



Article

What Is the Predictive Capacity of *Sesamum indicum* L. Bioparameters Using Machine Learning with Red–Green–Blue (RGB) Images?

Edimir Xavier Leal Ferraz ¹, Alan Cezar Bezerra ², Raquele Mendes de Lira ², Elizeu Matos da Cruz Filho ¹, Wagner Martins dos Santos ¹, Henrique Fonseca Elias de Oliveira ³, Josef Augusto Oberdan Souza Silva ³, Marcos Vinícius da Silva ⁴, José Raliuson Inácio da Silva ², Jhon Lennon Bezerra da Silva ³, Antônio Henrique Cardoso do Nascimento ², Thieres George Freire da Silva ^{1,*}, and Ênio Farias de França e Silva ¹

- ¹ Department of Agricultural Engineering, Federal Rural University of Pernambuco, Rua Dom Manoel de Medeiros, Dois Irmãos, Recife 52171-900, PE, Brazil; edimir.ferraz@ufrpe.br (E.X.L.F.); elizeu.cruz9@gmail.com (E.M.d.C.F.); wagner.martins@ufrpe.br (W.M.d.S.); enio.fsilva@ufrpe.br (Ê.F.d.F.e.S.);
- ² Academic Unit of Serra Talhada, Federal Rural University of Pernambuco, Avenida Gregório Ferraz Nogueira, Serra Talhada 56909-535, PE, Brazil; alan.bezerra@ufrpe.br (A.C.B.); raquele.lira@ufrpe.br (R.M.d.L.); raliuson.silva@ufrpe.br (J.R.I.d.S.); antonio.cardoso@ufrpe.br (A.H.C.d.N.);
- ³ Cerrado Irrigation Graduate Program, Goiano Federal Institute, Campus Ceres, GO-154, km 218, Zona Rural, Ceres 76300-000, GO, Brazil; henrique.fonseca@ifgoiano.edu.br (H.F.E.d.O.); josef.silva@estudante.ifgoiano.edu.br (J.A.O.S.S.); jhon.silva@ifgoiano.edu.br (J.L.B.d.S.);
- ⁴ Postgraduate Program in Forest Sciences, Federal University of Campina Grande (UFCG), Av. Univer-sitária, s/n, Santa Cecília, Patos 58708-110, PB, Brazil; mv.silva@ufma.br
- * Correspondence: thieres.silva@ufrpe.br



Academic Editors: Zhengjun Qiu, Yee Siang Gan and Sze-Teng Liong

Received: 3 December 2024

Revised: 17 January 2025

Accepted: 26 February 2025

Published: 3 March 2025

Citation: Ferraz, E.X.L.; Bezerra, A.C.; Lira, R.M.d.; Cruz Filho, E.M.d.; Santos, W.M.d.; Oliveira, H.F.E.d.; Silva, J.A.O.S.; Silva, M.V.d.; Silva, J.R.I.d.; Silva, J.L.B.d.; et al. What Is the Predictive Capacity of *Sesamum indicum* L. Bioparameters Using Machine Learning with Red–Green–Blue (RGB) Images?

AgriEngineering **2025**, *7*, 64.

<https://doi.org/10.3390/agriengineering7030064>

Copyright: © 2025 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Abstract: The application of machine learning techniques to determine bioparameters, such as the leaf area index (LAI) and chlorophyll content, has shown significant potential, particularly with the use of unmanned aerial vehicles (UAVs). This study evaluated the use of RGB images obtained from UAVs to estimate bioparameters in sesame crops, utilizing machine learning techniques and data selection methods. The experiment was conducted at the Federal Rural University of Pernambuco and involved using a portable AccuPAR ceptometer to measure the LAI and spectrophotometry to determine photosynthetic pigments. Field images were captured using a DJI Mavic 2 Enterprise Dual remotely piloted aircraft equipped with RGB and thermal cameras. To manage the high dimensionality of the data, CRITIC and Pearson correlation methods were applied to select the most relevant indices for the XGBoost model. The data were divided into training, testing, and validation sets to ensure model generalization, with performance assessed using the R^2 , MAE, and RMSE metrics. XGBoost effectively estimated the LAI, chlorophyll a, total chlorophyll, and carotenoids ($R^2 > 0.7$) but had limited performance for chlorophyll b. Pearson correlation was found to be the most effective data selection method for the algorithm.

Keywords: CRITIC; XGBoost model; photosynthetic pigments; leaf area index; UAVs

1. Introduction

Satellite remote sensing is an effective tool for predicting crop yields on a large scale by monitoring growing conditions and environments [1]. However, it is significantly affected by atmospheric conditions and has low resolution [2]. Compared to space-based platforms, unmanned aerial vehicles (UAVs) offer high spatiotemporal resolution due to

their flexibility in data acquisition and reduced atmospheric interference, making them more suitable for crop monitoring, which is crucial for decision-making by producers [3,4].

With the integration of RGB, multispectral, and hyperspectral sensors on UAVs, crop monitoring has become feasible, allowing for the assessment of growing conditions [5–7]. RGB sensors are characterized by capturing images composed of red (R), green (G), and blue (B) bands. These sensors provide a visual perspective of plant health and crop status, capturing phenological changes and color variations that may indicate different crop conditions [8,9]. Although RGB sensors collect less information compared to multispectral or hyperspectral sensors, particularly in the spectral range where vegetation responds most effectively, they are a more accessible alternative due to their relatively low cost and high spatial resolution [10,11].

The leaf area index (LAI) is an important parameter for climatic, ecological, and agronomic studies as it allows for the assessment of crop growth and yield estimation due to its significant influence on transpiration, solar radiation interception, and photosynthesis [12,13]. Additionally, the chlorophyll content is a parameter that indicates the physiological condition of plant health, as this content is crucial for plants to absorb light energy and assimilate CO₂ [14]. Estimating this parameter is useful for understanding the nutritional and physiological status of the plant under abiotic stress conditions, as lower chlorophyll concentrations are indicative of increased plant stress [15].

Typically, chlorophyll content quantification involves extraction with acetone and ethanol, spectrophotometry, and high-performance liquid chromatography. However, these methods are considered destructive, time-consuming, and unsuitable for phenotyping [16]. Another method for determining the chlorophyll content is to use spectroscopy and a portable chlorophyll meter, which can be used on live plants. However, these techniques do not spatially measure the distribution of chlorophyll [17].

The application of machine learning techniques in determining bioparameters, such as the LAI and chlorophyll content, has shown promise [4,18–21]. Several authors have found satisfactory performance when using a machine learning approach, compared to linear regression, for estimating bioparameters such as the chlorophyll content and leaf area index [11,22,23].

Globally, sesame (*Sesamum indicum* L.) production reached 6.7 million megagrams, with a cultivated area of 12.8 million hectares and an average yield of 508 kg ha⁻¹ [24]. This crop is considered sensitive to abiotic stresses, such as salinity, which directly affects its physiological aspects and development [25]. Determining the parameters that indicate these stresses, as well as plant health and productivity, is crucial for aiding agricultural management decisions. The application of UAV-acquired images for disease identification [26,27], phenotyping, and classification of different crops [8,28–30] is documented in the literature; however, it has not yet been reported for sesame crops.

Thus, this study aimed to evaluate the use of RGB images obtained from UAVs for estimating bioparameters, such as the LAI and chlorophyll content, in sesame crops using machine learning and data selection methods.

2. Materials and Methods

2.1. Location and Climate of the Study Area

This study was conducted at the Federal Rural University of Pernambuco, Serra Talhada Academic Unit (UFRPE/UAST), located at 07°59'31" south latitude and 38°17'54" west longitude, with an average altitude of 435 m (Figure 1). The region's climate is classified as BSw_h' according to Köppen [31], with an average air temperature ranging between 20.1 °C and 32.9 °C. The region experiences irregular spatial and temporal distribution of

rainfall, averaging 642 mm per year, and a potential evapotranspiration of 1800 mm per year [32].

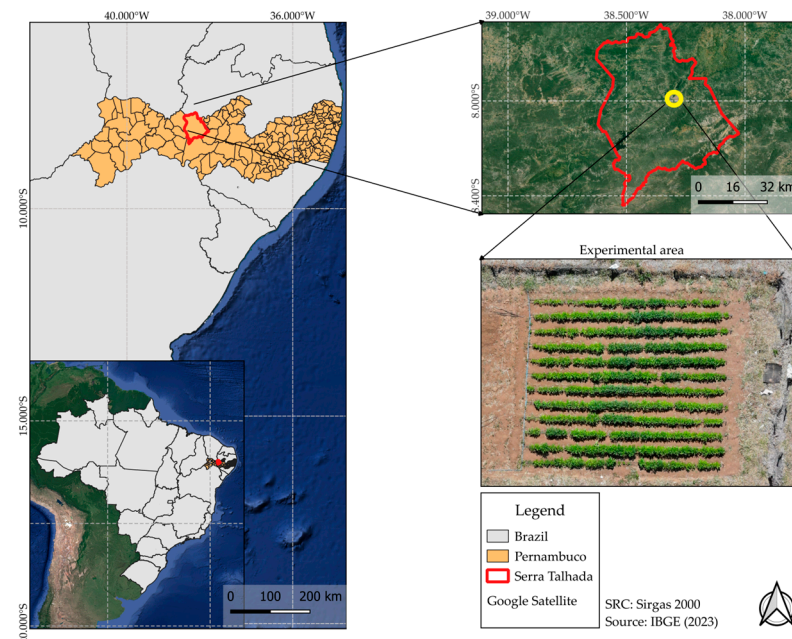


Figure 1. Spatial location of the experimental area, Serra Talhada, Pernambuco, Brazil.

2.2. Experimental Design

The experimental area cultivated with sesame measured 12×12 m in width and length and was divided into 48 plots, each containing 9 sesame plants. Twelve sesame cultivation rows were established in the area, spaced 0.8 m apart. Only 4 rows were considered for evaluation, while the remaining rows were treated as borders. Each experimental plot had a length of 1 m, totaling 12 experimental plots per evaluation row. Additionally, each plot was georeferenced using the RTK Stonex 850A (Stonex, Paderno Dugnano, Italy) satellite positioning system.

2.3. Planting and Cultivation of Sesame

Initially, the physical preparation of the soil was carried out, which included one plowing and two harrowings. Subsequently, based on a soil chemical analysis, fertilization was performed according to the recommendations of [33], which suggests 50, 14, and 60 kg ha^{-1} of $\text{N-P}_2\text{O}_5\text{-K}_2\text{O}$ for a production of 1000 kg ha^{-1} of sesame seeds.

Subsequently, the irrigation system was set up. For irrigation distribution, a drip irrigation system was used, employing self-compensating drippers. After preparing the area, sesame was sown with a spacing of 0.8×0.1 m between rows and between plants, respectively. The “BRS Seda” cultivar was used, known for its high productivity and early maturity with an average cycle of 90 days [34].

Irrigation was performed daily based on crop evapotranspiration (ET_c) using reference evapotranspiration (ET_o) data, the crop coefficient (K_c), and the average location coefficient (K_{lmed}). ET_o was calculated using the Penman–Monteith model [35]. The K_c values for each phenological stage of the sesame crop were those proposed by [36], and the K_{lmed} was the average of three location coefficient values for dense crops, as per [37].

Climate data were obtained from the automated data acquisition agrometeorological station (HOBO RX Station—RX3000) installed near the experimental area.

2.4. Data Collection

2.4.1. Determination of Leaf Area Index

To determine the LAI, the portable AccuPAR ceptometer (LP-80, Decagon Devices, Pullman, WA, USA) was used, with measurements taken in each experimental plot. LAI measurements were distributed throughout the sesame crop cycle, with readings taken at 45, 60, 75, and 90 days after sowing (DAS).

2.4.2. Determination of Pigment Concentrations in Sesame Leaves

To determine the levels of photosynthetic pigments, leaf discs were collected 45 days after sowing, following the methodology proposed by [38]. Using a perforator, five leaf discs with a diameter of five millimeters were collected per experimental plot, taken from the fourth leaf from the apex, without signs of herbivorous attack.

The extraction solution preparation followed the methodology of [39], which involved the addition of calcium carbonate (CaCO_3) at a ratio of 5 g L^{-1} to dimethyl sulfoxide (DMSO), with constant stirring with a magnetic stirrer for four hours. Subsequently, the reagent was filtered six times through two layers of filter paper in a Buchner funnel with the aid of a vacuum pump until crystallization.

The leaf discs were transferred to test tubes containing 5.0 mL of CaCO_3 saturated with DMSO, wrapped in aluminum foil, and placed in expanded polystyrene material to shield them from solar radiation and prevent enzyme and protein denaturation. The samples were kept at room temperature for 48 h. Subsequently, they were incubated in a water bath at 65°C for approximately 30 min.

The supernatant was then transferred to quartz cuvettes in 3.0 mL aliquots for reading on a Biochrom Libra UV–Visible spectrophotometer. To express the contents of chlorophyll a, b, total chlorophyll (a + b), and carotenoids in $\mu\text{g g}^{-1}$, at wavelengths of 665, 649, and 480 nm, respectively, Equations (1)–(4) based on the method described by [40] were used. The data were converted to $\mu\text{g cm}^{-2}$, considering the area of the leaf discs.

$$\text{Chlorophyll B (chl B)} = 12.47A_{665} - 3.62A_{649} \quad (1)$$

$$\text{Chlorophyll B (chl B)} = 25.06A_{649} - 6.50A_{665} \quad (2)$$

$$\text{Total chlorophyll (A + B)} = 7.15A_{665} - 18.71A_{649} \quad (3)$$

$$\text{Carotenoids} = \frac{1000A_{480} - 1.29\text{Chl A} - 53.78 \text{ Chl B}}{220} \quad (4)$$

2.4.3. Acquisition of Aerial Images with UAVs

A DJI Mavic 2 Enterprise Dual UAV (DJI, Shenzhen, China) was used to capture field images. This quadcopter model, equipped with GPS, has a flight time of approximately 30 min. It is important to highlight that the equipment used features an integrated Global Positioning System (GPS) attached to its sensors, enabling the recording of the aircraft's geographic coordinates when each image is captured. The reference data system used by this system is the World Geodetic System 1984 (WGS84), which is widely employed in geographic applications due to its global coverage and precision. Thus, when an image is captured, the device saves the associated geographic coordinates, allowing the identification of the exact position of each scene captured during the flight.

In addition, the Mavic 2 Enterprise Dual is equipped with two integrated sensors: an RGB sensor and a thermal sensor, both physically attached to the aerial vehicle, as illustrated in Figure 2. When a scene is recorded, two images are captured simultaneously, one by the RGB sensor and another by the thermal sensor. It is important to emphasize that, although the equipment captures both types of images, the analysis conducted in our study

exclusively considered the RGB images, with no temperature analyses performed using the thermal sensor for estimating the biophysical parameters of sesame. This configuration, with integrated sensors and geographic coordinates recorded for each image, ensures the precise identification of the position of the captured scene.



Figure 2. Details of the Mavic 2 Enterprise Dual: (A) General view of the complete equipment, and detailed view of the integrated RGB and thermal sensors (B).

To enhance the image quality, UAV flights were conducted around midday with minimal cloud cover and at an altitude of 40 m, with a minimum overlap of 70% laterally and 80% frontally [41]. Flights were carried out bi-weekly, starting 45 days after sowing.

2.5. Data Processing

2.5.1. Image Processing and Index Generation

With the acquisition of images, the processing for georeferencing and orthomosaic generation was performed using Agisoft Metashape Professional Edition 1.6.0 in its trial version. After generating the orthomosaic, the R environment was used with the Field-imageR package 0.6.2 [42] for image processing and the estimation of vegetation indices (Table 1).

Table 1. Vegetation indices and their corresponding equations.

Name	Abbreviation	Equation	Author
Green Leaf Index	GLI	$\frac{2G-R-B}{2G+R+B}$	[43]
Visible Atmospherically	VARI	$\frac{G-R}{G+R-B}$	[44]
Normalized Green Red Difference	NGRDI	$\frac{G-R}{G+R}$	[45]
Modified Green Red Vegetation Index	MGRVI	$\frac{G^2-R^2}{G^2+R^2}$	[46]
Red, Green, Blue Vegetation Index	RGBVI	$\frac{(G^2-B \times R)}{(G^2+B \times R)}$	[46]
Excess Red Vegetation Index	ExR	$1.4R - G$	[47]
Excess Blue Vegetation Index	ExB	$1.4B - G$	[48]
Excess Green Vegetation Index	ExG	$2G - R - B$	[48]
Excess Green Red Vegetation Index	ExGR	$ExG - ExR$	[48]
Vegetative	VEG	$\frac{G}{R^{0.667} \times B^{0.333}}$	[49]
Woebbecke Index	WI	$\frac{G-B}{R-B}$	[50]

“R”: Red band; “G”: Green band; “B”: Blue band.

To apply and extract the vegetation index values for each plot, a shapefile layer was created with georeferenced polygons delineating the plots on the orthomosaic (Figure 3A), as well as removing the soil (Figure 3B). Finally, the vegetation indices were generated (Figure 3C), according to Table 1, and the average pixel value for each plot delineated by the polygons was extracted.

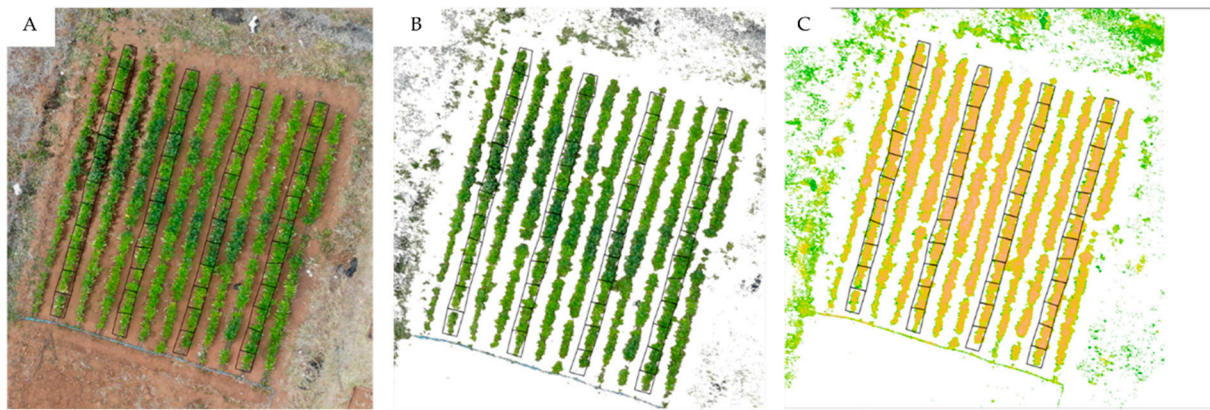


Figure 3. Plots delineated by the shapefile layer (A), soil removal (B), and applied vegetation index (C).

2.5.2. Selection of Indices and Model Estimation

To reduce the high dimensionality of the data, feature selection methods were employed to remove redundant variables that would not negatively impact the performance of the models. Therefore, two methods were used, namely, CRITIC (Criteria Importance Through Intercriteria Correlation) and Pearson correlation, to determine which indices would be used in the modeling process for each variable.

CRITIC is a method developed for multicriteria problems, using correlation to select less correlated variables and standard deviation to select variables with greater variability. The CRITIC value increases with lower correlation values and higher standard deviation values [51]. In contrast, correlation is used to assess the linear relationship between two variables, allowing for a simpler identification of the most redundant variables. Correlations range from -1 to 1 , representing a perfect negative linear correlation and a perfect positive linear correlation, respectively [52].

As a cutoff factor, for correlation, all indices that showed significant correlation at the 0.01 probability level were selected. Meanwhile, for the CRITIC method, the indices with weights greater than the average of all weights were chosen as the cutoff.

2.5.3. Parameter Modeling

The estimation of the parameters was performed using XGBoost, a machine learning algorithm for regression and classification based on the Gradient Boosting algorithm, designed for high performance and speed. The predictive model is constructed from a series of decision trees that are iteratively adjusted to correct errors from previous trees, with various hyperparameters being tuned to improve prediction [53]. Fourteen hyperparameters (Table 2) were adjusted through grid search using the dials package [54], employing the `grid_regular`, `grid_latin_hypcube`, and `grid_max_entropy` functions to provide broader coverage in the space defined by the limits set for each parameter. Additionally, the `grid_random` function was used to generate random numbers within this same space.

The models were fitted for the variables, that is, the LAI and pigments, constructing one model for the indices selected by CRITIC and another model for those selected by correlation. For the LAI, data from all collections (4 collections) were used, while for pigments, data from a single collection were utilized.

Table 2. Description and ranges of XGBoost hyperparameters [53].

Parameter	Definition	Range
max_depth	Maximum depth of a tree	4–10
min_child_weight	Minimum sum of instance weight required in a child	2–40
gamma	Minimum loss reduction required to make an additional partition at a tree leaf node	10–40
subsample	Proportion of training instances in subsample	0.1–1
mtry	Proportion of column subsample for each node	1–Number of columns
eta	Learning rate	0.0001–0.5

2.5.4. Statistical Analysis of the Models

To evaluate the performance of the models, the data were divided into the training, testing, and validation sets (65%, 20%, and 15%, respectively) to make the models more generalized, meaning they could perform better on data that the model had not seen during training. The performance was assessed using the following metrics: R^2 (coefficient of determination), MAE (mean absolute error), and RMSE (root mean squared error).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

3. Results

3.1. Correlation Analysis and Index Weighting for Selection

When using significant correlations with $p \leq 0.01$ as the selection criterion, the indices WI, VEG, ExGR, ExR, RGBVI, MGRVI, NGRDI, VARI, and GLI, as well as the red, blue, and green bands, showed significant correlations with the leaf area index (LAI) and were therefore selected for the modeling step aimed at estimating the LAI (Figure 4A). In the weighting analysis using the CRITIC method (Figure 4B), the indices WI, VEG, ExR, RGBVI, MGRVI, NGRDI, and VARI were selected.

Although the B band was not selected in the weighting analysis, it was included in the modeling due to its importance in the composition of the indices, and its use could improve the LAI estimation for sesame.

It can be observed that the indices showing the best correlations with the sesame LAI (Figure 4A) were MGRVI, VARI, ExR, and NGRDI, with only ExR exhibiting a negative correlation among them. The R, G, and B bands showed negative correlations, with absolute values exceeding 0.49.

In the analysis using the CRITIC method (Figure 4B), the MGRVI index had the highest weight, suggesting it is the parameter with the greatest heterogeneity and, possibly, is the most capable of explaining a significant portion of the LAI variations. Conversely, the B band had the lowest weight, indicating low heterogeneity and a limited ability to explain the variations, suggesting that this band may contribute little to distinguishing the variations in the studied bioparameters.

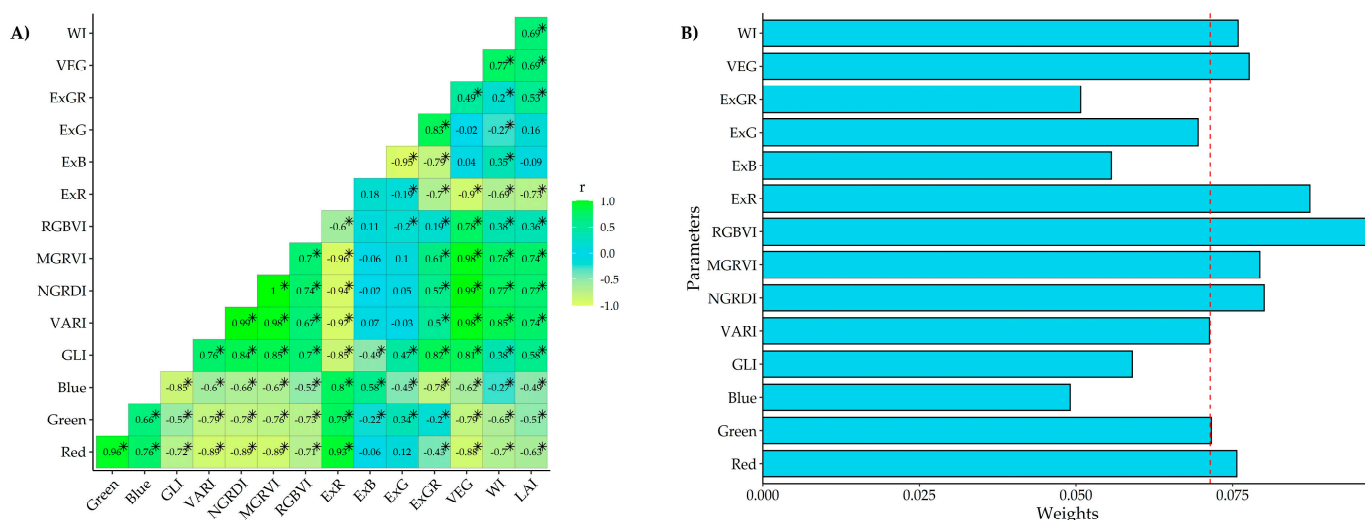


Figure 4. Correlation analysis of vegetation indices and leaf area index (A); application of the CRITIC method to vegetation indices (B). The asterisk (*) represents a statistically significant difference ($p < 0.05$).

Regarding pigments, in the correlation analysis (Figure 5A), it was observed that for chlorophyll a, chlorophyll b, and total chlorophyll, the indices that showed significant correlations ($p \leq 0.01$) were VARI, NGRDI, MGRVI, ExR, ExB, ExG, VEG, and WI. For carotenoids, the indices GLI, VARI, NGRDI, MGRVI, ExR, ExB, ExG, ExGR, VEG, and WI demonstrated significant correlations ($p > 0.01$). Based on the weights obtained from the CRITIC method, the indices selected for modeling were WI, ExG, ExB, and ExR. As in the LAI modeling, the bands R, G, and B were included in the model.

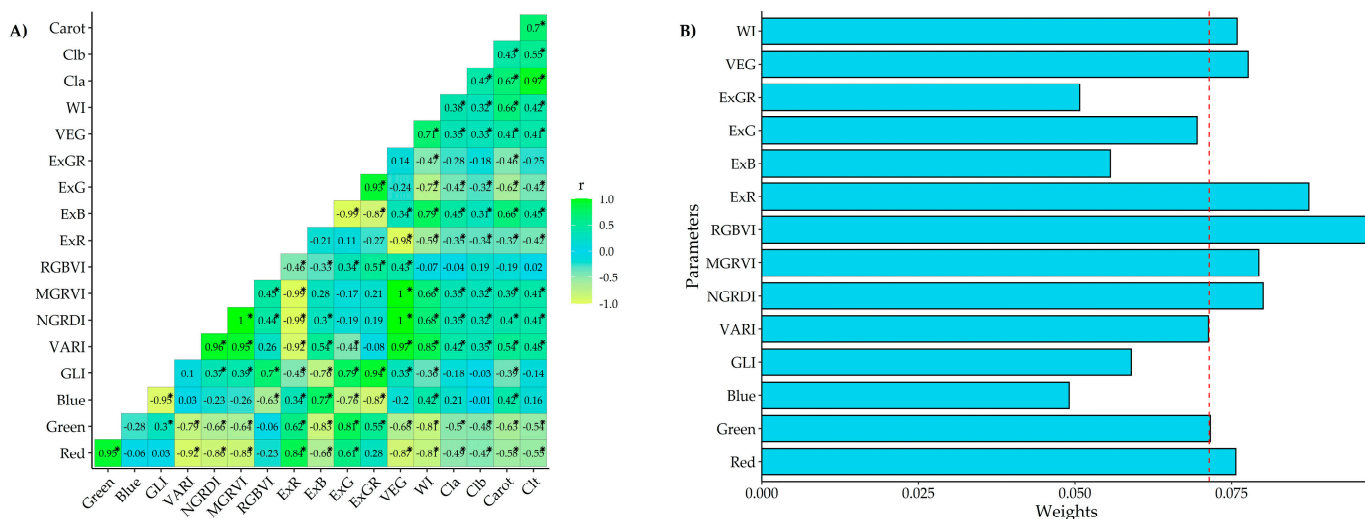


Figure 5. Correlation analysis of vegetation indices and photosynthetic pigments (A); and application of the CRITIC method to vegetation indices (B). The asterisk (*) represents a statistically significant difference ($p < 0.05$).

For chlorophyll a, the index ExB, followed by VARI and ExG, showed the highest correlations, with ExG having a negative correlation. For chlorophyll b and carotenoids, the index WI was the best correlated, with correlation coefficients of 0.42 and 0.67, respectively. Regarding total chlorophyll, the index VARI showed the best correlation. Concerning the RGB bands, for all pigments, bands G and R exhibited the best correlations, with both being negative.

3.2. Modeling Using Cutoff Methods

The grid search conducted using the dials package enabled the identification of the best hyperparameters for the various models tested (Table 3), employing the XGBoost machine learning algorithm. This hyperparameter tuning process is crucial for optimizing model performance, ensuring that it captures the complexities of the data more effectively. Careful selection of the hyperparameters can significantly impact the accuracy and robustness of predictions.

Table 3. Estimated hyperparameters for the XGBoost algorithm to model pigments and leaf area index (LAI).

Var	Eta	Max_Depth	Gamma	Colsample_Bytree	Colsample_Bynode	Min_Child_Weight	Subsample
caro_corr	0.5	4	10	1	0.111111	2	1
caro_critc	0.272557	5	11.829131	1	1	4	0.735277
chla_corr	0.5	4	10	1	0.111111	2	1
chla_critc	0.05334	8	13.348697	1	0.428571	2	0.598327
chlb_corr	0.021392	5	10.420759	1	0.4	3	0.617916
chlb_critc	0.33959	5	12.76788	1	0.285714	7	0.910488
chlt_corr	0.201963	4	11.346621	1	0.444444	2	0.740776
chlt_critc	0.5	10	10	1	0.142857	2	1
lai_corr	0.5	4	10	1	0.083333	2	1
lai_critc	0.5	4	10	1	1	2	1

caro_critc, chla_critc, chlb_critc, chlt_critc, and lai_critc—models for estimating carotenoids, chlorophyll a, chlorophyll b, total chlorophyll, and leaf area index (LAI) using the CRITIC method, respectively; caro_corr, chla_corr, chlb_corr, chlt_corr, and lai_corr—models for estimating carotenoids, chlorophyll a, chlorophyll b, total chlorophyll, and leaf area index (LAI) using Pearson correlation selection method, respectively.

The models developed to determine the LAI, both for indices selected by correlation significance (Figure 6A) and by the CRITIC weighting method (Figure 6B), achieved a coefficient of determination (R^2) of 0.73. This indicates that the machine learning models built with the selected indices were able to explain 73% of the variations in the data. However, despite the identical R^2 values between the methods, the MAE and RMSE were slightly higher in the model based on correlation significance, indicating greater error associated with this selection method.

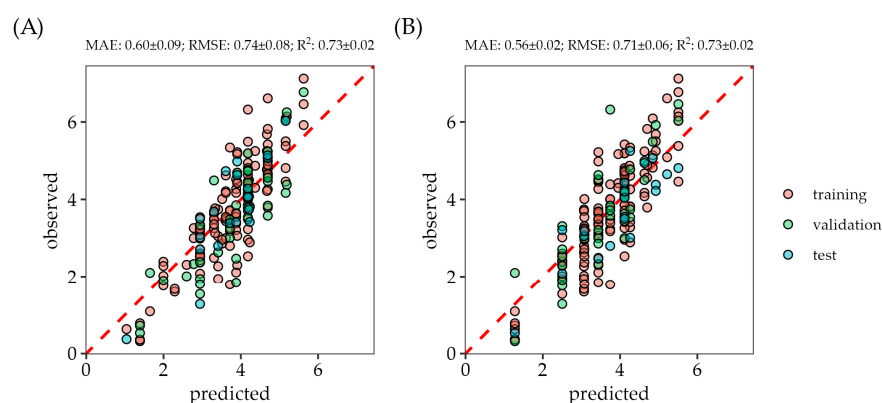


Figure 6. Leaf area index (LAI) estimated by the XGBoost algorithm using the significance cutoff correlation method (A) and the CRITIC weighting method (B).

In all phases of modeling (training, validation, and testing), the models exhibited minimal variations in performance. For the correlation method, the observed differences were 0.09, 0.08, and 0.02 for MAE, RMSE, and R^2 , respectively. With the CRITIC method, the differences were 0.02, 0.06, and 0.02 for MAE, RMSE, and R^2 , respectively. These results indicate that both methods produce robust models, although the CRITIC method demonstrated an advantage in terms of mean absolute error and root mean square error.

For chlorophyll a, the coefficient of determination (R^2) of the model obtained using the correlation method (Figure 7A) was higher compared to the CRITIC method (Figure 7B).

However, R^2 showed greater variation across different phases of modeling with the CRITIC method, with a deviation of 0.19, while the correlation method had a smaller deviation of 0.14. Additionally, the model built with the CRITIC method exhibited higher errors in both MAE and RMSE.

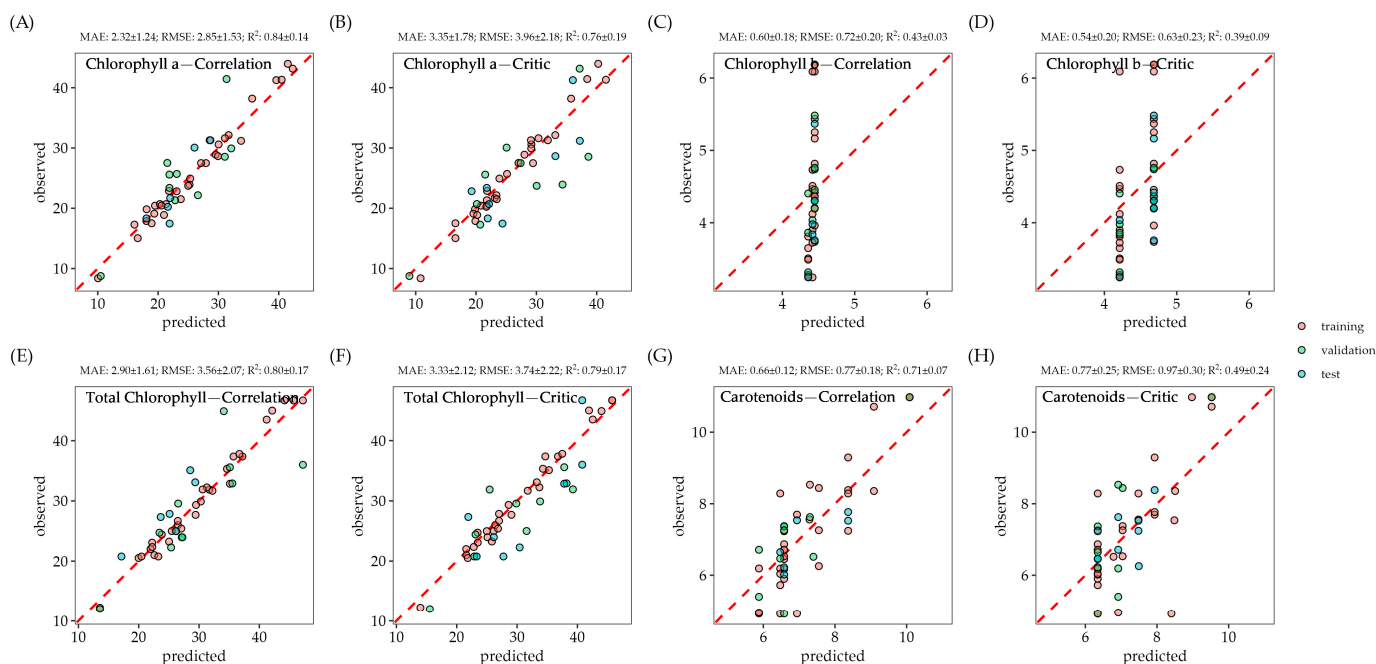


Figure 7. Chlorophyll a (A,B), chlorophyll b (C,D), total chlorophyll (E,F), and carotenoids (G,H) estimated by the XGBoost algorithm using the significance cutoff correlation method and the CRITIC weighting method.

In predicting chlorophyll b, both methods resulted in relatively low coefficients of determination, as well as high errors and greater deviations across the modeling phases. These results indicate that XGBoost was not effective in estimating chlorophyll b with the selected indices, the size of the database, or the visible radiation spectrum used (RGB). However, it is possible that using other spectral bands or a larger database could enable XGBoost to estimate this bioparameter more robustly.

For total chlorophyll (Figure 7E,F), XGBoost achieved a good fit with both cutoff methods, with the highest coefficient of determination obtained using the correlation method. Additionally, the MAE and RMSE values and their variations across the modeling phases were higher with the CRITIC method. A similar behavior was observed for carotenoids (Figure 7G,H), where the correlation-based cutoff method performed better, with an R^2 of 0.71 compared to 0.49 with the CRITIC method, and showed lower error.

For all the pigments studied, the model based on correlation significance proved to be more efficient in selecting indices for XGBoost. However, except for chlorophyll b and carotenoids, the models obtained using the CRITIC method showed R^2 values above 0.7, indicating a good fit. Among the estimated pigments, only chlorophyll b presented an R^2 between 0.39 and 0.43, which is considered low and insufficient to explain the majority of the data.

4. Discussion

In this study, the indices that showed the highest correlation with the LAI also demonstrated strong correlations with the red and green bands (Figure 3A). These results are consistent with the findings of [55], who observed in wheat crops that the VARI and MGRVI indices had the best correlations with the LAI. According to the authors, these indices

exhibit high absorption in the R and G bands, making them more sensitive to changes in the crop.

The model developed in this study, using the XGBoost algorithm to estimate the LAI, outperformed other studies, such as those by [55,56], which employed different approaches and crops. In the case of the sesame crop, the model demonstrated an ability to generalize the LAI across all stages of the crop cycle. This is because the model was built with data collected throughout the entire growth cycle and was validated and tested randomly using this dataset.

In the present study, the RMSE of the LAI predictive model was 0.74 and 0.71 for the correlation and CRITIC methods, respectively, which are lower values than those obtained by [57], whose lowest value was 0.85 with the PLSR model, using multispectral images in rice crops. This demonstrates that the use of RGB sensors, compared to multispectral ones, can be a viable alternative for monitoring the LAI, especially in sesame crops, due to the lower cost of RGB sensors [55].

The highest coefficient of determination obtained in this study was 0.73 for the LAI, which is considered moderate, as the model explains 73% of the observed variation in this parameter. Although the coefficients of determination did not meet the expected values for machine learning models, this performance can be attributed to factors such as the limited number of experimental samples, the restricted spectral range of RGB images, and the specific structural characteristics of sesame.

Sesame has a unique architecture, characterized by alternate leaves, variable height, and a less dense canopy [58,59], which hinders the accurate estimation of parameters such as the LAI in images obtained by UAVs. In contrast, crops such as rice and wheat exhibit a more uniform architecture, facilitating data acquisition and, consequently, resulting in higher coefficients of determination [57,60,61]. Therefore, when comparing sesame results with more homogeneous crops, it is expected that the values obtained are lower.

Nevertheless, the coefficient of determination of 0.73 is considered satisfactory for sesame, particularly due to the lack of other available studies for comparison with this crop. Furthermore, the use of UAVs to monitor the LAI in sesame represents an innovative approach, offering practical advantages for crop management, such as increased accessibility and cost reduction.

Therefore, we can consider that the XGBoost algorithm demonstrated good performance in determining the LAI in sesame, as observed in other studies, such as [62] for wheat. Thus, it can be inferred that this algorithm is efficient for determining this type of parameter.

The XGBoost model showed good performance in estimating the contents of chlorophyll a total chlorophyll, and carotenoids. However, the lower accuracy observed in estimating chlorophyll b can be attributed to the limitations of the spectrum used, as the RGB bands cover a narrow range, making it difficult to distinguish between the absorption bands of chlorophylls a and b. Although the authors of [63], using neural networks and RGB and thermal images in wheat crops, were able to estimate each type of pigment, they observed optimization when integrating RGB with thermal images.

Nevertheless, the model's good performance in estimating chlorophyll a may have been influenced by the total chlorophyll content, considering that the concentration of chlorophyll a is higher than that of chlorophyll b, in a ratio of approximately 3:1 [64]. The high correlation between chlorophyll a and total chlorophyll, with a coefficient of 0.97 as shown in Figure 5A, suggests that the model may not have effectively differentiated the chlorophyll fractions but instead quantified the total content. This high correlation could explain the similar performance observed in the estimates, indicating that the model

was efficient in quantifying the chlorophyll content without a clear distinction between its different forms.

Regarding carotenoids, the models performed well, particularly due to the strong relationship of these pigments with the green, blue, and red bands, allowing for efficient estimation [65]. In plants under stress or in the senescence phase, with chlorophyll degradation into colorless metabolites, other pigments such as carotenoids and anthocyanins become visible [66]. This parameter can indicate harvest points or stress, offering practical benefits for sesame management. The sesame harvest phase is critical, as delays in harvesting can result in grain loss due to the opening of the capsules that contain them [67]. In this sense, spatial monitoring of the carotenoid or chlorophyll content can serve as an indicator of the optimal harvest time.

Although the precise distinction between chlorophylls a and b was limited, the model's ability to reliably estimate the total chlorophyll content demonstrates a significant advantage compared to other models that use wide-spectrum camera sensors [68,69], especially in terms of cost [70]. The differentiation of pigment levels, such as chlorophylls, can reveal the presence of abiotic stresses that directly affect the relationship between these pigments. Using UAVs, the spatial determination of these stresses can aid in decision-making for precision agriculture practices, such as variable applications of water, nutrients, and pesticides.

Sesame has gained growing interest due to its wide applicability in food production, such as cakes, pastes, flours, and oils, and is widely cultivated in countries such as China, Tanzania, Myanmar, India, Ethiopia, Nigeria, and Sudan [71,72]. Its high drought resistance makes it a strategic crop for developing countries, contributing to food sovereignty and security, particularly in regions with water scarcity. The authors of [73] state that sesame, in addition to its nutritional value, plays a significant socioeconomic role by generating income for small farmers, especially women, thereby becoming a viable commercial alternative.

However, the production chains in these regions face economic challenges that require more accessible technological solutions. Our results indicate that the models, despite the limitations of the RGB bands, offer benefits that make the use of this technology viable for crops with lower technological development, such as sesame.

However, we recommend conducting further research using a broader spectral range to improve the differentiation between the types of chlorophyll, which could lead to significant advancements in both agricultural management and scientific research. Additionally, integrating RGB images with thermal imaging, as suggested by [63], could enhance the accuracy and effectiveness of pigment estimation.

5. Conclusions

The use of RGB images combined with machine learning, specifically the XGBoost algorithm, has proven to be an effective approach for estimating bioparameters such as the leaf area index (LAI), chlorophyll content (chlorophyll a and total chlorophyll), and carotenoids in sesame crops ($R^2 > 0.7$). These results provide relevant contributions both methodologically and practically to precision agriculture applied to agricultural species with lower levels of technological development.

Despite the limitations associated with the use of the RGB spectrum, the model exhibited satisfactory performance, particularly in estimating the LAI and chlorophyll a content. These findings suggest that RGB-based sensors can serve as a viable and cost-effective alternative for agricultural monitoring, especially in crops where more advanced technologies, such as multispectral or hyperspectral sensors, are not widely available.

However, it is recommended that future studies expand the experimental dataset, explore the use of other machine learning algorithms, and incorporate complementary data

sources, such as broader spectral information or data obtained from other types of sensors, to further enhance the accuracy of bioparameter estimation, especially for pigments.

Although the present study focused on sesame crops, the methods and approaches presented here can be applied to other agricultural species, contributing to the dissemination and validation of the methodologies developed in this work.

Author Contributions: Conceptualization: E.X.L.F., A.C.B. and R.M.d.L.; Methodology: E.X.L.F., W.M.d.S. and E.M.d.C.F.; Software: E.X.L.F., A.C.B. and W.M.d.S.; Validation: E.X.L.F. and W.M.d.S.; Formal Analysis: E.X.L.F., A.C.B., Ê.F.d.Fe.S. and R.M.d.L.; Investigation: E.X.L.F., W.M.d.S. and A.C.B.; Resources: R.M.d.L., Ê.F.d.Fe.S. and A.C.B.; Data Curation: E.X.L.F., W.M.d.S., R.M.d.L. and Ê.F.d.Fe.S.; Writing—Original Draft Preparation: E.X.L.F.; Writing—Review and Editing: E.X.L.F., A.C.B., R.M.d.L., Ê.F.d.Fe.S., H.F.E.d.O., J.A.O.S.S., M.V.d.S., T.G.F.d.S. and J.R.I.d.S.; Visualization: E.X.L.F., A.C.B., H.F.E.d.O., J.A.O.S.S., M.V.d.S., T.G.F.d.S., J.R.I.d.S., A.H.C.d.N. and J.L.B.d.S.; Supervision: A.C.B., R.M.d.L. and Ê.F.d.Fe.S.; Project Administration: A.C.B., R.M.d.L. and Ê.F.d.Fe.S.; Funding Acquisition: A.C.B., R.M.d.L., H.F.E.d.O. and Ê.F.d.Fe.S. All authors read and approved the final manuscript.

Funding: This research was funded by the Foundation for the Support of Science and Technology of the State of Pernambuco (FACEPE)—APQ-0733-1.07/21.

Data Availability Statement: The dataset is available upon request from the authors.

Acknowledgments: To the Graduate Program in Agricultural Engineering (PGEA) and the Academic Unit of Serra Talhada (UAST) at the Federal Rural University of Pernambuco (UFRPE) for their support in the development of this research. To the National Council for Scientific and Technological Development (CNPq), the Foundation for the Support of Science and Technology of Pernambuco (FACEPE), and the National Institute of Science and Technology in Sustainable Agriculture in the Tropical Semiarid Region (INCTAgriS) for the support provided.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Medina, H.; Tian, D.; Abebe, A. On Optimizing a MODIS-Based Framework for in-Season Corn Yield Forecast. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *95*, 102258. [\[CrossRef\]](#)
2. Zhang, Z.; Zhu, L. A Review on Unmanned Aerial Vehicle Remote Sensing: Platforms, Sensors, Data Processing Methods, and Applications. *Drones* **2023**, *7*, 398. [\[CrossRef\]](#)
3. Ji, Z.; Pan, Y.; Zhu, X.; Zhang, D.; Dai, J. Prediction of Corn Yield in the USA Corn Belt Using Satellite Data and Machine Learning: From an Evapotranspiration Perspective. *Agriculture* **2022**, *12*, 1263. [\[CrossRef\]](#)
4. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of Remote Sensing in Precision Agriculture: A Review. *Remote Sens.* **2020**, *12*, 3136. [\[CrossRef\]](#)
5. Schut, A.G.T.; Traore, P.C.S.; Blaes, X.; de By, R.A. Assessing Yield and Fertilizer Response in Heterogeneous Smallholder Fields with UAVs and Satellites. *Field Crops Res.* **2018**, *221*, 98–107. [\[CrossRef\]](#)
6. Feng, H.; Tao, H.; Li, Z.; Yang, G.; Zhao, C. Comparison of UAV RGB Imagery and Hyperspectral Remote-Sensing Data for Monitoring Winter Wheat Growth. *Remote Sens.* **2022**, *14*, 3811. [\[CrossRef\]](#)
7. Zhang, C.; Yi, Y.; Wang, L.; Zhang, X.; Chen, S.; Su, Z.; Zhang, S.; Xue, Y. Estimation of the Bio-Parameters of Winter Wheat by Combining Feature Selection with Machine Learning Using Multi-Temporal Unmanned Aerial Vehicle Multispectral Images. *Remote Sens.* **2024**, *16*, 469. [\[CrossRef\]](#)
8. Jeon, Y.-J.; Park, S.J.; Lee, H.; Kim, H.-Y.; Jung, D.-H. Deep Learning-Based Model for Effective Classification of Ziziphus Jujuba Using RGB Images. *AgriEngineering* **2024**, *6*, 4604–4619. [\[CrossRef\]](#)
9. Amarasingam, N.; Gonzalez, F.; Salgadoe, A.S.A.; Sandino, J.; Powell, K. Detection of White Leaf Disease in Sugarcane Crops Using UAV-Derived RGB Imagery with Existing Deep Learning Models. *Remote Sens.* **2022**, *14*, 6137. [\[CrossRef\]](#)
10. Zeng, L.; Peng, G.; Meng, R.; Man, J.; Li, W.; Xu, B.; Lv, Z.; Sun, R. Wheat Yield Prediction Based on Unmanned Aerial Vehicles-Collected Red–Green–Blue Imagery. *Remote Sens.* **2021**, *13*, 2937. [\[CrossRef\]](#)
11. Lu, N.; Zhou, J.; Han, Z.; Li, D.; Cao, Q.; Yao, X.; Tian, Y.; Zhu, Y.; Cao, W.; Cheng, T. Improved Estimation of Aboveground Biomass in Wheat from RGB Imagery and Point Cloud Data Acquired with a Low-Cost Unmanned Aerial Vehicle System. *Plant Methods* **2019**, *15*, 17. [\[CrossRef\]](#) [\[PubMed\]](#)

12. Dwyer, L.M.; Stewart, D.W. Effect of Leaf Age and Position on Net Photosynthetic Rates in Maize (*Zea mays* L.). *Agric. Meteorol.* **1986**, *37*, 29–46. [\[CrossRef\]](#)
13. Mendoza Pérez, C.; Ramirez Ayala, C.; Martinez Ruiz, A.; Ojeda Bustamante, W.; del Ruelas Islas, J.R.; Ascencio Hernández, R.; López Ordaz, A.; Núñez Ramírez, F. Leaf Area and Its Impact in Yield and Quality of Greenhouse Tomato (*Solanum lycopersicum* L.). *Rev. Fac. Cienc. Agrar. UNCuyo* **2022**, *54*, 57–69. [\[CrossRef\]](#)
14. Cui, B.; Zhao, Q.; Huang, W.; Song, X.; Ye, H.; Zhou, X. A New Integrated Vegetation Index for the Estimation of Winter Wheat Leaf Chlorophyll Content. *Remote Sens.* **2019**, *11*, 974. [\[CrossRef\]](#)
15. Doğru, A. Effects of Heat Stress on Photosystem II Activity and Antioxidant Enzymes in Two Maize Cultivars. *Planta* **2021**, *253*, 85. [\[CrossRef\]](#)
16. Gholizadeh, A.; Saberioon, M.; Borůvka, L.; Wayayok, A.; Mohd Soom, M.A. Leaf Chlorophyll and Nitrogen Dynamics and Their Relationship to Lowland Rice Yield for Site-Specific Paddy Management. *Inf. Process. Agric.* **2017**, *4*, 259–268. [\[CrossRef\]](#)
17. Zhang, H.; Ge, Y.; Xie, X.; Atefi, A.; Wijewardane, N.K.; Thapa, S. High Throughput Analysis of Leaf Chlorophyll Content in Sorghum Using RGB, Hyperspectral, and Fluorescence Imaging and Sensor Fusion. *Plant Methods* **2022**, *18*, 60. [\[CrossRef\]](#)
18. Impollonia, G.; Croci, M.; Blandinières, H.; Marcone, A.; Amaducci, S. Comparison of PROSAIL Model Inversion Methods for Estimating Leaf Chlorophyll Content and LAI Using UAV Imagery for Hemp Phenotyping. *Remote Sens.* **2022**, *14*, 5801. [\[CrossRef\]](#)
19. Li, D.; Chen, J.M.; Zhang, X.; Yan, Y.; Zhu, J.; Zheng, H.; Zhou, K.; Yao, X.; Tian, Y.; Zhu, Y.; et al. Improved Estimation of Leaf Chlorophyll Content of Row Crops from Canopy Reflectance Spectra through Minimizing Canopy Structural Effects and Optimizing Off-Noon Observation Time. *Remote Sens. Environ.* **2020**, *248*, 111985. [\[CrossRef\]](#)
20. Shao, G.; Han, W.; Zhang, H.; Liu, S.; Wang, Y.; Zhang, L.; Cui, X. Mapping Maize Crop Coefficient Kc Using Random Forest Algorithm Based on Leaf Area Index and UAV-Based Multispectral Vegetation Indices. *Agric. Water Manag.* **2021**, *252*, 106906. [\[CrossRef\]](#)
21. Xu, X.Q.; Lu, J.S.; Zhang, N.; Yang, T.C.; He, J.Y.; Yao, X.; Cheng, T.; Zhu, Y.; Cao, W.X.; Tian, Y.C. Inversion of Rice Canopy Chlorophyll Content and Leaf Area Index Based on Coupling of Radiative Transfer and Bayesian Network Models. *ISPRS J. Photogramm. Remote Sens.* **2019**, *150*, 185–196. [\[CrossRef\]](#)
22. Shah, S.H.; Angel, Y.; Houborg, R.; Ali, S.; McCabe, M.F. A Random Forest Machine Learning Approach for the Retrieval of Leaf Chlorophyll Content in Wheat. *Remote Sens.* **2019**, *11*, 920. [\[CrossRef\]](#)
23. Sun, Q.; Jiao, Q.; Chen, X.; Xing, H.; Huang, W.; Zhang, B. Machine Learning Algorithms for the Retrieval of Canopy Chlorophyll Content and Leaf Area Index of Crops Using the PROSAIL-D Model with the Adjusted Average Leaf Angle. *Remote Sens.* **2023**, *15*, 2264. [\[CrossRef\]](#)
24. FAO. Production Crops. Available online: <https://www.fao.org/faostat/en/#data/QCL/visualize> (accessed on 21 August 2024).
25. Dias, A.S.; de Lima, G.S.; Pinheiro, F.W.A.; Gheyi, H.R.; dos Anjos Soares, L.A.; Nobre, R.G.; de Padua Souza, L.; da Silva, S.S.; de Oliveira, S.G. Gas Exchanges and Growth of Sesame (*Sesamum indicum*, L.) Cultivated under Saline Waters and Nitrogen-Potassium Fertilizers. *Aust. J. Crop Sci.* **2019**, *13*, 1526–1532.
26. Lemes, E.M.; dos Santos, M.A.; Coelho, L.; de Andrade, S.L.; dos Oliveira, A.S.; Pessoa, I.D.; Cunha, J.P.A.R. Use of Visible Spectral Index and Soybean Plant Variables to Study Hidden Nematicide Phytotoxicity. *AgriEngineering* **2023**, *5*, 1737–1753. [\[CrossRef\]](#)
27. Neupane, K.; Baysal-Gurel, F. Automatic Identification and Monitoring of Plant Diseases Using Unmanned Aerial Vehicles: A Review. *Remote Sens.* **2021**, *13*, 3841. [\[CrossRef\]](#)
28. de Andrade, O.B.; de Montenegro, A.A.A.; da Silva Neto, M.A.; de Sousa, L.B.; Almeida, T.A.B.; de Lima, J.L.M.P.; de Carvalho, A.A.; da Silva, M.V.; de Medeiros, V.W.C.; Soares, R.G.F.; et al. UAV-Based Classification of Intercropped Forage Cactus: A Comparison of RGB and Multispectral Sample Spaces Using Machine Learning in an Irrigated Area. *AgriEngineering* **2024**, *6*, 509–525. [\[CrossRef\]](#)
29. dos Lima, C.S.; Junior, D.F.U.; Carvalho, I.R.; Bredemeier, C. Use of Phenomics in the Selection of UAV-Based Vegetation Indices and Prediction of Agronomic Traits in Soybean Subjected to Flooding. *AgriEngineering* **2024**, *6*, 3261–3278. [\[CrossRef\]](#)
30. Sánchez-Sastre, L.F.; Alte da Veiga, N.M.S.; Ruiz-Potosme, N.M.; Carrión-Prieto, P.; Marcos-Robles, J.L.; Navas-Gracia, L.M.; Martín-Ramos, P. Assessment of RGB Vegetation Indices to Estimate Chlorophyll Content in Sugar Beet Leaves in the Final Cultivation Stage. *AgriEngineering* **2020**, *2*, 128–149. [\[CrossRef\]](#)
31. Alvares, C.A.; Stape, J.L.; Sentelhas, P.C.; de Moraes Gonçalves, J.L.; Sparovek, G. Köppen's Climate Classification Map for Brazil. *Meteorol. Z.* **2013**, *22*, 711–728. [\[CrossRef\]](#)
32. de Sá Souza, M.; do Araújo Júnior, G.N.; de Souza, L.S.B.; Maniçoba da Rosa Ferraz Jardim, A.; da Silva, G.I.N.; de Araújo, G.G.L.; Campos, F.S.; de Leite, M.L.M.V.; Tabosa, J.N.; da Silva, T.G.F. Forage Yield, Competition and Economic Benefit of Intercropping Cactus and Millet with Mulch in a Semi-Arid Environment. *Afr. J. Range Forage Sci.* **2023**, *40*, 219–230. [\[CrossRef\]](#)
33. Arriel, N.H.C.; Beltrao, N.D.M.; Firmino, P.D.T. *Gergelim: O Produtor Pergunta, a Embrapa Responde*; Embrapa Informação Tecnológica; Embrapa Algodão: Campina Grande, Brazil, 2009.

34. Arriel, N.H.C.; de Gondim, T.M.S.; de Beltrão, N.E.M.; de Vasconcelos, R.A.; da Silveira, N.A.; de Sousa, S.L.; Dantas, E.S.B.; Pereira, J.R. *Gergelim BRS Seda*, 3rd ed.; Embrapa Informação Tecnológica; Empresa Brasileira de Pesquisa Agropecuária: Campina Grande, Brazil, 2007; ISBN 8573834420.
35. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. *Crop Evapotranspiration—Guidelines for Computing Crop Water Requirements—FAO Irrigation and Drainage Paper 56*; FAO: Rome, Italy, 1998; Volume 300, p. D05109.
36. Lourenço, E.R.C.; de Azevedo, P.V.; Pereira, A.R.; Bezerra, J.R.C.; Saboya, L.M.F.; Zonta, J.H. Necessidades Hídricas Da Cultura Do Gergelim Na Região Da Chapada Do Apodi, Rio Grande Do Norte (Water Consumption of Sesame Crop in the Region of the Plateau of Apodi-RN, Brazil). *Rev. Bras. Geogr. Física* **2018**, *11*, 1275–1289. [[CrossRef](#)]
37. Pizarro, F. *Drenaje Agrícola y Recuperación de Suelos Salinos*; Editura Agrícola Española: Madrid, Spain, 1985; Volume 2.
38. Hiscox, J.D.; Israelstam, G.F. A Method for the Extraction of Chlorophyll from Leaf Tissue without Maceration. *Can. J. Bot.* **1979**, *57*, 1332–1334. [[CrossRef](#)]
39. Santos, R.P.; Da Cruz, A.C.F.; Iarema, L.; Fernandes, K.R.G.; Kuki, K.N.; Otoni, W.C. Avaliação Da Eficiência Do Dimetilsulfóxido Na Extração de Pigmentos de *Vitis Vinifera* × *V. rotundifolia* e *V. riparia* Propagadas in Vitro. *Rev. Bras. Biociências* **2007**, *5*, 888–890.
40. Wellburn, A.R. The Spectral Determination of Chlorophylls a and b, as Well as Total Carotenoids, Using Various Solvents with Spectrophotometers of Different Resolution. *J. Plant Physiol.* **1994**, *144*, 307–313. [[CrossRef](#)]
41. Tondato Arantes, L.; Henrique Tondato Arantes, B.; Rogerio Giongo, P.; Zavatti Ceccato, G.; Hugo Moraes, V.; Kamei Saito, Y.; Fernando Gomes, L.; Carlos de Oliveira Castro, A. Comportamento Espectral e Detecção de Laranjeiras (*Citrus sinensis* L. Osbeck) Com Estresse Hídrico, Por Meio de Drone. *Rev. Bras. Geogr. Física* **2021**, *13*, 3625–3635. [[CrossRef](#)]
42. Matias, F.I.; Caraza-Harter, M.V.; Endelman, J.B. FIELDimager: An R Package to Analyze Orthomosaic Images from Agricultural Field Trials. *Plant Phenome J.* **2020**, *3*, e20005. [[CrossRef](#)]
43. Louhaichi, M.; Borman, M.M.; Johnson, D.E. Spatially Located Platform and Aerial Photography for Documentation of Grazing Impacts on Wheat. *Geocarto Int.* **2001**, *16*, 65–70. [[CrossRef](#)]
44. Gitelson, A.A.; Kaufman, Y.J.; Stark, R.; Rundquist, D. Novel Algorithms for Remote Estimation of Vegetation Fraction. *Remote Sens. Environ.* **2002**, *80*, 76–87.
45. Tucker, C.J. Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sens. Environ.* **1979**, *8*, 127–150. [[CrossRef](#)]
46. Bendig, J.; Yu, K.; Aasen, H.; Bolten, A.; Bennertz, S.; Broscheit, J.; Gnyp, M.L.; Bareth, G. Combining UAV-Based Plant Height from Crop Surface Models, Visible, and near Infrared Vegetation Indices for Biomass Monitoring in Barley. *Int. J. Appl. Earth Obs. Geoinf.* **2015**, *39*, 79–87. [[CrossRef](#)]
47. Meyer, G.E.; Neto, J.C. Verification of Color Vegetation Indices for Automated Crop Imaging Applications. *Comput. Electron. Agric.* **2008**, *63*, 282–293. [[CrossRef](#)]
48. Guijarro, M.; Pajares, G.; Riomoros, I.; Herrera, P.J.; Burgos-Artizzu, X.P.; Ribeiro, A. Automatic Segmentation of Relevant Textures in Agricultural Images. *Comput. Electron. Agric.* **2011**, *75*, 75–83. [[CrossRef](#)]
49. Hague, T.; Tillett, N.D.; Wheeler, H. Automated Crop and Weed Monitoring in Widely Spaced Cereals. *Precis. Agric.* **2006**, *7*, 21–32. [[CrossRef](#)]
50. Woebbecke, D.M.; Meyer, G.E.; Von Bargen, K.; Mortensen, D.A.M. Color Indices for Weed Identification Under Various Soil, Residue, and Lighting Conditions. *Trans. ASAE* **1995**, *38*, 259–269. [[CrossRef](#)]
51. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining Objective Weights in Multiple Criteria Problems: The Critic Method. *Comput. Oper. Res.* **1995**, *22*, 763–770. [[CrossRef](#)]
52. Senthilnathan, S. Usefulness of Correlation Analysis. *SSRN Electron. J.* **2019**. [[CrossRef](#)]
53. Chen, T.; Guestrin, C. XGBoost. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; ACM: New York, NY, USA, 2016; pp. 785–794.
54. Kuhn, M.; Frick, H. *Dials: Tools for Creating Tuning Parameter Values*; Posit Software, PBC: Boston, MA, USA, 2024.
55. Li, H.; Yan, X.; Su, P.; Su, Y.; Li, J.; Xu, Z.; Gao, C.; Zhao, Y.; Feng, M.; Shafiq, F.; et al. Estimation of Winter Wheat LAI Based on Color Indices and Texture Features of RGB Images Taken by UAV. *J. Sci. Food Agric.* **2024**, *105*, 189–200. [[CrossRef](#)]
56. Liu, X.; Wang, L. Feasibility of Using Consumer-Grade Unmanned Aerial Vehicles to Estimate Leaf Area Index in Mangrove Forest. *Remote Sens. Lett.* **2018**, *9*, 1040–1049. [[CrossRef](#)]
57. Panigrahi, N.; Das, B.S. Evaluation of Regression Algorithms for Estimating Leaf Area Index and Canopy Water Content from Water Stressed Rice Canopy Reflectance. *Inf. Process. Agric.* **2021**, *8*, 284–298. [[CrossRef](#)]
58. Bisht, I.S.; Mahajan, R.K.; Loknathan, T.R.; Agrawal, R.C. Diversidade Na Coleta de Gergelim Indiano e Estratificação de Acessos de Germoplasma Em Diferentes Grupos de Diversidade. *Genet. Resour. Crop Evol.* **1998**, *45*, 325–335. [[CrossRef](#)]
59. Monpara, B.A.; Gohil, V.N.; Akabari, V.R. Designing Model Plant Architecture through Assessment of Qualitative and Quantitative Traits in Sesame (*Sesamum indicum* L.). *Electron. J. Plant Breed.* **2019**, *10*, 1298. [[CrossRef](#)]
60. Hasan, U.; Sawut, M.; Chen, S. Estimating the Leaf Area Index of Winter Wheat Based on Unmanned Aerial Vehicle Rgb-Image Parameters. *Sustainability* **2019**, *11*, 6829. [[CrossRef](#)]

61. Yamaguchi, T.; Tanaka, Y.; Imachi, Y.; Yamashita, M.; Katsura, K. Feasibility of Combining Deep Learning and RGB Images Obtained by Unmanned Aerial Vehicle for Leaf Area Index Estimation in Rice. *Remote Sens.* **2020**, *13*, 84. [\[CrossRef\]](#)
62. Zhang, J.; Cheng, T.; Guo, W.; Xu, X.; Qiao, H.; Xie, Y.; Ma, X. Leaf Area Index Estimation Model for UAV Image Hyperspectral Data Based on Wavelength Variable Selection and Machine Learning Methods. *Plant Methods* **2021**, *17*, 49. [\[CrossRef\]](#)
63. El-Hendawy, S.; Tahir, M.U.; Al-Suhaibani, N.; Elsayed, S.; Elsherbiny, O.; Elsharawy, H. Potential of Thermal and RGB Imaging Combined with Artificial Neural Networks for Assessing Salt Tolerance of Wheat Genotypes Grown in Real-Field Conditions. *Agronomy* **2024**, *14*, 1390. [\[CrossRef\]](#)
64. Zhang, Y.; Huang, J.; Wang, F.; Blackburn, G.A.; Zhang, H.K.; Wang, X.; Wei, C.; Zhang, K.; Wei, C. An Extended PROSPECT: Advance in the Leaf Optical Properties Model Separating Total Chlorophylls into Chlorophyll a and b. *Sci. Rep.* **2017**, *7*, 6429.
65. Lopatin, J. Estimation of Foliar Carotenoid Content Using Spectroscopy Wavelet-Based Vegetation Indices. *IEEE Geosci. Remote Sens. Lett.* **2023**, *20*, 2500405. [\[CrossRef\]](#)
66. Sun, S.; Zhang, Q.; Yu, Y.; Feng, J.; Liu, C.; Yang, J. Leaf Coloration in *Acer Palmatum* Is Associated with a Positive Regulator ApMYB1 with Potential for Breeding Color-Leafed Plants. *Plants* **2022**, *11*, 759. [\[CrossRef\]](#)
67. Teklu, D.H.; Shimelis, H.; Abady, S. Genetic Improvement in Sesame (*Sesamum indicum* L.): Progress and Outlook: A Review. *Agronomy* **2022**, *12*, 2144. [\[CrossRef\]](#)
68. Qiao, L.; Gao, D.; Zhao, R.; Tang, W.; An, L.; Li, M.; Sun, H. Improving Estimation of LAI Dynamic by Fusion of Morphological and Vegetation Indices Based on UAV Imagery. *Comput. Electron. Agric.* **2022**, *192*, 106603. [\[CrossRef\]](#)
69. Zhang, C.; Chen, Z.; Yang, G.; Xu, B.; Feng, H.; Chen, R.; Qi, N.; Zhang, W.; Zhao, D.; Cheng, J.; et al. Removal of Canopy Shadows Improved Retrieval Accuracy of Individual Apple Tree Crowns LAI and Chlorophyll Content Using UAV Multispectral Imagery and PROSAIL Model. *Comput. Electron. Agric.* **2024**, *221*, 108959. [\[CrossRef\]](#)
70. Baresel, J.P.; Rischbeck, P.; Hu, Y.; Kipp, S.; Hu, Y.; Barmeier, G.; Mistele, B.; Schmidhalter, U. Use of a Digital Camera as Alternative Method for Non-Destructive Detection of the Leaf Chlorophyll Content and the Nitrogen Nutrition Status in Wheat. *Comput. Electron. Agric.* **2017**, *140*, 25–33. [\[CrossRef\]](#)
71. Yaseen, G.; Ahmad, M.; Zafar, M.; Akram, A.; Sultana, S.; Ahmed, S.N.; Kilic, O. Sesame (*Sesamum indicum* L.). In *Green Sustainable Process for Chemical and Environmental Engineering and Science*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 253–269.
72. Wei, P.; Zhao, F.; Wang, Z.; Wang, Q.; Chai, X.; Hou, G.; Meng, Q. Sesame (*Sesamum indicum* L.): A Comprehensive Review of Nutritional Value, Phytochemical Composition, Health Benefits, Development of Food, and Industrial Applications. *Nutrients* **2022**, *14*, 4079. [\[CrossRef\]](#)
73. Dossa, K.F.; Enete, A.A.; Miassi, Y.E.; Omotayo, A.O. Economic Analysis of Sesame (*Sesamum indicum* L.) Production in Northern Benin. *Front. Sustain. Food Syst.* **2023**, *6*, 1015122. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.