Scientific Papers. Series A. Agronomy, Vol. LXVII, No. 1, 2024
ISSN 2285-5785; ISSN CD-ROM 2285-5793; ISSN Online 2285-5807; ISSN-L 2285-5785

IMAGING ANALYSIS IN CORN CROP EVALUATION UNDER HYDRIC STRESS CONDITION

Ciprian BUZNA[1], Marinel Nicolae HORABLAGA[1, 2], Florin SALA[1, 2]

[1]Agricultural Research and Development Station Lovrin, Lovrin, 307250, Romania
[2]University of Life Sciences "King Mihai I" from Timisoara,
119 Calea Aradului, 300645, Timisoara, Romania

Corresponding author email: florin_sala@usvt.ro

Abstract

Imaging analysis (UAV images) was used to evaluate a corn crop under hydric stress conditions. From the analysis of the series of images (June 29 – T1, July 20 – T2, year 2022) the values of the RGB parameters resulted. Suplementary the luminance (Lum), normalized values (rgb), values in the HSB system, and INT, NDI and DGCI indices, were determined. The correlation analysis identified 18 very strong correlations between the parameters considered at the time of T1, and 10 very strong correlations at the time of T2. The PCA analysis led to the classification of the components: seven components in PC1 (R = -9.93 the highest value) and three components in PC2 (Lum = 0.970 the highest value) at the time of T1; four components in PC1 (r = -0.990 the highest value) and four components in PC2 (Lum = 0.949 the highest value) at time T2. The differences between the series of parameters, at the moments T1 and T2, were confirmed by values U = 18, p = 0.017 in the case of parameter G; U = 10, p = 0.0028 in the case of the B parameter; t = 9.4202, p < 0.01 in the case of NDI; t = 9.2066, p<0.001, U = 1, p < 0.001 in the case of INT; t = 9.3176, p < 0.001 in the case of DGCI; t = 7.5581, p < 0.001, U = 3, p < 0.001 in the case of Lum.

Key words: *component loadings, hydric stress, imaging analysis, maize, PCA.*

INTRODUCTION

Farmers are currently faced with an accumulation of factors that affect the yield of agricultural crops, and the crops stressors, including water stress, represents a challenge that requires immediate solutions (Ahmad et al., 2021; Weng, 2023).

Improved genotypes are present in agricultural practice, and new ones, with indices of productivity, quality and tolerance to stress factors, adapted for current and prospective agricultural technologies, are in breeding programs and laboratories, and are to be promoted and cultivated. At the same time, a series of relevant parameters and physiological indices that reflect the response of the plants to water stress were identified. They are in the attention of the breeding programs and of the agricultural pact for early interventions with irrigation measures (Chen et al., 2014).

There are concerns for the future development of genotypes with drought resistance in crop plants, and studies to evaluate the response of plants to water stress (Ismael et al., 2022; Kim et al., 2023; Quagliata et al., 2023).

Considering the increase of the global water deficit, more and more effective methods for assessing the water stress on crop plants associated with cost modeling, and the early programming of irrigations have proven to be necessary (Zhou et al., 2021). Thus, the methods based on image analysis (UAV) become more and more present in agricultural practice, accessible to farmers, being based on specific indices that facilitate effective analyzes and prognoses, under the cost-benefit aspect.

The traditional methods of monitoring crops and water deficit have been replaced over time with alternative methods based on image analysis associated and combined with automatic learning applications, with calculation algorithms and prediction models for the purpose of early estimation of water stress and effective intervention decisions (Kamarudin et al., 2022).

In order to identify early the response of plants to water stress and the decision of some irrigation works, the phenotyping of plants, of agricultural crops, is an increasingly promoted practice (Al-Tamimi et al., 2022).

Numerous studies have been carried out that addressed image analysis technologies suitable for plant phenotyping (sensors, spectra, resolutions, etc.) but also aspects of information processing and analysis, such as new algorithms (Das Choudhury, 2023).

The monitoring of agricultural crops and the early detection (in real time) of crop water stress through techniques based on remote sensing, which evaluate through specific techniques (spectral, multispectral information) evapotranspiration, chlorophyll florescence, as well as other representative indicators, offer a series of benefits (Weng, 2023; Karmakar et al., 2024).

Some studies analyzed the performance of water stress estimation in agricultural crops (e.g. corn) based on UAV images in relation to the image resolution, and proposed water stress indicators (Zhang et al., 2022).

A large base of indices were developed over time for the study of plants and agricultural crops based on satellite images, but with the promotion of UAV techniques, specific indices were developed for this technique in the study of water stress (Hoffmann et al., 2016).

For the analysis and evaluation of the water stress of plants and crops, phenotyping methods based on free applications (e.g. Canopeo) were tested, due to accessibility and financial considerations (Kim et al., 2022). The authors of the study communicated positive correlations between vegetative parameters, elements of productivity (e.g. the number of nodes in soybeans), with parameters resulting from imaging analysis.

The present study is using imaging analysis techniques (UAV images) to obtain color parameters (RGB) and specific indices (NDI, INT, DGCI) and appropriate mathematical and statistical analysis methods, to identify the differences in the evolution of corn crop in water stress conditions.

MATERIALS AND METHODS

The study was conducted at Agricultural Research and Development Station (ARDS) Lovrin, in the pedoclimatic conditions specific to the Western Plain, Romania.

The corn commercial hybrid (CH), was grown on a chernozem soil, in a non-irrigated crop system. In the context of climate change, the year 2022 was characterized by a major precipitation deficit, with high temperatures and prolonged heat. Thus, the plants were affected by drought and the purpose of the study was to characterize the corn crop based on UAV images, at two different times, at an interval of 30 days, between July and August, 2022. Series of ten aerial images (UAV) were taken at each time (T1, and T2), at different heights from the crop level. The images were image analyzed (Rasband, 1997) and the spectral information in the RGB system was obtained. Starting from the RGB data, the normalized values (rgb), equation (1), Lee and Lee (2013) and the values of the color parameters in the HSB system were calculated.

$$\begin{cases} r = \dfrac{R}{(R+G+B)} \\ g = \dfrac{G}{(R+G+B)} \\ b = \dfrac{B}{(R+G+B)} \end{cases} \qquad (1)$$

Additionally, specific vegetation characterization indices were calculated, respectively NDI (Normalized Difference Indices), equation (2), INT (Intensity), equation (3), and DGCI (Dark Green Color Index), equation (4) (Ahmad and Reid, 1996; Karcher and Richardson, 2003; Mao et al., 2003; Rorie et al., 2011).

$$NDI = \frac{(r-g)}{(r+g+0.01)} \qquad (2)$$

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

$$DGCI = \left[\frac{(H-60)}{60} + (1-S) + (1-B)\right]/3 \qquad (4)$$

The data series for determined parameters were analyzed comparatively, at the two moments of determination (T1, T2).

PCA analysis was used to rank the parameters by components. In order to point out the differences between the data series, specific mathematical and statistical tests were used.

Correlation analysis between parameters, data series at the two moments (T1, T2) was used to analyze the evolution of the interdependence between parameters, associated with the state of the crop. The results of the mathematical and statistical analyzes were interpreted in relation to the statistical safety thresholds (Hammer et al., 2001; JASP, 2022).

RESULTS AND DISCUSSIONS

The series of UAV digital images, taken at the two study moments (T1, T2) were analyzed and the values of the RGB color parameters were obtained. Starting from this basic spectral information, the luminance values (Lum), the normalized values (rgb) and the values in the HSB color system were determined. Based on these parameters, the INT, NDI and DGCI indexes were calculated. The data series for the parameters considered in the study, resulting from the analysis of the images and through calculations, are presented in Table 1 (moment T1) and Table 2 (moment T2). The ANOVA test confirmed the reliability of the data and the presence of variance in the data set (Table 3).

Table 1. Statistical values of the parameters determined at time T1

Statistical Parameters	RGB color parameter			Calculated indices			Luminance
	R-T1	G-T1	B-T1	NDI-T1	INT-T1	DGCI-T1	Lum-T1
N	10	10	10	10	10	10	10
Min.	82.74	86.73	39.26	-0.202	70.993	0.358	32.00
Max.	90.20	93.02	61.40	-0.092	79.053	0.539	34.00
Sum	873.38	882.70	426.27	-1.108	727.450	3.889	326.00
Mean	87.34	88.27	42.63	-0.111	72.745	0.389	32.60
Std. error	0.70	0.61	2.10	0.010	0.740	0.017	0.22
Variance	4.94095	3.67527	44.25707	0.00108	5.47311	0.00295	0.48889
Stand. Dev.	2.223	1.917	6.653	0.033	2.339	0.054	0.699
Median	87.550	87.565	40.635	-0.1014	71.8584	0.3733	32.500
25 prcntil	86.098	86.905	40.010	-0.1116	71.4442	0.3608	32.00
75 prcntil	89.170	89.185	41.665	-0.0937	73.0959	0.3933	33.00

Table 2. Statistical values of the parameters determined at time T2

Statistical Parameters	RGB color parameters			Calculated indices			Luminance
	R-T2	G-T2	B-T2	NDI-T2	INT-T2	DGCI-T2	Lum-T2
N	10	10	10	10	10	10	10
Min.	103.53	82.05	42.62	-0.043	76.067	0.202	33.00
Max.	113.88	98.75	48.72	0.015	85.837	0.263	38.00
Sum	1111.07	904.66	465.50	0.002	827.077	2.201	361.00
Mean	111.11	90.47	46.55	0.000	82.708	0.220	36.10
Std. error	0.95	1.25	0.61	0.006	0.790	0.006	0.41
Variance	9.12000	15.68347	3.70849	0.00031	6.23686	0.00033	1.65556
Stand. Dev.	3.020	3.960	1.926	0.018	2.497	0.018	1.287
Median	111.195	90.580	47.020	0.0053	83.2667	0.2150	36.000
25 prcntil	110.428	90.028	45.163	-0.0070	82.7217	0.2081	36.000
75 prcntil	113.525	90.898	48.030	0.0133	83.3909	0.2258	37.000

Table 3. ANOVA Test

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups	199758.8	6	33293.13	1020.0816	1.4E-108	4.013174
Within Groups	4340.816	133	32.63772			
Total	204099.6	139				

PCA analysis led to the classification of components: seven factors in PC1 (color parameter R, r = -9.93, highest value) and three factors in PC2 (Luminance, Lum, r = 0.970 highest value) at T1 time ($p < 0.001$) (Table 4); four factors in PC1 (normalized value r, r = -0.990, highest value) and four factors in PC2 (Luminance, Lum, r = 0.949 highest value) at time T2 ($p<0.001$) (Table 5).

Table 4. Component Loadings (T1)

Parameter	PC1	PC2	Uniqueness
R	-0.993		0.012
g	0.876		0.007
DGCI	0.872		0.002
NDI	-0.868		0.000
r	-0.867		0.000
b	0.849		0.008
B	0.797		0.007
Lum		0.970	0.045
G		0.899	0.025
INT		0.826	0.011

Table 5. Component Loadings (T2)

Parameter	PC1	PC2	Uniqueness
r	-0.990		0.002
DGCI	0.957		0.080
NDI	-0.952		0.037
g	0.880		0.117
Lum		0.949	0.028
R		0.937	0.059
INT		0.914	0.036
G		0.826	0.021
B			0.402
b			0.508

This analysis facilitated the grouping of determined parameters, as factors in the characterization of corn crop, by components, with the degree of involvement or representativeness of each factor. The characteristics of the components, at the two moments of determination (T1, T2), resulted based on the analysis, are presented in Table 6.

Table 6. Component Characteristics

Component	Unrotated solution			Rotated solution		
	Eigenvalue	Proportion var.	Cumulative	Sum Sq. Loadings	Proportion var.	Cumulative
	Values for T1 moment					
Component 1	8.575	0.858	0.858	5.861	0.586	0.586
Component 2	1.307	0.131	0.988	4.021	0.402	0.988
	Values for T2 moment					
Component 1	5.987	0.599	0.599	4.923	0.492	0.492
Component 2	2.723	0.272	0.871	3.787	0.379	0.871

Between the average values of the parameters, at the two study moments (T1, T2), some differences were identified, and the level of statistical safety of the differences was analyzed. For this, specific mathematical analyzes were used.
Based on the t-test (Equality of Means) and the Mann-Whitney test (Two-sample tests), the following values were obtained for the data series related to the considered parameters: U = 18, p = 0.017 in the case of the G parameter; U = 10, p = 0.0028 in the case of parameter B; t = 9.4202, $p<0.01$ in the case of NDI; t = 9.2066, $p<0.001$, U = 1, $p<0.001$ in the case of INT; t = 9.3176, $p<0.001$ in the case of DGCI; t = 7.5581, $p<0.001$, U = 3, $p<0.001$ in the case of Lum. Starting from the differences recorded between the parameters at the two moments (T1 and T2), based on the One-sample test, the analysis was made on the data series of each parameter at the moment T2, in relation to the average from the moment T1. Thus, according to the analysis, the values presented in Table 7 resulted.
From the analysis of the resulting values based on the t test, it was found that the average values related to the data series of the R and B color parameters, of the calculated NDI, INT, DGCI indices, and respectively the Luminance values at the moment T2 showed statistically guaranteed differences ($p<0.001$) compared to the average of the same parameters, calculated at time T1.

Table 7. One-sample test results

Statistical Parameters	R-T2	G-T2	B-T2	NDI-T2	INT-T2	DGCI-T2	Lum-T2
	t test						
Given mean: T1	87.34	88.27	42.63	-0.1110	72.7450	0.3890	32.60
Sample mean:	108.95	90.27	46.19	-0.0099	81.8020	0.2355	35.78
95% conf. interval:	(103.76 114.13)	(87.703 92.829)	(44.732 47.655)	(-0.035023 0.01526)	(79.232 84.372)	(0.19931 0.2716)	(34.698 36.866)
Difference:	21.6060	1.9964	3.5636	0.1011	9.0570	0.1536	3.1818
95% conf. interval:	(16.422 26.791)	(-0.56652 4.5592)	(2.1018 5.0254)	(0.075977 0.12626)	(6.4868 11.627)	(0.1174 0.18969)	(2.0978 4.2658)
t:	9.2854	1.7356	5.4319	8.9615	7.8517	-9.4660	6.5401
p (same mean):	3.12E-06	0.11329	0.00029	4.30E-06	1.39E-05	2.62E-06	6.55E-05
Significance of Means	Means are significantly different	Means are not significantly different	Means are significantly different	Means are significantly different	Means are significantly different	Means are significantly different	Means are significantly different
	Wilcoxon test						
Given median: T1	87.550	87.565	40.635	-0.1014	71.8584	0.3733	32.500
Sample median:	111.120	90.390	47.000	0.0039	83.2100	0.2156	36.000
W:	55	46	55	55	55	55	55
Normal appr. z:	2.8031	1.8857	2.8031	2.8031	2.8031	2.8067	2.8710
p (same median):	0.00506	0.05934	0.00506	0.00506	0.00506	0.00501	0.00409
p (exact):	0.00195	0.06445	0.00195	0.00195	0.00195	0.00195	0.00195
Significance of Medians	Medians are significantly different	Medians are not significantly different	Medians are significantly different	Medians are significantly different	Medians are significantly different	Medians are significantly different	Medians are significantly different

The exception was the color parameter G, for which the differences did not show statistical certainty (Table 7).

The additional test applied (Wilcoxon test), confirmed the results of the t test, with the median values of the data series related to each parameter at the moment T2 that showed differences compared to the median values of the data series at time T1. The exception was the color parameter G (Table 7).

Through the correlation analysis, the level of interdependence between the studied parameters was evaluated, at the two moments of determination (Figures 1 and 2).

From the analysis of the correlation coefficient values, 18 very strong correlations ($r>0.900$) were identified between the parameters considered at the moment T1 and only 10 very strong correlations, at the time of T2.

This shows the variation of the parameters and their interdependence, a fact that shows a significant level of change in the status of the plants, and the relationships between their description parameters, based on the UAV images.

The obtained results pointed out that color parameters in the RGB system, calculated indices, and Luminance have shown the corn crop state of vegetation. The mathematical and statistical analysis tools have clearly detected, with statistical certainty, the differences at the two moments of determination.

Using the analysis for the parameters position in the two components (PC1, PC2) and moments (T1 and T2), as factors associated with the state of the corn crop, captured in the UAV images, the existence of some parameters with a stable or variable position were identified.

Stable parameters or factors, which were maintained in PC1 at the two moments of determination (T1 and T2) were r and g parameters (normalized values), and DGCI and NDI indices. Stable parameters or factors in PC2, at the two moments of determination (T1 and T2), were the color parameter G, Luminance (Lum) and the INT index.

The color variable parameter represented by R was identified both with negative action ($r = -0.993$) when was positioned in PC2 at time T1, and respectively with positive action ($r = 0.937$) at time T2 in PC2. So, the parameter R expressed sensitivity in relation to the state of the crop, and can be considered a relevant parameter associated with water stress, both by changing the position between classes, the direction of action (positive in class PC1 at time T1 and negative in class PC2, at time T2) as well as by the very strong value of the effect (r = -0.991 in PC1, at time T1; r = 0.937 in PC2 at time T2).

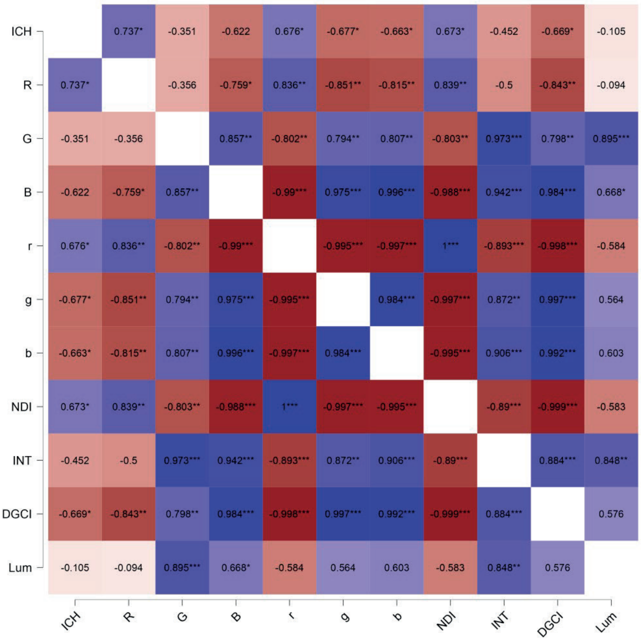

Figure 1. The level of correlations between the analyzed parameters at the moment T1

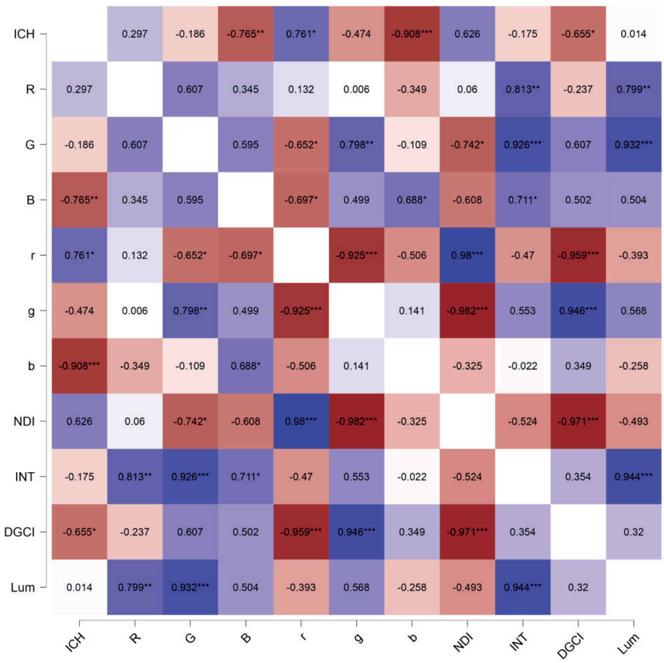

Figure 2. The level of correlations between the analyzed parameters at the moment T2

The normalized value g, was maintained in PC1 both at time T1 and at time T2. Also, the (positive) effect was maintained, as well as the level of action (r = 0.876 at T1 time; r = 0.880 at T2 time). The normalized value r, as a factor in the PCA analysis, was maintained in PC1, both at the time T1 and at the time T2, with negative action (r = -0.867 at the time T1; r = -0.990 at the time T2).

The DGCI index remained in PC1 at the two determination moments (T1 and T2), with positive action, strong at T1 (r = 0.872) and very strong at T2 (r = 0.957). The NDI index was also maintained in PC1 at both determination moments, with negative action, strong at T1 (r = -0.967) and very strong at T2 (r = -0.952).

Color parameters B and b (normalized value), present in PC1 at T1, with positive, strong and moderate action (r = 0.849 in the case of b; r = 0.797 in the case of B), doesn't belong into the classes PC1 or PC2 at time T2. The color parameter G, Luminance (Lum) and the INT index remained in the PC2 class, both at T1 and at T2. Luminance presented a positive, very strong action in both PC1 and PC2 (r = 0.970, respectively r = 0.949). The INT index showed positive action, strong in T1 (r = 0.826) and very strong in PC2 (r = 0.914). The color parameter G presented a strong positive action in both cases (r = 0.899 at T1; r = 0.826 at T2).

The interest for the study of crops based on imaging analysis is very high, with the use of different databases in the form of images, remote sensing, aerial images (UAV) or terrestrial images. AbdulHussein and Mihalache (2021) evaluated the land condition based on specific soil and vegetation indices, through remote sensing and GIS techniques. Gulyaev et al. (2023) communicated the results of a study based on remote sensing techniques for cotton crop, and simulation models of plant growth dynamics. Sala et al. (2020) analyzed a wheat crop based on terrestrial images, to describe the variation of spectral information in relation to the image capture mode, and communicated variation models and correction coefficients in relation to the image acquisition conditions. Zhou et al. (2021) used the technique based on UAV images for the study of water stress, with advantages in cost modeling by planning irrigation at early times and reducing the effects associated with drought. Zhang et al. (2022) carried out a study to estimate water stress in corn based on UAV images, in relation to the resolution of the images, and based on the recorded results, the authors proposed a water stress indicator. The authors of the study considered as representative the excess of green, quantified based on the "average value of the Gaussian distribution index (MGDEXG)" which they proposed as a relevant index for the study. A series of indices, based on UAV images data, were generated over time by different studies (Hoffmann et al., 2016), and the fact that new indices are proposed, associated with methods, techniques, models for the analysis of UAV images, shows the increased interest in this direction of study, research and agricultural practices.

CONCLUSIONS

The data in the form of UAV images, spectral information in the RGB system, and specific calculated indices (NDI, INT, DGCI) facilitated the description of the maize crop, a commercial hybrid, under conditions of drought and water stress, at two moments with an interval of 30 days. Multivariate analysis (PCA) led to the classification of factors and components, highlighting the direction of action and effect. The differentiated positioning of the factors in the two components (PC1, PC2) at the moments T1 and T2, facilitated the identification of the stable factors and the sensitive ones in relation to the state of the crop, captured in image data and spectral information.

The parameter R expressed sensitivity in relation to the state of the crop, and can be considered a relevant parameter associated with water stress, both by changing the position between classes, the direction of action (positive in class PC1 at time T1 and negative in class PC2, at moment T2) as well as by the very strong value of the effect (r = -0.991 in PC1, at moment T1; r = 0.937 in PC2 at moment T2). Through appropriate mathematical analyzes (Two-sample tests, and One-sample tests) the data series were compared for each parameter, the differences between the data series (T2) and the average of the data (T1) were analyzed and values that confirmed the differences under statistical safety conditions were obtained. There were also variations in the level of correlation between the parameters at the two moments of determination, with a weak level of correlation at the time of T2, a fact that confirms major changes at the crop level associated with vegetation conditions, respectively water stress.

ACKNOWLEDGMENTS

The authors thank the ARDS Lovrin for facilitating this study.

REFERENCES

AbdulHussein, A.S.A., Mihalache, M. (2021). Use of remote sensing techniques and geographic information systems to identify degraded land in Dhi Qar region from Irak. *Scientific Papers. Series A. Agronomy*, LXIV(2), 13–21.

Ahmad, I.S., Reid, J.F. (1996). Evaluation of color representations for maize images. *Journal of Agricultural Engineering Research*, 63(3), 185–195.

Ahmad, U., Alvino, A., Marino, S. (2021). A review of crop water stress assessment using remote sensing. *Remote Sensing*, 13, 4155.

Al-Tamimi, N., Langan, P., Bernád, V., Walsh, J., Mangina, E., Negrão, S. (2022). Capturing crop adaptation to abiotic stress using image-based technologies. *Open Biology*, 12(6), 210353.

Chen, D., Neumann, K., Friedel, S., Kilian, B., Chen, M., Altmann, T., Klukas, C. (2014). Dissecting the phenotypic components of crop plant growth and drought responses based on high-throughput image analysis. *The Plant Cell*, 26(12), 4636–4655.

Das Choudhury, S., Saha, S., Samal, A., Mazis, A., Awada, T. (2023). Drought stress prediction and propagation using time series modeling on multimodal plant image sequences. Frontiers in Plant Science, 14, 1003150.

Gulyaev, R., Sultonov, A., Yunusov, R., Rafikov, D., Gulyaeva, K., Kimsanbaev, O., Kakhkhorov, B. (2023). Results of automatic cotton crops mapping using remote sensing data and a plant growth simulation model. *AgroLife Scientific Journal*, 12(2), 81–86.

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.

Hoffmann, H., Jensen, R., Thomsen, A., Nieto, H., Rasmussen, J., and Friborg, T. (2016). Crop water stress maps for an entire growing season from visible and thermal UAV imagery. *Biogeosciences*, 13, 6545–6563.

Ismael, A., Xue, J., Meason, D.F., Klápště, J., Gallart, M., Li, Y., Bellè, P., Gomez-Gallego, M., Bradford, K.-T., Telfer, E., Dungey, H. (2022). Genetic variation in drought-tolerance traits and their relationships to growth in *Pinus radiata* D. Don under water stress. *Frontiers in Plant Science*, 12, 766803.

JASP Team (2022). JASP (Version 0.16.2) [Computer software].

Kamarudin, M.H., Ismail, Z.H. (2022). Lightweight deep CNN models for identifying drought stressed plant. *IOP Conference Series: Earth and Environmental Science*, 1091, 012043.

Karmakar, P., Teng, S.W., Murshed, M., Pang, S., Li, Y., Lin, H. (2024). Crop monitoring by multimodal remote sensing: A review. *Remote Sensing Applications: Society and Environment*, 33, 101093.

Karcher, D.E., Richardson, M.D. (2003). Quantifying turfgrass color using digital image analysis. *Crop Science*, 43(3), 943–951.

Kim, J., Yu, J.K., Rodrogues, R., Kim, Y., Park, J., Jung, J.-H., Kang, S.T., Kim, K.-H., Baek, J.H., Lee, E., Chung, Y.S. (2022). Case study: cost-effective image analysis method to study drought stress of soybean in early vegetative stage. *Journal of Crop Science and Biotechnology*, 25, 33–37.

Kim, J., Lee, C., Park, J., Kim, N., Kim, S.-L., Baek, J., Chung, Y.-S., Kim, K. (2023). Comparison of various drought resistance traits in soybean (*Glycine max* L.) based on image analysis for precision agriculture. *Plants*, 12, 2331.

Lee, K.-J.; Lee, B.-W. (2013). Estimation of rice growth and nitrogen nutrition status using color digital camera image analysis. *European Journal of Agronomy*, 48, 57–65.

Mao, W., Wang, Y., Wang, Y. (2003). Real-time detection of between-row weeds using machine vision. *ASAE Annual Meeting*, 031004.

Quagliata, G., Abdirad, S., Celletti, S., Sestili, F., Astolfi, S. (2023). Screening of Triticum turgidum genotypes for tolerance to drought stress. *Plant Physiology and Biochemistry*, 194, 271–280.

Rasband, W.S. (1997). ImageJ. U. S. National Institutes of Health, Bethesda, Maryland, USA, pp. 1997–2014.

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.

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.

Weng, S. (2023). Editorial: Spectroscopy, imaging and machine learning for crop stress. Frontiers in Plant Science, 14, 1240738.

Zhang, L., Zhang, H., Han, W., Niu, Y., Chávez, J.L., Ma, W. (2022). Effects of image spatial resolution and statistical scale on water stress estimation performance of MGDEXG: A new crop water stress indicator derived from RGB images. *Agricultural Water Management*, 264, 107506.

Zhou, Z., Majeed, Y., Naranjo, G.D., Gambacorta, E.M.T. (2021). Assessment for crop water stress with infrared thermal imagery in precision agriculture: A review and future prospects for deep learning applications. *Computers and Electronics in Agriculture*, 182, 106019.