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Development of tropical grassland biomass prediction model based on UAV RGB images

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Abstract. The objective of this study is to assess the predictive potential of indices derived from RGB images captured by a camera mounted on a remotely piloted vehicle (RPV) to estimate the fresh and dry forage yield of grasses from the *Urochloa* genus. The experiment was conducted between December 2021 and January 2023, involving four cultivars of the *Urochloa* genus (*U. brizantha cv*. Braúna, *U. brizantha cv*. Paiaguás, *U. hybrid* cv. Camello, and *U. decumbens* cv. Basilisk), with flights conducted at two heights (20 and 100 metres). The values of the Green Leaf Index (GLI) and Digital Vegetation Model (DVM) extracted were correlated with the yields of fresh (FFY), dry forage yield (DFY), dry matter content (DM), and crude protein (CP). The results showed that DVM exhibited greater efficiency in estimating DM and CP at a flight altitude of 20 m. In contrast, GLI proved more efficient in estimating FFY and DFY at 100 m altitude, suggesting the potential for combining DVM and GLI to develop predictive models. The RGB images obtained via RPV have potential for estimating forage productivity and quality, expanding the possibilities of pasture management techniques.

Key words: drone, digital vegetation model, green leaf index, pasture, production.

INTRODUCTION

The prediction of tropical forage yield has become an increasingly important tool for sustainable pasture management. This interest is driven by the need to adjust stocking rates and carrying capacity, optimising the efficient use of natural resources. In Brazil, approximately 95% of beef production is based on grazing systems (Embrapa, 2022), which provides the country with a competitive advantage in the global beef market.

Therefore, strategies that enhance pasture management are crucial for maintaining productivity and sustainability in the agricultural sector.

In tropical regions, the use of emerging technologies has proven to be a promising approach to optimising forage production. Among these technologies, the use of red, green, blue (RGB) images captured by remotely piloted aircraft (RPA) stands out as an effective alternative for estimating forage yield. Conventional methods, both direct and indirect, such as the use of rulers and rising plate meters, are limited in terms of their temporal and spatial representativeness, particularly in remote and inaccessible areas (Wachendorf et al., 2017).

The potential of RGB images for estimating forage yield was highlighted by Acorsi et al. (2019), who demonstrated their viability as an alternative to traditional measurement methods. Through image processing algorithms and machine learning techniques, it is possible to extract valuable information regarding vegetation density and vigor, leading to more accurate predictions of available forage mass. Furthermore, studies such as those by Meshesha et al. (2020) have explored the integration of RGB data with other sources of information, such as meteorological data and soil characteristics, to improve the accuracy of forage yield estimates.

The ability to monitor and predict forage availability in real time allows producers to make more informed decisions regarding pasture management, promoting the optimisation of natural resource use and maximising productivity. In this context, the aim of this study was to develop predictive models to estimate fresh and dry forage yield, dry matter, and the protein content in grasses of the *Urochloa* genus.

MATERIALS AND METHODS

The experiment was conducted at the experimental field of the State University of Southwest Bahia (UESB), located in Vitória of Conquista, Bahia, Brazil (14º52'58.66" S, 40º47'33.839" W, 892 m altitude), from December 2021 to January 2023. The region's climate is classified as Cwb according to Köppen, characterised as a tropical highland climate with wet summers and dry winters, minimum and maximum temperatures of 18 °C and 22 °C, respectively, and an average annual rainfall of 771 mm (SEI, 1999). The soil in the experimental area was classified as a red-yellow latosol, with a sandy loam texture (Embrapa, 2006).

The experimental area was composed of four cultivars of grasses from the *Urochloa* genus: *Urochloa brizantha* cv. Braúna, *Urochloa brizantha* cv. BRS Paiaguás, *Urochloa decumbens* cv. Basilisk, and *Urochloa hybrid* cv. Camello. The experimental design was a randomised complete block design with five replications, totaling plots of 64 m² (8×8 m). The grasses were sown in December 2021 and fertilised with 29 kg ha^{-1} of P_2O_5, 4.5 kg ha^{-1} of K_2O, and 100 kg ha^{-1} of nitrogen between sowing and the end of the rainy season (March–April 2022).

The forage was harvested when the plants reached the following heights: 45 cm for the Braúna cultivar, 35 cm for the Camello and BRS Paiaguás cultivars, and 30 cm for the Basilisk cultivar, maintaining a residual height of 50% of the pre-grazing height for all cultivars. Representative forage samples were collected from two 1 m² areas per plot and weighed to determine the fresh forage yield (FFY). The material was placed in paper bags and dried in a forced-ventilation oven at 55 °C for 72 hours. After this period, using the weight of the fresh mass (FM, in g) and the weight of the air-dried sample (ADS, in g), the percentage of air-dried sample (%ADS) was calculated.

$$\%\mathrm{ADS} = \frac{\mathrm{ADS(g)}}{\mathrm{FM\ (g)}} \cdot 100 \tag{1}$$

After pre-drying, the samples were ground in a Wiley mill fitted with a 1 mm mesh sieve and then dried in an oven at 105 °C for 16 hours to determine the final dry sample. Based on the weight of the oven-dried sample (and the final dry sample, the dry matter content (%DM) and dry forage yield (DFY, kg ha^{-1}) were calculated, according to the INCT-CA G-003/1 method.

$$\%\mathrm{ODS} = \frac{\mathrm{ADS}}{\mathrm{ODS}} \cdot 100 \tag{2}$$

$$\%\mathrm{DM} = \frac{\mathrm{ADS} \cdot \mathrm{ODS}}{100} \tag{3}$$

$$\mathrm{DFY} = \mathrm{FM\ (kg)} \cdot \%\mathrm{DM} \tag{4}$$

Forage yield evaluations of the treatments were based on the total annual production of the grasses over an experimental period of 418 days. Within this production cycle, six harvests were conducted for evaluation, except for the grasses without fertilisation and the Braúna and Camello cultivars, which only allowed for five harvests. Crude protein (CP) was analysed using the INCT-CA N-001/1 method as described by Detmann et al. (2012). These parameters were used as indicators of pasture performance in this study.

The experiment utilised a DJI Phantom 4 Advanced quadcopter equipped with a 20-megapixel complementary metal-oxide semiconductor (CMOS) sensor camera, with a focal length of 9 mm and a maximum aperture of 2.97, mounted on a gimbal. The system includes an integrated GNSS (Global Navigation Satellite System) receiver, enabling autonomous flight missions using pre-loaded flight plans from third-party software.

Ten control points were distributed throughout the experimental field to obtain the geographical coordinates. Additionally, the coordinates of each plot vertex were collected using a geodetic receiver with real-time kinematic (RTK) technology, which assisted positional image correction and geospatial index extraction. Flight missions were planned using DroneDeploy software (DroneDeploy Inc., San Francisco, CA, USA) and uploaded to the UAV controller. The missions covered a total area of 8,000 m², with autonomous flights were conducted prior to sample collection between 10:00 and 12:00. Images were captured with 80% lateral and frontal overlap at two altitudes: 100 m and 20 m above ground level.

Flight heights were determined according to the detailing and coverage capacity, in which the height of 20 meters has greater detail and the height of 100 meters has greater area coverage. Thus, one height to represent greater detail in the images (20 meters) and another to expand the area coverage (100 meters).

The captured RGB images were processed using Agisoft PhotoScan photogrammetry software (v. 1.5.1, Agisoft LLC, St. Petersburg, Russia), which employs the structure-from-motion (SfM) algorithm to stitch the overlapping images and generate a 3D point cloud (Verhoeven, 2011). The workflow was implemented based on Schirrmann et al. (2016) and adjusted to suit the study's requirements. The proposed method included the following steps: importing the coordinates of the control points, importing the images, camera calibration, setting the geographic coordinates, analysing and aligning the images to generate a sparse point cloud, adjusting the images based on the CPs, constructing a dense point cloud, classifying ground points, constructing the Digital Surface Model (DSM), Digital Terrain Model (DTM), and orthomosaic. The digital vegetation model is used in Brazil to obtain detailed information about vegetation, such as its distribution, production, and chemical composition.

The generated products were processed in Quantum GIS (QGIS) software for index extraction, represented as layers (shapefiles) of the experimental treatments, created from the geographic coordinates of each plot vertex. Extraction of the Digital Vegetation Model (DVM) and the Green Leaf Index (GLI) was carried out using the RGB (Red, Green, Blue) bands, as described in Table 1. The DVM values were obtained by subtracting the data extracted from the surface (DSM) from the values extracted from the terrain (MDT), thus forming a reference value for vegetation (DVM). Regarding GLI, its values are obtained from the behavior observed in the red, blue and green bands (Table 1).

Table 1. Description of the DVM and GLI indices extracted from the products (orthomosaic, DSM, and DTM) generated from image processing

Digital indices	Type	Formula	Author
Digital Vegetation Model (DVM)	Vertical	$\mathrm{DVM} = \mathrm{DSM} - \mathrm{DTM}$	
Green Leaf Index (GLI)	Spectral	$\mathrm{GLI} = \frac{(2 * \mathrm{G}) - \mathrm{R} - \mathrm{B}}{(2 * \mathrm{G}) + \mathrm{R} + \mathrm{B}}$	Louhaichi et al. (2001)

The means of the cultivars regarding pasture and digital indices were compared using Tukey's test at a 5% significance level, performed with the SAS (Statistical Analysis System) software. Correlations between the pasture indices and digital indices (spectral and vertical) were assessed using Pearson's correlation test at a 1% significance level, employing the SPSS (Statistical Package for the Social Sciences) software. Subsequently, the data for each cultivar were subjected to multiple linear regression analysis, applying the stepwise method.

The regression analysis was performed in two ways, the first using all the data obtained from the cultivars, forming a single database. In the second way, the data were separated according to cultivar. In this way, the models obtained are represented broadly and specifically, by classifying them as a general model and models for each cultivar. From a cross-sectional analysis, regression analysis and model construction were performed using the aggregated data.

RESULTS AND DISCUSSION

The annual production of FFY, DFY, DM, and CP did not differ ($P > 0.05$) among the *Urochloa* grass species (Table 2). The annual average cutting cycle production of the cultivars was 40.9 t ha^{-1} and 10.4 t ha^{-1} for FFY and DFY, respectively. Furthermore, the average DM content across the cultivars was 24.5%, and the CP content was 10.3%. All evaluated cultivars exhibited high FFY and DFY, despite their agronomic and morphological differences. Regarding chemical composition, under the evaluated management conditions, the grasses showed crude protein (CP) levels compatible with the range observed for grasses of the genus when fertilised with nitrogen (Sales et al., 2020).

Table 2. Production and chemical composition of grasses *Urochloa* genus

Grasses	FFY (t ha^{-1})	DFY (t ha^{-1})	DM (%)	CP (%)
U. brizantha cv. Braúna	39.7	11.2	25.3	10.7
U. híbrida cv. Camello	41.4	10.9	23.5	8.9
U. decumbens cv. Basilisk	41.9	10.0	24.5	10.9
U. brizantha cv. BRS Paiaguás	40.6	9.6	24.6	10.7
P-value	0.90	0.13	0.81	0.05

FFY: Fresh Forage Yield; DFY: Dry Forage Yield; DM: Dry Matter; CP: Crude Protein. Means followed by the same letter in the column do not differ according to the *Tukey test* ($P < 0.05$).

The cultivars did not differ significant ($P > 0.05$) in terms of GLI and DVM (Table 3). Although no significant difference were identified, it is important to highlight that the highest numerical values for GLI and DVM were observed for the Paiaguás cultivar, whereas the lowest values were recorded for the Braúna cultivar, possibly due to morphological differences between the cultivars.

Table 3. Green leaf index (GLI) and digital vegetation model (MDV) of cultivars *Urochloa*

Grasses	GLI	DVM (m)
U. brizantha cv. Braúna	0.159	0.052
U. híbrida cv. Camello	0.172	0.060
U. decumbens cv. Basilisk	0.180	0.052
U. brizantha cv. BRS Paiaguás	0.192	0.087
P-value	0.03	0.05

Means followed by the same letter in the column do not differ according to the *Tukey test* ($P < 0.05$).

The spectral response of plants, as observed in GLI, results from the reflectance at wavelengths between 400 and 700 nm, which is regulated by leaf pigments such as chlorophyll and carotenoids (Asprilla et al., 2019). Chlorophyll strongly absorbs the blue (B) and red (R) bands of the visible spectrum, reflecting the green (G) band more intensely (Meer & Jong, 2001). This characteristic contributes to the definition of GLI, which considers the saturated green band in relation to the other two bands.

The DVM, in turn, can be interpreted as an indicator of vegetation height because its calculation involves subtracting the terrain model from the surface model. This is relevant because a greater number of leaf blades arranged parallel to the ground tends to significantly contribute to the estimation of parameters such as forage canopy height, which has shown a positive and consistent correlation with forage mass, as evidenced in several studies (Da Silva et al., 2015; Deminicis, 2015; Martins et al., 2020). Therefore, the DVM is a potential tool for accurately estimating pasture forage mass.

At a flight altitude of 20 m, a weak negative correlation was recorded between DFY (-0.36) and DVM, a value higher than that observed at 100 m (0.03) (Fig. 1 and 2). However, a moderate negative correlation was found between DM (-0.68) and DVM, alongside a strong positive correlation for CP (0.79) at 20 m altitude (Fig. 1). These results differ from those at 100 m, where a weak negative correlation for DM (-0.25) and a weak positive correlation for CP (0.26) were observed (Fig. 2).

GLI showed a moderate positive correlation (0.45) with FFY and a weak positive correlation (0.25) with DFY at a flight altitude of 20 m (Fig. 1). At 100 m altitude, the correlation of GLI was moderate positive (0.65) for FFY and weak positive (0.27) for

DFY (Fig. 2). For CP and DM, GLI showed a moderate negative correlation (-0.43) with DM and a weak positive correlation (0.33) with CP at 20 m altitude. At 100 m, the correlation was strong negative (-0.80) for DM and weak positive (0.38) for CP (Fig. 2).

	FFY	DFY	GLI	DVM	DM
DFY	0.93*				
GLI	0.45*	0.25*			
DVM	-0.15	-0.36*	0.25*		
DM	0.07	0.42*	-0.43*	-0.68*	
CP	-0.12	-0.35*	0.33*	0.79*	-0.73*

0.99 a 0.70	Strong positive
0.69 a 0.40	Moderate positive
0.39 a 0.10	Weak positive
0.10 a -0.10	Insignificant
-0.39 a -0.10	Weak negative
-0.69 a -0.40	Moderate negative
-0.99 a -0.70	Strong negative

Figure 1. Pearson correlation between pasture and digital indices, at 20 m of flight height.
*Significant correlation at 1%. FFY = Fresh Forage Yield; DFY = Dry Forage Yield; GLI = Green Leaf Index; DVM = Digital Vegetation Model; DM = Dry Matter; CP = Crude Protein.

For the FFY and DM, the correlation at 20 m was lower than that recorded at 100 metres. However, the correlation between CP and DVM shifted from weakly positive to strongly positive, and a similar effect was observed for DM content. As evidenced by the correlations observed in this study, DVM exhibits a weak correlation with forage biomass production but a strong correlation with CP. In contrast, the GLI showed strong correlation with the DM and a moderate correlation with the FBY at a flight altitude of 100 m, suggesting its potential for the development of predictive models.

At a flight altitude of 100 m, GLI showed moderately positive correlations with the FFY and a weak positive correlation with the DFY. Additionally, the DM and CP levels demonstrated moderately negative and weakly positive correlations, respectively (Fig. 2 (Rumsey, 2023)). The GLI expression is obtained through the equation presented by Louhaichi et al. (2001), where the pixel values can range between -1 and +1.

	FFY	DFY	GLI	DVM	DM
DFY	0.86*				
GLI	0.65*	0.27*			
DVM	0.16*	0.03*	0.31*		
DM	-0.46*	0.00	-0.80*	-0.25*	
CP	0.05	-0.25*	0.38*	0.26*	-0.51*

0.99 a 0.70	Strong positive
0.69 a 0,40	Moderate positive
0.39 a 0,10	Weak positive
0.10 a -0.10	Insignificant
-0.39 a -0.10	Weak negative
-0.69 a -0.40	Moderate negative
-0.99 a -0.70	Strong negative

Figure 2. Pearson correlation between pasture and digital indices, at 100 m of flight height.
*Significant correlation at 1%. FFY = Fresh Forage Yield; DFY = Dry Forage Yield; GLI = Green Leaf Index; DVM = Digital Vegetation Model; DM = Dry Matter; CP = Crude Protein.

According to these authors, negative values tend to represent non-living areas, whereas positive values are associated with green leaves and stems. In this context, the presence of green, especially in leaves, is directly related to chlorophyll, which absorbs light energy in the range of 680–700 nm (Streit et al., 2005). Studies have indicated satisfactory correlations (R^2 = -0.49) between GLI obtained from images and chlorophyll content, which is strongly association with fresh biomass production and nitrogen content in plants (Hunt Jr. et al., 2013).

In this context, predictive models were evaluated for the FFY, DFY, DM and CP, adjusted based on the data collected throughout the experimental period and as a function of flight altitude. Both general and specific models were considered for each cultivar. The predictive model for the FFY was adjusted for a flight altitude of 100 m, incorporating the GLI in its formulation. This adjustment was justified by the significant correlations (R) and the coefficients of determination (R^2) values, which were higher than those obtained at a flight altitude of 20 m (Fig. 3).

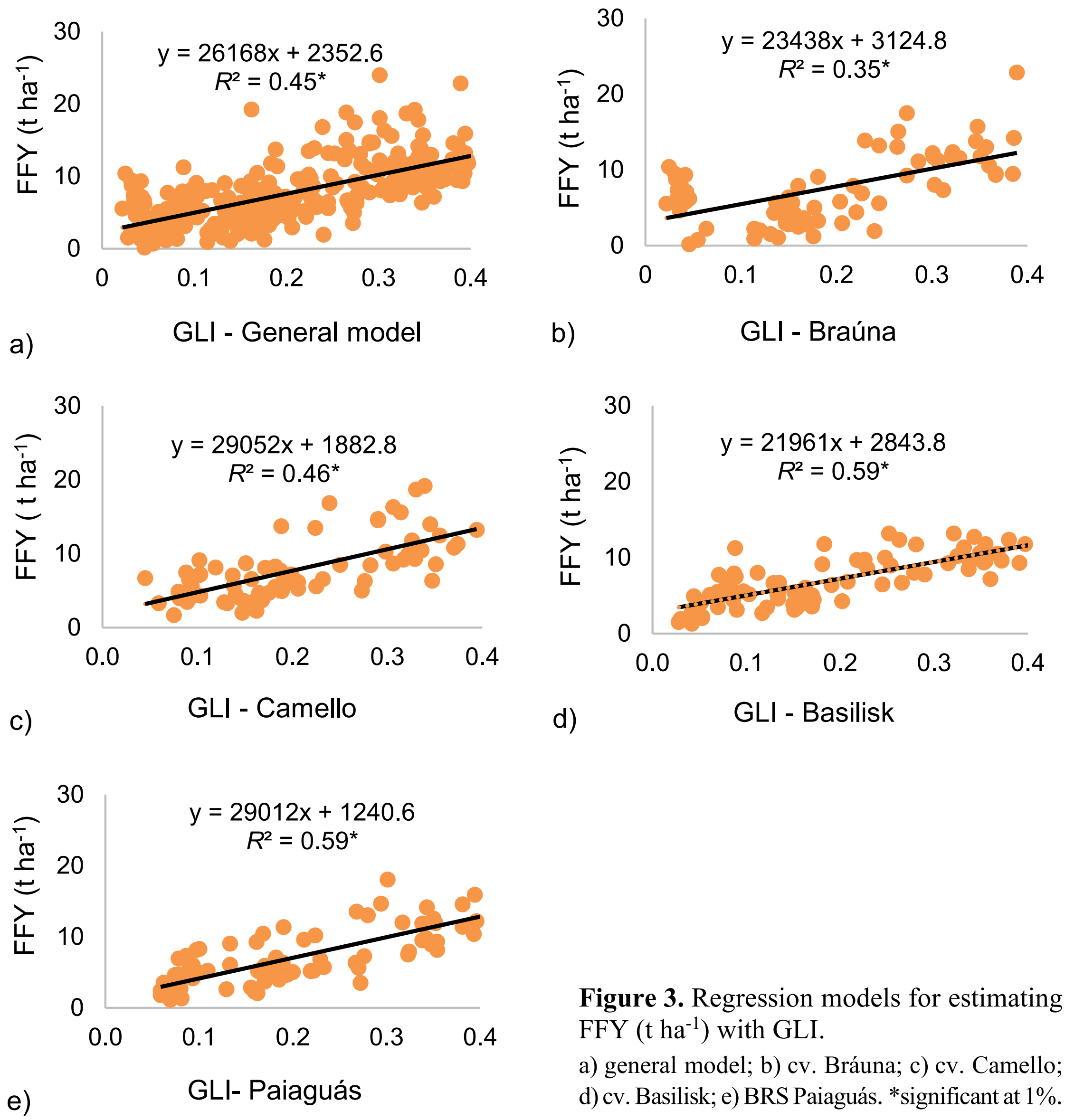


Figure 3. Regression models for estimating FFY (t ha^{-1}) with GLI.
a) general model; b) cv. Bráuna; c) cv. Camello; d) cv. Basilisk; e) BRS Paiaguás. *significant at 1%.

The model that considered all data (Fig. 3, a) exhibited an R^2 of 0.45, indicating that 45% of the variability in FFY can be explained by this model. When analysed by cultivar, this R^2 decreases for the Braúna cultivar (0.35) (Fig. 3, b) and increased for the

Camello (0.46) (Fig. 3, c), Basilisk (0.59) (Fig. 3, d), and BRS Paiaguás (0.59) (Fig. 3, e) cultivars. The behaviour of the GLI in relation to FFY increases linearly; that is, the higher the GLI value obtained, the greater is the FFY.

According to Yamaguchi et al. (2020), the behaviour of the GLI in the regression equation is increases linearly for rice crops, a pattern also observed in this study. The higher the GLI extracted from the images, the greater was the forage biomass. Barbosa et al. (2019) reported that higher vegetation index indicates a greater presence of vegetation in a given area, resulting from increased green reflectance.

Due to the behaviour observed in the different predictive models, the growth habit characteristics of the cultivars may have influenced the response of the indices. For instance, Braúna grass, which has thinner and more upright leaves with fewer pronounced angles, showed a FFY model with a lower fit compared to the other cultivars. This suggests that the sensor may have detected and considered this difference, which influenced the construction of the predictive model. On the other hand, DFY did not present significant results above 0.1 for the GLI and DVM indices at a flight altitude of 100 m (Fig. 4), either separately or together, with R^2 values of 0.05 and 0.03, respectively.

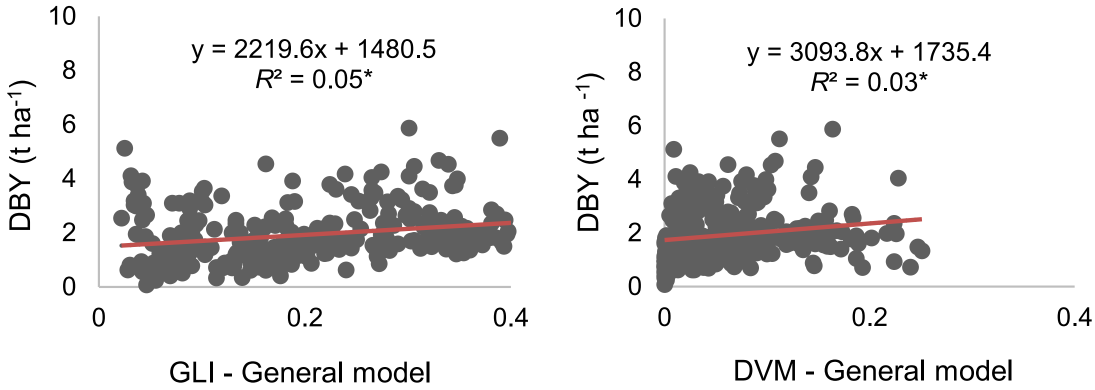


Figure 4. Regression model for DFY at 100 m flight height.
*significant at 1%.

When analysed together, the GLI and DVM models produced significant predictive models for the DFY at a flight altitude of 20 m, with R^2 values exceeding 0.50, as shown in Table 4. However, no significant predictive model for DFY was obtained of the Paiaguás cultivar. Estimating the DFY using the general equation predicts a higher amount of dry matter, ranging from 2,000–5,000 kg ha^{-1}, when the GLI exceeds 0.20 and the DVM is below 0.20.

Conversely, GLI values below 0.20 and DVM values above 0.4 tend to result in an estimated DFY of less than 1,000 kg ha^{-1} (Fig. 5, a). This behaviour of the digital indices (GLI and DVM) extends the analysis of individual cultivars. It can be observed that the DVM has a negative correlation with DFY, whereas the GLI shows a positive correlation. The model fit (R^2) reaches 0.69 for the Basilisk cultivar, 0.66 for the Camello cultivar, and 0.64 for the Braúna cultivar (Table 4).

Table 4. Regression models for dry forage yield (DFY) at 20 metres flight height.

Cultivar	*Regression models	R^2
Basilisk	DFY = 697 – 2,865*DVM + 6,300*GLI	0.69
Camello	DFY = 183 – 5,312*DVM + 13,474*GLI	0.66
Braúna	DFY = 375 – 4,059*DVM + 11,958*GLI	0.64
General model	DFY = 650 – 3,025*DVM + 8,078*GLI	0.50

*significant at 1%.

It is important to note that the DFY model results from the combined contributions of the GLI and DVM. This approach was also observed by Zhang et al. (2022), who, using RGB images from unmanned aerial vehicles (UAV), reported a better performance (R^2) in predictive models that integrated texture features obtained from pixels. Pixel-by-pixel selection at different heights (canopy and ground) helps distinguish vegetation from soil, as reported by Raj et al. (2021) used in the extraction of the digital surface model (DSM). This same principle can be applied to the DVM in this study, which can differentiate between soil and vegetation, thereby contributing to the prediction of forage mass in pastures.

These correlations corroborate the results presented by Acorsi et al. (2019), who also obtained an R^2 of 0.69 for the predictive model of dry matter production in black oat, whereas Gruner et al. (2019) achieved R^2 accuracies ranging from 0.62 to 0.81 in temperate pastures. The only cultivar that did not present a predictive dry matter model with satisfactory and significant correlations using both indices (GLI and DVM) was BRS Paiaguás. As stated by Roth & Streit (2018), vegetation indices (VIs) have also shown non-significant correlations for certain legume species, indicating that the performance of VIs is highly species-specific when estimating dry biomass.

The predictive models for FFY and DFY showed R^2 values of 0.45 and 0.50, respectively, in the general model. Similar results were observed by Gruner et al. (2019), who, evaluated temperate pastures, obtained an R^2 of 0.43 for a grass mixture, improving the model through species-specific analysis. This variation in response may be related to the morphological and structural differences observed between the different cultivars and species, which can influence both the interpretation of the images and the predictive efficiency of the model (Silva et al., 2016).

This same behaviour is evident in the present study, where higher R^2 values were achieved when the data were analysed separately by cultivar, reaching R^2 values of 0.59 for BRS Paiaguás and Basilisk in FFY, and R^2 of 0.69 for the Basilisk cultivar in the DFY. These correlations support the findings of Acorsi et al. (2019), who also obtained an R^2 of 0.69 for the predictive model of dry matter in black oat, whereas Gruner et al. (2019) achieved R^2 accuracies ranging from 0.62 to 0.81 in temperate pastures. It is important to highlight that the forage yield values refer to the sum of all harvests, which may show differences when individual harvests are analysed.

The predictive models for DM were obtained at a flight altitude of 100 m. The equation considering all data (general model) presented an R^2 of 0.64 (Fig. 5, a) using GLI as the predictive variable. The model fit (R^2) increased when the analyses were separated by cultivar, with the Braúna cultivar presenting a predictive model with an R^2

of 0.82 (Fig. 5, b), followed by the Camello cultivar with an R^2 of 0.73 (Fig. 5, c), Basilisk with an R^2 of 0.63 (Fig. 5, d), and BRS Paiaguás with an R^2 of 0.57 (Fig. 5, e).

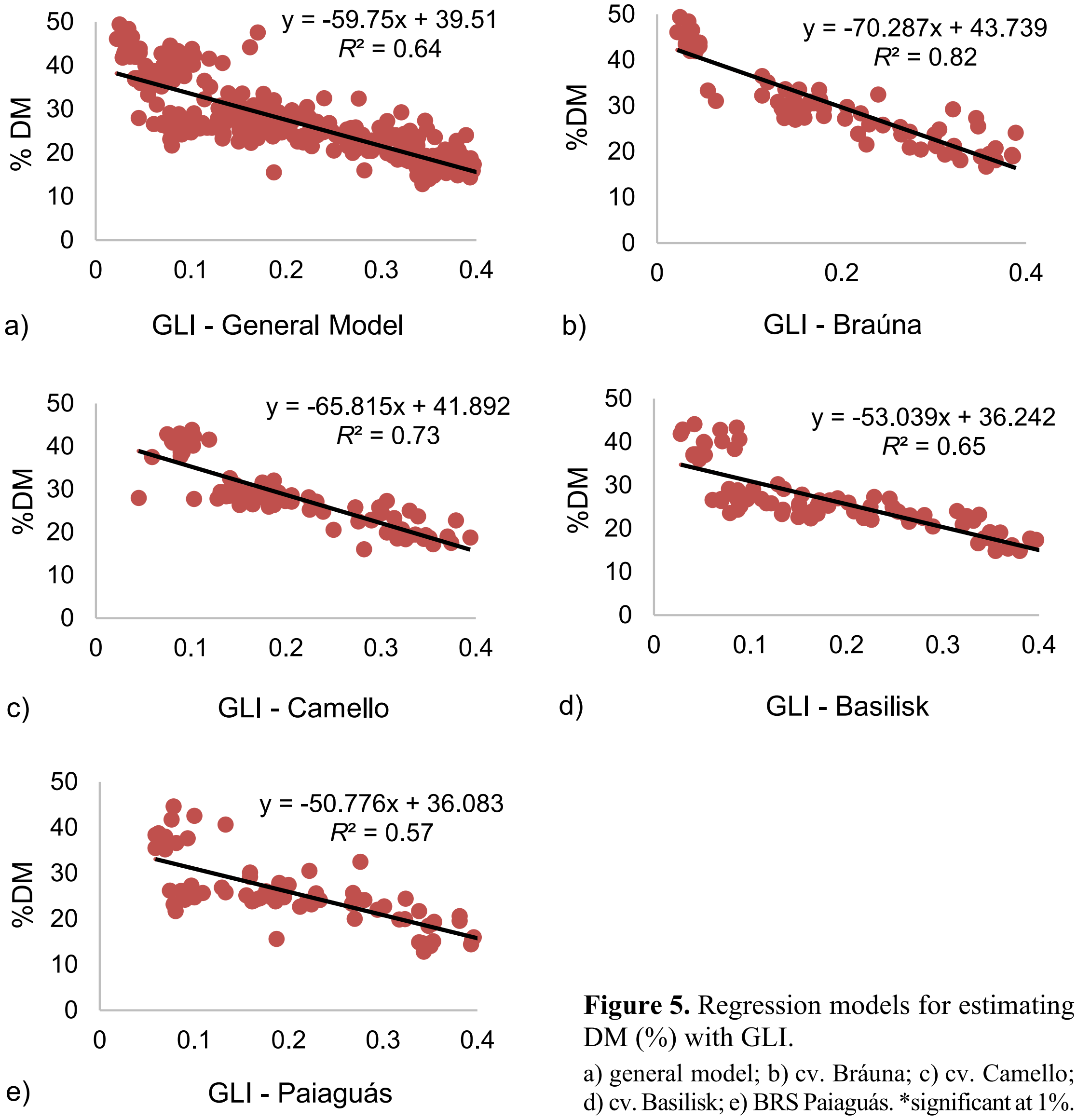
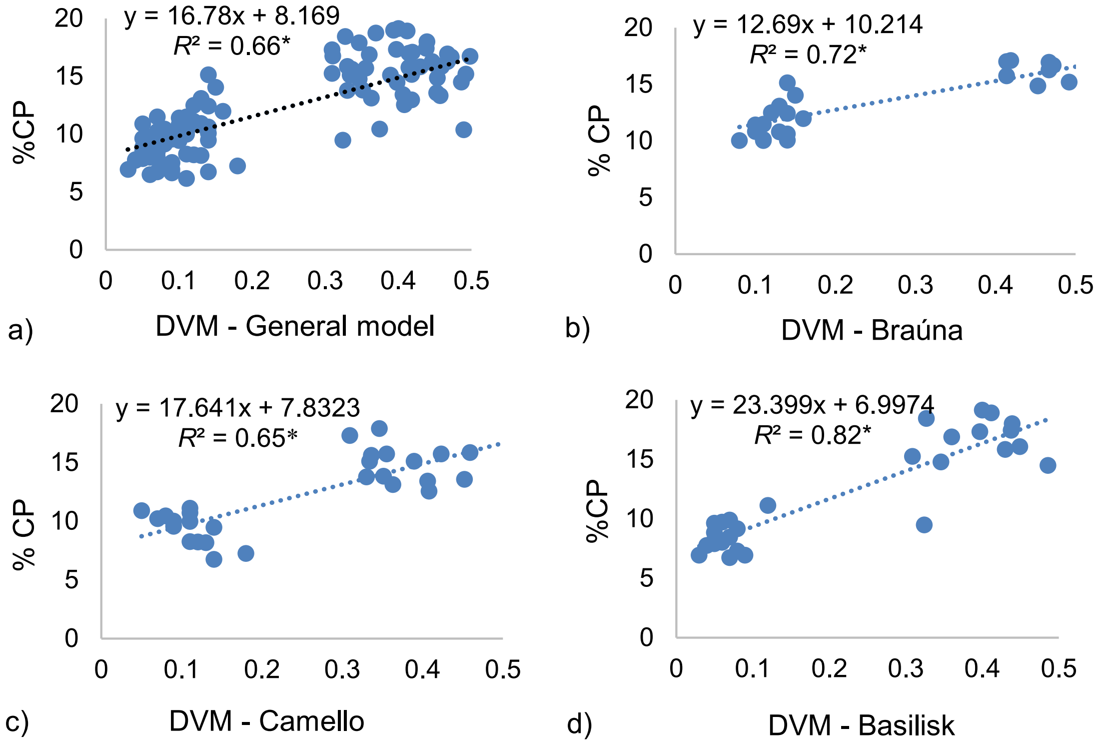


Figure 5. Regression models for estimating DM (%) with GLI.
a) general model; b) cv. Bráuna; c) cv. Camello; d) cv. Basilisk; e) BRS Paiaguás. *significant at 1%.

The DM estimation was negatively correlated with the GLI, meaning that the higher the GLI, the lower the DM of the forage. This behaviour is expected, as DM is closely associated with plant maturity (Stabile et al., 2010). As the plant matures, there is a greater accumulation of DM, resulting from the elongation of leaves and, especially, the stem, leading to thickening and lignification of the cell wall (Deschamps, 1999). Consequently, there is a lower concentration of non-structural compounds, such as pigments, lipids, and nitrogen.

The regression model for estimating CP was based on the vertical index of the DVM, which showed positive and significant correlations. The general model has an R^2

fit of 0.66 (Fig. 6, a). When analysing the cultivars separately, better fits were observed for the Braúna (R^2 of 0.72) (Fig. 6, b) and Basilisk (R^2 of 0.82) (Fig. 6, d) cultivars, with increases of 9.09% and 24.24%, respectively, compared to the general model. In contrast, the Camello (Fig. 6, c) and BRS Paiaguás (Fig. 6, e) cultivars showed R^2 values of 0.65 and 0.54, respectively, demonstrating moderate and significant correlations, although lower than the general model.



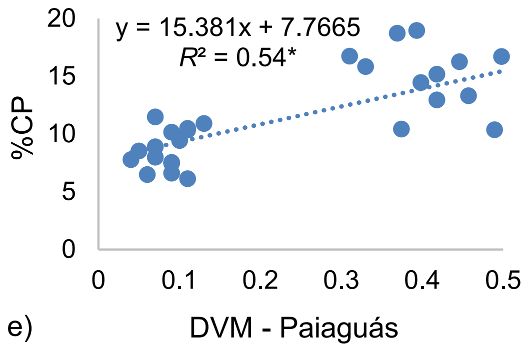


Figure 6. Regression models for CP at 20 m flight height.
a) Geral; b) cv. Bráuna; c) cv. Camello; d) cv. Basilisk; e) BRS Paiaguás. *significant at 1%.

The predictive model for CP demonstrated better performance with the DVM index ($R^2 = 0.66$). Although GLI demonstrated a significant positive correlation for the CP model, it correlation was considered weak, with negligible gains (0.019 units). A strong positive correlation is observed in the predictive model when analysed by cultivar, with the Basilisk cultivar showing an R^2 of 0.82, highlighting the potential of this model for estimating %CP. Satisfactory correlations were also observed for the other grasses.

These results are similar to those found in studies using RGB images, such as those for peanut crops ($R^2 = 0.98$) (Janani & Jebakumar, 2023) and rice ($R^2 = 0.82$) (Shi et al., 2021), and surpass those found in maize research ($R^2 = 0.47$) (Lu et al., 2021). However, these studies focused on estimating plant nitrogen content, whereas the predictive model in this study demonstrated better R^2 results by utilising the digital vegetation model.

The low GLI performance in estimating CP may reflect the fact that visible light alone cannot indicate changes in the nutrient components of leaves, particularly nitrogen content (Jin et al., 2020). Studies indicate that better predictions are obtained in models that utilise multispectral and hyperspectral cameras, which capture bands from the infrared and near-infrared spectrum, and these models are proven to be more sensitive in capturing the structural and nutritional characteristics of plants (Prey et al., 2018).

Thus, given that the predictive model for CP is derived from the DVM, which considers the structural characteristics of the plant, this index has excellent potential for predicting CP in tropical grasses of the genus *Urochloa*, explaining up to 82% of the variation in the data. The potential of this model achieves strong and significant correlations, similar to research that utilised multispectral cameras to estimate nitrogen levels in leaves of maize crops (Wei et al., 2019), which explained 80% or more of the variation in the data.

The use of RGB images in photogrammetric processing presents a promising alternative for predicting the yield of fresh and/or dry forage mass, as well as the levels of dry matter and crude protein in pasture, as reported by Gruner et al. (2019) and Acorsi et al. (2019). It is important to consider the specificity that must be observed in the field to obtain these data efficiently. The better performance of the predictive models for each cultivar results from the particularities of each species, reflected in their morphological and structural characteristics.

As observed by Varlet-Grancher et al. (1989) and Santos et al. (2011), foliar pigments, along with leaf size and angle, plant arrangement, species, and management practices, influence the efficiency of solar light absorption and consequently the reflectance of RGB bands. However, to date, no studies have successfully related these attributes to RGB sensor capacity for estimating the forage mass of tropical grasses. Nevertheless, the present study highlights that the morphological and structural characteristics of tropical grasses may interfere with the expression of digital indices.

CONCLUSIONS

To estimate the production of fresh mass and dry mass, it is recommended to conduct a flight at an altitude of 100 m and extract the green leaf index. To estimate the DFY, a flight at an altitude of 20 m is necessary, extracting both the GLI and DVM. Finally, to estimate the CP of the pasture, a flight at 20 metres should also be conducted, extracting only the DVM. Based on the models developed in this study, the efficient application of these methods should consider the specific objective - be it green or dry mass production - and the grass species that comprise the pasture. In this way, it is possible to define the most suitable flight altitude and obtain reliable results.

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