

Estimating growth attributes of Tifton85 forage using unmanned aerial vehicles and multivariate models¹

Estimativa de atributos de crescimento da forrageira Tifton85 utilizando veículos aéreos não tripulados e modelos multivariados

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HIGHLIGHTS:

A single principal component from multispectral drone imagery captures 99.94% of vegetation index variance for Tifton85 forage modeling.

The crop growth index (CGI) summarizes vegetation indices into a single weighted composite indicator.

CGI-based maps effectively represent the spatial variability of forage attributes.

ABSTRACT: Spatial and temporal variability of spectral responses creates challenges for developing models to estimate crop growth attributes, requiring more robust modeling approaches. This study proposes a protocol to generate multivariate models that estimate the growth attributes of Tifton85 forage (*Cynodon* spp.) from spectral responses derived from multispectral images by unmanned aerial vehicles. The experiment was conducted in a production area in Seropédica, Rio de Janeiro, Brazil. At each evaluation date, plant chlorophyll index, plant height, and leaf area index were measured. Multispectral images captured by a camera mounted on an unmanned aerial vehicle were also collected to calculate vegetation indices. Principal component analysis was used to develop an index that integrates vegetation indices over the crop growth period (CGI, crop growth index). Estimation models and spatial variability maps were generated from the linear relationship between crop growth attributes and the CGI. The responses of the vegetation indices were combined into a single principal component, which explained 99.94% of the variance. Models based on the CGI achieved greater accuracy than univariate models and produced spatial-variability maps consistent with observed crop growth attributes. These findings indicate that the CGI has strong potential for estimating Tifton85 growth attributes and is particularly effective for crops exhibiting high spatial and temporal variability.

Key words: *Cynodon* spp., remote sensing, pasture management, vegetation indices

RESUMO: A variabilidade espacial e temporal das respostas espectrais cria desafios para o desenvolvimento de modelos destinados a estimar atributos de crescimento das culturas, exigindo abordagens de modelagem mais robustas. Este estudo propõe um protocolo para gerar modelos multivariados capazes de estimar os atributos de crescimento da forragem Tifton85 (*Cynodon* spp.) utilizando respostas espectrais de imagens multiespectrais adquiridas por Veículos Aéreos Não Tripulados. O experimento foi conduzido em uma área de produção localizada em Seropédica, Rio de Janeiro, Brasil. Em cada época de avaliação, foram mensurados o teor de clorofila das plantas, a altura das plantas e o índice de área foliar. Imagens multiespectrais capturadas por uma câmera acoplada a um veículo aéreo não tripulado também foram coletadas para o cálculo dos índices de vegetação. A análise de componentes principais foi utilizada para desenvolver um índice integrando os índices de vegetação ao longo do período de crescimento da cultura (ICC - índice de crescimento da cultura). Modelos de estimativa e mapas de variabilidade espacial foram gerados a partir da relação linear entre os atributos da cultura e o ICC. As respostas dos índices de vegetação foram consolidadas em um único componente principal, que explicou 99,94% da variância. Os modelos baseados no ICC apresentaram maior acurácia que os modelos univariados e produziram mapas de variabilidade espacial consistentes com os atributos de crescimento observados. Esses resultados indicaram que o ICC possui forte potencial para estimar os atributos de crescimento do Tifton85, sendo particularmente eficaz para culturas que apresentam alta variabilidade espacial e temporal.

Palavras-chave: *Cynodon* spp., sensoriamento remoto, manejo de pastagem, índices de vegetação

INTRODUCTION

Agriculture is the foundation of food security and a major economic pillar for many countries. According to the most recent land-use estimates, permanent pastures covered approximately 3.23 billion hectares worldwide in 2023, accounting for about 67% of global agricultural land (FAO, 2025). Given their economic relevance and the need to improve pasture management, developing efficient methods to optimize the management and monitoring of agricultural systems is essential.

Forage crops are the primary feed source for livestock and must sustain year-round livestock nutritional requirements (İleri & Koç, 2022). Among these crops, Tifton85 (*Cynodon* spp.) stands out due to its digestibility, crude protein content, high dry matter yield, and excellent nutritional value (Souza et al., 2020). Its production cycle typically ranges from 30 to 60 days and is shorter in regions with high temperature and humidity, or when irrigation and nitrogen fertilization are applied (Medeiros et al., 2024).

Precision agriculture techniques have become an important strategy for improving forage crop management. These techniques increase yield, provide greater control of nutritional values, optimize input use, and generate detailed information on the spatial variability of soil and crop growth attributes, which support more efficient pasture management (Ali & Kaul, 2025). Combining an advanced understanding of grazing dynamics with data from plant and soil monitoring sensors has further expanded the potential of precision agriculture for pasture systems (Saini & Yadav, 2024).

Remote sensing technologies play a key role in these systems, enabling cost-effective crop monitoring, timely information acquisition, and indirect estimation of crop condition and growth parameters (Barros et al., 2021; Souza et al., 2024). High-resolution multispectral images obtained with unmanned aerial vehicles (UAVs) combine spatial detail, operational flexibility, and data accuracy, making them valuable for estimating forage attributes related to biomass production (Théau et al., 2021). Vegetation indices (VIs) derived from these images are correlated with biophysical and productive parameters and provide a non-destructive means of estimating productivity (Bazrafkan et al., 2023), biomass (Meshesha et al., 2020), nitrogen content (Calderón et al., 2020), plant height, and leaf area index (Fonseca & González, 2022).

Traditionally, estimation models using VIs rely on univariate regressions because of their simplicity and interpretability. However, univariate models often fail to account for interactions among multiple independent variables, reducing their predictive accuracy. Advances in computing capacity now make it possible to use multivariate models that incorporate several VIs simultaneously. These models are more robust, capture complex patterns in the data, and reduce prediction uncertainty (Behpour et al., 2023). In the case of forage crops, recent studies have prioritized multivariate and machine learning models, integrating spectral bands and vegetation indices with meteorological and ecological factors to estimate biomass (Alckmin et al., 2022), leaf area (Wang et al., 2023),

nutritional attributes (Zwick et al., 2024), and other variables of zootechnical and agronomic interest.

Applying multivariate approaches to examine the relationships between VIs and forage crop growth attributes offers significant potential for real-time pasture management, particularly in areas with high spatial variability caused by topography, management practices, or environmental conditions during the production cycle. This study proposes a protocol for generating multivariate models to estimate the growth attributes of Tifton85 forage from the spectral responses of UAV-acquired multispectral images.

MATERIAL AND METHODS

The experiment was conducted at FenoRio Farm in a commercial Tifton85 forage (*Cynodon* spp.) production area in Seropédica, Rio de Janeiro State, Brazil (22° 47' 05" S, 43° 40' 44" W). The predominant soil was classified as Ultisols (Soil Survey Staff, 2022). According to Köppen's classification, the region has an Aw climate, characterized by a tropical regime with a rainy summer and a dry winter.

The study area covered 0.7 ha (Figure 1), and the experiment lasted 48 days, from May to June 2023 (fall), starting after the forage standardization harvest. Within the experimental area, 39 georeferenced sampling points were established using a high-precision GNSS (Global Navigation Satellite System) receiver (Hiper V, Topcon, Japan) with horizontal and vertical accuracies of 5 mm + 0.5 ppm and 10 mm + 0.8 ppm, respectively.

To standardize crop growth, Tifton85 was cut to a height of 0.05 m using a brush cutter attached to the hydraulic lift system and the PTO (540 rpm) of a John Deere 5403 tractor (65 HP). Fertilization was performed five days later, applying 100 kg ha⁻¹ of urea (46-00-00 NPK) in a single application, as described by Souza et al. (2024). The fertilizer was distributed with a rotary-disc spreader coupled to a Massey Ferguson 4275 tractor (75 HP).

Multispectral images were collected during five evaluation periods using a UAV (Phantom 4 Multispectral, SZ DJI Technology, China). The first flight was performed ten days after the standardization cut, and subsequent flights followed the schedule shown in Table 1. Flight intervals were defined to coincide with visible changes in crop height and biomass accumulation.

The UAV used for image acquisition was equipped with a 20-MP multispectral camera capable of capturing images in five spectral bands: Band 1 – Blue (450 ± 16 nm), Band 2 – Green (560 ± 16 nm), Band 3 – Red (650 ± 16 nm), Band 4 – Red Edge (730 ± 16 nm), and Band 5 – Near Infrared (840 ± 16 nm). A radiometer mounted on top of the UAV measured solar irradiance, enabling subsequent radiometric correction of the imagery.

Flights were planned with 80% forward longitudinal overlap and 70% side overlap. Images were captured at a flight altitude of 90 m, producing 305 images (61 per band) with a ground sample distance (GSD) of 4.67 cm pixel⁻¹ during a 5-min flight. Orthorectification, aerial triangulation, and

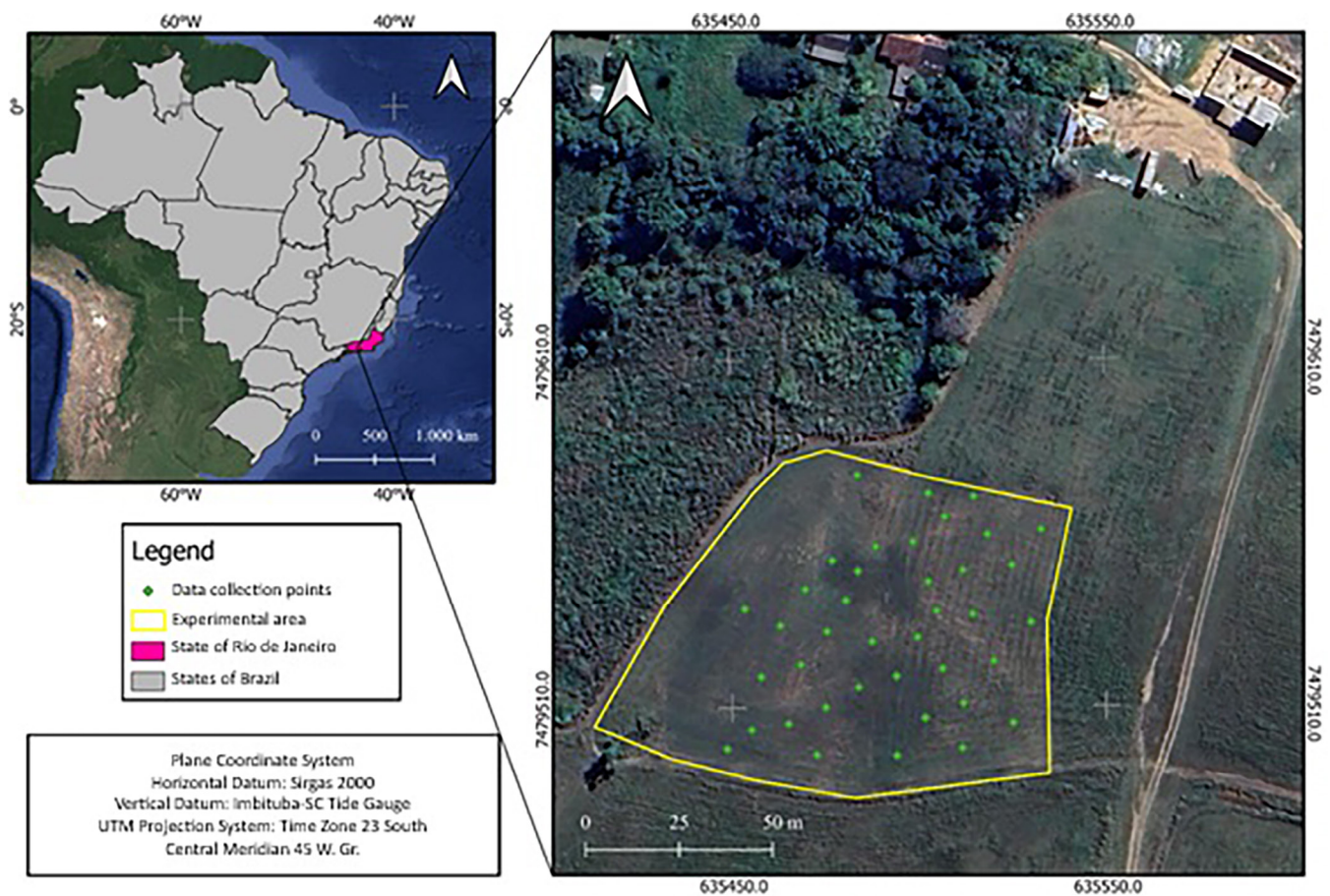


Figure 1. Location of the experimental site (Fazenda FenoRio/UFRRJ) with 39 georeferenced sampling points, in Seropédica, Rio de Janeiro State, Brazil

Table 1. Schedule of unmanned aerial vehicles (UAVs) based crop assessments and attribute monitoring

Evaluation period (EP)	Date	Days after the standardization cut	Intervals between assessments
1st EP	05/15/2023	10 days	---
2nd EP	05/22/2023	17 days	7 days
3rd EP	06/07/2023	33 days	16 days
4th EP	06/14/2023	40 days	7 days
5th EP	06/22/2023	48 days	8 days

radiometric and geometric corrections were performed in Agisoft® Metashape using default settings to generate the orthomosaic for each flight date. Vegetation indices (VIs; Table 2) were then calculated in QGIS by creating a 1-m radius buffer around each of the 39 georeferenced points and computing the mean VI value within each buffer. The VIs used were: Green Normalized Difference Vegetation Index (GNDVI) (Gitelson, 1996), according to Eq. (1); Normalized Difference Vegetation Index (Rouse Jr et al., 1973), by Eq. 2; Normalized Green-Red Difference Index (Hunt et al., 2005), by Eq. 3; Ratio Vegetation Index (Jordan, 1969), by Eq. 4; Soil-Adjusted Vegetation Index (Huete, 1988), by Eq. 5; Visible Atmospherically Resistant Index (VARI) (Gitelson et al., 2002), by Eq. 6; and Visible Difference Vegetation Index (Xiaoqin et al., 2015), by Eq. 7.

$$\text{GNDVI} = \frac{(\text{NIR} - \text{G})}{(\text{NIR} + \text{G})} \quad (1)$$

$$\text{NDVI} = \frac{(\text{NIR} - \text{R})}{(\text{NIR} + \text{R})} \quad (2)$$

$$\text{NGRDI} = \frac{(\text{G} - \text{R})}{(\text{G} + \text{R})} \quad (3)$$

$$\text{RVI} = \frac{(\text{NIR})}{(\text{R})} \quad (4)$$

$$\text{SAVI} = \frac{(\text{NIR} - \text{R})}{(\text{NIR} + \text{R} + \text{L}) * (1 + \text{L})} \quad (5)$$

$$\text{VARI} = \frac{(\text{G} - \text{R})}{(\text{G} + \text{R} - \text{B})} \quad (6)$$

$$\text{VDVI} = \frac{(2 * \text{G} - \text{R} - \text{B})}{(2 * \text{G} + \text{R} + \text{B})} \quad (7)$$

Where:

R - reflectance in the red band of the visible spectrum;

G - reflectance in the green band;

B - reflectance in the blue band;

NIR - reflectance in the near-infrared band; and,

L - soil-adjustment constant used to minimize the influence of soil background, with values ranging from 0 to 1: L = 1 is applied to low vegetation densities, L = 0.5 to medium densities, and L = 0.25 to high densities. In this study, L was set to 1 because the pasture exhibited low vegetation density (Ponzoni et al., 2012).

Plant height, leaf area index (LAI), and chlorophyll index were measured at 39 georeferenced sampling points randomly distributed across the experimental area. Data were collected at five evaluation periods, coinciding with the UAV imagery, yielding 195 measurements per growth attribute.

Plant height was determined by taking five measurements around each georeferenced point using a graduated ruler with millimeter precision. The mean of these five measurements was recorded as the value for that point (Li et al., 2024).

LAI was measured using a ceptometer (LP-80 AccuPAR, METER Group, USA). Measurements were taken with the sensor bar positioned at ground level below the crop canopy, while an external sensor was placed above the canopy to provide a reference for incident radiation. The instrument estimates LAI based on the relationship between photosynthetically active radiation measured above and below the canopy. Five measurements were taken at each sampling point, with the ceptometer rotated between readings (Campbell & Norman, 1998).

The chlorophyll index of Tifton85 biomass was determined using a portable meter (Chlorophyll CF1030, Falker™). For this analysis, readings associated with chlorophyll b were used, expressed in Falker units (uF), corresponding to absorption peaks at 453 nm (blue) and 642 nm (orange region). Chlorophyll b was selected for its association with light-harvesting complexes, enabling assessment of adjustments in light capture across different growth conditions.

Crop growth and development are closely related to air temperature. Monitoring crop development using degree-days is a widely adopted approach in agricultural planning (Zhou et al., 2025) because it tracks thermal time rather than chronological time, providing a more accurate estimate of the period required for a crop to reach a given phenological stage.

During the experiment, air temperature and relative humidity (RH) were recorded by the automatic surface weather station of the National Institute of Meteorology (INMET), located in Seropédica (22° 45' 13" S, 43° 40' 23" W; and 35 m elevation).

Degree-day (DD) accumulation was calculated using the smallest standard deviation method proposed by Arnold (1959), also known as the residual method (Eq. 8). For these calculations, the maximum and minimum daily temperatures corresponding to the dates of UAV image acquisition were used.

$$GDD = \sum_i^n \left[\left(\frac{T_{\max_i} + T_{\min_i}}{2} \right) - T_{\text{base}} \right] \quad (8)$$

Where:

GDD - degree-days (°C);

$T_{\max}$ - daily maximum air temperature (°C);

$T_{\min}$ - daily minimum air temperature (°C); and,

T_{base} - base temperature (°C), which in this study was set at 10 °C (Cooper & Tainton, 1968).

Degree-days were calculated for each interval to quantify the thermal time accumulated during the study period. Cumulative degree-days were obtained by summing the values from successive intervals, and their proportion relative to the total accumulated degree-days between the standardization cut and the harvest of Tifton85 was also determined.

Based on the distribution of crop attribute values throughout the evaluation period, simple regression analyses were performed using growing degree days (GDD) as the independent variable. GDD was used as a thermal-time indicator to track crop development over time. The dependent variables included leaf area index (LAI), chlorophyll index, and plant height, which are commonly used indicators of crop growth and physiological status. LAI represents the total leaf area per unit ground area and reflects canopy development; the chlorophyll index indicates the photosynthetic potential and nutritional status of the plants; and plant height is associated with vegetative growth and biomass accumulation. These variables were selected because they are widely used as indicators of forage growth and can also be related to spectral information obtained from multispectral imagery.

To describe the variability of chlorophyll index, plant height, and LAI, the coefficient of variation and standard deviation were calculated from the values obtained at each evaluation period. Simple linear regressions were then fitted between each plant attribute and the vegetation index (VI) showing the highest correlation, and the strength of these relationships was assessed using the coefficient of determination.

Subsequently, the VIs were analyzed through principal component analysis (PCA) performed in RStudio 4.3.3. PCA was applied to identify patterns in the data structure, reduce dimensionality, and select the most relevant indices. The data matrix comprised 195 observations and seven variables (VIs). PCA was based on the correlation matrix, which standardizes all variables to unit variance before extraction. This approach is appropriate when variables are measured on different scales, as it prevents variables with larger variances from disproportionately influencing the principal components.

For each principal component (PC), the explained variance and cumulative explained variance were calculated. The most relevant PC (i.e., the one with the highest explanatory power) was selected. The correlations and loadings (coefficients) between the spectral indices and the relevant PCs were evaluated. The loadings associated with the relevant PC were used to construct a composite crop growth index (CGI).

Finally, multivariate models were developed to estimate Tifton85 growth attributes from the linear relationships between crop growth attributes and the CGI. Model performance was evaluated using the root mean square error (RMSE), to emphasize larger deviations, the mean absolute error (MAE), which provides a measure of the average magnitude of the error, and bias, which allows the assessment of systematic overestimation or underestimation by the models. In addition, residual diagnostics were performed to verify the validity of model assumptions and to support the reliability of statistical inferences and predictive performance. Heteroscedasticity in the residuals was assessed using the Breusch–Pagan test, and residual independence was examined using the Durbin–Watson test. All statistical tests were conducted at $p \leq 0.05$ using PAST software (version 4.03). The resulting equations were implemented in QGIS to generate spatial maps of crop growth attributes based on the multivariate CGI.

RESULTS AND DISCUSSION

Analysis of thermal accumulation during the experiment (Table 2) showed a progressive increase in degree-days throughout the evaluation period, reaching a cumulative total of 548.692 °C day. The highest single-day value was recorded at the start of the experiment, at the time of the standardization cut, when 13.9 °C was accumulated. The largest increase in cumulative degree-days occurred between the second and third evaluation periods (2EP and 3EP), corresponding to a proportional gain of 32.23%. Although the observed relationship between GDD and crop growth attributes suggests that thermal accumulation plays a fundamental role in biomass production, interpreting these results should consider that GDD captures only part of the complexity of forage growth dynamics (Zhou et al., 2025). These results suggest that peak biomass production likely occurred at the 3EP stage.

The pattern of thermal accumulation was consistent with the physiological response of forage grasses, in which

temperature-driven metabolic activity enhances leaf expansion and canopy development, directly influencing attributes such as plant height and leaf area index (LAI) (Cruz et al., 2021).

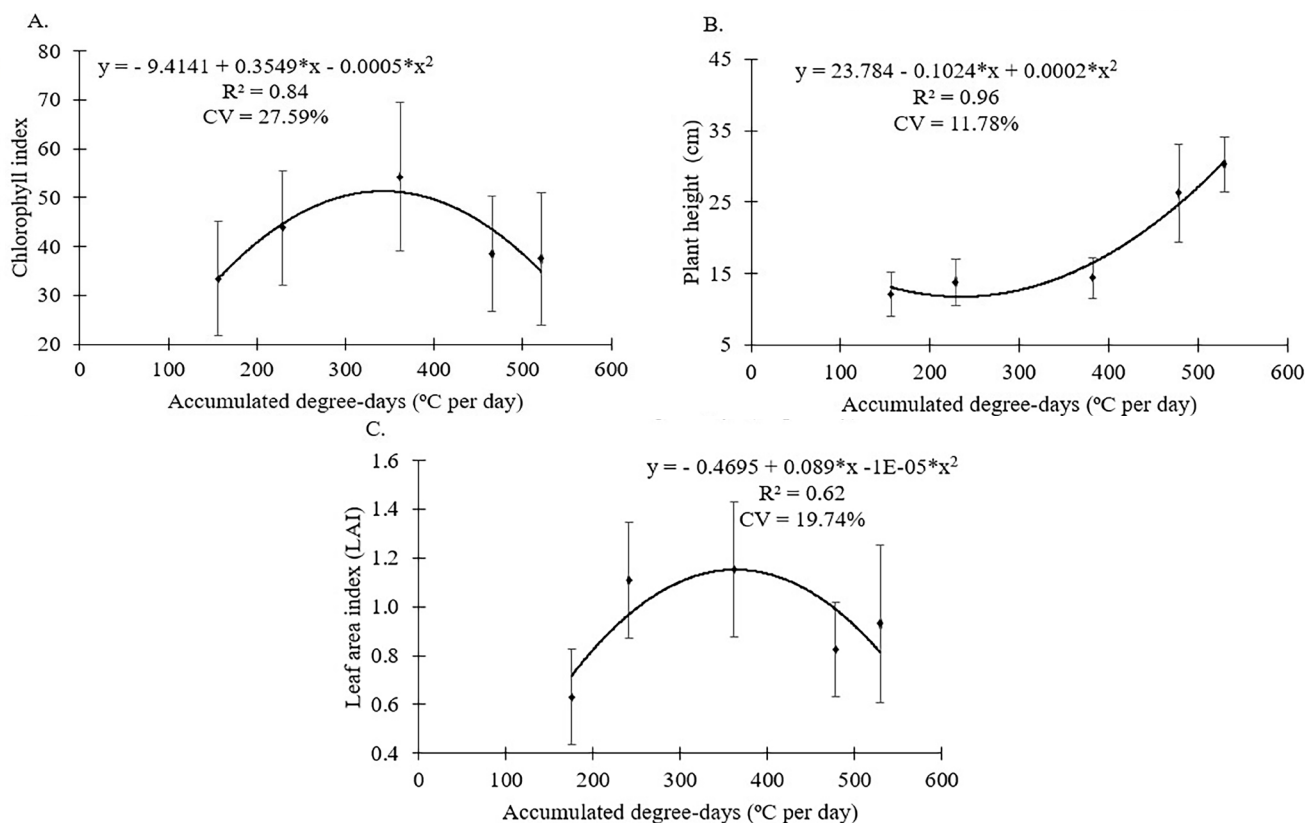
Although GDD provides a useful indicator of crop development, it represents a simplified model that assumes temperature as the main driver of growth (Kim et al., 2024). However, forage biomass production is also influenced by other factors, such as water availability, solar radiation, and nutritional status, which are not explicitly accounted for in the thermal model. In addition, using a constant base temperature (10 °C) may not fully capture the variability in physiological thresholds across different growth stages of the Tifton85 variety.

Analysis of Tifton85 attributes as a function of cumulative GDD showed that chlorophyll index, plant height, and LAI followed a pattern best described by second-degree polynomial regression. For chlorophyll (Figure 2A) and LAI (Figure 2C), the concave, downward-oriented trend lines indicate a maximum point near 350 °C day, corresponding to the accumulation observed between the second and third

Table 2. Accumulated degree-days recorded for each evaluation period (EP) throughout the experiment

Period	Cut	1 EP	2 EP	3 EP	4 EP	5 EP
Number of days	0	10	17	33	40	48
GDD	13.863	10.879	10.917	9.746	12.858	10.258
GDDa	13.863	136.544	205.031	381.892	465.479	548.692
R (%)	2.526	22.359	12.482	32.233	15.234	15.166
Ra (%)	2.526	24.885	37.367	69.600	84.834	100.000

GDD - Growing degree-days; GDD_a - Accumulated growing degree-days; R - Rate (%); R_a - Accumulated rate (%); Cut - Standardization cut; 1 EP - 10 days after the standardization cut; 2 EP - 17 days after the standardization cut; 3 EP - 33 days after the standardization cut; 4 EP - 40 days after the standardization cut; 5 EP - 48 days after the standardization cut



* - Significant at $p \leq 0.05$ by the F-test. Vertical bars represent the standard deviation of the mean

Figure 2. Effect of the relationship between chlorophyll index and accumulated degree-days on Tifton85 forage growth (A), relationship between plant height and accumulated degree-days on Tifton85 forage growth (B), and relationship between leaf area index (LAI) and accumulated degree-days on Tifton85 forage growth (C)

evaluation periods (2EP and 3EP). For plant height (Figure 2B), a consistent upward trend was observed throughout the experiment; however, after approximately 300 °C per day of accumulation, the growth rate increased more sharply.

This growth response depends on several factors, including heat accumulation (Marchegiani et al., 2025), time of year (Medeiros et al., 2024), and fertilization practices (Qin et al., 2023).

The interaction among these factors can lead to significant variation in pasture productivity. Based on the analysis of leaf area index and chlorophyll, an early harvest at 3EP (33 days after the uniformity cut) could have been carried out. In forage crop systems, multiple harvests are commonly performed during the growth cycle, and these successive cuts often allow the crop to regain peak vigor more quickly, improving both forage yield and quality (Mello et al., 2023).

Remote sensing techniques have been widely applied to monitor and estimate crop growth attributes by relating them to vegetation indices (VIs) (Vidican et al., 2023). In this study, as shown in Table 3, the NGRDI, VARI, and VDMI indices exhibited the smallest differences between their mean and median values (less than 0.01), indicating distributions concentrated around their central values and low variability.

Analysis of kurtosis showed that the GNDVI, NDVI, and SAVI indices had leptokurtic distributions, characterized by pronounced peaks and heavy tails. In contrast, NGRDI, VARI, and VDMI showed platykurtic distributions, indicating flatter curves, while RVI displayed a mesokurtic distribution, with values closest to a normal distribution. Regarding skewness, only the RVI index was right-skewed; all other VIs were left-skewed. Based on the classification proposed by Warrick & Nielsen (1980), the coefficient of variation indicated that GNDVI exhibited low variability ($CV < 12\%$), whereas all other VIs showed medium variability ($12\% < CV < 60\%$).

Vegetation indices are widely used in agriculture because they provide a direct and reliable assessment of crop conditions (Chatterjee et al., 2025). However, generating large

datasets poses challenges, particularly the need for robust computational resources (Stellacci et al., 2021). Moreover, field-collected data are subject to external factors, such as soil and plant heterogeneity, environmental conditions, fertilization, and crop management, which increase variability and complicate traditional univariate analyses.

Several studies have highlighted how spatial heterogeneity influences the quality of VI datasets. For example, Andrade et al. (2024) used VIs derived from UAV imagery to estimate agronomic attributes of *Urochloa ruziziensis*. Their estimation maps showed that areas with exposed soil or damage from pasture spittlebugs (*Deois flavopicta*) affected biomass estimates compared with areas with healthy crop development. Similarly, Santos et al. (2020) observed that temporal variation in climate, especially rainfall and temperature, limited the correlation between VIs and chlorophyll in coffee plantations. During the dry season, water deficits caused by low precipitation reduced the predictive capacity of VIs.

Such variability makes univariate models inadequate, as they consider each variable in isolation, without accounting for interactions among variables. In the present study, univariate models produced poor results, with linear coefficients of determination (R^2) below 0.30, primarily due to high spatial variability caused by weeds, sloping terrain, and the absence of topdressing. In these cases, a multivariate approach, such as the crop growth index (CGI), offers a promising alternative for modeling crop growth attributes, even under conditions of pronounced heterogeneity.

Under conditions of high data variability, multivariate analyses provide a better understanding of the complex interactions within agricultural systems. This advantage has been demonstrated by Souza et al. (2024), who analyzed the relationships between spectral indices and nutritional parameters of Tifton85 forage (*Cynodon* spp.) using RGB and RG-NIR images captured at different intervals after the standardization cut. Their multivariate models achieved coefficients of determination greater than 0.85.

In this study, PCA was applied to the VIs derived from UAV images to evaluate the response of Tifton85. The first

Table 3. Descriptive statistics of vegetation indices calculated from unmanned aerial vehicles (UAVs) multispectral data

	GNDVI	NDVI	NGRDI	RVI	SAVI	VARI	VDMI
Number of samples	195	195	195	195	195	195	195
Mean	0.4843	0.5822	0.1458	4.1178	0.8732	0.1110	0.2177
Median	0.4970	0.6012	0.1539	4.1381	0.9016	0.1175	0.2243
Minimum	0.3122	0.3060	-0.0065	1.9142	0.4589	-0.0056	0.1107
Maximum	0.5886	0.7679	0.3279	7.6858	1.1516	0.2519	0.3513
Range	0.2764	0.4619	0.3344	5.7716	0.6927	0.2574	0.2406
Standard deviation	0.0568	0.0912	0.0627	1.0540	0.1367	0.0479	0.0442
Normality (p-value)	0.000018*	0.0000036*	0.00396*	0.2375 ^{ns}	0.0000037*	0.0342 ^{ns}	0.0173*
Kurtosis	0.1539	0.2415	-0.2345	-0.0399	0.2414	-0.2058	-0.2734
Skewness	-0.7211	-0.7912	-0.2431	0.1957	-0.7911	-0.2416	-0.1696
Sum	94.4341	113.5298	28.4327	802.9715	170.2661	21.6496	42.4420
CV (%)	11.73	15.66	43.00	25.60	15.66	43.15	20.30

GNDVI - Green normalized difference vegetation index; NDVI - Normalized difference vegetation index; NGRDI - Normalized green-red difference index; RVI - ratio vegetation index; SAVI - Soil-adjusted vegetation index; VARI - Visible atmospherically resistant index; VDMI - Visible difference vegetation index; Normality test - * - Significant and ns - Not significant at $p \leq 0.05$ according to the Shapiro-Wilk test, respectively

principal component (PC1) alone accounted for 99.94% of the variation in spectral indices associated with Tifton85 growth (Table 4). This result indicates that a single component can effectively summarize most of the variability in the VIs. The eigenvalues greater than 1 further support the reduction of the original variables to a single principal component.

The very high proportion of variance explained by PC1 (99.94%) reflects the strong collinearity between the VIs used in this study. Since PCA was performed based on the correlation matrix, all variables were standardized, ensuring that scale differences did not influence the results. The fact that the VIs were derived from specific spectral bands (R, G, B, and NIR) enabled the capture of common aspects of canopy reflectance and plant vigor. Thus, the information contained in the VIs can be effectively summarized in a single dimension (PC1), supporting the use of a composite index.

Additionally, Table 5 shows the correlations between VIs and PC1, along with the corresponding coefficients (loadings). All indices exhibited strong correlations with PC1 ($r > 0.95$), indicating that this component can represent them. The loadings describe the contribution of each original variable to the component, with positive values denoting a positive association with PC1. The VIs analyzed showed similar loadings, indicating that each index contributed similarly to characterizing Tifton85 growth.

Since PC1 effectively captured the variability in VIs associated with crop growth, it was used to develop a global growth-monitoring model for Tifton85. Based on PC1, this study proposes a new index, termed the Crop Growth Index (CGI). The CGI is a weighted combination of the original VIs, with coefficients corresponding to the loadings of PC1 (Eq. 9). Higher CGI values indicate more advanced crop development.

$$\text{CGI} = C_1 \times \text{GNDVI} + C_2 \times \text{NDVI} + C_3 \times \text{NGRDI} + C_4 \times \text{RVI} + C_5 \times \text{SAVI} + C_6 \times \text{VARI} + C_7 \times \text{VDVI} \quad (9)$$

Where:

C_x - loadings associated with each original variable that compose principal component 1 (PC1).

Table 4. Eigenvalues, explained variance, and cumulative explained variance for the principal components derived from vegetation indices

Principal component	PC1	PC2	PC3
EV	6.795	0.155	0.041
ExpVar (%)	99.944	0.052	~ 0.00
CumVar (%)	99.944	99.996	~ 100

PC - Principal component; EV - Eigenvalues; ExpVar (%) - Explained variance; CumVar (%) - Cumulative explained variance

Table 5. Correlations and loadings of vegetation indices (VIs) with principal component 1 (PC1)

GNDVI	NDVI	NGRDI	RVI	SAVI	VARI	VDVI

GNDVI - Green normalized difference vegetation index; NDVI - Normalized difference vegetation index; NGRDI - Normalized green-red difference index; RVI - ratio vegetation index; SAVI - Soil-adjusted vegetation index; VARI - Visible atmospherically resistant index; VDVI - Visible difference vegetation index

Multivariate approaches integrate information from multiple spectral variables within a unified analytical framework, capturing data variability more effectively and improving the robustness of crop monitoring models (Alckmin et al., 2022).

Previous studies, such as Souza et al. (2024), also applied multivariate analysis to summarize spectral information from Tifton85. However, in that study, PCA was primarily used as a dimensionality-reduction step, and the adjusted PC1 scores were directly used as explanatory variables in quadratic regression models fitted separately for each growth stage and each quality attribute. In contrast, the present study advances this approach by using the loadings associated with PC1 to formulate an explicit composite index, the CGI, expressed as a weighted combination of the original vegetation indices. Therefore, rather than generating stage-specific models based on latent PC1 scores, the proposed approach yields a single global index with direct operational meaning, capable of synthesizing the joint spectral response of the crop throughout the evaluation period. This approach represents a methodological advance by enabling the reduction of redundancy between correlated indices, improving interpretability, and providing a standardized indicator for monitoring crop growth from multispectral images obtained by UAVs.

The distribution of sampled points on a two-dimensional plane defined by the first two principal components (PC1 and PC2) is shown in Figure 3. An increase in PC1 values from 1EP to 3EP was observed, reflecting a clear pattern of crop growth during this period. After 3EP, the points became more clustered (3EP, 4EP, and 5EP), suggesting a reduced ability of VIs to distinguish growth phases beyond this stage. These results indicate that the strongest relationships between Tifton85 attributes and VIs occur up to 3EP (33 days after the standardization cut).

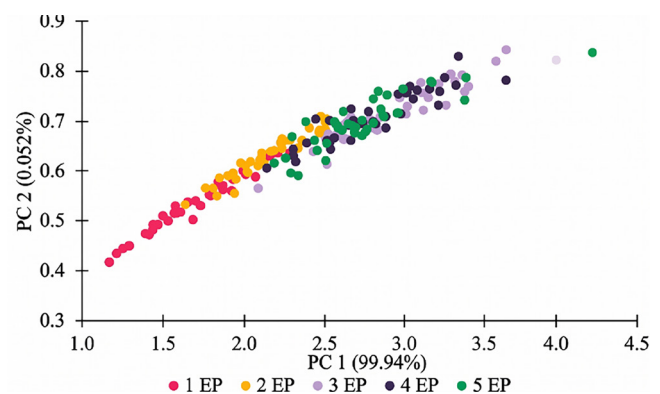


Figure 3. Two-dimensional distribution of scores for the first and second principal components (PC1 and PC2) derived from vegetation indices (VIs) across evaluation periods (EPs) during Tifton85 growth

Because the proposed CGI index is derived from PC1, higher CGI values correspond to more advanced stages of crop growth. Transitional periods may occur in which a single CGI value represents multiple growth stages. In this experiment, CGI values below 2.00 were predominantly associated with growth up to 10 days after the standardization cut (1EP). Values between 2.00 and 2.50 generally indicated growth up to 2EP (17 days), whereas values above 2.50 were associated with growth beyond 3EP (33 days). Under these experimental conditions, CGI estimates were more accurate during the early growth stages, before 33 days of Tifton85 development.

The CGI was derived from multiple spectral indices, making it a robust and comprehensive indicator of crop growth. Once calibrated to field conditions, it has strong potential as an innovative alternative index for monitoring crop growth using spectral information. Moreover, the CGI is particularly suitable for crops with high variability in growth parameters, where models based on a single VI are less effective.

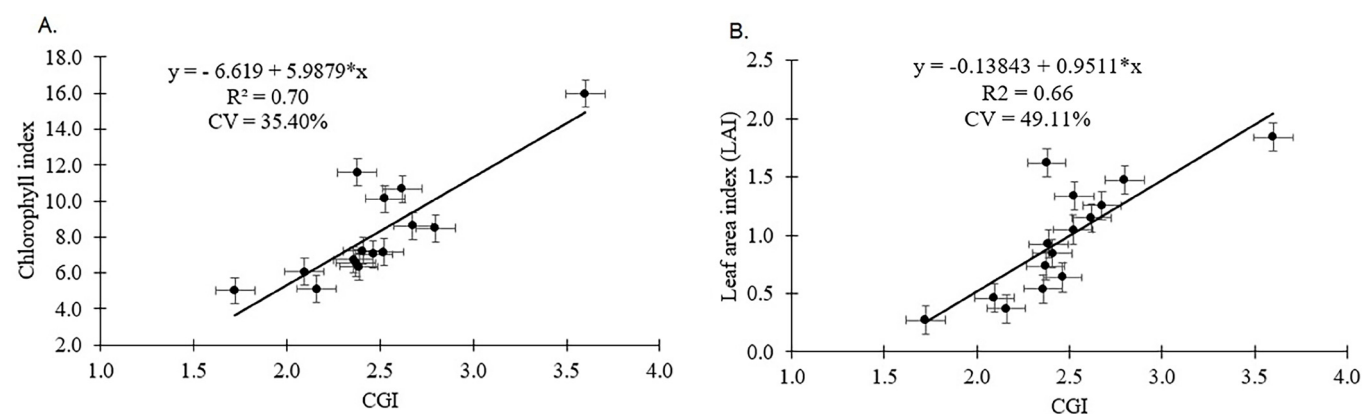
In this study, the linear relationship between CGI and crop growth attributes enabled the development of models to estimate the chlorophyll index (Figure 4A), LAI (Figure 4B), and plant height. These models achieved coefficients of determination (R^2) of 0.70, 0.65, and 0.53 for chlorophyll, LAI, and plant height, respectively. These values were higher than those obtained with univariate models based on individual VIs, demonstrating the potential of CGI to estimate crop growth attributes even under high data variability.

Additionally, model performance was evaluated using error metrics and residual diagnostics (Table 6). The lowest errors were observed for the LAI (RMSE = 0.18; MAE = 0.14), followed by chlorophyll (RMSE = 1.53;

MAE = 1.29). Plant height showed the highest error values (RMSE = 2.55; MAE = 2.07), indicating greater variability in its estimation. Bias values were close to zero across all attributes, suggesting that the model did not systematically over- or underestimate.

Residual diagnostics indicated that the chlorophyll model satisfied the assumptions of homoscedasticity and independence ($p > 0.05$), suggesting constant variance and no autocorrelation in the residuals, which supports the adequacy of the linear model and the reliability of the inferences. For LAI, the residuals showed independence ($p > 0.05$); however, heteroscedasticity ($p < 0.05$) indicates non-constant error variance across the range of fitted values. From a practical perspective, this suggests that the model is suitable for capturing trends in this attribute, although the precision of the estimates may vary across different canopy development stages. Finally, the plant height model showed evidence of heteroscedasticity and autocorrelation ($p < 0.05$), suggesting a systematic structure in the residuals. In this case, the results should be interpreted with caution, particularly when used for more precise predictive purposes.

The CGI models for the experimental area at the 1st EP (Figure 5A), 3rd EP (Figure 5B), and 5th EP (Figure 5C) generated maps of the spatial distribution of crop growth attributes across the study area. Analysis of the temporal evolution of chlorophyll showed an overall increase in chlorophyll index from 1EP (Figure 5D) to 3EP (Figure 5E). By 5EP (Figure 5F), the chlorophyll index stabilized compared to 3EP, with slight reductions observed in some areas. This pattern aligns with the response of chlorophyll to heat accumulation (Figure 2), where a peak was reached at 3EP, followed by a gradual decline during the final weeks of evaluation.



* - Significant at $p \leq 0.05$ by the F-test. Horizontal bars represent the standard deviation of the mean

Figure 4. Linear regression relating crop growth index (CGI) to chlorophyll index (A) and Leaf area index (B)

Table 6. Error metrics and residual diagnostics for observed and predicted crop growth attributes

	RMSE	MAE	Bias	Heteroscedasticity (p-value)	Autocorrelation (p-value)
Chlorophyll	1.53	1.29	0.002	0.954 ^{ns}	0.277 ^{ns}
Plant height	2.55	2.07	0.190	0.028*	0.027*
Leaf area index	0.18	0.14	0.020	0.030*	0.670 ^{ns}

RMSE - Root mean square error; MAE - Mean absolute error; Residual heteroscedasticity - * - Significant and ns - Not significant at $p \leq 0.05$ according to the Breusch-Pagan test; Residual autocorrelation - * - Significant and ns - Not significant at $p \leq 0.05$ according to the Durbin-Watson test

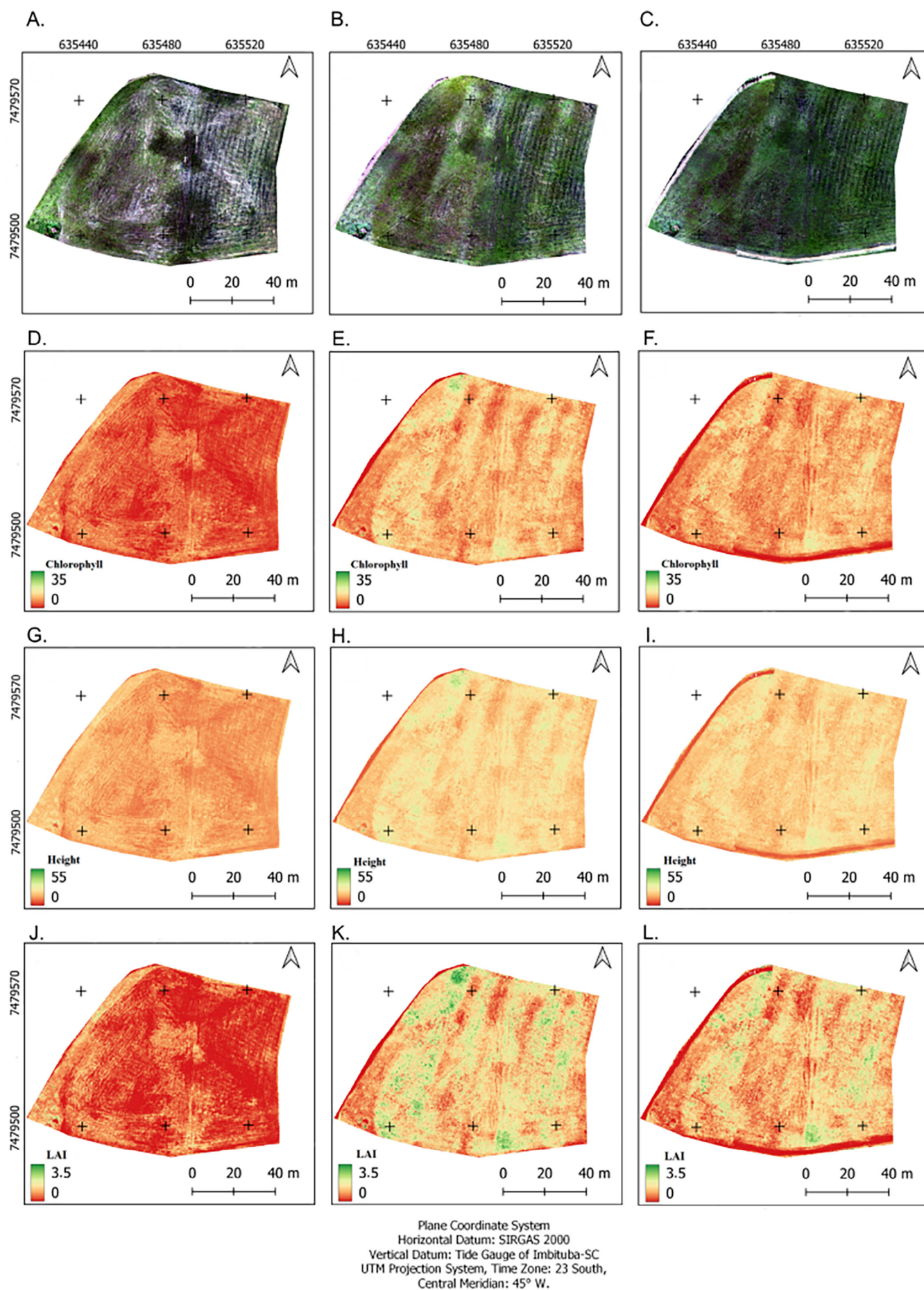


Figure 5. Unmanned aerial vehicles (UAVs) images of the experimental area obtained in each evaluation period (EP): 1EP (A), 3EP (B), and 5EP (C); and maps of estimated attributes generated from the crop growth index (CGI): chlorophyll at 1EP (D), 3EP (E), and 5EP (F); plant height at 1EP (G), 3EP (H), and 5EP (I); and leaf area index at 1EP (J), 3EP (K), and 5EP (L)

For plant height, the CGI-based maps revealed a progressive increase from 1EP (Figure 5G) through 5EP (Figure 5I), with the highest growth rates occurring between 1EP and 3EP (Figure 5H). After 3EP, height estimates stabilized. These results show that the CGI effectively captured temporal changes in plant height, highlighting the value of multivariate indices for improving spatial estimation by integrating information from multiple vegetation indices simultaneously.

The temporal evolution of LAI followed a similar trend. CGI-based maps indicated an overall increase in LAI from 1EP (Figure 5J) to 5EP (Figure 5L). However, between 1EP and 3EP (Figure 5K), localized decreases in estimated values were observed. Some areas showed model overestimation, likely due to management-related factors such as the absence of topdressing and the presence of weeds, which directly affect crop growth.

These results demonstrate that UAV-based image acquisition combined with multivariate analysis is an effective approach for estimating Tifton85 attributes, with potential applications to other forage crops. The proposed protocol provides accurate, non-destructive analyses that can support more efficient and data-driven management strategies. The maps generated from the CGI proved capable of estimating Tifton85 attributes even under high variability in the dataset. This condition often limits the performance of models based on a single vegetation index.

Therefore, the CGI models developed in this study represent a practical alternative for mitigating the effects of variability, enabling reliable estimation of crop growth attributes, and offering a valuable tool for monitoring and managing forage crops.

CONCLUSIONS

1. The use of multispectral images obtained from unmanned aerial vehicles (UAVs), combined with multivariate modeling, enabled the estimation of Tifton85 crop growth attributes (chlorophyll, plant height, and leaf area index) from spectral characteristics.

2. Principal component analysis of vegetation indices reduced the dataset's dimensionality to a single component (PC1), explaining 99.94% of the variance and revealing a strong association between the vegetation indices and the crop growth attributes, particularly up to 33 days of growth (3EP).

3. The crop growth index (CGI) proposed in this study showed potential for estimating Tifton85 attributes, providing an alternative to traditional univariate models. The CGI-based models achieved coefficients of determination of 0.70, 0.65, and 0.53 for chlorophyll index, leaf area index (LAI), and plant height, respectively, outperforming all univariate models ($R^2 < 0.30$) tested under high spatial variability conditions.

4. The maps generated from CGI-based models allowed characterization of the spatial variability of Tifton85 attributes, revealing patterns consistent with crop growth stages.

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