



# Modeling Biometric Variables of Olive Trees Using Linear Regression and Spectral Indices from UAV RGB Imagery

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## Abstract

This study evaluated the use of unmanned aerial vehicles (UAVs) to estimate biometric variables of *Olea europaea* L. in a commercial orchard in São Gabriel, Rio Grande do Sul, Brazil. A total of 349 trees were sampled for total height, stem circumference at 60 cm above ground level, and canopy dimensions. RGB imagery acquired with a DJI Mavic 3M was processed in Agisoft Metashape to generate an orthomosaic, digital models, and vegetation indices. Six RGB-derived indices were used as predictors in linear regression models for stem diameter at 60 cm, total height, and canopy area. Models including vegetation indices showed better performance, with higher adjusted  $R^2$  and lower errors. UAV-derived metrics were consistently correlated with field measurements, indicating strong potential for inventory, monitoring, and management of olive orchards.

## Keywords

Forest inventory — UAV — Digital surface models — Individual tree mapping

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## 1. Introduction

The olive (or olive fruit) is the fruit of the olive tree (*Olea europaea* L.), a species native to the Mediterranean basin, traditionally cultivated primarily for olive oil production. In its region of origin, winters are cold but do not reach temperatures below freezing. In Brazil, olive cultivation is relatively recent and is concentrated mainly in the South and, to a lesser extent, in the Southeast, due to the more favorable agroclimatic conditions for the species (LEITE & PANDOLFO, 2022; APARECIDO et al., 2024).

Belonging to the Oleaceae family, the olive tree is characterized by slow growth and great longevity, with height typically ranging from 4 to 8 meters, and potentially exceeding 15 meters in older trees. The trunks are twisted, and the crowns, generally rounded, are composed of lanceolate leaves that are green on the upper surface and silvery on the underside (BACELAR et al., 2006; SARWAR et al., 2023).

In Brazil, olive cultivation is concentrated mainly in the South and Southeast, with Rio Grande do Sul standing

out as the leading producing state and an important hub of the national olive oil chain (BELARMINO et al., 2022; APARECIDO et al., 2024).

The biometric monitoring of olive trees, with emphasis on height, diameter, and canopy area, is essential for evaluating plant development, estimating productivity, and planning management practices. However, conventional manual inventory is a costly activity that requires time, labor, and specific equipment, in addition to exposing workers to inherent field risks, such as accidents involving animals or uneven terrain that may lead to sprains or falls (FLORIANO, 2021; MARTINS et al., 2022).

Forest inventory technologies have evolved from visual assessment to computerized and remote approaches, with UAVs expanding efficiency, spatial detail, and operational safety in agricultural and forest surveys (FLORIANO, 2021).

In this context, the use of UAVs emerges as an effective technological alternative, allowing data to be collected accurately, safely, and in less time. These systems have been widely used in forest and agricultural invento-



ries, enabling the acquisition of high-resolution imagery, the generation of orthomosaics and digital surface models, and the extraction of information on plant structure and health (GIRALDELI, 2019; KOLLING & RAMPIM, 2021; ROMA & CATANIA, 2022).

Images obtained from RGB sensors onboard UAVs enable the generation of spectral indices that capture information on vegetation reflectance. These indices are related to physiological characteristics of vegetation, such as chlorophyll content, biomass, and canopy structure.

Based on these indices and traditional inventory data, statistical models can be fitted to estimate dendrometric variables with accuracy. Linear modeling, in addition to being a robust statistical tool, offers ease of interpretation and practical application, and is widely used in studies on plant growth prediction and orchard structure assessment (CARUSO et al., 2021; VACCA & VECCHI, 2024).

Therefore, the present study aimed to adjust and evaluate linear regression models to estimate stem diameter at 60 cm above ground level, total height, and canopy area of olive trees (*Olea europaea* L.), based on field biometric variables and spectral indices derived from RGB imagery obtained by UAVs, with the objective of providing accessible and interpretable tools for monitoring commercial orchards in southern Brazil.

## 2. Materials and Methods

### 2.1 Study area location and characterization

The study was conducted in an olive orchard located along highway BR-290, at kilometer 423, in the municipality of São Gabriel, Rio Grande do Sul, Brazil (Figure 1). According to the Köppen climate classification, the local climate is classified as Cfa, characterized as humid subtropical with hot summers. The region has an average annual precipitation of 1,424 mm and a mean annual temperature of 19.5 °C (ALVARES et al., 2013).

The predominant soil in the study area is poorly drained and is mostly classified as a Typical Eutrophic Haplic Planosol. The orchard covers an area of 18 hectares, and the site was previously used for rice and soybean cultivation.

Soil preparation for orchard establishment was carried out in 2015. A total of 550 kg ha<sup>-1</sup> of NPK fertilizer (10-23-20, granular), 13 t ha<sup>-1</sup> of lime, 2 t ha<sup>-1</sup> of gypsum (powdered), and 2 t ha<sup>-1</sup> of organic fertilizer (granulated) were applied. After the application of these inputs, incorporation was performed through full-area subsoiling, reaching a depth of 25 cm. Following subsoiling, raised beds with a wide base were formed and smoothly finished to avoid impairing root development. Subsequently, planting holes with a depth of 60 cm were opened, into

which 2 kg of lime and 2 kg of organic fertilizer were added and incorporated.

After soil preparation, olive seedlings were planted at a spacing of 5 m between plants and 6 m between rows. The following cultivars were established in the area: Picual (2 rows), Arbequina (4 rows), Koroneiki (2 rows), and Coratina (2 rows), oriented in a north-south direction. During the first two years after planting, irrigation was carried out during periods of water deficit. Chemical control to reduce competition with weeds was applied around the seedlings, while mechanical control was performed between rows using a tractor-mounted mower. After each winter, formative pruning was carried out to shape the trees into a polyconic vase form.

### 2.2 Orchard inventory

The field inventory was conducted using random point sampling, generated with the Random Points in Polygons tool available in the QGIS 3.34 software.

A total of 349 random points were generated, with each point representing an individual tree measured within the polygon (Figure 2). To locate the selected individuals within the orchard, trees were counted row by row, starting from the first row on the eastern side of the orchard. The counting followed an alternating pattern, proceeding from south to north in one row and from north to south in the next, in order to optimize time.

The biometric variables obtained were total height (h), stem circumference at 60 cm above ground level, subsequently converted to diameter at 60 cm above ground level ( $d_{0.6}$ ), and canopy radius measured in the north, south, east, and west directions. Total height was measured using a topographic rod graduated in centimeters up to 4 m; when trees exceeded 4 m in height, a Haglöff digital hypsometer was used. Stem circumference (CAP) was measured using a 1.50 m measuring tape, while canopy radius was measured using a 5 m measuring tape, taken at the cardinal points identified with the aid of a compass.

The canopy radii measured in the perpendicular directions N (north), S (south), E (east), and W (west) were summed, and the mean canopy diameter (dc) was subsequently calculated. Canopy area (ac) was then calculated using Equation 1.

$$ac = \pi * \frac{dc^2}{4} \quad (1)$$

Where:

ac = canopy area; dc = mean canopy diameter.

The collected data were organized and processed in a spreadsheet using Microsoft Excel software.

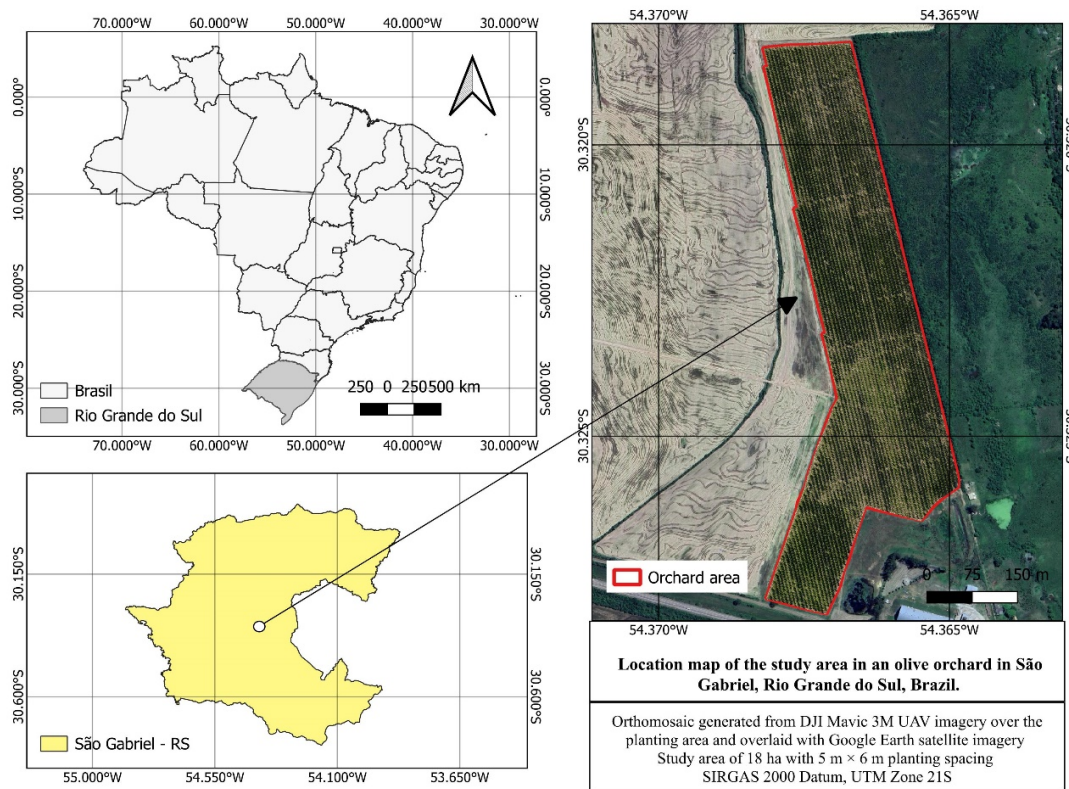
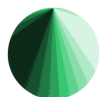


**Figure 1.** Location map of the study area of an *Olea europaea* L. orchard in the municipality of São Gabriel, RS, Brazil.

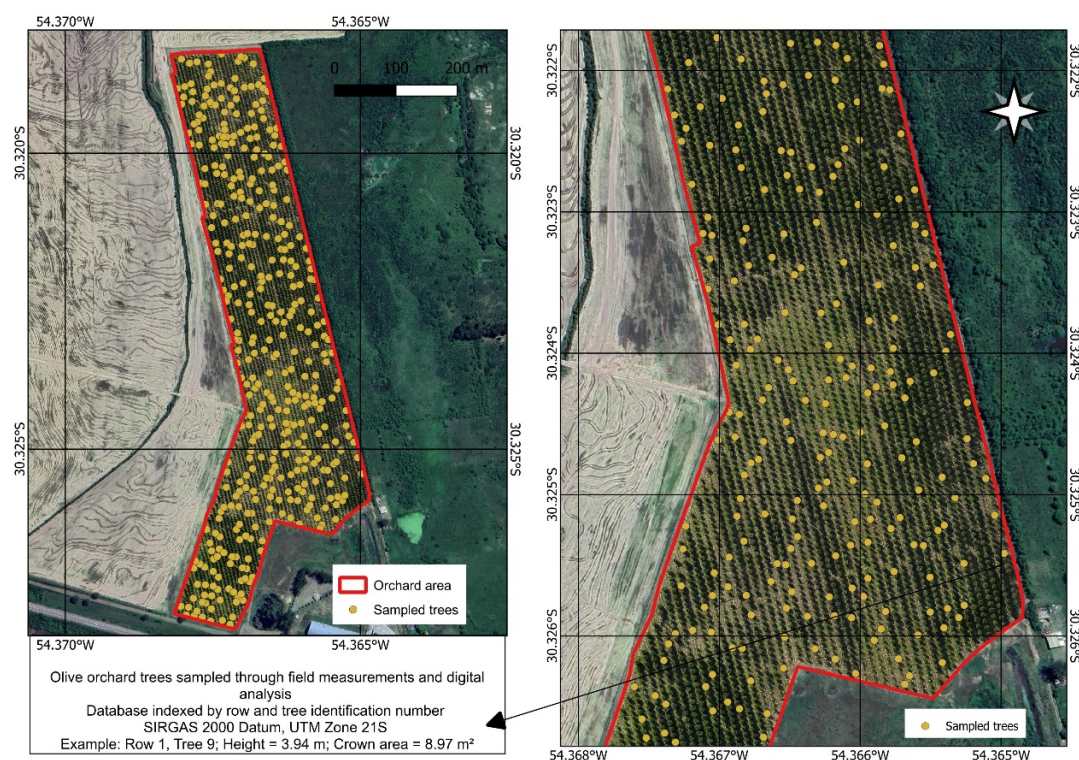


**Figure 2.** Orthomosaic with delineation of the study area, distribution of random points, and location of trees in an *Olea europaea* L. orchard in São Gabriel, RS, Brazil.



### 2.3 Aerial Data Acquisition

The aerial data acquisition was conducted using a DJI Mavic 3M drone. This equipment integrates a high-resolution RGB camera with 20 MP, an aperture ranging from f/2.8 to f/11, a 4/3 CMOS sensor, an image size of 5280 × 3956 pixels, and an ISO range from 100 to 6400 (DJI, 2024). The RGB camera is equipped with a mechanical shutter to prevent motion blur and, for the present study, was configured in manual mode with ISO 100, shutter speed of 1/240, and an aperture of f/5.6.

The flight was carried out on June 20, 2024, at 15:00, and was planned using the flight planning software integrated into the UAV controller, referred to as “flight route.” The mission was configured with 80% forward and side overlap and a flight altitude of 120 m over the study area.

### 2.4 Image processing

Image processing was carried out using Agisoft MetaShape Professional Edition 1.6.0 (AGISOFT, 2026), in its trial version. The coordinate reference system was defined as SIRGAS 2000 / UTM zone 21S.

Initially, image alignment was performed with the quality set to medium. During this step, the software determines the camera position and orientation for each image and generates a sparse point cloud. After generating the sparse point cloud, a dense point cloud was produced, also with medium quality. Based on the estimated image positions, the software calculates depth information for each image and combines them to generate a densified point cloud. From the dense point cloud, a digital surface model (DSM) was generated, with medium quality settings.

The digital surface model represents the surface as a regular grid of elevation values. From this product, it is possible to obtain height, volume, and contour lines (AGISOFT, 2026). An orthomosaic was generated from the DSM, consisting of a mosaic of high-resolution orthorectified images, also using medium quality settings.

A filtering process of the dense point cloud was performed using the Classify Ground Points tool, creating a class of ground points. Subsequently, a digital terrain model (DTM) was generated by selecting only the ground point class, also with medium quality. The mean camera location errors during data acquisition for the olive orchard at a flight altitude of 120 m were analyzed for the longitudinal (X), latitudinal (Y), and altitudinal (Z) coordinates.

### 2.5 Generated Indices

Vegetation indices were calculated using procedures performed in QGIS software. Initially, a new shapefile

layer was created. Subsequently, a polygon was delineated around the tree canopy and configured with a red outline and no fill. Before calculating any index, only the canopy area was extracted from the full orthomosaic by clipping the raster using a mask layer. The input layer consisted of the UAV-derived image mosaic, while the mask layer corresponded to the shapefile delineating the canopy. The specific formula for each index was then applied using the raster calculator.

After delineating the canopies of the sampled trees, zonal statistics were generated to obtain statistical values of interest associated with each individual and the corresponding calculated index. The desired statistical values for each index were then obtained from the attribute table.

Six indices related to the physiological and biometric characteristics of the plants were calculated using the R (Red), G (Green), and B (Blue) bands. The indices used were Brightness Index (BI), Blue Green Pigment Index (BGI), Visible Atmospherically Resistant Index (VARI), Excess of Green Index (ExG), Green Leaf Index (GLI), and Normalized Green Red Difference Index (NGRDI). These indices were derived from unmanned aerial vehicle (UAV) imagery; their formulas, descriptions, and main applications are presented below.

The BI (Brightness Index) is related to vegetation cover and vegetation water content, according to Richardson and Wiegand (1977).

$$BI = \sqrt{R^2 + G^2 + B^2} \quad (2)$$

The BGI (Blue Green Pigment Index) is associated with chlorophyll presence and the Leaf Area Index (LAI) (Zarco-Tejada et al., 2005).

$$BGI = \frac{B - G}{B + G} \quad (3)$$

The VARI (Visible Atmospherically Resistant Index) is used to assess canopy, biomass, and chlorophyll (Gitelson et al., 2002).

$$VARI = \frac{G - R}{G + R - B} \quad (4)$$

The ExG (Excess of Green Index) was developed to differentiate healthy plants from diseased or dead ones, as well as to identify exposed soil (Woebbecke et al., 1995).

$$EXG = 2G - R - B \quad (5)$$



The GLI (Green Leaf Index) is associated with chlorophyll (Louhaichi et al., 2001).

$$GLI = \frac{2G - R - B}{2G + R + B} \quad (6)$$

The NGRDI (Normalized Green Red Difference Index) is associated with chlorophyll, biomass, and water content (Tucker, 1979).

$$NGRDI = \frac{G - R}{G + R} \quad (7)$$

Where:

$G$  (green band –  $560 \pm 16$  nm),  $R$  (red band –  $650 \pm 16$  nm),  $B$  (blue band –  $650 \pm 16$  nm).

The indices were obtained with the aim of generating new variables that could contribute to the modeling and estimation of variables of interest. Thus, they were used as mean pixel reflectance values within the canopy regions of the individual trees.

## 2.6 Modeling and statistical analysis

Based on the inventory data and the indices generated from aerial imagery, mathematical models were fitted to describe variables of interest related to the olive orchard, such as diameter at 60 cm above ground level, total height, and canopy area.

Several models were tested for these variables in order to assess the possibility of obtaining reliable estimates. However, Table 1 presents only the models with the best fit that were tested to estimate these variables, as well as the indices derived from UAV imagery used in the analyses.

The best equations were selected based on the statistical criteria of the adjusted coefficient of determination ( $R^2_{adj}$ ), the standard error of the estimate ( $S_{yx}$ ), and the residual distribution.

$$R^2_{adj} = R^2 - \left[ \frac{K - 1}{N - K} \right] * (1 - R^2) \quad (8)$$

Where:

$R^2_{adj}$  = adjusted coefficient of determination;  $R^2$  = coefficient of determination;  $K$  = number of model coefficients;  $N$  = number of observations.

$$S_{yx} = \sqrt{MS_{res}} \quad (9)$$

Where:

$S_{yx}$  = standard error of the estimate;  $MS_{res}$  = mean square of the residual.

**Table 1.** Models tested to estimate diameter at 60 cm above ground level, total height, and canopy area of individual trees in an *Olea europaea* L. orchard in São Gabriel, RS, Brazil.

| Models                             | Diameter at 60 cm height (cm)                                                                                      |
|------------------------------------|--------------------------------------------------------------------------------------------------------------------|
| 1                                  | $\ln(d_{0.6}) = \beta_0 + \beta_1 \ln(h) \pm \varepsilon$                                                          |
| 2                                  | $\ln(d_{0.6}) = \beta_0 + \beta_1 \ln(h) + \beta_2 \ln(ac) \pm \varepsilon$                                        |
| 3                                  | $\ln(d_{0.6}) = \beta_0 + \beta_1 \ln(h) + \beta_2 \ln(ac) + \beta_3 \ln(VARI) \pm \varepsilon$                    |
| <b>Total height (m)</b>            |                                                                                                                    |
| 4                                  | $\ln(h) = \beta_0 + \beta_1 \ln(d_{0.6}) \pm \varepsilon$                                                          |
| 5                                  | $\ln(h) = \beta_0 + \beta_1 \ln(d_{0.6}) + \beta_2 BGI \pm \varepsilon$                                            |
| 6                                  | $\ln(h) = \beta_0 + \beta_1 \ln(d_{0.6}) + \beta_2 BGI + \beta_3 BI + \beta_4 EXG + \beta_5 NGRDI \pm \varepsilon$ |
| <b>Canopy area (m<sup>2</sup>)</b> |                                                                                                                    |
| 7                                  | $\ln(ac) = \beta_0 + \beta_1 \ln(d_{0.6}) \pm \varepsilon$                                                         |
| 8                                  | $\ln(ac) = \beta_0 + \beta_1 \ln(d_{0.6}) + \beta_2 \ln(GLI) \pm \varepsilon$                                      |
| 9                                  | $\ln(ac) = \beta_0 + \beta_1 \ln(d_{0.6}) + \beta_2 GLI + \beta_3 VARI \pm \varepsilon$                            |

\*Where:  $h$  = total height (m);  $(d_{0.6})$  = diameter measured at 0.6 m above ground level;  $ac$  = canopy area;  $VARI$ ,  $BGI$ ,  $BI$ ,  $EXG$ ,  $NGRDI$ , and  $GLI$  = spectral indices;  $\ln$  = natural logarithm; 0, 1, and 2 = model coefficients. Prepared by the author (2026).

Residual distribution is one of the most important elements in assessing the performance of a regression function, as it allows the identification of possible trends in the estimates. The selected model should not exhibit tendencies to overestimate or underestimate the observed values. Residuals were graphically represented in an orthogonal coordinate system, distributed across the full range of the estimated dependent variable on the x-axis and centered around zero on the y-axis, allowing both positive and negative values to be visualized.

## 3. Results And Discussion

The analysis of the data obtained in the forest inventory conducted in the olive orchard presented valuable information regarding the structure and development of the trees, considering several important variables. Silva et al. (2012) confirm the relevance of studies evaluating trunk diameter, tree height, canopy projection, among others, since these variables directly influence the productive performance of the species, especially with regard to fruiting.

The average height of the olive trees is 3.4 meters, and the standard deviation of 0.6 meters reflects moderate variation, indicating that most trees are close to the mean. However, some heights differed significantly from this mean. The 1st quartile (3.0 m) reveals that 25% of the trees are smaller, while the 3rd quartile (3.8 m) shows that 25% are among the tallest. The maxi-



maximum recorded height was 5.2 meters, highlighting the growth potential and orchard management. Vieira Neto et al. (2008) recommend that plant height, after pruning, should be maintained around 5.0 m, benefiting fruit harvesting. Silva et al. (2019), on the other hand, point out that adult trees ranging from 8.0 m to 10.0 m in height ensure olive production and also facilitate harvesting.

The average diameter ( $d_{0.6}$ ) obtained for this orchard is 12.3 cm, and the standard deviation of 3.4 cm indicates moderate variation, with differences that may be attributed to environmental conditions, management, and genetics. The 1st quartile (10.1 cm) indicates that 25% of the trees have thinner trunks, while the 3rd quartile (14.6 cm) includes the thickest trunks, with the maximum reaching 21.5 cm. In an *O. europaea* orchard located in Formigueiro, RS, Silva et al. (2019) found average and maximum diameter values at 0.3 m above ground level of 10.3 cm and 13.9 cm, respectively, which are similar to those observed in the present study.

Another important variable is canopy diameter, upon which tree production and growth directly depend (HOFIÇO et al., 2021). Thus, the average canopy diameter of the olive orchard is 3.6 meters, reflecting good overall development of the individuals. According to Silva et al. (2019), a canopy diameter of 2.95 m positively affected the vigor of an *O. europaea* stand in the Central Region of Rio Grande do Sul, contributing to its growth and development. The moderate variation (standard deviation of 0.8 m) suggests that some canopies stand out in size, while the quartiles (3.1 to 4.2 m) indicate that most trees present diameters close to the mean. The average canopy area obtained through the inventory was 8.3 m<sup>2</sup>, representing good soil coverage and potential for light interception. The standard deviation of 4.4 m<sup>2</sup> highlights a specific variation, with values ranging between 5.1 m<sup>2</sup> (1st quartile) and 10.5 m<sup>2</sup> (3rd quartile). It is worth mentioning that, in a study conducted with different olive cultivars, individuals with larger canopy parameters and greater trunk section presented higher production, greater productivity, and a higher number of fruits (SILVA et al., 2012).

The basic statistics for the variables delineated canopy area and vegetation indices obtained from the post-processing of the orchard orthomosaic reveal wide variability both for delineated canopy area and for vegetation indices derived from RGB images. The canopy area presented an average value of 8.39 m<sup>2</sup>, with a standard deviation of 3.47 m<sup>2</sup>, indicating high heterogeneity in the size of the evaluated canopies. The minimum (0.73 m<sup>2</sup>) and maximum (19.35 m<sup>2</sup>) values reinforce the presence of trees at different stages of development, which is expected in orchards with structural variability.

Among the spectral indices, the BI (Brightness Index)

presented an average of 66.40, with a standard deviation of 8.89, reflecting variations in the overall intensity of surface reflectance, possibly associated with differences in lighting, leaf density, and shading. The BGI presented an average of 0.58, with low relative dispersion ( $SD = 0.0747$ ), indicating more stable behavior among observations. Indices aimed at enhancing green vegetation, such as ExG, GLI, NGRDI, and VARI, presented relatively low averages, ranging from 0.08 (NGRDI) to 0.24 (ExG), with reduced standard deviations. This pattern suggests lower spectral variation amplitude when compared to BI, indicating greater consistency of these indices in the discrimination of green vegetation. It is noteworthy that VARI, frequently used in studies with UAVs and RGB sensors, presented an average of 0.12 and a standard deviation of 0.047, values compatible with homogeneous vegetated areas. In general, the results indicate that, while the canopy area and brightness index presented greater variability, normalized indices based on the relationship between RGB bands demonstrated more stable behavior, a desirable characteristic for applications in statistical modeling and vegetation analysis.

In general, the olive trees in the orchard show homogeneity in the evaluated variables, with some differences reflecting local conditions, management practices, or genetics. Height and diameter are good indicators of tree development, while canopy area suggests diversity in growth and productive potential. An aerated and well-illuminated canopy tends to favor productive performance and fruit quality, reinforcing the relevance of characterizing the variables described in this research (ROMA & CATANIA, 2022). The data indicate a well-structured orchard, with some trees possibly more adapted or vigorous, which may contribute to the overall performance of the crop.

The orthomosaic was generated from the processing of 465 images, resulting in a resolution (Ground Resolution) of 3.5 cm/pixel and camera location error, for the X, Y, and Z coordinates in meters, respectively, of 0.52, 0.48, and 1.35. The mosaic provided a high-definition aerial perspective of the orchard, enabling a detailed analysis of the arrangement of the olive trees and the surrounding terrain. Products generated from the images captured by the UAV were obtained. In addition to the orthomosaic, digital surface models (DSM), digital terrain models (DTM), and height models (HM) were also generated, as shown in Figure 3.

The post-processing of these products generated new outputs, which were directly related to variables such as canopy area, delineated from the images, and vegetation indices with their respective mean pixel values, used in the modeling process to estimate variables such as diameter, height, and canopy area.



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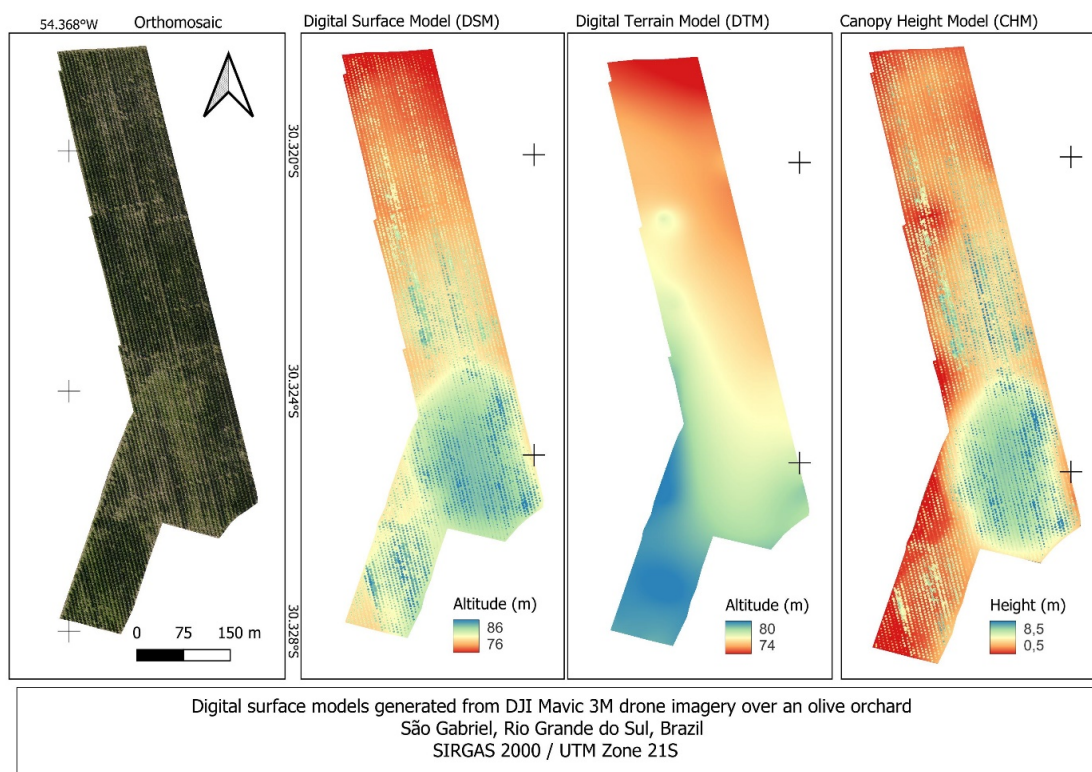


**Figure 3.** Orthomosaic and digital models generated from the processing of UAV images of an *Olea europaea* L. orchard in São Gabriel/RS.

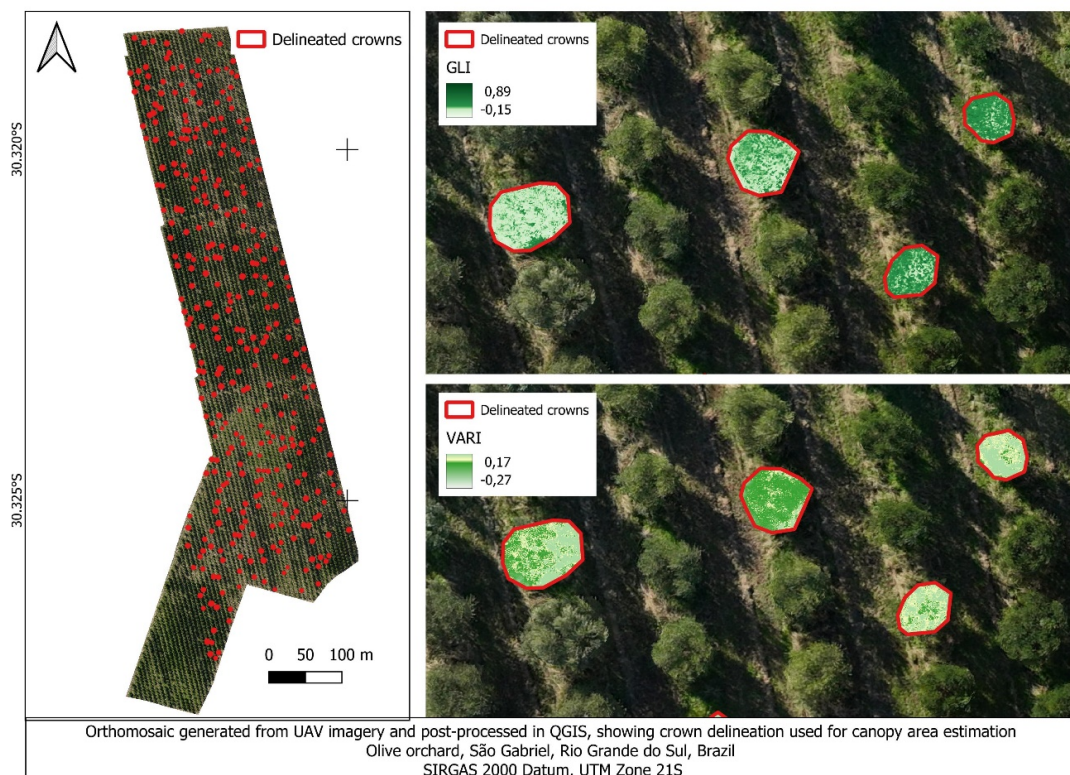


**Figure 4.** Representation of tree canopies manually delineated using QGIS software, as well as the VARI index calculated for an *Olea europaea* L. orchard in São Gabriel/RS.

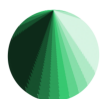


Figure 4 represents a specific area of the orchard, in which the delineation of olive tree canopies is demonstrated, along with the calculation of vegetation indices. It can be observed that these indices vary according to the reflectance values associated with the pixels composing the image, more specifically the canopy of each analyzed individual, whether assessed through image analysis or field inventory.

The most important correlations identified, in descending order, are: Canopy Diameter (CD) with Canopy Area (CA) (0.79), Diameter (D) with Canopy Diameter (CD) (0.79), Diameter (D) with Canopy Area (CA) (0.74), Height (H) with Diameter (D) (0.76), and Height (H) with Canopy Diameter (CD) (0.68). This indicates that trees with greater diameter have wider canopies and, consequently, greater canopy area, demonstrating coherent physical relationships among the structural variables of the trees. Furthermore, fruit quality in *O. europaea* is influenced by the balance between vegetative growth, canopy architecture, and orchard management conditions (ROMA & CATANIA, 2022).

Furthermore, Figure 5 shows that spectral indices such as NGRDI<sub>mean</sub> and GLI<sub>mean</sub> presented moderate negative correlations with the physical variables (e.g., H and D), suggesting that these spectral metrics may capture variations related to vegetation structure and vigor. Finally, indices such as EXG<sub>mean</sub> and VARI<sub>mean</sub> presented a high positive correlation with each other (~0.80), indicating that they possess informational redundancy in describing similar canopy characteristics of the trees.

The statistical criteria and the coefficients of the models tested to estimate the biometric variables of the olive trees are presented in Table 2.

For the estimation of canopy areas of individual olive trees, as well as for the other variables such as diameter and height, little significant variation was observed in the results of the statistical criteria. However, acceptable estimates were observed, in addition to improved results, when vegetation indices were added as independent variables in the tested models.

Through the regression analyses, it was observed that the equations presented good fits. In general, the equations that stood out the most were those that presented vegetation indices as independent variables, namely: for diameter estimation, equation 3; for total height, equation 6; and for the canopy area variable, equation 9. The estimation of diameter at 60 cm that showed the best performance was equation 3, with higher adjusted  $R^2$  values and lower standard error of estimate, and thus the residual plot was developed, which presents regular patterns with coherent estimates, small trends, and observed versus estimated variables for the model (Figure 6). The VARI independent variable stands out in the diam-

**Table 2.** Statistical criteria of the tested models and their respective coefficients for estimating biometric variables of individual trees in an *Olea europaea* L. orchard in São Gabriel/RS.

| Models                        | $\beta_0$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_5$ | $R^2_{adj}$ | $S_{yx}$ |
|-------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|-------------|----------|
| Diameter at 60 cm height (cm) |           |           |           |           |           |           |             |          |
| 1                             | 0.8661    | 1.344014  |           |           |           |           | 0.6157      | 0.1893   |
| 2                             | 0.7893    | 0.769572  | 0.3352    |           |           |           | 0.7796      | 0.1434   |
| 3                             | 0.7376    | 0.7560    | 0.3432    | 0.4069    |           |           | 0.7828      | 0.1423   |
| Total height (m)              |           |           |           |           |           |           |             |          |
| 4                             | 0.0591    | 0.458998  |           |           |           |           | 0.6157      | 0.1106   |
| 5                             | 0.0384    | 0.454679  | 0.0544    |           |           |           | 0.6150      | 0.1107   |
| 6                             | -1.2342   | 0.444967  | 1.7283    | -0.002    | 3.2830    | -3.5691   | 0.6226      | 0.1096   |
| Canopy area (m <sup>2</sup> ) |           |           |           |           |           |           |             |          |
| 7                             | -0.8774   | 1.275855  |           |           |           |           | 0.6600      | 0.2795   |
| 8                             | -1.3073   | 1.214918  | -0.3233   |           |           |           | 0.6809      | 0.2707   |
| 9                             | -0.3375   | 1.205792  | -2.1139   | -0.054    |           |           | 0.6862      | 0.2685   |

\*Where: 0, 1, 2, 3, 4, and 5 = coefficients of the tested models;  $R^2_{adj}$  = adjusted coefficient of determination;  $S_{yx}$  = standard error of estimate. Authors' elaboration (2026).

eter modeling, as it is a vegetation index obtained from drone imagery that significantly contributed to improving the estimation of olive tree diameter.

For the estimation of the total height variable, equation 6 presented the best performance, with higher adjusted  $R^2$  values and lower standard error of estimate. Thus, the residual plot and the observed versus estimated values plot were developed for the model in question, as shown in Figure 7. Regarding residual dispersion as a function of total height, regular patterns with coherent estimates and slight trends can be observed, with residual variation concentrated between 30 and 40%.

For the estimation of canopy area, model 9 stood out. Thus, the graph representing the estimation of the variables in question was developed, as well as the residual distribution as a function of canopy area, which showed a slight trend and somewhat higher residual variation. However, when the observed versus estimated data plots are analyzed, it can be observed that the estimates adequately represent the dataset, showing good agreement between observed and estimated values.

## 4. Conclusions

The random selection of trees based on random point sampling proved to be an effective methodology, optimizing time in forest inventory and improving the identification of individual trees within the orchard.

An advantage of using the Random Points in Polygons tool in QGIS 3.34 for forest inventory is that it automates the process of sample point selection, saving time and effort compared to manual selection. This makes inventory

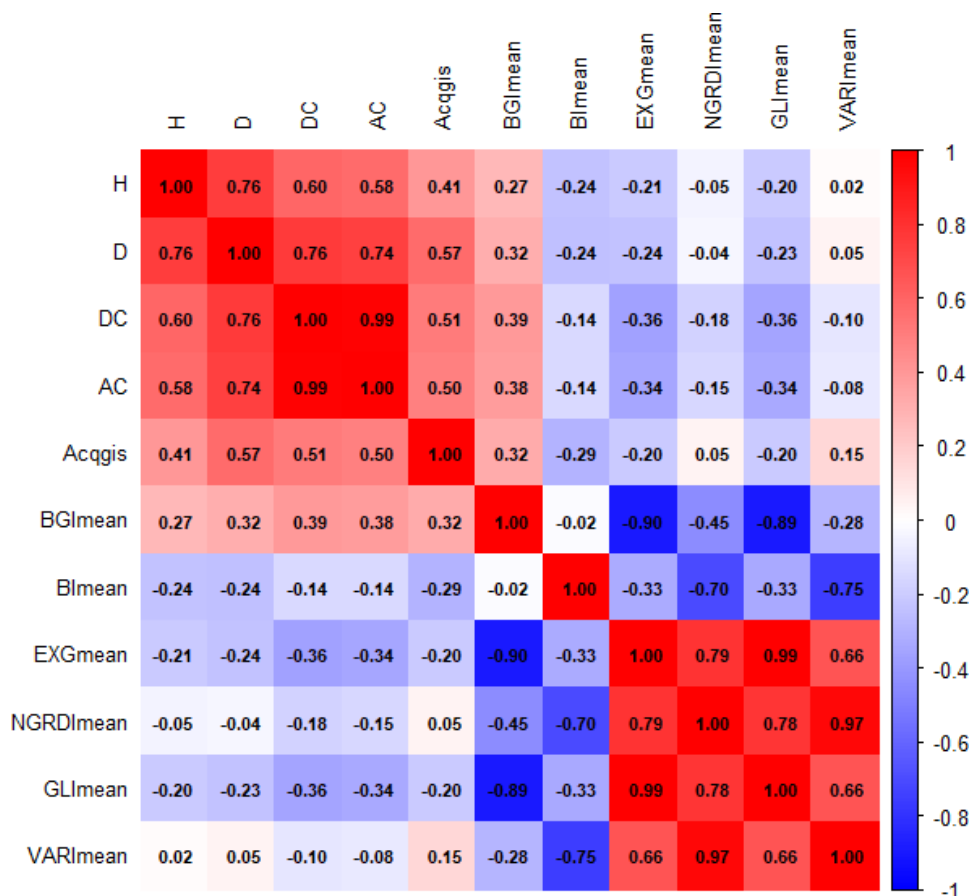
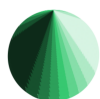


**Figure 5.** Heatmap of the correlations between field inventory variables and spectral indices obtained in an *Olea europaea* L. orchard through UAV RGB imagery. São Gabriel/RS (2024).

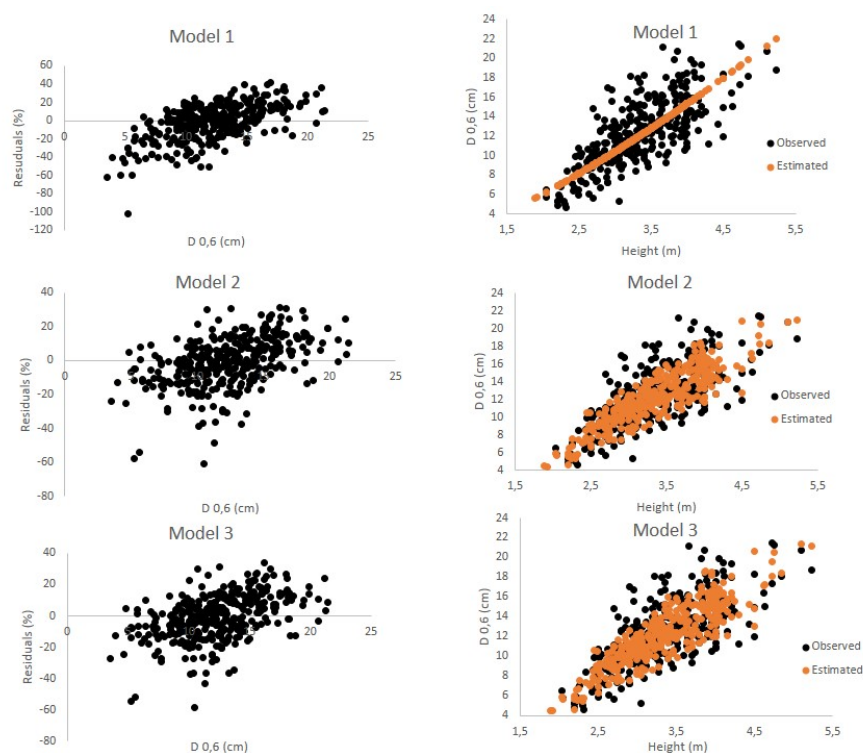


**Figure 6.** Residual distribution and observed versus estimated variables for models 1, 2, and 3 for the fitted equations in relation to the diameter variable estimates obtained in the field and from variables obtained by UAV for individual trees in an *Olea europaea* L. orchard in São Gabriel, RS.

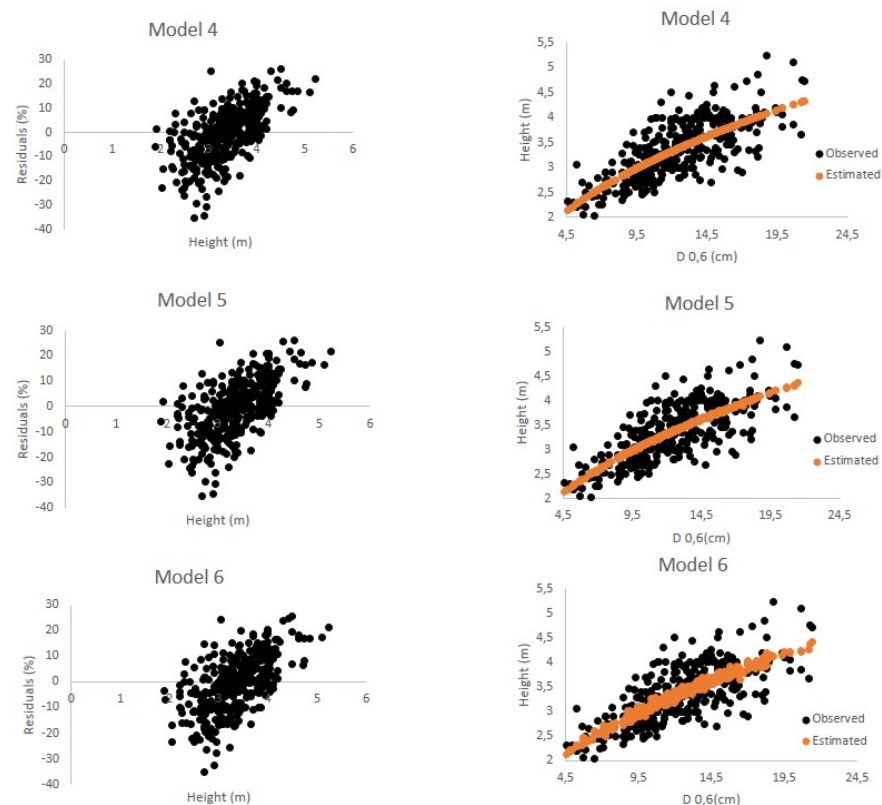


**Figure 7.** Residual distribution and observed versus estimated variables for models 4, 5, and 6 for the fitted equations in relation to the height variable estimates obtained in the field and from variables obtained by UAV for individual trees in an *Olea europaea* L. orchard in São Gabriel, RS.

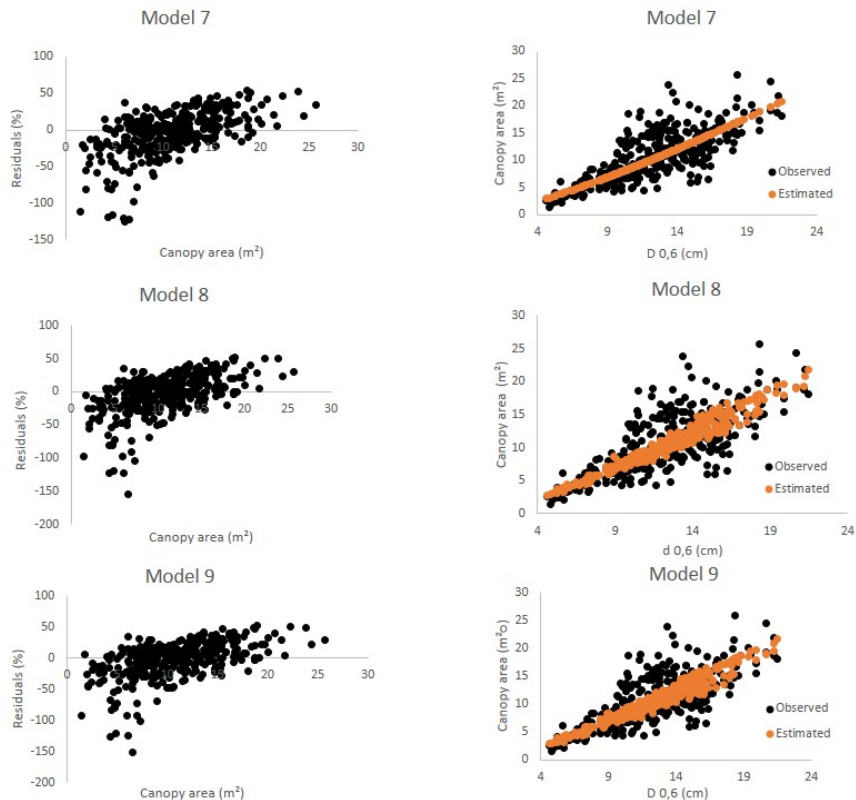


**Figure 8.** Residual distribution and observed versus estimated variables for models 4, 5, and 6 for the fitted equations in relation to the canopy area variable estimates obtained in the field and from variables obtained by UAV for individual trees in an *Olea europaea* L. orchard in São Gabriel, RS.



planning more efficient, especially in large areas, and helps distribute points evenly within the defined polygons, ensuring a more uniform survey coverage.

The generation of the Digital Surface Model (DSM), Digital Terrain Model (DTM), Digital Height Model (DHM), and orthomosaic proved essential in the current context of hardware and software use for more precise and individual-level analyses of target species in fruit orchards. These models not only support the extraction of individual tree variables but are also valuable for providing an overall view of the orchard, contributing to more accurate decision-making processes.

With the possibility of extracting vegetation indices from individual trees using geotechnologies, their use as predictor variables in modeling proved effective for estimating relevant variables in olive orchards. This approach enables further investigation using both infrared spectral indices and the estimation of other variables, such as fruit weight.

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## Author Statements

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- ✓ There is no evidence of plagiarism in this article.

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