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CLASSIFICATION OF IRRIGATION MANAGEMENT PRACTICES IN MAIZE HYBRIDS USING MULTISPECTRAL SENSORS AND MACHINE LEARNING TECHNIQUES

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KEYWORDS

Random Forest, Vegetation Indices, Artificial Neural Networks.

ABSTRACT

The integration multispectral sensors with machine learning algorithms has demonstrated increasing efficacy in the classification of various maize morphophysiological characteristics. The hypothesis of this study is that maize plants subjected to different irrigation management practices exhibit distinct spectral behaviors, allowing for their classification through machine learning modeling. Thus, the objective of this study is to classify maize hybrids in different irrigation management practices using multispectral images. This involves identifying the most effective machine learning algorithms and inputs variables that enhance model performance for accurate classification. The experiment was conducted at the experimental facility of the Federal University of Mato Grosso do Sul, in Chapadão do Sul – MS. Seven hybrids were evaluated: H1 (AS 1868), H2 (DKB 360), H3 (FS 615 PWU), H4 (K 7510 VIP3), H5 (NK 520 VIP3), H6 (P 3858 PWU), and H7 (SS 182E VIP3). These hybrids were subjected to irrigation and non-irrigation management practices. Sixty days after crop emergence, images were captured in the blue (475 nm, B_475), green (550 nm, G_550), red (660 nm, R_660), red edge (735 nm, RE_735), and near-infrared (790 nm, NIR_790) bands using the Sensefly eBee RTK fixed-wing Remotely Piloted Aircraft, equipped with a Parrot Sequoia multispectral sensor and RTK (Real-Time Kinematics) technology. Through the collected band data, the ESRI ArcGIS 10.5 geographic information system software was used to calculate 41 vegetation indices (VIs). Data were analyzed using machine learning techniques, testing six algorithms: Logistic Regression (RL), REPTree (DT), J48 Decision Trees (J48), Random Forest (RF), Artificial Neural Networks (ANN) and Support Vector Machine (SVM). Three accuracy metrics were utilized to evaluate the algorithms in the classification of irrigation management: correct classifications (CC), Kappa coefficient and F-Score. The ANN and RF algorithms demonstrated better accuracy in classifying maize hybrids with respect to irrigation management. The use of Vegetation Indices (IVs) and Spectral Bands + Vegetation Indices (SB+IVs) enhanced performance of these algorithms.

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INTRODUCTION

The most commonly employed techniques in phenotyping are limited by their high cost, substantial labor requirements, and delays in the evaluation processes (Ampatzidis, 2019). Therefore, using immediate response measurement platforms to assess crop status can help collect information about the phenotype, contributing to plant improvement (Banerjee et al., 2020). Leaves are primary indicators of biochemical changes, providing rapid responses that reflect the physiological and health status of plants (Zhang et al., 2023).

Remote sensing enables the acquisition of information about the chemical composition, cellular structure, and metabolic properties of plants by analyzing leaf reflectance. This method allows for non-destructive assessments and provides insights based on prior diagnostics (Kovar et al., 2019; Wu et al., 2019). The use of multispectral sensors for data collection facilitates more frequent assessments and, consequently, the acquisition of data throughout the crop cycle (Xie & Yang, 2020).

The water condition of plants induces several morphophysiological changes in maize (*Zea mays* L.), impacting photosynthetic efficiency and productivity parameters (Sah et al., 2020). Vegetation indices (VIs) are derived from spectral bands and mathematical models that are sensitive in detecting information related to water-dependent cellular changes, like osmotic adjustment. They can provide insights into cellular water conditions under different irrigation levels (Li et al., 2022; Javornik et al., 2023).

Approaches through traditional data analysis are less efficient compared to machine learning (ML) models, which have demonstrated high capacity for integrating numerical characteristics and extracting information about phenotypes (Spišić et al., 2022). Thus, algorithms such as neural networks are increasingly being used to classify genotypes and phenotypes (Maxwell et al., 2018).

The hypothesis of this study is that plants subjected to different irrigation management practices exhibit different spectral behavior, which can be used for classification through machine learning modeling. Thus, the aim of this study is to classify maize hybrids under different irrigation management practices using multispectral images, with the goal of identifying the most effective machine learning algorithm and input variables that enhance model performance.

MATERIAL AND METHODS

The experiment was conducted in the experimental area of the Federal University of Mato Grosso do Sul, located in Chapadão do Sul - MS, at geographic coordinates, 18°41’33’’ S latitude; 52°40’45’’ W longitude, with an average altitude of 810 m. The soil in the area was classified as a Dystrophic Red Oxisol (Santos et al., 2018) with a clayey content of 48%. The physicochemical characteristics of the soil are presented in Table 1.

TABLE 1. Physicochemical characteristics of the soil water in the experimental area.

Layer	pH (H_2O)	Al	Ca+Mg	P	K+	SB²	CEC³	OM⁴	V%⁵	Sand	Silt	Clay
m				cmolc dm^{-3}					g dm^{-3}	%	g kg^{-1}	
0–0.20	6.2	0.0	4.3	41.3	0.2	2.3	5.1	19.7	45.0	515.0	25.0	460.0

[1]pH = hydrogen potential in water; [2]SB= sum of bases; [3]CEC= Cation Exchange Capacity; [4]OM = Organic matter; [5]V%= Base saturation.

The region's climate is classified as Tropical Savanna (Aw), according to the Köppen, (1931) classification. Proper development of maize typically requires approximately 500 mm of rainfall (Monfreda et al., 2008), which was not achieved during the cultivation period as shown in Figure 1 (373.5 mm). Consequently, supplementary irrigation was necessary to prevent water stress during the vegetative period and grain filling (Hanjra & Qureshi, 2010) (Figure 2).

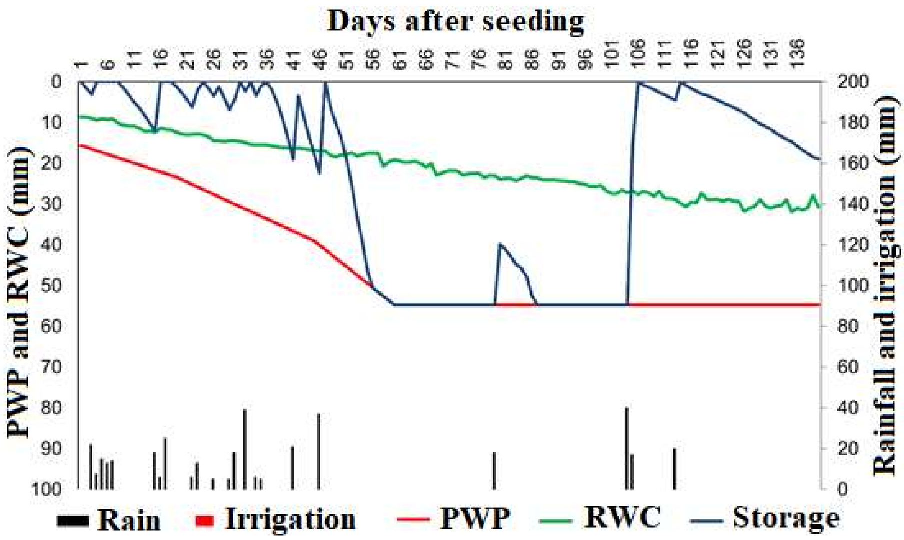

FIGURE 1. Dry water balance during the second harvest 2021/2022.

*PWP = Permanent wilting point. RWC = Real water capacity.

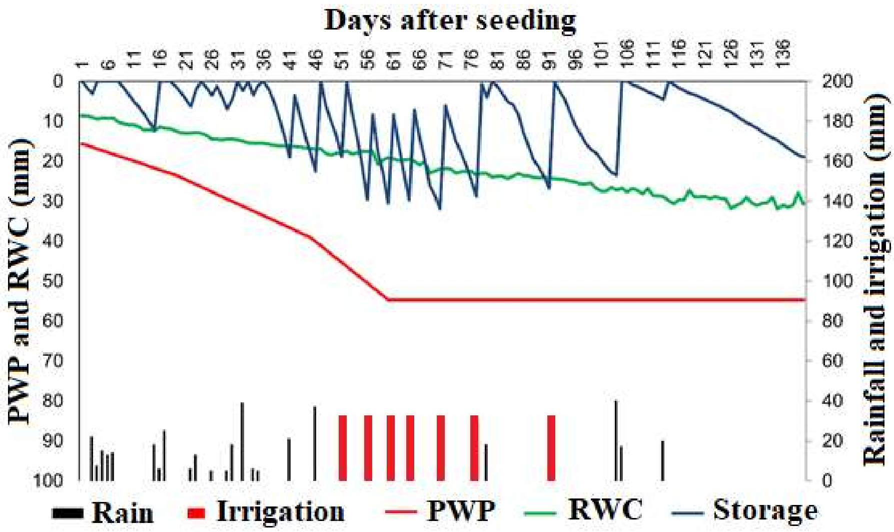

FIGURE 2. Irrigated water balance during the second harvest 2021/2022.
*PWP = Permanent wilting point. RWC = Real water capacity.

The experiment was conducted in a strip-plot design with seven maize hybrids: H1 (AS 1868), H2 (DKB 360), H3 (FS 615 PWU), H4 (K 7510 VIP3), H5 (NK 520 VIP3), H6 (P 3858 PWU), and H7 (SS 182E VIP3). These hybrids were subjected to both irrigated and rainfed management practices. Irrigation was applied using a conventional sprinkler system, with sprinklers spaced 12 m apart, creating an irrigated strip 18 m wide that covered all hybrid plots.

The Penman-Monteith-FAO method was employed, using data from an automatic meteorological station of the National Institute of Meteorology (INMET). Irrigation was applied to replace 100% of crop evapotranspiration – ETc, whenever the soil water balance approached the lower limit of the Real Soil Water Capacity-CRA, following the guidelines of Allen et al. (1998). Soil preparation followed the conventional method, consisting of plowing and leveling with harrowing. Hybrids were sown using a fertilizer seeder equipped with a rod-type furrowing mechanism for fertilizer distribution, and a misaligned double-furrowing mechanism for the seed placement at a depth of approximately 3 cm. The row spacing was 0.45 m, with an average plant density of 2.65 plants per meter. Sowing was conducted on February 25, 2022. Experimental plots were delineated with a total area of 18.62 m^2 (3.8 m x 4.9 m). Base fertilization was applied in the furrow with 200 kg ha^{-1} of monoammonium phosphate (MAP) with a formulation of 11-52-00. Top dressing was performed at stage V4 (maize with four fully developed leaves) using a dose of 150 kg ha^{-1} of Urea (45% N).

Sixty days after crop emergence, during the full flowering stage when maize reaches its peak of nutrient absorption and photosynthetic activity, a flight was carried out at 9:00 am under clear sky conditions. The flight was performed at an altitude of 100 m with spatial resolution of 0.10 m, using a fixed-wing Sensefly eBee RTK (Remotely Piloted Aircraft). The ARP was equipped with a Parrot Sequoia multispectral sensor, integrated with Real-Time Kinematics (RTK) technology, enabling precise image capture with a positioning accuracy of 2.5 cm. The images were subsequently mosaicked and orthorectified using the Pix4Dmapper software, version 1.70.1.

The Parrot Sequoia is equipped with a reflective surface for radiometric calibration, as provided by the manufacturer, and a luminosity sensor for calibrating acquired values. The sensor collects data across the following spectral bands (SB): blue (475nm, B_475), green (550 nm, G_550), red (660 nm, R_660), red edge (735 nm, RE_735) and NIR (790 nm, NIR_790). The band data collected from the area were analyzed using the geographic information system (GIS) software ESRI ArcGIS 10.5. This analysis involved calculating 41 vegetation indices (IVs), ranging from simple ratios between bands to more complex calculations (Table S1 (supplementary). These indices were designed with different configurations to address atmospheric corrections and mitigate the influence of the soil (Silva et al., 2020; Ramos et al., 2020).

Seventy samples were collected from each treatment (each irrigated and non-irrigated genetic material), and readings were taken from the samples to obtain the reflectance values of 5 different spectral bands. The number of variables is influenced by the input used, 5 for spectral bands and 41 for vegetation indices. Data standardization was normalized for machine learning analysis. It follows the same methodology described by Teodoro et al. (2023).

After data collection, the analysis was conducted using the Weka 3.8.5 software, which facilitated the testing of various machine learning algorithms (Table 2). Teodoro et al. (2024) and demonstrates promising results in the use of algorithms such as DT and ANN for classification between different genetic materials in agriculture. For the development of the J48 algorithm, an adaptation of the C4.5 classifier was made, as it has additional pruning based on an error reduction strategy (Al Snousy, et. al., 2011). The Random Forest (RF) model generates multiple decision trees from the same data set and uses a voting scheme among all the trees created to predict new values (Belgiu & Drăguţ, 2016). For all algorithms, hyperparameters were tested and followed the default settings of the Weka software; however, no significant improvement in accuracy was observed. Standard program architectures were employed for each algorithm, with logistic Regression (LR) serving as the baseline for performance comparison. Hybrid classification was performed using stratified cross-validation with k = 10 folds and ten replications, resulting in a total of 100 runs for each model.

TABLE 2. List of machine learning models used in classification.

Acronym	Machine Learning Model	Reference
LR	Logistic regression	(Stepanovský et al., 2017)
DT	REPTree	(Snousy et al., 2011)
J48	Decision Trees J48	(Quinlan, 1993)
RF	Random forest	(Belgiu & Drăguţ, 2016)
ANN	Artificial neural networks	(Egmont-Petersen; De Ridder; Handels, 2002)
SVM	Support Vector Machine	(Nalepa; Kawulok, 2019)

Three accuracy metrics were used to evaluate the performance of the algorithms in classifying different irrigation management practices: correct classification (CC), kappa coefficient and F-Score. The analyses and graphs were prepared using the ggplot2 and ExpDes.pt packages of the R software (Team, 2013).

RESULTS AND DISCUSSION

The reflectance of the hybrids under various management conditions and different wavelengths is illustrated in Figure 3. Hybrids grown under rainfed conditions exhibited higher reflectance at the wavelengths R_660 and NIR_790. No significant differences were observed between treatments at the wavelengths B_475, G_550 and RE_735.

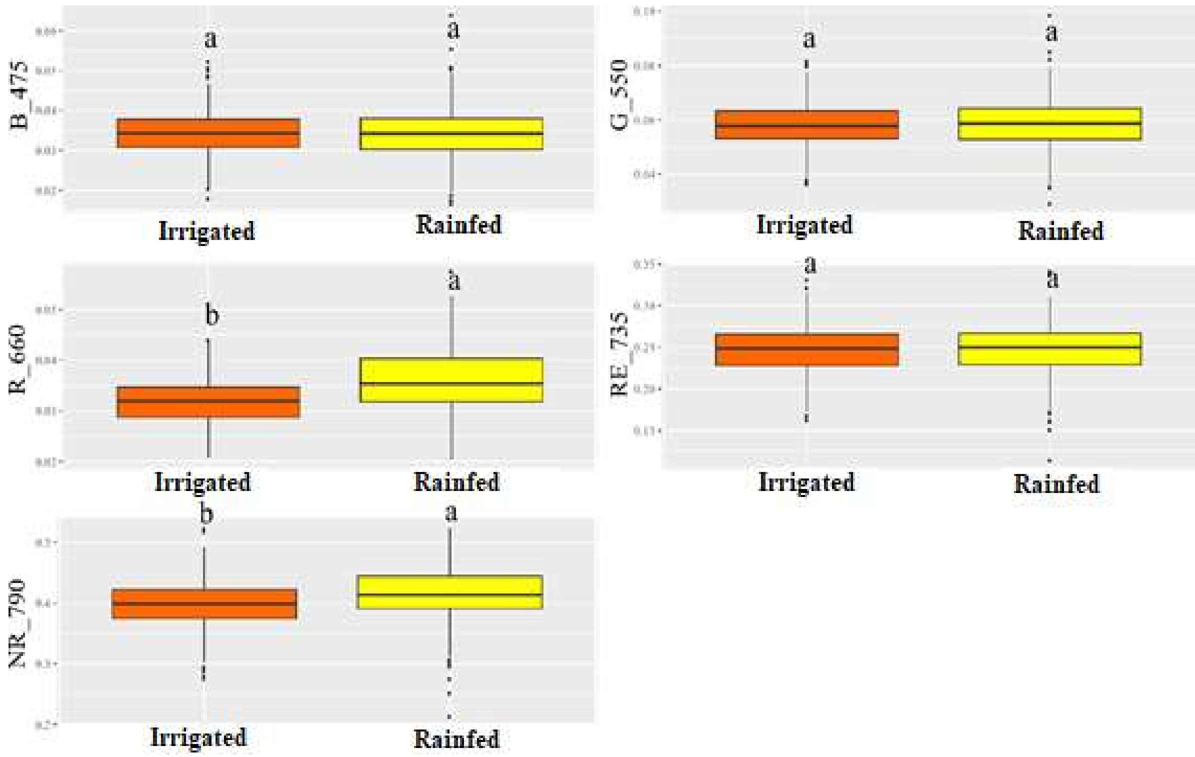

FIGURE 3. Boxplot for reflectance averages at blue (B, 475 nm), green (G, 550 nm), red (R, 660 nm), red edge (RE, 735 nm), and NIR (790 nm) wavelengths (nm) in maize under irrigation and rainfed management.

The means followed by the same letters for the different irrigation management inputs do not differ by the t test at 5% probability.

A significant interaction was observed between the machine learning (ML) algorithms and the tested inputs. Using the correct classification (CC) accuracy metric, it was found that the best-performing algorithms were Artificial Neural Networks (ANN) in the different inputs and Random Forest (RF) when using Vegetation Indices (IVs) and SB+IVs (Figure 4). No statistical difference was detected between the inputs for Reinforcement Learning (RL). Overall, other algorithms demonstrated improved performance with the IVs and SB+IVs inputs.

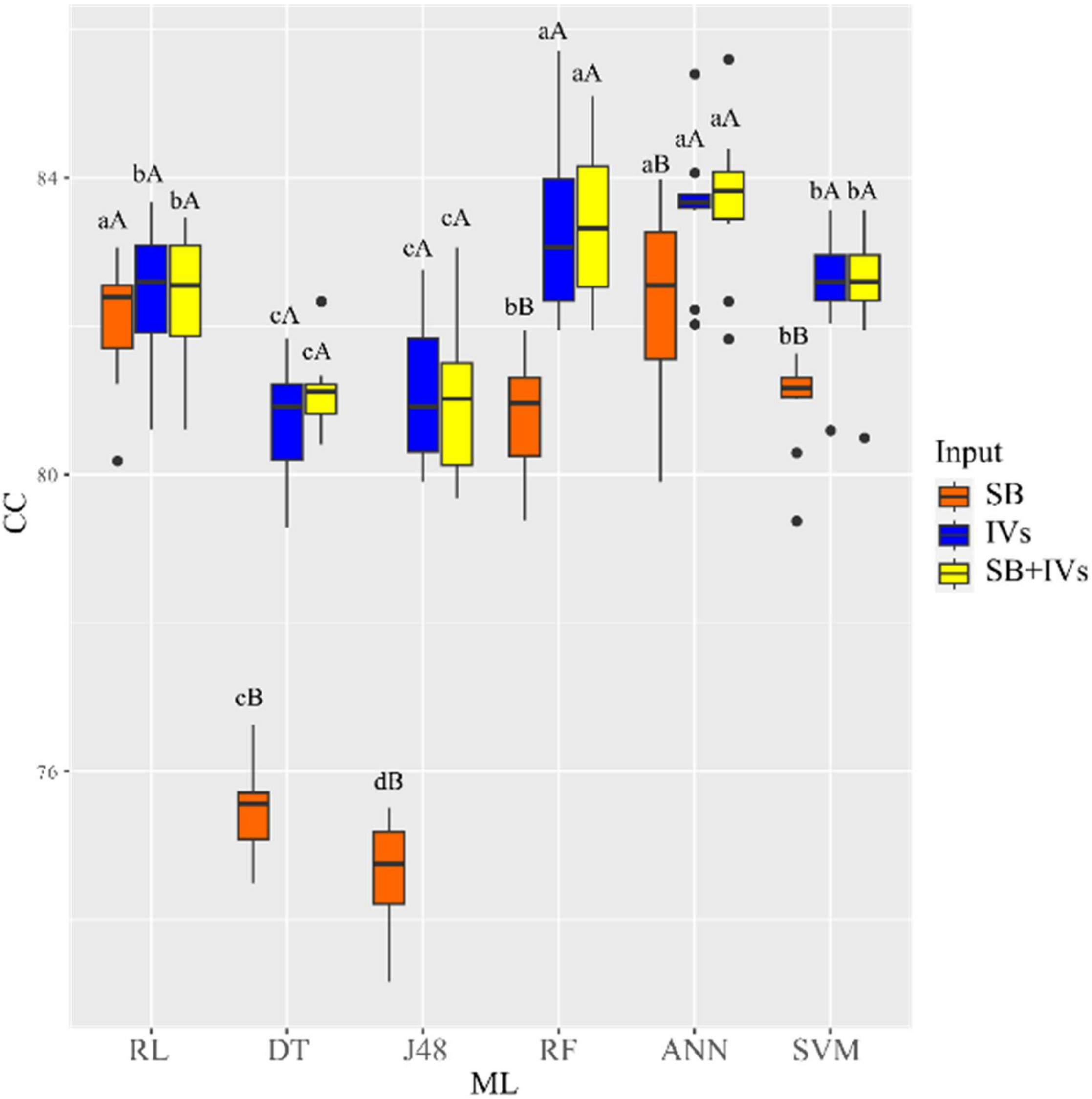

FIGURE 4. Boxplot for percentage of correct classification (CC) considering the significant interaction between the machine learning (ML) algorithms and the tested inputs.

Means followed by the same uppercase letters for the different inputs and same lowercase letters for the different ML algorithms do not differ by the Scott-Knott (1974) test at 5% probability.

The analysis of F-Score metric indicates that the Artificial Neural Network (ANN) algorithm achieved the highest classification performance among the input types (Figure 5). The Random Forest (RF) algorithm showed statistically equivalent performance when using Vegetation Indices (IVs) and Spectral Bands + Vegetation Indices (SB+IVs). Considering the Reinforcement Learning (RL) algorithm, all inputs provided the same level of accuracy. Other models exhibited optimal classification performance with IVs and SB+IVs inputs. No significant difference in performance was observed among the input types for the RL algorithm.

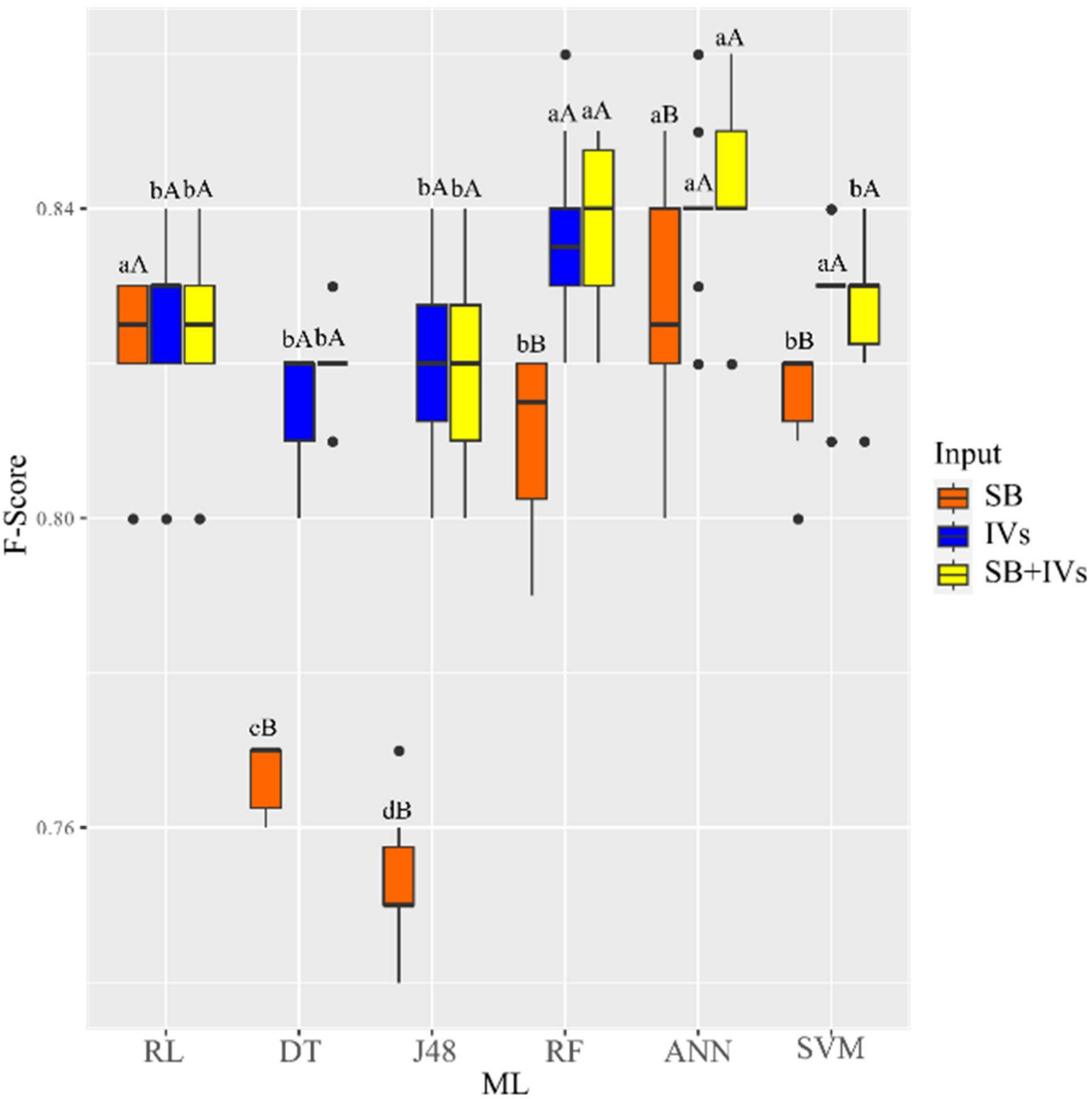

FIGURE 5. Boxplot for F-Score considering the significant interaction between the ML algorithms and the tested inputs.
Means followed by the same uppercase letters for the different inputs and same lowercase letters for the different ML algorithms do not differ by the Scott-Knott (1974) test at 5% probability.

The evaluation of the machine learning models using the Kappa accuracy metric indicated that the Artificial Neural Network (ANN) was the most effective classification algorithm among all inputs types (Figure 6). No significant difference in performance was observed between ANN and RF when using IVs and SB+IVs. For the Reinforcement Learning (RL) algorithm, no statistical difference was found between the inputs types. IVs and SB+IVs were identified as the best input types for the other algorithms.

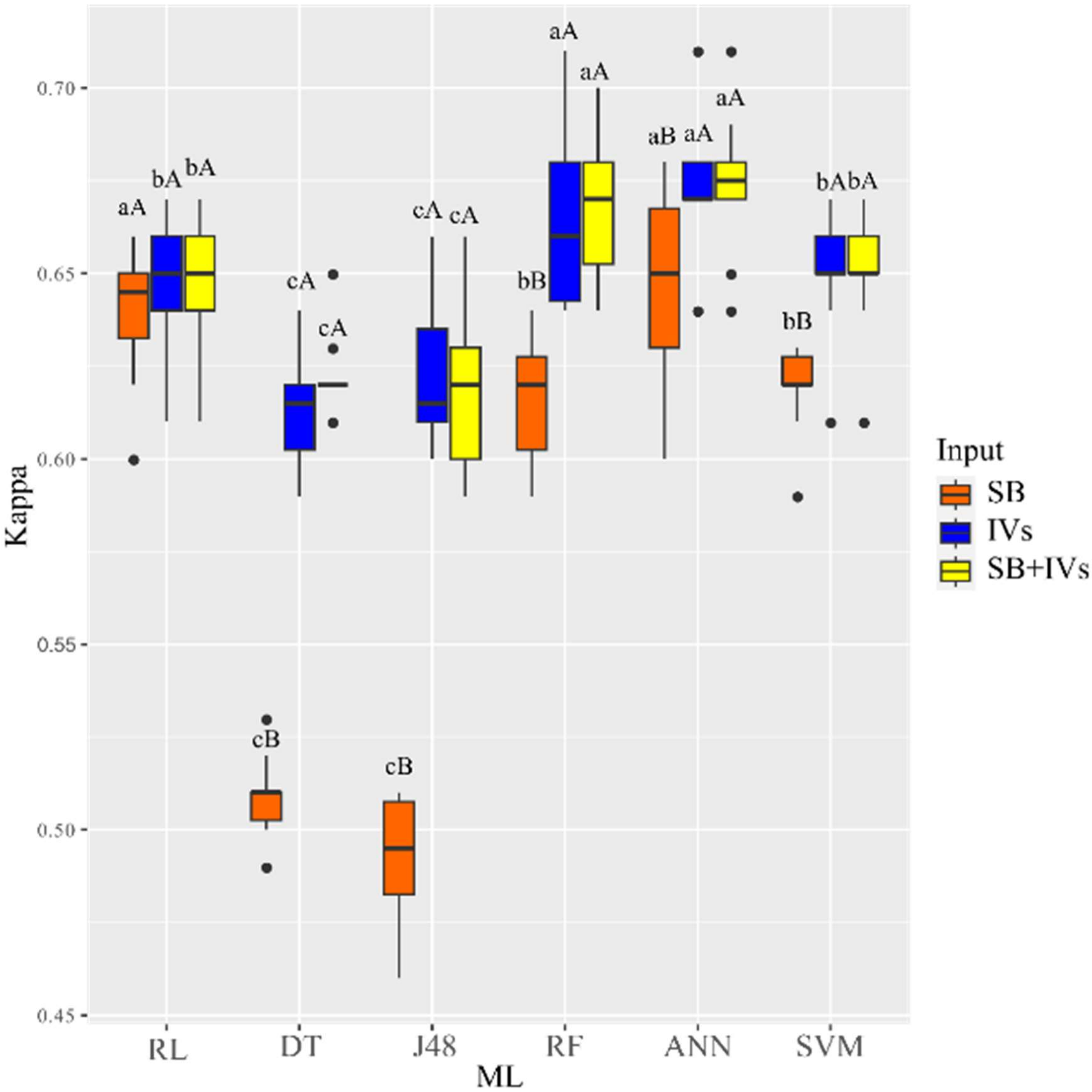

FIGURE 6. Boxplot for Kappa coefficient considering the significant interaction between the ML algorithms and the tested inputs. Means followed by the same uppercase letters for the different inputs and same lowercase letters for the different ML algorithms do not differ by the Scott-Knott (1974) test at 5% probability.

It is possible to verify that the evaluation metrics used to assess the algorithms demonstrated statistically equivalent results, confirming that ANN and RF were the most effective models for classification. Additionally, the best-performing input types were identified as IVs and SB+IVs.

Water scarcity exposes plants to abiotic stress both due to water deficit and thermal stress, which negatively affects the growth and productivity of crops, especially maize (Bheemanahalli et al., 2022). Using remote sensing to detect water problems faced by maize allows us to obtain precise information about the condition of the crop while it is still in the field (Devaraj Naik & Udayakumar, 2021). The main spectral difference between maize hybrids subjected to irrigation and rainfed conditions occurs at wavelengths 660 nm and 790 nm, where irrigated plants exhibit a lower reflectance factor. This spectral range provides information indicative of plant health, differentiating between healthy and stressed condition (Sun et al., 2021).

Based on Figure 1, which illustrates the rainfed water balance of maize crops, we can identify a distinct period of intense summer between days 56 and 105 after planting. During this period, the crop experienced stress due to severe water deficit, which is reflected in its physiological state (Bheemanahalli et al., 2022). Comparison of the water balance for rainfed (Figure 1) and irrigated (Figure 2) crops reveals a significant difference in water conditions, particularly between 50 and 105 days after planting. At this stage of crop development, irrigated maize experienced optimal water conditions, while rainfed plants faced a completely opposite condition.

Although the visible (VIS) region does not directly provide information on plant water status, wavelengths within this range can indirectly reflect water conditions through changes in leaf pigments caused by dehydration (El-Hendawy et al., 2019 Vescovo et al., 2012). Healthy plants exhibit high absorption in the red wavelength due to chlorophyll, indicating high photosynthetic activity that is influenced by the adequate water supply (Wasonga et al., 2021).

The reflectance in the 790 nm region, which corresponds to the Near Infrared (NIR) spectrum, is closely related to the internal leaf structure, including the intracellular air spaces, cuticle, mesophyll, all of which are associated with the plant's water status. The water condition of the plant influences biochemical and biophysical changes, which can be detected through variations in chlorophyll content, as measured by wavelengths within the VIS/NIR spectrum (400-790 nm) (El-Hendawy et al., 2019).

Distinct differences in the spectral signature of irrigated and non-irrigated hybrids are observable, with the most pronounced differentiation occurring at 660 nm and a greater disparity at 790 nm. The environmental and management conditions to which plants are exposed affect their phenotypic expression. Spectral behavior is closely related to the different characteristics exhibited by the plant, enabling the indirect assessment of physiological and agronomic parameters associated with healthy or stressed conditions (El-Hendawy et al., 2019). It is worth highlighting that well-used irrigation management, in addition to presenting distinct spectral behaviors, improving the classification of corn hybrids, is of utmost importance for increasing crop productivity, contributing to increased producer income, generating sustainability in the field (Rocha et al., 2024; Araújo et al., 2024)

To mitigate the negative effects of water deficit, maize develops physiological mechanisms that lead to phenotypic changes, such as alterations in leaf color and texture (Zhuang et al., 2017). These phenotypic changes can, therefore, be inferred as indicators of water stress. By applying spectral data to machine learning techniques, it is possible to classify maize hybrids based on their response to water stress (An et al., 2019). The integration of machine learning with spectral data acquisition techniques has been widely employed in research on phenotypic changes resulting from abiotic stress in crops (Chemura et al., 2018; Naik et al., 2017).

Among the machine learning algorithms, ANN and RF demonstrated superior accuracy in classifying maize hybrids concerning irrigation management. ANN is a robust technique for modeling non-linear relationships between input and output variables (Safa et al., 2019). It effectively addresses issues related to varying parameters affecting the forage maize productivity, and exhibit high accuray in predicting these parameters (Sepehri et al., 2019). The RF is efficient in handling large datasets that do not follow a normal distribution (López-Calderón et al., 2020), and is effective in machine learning modeling for predicting maize productivity under irrigation management (Baio et al., 2022). The ANN and RF algorithms performed best in crop classification. These two algorithms work very differently from each other, showing that results corroborate even with different analyses.

The applicability of the findings of this study is valuable. Hyperspectral data can provide better insights into irrigation management for corn hybrids. This allows producers to save water and energy through targeted management of the hybrid crop.

To enhance the performance of the algorithms, different spectral inputs were tested. IVs and SB+IVs provided better accuracies for both ANN and RF. Ramos et al. (2020), demonstrated an improvement in RF performance for predicting maize productivity when using IVs. VIs are mathematical calculations used in remote sensing to assess physiological processes of maize hybrids based on the reflected wavelengths (Adak et al., 2021). As previously mentioned, maize plants experiencing water stress undergo biological and physiological changes that affect spectral reflectance, which may be more noticeable when using IVs (Niu et al., 2021).

The use of spectral data in conjunction with machine learning models for classifying crops based on water conditions is relatively recent advancement. Under the conditions of this study, the ANN and RF algorithms demonstrated superior performance, particularly when IVs were employed as inputs variables. The use of hyperspectral data and different irrigation levels can provide more detailed insights into the spectral behavior of maize hybrids.

CONCLUSIONS

Different irrigation management practices resulted in distinct spectral behaviors. The ANN and RF algorithms showed enhanced accuracy in classifying maize hybrids according irrigation management. The use of IVs and SB+IVs improved the performance of these algorithms.

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REFERENCES

Adak, A., Murray, S. C., Božinović, S., Lindsey, R., Nakasagga, S., Chatterjee, S., Wilde, S. (2021). Temporal vegetation indices and plant height from remotely sensed imagery can predict grain yield and flowering time breeding value in maize via machine learning regression. *Remote Sensing* 13(11). https://doi.org/10.3390/rs13112141

Al Snousy, M. B., El-Deeb, H. M., Badran, K., Al Khlil, I. A. (2011). Suite of decision tree-based classification algorithms on cancer gene expression data. *Egyptian Informatics Journal*, 12(2): 73-82. https://doi.org/10.1016/j.eij.2011.04.003

Allen, R. G., Pereira, L. S., Raes, D., Smith, M. (1998). *Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56*. Fao, Rome 300(9): 05109. ISBN 92-5-104219-5

Ampatzidis, Y. P. (2019). UAV-based high throughput phenotyping in citrus utilizing multispectral imaging and artificial intelligence. *Remote Sensing* 11(4). https://doi.org/10.3390/rs11040410

An, J., Li, W., Li, M., Cui, S., Yue, H. (2019). Identification and classification of maize drought stress using deep convolutional neural network. *Symmetry* 11(2): 256. https://doi.org/10.3390/sym11020256

Araújo, E. D., Ferreira, L. B., Oliveira, J. T., Borges, A. C., Cunha, F. F. (2024). Impacts on Soil and Cowpea Plants Fertigated with Sanitary Sewage through Subsurface Drip Irrigation. *Water*, 16(9), 1194. https://doi.org/10.3390/w16091194

Baio, F. H. R., Santana, D. C., Teodoro, L. P. R., Oliveira, I. C. D., Gava, R., Oliveira, J. L. G., Shiratsuchi, L. S. (2022). Maize Yield Prediction with Machine Learning, Spectral Variables and Irrigation Management. *Remote Sensing* 15(1): 79. https://doi.org/10.3390/rs15010079

Banerjee, B. P., Joshi, S., Thoday-Kennedy, E., Pasam, R. K., Tibbits, J., Hayden, M., Kant, S. (2020). High-throughput phenotyping using digital and hyperspectral imaging-derived biomarkers for genotypic nitrogen response. *Journal of Experimental Botany* 71(15): 4604 - 4615. https://doi:10.1093/jxb/eraa143

Belgiu, M., Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24 - 31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Bheemanahalli, R., Ramamoorthy, P., Poudel, S., Samiappan, S., Wijewardane, N., Reddy, K. R. (2022). Effects of drought and heat stresses during reproductive stage on pollen germination, yield, and leaf reflectance properties in maize (*Zea mays* L.). *Plant Direct* 6(8): e434. https://doi.org/10.1002/pld3.434

Chemura, A., Mutanga, O., Sibanda, M., Chidoko, P. (2018). Machine learning prediction of coffee rust severity on leaves using spectroradiometer data. *Tropical Plant Pathology* 43(2): 117–127. https://doi.org/10.1007/s40858-017-0187-8

Devaraj Naik, B., Udayakumar, M. (2021). Comparative assessment of response surface methodology and artificial neural networks in forecasting biodiesel yield from waste cooking sunflower oil. Materials Today: *Proceedings* 46: 9908–9913. https://doi.org/10.1016/j.matpr.2021.02.291

El-Hendawy, S. E., Alotaibi, M., Al-Suhaibani, N., Al-Gaadi, K., Hassan, W., Dewir, Y. H., Schmidhalter, U. (2019). Comparative performance of spectral reflectance indices and multivariate modeling for assessing agronomic parameters in advanced spring wheat lines under two contrasting irrigation regimes. *Frontiers in plant science* 10: 1537. https://doi.org/10.3389/fpls.2019.01537

Hanjra, M. A., Qureshi, M. E. (2010). Global water crisis and future food security in an era of climate change. *Food policy* 35(5): 365-377. https://doi.org/10.1016/j.foodpol.2010.05.006

Javornik, T., Carović-Stanko, K., Gunjača, J., Vidak, M., Lazarević, B. (2023). Monitoring Drought Stress in Common Bean Using Chlorophyll Fluorescence and Multispectral Imaging. *Plants* 12(6): 1 mar. https://doi.org/10.3390/plants12061386

Köppen, W. P. (1931). *Grundriss der klimakunde*. W. de Gruyter, xii, 388 pages diagrams, maps (some folded, some color), Número da OCLC/Identificador único:25499421931

Kovar, M., Brestic, M., Sytar, O., Barek, V., Hauptvogel, P., Zivcak, M. (2019). Evaluation of hyperspectral reflectance parameters to assess the leafwater content in soybean. *Water* (Switzerland) 11(3). https://doi.org/10.3390/w11030443

Li, X., Ba, Y., Zhang, M., Nong, M., Yang, C., Zhang, S. (2022). Sugarcane Nitrogen Concentration and Irrigation Level Prediction Based on UAV Multispectral Imagery. *Sensors* 22(7). https://doi.org/10.3390/s22072711

López-Calderón, M. J., Estrada-Ávalos, J., Rodríguez-Moreno, V. M., Mauricio-Ruvalcaba, J. E., Martínez-Sifuentes, A. R., Delgado-Ramírez, G., Miguel-Valle, E. (2020). Estimation of total nitrogen content in forage maize (*Zea Mays* l.) Using Spectral Indices: Analysis by Random Forest. *Agriculture* 10(10): 451. https://doi.org/10.3390/agriculture10100451

Ramos, A. P. M., Osco, L. P., Furuya, D. E. G., Gonçalves, W. N., Santana, D. C., Teodoro, L. P. R., Pistori, H. (2020). A random forest ranking approach to predict yield in maize with uav-based vegetation spectral indices. *Computers and Electronics in Agriculture* 178: 105791. https://doi.org/10.1016/j.compag.2020.105791

Maxwell, A. E., Warner, T. A., Fang, F. (2018). Implementation of machine-learning classification in remote sensing: an applied review. *International Journal of Remote Sensing* 39(9): 2784–2817. https://doi.org/10.1080/01431161.2018.1433343

Monfreda, C., Ramankutty, N., Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global biogeochemical cycles* 22(1). https://doi.org/10.1029/2007GB002947

Naik, H. S., Zhang, J., Lofquist, A., Assefa, T., Sarkar, S., Ackerman, D., Ganapathysubramanian, B. (2017). A real-time phenotyping framework using machine learning for plant stress severity rating in soybean. *Plant methods* 13(1): 1–12. https://doi.org/10.1186/s13007-017-0173-7

Niu, Y., Han, W., Zhang, H., Zhang, L., Chen, H. (2021). Estimating fractional vegetation cover of maize under water stress from UAV multispectral imagery using machine learning algorithms. *Computers and Electronics in Agriculture* 189: 106414. https://doi.org/10.1016/j.compag.2021.106414

Rocha, M. O., de Miranda, A. G. S., da Silva, P. A., de Oliveira, J. T., da Cunha, F. F. (2024). Growth Performance of Sabia Grass Irrigated by Drippers Installed in Subsurface. *AgriEngineering*, 6(3), 3443. https://doi.org/10.3390/ agriengineering6030196

Safa, B., Arkebauer, T. J., Zhu, Q., Suyker, A., Irmak, S. (2019). Net Ecosystem Exchange (NEE) simulation in maize using artificial neural networks. *IFAC Journal of Systems and Control* 7: 100036. https://doi.org/10.1016/j.ifacsc.2019.100036

Sah, R. P., Chakraborty, M., Prasad, K., Pandit, M., Tudu, V. K., Chakravarty, M. K., Moharana, D. (2020). Impact of water deficit stress in maize: Phenology and yield components. *Scientific Reports* 10(1): 2944. https://doi.org/10.1038/s41598-020-59689-7

Santos, H. G., Jacomine, P., Anjos, L., Oliveira, V., Lumbreras, J., Coelho, M., Oliveira, J. (2018). *Sistema brasileiro de classificação de solos*. [s.l.] Brasília, DF: Embrapa. ISBN 978-85-7035-198-2

Scott, A.J., Knott, M. (1974) A cluster analysis method for grouping means in the analysis of variance. *Biometrics* p. 507–512. https://doi.org/10.2307/2529204

Sepehri, S., Abbasi, F., Nakhjavanimoghaddam, M. M. (2019). Prediction of Forage Maize Yield and Sensitivity Analysis of Management Parameters using Artificial Neural Network Models. Iranian *Journal of Irrigation & Drainage* 13(5): 1460–1470. DOI: 20.1001.1.20087942.1398.13.5.24.8

Silva, E. E., Baio, F. H. R., Teodoro, L. P. R., Silva Junior, C. A., Borges, R. S., Teodoro, P. E. (2020). UAV-multispectral and vegetation indices in soybean grain yield prediction based on in situ observation. *Remote Sensing Applications: Society and Environment* 18: 100318. https://doi.org/10.1016/j.rsase.2020.100318

Spišić, J., Šimić, D., Balen, J., Jambrović, A. G. (2022). Machine Learning in the Analysis of Multispectral Reads in Maize Canopies Responding to Increased Temperatures and Water Deficit. *Remote Sensing* 14(11). https://doi.org/10.3390/rs14112596

Sun, J., Yang, L., Yang, X., Wei, J., Li, L., Guo, E., Kong, Y. (2021). Using Spectral Reflectance to Estimate the Leaf Chlorophyll Content of Maize Inoculated With Arbuscular Mycorrhizal Fungi Under Water Stress. *Frontiers in Plant Science* 12. https://doi.org/10.3389/fpls.2021.646173

R Core Team. (2013). *A language and environment for statistical computing*.

Teodoro, L. P. R., Estevão, R., Santana, D. C., Oliveira, I. C. D., Lopes, M. T. G., Azevedo, G. B. D., Teodoro, P. E. (2023). Eucalyptus Species Discrimination Using Hyperspectral Sensor Data and Machine Learning. *Forests*, 15(1): 39. https://doi.org/10.3390/f15010039

Teodoro, L. P. R., Silva, M. O., dos Santos, R. G., de Alcântara, J. F., Coradi, P. C., Biduski, B., Teodoro, P. E. (2024). Machine learning for classification of soybean populations for industrial technological variables based on agronomic traits. *Euphytica* 220, 40. https://doi.org/10.1007/s10681-024-03301-w

Vescovo, L., Wohlfahrt, G., Balzarolo, M., Pilloni, S., Sottocornola, M., Rodeghiero, M., Gianelle, D. (2012). New spectral vegetation indices based on the near-infrared shoulder wavelengths for remote detection of grassland phytomass. *International journal of remote sensing* 33(7): 2178–2195. https://doi.org/10.1080/01431161.2011.607195

Wasonga, D. O., Yaw, A., Kleemola, J., Alakukku, L., Mäkelä, P. S. (2021). Red - green - blue and multispe ctral imaging as potential tools for estimating growth and nutritional performance of cassava under deficit irrigation and potassium fertigation. *Remote Sensing* 13(4): 1 – 20. https://doi.org/10.3390/rs13040598

Wu, J., Rogers, A., Albert, L. P., Ely, K., Prohaska, N., Wolfe, B. T., Serbin, S. P. (2019). Leaf reflectance spectroscopy captures variation in carboxylation capacity across species, canopy environment and leaf age in lowland moist tropical forests. *New Phytologist* 224(2): 663–674. https://doi.org/10.1111/nph.16029

Xie, C., Yang, C. (2020). A review on plant high-throughput phenotyping traits using UAV-based sensors. *Computers and Electronics in Agriculture* 178: 105731. https://doi.org/10.1016/j.compag.2020.105731

Zhang, H., Wang, L., Jin, X., Bian, L., Ge, Y. (2023). High-throughput phenotyping of plant leaf morphological, physiological, and biochemical traits on multiple scales using optical sensing. *The Crop Journal*. https://doi.org/10.1016/j.cj.2023.04.014

Zhuang, S., Wang, P., Jiang, B., Li, M., Gong, Z. (2017). Early detection of water stress in maize based on digital images. *Computers and Electronics in Agriculture* 140: 461 – 468. https://doi.org/10.1016/j.compag.2017.06.022