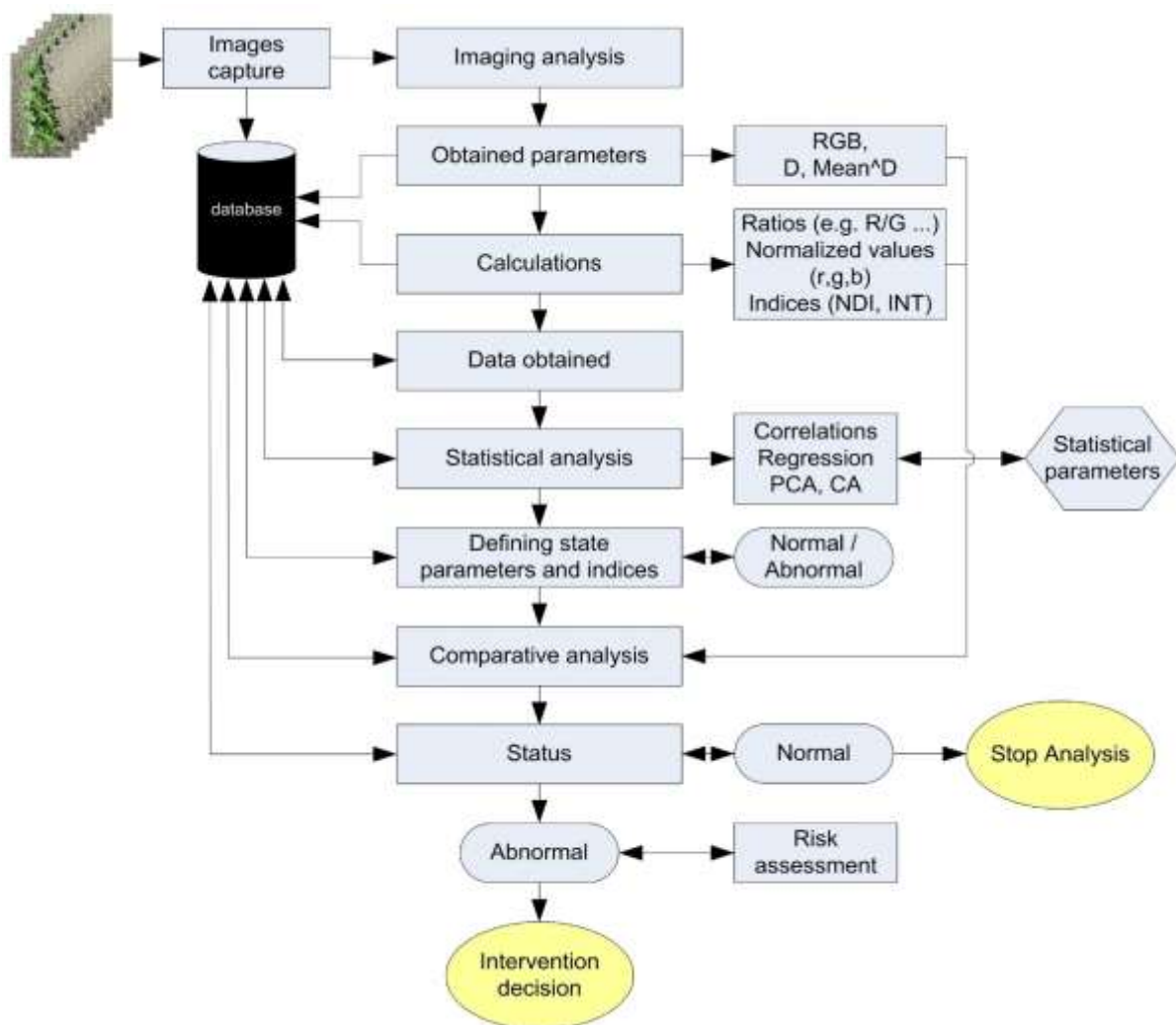


Fig. 1. Flow chart for the soybean crop study
 Source: Original figure.

RESULTS AND DISCUSSIONS

For the characterization of soybean crop, information was obtained from the analysis of digital images in the form of data regarding total pixels (TP), foreground pixels (FP), fractal dimension (D, Mean[^]D), degree of vegetation cover (DVC), and color parameters in the RGB system (R,G,B). The values resulting from the imaging analysis are presented in Table 1. The TP parameter has the same value for each image, the images having the same size (2,988 x 5,312 pixels; Width, Height). In the case of foreground pixels (FP), different values were recorded, depending on the composition of each image, composition given by the component elements, respectively soil, soybean plants, and weeds. The fractal dimension (D) varied between 1.827 in the case of the s9 variant

and 1.886 in the case of the s5 variant. Degree of vegetation cover (DVC) had values between DVC=0.00% in the case of variant s1 (land without vegetation) and DVC=78.25% in the case of variant s9 with a high percentage of weeds. RGB color parameters show values between 101.52 and 150.51 in the case of the R parameter; 129.62 and 152.36 in the case of parameter G; respectively between 67.27 and 127.70 in the case of parameter B.

Starting from the primary recorded data, table 1, the ratios between color parameters (RGB) were calculated, the normalized values (rgb) were calculated, according to equations (1), (2), (3) and the NDI indices were calculated and INT, according to equations (4) and (5). The values resulting from the calculations are presented in Table 2.

Table 1. Data on imaging analysis parameters for image samples, soybean crop

Trials	TP	FP	D	Mean [^] D	DVC	R	G	B
s1	15872256	5550575	1.916	1.882	0.00	140.32	129.62	117.07
s2	15872256	5828698	1.915	1.876	6.16	139.51	134.64	115.70
s3	15872256	5584039	1.915	1.873	9.21	150.51	149.61	127.70
s4	15872256	5614623	1.918	1.882	13.02	152.31	152.36	126.68
s5	15872256	6357696	1.920	1.886	15.86	128.53	131.39	106.37
s6	15872256	6056106	1.922	1.873	18.56	145.86	152.25	125.23
s7	15872256	6430957	1.916	1.862	22.51	136.26	144.25	112.83
s8	15872256	6491138	1.905	1.842	37.49	124.05	139.18	99.02
s9	15872256	6428950	1.827	1.755	78.25	101.52	134.06	67.27

Source: Original data.

Table 2. Normalized values, ratios and indices calculated for image samples, soybean crop

Trials	R/G	R/B	G/R	G/B	B/R	B/G	r	g	b	NDI	INT
s1	1.0825	1.1986	0.9237	1.1072	0.8343	0.9032	0.3626	0.3349	0.3025	0.0391	129.00
s2	1.0362	1.2058	0.9651	1.1637	0.8293	0.8593	0.3579	0.3454	0.2968	0.0175	129.95
s3	1.0060	1.1786	0.9940	1.1716	0.8484	0.8536	0.3518	0.3497	0.2985	0.0030	142.61
s4	0.9997	1.2023	1.0003	1.2027	0.8317	0.8315	0.3531	0.3532	0.2937	-0.0002	143.78
s5	0.9782	1.2083	1.0223	1.2352	0.8276	0.8096	0.3509	0.3587	0.2904	-0.0109	122.10
s6	0.9580	1.1647	1.0438	1.2158	0.8586	0.8225	0.3445	0.3596	0.2958	-0.0211	141.11
s7	0.9446	1.2077	1.0586	1.2785	0.8280	0.7822	0.3464	0.3667	0.2869	-0.0281	131.11
s8	0.8913	1.2528	1.1220	1.4056	0.7982	0.7115	0.3424	0.3842	0.2733	-0.0567	120.75
s9	0.7573	1.5091	1.3205	1.9929	0.6626	0.5018	0.3352	0.4427	0.2221	-0.1364	100.95

Source: Original data.

From the correlation analysis, the values of the correlation coefficient (r) resulted, which expressed different levels of intensity of

correlations, and types of correlations (positive, negative) between considered parameters, under conditions of statistical

certainty. The obtained data are presented in Figure 2, as correlation matrix plot.

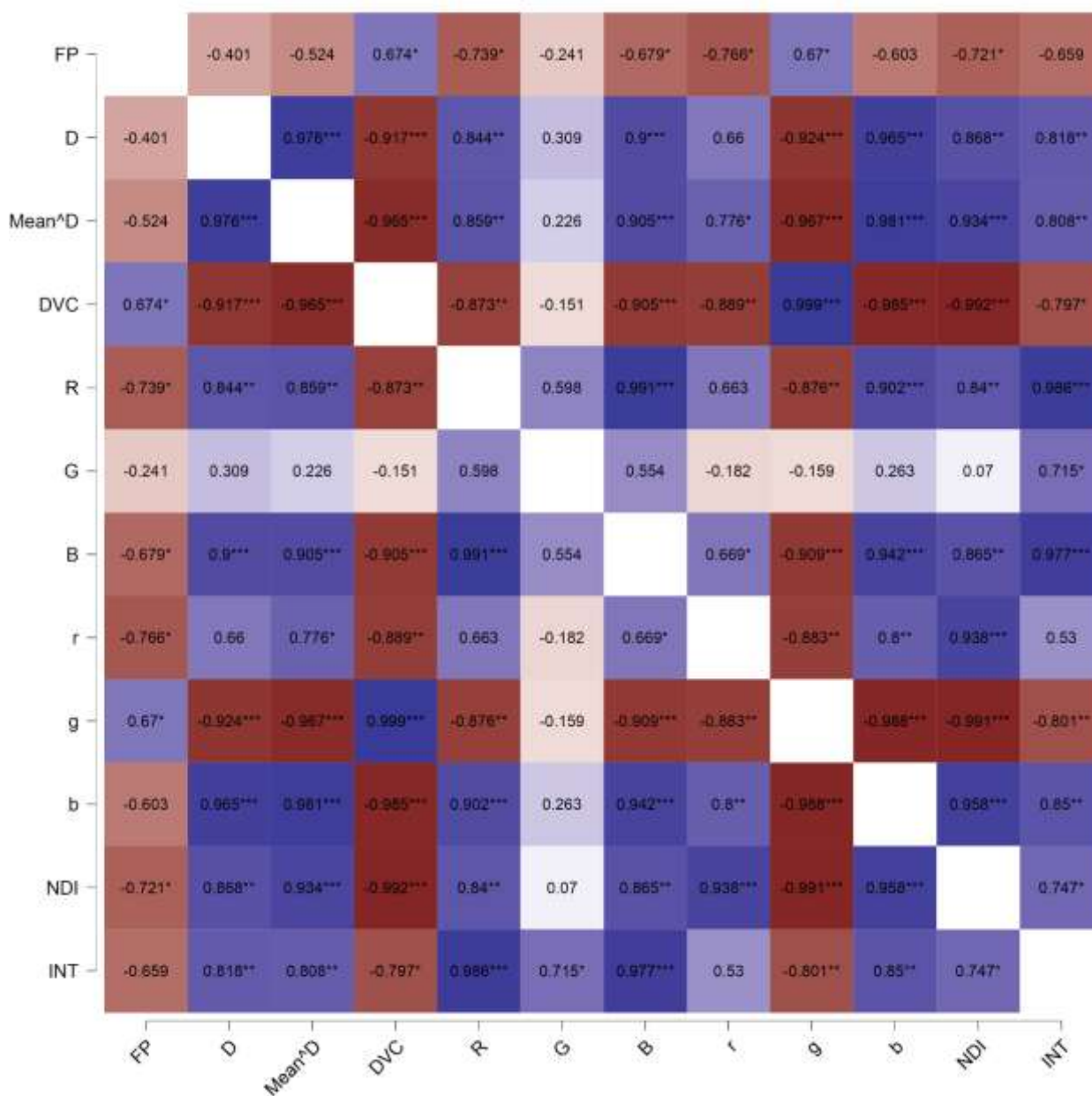


Fig. 2. Correlation matrix plot between analyzed parameters for the characterization of soybean crop
 Source: Original figure, generated by analysis.

The main aspect of the study was to evaluate the soybean crop from the perspective of the crop uniformity (rows with plants, without gaps) and the presence of weeds, based on the calculated parameters and indices. Based on the simple regression analysis, the DVC variation was evaluated in relation to each parameter determined from the imaging analysis, and the results are presented in Table 3 in the form of equations, and the statistical confidence level (R^2 , p). From the analysis of the data presented in

table 3, it was found that a very high level of precision and statistical certainty in the description of the DVC variation was recorded in the case of using the R/G ratio ($R^2=0.998$), the parameter g (normalized values) ($R^2=0.998$), followed by the cases of using the G/R values ($R^2=0.997$), and the NDI index values ($R^2=0.997$), and followed by the case where the values of the G/B ratio ($R^2=0.996$) and the B ratio were used/G ($R^2=0.995$). The multiple regression analysis facilitated

the description of the DVC variation in relation to the different parameters considered in the analysis, as a direct and interaction effect, according to equation (23).

Table 3. Equations and statistical safety parameters for the description of the DVC variation in relation to different parameters

Parameter	Equations	Eq. No.	R ²	p
FP	$DVC = 5.2588E - 11x^2 - 0.0005934x + 1681$	(6)	0.485	0.136
D	$DVC = -4389x^2 + 1.572E04x - 1.399E04$	(7)	0.846	0.0036
Mean^D	$DVC = -1033x^2 + 3206x - 2368$	(8)	0.934	<0.001
R	$DVC = 0.03299x^2 - 9.722x + 726.6$	(9)	0.899	0.0010
G	$DVC = -0.1963x^2 + 55.19x - 3842$	(10)	0.189	0.531
B	$DVC = 0.01729x^2 - 4.521x + 305.6$	(11)	0.891	0.0012
R/G	$DVC = 398.7x^2 - 975.8x + 588.9$	(12)	0.998	<0.001
R/B	$DVC = -83.38x^2 + 432.7x - 384.4$	(13)	0.862	0.0026
G/R	$DVC = 90.21x^2 - 1.856x - 76.26$	(14)	0.997	<0.001
G/B	$DVC = -64.67x^2 + 289x - 240.8$	(15)	0.996	<0.001
B/R	$DVC = 382.2x^2 - 948x + 539.3$	(16)	0.862	0.0025
B/G	$DVC = -196.8x + 177$	(17)	0.995	<0.001
r	$DVC = 1.252E05x^2 - 8.992E04x + 1.615E04$	(18)	0.950	<0.001
g	$DVC = 737.7x - 247.7$	(19)	0.998	<0.001
b	$DVC = -5318x^2 + 1845x - 69.16$	(20)	0.981	<0.001
NDI	$DVC = 939.1x^2 - 360.6x + 11.97$	(21)	0.997	<0.001
INT	$DVC = 0.05524x^2 - 15.05x + 1036$	(22)	0.861	0.0026

Source: Original data resulted by calculations.

The values of the coefficients of equation (23) depending on the considered parameters are presented in Table 4. Examples of the graphic distribution of DVC values, in 3D and isoquants form, depending on the considered parameters, are presented in Figures 3 and 4.

$$DVC = ax^2 + by^2 + cx + dy + exy + f \quad (23)$$

where: DVC – degree of vegetation cover (%); x, y – parameters considered in the analysis (table 4); a, b, c, d, e, f – coefficients of the equation (23), Table 4.

Table 4. Values of the coefficients of the equation (23) in the description of the DVC variation in the soybean crop

Coefficients of equation (23)	Indexes used					
	x=R y=G	x=R y=B	x=G y=B	x=r y=b	x=g y=b	x=FP y=D
a	0.02129543	-0.79747437	0.01271909	-3972.37229158	0.01271909	2.05E-11
b	0.00859978	-0.67424189	0.00369149	-723.41469798	0.00369149	3786.77644459
c	-2.92364198	46.17134462	-0.16037879	1916.03732249	-0.16037879	0.00211460
d	3.13743287	-54.80744364	0.24541609	-521.07927517	0.24541609	-6929.62610279
e	-0.03081279	1.51534052	-0.01796363	454.45390935	-0.01796363	-0.00122121
f	0	0	0	0	0	0
R ²	0.999	0.949	0.998	0.999	0.998	0.980
p	<0.001	0.024	<0.001	<0.001	<0.001	0.0059
RMSEP	0.87658	7.08707	1.01070	0.96286	1.0107	4.38567

Source: Original data resulted by calculations.

Under the conditions of the present study, trial s7 presented the normal state of soybean crop, at stage 5 BBCH code, Principal growth stage. From the imaging analysis, this state was characterized by the values of the considered parameters presented in Table 1 and Table 2. According to PCA, based on the values of the

calculated ratios, the diagram in figure 6 was generated, in which the variants were distributed in relation to the values considered in the analysis. Variant s1 (land without plants) was positioned independently, in quadrant IV, associated with R/G, B/G ratios. The s7 variant, which represented the normal

state of the culture at the time of the study, was associated with the B/R ratio (quadrant II). Variants s2 – s6, weed-free culture, with

variable number of plants per row, were positioned grouped, quadrant III and IV, associated with R/G, B/G, B/R ratios.

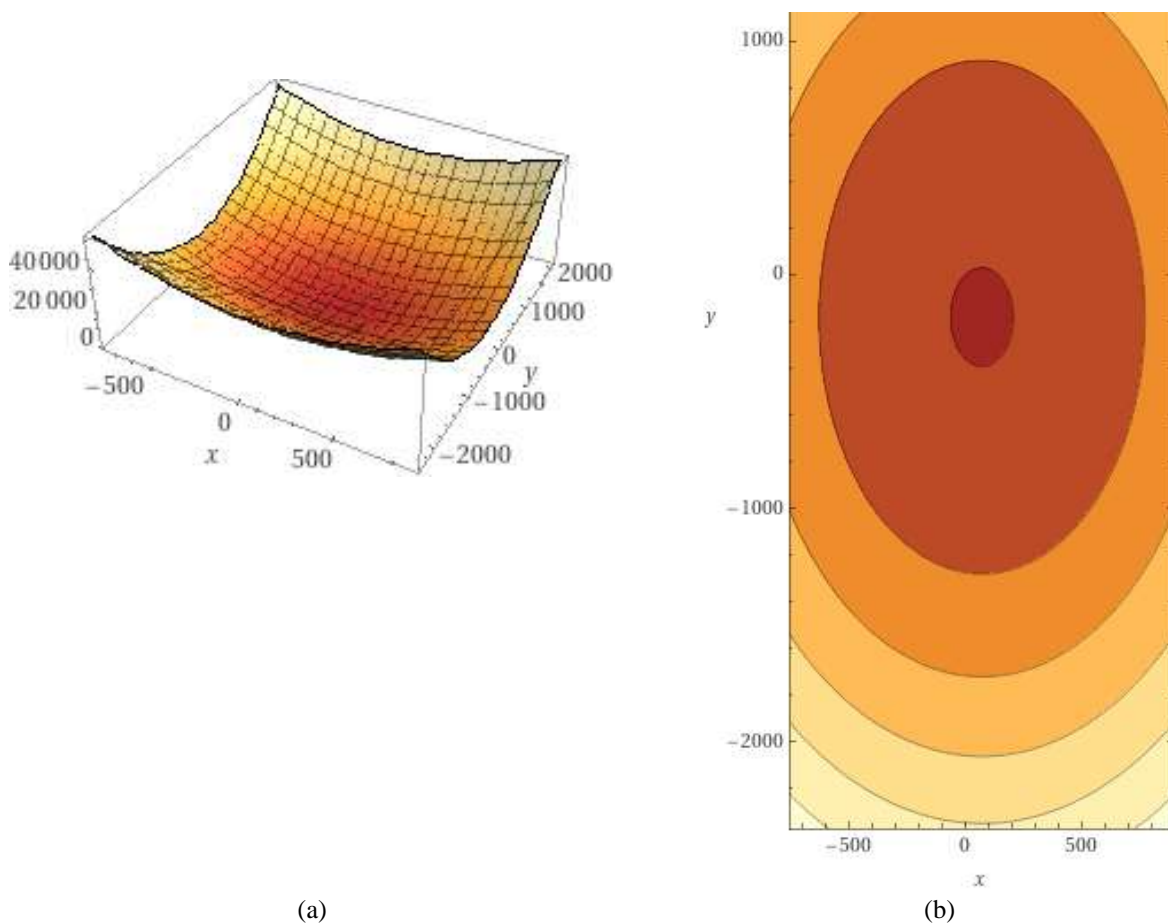


Fig. 3. Distribution of DVC values in relation to R and G in soybean crop; (a) 3D format, (b) isoquants format
 Source: Original figure.

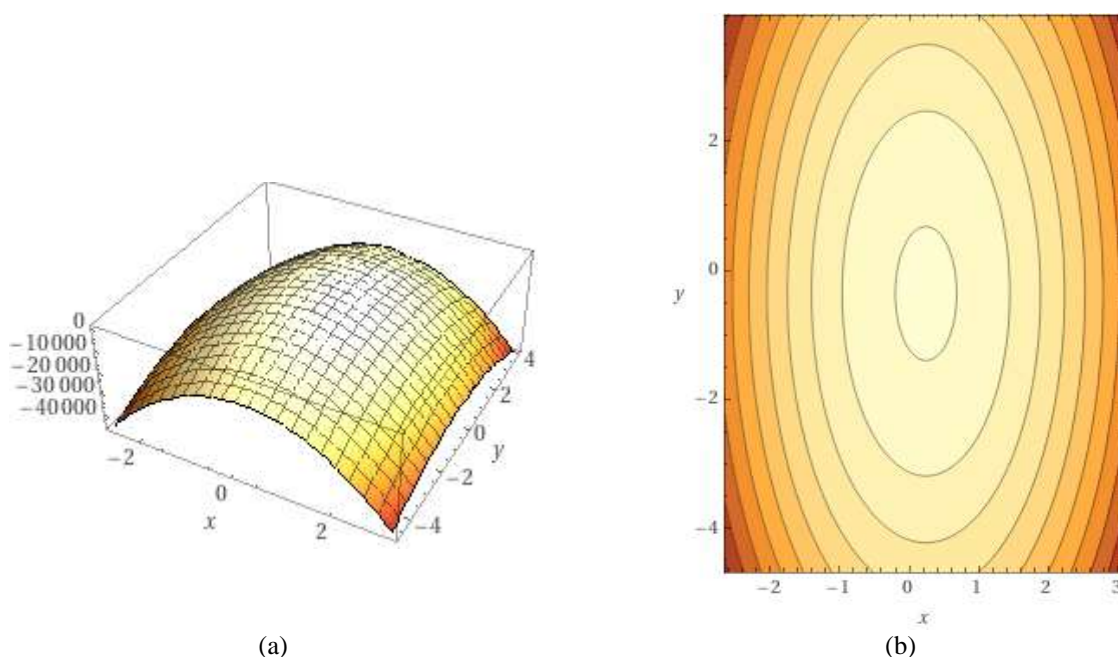


Fig. 4. Distribution of DVC values in relation to r and b in soybean crop; (a) 3D format, (b) isoquants format
 Source: Original figure.

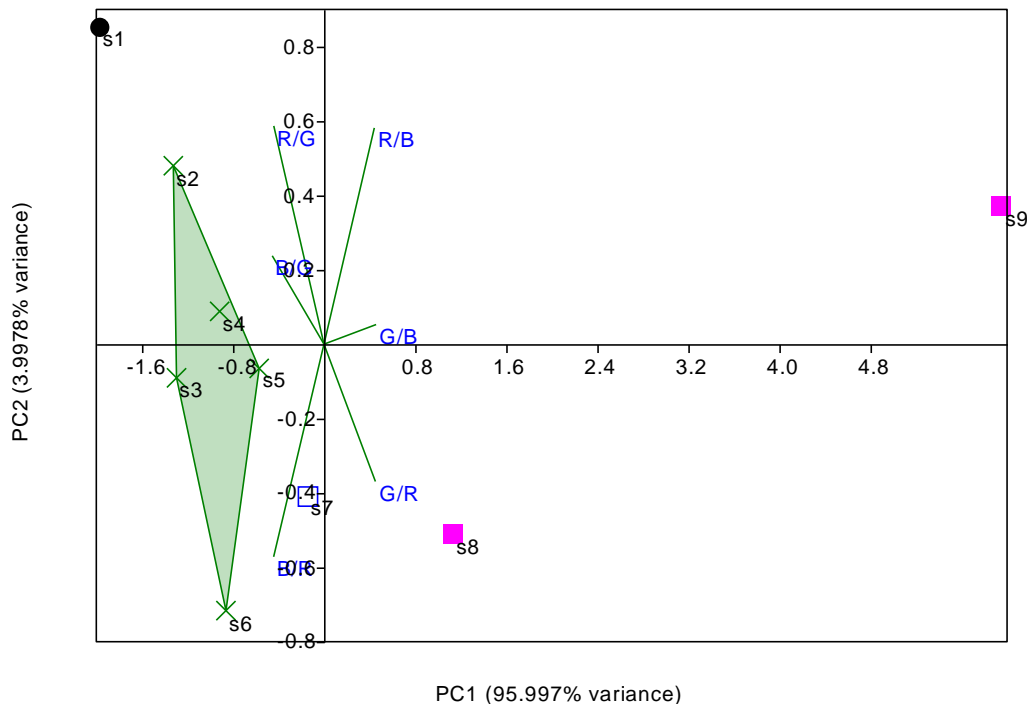


Fig. 5. PCA diagram in the analysis of soybean crop
 Source: Original figure.

Variants s8 and s9, with variable degree of weeds, were placed associated with G/R ratios (s8) quadrant II, and G/B, R/B (s9) ratios, quadrant I. PC1 explained 95.997% of variance, and PC2 explained 3.9978% of variance.

The cluster analysis led to the dendrogram in Figure 6, under conditions of Coph.corr.= 0.978, in which the variants were grouped based on Euclidean distances.

The independent positioning of variant s9 (high degree of weeds) and close to variant s8 (both variants with weeds) was found. Within a sub-cluster C1, variant s1 (plant front, empty land) was placed independently.

The other variants, s2 to s7 (without weeds, with variable number of plants) were positioned grouped in two sub-clusters, in relation to the growing number of plants per row. Thus, on the basis of similarity, the variants (s2,s3,s4) were grouped within a sub-cluster, and the variants ((s5,s6),s7) within another sub-cluster.

The calculated SDI values confirmed the association and grouping of the variants (SDI=0.07122 in the case of s7 with s5; SDI=0.09348 in the case of s7 with s6; SDI=0.72824 in the case of s9 with s8;

SDI=1.1553 in the case of s1 with s9, the highest value SDI).

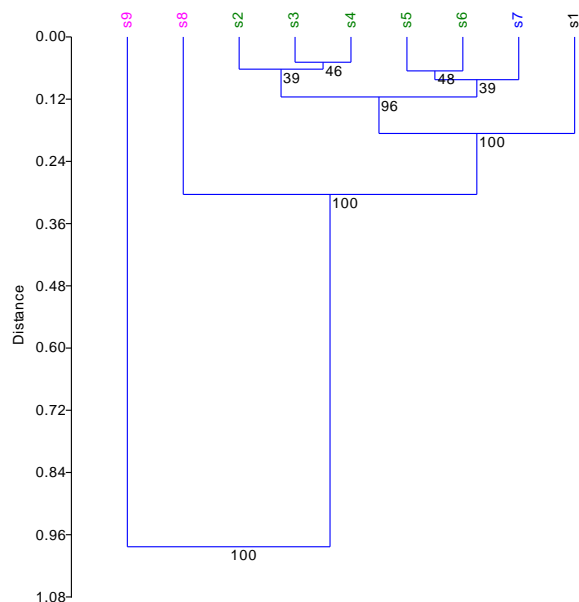


Fig. 6. Dendrogram of variants grouping based on Euclidean distances
 Source: Original figure.

The imaging analysis used in the present study facilitated the description of the soybean culture in relation to aspects regarding the uniformity of the culture, the degree of coverage of the land with soybean plants, but

also in relation to the presence of weeds. Imaging methods are very frequently used for crop control, crops mapping, plant density, plant nutrition and health status [26, 28].

Imaging analysis has given very good results in studies of identification and analysis of weeds in different agricultural crops [13, 32]. The identification of weeds in real time in agricultural crops presents high advantages for the differentiated application of herbicides, only on the affected areas, thus ensuring a precise dosage of treatments, sustainable technologies for agricultural crops and environmental protection [4, 13].

The present study contributes to the development of the database and information regarding the evaluation of agricultural crops in terms of uniformity and the presence of weeds, through methods based on imaging analysis, and proposes some models for describing the degree of land cover based on some color parameters (RGB), calculated reports and specific indices.

CONCLUSIONS

Imaging analysis based on digital images (cell phone camera) facilitated obtaining information in the form of color parameters (RGB, rgb), calculated ratios (e.g. R/G, R/B), specific indices (NDI, INT) and degree of vegetation cover (DVC), for the analysis and characterization of the soybean culture in terms of uniformity and weeds degree.

The correlation analysis facilitated the identification of the degree of interdependence between the parameters considered in the characterization and analysis of the soybean crop.

The regression analysis facilitated the description by equations (linear and polynomial) of the degree of vegetation cover (DVC) variation according to each considered parameter, under statistical safety conditions. A high level of precision and safety efforts were recorded in the case of the equations based on the R/G ratio, of the corrected value g ($R^2=0.998$, $p<0.001$), immediately followed by the equations based on the G/R ratio and the NDI index ($R^2= 0.997$, $p<0.001$).

3D models and in the form of isoquants were generated to describe the variation of DVC in relation to considered parameters, as a direct and interaction effect.

According to PCA, a distribution diagram of the variants was generated in relation to the considered parameters, as biplot; PC1 explained 95.997% of variance, and PC2 explained 3.9978% of variance in the case of analysis based on calculated ratios (RGB).

Cluster analysis led to the grouping of the variants based on similarity, highlighting the variants with a high degree of weeding (s8, s9), the variant with a normal state (s7) and the other experimental variants.

ACKNOWLEDGEMENTS

The authors thank the ARSD Lovrin for facilitating this study.

REFERENCES

- [1]Ahmad, I.S., Reid, J.F., 1996, Evaluation of color representations for maize images, *J. Agric. Eng. Res.*, 63(3):185-195.
- [2]Ahmad, U., Nasirahmadi, A., Hensel, O., Marino, S., 2022, Technology and data fusion methods to enhance site-specific crop monitoring, *Agronomy*, 12:555
- [3]Bouguettaya, A., Zarzour, H., Kechida, A., Taberkit A.M., 2022, Deep learning techniques to classify agricultural crops through UAV imagery: a review, *Neural Comput & Applic.*, 34:9511-9536.
- [4]Burgos-Artizzu, X.P., Ribeiro, A., Guijarro, M., Pajares, G., 2011, Real-time image processing for crop/weed discrimination in maize fields, *Comput. Electron. Agric.*, 75(2):337-346.
- [5]Espinosa-Herrera, J.M., Macedo-Cruz, A., Fernández-Reynoso, D.S., Flores-Magdaleno, H., Fernández-Ordoñez, Y.M., Soria-Ruiz, J., 2022, Monitoring and identification of agricultural crops through multitemporal analysis of optical images and machine learning algorithms, *Sensors (Basel)*, 22(16):6106.
- [6]Fan, C., Lu, R., 2021, UAV image crop classification based on deep learning with spatial and spectral features, *IOP Conf. Ser. Earth Environ. Sci.*, 783:012080.
- [7]Halstead, M., Ahmadi, A., Smitt, C., Schmittmann, O., McCool, C., 2021, Crop agnostic monitoring driven by deep learning, *Front. Plant Sci.*, 12:786702.
- [8]Hammer, Ø., Harper, D.A.T., Ryan, P.D., 2001, PAST: Paleontological Statistics software package for education and data analysis, *Palaeontol. Electron.*, 4(1):1-9.

- [9]Hsiou, D.-C., Huang, F., Tey, F.J., Wu, T.-Y., Lee, Y.-C., 2022, An automated crop growth detection method using satellite imagery data, *Agriculture*, 12:504.
- [10]Huete, A.R., 1988, A soil-adjusted vegetation index (SAVI), *Remote Sens. Environ.*, 25(3):295-309.
- [11]JASP Team, 2022, JASP (Version 0.16.2) [Computer software].
- [12]Lee, K.-J., Lee, B.-W., 2013, Estimation of rice growth and nitrogen nutrition status using color digital camera image analysis, *Eur. J. Agron.*, 48:57-65.
- [13]Li, Y., Al-Sarayreh, M., Irie, K., Hackell, D., Bourdot, G., Reis, M.M., Ghamkhar, K., 2021, Identification of weeds based on hyperspectral imaging and machine learning, *Front. Plant Sci.*, 11:611622.
- [14]Madec, S., Irfan, K., Velumani, K., Baret F., David E., Daubige G., Samatan L.B., Serouart ., Smith D., James C., Camacho F., Guo W., De Solan B., Chapman S.C., Weiss M., 2023, VegAnn, Vegetation Annotation of multi-crop RGB images acquired under diverse conditions for segmentation, *Sci. Data*, 10:302.
- [15]Mao, W., Wang, Y., Wang, Y., 2003, Real-time detection of between-row weeds using machine vision, *ASAE Annual Meeting*, 2003:031004.
- [16]Mesías-Ruiz, G.A., Pérez-Ortiz, M., Dorado, J., de Castro, A.I., Peña, J.M., 2023, Boosting precision crop protection towards agriculture 5.0 via machine learning and emerging technologies: A contextual review, *Front. Plant Sci.*, 14:1143326.
- [17]Patrignani, A., Ochsner, T.E., 2015, Canopeo: A powerful new tool for measuring fractional green canopy cover, *Agron. J.*, 107(6):2312-2320.
- [18]Pei, H., Sun, Y., Huang, H., Zhang, W., Sheng, J., Zhang, Z., 2022, Weed detection in maize fields by UAV images based on crop row preprocessing and improved YOLOv4, *Agriculture*, 12:975.
- [19]Radočaj, D., Šiljeg, A., Marinović, R., Jurišić, M., 2023, State of major vegetation indices in precision agriculture studies indexed in Web of Science: A Review, *Agriculture*, 13:707.
- [20]Rasband, W.S., 1997, *Image J*. U. S. National Institutes of Health, Bethesda, Maryland, USA, p. 1997-2014.
- [21]Rivera, A.J., Pérez-Godoy, M.D., Elizondo, D., Deka, L., del Jesus, M.J., 2022, Analysis of clustering methods for crop type mapping using satellite imagery, *Neurocomputing*, 492:91-106.
- [22]Rouse, J.W.Jr., Haas, R.H., Schell, J.A., Deering, D.W., 1974, Monitoring vegetation systems in the Great Plains with ERTS. Third Earth Resource Technology Sattelite - 1 Symposium, NASA SP-351(I):309-317.
- [23]Sala, F., Iordănescu, O., Dobrei, A., 2017, Fractal analysis as a tool for pomology studies: case study in apple, *AgroLife Sci. J.*, 6(1):224-233.
- [24]Sala, F., Popescu, C.A., Herbei, M.V., Rujescu, C., 2020, Model of color parameters variation and correction in relation to “Time-View” image acquisition effects in wheat crop, *Sustainability*, 12(6):2470.
- [25]Shahi, T.B., Xu, C.-Y., Neupane, A., Guo, W., 2023, Recent advances in crop disease detection using UAV and Deep Learning techniques, *Remote Sens.*, 15:2450.
- [26]Shirzadifar, A., Maharlooei, M., Bajwa, S.G., Oduor, P.G., Nowatzki, J.F., 2020, Mapping crop stand count and planting uniformity using high resolution imagery in a maize crop, *Biosyst. Eng.*, 200:377-390.
- [27]Thomas, R.J., O’Hare, G., Coyle, D., 2023, Understanding technology acceptance in smart agriculture: A systematic review of empirical research in crop production, *Technol. Forecast. Soc. Change*, 189:122374.
- [28]Vong, C.N., Conway, L.S., Feng, A., Zhou, J., Kitchen, N.R., Sudduth, K.A., 2022, Corn emergence uniformity estimation and mapping using UAV imagery and deep learning, *Comput. Electron. Agric.*, 198:107008.
- [29]Voss, R., 1985, Random fractal forgeries. In: Earnshaw R. (Ed.) *Fundamental algorithms for computer graphics*, Springer Verlag, Berlin, pp. 805-835.
- [30]Vrchota, J., Pech, M., Švepešová, I., 2022, Precision agriculture technologies for crop and livestock production in the Czech Republic, *Agriculture*, 12:1080.
- [31]Wolfram, Research, Inc., *Mathematica*, Version 12.1, Champaign, IL (2020).
- [32]Wu, Z., Chen, Y., Zhao, B., Kang, X., Ding, Y., 2021, Review of weed detection methods based on Computer Vision, *Sensors (Basel)*, 21(11):3647.
- [33]Yin, H., Huang, W., Li, F., Yang, H., Li, Y., Hu, Y., Yu, K., 2023, Multi-temporal UAV imaging-based mapping of chlorophyll content in potato crop, *PGF – J. Photogramm. Rem.* 91:91-106.
- [34]Yu, F., Jin, Z., Guo, S., Guo, Z., Zhang, H., Xu, T., Chen, C. 2022, Research on weed identification method in rice fields based on UAV remote sensing, *Front. Plant Sci.*, 13:1037760.
- [35]Zhang, C., Marzougui, A., Sankaran, S., 2020, High-resolution satellite imagery applications in crop phenotyping: An overview, *Comput. Electron. Agric.*, 175:105584.
- [36]Zhu, Y., Cao, Z., Lu, H., Li, Y., Xiao, Y., 2016, In-field automatic observation of wheat heading stage using computer vision, *Biosyst. Eng.*, 143:28-41.