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CROP PRODUCTION

Using aerial images to estimate production in forage cactus cultivars

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ABSTRACT. Predicting forage palm yield is a valuable tool for producers, aiding in harvest planning and crop management. This study aimed to evaluate the efficiency of using aerial images from a low-cost setup to estimate cladode production in four forage cactus cultivars. The experiment followed a randomized block design in a 4 x 4 factorial arrangement, with four replications. The first factor included the four cultivars: Giant, Miúda, Elephant Ear, and IPA Sertânia. The second factor involved four cladode harvest management strategies: (1) harvest at nine months, preserving the mother cladode; (2) harvest at nine months, preserving the mother and primary cladode; (3) harvest at 15 months, preserving the mother and primary cladode; and (4) harvest at 21 months, preserving the mother cladode. Before each harvest, aerial images were captured for each plot. The number of cladodes, fresh matter, and dry matter yield per harvest were calculated. Image processing was performed using the ExpImage package in the R software. The efficiency of predicting cactus yield using aerial images obtained with low-cost equipment was confirmed. Individually adjusted models for each cultivar provided greater precision in estimates. However, a single model for all four cultivars achieved a coefficient of determination greater than 77% for estimating fresh matter yield.

Keywords: *Opuntia ficus-indica* Mill; estimated yield; pixels; regression model.

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Introduction

Forage palm (*Opuntia ficus-indica* Mill.) is a species well-adapted to semi-arid and arid regions due to its anatomy and physiology, which allow for low water demand and high water-use efficiency (Ferraz et al., 2019; Lopes et al., 2019). It is an important source of water, minerals, fats, carbohydrates, fibers, and antioxidants (Ferraz et al., 2019). These attributes make it a viable option for both animal and human consumption, as well as for biofuel and medicine production (Bayar et al., 2018; Volpe et al., 2018).

In the Brazilian Northeast, this cactus is cultivated as an alternative for feeding and hydrating ruminants and other animals (Guimarães et al., 2019). Consequently, scientific studies are necessary to provide results that facilitate crop management for researchers and rural producers (Cargnelutti Filho et al., 2018; Guimarães et al., 2018; Guimarães et al., 2019). Yield predictions are crucial for producers to plan harvests for each cultivation cycle and manage crops effectively. For forage palms, morphological attributes such as total cladode area, plant height, and cladode thickness and length, can contribute to predicting crop yields (Guimarães et al., 2018).

Another method for estimating crop yields is using aerial images (Bertolin et al., 2017; Yuan et al., 2019), facilitated by Unmanned Aerial Vehicles (UAVs), commonly known as drones. These drones can capture aerial images with high spatial and temporal resolution (Nhamo et al., 2018). Utilizing unmanned aircraft helps producers obtain information and make decisions in production areas (Shi et al., 2016; Hunt & Daughtry, 2018). However, this equipment is expensive and challenging to operate, which increases costs, especially for small rural producers in economically deprived regions (Nhamo et al., 2020). A viable alternative is using low-cost strategies to obtain aerial images with common cameras.

Therefore, the ability to predict yield through forage palm images using low-cost strategies can significantly aid small producers in managing and planning their crops. This study aimed to evaluate the efficiency of using aerial images from a low-cost setup to estimate cladode production in four forage palm cultivars.

Material and methods

The study was conducted in the experimental field of the Institute of Agricultural Sciences (ICA) at the Federal University of Minas Gerais (UFMG), Campus Montes Claros, Minas Gerais State, Brazil. The location is situated between the parallels 16°51'00" southern latitude and the meridians 44°55'00" west, at an altitude of 630 meters. The soil is classified as Haplic Cambisol (International Union of Soil Science Working [IUSS], 2015). The climate in the region is Aw-type, characterized by dry winters and rainy summers (Alvares et al., 2013).

To set up the experiment, the following species and cultivars were used: *Nopalea cochenillifera* Salm Dyck (cultivars Giant and Miúda) and *Opuntia ficus-indica* and *Opuntia stricta* (cultivars Elephant Ear and IPA Sertânia), donated by the State University of Montes Claros, Janaúba, Minas Gerais State, Brazil, and Model Site (Janaúba, Minas Gerais State, Brazil).

Cladodes were removed from one- to two-year-old plants that had not been harvested. Uniform and mature cladodes were selected, specifically, those that had already emitted shoots or were close to doing so. Cuts were made with a machete as close as possible to the junction between the cladodes to minimize large wounds and reduce healing time. Tender cladodes were avoided due to their susceptibility to rotting, as well as old cladodes, which are difficult to root.

Planting was carried out after 15 days of cladode healing (10/20/2018). The distance between plants (cladodes) was 0.20 meters, and the planting depth was approximately 50% of their total length. Cladodes were planted vertically. Fertilization was done with P_2O_5 at 150 kg ha^{-1} (Donato et al., 2014). Top dressing followed the recommended guidelines for the crop, with 150 kg ha^{-1} of N and 75 kg ha^{-1} of K, divided into three applications on 02/15/2019, 07/24/2020 (after harvest), and 01/23/2020 (after harvest). Actara 750 SG was applied three times at 100 g ha^{-1} for scale insect (*Diaspis echinocacti*) control. Manual weeding was carried out as needed.

The experiment was set up using a randomized block design in a 4 x 4 factorial scheme, with four replications, totaling 64 plots. Each plot consisted of two rows with seven plants each, spaced 0.20 meters apart, with 2.0 meters between rows. The first factor consisted of four forage palm cultivars (Giant, Miúda, Elephant Ear, and IPA Sertânia). The second factor involved four cladode harvest management strategies (Figure 1): (1) harvest at nine months, preserving the mother cladode; (2) harvest at nine months, preserving the mother and primary cladode; (3) harvest at 15 months, preserving the mother and primary cladode; and (4) harvest at 21 months, preserving the mother cladode (Figure 1). Each plot consisted of 14 plants (seven in each row). These management strategies aimed to achieve greater variability in yield, number of cladodes, and consequently, a larger and more diverse image bank for each cultivar.

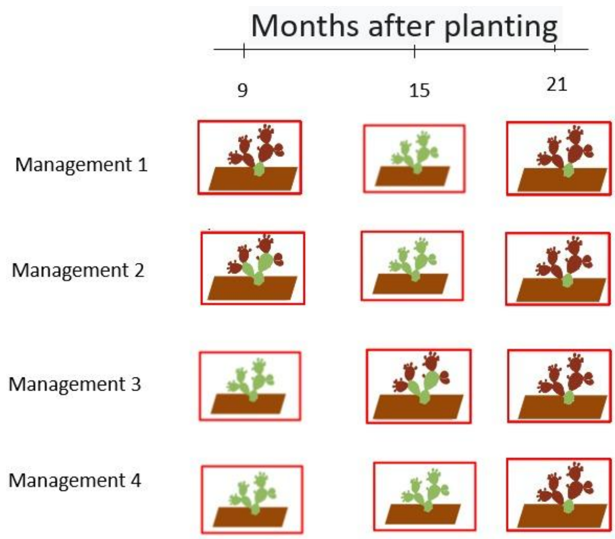

Figure 1. Harvest chronological planning (red cladodes) of forage palm plants.

At each harvest, cladodes were counted, and their yield was estimated. Fresh matter yield was determined by weighing all harvested cladodes on a precision scale. Nearly 300 grams of cladodes were placed in a forced-air circulation oven at 55°C for 72 hours to dry the material. The dried material was then weighed, and using the dry sample weight data, the dry matter content per plot was calculated (100 x dry matter / fresh matter) and subsequently the dry matter yield.

Aerial images of the plots were obtained before each harvest. A structure made of eucalyptus slats, with a height of 1.90 meters and a width of 2.50 meters, was used for this purpose (Figure 2a). The height of this structure was chosen to capture only the evaluated portion in the image (Figure 2b). A Canon PowerShot SX400 IS digital camera was attached to the center of the structure.

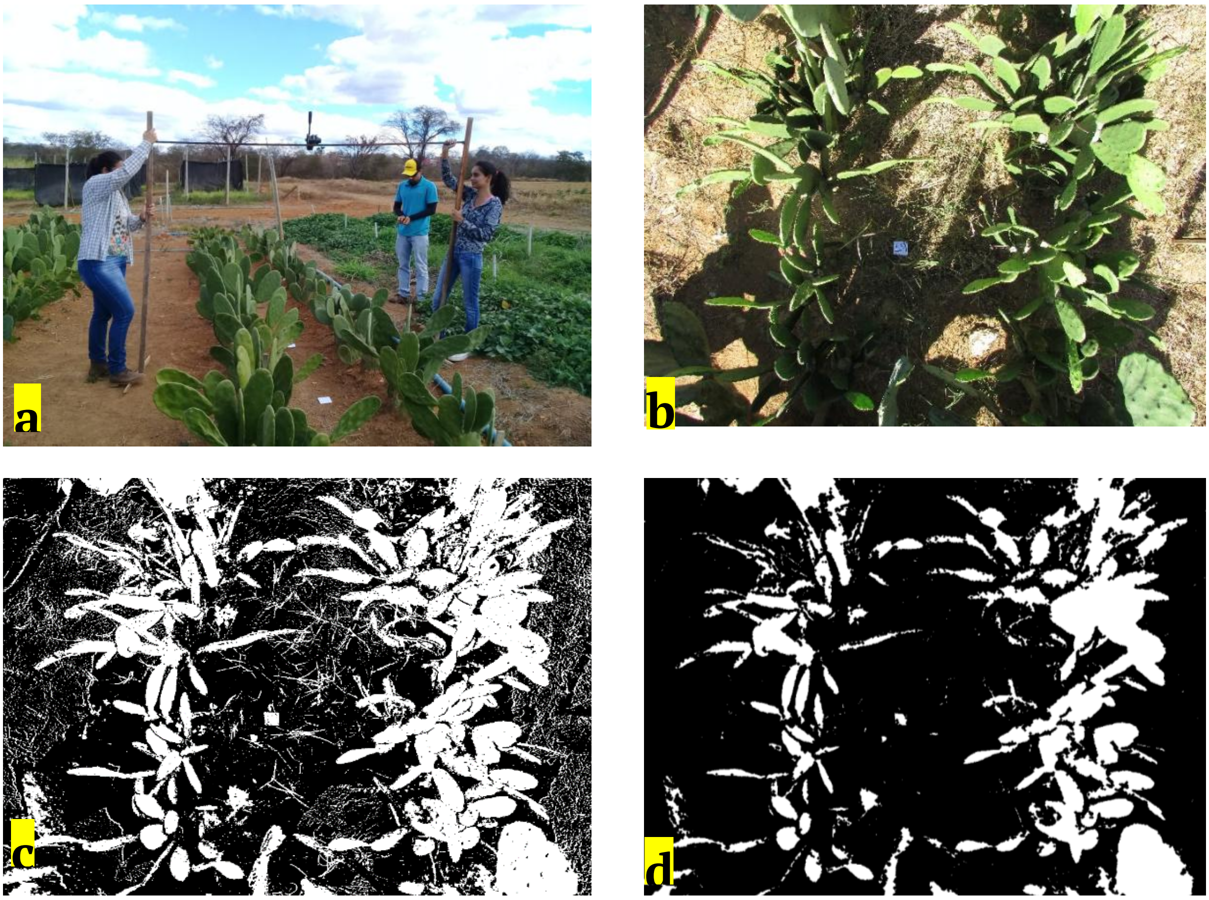

Figure 2. Low-cost structure for acquisition of forage palm aerial images (a), original image (b), segmented image (c), eroded segmented image (d).

After capturing, images were processed using the ExpImage package (Azevedo, 2022) in the R software. Each image, originally 4608 x 3456 pixels, was resized to 1000 x 750 pixels using the "resize_image" function to reduce processing time. For segmentation, two color palettes were created: one for pixels corresponding to the forage palm (foreground) and one for pixels not belonging to the forage palm (background). Segmentation was then performed using Logit regression based on the red, green, and blue channels, utilizing the "segmentation_logitGUI" function to obtain images like the one shown in Figure 2b.

To reduce noise, the segmented image was first eroded using the "erode_image" function, followed by dilation with the "dilate_image" function, resulting in images similar to Figure 2d. The number of pixels corresponding to the forage palm in each image was then computed. This estimated number of pixels was used to predict the number of cladodes, fresh matter yield, and dry matter yield through first-degree polynomial regression adjustment, using the "lm" function from the "stats" package.

Results and discussion

For the Elephant Ear cultivar, higher yields of green matter, dry matter, and a higher percentage of pixels corresponding to the forage palm were observed (Table 1). In contrast, IPA Sertânia showed lower averages for these characteristics. The Miúda cultivar had a higher average number of cladodes. Miúda is known for having more cladodes that are short and narrow (Pereira et al., 2021). However, despite the greater number of cladodes in the Miúda cultivar, this does not indicate greater soil coverage, as evidenced by the percentage of pixels corresponding to cladodes.

Table 1. Minimum (Min), maximum (Max), average, and coefficient of variation (CV) for the number of cladodes (NC), fresh matter yield in t ha^{-1} (FMY), dry matter yield in t ha^{-1} (DMY), and percentage of pixels (P%) corresponding to cladodes in aerial images of forage palm plants.

Cultivar	Parameters	NC	FMY	DMY	P%
Giant	Min	9.00	10.00	0.90	5.03
	Max	106.00	75.00	7.51	56.58
	Average	66.24	46.75	4.66	35.07
	CV(%)	47.10	51.34	52.06	48.06
Miúda	Min	35.00	3.64	0.58	4.63
	Max	513.00	124.61	13.71	86.51
	Average	218.21	46.11	5.31	32.95
	CV(%)	54.12	68.79	66.04	66.13
Elephant Ear	Min	75.00	13.98	1.90	18.77
	Max	165.00	129.94	14.03	93.46
	Average	118.55	67.24	7.43	46.51
	CV(%)	25.17	54.49	47.08	47.36
IPA Sertânia	Min	26.00	5.40	0.65	9.76
	Max	201.00	132.20	11.90	77.10
	Average	85.63	45.96	5.07	31.33
	CV(%)	56.15	74.26	65.03	58.29

Among cultivars, IPA Sertânia exhibited the greatest variability (CV) in the number of cladodes and green matter. Generally, high CV estimates were found for most traits in each genotype. High variability is desirable since it reflects a diverse dataset that strengthens the generalizability of regression models to be adjusted.

All evaluated forage palm cultivars showed coefficients of determination (R^2) above 70%, indicating the potential to estimate the number of cladodes using the percentage of pixels (Figure 3). A higher production of cladodes, their size, and higher dry mass production provide better coverage of the area occupied by the plant. The Giant cultivar showed the highest quality of fit compared to the other cultivars (Figure 3A).

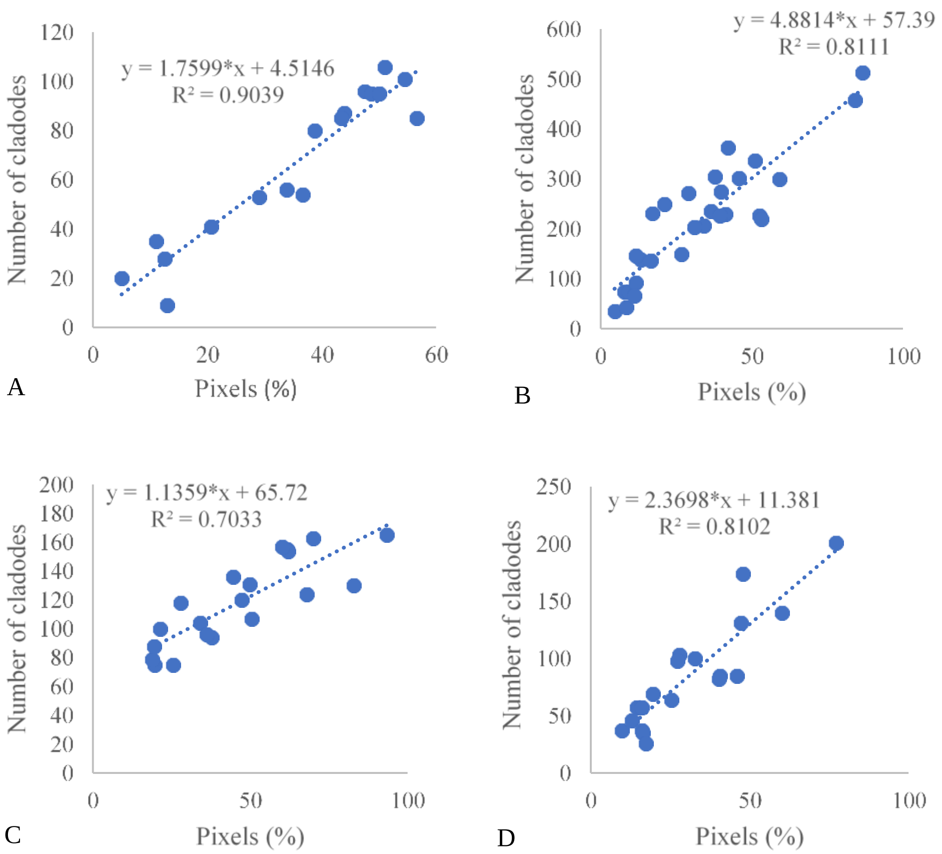

Figure 3. Number of cladodes estimated using aerial images of forage palm plants of the cultivars Giant (A), Miúda (B), Elephant Ear (C), and IPA Sertânia (D).

High coefficients of determination, above 70%, suggest that the evaluated characteristics can be estimated via digital imaging for forage palms, regardless of the cultivar. The Giant cultivar stood out because it presented a higher coefficient of determination (Figure 3). Noori and Panda (2016) studied digital images to predict olive tree yield and observed excellent coefficients of determination, above 90%, reinforcing that farmers can use their algorithms to estimate the physical characteristics of olive trees using remote sensing. For soybeans, Trindade et al. (2019) observed that during the physiological reproductive stage, digital images, via satellite, can predict grain yield.

The Elephant Ear cultivar had a higher percentage of vegetation cover. This coverage, estimated by the area of aerial images corresponding to cladodes, is due to the number of cladodes and their sizes, correlating with crop yield. This suggests that this parameter can predict future production of forage palm cultivars Miúda and Elephant Ear (Ruwanpathirana et al., 2024). Thus, the use of images has enormous potential to increase the yield and precision of phenotyping activities in plants (Pound et al., 2017).

High coefficients of determination (>75%, Figure 4) were observed for the models estimating the fresh matter yield of all forage palm cultivars. The model specifically adjusted for IPA Sertânia demonstrated the best fit. In addition, pixel percentage significantly influenced the models predicting fresh and dry matter (Figures 4 and 5).

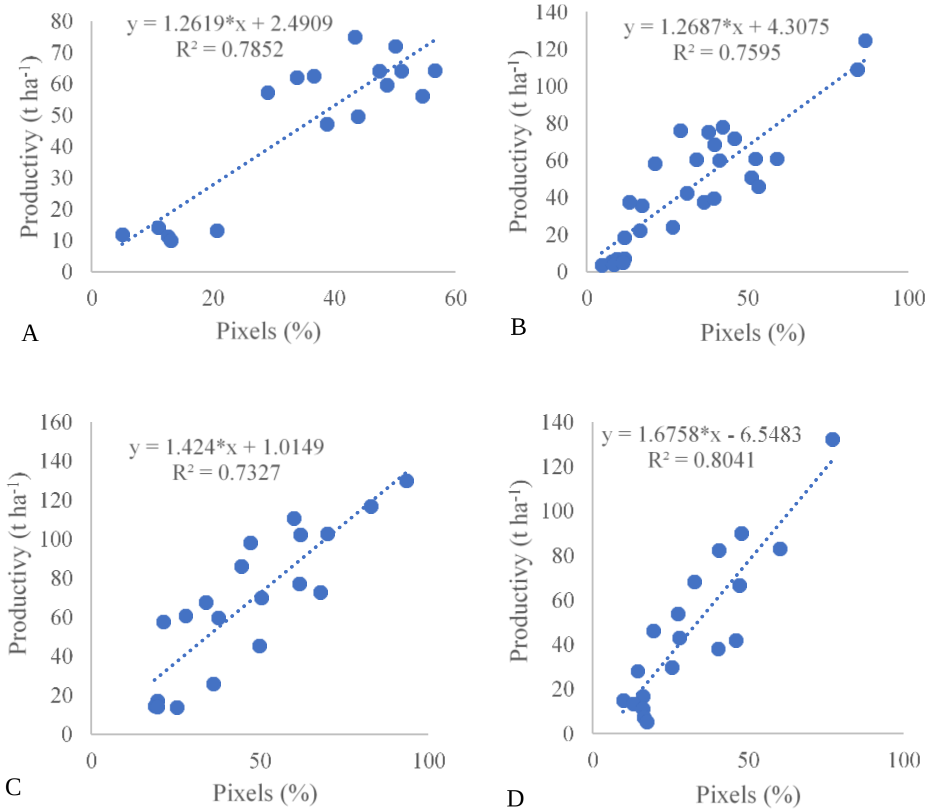

Figure 4. Fresh matter yield estimated using aerial images of forage palm plants of the cultivars Giant (A), Miúda (B), Elephant Ear (C), and IPA Sertânia (D).

All palm cultivars achieved high dry matter yield prediction accuracy (R^2 > 72%) based on the percentage of pixels (Figure 5). Both fresh mass (R^2 > 73%) and dry matter yield (R^2 > 70%) exhibited high coefficients of determination. The lower coefficient of determination (R^2) for dry matter yield compared to fresh mass might suggest higher experimental error. This is because dry matter measurement involves drying the sample to remove moisture and then weighing the remaining material, introducing a potential step for error.

Predicting cladode numbers using a single model for all cultivars resulted in a low coefficient of determination (Figure 6A). Conversely, fresh matter yield prediction achieved a high coefficient of determination (77%), indicating the feasibility of a single model for all four cultivars. Dry matter yield prediction, however, yielded a lower coefficient of determination (below 68%, Figure 6C).

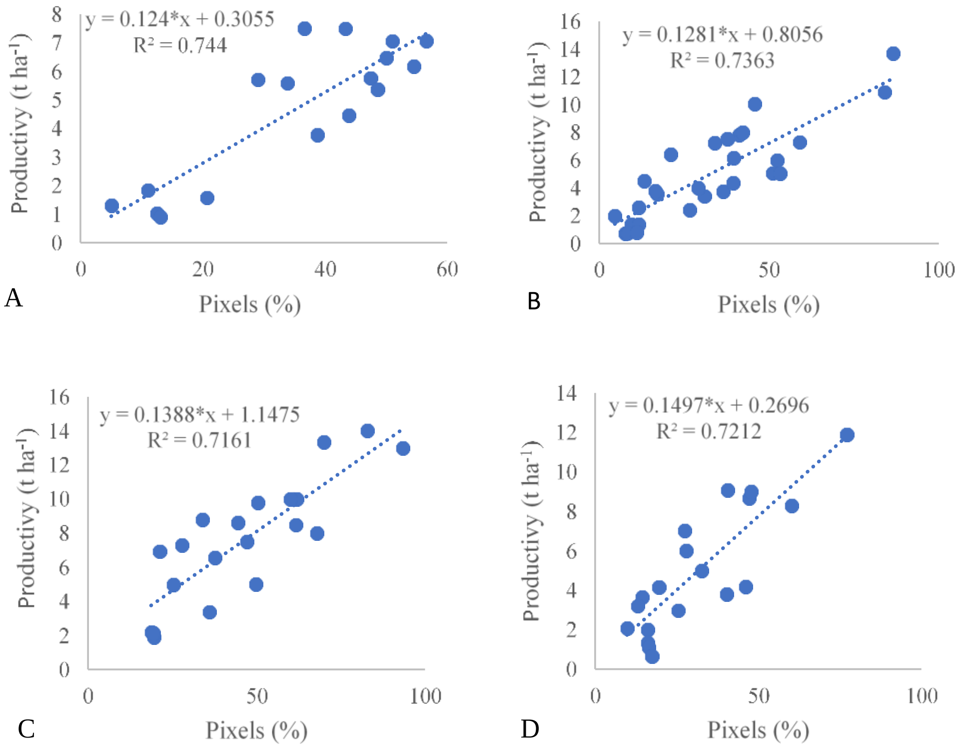

Figure 5. Dry matter yield estimated using aerial images of forage palm plants of the cultivars Giant (A), Miúda (B), Elephant Ear (C), and IPA Sertânia (D).

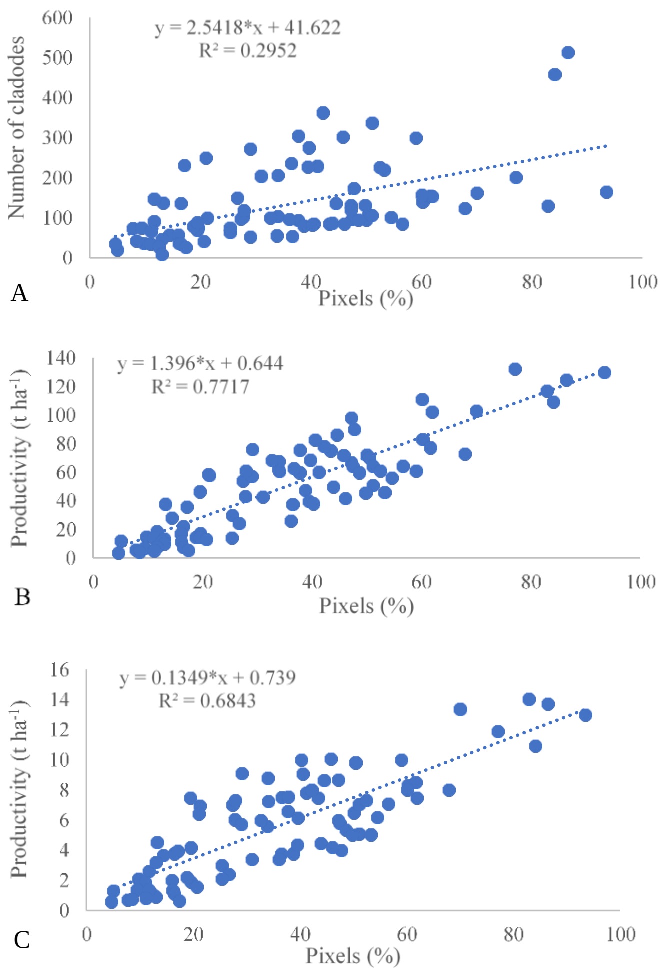

Figure 6. Number of cladodes (A), fresh matter yield (B), and dry matter yield (C) estimated using aerial images of forage palm plants of the cultivars Giant, Miúda, Elephant Ear, and IPA Sertânia.

Using a single regression model is not ideal for predicting the number of cladodes and dry matter yield (Figure 6A and C). This discrepancy likely arises from the varying cladode production of each cultivar, such as the Miúda cultivar, which has more but smaller cladodes compared to other forage palm cultivars (Table 1). However, satisfactory results were obtained for fresh matter yield with a coefficient of determination of 77% (Figure 6B). Utilizing biomass or characteristics such as height and number of leaves is important for evaluating crop yield. Using images or pixels to predict grain yields, crop health, or stand failures optimizes time and management for farmers without increasing production costs (Nhamo , 2020; Trindade et al., 2019; Sandra et al., 2020).

Low-cost digital images can facilitate field management and predict fresh and dry mass production of forage palm cladodes. The method used in this research is economical and non-destructive, making it a valuable tool for future agriculture (Noori & Panda, 2016).

As it is non-destructive, multiple assessments can be conducted on the same plants throughout the crop cycle or experiment, offering the advantage of being fast and accurate (Haque et al., 2021; Prilianti et al., 2019). Therefore, the developed method has a high potential for high-efficiency phenotyping through image analysis to predict forage palm yield. This could lead to the development of equipment for field data extraction and storing images in a database for future queries and comparisons.

Conclusion

Estimating forage palm yield becomes accessible with low-cost aerial imaging technology. While individually adjusted models offer the highest precision for yield estimates, a single model for all four cultivars achieved a coefficient of determination exceeding 77% for fresh matter yield, indicating good overall accuracy.

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