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BIOENERGETIC CULTURES: ESTIMATE OF OIL CONTENT IN MACAW PALM VIA COMPUTER VISION

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KEYWORDS

bioenergetic matrix, biodiesel, digital images principal component analysis.

ABSTRACT

Macaw palm (*Acrocomia aculeata*) is a potential raw material for biodiesel production owing to its high oil content. In this study, a model is created that can estimate the oil percentage in Macaw fruit using spectral indices obtained via computer vision. Ninety Macaw fruits are used to perform an experiment. They are categorized into three stages of maturation and counted in terms of weeks after flowering. Images of the fruits are captured using a multispectral camera in the visible spectral region (RGB) and infra-red regions (NIR), which allows spectral indices to be obtained. A model is established using the principal component regression method and used to estimate the oil content based on the colorimetric characteristics of Macaw palm fruits. The selected model is composed of the first two principal components, which indicate an explanatory potency of 91.57% of the variance. Applying this information to the validation data, the model exhibits a determination coefficient of 0.91, mean square error of 10.61%, and standard error of 5.46% in terms of the oil content, which indicates that computer vision is a promising alternative method for estimating oil content.

INTRODUCTION

Owing to the worldwide demand for clean and renewable energy sources for the development of bioenergy matrices, biodiesel technology has gained increasing importance (Altarazi et al., 2022). In Brazil, biodiesel production in 2021 reached a volume of 6,758,382 m³, with oil from soybeans constituting 72% of the total production (ABIOVE, 2022). The use of biodiesel as a fuel offers economic and environmental benefits, primarily by improving air quality through low CO_2 emissions (Fernández-Coppel et al., 2018; Mukhopadhyay et al., 2022).

With the expansion and consolidation of the use of renewable biofuels, such as ethanol and biodiesel (Nakamya, 2022), alternative crops that can be used in a bioenergy matrix, such as palm oil, must be investigated (Dey et al., 2021). In this context, a palm tree native to tropical forests and cerrados, known as Macaw palm (*Acrocomia aculeata*), has been investigated as a raw material for the production of biodiesel owing to its high concentration of oil (Borges et al., 2021; Suhartini et al., 2022).

The high presence of oleic acid, in addition to palmitic acid, in the oil extracted from the pulp of Macaw palm fruits, is vital to the production of biofuels as it offers greater stability against oxidation as well as operability at low temperatures (Harter et al., 2019). The oil contained in the mesocarp of Macaw palm fruits comprises primarily three fatty acids: palmitic (C16:0), oleic (C18:1), and linoleic (C18:2), which constitute 95% of the total fatty acid in the oil (Mota et al., 2011).

Identifying the ideal harvest time is important to obtain high levels of oil with adequate quality for the production of biofuels. Montoya et al. (2016) and Costa et al. (2018) reported changes in the colorimetric aspect of fruits during maturation and reported that harvesting more

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than 60 weeks after flowering allow one to obtain fruits with a high oil content. Despite advances in the study of this crop (Grupioni et al., 2020, Ampese et al., 2021), studies that focus on the development of technologies applicable to the production system are necessary such that macaúba can be consolidated as an alternative to the Brazilian bioenergetics matrix.

In this context, computer vision systems have been applied as an alternative for evaluating, selecting, and monitoring various processes involving agricultural products (Bhargava & Bansal, 2021; Amani et al., 2022). In palm trees, digital images have been successfully applied to evaluate the maturation stages (Ali et al., 2020; Lai et al., 2023), perform post-harvest monitoring (Septiarini et al., 2021) and estimate the oil content (Matsimbe et al., 2015; Oliveira et al., 2021). This technique, which involves multivariate analysis and machine learning, enables the development of protocols and technologies that can reduce sampling costs, allows an instantaneous evaluation of samples without the necessity to destroy the fruit, and facilitates the determination of standardization parameters for fruit classification and selection (Khan et al., 2021).

The objective of this study is to use spectral indices obtained from digital images to create a model that can estimate the oil content of Macaw palm fruits.

MATERIAL AND METHODS

Sample characterization and image acquisition

The fruits used in the experiment were obtained in an area located in the County of Acaiaca, Minas Gerais - Brazil at 20º 23' 33″S latitude and 47º 07' 31″W, with an average altitude of 601 m. The evaluated Macaw palm trees were of the *Acrocomia aculeata* species, over 10 years old, in the reproductive stage, cultivated in an extractive system, and without commercial purposes.

To perform an experiment, 90 fruit images were used and classified into three different maturation stages (30 fruits per stage). The maturation stages were associated with the onset flowering time of bunches, counted as weeks after flowering (WAF). The fruits were harvested at the 41st, 57th, and 61st WAF. According to Montoya et al. (2016) and Costa et al. (2018), harvesting from 60th WAF yielded fruits with the highest oil content. The fruits were harvested manually and belonged to the same cluster. After harvesting, the image of the fruits were captured to determine the oil content.

To acquire the images, a computer was used for storing and processing the images. Additionally, two halogen lamps (100 W each) and a multispectral CCD camera (Fluxdata, model FD-1665), were used to obtain images in the visible and near-infrared (NIR) spectral regions. The digital camera was positioned 0.25 m above the fruit. In the visible region (RGB color space), the images were captured at a depth of eight bits, which allowed the obtained average intensity values to be between 0 and 255 of the red (R), green (G), and blue (B) bands. Similarly, in the NIR region, the images were captured at a depth of eight bits, which allowed average intensity values between 0 and 255 to be obtained. Figure 1 shows an illustration of the experimental apparatus for capturing the images.

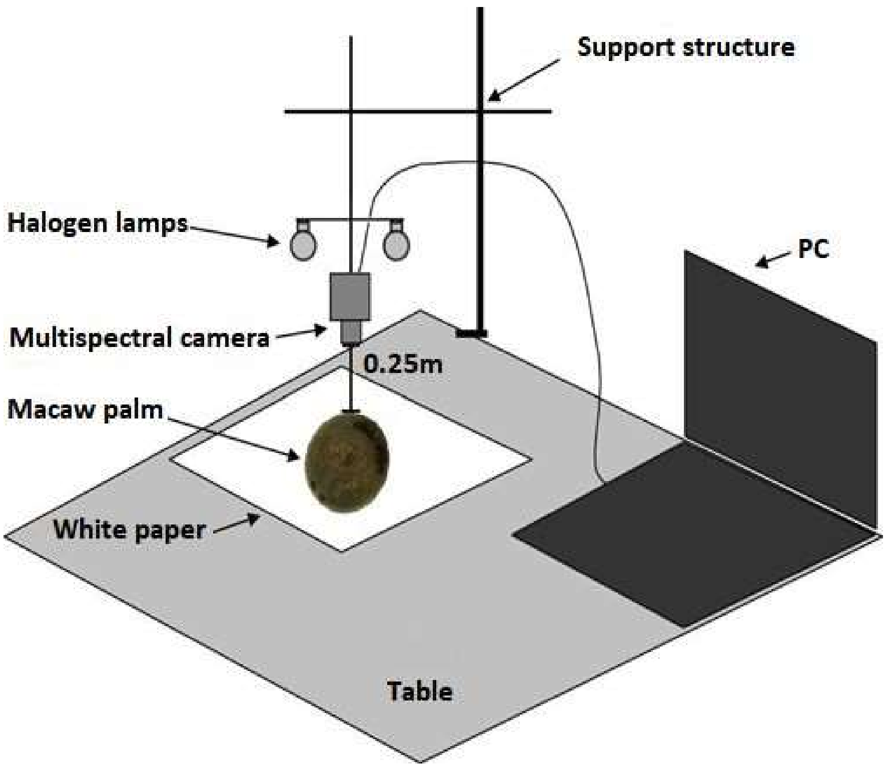

FIGURE 1. Experimental layout for image acquisition using multispectral camera.

As shown by Costa et al. (2018), after image acquisition, the region of interest (fruit) enhanced, whereas the background and possible image noise were eliminated. Thresholding was performed on each image using the Otsu method (Otsu, 1975). The region of interest was highlighted from the logical union operation between the original and binarized images.

The average values of the RGB bands and the intensity of the NIR band were obtained using the ImageJ software and then used to calculate the spectral indices, as shown in Table 1.

TABLE 1. Spectral indices calculated from intensity of red (R), green (G), blue (B), and near-infrared (NIR) bands.

Index name	Equations	
Normalized difference	$NDVIr = \frac{(NIR - R)}{(NIR + R)}$	(1)
Green normalized difference	$NDVIg = \frac{(NIR - G)}{(NIR + G)}$	(2)
Ratio between red - near infrared	$RNIR = \frac{R}{NIR}$	(3)
Ratio between green - near infrared	$GNIR = \frac{G}{NIR}$	(4)
Plant pigment ratio	$PPR = \frac{(G - B)}{(G + B)}$	(5)
Green-red normalized difference	$NDGRI = \frac{(G - R)}{(G + R)}$	(6)

Determination of oil content of Macaw palm fruits

Oil extraction was performed for each fruit using n-hexane solvent in a Soxhlet extractor (AOAC, 2016). The fruit mesocarp was cut and dried in a ventilated oven at 65 °C for 72 h. After drying, the samples were weighed and placed in paper filter cartridges, which were then placed in a Soxhlet extractor, where they were submerged in 150 mL of n-hexane for 8 h until the colorless extract was removed.

The extract was transferred to an oven at 105 °C for 24 h to evaporate the n-hexane and water in the mesocarp. Subsequently, the samples were weighed. The extraction was performed to obtain the oil content value for each evaluated sample (Equation 7).

$$OC = \left(\frac{Mo}{Ma}\right) x\ 100 \qquad (7)$$

Where:

OC = oil content, %;

Mo = mass of oil in Macaw palm fruit, g,

Ma = total mass of Macaw palm fruit, g.

Estimation of oil content via principal component regression (PCR)

The spectral indices were subjected to exploratory analysis, which involved calculating the arithmetic mean, maximum, and minimum values, as well as the standard deviation, coefficient of variation (CV), kurtosis, and skewness for each variable.

Principal component analysis (PCA) was applied to the spectral indices to compile the explanatory power of the variance generated by the difference in fruit maturation into a fewer variables. First, the data were normalized based on the relationship between the mean and standard deviation at each maturation stage to construct the covariance matrix to obtain the main components (Machado et al., 2020). The explanatory percentages of each principal component and the correlation between the principal components and the spectral indices were assessed.

To estimate the oil content as a function of the spectral indices, multiple linear regression models (MLRMs) were used, which were obtained via principal component regression (PCR) from the most representative principal components (defined in this study as an accumulated percentage greater than 90%). The data were separated into data for the calibration and validation of the regression models in proportions of 2/3 and 1/3, respectively.

The principal components selected for the model were subjected to an ANOVA variance test and a significance test of the model coefficients at a 5% level. The regression model was obtained from the calibration set samples, and the performance was evaluated based on the determination coefficient (R^2), mean squared error of calibration (MSEV), standard error of calibration (SEC), as well as the estimated and reference oil content values obtained using the Soxhlet extractor.

The generated model was applied to the validation dataset to determine its ability to estimate the oil content. Additionally, the R^2, mean squared error of validation (MSEV), and standard error of validation (SEV) between the estimated and actual oil content values obtained using the conventional method were calculated (Figure 2). The PCA as well as the generation and development of MLRM–PCR were analyzed using the Past software, version 4.02.

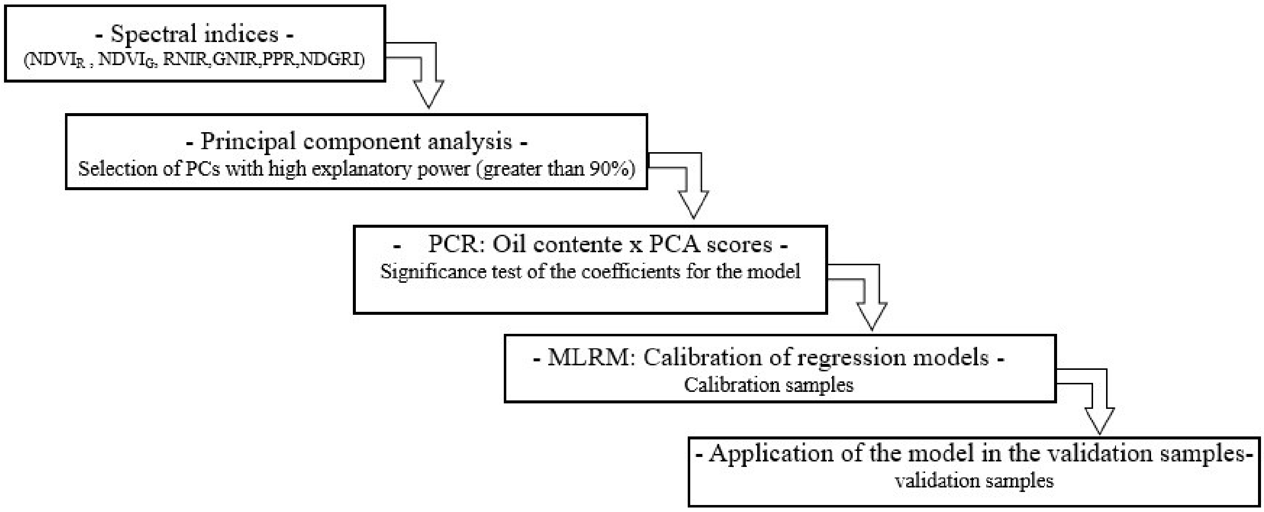

FIGURE 2. Steps for obtaining and applying PCR regression model generated to estimate oil content of Macaw palm fruits based on spectral indices.

RESULTS AND DISCUSSION

Based on an analysis of the spectral indices (Table 2), PPR and NDGRI, which were obtained from the intensity values of the visible spectrum bands, presented approximate mean and median, indicating that these indexes presented a distribution close to a central value. The analysis of the CV showed that, based on the classification proposed by Warrick & Nielsen (1980), the NDVIr, NDVIg, and NDGRI indicated high variations (CV > 60%); in fact, these indices were affected the most by the variation in fruit maturation. The GNIR showed medium variation (12% < CV < 60%), whereas the GNIR showed low variation (CV < 12%).

TABLE 2. Analysis of spectral indices in three maturation stages. Sample number = 90.

	Mean	Median	Minimum	Maximum	CV (%)	Kurtosis	Skewness
NDVIr	0.09	0.06	0.02	0.25	66.49	0.39	1.36
NDVIg	0.11	0.08	0.03	0.27	64.56	0.27	1.30
RNIR	0.83	0.88	0.60	0.96	11.63	0.20	-1.27
GNIR	0.81	0.87	0.58	0.95	13.11	0.07	-1.19
PPR	0.12	0.11	0.05	0.21	28.25	1.62	0.91
NDGRI	-0.02	-0.01	-0.05	0.03	99.57	-0.07	-0.14

NDVIr: red normalized difference vegetation index; NDVIg: green normalized difference vegetation index; RNIR: red near-infrared ratio; GNIR: green near-infrared ratio; PPR: Plant pigment ratio; NGDVI: normalized green-red difference; CV (%): coefficient of variation.

Regarding the kurtosis coefficient, except the NDVGRI, the spectral indices showed a leptokurtic distribution with elongated peaks and tails. The NDVIr, NDVIg, and PPR, presented an asymmetric distribution to the right (Ass. > 0), whereas the RNIR, GNIR, and NDGRI presented an asymmetric distribution to the left (Ass. < 0).

During fruit development, several biochemical, physiological, and structural changes modify the accumulation of pigments, volatile compounds, organic acids, and sugars. These changes occur gradually, and some change the physical appearance of the fruits in a visible manner, e.g., the color and size (Posé et al., 2019). In general, the color of palm fruits changes from green in the immature stage to dark colors such as purple, which signals that the fruit is ripe for harvest (Septiarini et al., 2021).

For the Macaw palm, its ripeness for harvest is characterized by the brown color, which also indicates a high oil content (Montoya et al., 2016). In a study by Oliveira et al. (2021), the Macaw palm fruits used to develop predictive models to obtain the oil content showed an average oil content of 55.7%, with maximum values of up to 74.5% indicated in the stages of greatest oil accumulation in the mesocarp.

When evaluating the oil content response for the three maturation stages (Figure 1), the expected increase in the oil content during fruit maturation must be verified. At the 41st WAF, the oil content varied between 7.0% and 35.0%, with a distribution around a central value of approximately 25.0%. At the 57th WAF, the variation between the values obtained was the greatest; this occurred because it is an intermediate stage where the fruits exhibited various characteristics. The oil content varied between 40.0% and 50.0%, with values distributed around 43.0%. At 61st WAF, the smallest variation between the values obtained was detected, indicating greater uniformity in the amount of oil in the fruit during the more advanced maturation stages. Meanwhile, the oil content varied between 52.0% and 65.0%, with values distributed around 57.0%. The period above is the maturation period recommended for harvesting the fruits in bunches with the highest oil content.

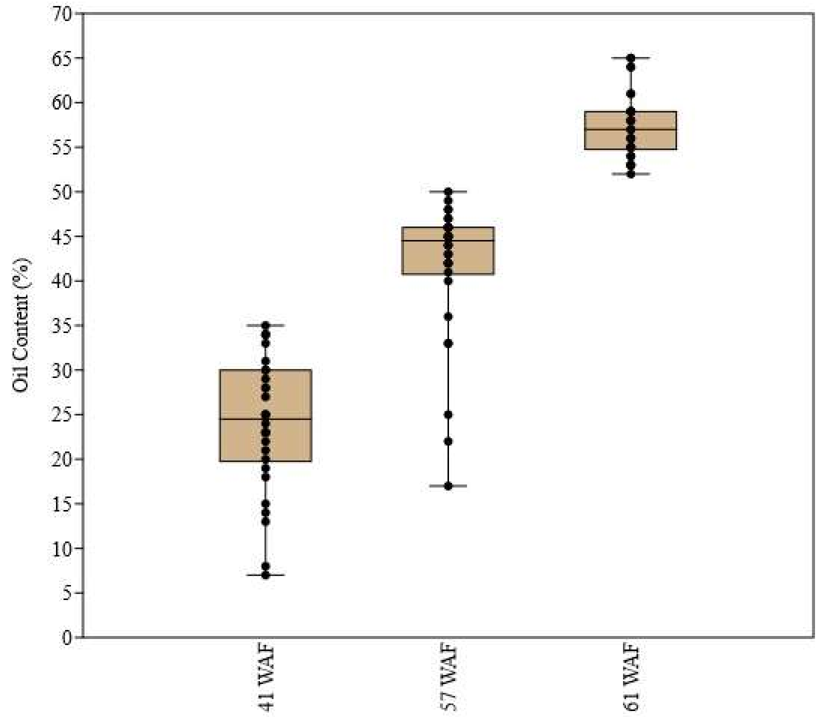

FIGURE 3. Boxplot showing values of oil content obtained in fruits at different maturation stages (41st, 57th, and 61st WAF).

Harvesting fruits with high oil content and adequate quality is important to consolidate the Macaw palm as a crop that constitutes the Brazilian bioenergy matrix to produce biodiesel. Harter et al. (2019) demonstrated that biodiesel obtained from Macaw palm almond oil contained a high percentage of 12-carbon methyl esters, thus confirming its high lauric acid content. Mota et al. (2011) reported that biodiesel produced from Macaw palm mesocarp oil may be more advantageous than soybean oil because of the presence of 7% to 9% linolenic acid, which provides greater stability to palm oil.

Instantaneous and non-destructive methods for assessing maturity stages and quantifying oil content in palm fruits have been investigated (Alfatni et al., 2022; Septiarini et al., 2021; Lai et al., 2023) to develop techniques that can assist in decision-making based on the harvest time and selection of fruits, thus reducing the necessity for laboratory analysis.

In the case of Macaw palm, non-destructive and reliable methods that allow the oil content in a significant number of fruits have been investigated (Matsimbe et al., 2015; Evaristo et al., 2016; Costa et al., 2018) as an alternative to conventional oil extraction methods, which are costly, time consuming, and require skilled labor.

To create a model for estimating oil content based on spectral indices obtained from images of Macaw palm fruits at different stages of maturation, multivariate principal component analysis was applied to obtain a model with fewer variables.

Based on an analysis of the explanatory percentages (Table 3), PC1 and PC2 (PC = principal component) constitute 91.57% of the variation in spectral indices as a function of fruit maturation, indicating that these components are potential candidates for the proposed model. All spectral indices show a correlation greater than 0.5 or -0.5 with PC1, indicating that all calculated indices affect the values obtained by PC1. Furthermore, the PPR and NDGRI present a correlation greater than 0.5 with PC2, indicating a significant effect of the indices obtained from the relationship of the RGB bands for this component.

TABLE 3. Explanatory percentage (EP) and accumulated explanatory percentage (AEP) of variance associated with principal components (PC) and correlation between PCs and original variables.

	PC1	PC2	PC3	PC4	PC5	PC6
Variance	4.58	0.92	0.50	1.33E-04	3.37E-04	4.81E-07
EP (%)	76.32	15.26	8.40	0.02	0.0056	8.02E-06
AEP (%)	76.32	91.57	99.97	99.99	~100.00	100.00
Correlation between PCs and original variables						
NDVIr	-0.978	0.081	0.194	0.020	0.001	~ 0.00
NDVIg	-0.995	-0.064	0.069	0.015	0.003	~ 0.00
RNIR	0.975	-0.072	-0.208	0.012	0.014	~ 0.00
GNIR	0.993	0.088	-0.075	0.023	-0.011	~ 0.00
PPR	-0.549	0.712	-0.437	0.001	~ 0.00	~ 0.00
NDGRI	0.628	0.620	0.4711	0.001	0.003	~ 0.00

NDVIr: red normalized difference vegetation index; NDVIg: green normalized difference vegetation index; RNIR: red near-infrared ratio; GNIR: green near-infrared ratio; PPR: Plant pigment ratio; NGDVI: normalized green–red difference.

By comparing PC1 and PC2 with the oil content obtained using the conventional extraction method in the calibration set samples from an MLRM model (Table 4), the coefficients associated with each component of the model can be obtained. Both coefficients were significant (p-value < 0.05) and yielded $R^2 = 0.75$, which demonstrates the potential of the model to estimate the oil content from colorimetric indices.

TABLE 4. Coefficients and their performance parameters in PCR model generated from calibration dataset.

	Coefficient	Std. error	p-value	R²
Constant	39.11	1.11	2.69E-40	
PC1	-2.41	0.52	1.81E-05	0.67
PC2	-15.63	1.23	3.06E-18	0.08

PC: principal component; Std. error: Standard error; R²: coefficient of determination.

The application of the generated model (OC = 39.11 -2.41PC1 − 15.63PC2) in the validation sample set showed a relationship ($R^2 = 0.91$) that allowed the oil content of Macaw fruits to be estimated from the intensities of each spectral band (Table 5). The analysis of the SEV and MSEV of the validation data show that the estimated oil content values did not differ significantly from the actual values.

TABLE 5. Performance parameters of proposed model applied to calibration and validation datasets.

	Number of samples	R²	MSE	Standard error
Calibration set data	60	0.75	7.33	2.86
Validation set data	30	0.91	10.61	5.46

The optical properties obtained on the surface of palm fruits (Khan et al., 2021) were used as an indicator of maturation, and the oil content in the fruits was associated with the degree of physiological maturation; different methods for obtaining and analyzing fruit spectral responses have been evaluated to develop alternative methods for estimating fruit oil content.

Ali et al. (2020) combined parameters obtained via computer vision and laser light backscattering (biospeckle laser) to generate a model ($R^2 = 0.85$) to classify the quality of palm fruit oil in bunches (fresh fruit bunches) based on the maturation of the fruit. Oliveira et al. (2021) performed NIR spectroscopy to develop models to predict the maximum oil content of Macaw fruit up to 25 days in advance. The prediction models obtained from unripe fruits showed better results than those from ripe fruits, with an R^2 index of up to 92%. Matsimbe et al. (2015) successfully applied visible and near-infrared spectroscopy (VIS-NIR) to the mesocarp of Macaw palm to estimate its oil content. However, the adjustment of the VIS-NIR model with reflectance data obtained from the epicarp of the fruits was not carried out.

Optical methods have been presented as an alternative for estimating palm oil content rapidly without the use of solvents for extraction. However, these methods yield better results when applied under specific conditions, such as directly on bunches (Ali et al., 2020), immature fruits (Oliveira et al., 2021) or the mesocarp of Macaw fruits (Matsimbe et al., 2015).

In this study, the values estimated by the PCR model (Table 4) for the validation data were more similar to the reference values when the fruits in the most advanced maturation stages that contained higher oil contents were evaluated (Figure 3). When evaluating fruits with lower oil content (below 35%), a standard error of 6.62 was observed. When evaluating fruits with higher oil content (above 45%), a decrease in the standard error (SE = 4.30) was observed, which indicates that this model is more suitable for fruits that have a high oil content and are closer to the harvest time.

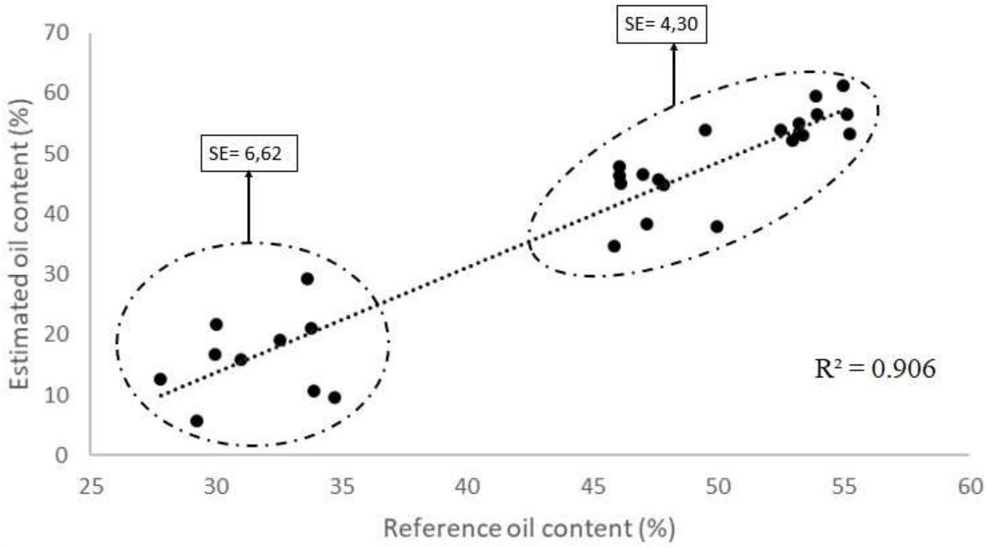

FIGURE 4. Comparison between standard error (SE) of estimated and reference oil content values (using Soxhlet extractor) for validation dataset.

Biofuels derived from renewable biomass contribute to the global bioenergy matrix by partially or completely replacing petroleum derivatives (Borges et al., 2021) as well as by the ability of palm trees to store carbon (Moreira et al., 2020). The development of techniques and technologies applicable to macaúba cultivation is fundamental to its consolidation as an alternative source of bioenergy.

Using the appropriate techniques and optical sensors is important for increasing the efficiency of crop production processes, which will enable a direct and instantaneous evaluation in the field without having to destroy the fruit; additionally, the volume of laboratory analyses and the reliance on solvents for detecting oil content can be reduced.

CONCLUSIONS

The use of digital images proved to be promising for estimating the oil content of Macaw palm fruits in an instantaneous and non-invasive manner, which can facilitate the development of techniques and technology applied in decision-making related to the harvest time and fruit selection in the field and laboratory.

Principal component analysis rendered it possible to reduce the dimensionality of the response variables (spectral indices) for two principal components, which presented an explanatory power of the variance of 91.57% as a function of fruit maturation.

The model generated from principal component regression was composed of coefficients associated with the first two principal components of greater explanatory power. It presented an R^2 of 0.906 when applied to the validation samples, which demonstrates a strong relationship between the estimated and reference values of oil content.

The estimated oil content showed a lower standard error in relation to the reference values when applied to fruits with a higher oil content (above 45%). This indicates that oil content estimation models from digital images tend to exhibit better performance when applied to Macaw palm fruits that are at a maturation stage closer to the harvest time.

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