

Master in Geomatics, Remote Sensing and Spatial Models
Applied to Forest Management

Integrating UAV Photogrammetry and High-
Resolution Soil Data for Spatial Prediction of Forest
Productivity in *Eucalyptus grandis* Plantations

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Córdoba, September 2026

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That the aforementioned work is of a research nature, and we certify its suitability and grant our approval of its content for submission to the Master's Thesis Examination Committee.

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Abstract

Accurate estimation of dendrometric variables in mature *Eucalyptus grandis* plantations is fundamental for decision-making in both harvesting and silvicultural activities and the quantification of carbon stock; however, traditionally certain field activities present limitations in precision due to canopy closure and intra-stand spatial heterogeneity. This research integrates structural metrics derived from aerial photogrammetry, high-resolution soil data obtained by grid sampling and interpolation by ordinary Kriging (1×1 m), and field inventory data collected from 36 plots established in *E. grandis* plantations (9, 12, and 15 years old) in northern Uruguay, with the objective of estimating diameter at breast height (DBH), total height (Ht), volume per hectare (Vol), and dominant mean Assmann height (MDH) using Random Forest models. Prior to spatial modelling, a site-specific allometric equation was fitted to estimate stem volume using 75 destructively sampled trees ($R^2_{\text{adj}} = 96.44 \%$, $\text{RMSE} = 0.17 \text{ m}^3$). Random Forest models, trained by iterative variable selection (Forward Feature Selection) in a 10-fold cross-validation scheme, achieved high predictive accuracy for all target variables (DBH: $R^2 = 0.95$, $\text{RMSE} = 1.57 \text{ cm}$; Ht: $R^2 = 0.98$, $\text{RMSE} = 1.08 \text{ m}$; Vol: $R^2 = 0.94$, $\text{RMSE} = 62.25 \text{ m}^3 \text{ ha}^{-1}$; MDH: $R^2 = 0.98$, $\text{RMSE} = 1.06 \text{ m}$). Soil pH was shown to be the dominant soil predictor across all four models and the overall dominant variable for volume estimation, explaining 62.26 % of the relative importance in the volume model and ranking second in DBH (45.44 %), Ht (33.36 %), and MDH (32.25 %), highlighting its critical role in these models and the fact that it is usually underestimated among soil factors in regulating productivity at the microsite level. UAV photogrammetry also efficiently captured structural metrics, serving as a low-cost alternative to airborne LiDAR without compromising predictive capabilities. The resulting productivity maps are operational products for the digital inventory and sustainable management of commercial *Eucalyptus* plantations.

Keywords: *Eucalyptus grandis*; UAV photogrammetry; digital soil mapping; Random Forest; forest inventory; spatial prediction; precision forestry

1. Introduction

Eucalyptus plantations represent a sustainable strategy for carbon sequestration in the short and medium term, due to their high accumulation of biomass in structural components, representing more than 50% of the total biomass (Du et al., 2015; Behera et al., 2020; White et al., 2022). Short rotation monocultures offer economic advantages; however, in the face of resource scarcity and intense climate change, proper management of mixed species plantations (two to four species) generally shows more productive results with benefits in terms of both economics and forest health and biodiversity (Liu et al., 2018). Efficient management of these plantations also promotes climate change mitigation through carbon sequestration (Du et al., 2015) and reduces the pressure on native forest (Almeida et al., 2021).

Building on this global context, in Uruguay, forestry development took hold following the enactment of the Second Forestry Law (Law N.º 15.939, 1987), which provided tax incentives and encouraged private investment in the sector (Panario and Gutiérrez, 2007; MGAP, 2023). As a result, forest plantations currently occupy 1.16 million hectares (ha), representing 6.6% of the national territory and 26.6% of priority forest lands (DGF, 2024). The predominant genus is *Eucalyptus* with *E. dunnii* (283,012 ha) primarily used for pulp production and *E. grandis* (250,457 ha) for sawn timber and panels (DGF, 2024; Uruguay XXI, 2025). Most *E. grandis* is concentrated in the northern region of the country, with a total of 128,917 ha (45.6% of the area planted with this species) (DGF, 2024). By 2022, 83% of *E. grandis* seedling production originated from clonal material, while the remaining 17% came from seed (DGF, 2022).

Currently, the demand for raw materials has grown steadily, driven primarily by the pulp industry in the case of *E. dunnii* (OPYPA, 2024) and by the production of higher value-added goods, such as panels, in the case of *E. grandis* (Uruguay XXI, 2025). This scenario highlights the need for precise methodologies to reliably estimate and project timber volume (Hirigoyen et al., 2021). Accurate estimation of stem volume is therefore crucial for decision-making as it represents the component with the highest commercial value (Fassnacht et al., 2016).

Traditionally, stem volume has been estimated using destructive sampling or allometric equations based on diameter at breast height (DBH) and total tree height (Ht). However, these approaches are often calibrated for short rotations or site-specific conditions, limiting their applicability to mature stands of *E. grandis* (Picard et al., 2012; Forrester et al., 2021). Promising progress has been made regionally: studies in Uruguay demonstrated high-precision biomass models for *E. grandis* (Hirigoyen et al., 2021), while Resquín et al. (2018) proposed yield models for above ground biomass for energy purposes. Yet despite this progress, traditional allometric equations alone fail to capture the variability associated with edaphic factors, competition, or plantation-design. Forrester et al. (2021) demonstrated that including variables related to canopy shape improves the

accuracy and applicability of biomass models. Reichert et al. (2023) emphasized the role of soil properties, noting that physical, morphological, and chemical factors regulate productivity beyond what is explained by DBH and Ht. At a broader scale, digital soil mapping and global soil property datasets highlight the need to integrate spatially explicit soil information into plantation growth models (Dai et al., 2019). The incorporation of edaphic variables such as texture, bulk density, and organic carbon content has proven to be a relevant predictor of productivity in *Eucalyptus* plantations (Stape et al., 2010). In Uruguay specifically, soil texture and organic carbon content have been shown to regulate water and nutrient retention, directly influencing *E. grandis* yield (Stape et al., 2010; Hirigoyen, 2018). However, they are still rarely used in volume estimation, revealing a methodological gap. By integrating these variables with UAV-derived metrics, it is possible to overcome the limitations of traditional models based solely on DBH and Ht values (Baietto et al., 2025).

Remote sensing offers a complementary solution to these limitations, allowing assessment of forest stands with high spatial resolution and temporal frequency (White et al., 2016; Mohan et al., 2021; Rizzo-Martín et al., 2023). Aerial photogrammetry using drones offers a significant cost-benefit advantage for monitoring at the plot and tree-level (Torres-Sánchez et al., 2015), while LiDAR and multispectral and hyperspectral sensors have proven highly efficient for estimating productive variables such as volume, dominant height, and biomass (Hirigoyen, 2018; Martello et al., 2022). Existing works combine active and passive sensors, integrating complementary structural and spectral metrics to reduce model uncertainty (Hirigoyen et al., 2021). Some recent studies (Hirigoyen et al., 2021; Baietto et al., 2025) have partially included soil-derived covariates; however, a gap persists in the systematic integration of high-resolution soil data with UAV-derived metrics.

The systematic integration of photogrammetric structural metrics and high-resolution soil data represents a methodological advance that has not been previously applied to mature stands of *E. grandis* in Uruguay. While Baietto et al. (2025) demonstrated the value of soil variables in *E. dunnii* structural variables estimation using global data with resolution of 250 m, and Hirigoyen et al. (2021) established highly precise allometric frameworks for the same species, these approaches do not capture the edaphic variability at the microsite level that this research addresses through intensive grid sampling and Kriging interpolation. The resulting high-resolution productivity maps represent a methodological template directly applicable to precision forest management in the commercial *Eucalyptus* sector of northern Uruguay, with clear potential extension to other species and soil contexts.

To address these gaps, we hypothesize that high-resolution soil properties provide a significant contribution to the estimation of dendrometric variables in mature *E. grandis* plantations when integrated with UAV-derived structural metrics.

Thus, the present study develops and validates a machine learning model to estimate various metrics in mature *E. grandis* plantations, integrating field data, remote sensing structural metrics, and soil variables. To achieve this, three specific objectives are proposed: i) to fit an allometric equation to estimate tree-level volume in *E. grandis*, ii) to integrate soil data and aerial photogrammetry metrics for plot-level volume estimation using predictive machine learning models, and iii) to generate spatial estimates of DBH, Ht, volume per hectare (Vol), and Assmann mean dominant height (MDH) for the study area based on the trained model. Together, these objectives provide a comprehensive framework to improve the accuracy and spatial resolution of forest productivity estimation, while advancing the integration of soil and UAV-derived data in precision forestry.

2. Materials and methods

2.1 Study area

The study was conducted in the departments of Treinta y Tres (32° 22' 47.75" S, 54° 24' 56.86" W; 31° 54' 0.27" S, 54° 6' 32.17" W) and Cerro Largo (32° 10' 49.65" S, 54° 13' 34.87" W), Uruguay (32° 31' 22.00" S, 55° 45' 57.01" W) (Fig. 1). The total area covered by fieldwork was 25.53 ha. The climate in this area is subtropical, with an average annual temperature between 17 and 18 °C and annual rainfall ranging from 1400 to 1500 mm (Castaño et al., 2011). According to the Köppen classification, it corresponds to category Cfa: temperate humid, with rainfall distributed throughout the year and warm summers. The soils in the study area belong to group 2.14 of the CONEAT classification, developed on the crystalline basement of eastern Uruguay. They are characterized by a sandy loam to sandy texture, good effective depth, and moderate to good drainage. They have low natural fertility, medium organic matter content, and a slightly acidic pH (MGAP, 1979). While these soil conditions are marginal for intensive agricultural systems, they are suitable for the establishment of forest plantations of *E. grandis*, due to the species' deep root exploration and adaptation to low-fertility soils (MGAP, 1979; Martino, 2006). According to the Uruguay Soil Survey Map (MGAP, 1979), the soils present in the study area correspond to the taxonomic groups Mollic Hapludalfs, Typic Argiudolls, and Lithic Udorthents under the USDA Soil Taxonomy system (Soil Survey Staff, 1999). Regarding land use, in Treinta y Tres and Cerro Largo, natural grasslands for extensive livestock farming, commercial *Eucalyptus* plantations, and, to a lesser extent, extensive agriculture predominate (DGF, 2023; Uruguay XXI, 2024).

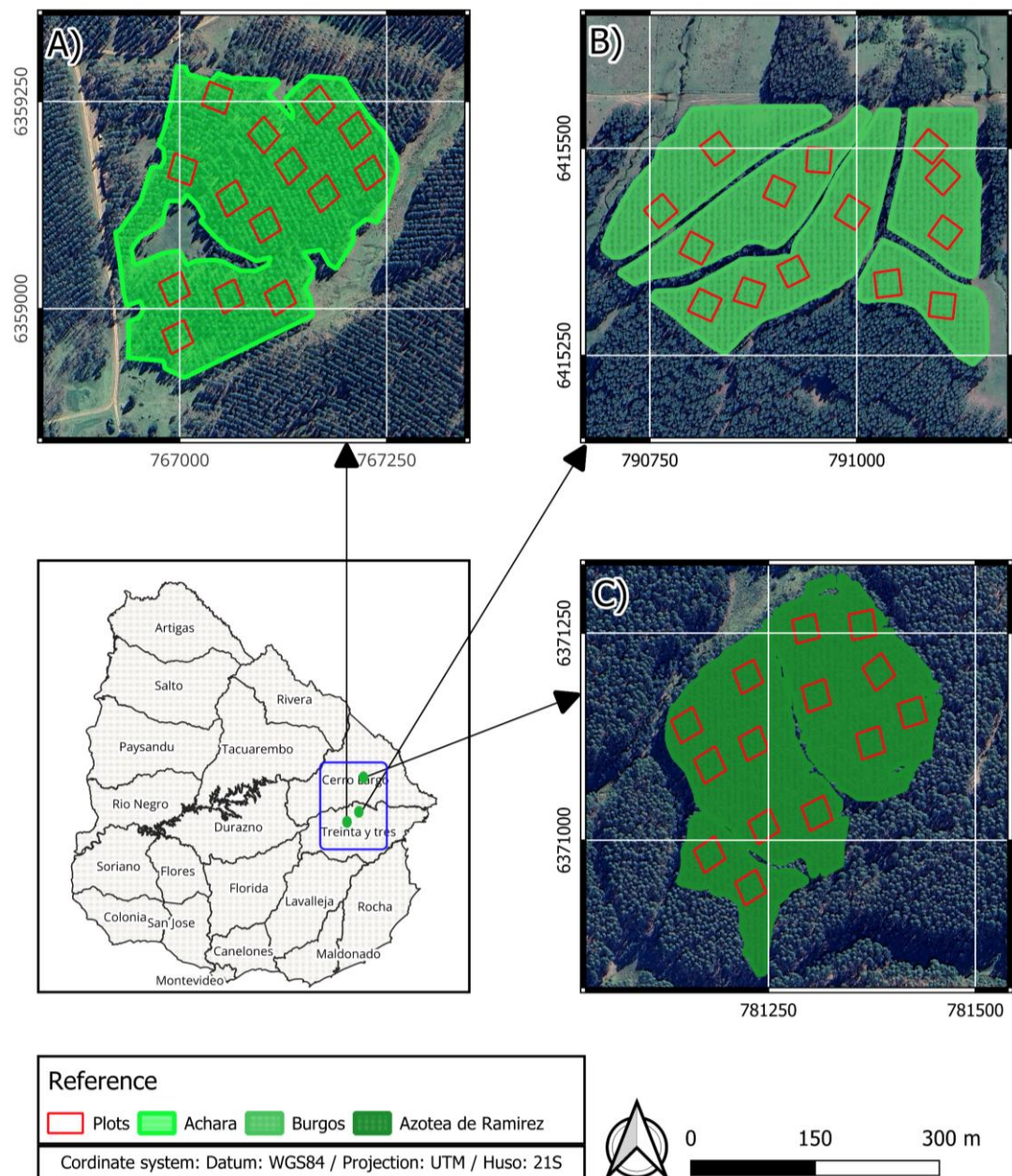


Figure 1. Study area and spatial distribution of sampling plots in three *Eucalyptus grandis* stands located in northern Uruguay. Panels (A), (B), and (C) show the spatial extent of each stand (Achara, Burgos, and Azotea de Ramírez, respectively), with sampling plots represented as red squares. The lower panel indicates the geographic location of the study sites within Uruguay. All coordinates are shown in UTM (WGS84, Zone 21S). *Note.* Stand 1 (A); Stand 2 (B); Stand 3 (C).

2.2 Field data

2.2.1 Forest inventory

For the forest inventory, a total of 36 plots of 900 m² (30 m x 30 m) were established within *Eucalyptus grandis* stands, aged 9, 12, and 15 years. The selected plantation areas were 8.36 ha, 9.04 ha, and 8.15 ha, respectively, with mean stand densities of 305, 316, and 257 trees ha⁻¹, reflecting differences in survival and silvicultural history across stands. The plots were randomly established within the study area and georeferenced with centimeter-level accuracy (2 to 20 cm accuracy) using a Trimble DA2 GNSS receiver (Trimble Inc., Westminster, Colorado, USA). Within each plot, measurements were taken of all individuals, including DBH, Ht, and general observations for each tree (e.g., structural or biological damage), which served as the basis for selecting target individuals. A Haglöf Mantax caliper (Haglöf, Långsele, Sweden) was used to measure DBH, and a Haglöf EC II electronic clinometer (Haglöf, Långsele, Sweden) was used for Ht. A total of 1,107 trees were measured.

For the complete inventory, diameter classes were identified and 75 trees selected for destructive measurement, to represent the full frequency distribution of each class. After felling, stem diameters were recorded at 0.5 m intervals up to 2 m height and at 2 m intervals thereafter until a minimum top diameter of 5 cm was reached. Individual stem volume was then calculated by applying Smalian's formula (Equation 1) to each section, following Picard et al. (2012). This destructive dataset, spanning DBH values from 21.3 to 50.2 cm and heights from 24.9 to 47.1 m across the three age classes, provided the ground-truth volume observations against which all nine candidate allometric models were calibrated and validated.

$$V_i = \sum_{j=1}^{n_i} \frac{\pi}{8} L_{ij} (DB_{ij}^2 + DT_{ij}^2) \quad \text{Equation 1}$$

where V_i corresponds to the total volume of tree i , n_i is the number of sections of tree i , L_{ij} is the length of section j of tree i , DB_{ij} is the base diameter of section j of tree i , and DT_{ij} is the top diameter of section j of tree i .

2.2.2 Soil variables

For soil sampling, a systematic grid of 30 m x 30 m was established, covering the entire study area at each site. From the centroid of each grid cell, a sample was extracted from a depth of 0-20 cm using a soil probe (Fig. 2). Samples were oven-dried at 60 °C to constant weight and subsequently ground to < 0.15 mm prior to laboratory analysis (Fig. 2).

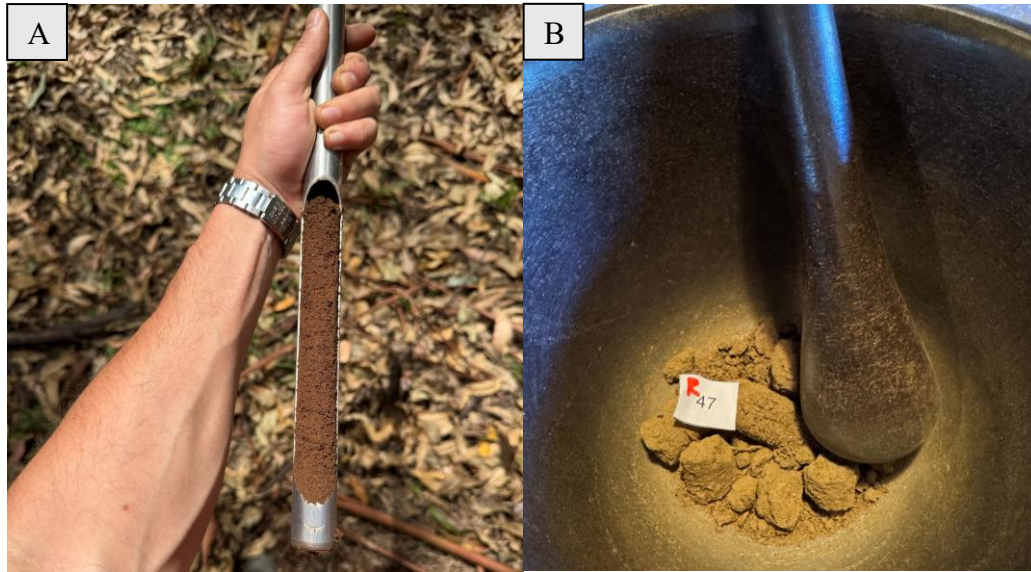


Figure 2. Soil sample extraction with a probe to a depth of 20 cm (A) and sample grinding with a mortar (B).

Soil texture was determined using the hydrometer method (Forsythe, 1975), and bulk density (BD) was calculated from the volume of the soil core and its oven-dry weight, following established protocols for forest soil (Campbell and Henshall, 2000). Soil nitrogen and carbon content were obtained by dry combustion using an elemental analyzer (Flash Smart, Thermo Fisher Scientific, Bremen, Germany) (Bremner and Mulvaney, 1982; Sikora and Stott, 1997). Soil pH was measured in a 1:5 soil-to-water suspension (Lierop and MacKenzie, 1977). After obtaining all the soil variables (BD, Clay, Silt, Sand, pH, Carbon, Nitrogen), the points were interpolated to obtain a continuous surface (McBratney et al., 2003). The interpolation method used was Ordinary Kriging, which is often the most widely used method for predicting soil properties because it is a robust geostatistical method (Webster & Oliver, 2007). To model the autocorrelation of the data, a variogram was calculated for each of the target variables. The spherical model was used, as it showed the best performance for the soil variables.

Interpolation was performed at 1×1 m resolution using up to 16 nearest neighbours per prediction point, with a variogram of 150 m and a block size of 60×60 m to provide spatial smoothing. To reduce noise from the high-resolution pixel-based predictions, a 3×3 focal filter was applied to the resulting surfaces. To assess spatial accuracy, a 10-fold cross-validation (CV) was performed, calculating the root mean square error (RMSE) for each interpolated variable as the performance indicator.

Geostatistical modeling was performed in R (version 4.5.2) (R Foundation for Statistical Computing, Vienna, Austria) within the RStudio environment (version 2026.01.0) (RStudio, Boston, MA, USA). The packages used for handling vector files were *sp* (Bivand et al., 2013) and *sf* (Pebesma,

2018). The *gstat* package allowed for the adjustment of variogram models and the performance of interpolation (Pebesma, 2004). Finally, the *raster* and *terra* packages were used together to apply focal filters and export the resulting layers (Hijmans, 2023).

2.3 Tree volume modeling.

Nine regression models, including both linear and nonlinear forms, were evaluated for estimating individual tree volume (Table S1). The weighted least squares (WLS) method was used, as this technique corrects for heteroscedasticity in the data by assigning greater weight to observations with lower residual variance (Draper and Smith, 1998; Parresol, 1999). The models were fitted using the dataset of 75 felled trees, with DBH and Ht included as predictor variables. The weighting strategy was applied because the error variance tends to increase with tree size, a common characteristic of allometric relationships (Parresol, 1999). Selected individuals presented DBH values ranging from 21.3 to 50.2 cm (mean = 34.68 cm) and Ht between 24.9 and 47.1 m (mean = 36.89 m). Real stem volume (Vr), determined by destructive sampling, varied between 0.159 and 3.680 m³ per tree.

Table 1. Descriptive statistics of dendrometric variables for destructively sampled *Eucalyptus grandis* trees (n = 75) used for the calibration and validation of allometric models. Variables include diameter at breast height (DBH), total height (Ht), real stem volume (Vr), and age. Values are expressed as minimum (Min), mean (Mean), maximum (Max), and standard deviation (SD).

	Variable	Min	Mean	Max	SD
<i>E. grandis</i> (n=75)	DBH	21.3	34.68	50.20	7.77
	Ht	24.90	36.89	47.10	6.40
	Vr	0.159	1.683	3.680	0.921
	Age	9	12	15	3

Note. DBH: diameter at breast height (cm); Ht: total height (m); Vr: real volume (felled) (m³ tree⁻¹).

Based on this dataset, each tested model was evaluated using the adjusted coefficient of determination (R²adj), prioritizing models with the highest predictive capacity, and the root mean square error (RMSE), aiming for the lowest possible values. Additionally, the Kolmogorov-Smirnov and White tests were used to verify the normality of the residuals and the presence of heteroscedasticity, respectively. These statistical evaluations were complemented by exploratory plots of observed versus predicted values and standardized residuals versus predicted values of each model's performance (Draper and Smith, 1998; Balzarini et al., 2008).

All analyses were performed in R (version 4.5.2) within RStudio (version 2026.01.0), using the *minpack.lm* package for nonlinear model fitting, *cvTools* for leave-one-out cross-validation with a 10% trimming threshold to limit outlier influence (Kohavi, 1995), and *nortest* and *lmtest* for normality and homoscedasticity testing, respectively.

2.4 Data acquisition and processing of remote sensing.

Photogrammetric data acquisition was achieved through three flight missions using a DJI Inspire 1 drone (DJI Shenzhen, China), equipped with a Sentera 6x thermal multispectral camera (Sentera, MN, USA). Flights were planned for each study area maintaining the same flight parameters: an altitude of 210 m, an 85% overlap, a double grid pattern, a forward speed of 15 m/s, and total flight areas of 12.43 ha, 10.87 ha, and 15.14 ha for Stand 1, Stand 2, and Stand 3 respectively. For accurate georeferencing of point clouds, 15 ground control points (GCPs) were installed, achieving an accuracy of less than 10 cm.

Point cloud generation was performed in Agisoft Metashape Professional v2.2.1 (Agisoft LLC, 2025). Image alignment and dense cloud reconstruction were carried out at ultra-high-quality settings, with alignment refined using 15 GCPs per stand, yielding final georeferencing errors of 0.034-0.050 m. Ground point classification was applied to separate vegetation returns from terrain, using a maximum angle of 10°, maximum distance of 0.1m, and a cell size of 50m. After noise filtering, a Digital Terrain Model (DTM) was generated for each stand from the classified ground points in the UTM Zone 21S coordinate system (EPSG:32721).

Point cloud normalization and metric extraction were performed in R using the *lidR*, *terra*, and *sf* packages. Height distribution metrics were computed at plot level and included the mean, median, maximum, standard deviation and the 70th to 99th height percentiles. Higher percentiles reflect dominant canopy height and are closely correlated with stand volume (Hirigoyen, 2018), while lower percentiles capture vertical stand structure and competitive dynamics (Torres-Sánchez et al., 2015). Canopy asymmetry was characterized through skewness, with positive values indicating the presence of structurally dominant trees (Laclau et al., 2008).

2.5 Machine Learning

The modelling process consisted of four consecutive phases: preprocessing, iterative variable selection, model training and validation, and finally, spatial prediction. The Random Forest (RF) algorithm was selected for its ability to model complex nonlinear relationships and its robustness to outliers (Breiman, 2001), key factors in the study of *Eucalyptus* growth (Stape et al., 2010; Oliveira et al., 2021). To optimize model accuracy and overfitting, the Advanced Feature Selection (FFS) algorithm was implemented using the *CAST* package (Meyer et al., 2018). This algorithm iteratively tests various combinations of predictor variables and automatically selects the optimal subset that minimizes the cross-validation model error. Once the predictor variables are selected their importance is assessed using permutation-based dropout loss with the *DALEX* package (Biecek & Burzykowski, 2021). This approach allows for evaluating the net increase in RMSE when the values of a given

variable are randomly permuted. Finally, the net importances are standardized to a 100% relative scale to determine the contribution of each predictor in the model.

Using the optimal set of predictors, the FFS algorithm directly provided the final model fit for each target variable (DBH, Ht, Vol, MDH) using the *randomForest* package within the *caret* framework. The *mtry* parameter (considered at each tree split) was optimized through a grid search over candidate values of 2, 4, and 6, with the optimal value selected based on cross-validation RMSE (DBH: *mtry* = 6; Ht: *mtry* = 6; Vol: *mtry* = 2; MDH: *mtry* = 6), while the number of trees (*ntree*) was set to 500 to ensure error convergence (Kuhn, 2008). Model validation was performed using 10-fold cross-validation (CV). This procedure provided unbiased estimates of the coefficient of determination (R^2), and the root mean square error (RMSE). The model fit and diagnostic plots were generated using the *ggplot2* package. Finally, the trained models were applied to the raster data for the three stands. Using the *terra* package, the spatial predictor variables were loaded, ensuring an exact match with the selected predictors. Pixel-by-pixel predictions were made to generate continuous maps, allowing the visualization of the spatial variability of productivity within plantations.

3. Results

3.1 Allometric model equation

Model 3 achieved the best performance (Table 2), with an R^2_{adj} of 0.9644 and the lowest cross-validation error (RMSE = 0.17 m³). The graphical analysis of the predicted versus observed values is presented in Supplementary Material Table S1, along with the residual versus predicted values (Supplementary Material Figures S1 to S3).

Table 2. Comparison of allometric models fitted to estimate stem volume in *Eucalyptus grandis*, including cross-validation performance metrics and estimated model parameters. Models are evaluated based on the adjusted coefficient of determination (R^2_{adj}) and root mean square error (RMSE), and are ranked according to predictive accuracy.

Model	R^2_{adj}	RMSE	β_0	β_1	β_2
3	96.44	0.17	2.38E-05	1.484918	1.606559
5	96.15	0.18	-0.00089	0.012257	4.76E-05
8	95.85	0.18	-0.04811	0.000559	0.002002
2	94.59	0.21	6.1E-05	0.947108	
9	94.59	0.21	-9.70531	0.947108	
7	89.1	0.30	0.000862	3.01E-07	
6	87.79	0.31	4.67115	0.21994	0.00205
4	87	0.33	0.29013	0.001562	
1	86.12	0.34	0.000384	2.34399	

Note. R^2_{adj} : coefficient of determination for cross-validation; RMSE: cross-validation root mean square error; $\beta_{0,1,2}$: model parameters.

This model represents a crucial intermediate result, as it allows for volume estimations based on field inventory data. Subsequently, the volume was estimated at the plot level to then obtain the productivity per hectare (Vol), which provided one of the target variables for the machine learning modeling stage. The remaining target dendrometric variables (DBH, Ht, Vol, and MDH) came from the forest inventory described below.

3.2 Forest inventory

The forest inventory conducted in the thirty-six sampling plots revealed a clear growth gradient associated with the age of the plantation. A summary of the main dendrometric variables (DBH, Ht, Vol, and MDH) is presented in Table 3.

Table 3. Summary statistics of dendrometric variables for the three *Eucalyptus grandis* stands of different ages, including diameter at breast height (DBH), total height (Ht), volume per hectare (Vol), and mean dominant Assmann height (MDH). Values are presented as mean, standard deviation, minimum, and maximum.

Stand		DBH (cm)	Ht (m)	Vol (m ³ ha ⁻¹)	MDH (m)
1	Mean	26.29	27.70	183.30	28.54
	Standard deviation	1.23	1.46	33.89	1.50
	Min	23.48	23.76	84.30	23.78
	Max	28.36	29.28	225.52	30.27
2	Mean	34.79	36.62	460.42	38.43
	Standard deviation	1.71	0.88	73.42	0.77
	Min	31.75	35.08	377.50	36.90
	Max	36.96	38.12	586.82	39.84
3	Mean	40.79	43.46	599.88	44.56
	Standard deviation	1.77	1.20	119.88	1.17
	Min	38.32	40.29	424.14	41.79
	Max	44.01	45.32	847.72	46.81

Note. DBH: diameter at breast height; Ht: total height; Vol: Volume per hectare; MDH: mean dominant Assmann height.

The youngest stand (9 years old) had an average DBH of 26.29 cm (± 1.23 cm) and an average height of 27.70 m (± 1.46 m). The mean dominant Assmann height (MDH) was 28.54 m, with values ranging from a minimum of 23.78 to a maximum of 30.27 m, while the volume (Vol) reached an average of 183.30 m³ ha⁻¹. In stand 2 (12 years old), the dendrometric variables increased to an average DBH of 34.79 cm (± 1.71 cm) and a height of 36.62 m (± 0.88 m). The MDH in this stand reached 38.43 m, exhibiting high uniformity with a standard deviation of 0.77 m, and productivity reached 460.42 m³ ha⁻¹. Finally, stand 3 (15 years old) reached an average DBH of 40.79 cm (± 1.77 cm) and an average height of 43.46 m (± 1.20 m). The MDH was 44.56 m, highlighting the high productivity potential of the site at this advanced stage of growth, with an average total volume of 599.88 m³ ha⁻¹. The variability observed within each age group, particularly in the 15-year-old stand, where the volume ranged

between 424.14 and 847.72 m³ ha⁻¹, underscores the significant influence of edaphic factors on forest growth, which, along with stand age and silvicultural management (such as pruning and thinning regimes), determine overall productivity.

3.3 Soil attributes and spatial variability

Soil characterization across the three stands revealed physical and chemical heterogeneity that cannot be captured by stand-level averages alone. The 349 sampling points distributed across 30 × 30 m grid (109 in stand 1, 127 in stand 2, and 113 in stand 3) showed that even within a single stand, clay content ranged from 62 to 237 g kg⁻¹ and pH from 4.13 to 6.68, a variation wide enough to shift nutrient availability regimes and water retention capacity. This degree of intra-stand heterogeneity has direct implications for productivity: where pH drops below 4.5 and sand content exceeds 600 g kg⁻¹, conditions approach the lower tolerance threshold for *E. grandis* root development, which may explain the low volume observed in the 15-year-old stand. Conversely, the presence of near-neutral pH, moderate clay content, and higher organic carbon in localized areas likely drives the more extreme stand productivity values: plots exceeding 800 m³ ha⁻¹ that would be invisible to any model relying on stand-averaged soil inputs.

Table 1. Descriptive statistics of soil physical and chemical properties (0–20 cm depth) across the three study stands, including bulk density (BD), texture fractions (clay, silt, and sand), pH (H₂O), organic carbon (C), and nitrogen (N). Values are presented as mean, standard deviation, minimum, and maximum.

Stand		BD (g cm ⁻³)	Clay (g kg ⁻¹)	Silt (g kg ⁻¹)	Sand (g kg ⁻¹)	pH (H ₂ O)	C (g kg ⁻¹)	N (g kg ⁻¹)
1	Mean	1.78	145	378	477	5.35	20.13	1.53
	Standard deviation	0.14	26	50	50	0.31	2.72	0.24
	Min	1.43	82	280	321	4.87	12.11	0.83
	Max	2.23	237	521	561	6.68	26.48	2.26
2	Mean	1.74	117	363	520	4.76	18.19	1.61
	Standard deviation	0.12	24	67	72	0.25	3.10	0.26
	Min	1.41	62	205	340	4.28	11.76	0.95
	Max	2.04	182	502	661	5.94	28.38	2.32
3	Mean	1.69	132	327	542	4.90	20.44	1.84
	Standard deviation	0.13	28	50	53	0.28	3.06	0.31
	Min	1.35	79	221	320	4.13	13.15	1.21
	Max	2.13	204	493	659	5.98	32.39	2.85

Note. BD: Bulk Density; pH: pH measured in water; C: organic carbon; N: organic nitrogen.

For stand 1, the 109 sampling points showed a mean BD of 1.78 g cm⁻³ and a mean pH of 5.35. The texture in this stand was characterized by a mean sand content of 477 g kg⁻¹ and a clay content of 145 g kg⁻¹, although the clay values showed significant internal variation, ranging from 82 to 237 g

kg⁻¹. Regarding stand 2, the 127 samples indicated a mean BD of 1.74 g cm⁻³ and a more acidic mean pH of 4.76. This stand exhibited a mean clay content of 117 g kg⁻¹. Finally, stand 3 was characterized using 113 sampling points, exhibiting the lowest mean bulk density of the three sites (1.69 g cm⁻³) and a mean pH of 4.90. The oldest stand had the highest mean sand content at 542 g kg⁻¹ and a mean clay content of 132 g kg⁻¹. In all stands, the wide ranges between minimum and maximum values, particularly for clay and silt content, underscore a high degree of intra-stand soil heterogeneity. This spatial variability, captured through intensive sampling, provides high-resolution data for integration with UAV-derived metrics in subsequent machine learning modeling phases.

Figure 3 illustrates the continuous raster layer for each physical property, generated by ordinary kriging interpolation of the sampling grid. These maps represent key results, as they transform discrete laboratory analysis data, summarized in Table 4, into high-resolution (1 × 1 m) spatial variables. This visual representation confirms the previously quantified soil heterogeneity, showing clear spatial gradients in BD and texture that reflect the laboratory values. Additionally, the RMSE of each variable was estimated as a performance indicator. The RMSE values confirm acceptable interpolation accuracy across all variables: BD 0.15 g cm³, Clay 27 g kg⁻¹, Silt 47 g kg⁻¹, and Sand 54 g kg⁻¹.

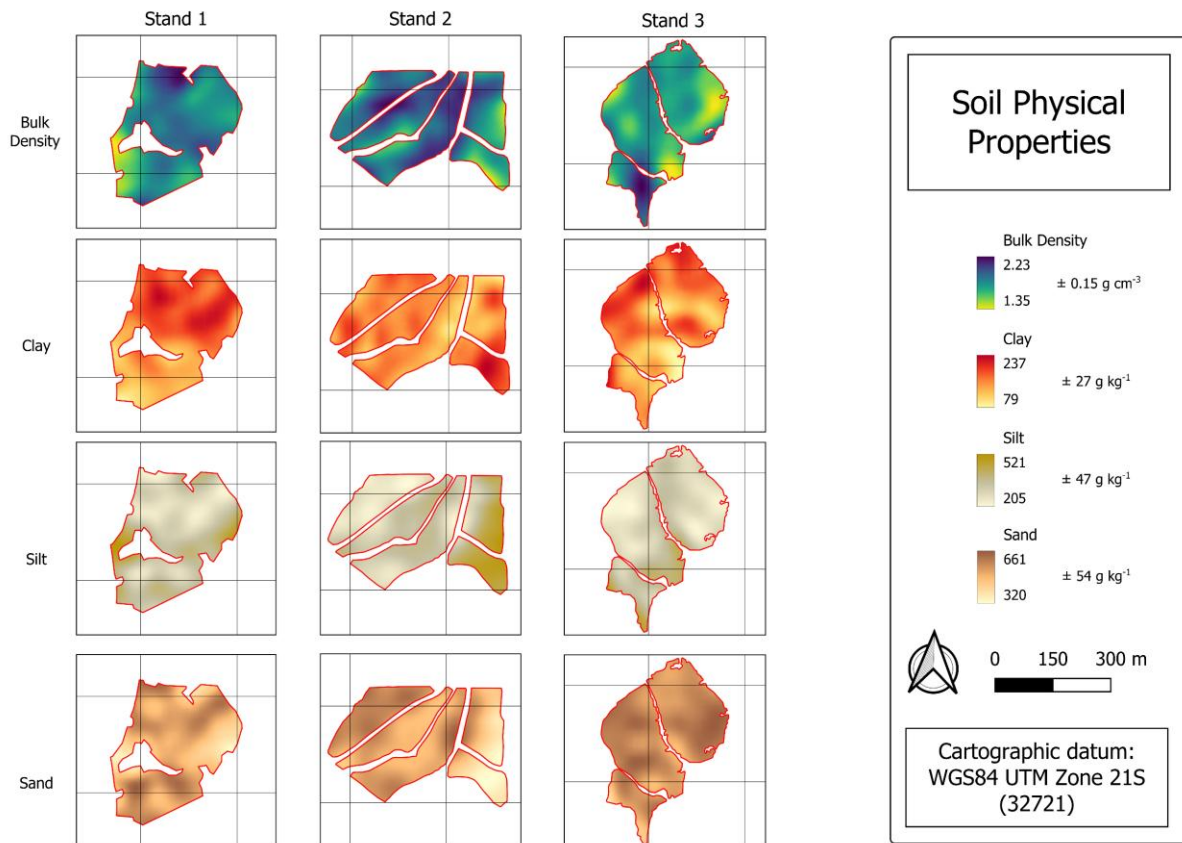


Figure 3. Spatial distribution of soil physical properties (0–20 cm depth) across the three study stands. Interpolated maps represent bulk density and soil texture fractions (clay, silt, and sand) for each stand, highlighting the spatial heterogeneity of soil conditions at the microsite level. Kriging interpolation accuracy (RMSE): BD = 0.15 g cm⁻³; Clay = 27 g kg⁻¹; Silt = 47 g kg⁻¹; Sand = 54 g kg⁻¹.

Regarding the characterization of the soil's chemical properties (Fig. 4), stand 2 exhibited the most acidic conditions of the three sites (pH 4.76), while stand 3 showed a slightly higher mean pH (4.90) despite being the oldest stand, suggesting that factors beyond stand age contribute to soil acidification patterns. These pH values align with those reported for forest soils in the northern region, which developed on crystalline basement rock (MGAP, 1979). Stand 1 had an average pH of 5.35, with values ranging from 4.87 to 6.68. The organic carbon (C) content averaged 20.13 g kg⁻¹, ranging from 12.11 to 26.48 g kg⁻¹. Organic nitrogen (N) averaged 1.53 g kg⁻¹, ranging from 0.83 to 2.26 g kg⁻¹. Stand 2 had the most acidic average pH of the three sites, at 4.76. Its C content was also the lowest of the three sites, at 18.19 g kg⁻¹, although it exhibited a wide internal variation, with a minimum of 11.76, and a maximum of 28.38 g kg⁻¹. The average N content in this case was 1.61 g kg⁻¹. Finally, stand 3 was characterized by having an average pH of 4.90, with values between 4.13 and 5.98, in turn, it showed the highest average values for C and N, being 20.44 g kg⁻¹ with a maximum of 32.39 g kg⁻¹, and 1.84 g kg⁻¹ with a maximum of 2.85 g kg⁻¹, respectively.

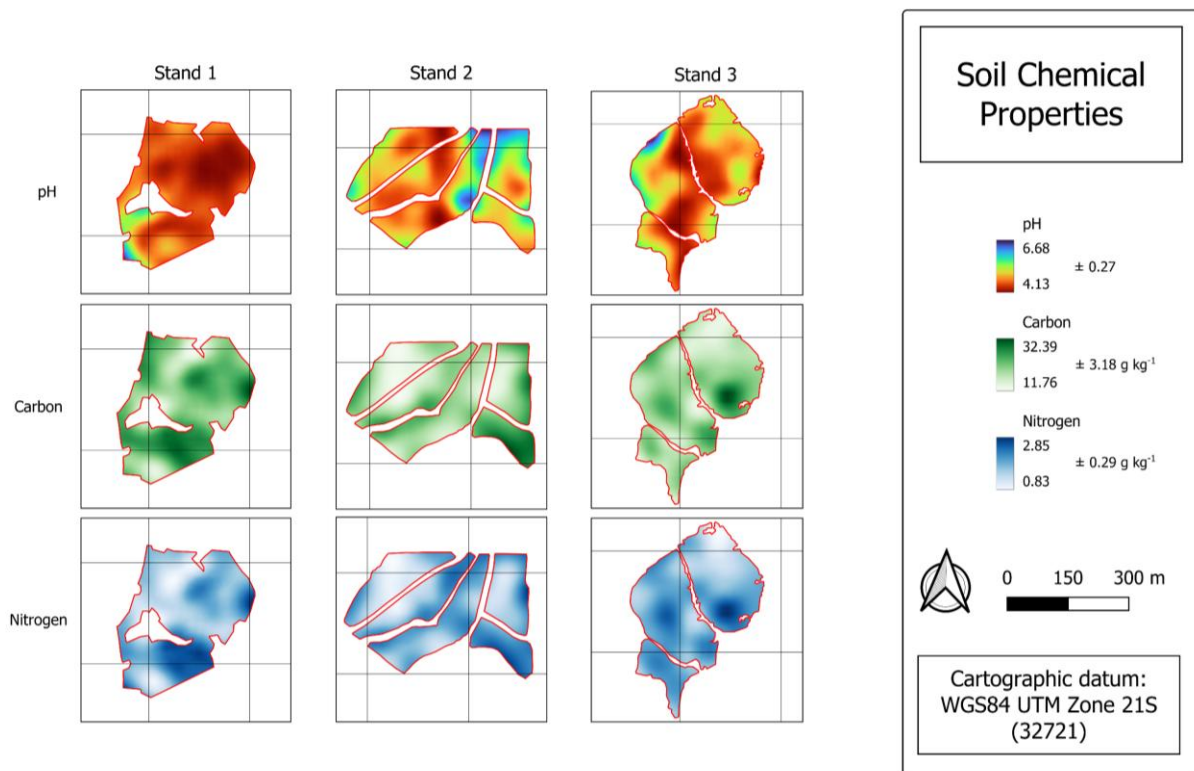


Figure 4. Spatial distribution of soil chemical properties (0–20 cm depth) across the three study stands. Interpolated maps represent pH, organic carbon, and nitrogen content, highlighting the spatial variability of soil fertility conditions at the microsite level. Kriging interpolation accuracy (RMSE): pH = 0.27; Carbon = 3.18 g kg⁻¹; Nitrogen = 0.29 g kg⁻¹.

3.4 Spatial estimation

Integrating UAV-derived structural metrics with high-resolution soil variables using the Random Forest (RF) algorithm enabled robust estimation of dendrometric variables. The predictive performance of the models was assessed through 10-fold cross-validation, and the results are summarized in Table 5. The models for Ht and MDH showed outstanding accuracy, with R^2 value of 0.98. The volume per hectare estimation model also achieved high predictive capacity ($R^2 = 0.94$; $RMSE = 62.25 \text{ m}^3 \text{ ha}^{-1}$). Finally, DBH showed great predictive power with an R^2 of 0.95 and an RMSE of 1.57 cm.

Table 4. Cross-validation performance of Random Forest models for the prediction of dendrometric variables (DBH, Ht, Vol, and MDH) in *Eucalyptus grandis*. Model accuracy is evaluated using the coefficient of determination (R^2) and root mean square error (RMSE).

Model	R^2	RMSE
DBH	0.95	1.57
Ht	0.98	1.08
Vol	0.94	62.25
MDH	0.98	1.06

Note. DBH: diameter at breast height (cm); Ht: total height (m); Vol: volume per hectare ($\text{m}^3 \text{ ha}^{-1}$); MDH: mean dominant Assmann height (m); R^2 : coefficient of determination of RF cross-validation; RMSE: mean squared error the RF cross-validation model.

This level of accuracy among the four modelled variables is visually confirmed in Figure 5, which illustrates the strong correlation between the values observed in the field and those predicted by the algorithm for each model.

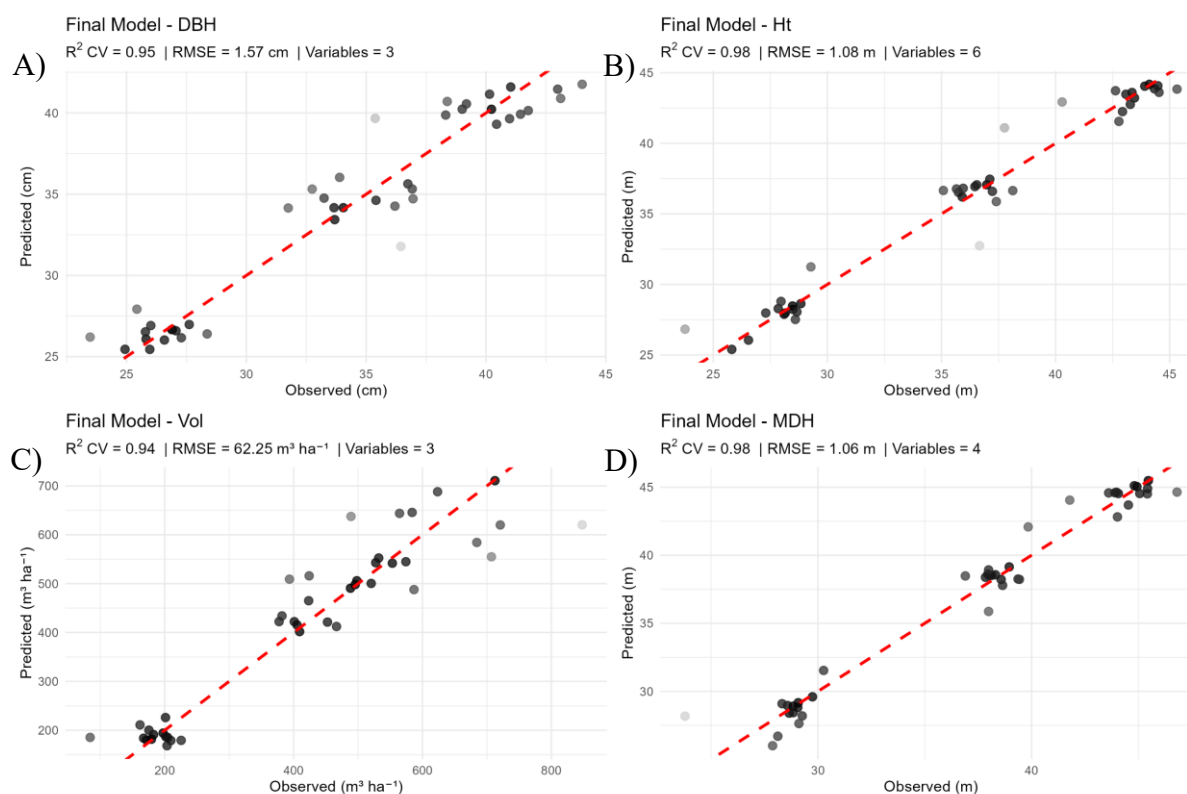


Figure 5. Observed versus predicted values for the final Random Forest models of dendrometric variables (DBH, Ht, Vol, and MDH) in *Eucalyptus grandis*. Model performance is indicated by cross-validation metrics (R^2 and RMSE), and the dashed red line represents the 1:1 relationship, showing the high predictive accuracy of the models.

Table 6 presents the predictor variables selected using the *Forward Feature Selection* (FFS) algorithm for estimating the evaluated parameters: DBH, Ht, Vol, and MDH. Soil covariates featured prominently in all four models, with pH ranking as the single most influential predictor for volume estimation and the second most important for DBH, Ht, and MDH. In particular, the pH variable showed high relative importance in all the evaluated models, establishing itself as a determining factor in explaining the existing variability.

In the DBH model, the variables of greatest relative importance were the 75th percentile and pH, followed to a lesser extent by nitrogen. The dominance of the 75th height percentile reflects its sensitivity to competition dynamics within canopy, as upper-percentile metrics are directly linked to radial growth under silvicultural management regimes (Nutto et al., 2006). The high importance of pH is consistent with its role as a regulator of nutrient availability and cation exchange capacity, processes that directly constrain secondary growth in the acid soils developed on the crystalline basement of northern Uruguay (Laclau et al., 2010). In the case of Ht, the structural metric Median, along with pH, had the greatest predictive weight, while the asymmetric indicator (Skewness) and other physical soil properties showed a smaller contribution. In the volume model, pH emerged as the dominant variable,

followed by sand content and Skewness. Similarly, for MDH, 75th percentile and pH explained most of the variability, while sand and BD had minor contributions. Taken together, these results reinforce the need to integrate data from soil variables and structural metrics derived from aerial photogrammetry, highlighting the dominant role of pH in driving stand growth dynamics.

Table 5. Relative importance (%) of predictor variables in the final Random Forest models for dendrometric variables (DBH, Ht, Vol, and MDH) in *Eucalyptus grandis*. Variable importance values indicate the contribution of each predictor to model performance.

Model	Variable	Relative importance (%)
DBH	Percentile_75	51.46
	pH	45.44
	Nitrogen	3.10
Ht	Median	63.16
	pH	33.36
	Skewness	1.48
	BD	0.90
	Silt	0.79
	Sand	0.31
Vol	pH	62.26
	Sand	32.93
	Skewness	4.81
MDH	Percentile_75	64.52
	pH	32.24
	Sand	2.24
	BD	1.00

Note. DBH: diameter at breast height; Ht: total height; Vol: volume per hectare; MDH: mean dominant Assmann height; BD: bulk density; pH: pH (H₂O).

The predicted values for the three stands are presented in Figure 6 through 9, each accompanied by the pixel-level frequency distribution of the predictions. The figures show the growth gradient observed in the inventory data, with stand 1 (9 years) exhibiting the lowest growth values, while stand 2 and 3 (12 and 15 years) show higher values. The frequency histograms also illustrate the data concentration. The distribution for stand 1 is narrower and skewed to the left, while for the other stands it is wider, reflecting the spatial heterogeneity associated with intraspecific competition and soil variability in later stages of crop rotation.

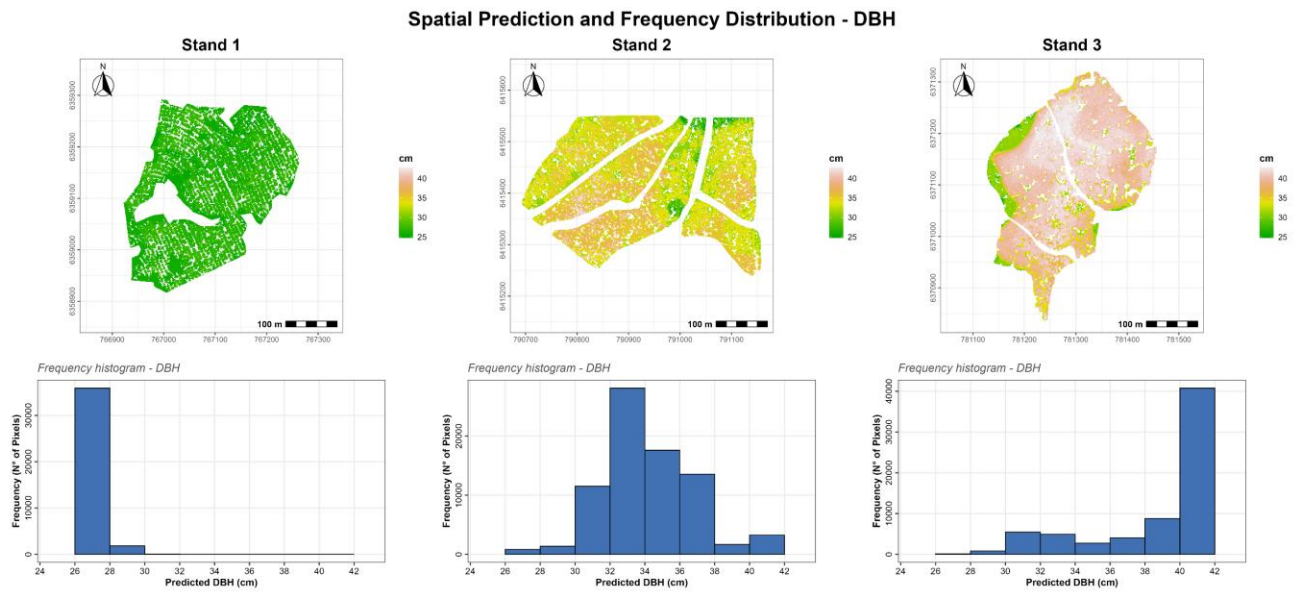


Figure 6. Spatial prediction and frequency distribution of diameter at breast height (DBH) across the three study stands. Upper panels display interpolated maps of predicted DBH values, while lower panels show the corresponding frequency histograms, illustrating the variability and distribution of tree size within each stand.

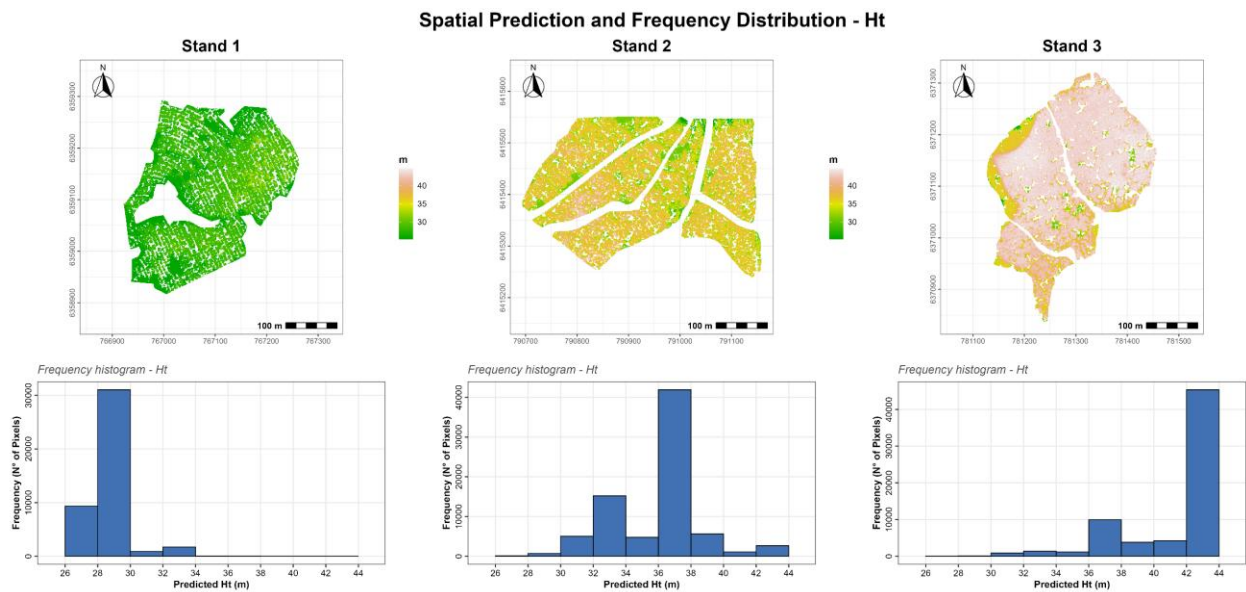


Figure 7. Spatial prediction and frequency distribution of total height (Ht) across the three study stands. Upper panels display interpolated maps of predicted Ht values, while lower panels show the corresponding frequency histograms, illustrating the variability and distribution of tree size within each stand.

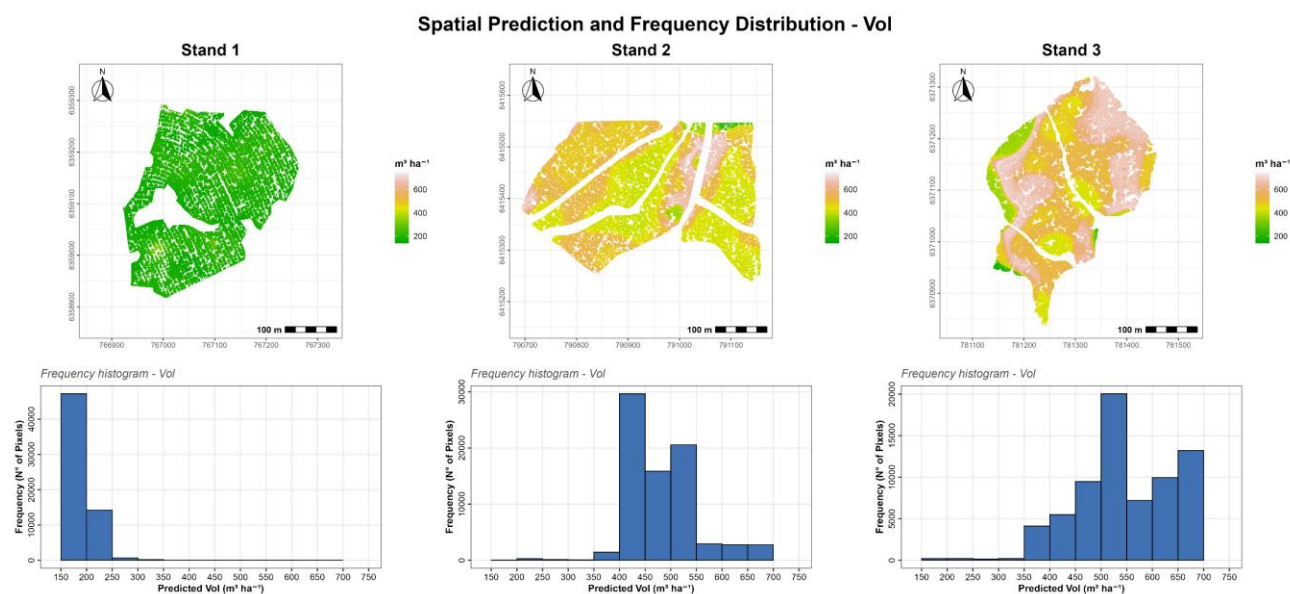


Figure 8. Spatial prediction and frequency distribution of volume per hectare (Vol) across the three study stands. Upper panels display interpolated maps of predicted Vol values, while lower panels show the corresponding frequency histograms, illustrating the variability and distribution of tree size within each stand.

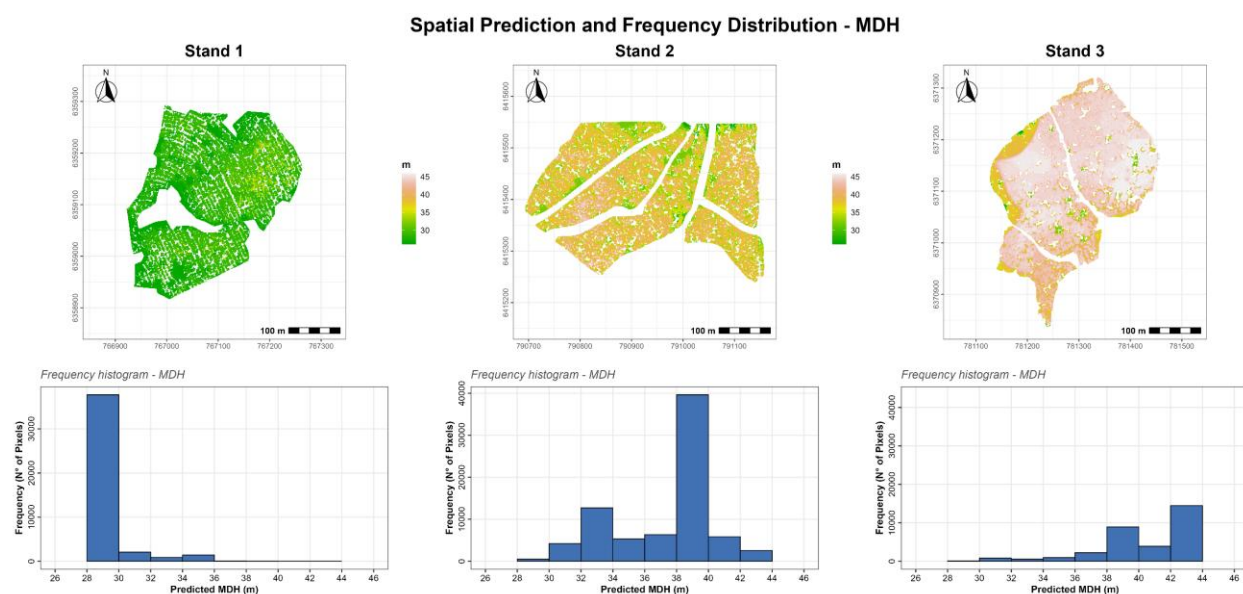


Figure 9. Spatial prediction and frequency distribution of dominant Assmann height (MDH) across the three study stands. Upper panels display interpolated maps of predicted MDH values, while lower panels show the corresponding frequency histograms, illustrating the variability and distribution of tree size within each stand.

4. Discussion

Accurate estimation of productive variables in mature *Eucalyptus grandis* plantations subjected to silvicultural treatments presents certain limitations during field inventories. Variations in stem shape and crown diameter, due to silvicultural treatments, alter the allometry of the trees, decreasing the representativeness of standard equations (Nutto et al., 2006). At an operational level, the progressive canopy closure in mature plantations makes it difficult to visualize each apex, hindering traditional field measurements of total height and increasing the bias associated with human error (da Silva et al., 2021). Furthermore, at the stand level, there is a tendency for spatial heterogeneity to increase, which means that traditional field sampling requires greater intensity to maintain acceptable accuracy (de Oliveira et al., 2021). In contrast to these limitations, the results obtained in this research demonstrate that integrating structural metrics from UAVs, soil data, and machine learning algorithms allows us to overcome these barriers. The following subsections address each component of this integration in turn.

4.1 Allometric model equation

The dependence of Model 3 on DBH and Ht reflects a change in stand allometry under silvicultural management. In short-rotation *Eucalyptus* plantations, DBH alone largely captures the existing volume variation because competition is uniform. However, in mature stands with certain silvicultural management practices, repeated thinning through pruning and harvesting within the rotation results in uneven growth between diameter and height. Released individual accelerate diameter growth, and those that were previously suppressed grow proportionally taller relative to their diameter (Nutto et al., 2006). This mismatch in growth means that a model with a single predictor systematically underestimates the volume of dominant trees and overestimates it in codominant ones, and this bias could accumulate at the stand level. The nonlinear structure of Model 3 efficiently fit this heterogeneity and is consistent with the accuracy reported by Hirigoyen et al. (2021) for *E. grandis* in Uruguay using similar structural predictors.

The nonlinear structure of Model 3 successfully captured and explained morphological variation with high accuracy. However, it is worth noting that this model's dependence on the Ht variable presents an operational challenge in mature stands. As highlighted by da Silva et al. (2021), canopy closure in mature stands increases bias in traditional measurements due to canopy occlusion. This difficulty justifies the need to integrate UAV photogrammetry to measure this fundamental variable accurately and on an operational scale.

4.2 Forest inventory

At the stand level, the forest inventory revealed a clear growth gradient associated with the age of plantations (9, 12, and 15 years), reflecting the expected dynamics for *E. grandis* plantations under silvicultural management conditions. As the rotation period progresses, an increase is observed in both the structural variables of the plantations and in the volume per hectare (Table 3), which is consistent for this species (Stape et al., 2010; Resquín et al., 2018). The values obtained, especially in the 12- and 15-year-old stands, confirm the high productive potential of these plantations under Uruguay's soil and climate conditions, which agrees with what has been reported by local studies (Resquín et al., 2018; Hirigoyen et al., 2021). As competition for resources intensifies in mature stands, resource allocation changes, favoring diameter growth over height growth, specifically in the stages near the end of the rotation (Nutto et al., 2006). This spatial heterogeneity, particularly pronounced in the 15-year-old stand, cannot be explained solely by stand age. This behavior suggests the influence of environmental factors as determinants of productivity, primarily soil properties (Stape et al., 2010; Reichert et al., 2023).

4.3 Soil attributes and spatial variability

The spatial heterogeneity of soil properties at the microsite scale (rather than their stand-level averages) proved to be the primary explanatory axis of intra-stand productivity variation. Traditionally, characterization in forest inventories is restricted to average values at the stand level, which masks variability at the microsite level. Kriging interpolation of physical and chemical properties addressed this limitation directly, providing continuous maps that minimize estimation error in unsampled areas (Oliver & Webster, 2014).

To spatially represent this heterogeneity, continuous raster layers were generated through ordinary kriging interpolation of discrete data derived from laboratory analysis into high-resolution (1×1 m) spatial variables. This spatial scale is important because the soil information will later be combined with the level of detail obtained from aerial photogrammetry metrics. By spatializing these variables, it is possible to observe soil gradients within the same stand. Such gradients, in turn, help explain the structural variability observed in mature *E. grandis* stands, which is strongly associated with the resources present at the site (Stape et al., 2010). pH, the most influential variable among soil predictors all four models across all four models, and the dominant predictor overall for volume, regulates nutrient availability and organic matter dynamics, highlighting that both factors limit growth in these plantations (Laclau et al., 2010). In the sandy loam of eastern Uruguay, where base saturation is low and cation exchange capacity is limited by the crystalline basement, pH exerts a control over

phosphorus fixation and nitrogen mineralisation rates (Laclau et al., 2010). A reduction of just 0.5 pH units below the optimum range for *E. grandis* (5.5-6.5) can lead to aluminium solubilization and phosphate immobilization, reducing root elongation. This mechanism explains why pH emerged as the most important soil predictor in all four models, even competing with texture and bulk density variables that directly affect water dynamics. Physical properties also have an impact, with both sand content and bulk density directly affecting water retention and resistance to root exploration. These factors are critical in advanced stages where there is high intraspecific competition (Reichert et al., 2023). The spatial distribution of physical and chemical properties is not only descriptive of the site but will also be a fundamental input for modelling forest growth with high precision.

4.4 Spatial estimation

The integration of metrics derived from aerial photogrammetry with soil variables using the Random Forest algorithm provided an accurate and operationally efficient approach for estimating DBH, Ht, Vol, and MDH variables in *E. grandis* stands. Traditionally, the prediction of structural variables relied on metrics taken directly from the canopy, primarily obtained through airborne LiDAR sensors (ALS). This technology remains the gold standard given its ability to penetrate the stand canopy (Rizzo et al., 2023). However, photogrammetry point clouds successfully captured the canopy height metrics necessary to generate high-precision predictive models. This result is consistent with that of Torres-Sánchez et al. (2015) and Baietto et al. (2025), who demonstrated that structural data obtained using UAVs provide sufficient canopy characterization for plot-level estimation in *Eucalyptus* plantations, even in the absence of LiDAR data.

These results align with what is expected for mature *E. grandis* plantations with a closed canopy; the upper canopy surface concentrates the height signal most strongly correlated with stand volume. The subcanopy structure, where LiDAR offers its main advantage, contributes proportionally less to volume prediction in dense, uniformly aged stands approaching the end of the rotation. In this context, the penetration limitation of photogrammetric point clouds is less relevant. It is worth noting, however, that photogrammetric canopy metrics did not emerge among the dominant predictors for volume estimation, where height percentiles and soil pH captured most of the explained variance. In this regard, while structural metrics obtained from UAVs are sufficient to fit the models, their low contribution to volume, relative to soil variables, warrants further investigation using ablation analyses that systematically isolate the predictive role of each group of variables.

A key finding of this research was demonstrating the critical role of soil variables (especially pH) in the predictive performance of these models. Recent research supports these findings; Baietto et al. (2025) showed that integrating continuous soil data into remote sensing-based models significantly increases the accuracy of structural variable estimates in *E. dunnii*. The present study obtained similar

results by operating at a high spatial resolution (1×1 m), which allowed the Random Forest model to capture soil variability at the microsite level, a factor that influences individual growth and is often underestimated in other models. However, this research revealed some limitations. First, the fitted models are site-specific, calibrated in three stands in the departments of Treinta y Tres and Cerro Largo, and their transferability to plantations with different soil types or similar silvicultural histories has not been validated. Second, the photogrammetry data were acquired at a single point in time, which prevents the assessment of canopy structure variability and its potential effect on model predictions. Third, the relatively small number of sampling plots ($n = 36$) may limit the ability of Random Forest models to capture all the site variability present in northern Uruguay. Future work should address these limitations by expanding the sampling network, incorporating multi-temporal UAV acquisitions, and testing the model's transferability across different soil groups and rotation ages.

The operational relevance of this approach extends beyond the study area. The need to improve spatial estimation tools for the forestry sector has recently been highlighted locally by Paiz-Díaz (2024), who emphasizes the importance of integrating remote sensing technologies adapted to Uruguay's operational conditions for silvicultural decision making. While satellite platforms offer significant advantages for regional monitoring (Baietto et al., 2025), the spatial resolution achieved with UAV sensors is practically indispensable for capturing intra-stand variability towards the end of the rotation period. Thus, the proposed methodology is positioned as a highly accurate and efficient tool, directly addressing current demands for digital inventory in commercial plantations.

5. Conclusions

This study demonstrates that integrating high-resolution soil data, structural metrics obtained via UAVs, and machine learning provides a robust and efficient approach for estimating productive variables in mature *Eucalyptus grandis* plantations. Allometric analysis demonstrated the need to consider the existing complexity of the stands by incorporating DBH and Ht variables into the model's structure. The fitted equation provides a precise and specific tool for estimating volume in northern Uruguay.

The forest inventory revealed a productivity gradient in the stands under study, thus confirming the high productivity potential of *E. grandis* in northern Uruguay. The significant intra-stand variability observed, primarily in the oldest stand, indicates that soil conditions at the microsite are a more important determinant of productivity than stand age alone. High-resolution spatial characterization of soil properties using geostatistics proved essential for capturing the observed variability. Among the soil properties, pH emerged as the most influential factor in all models and the dominant factor in volume, highlighting its role in regulating nutrient availability and forest production. Random forest

models achieved high predictive capacity for all target variables, confirming the value of combining UAV-derived structural metrics with intensive soil characterization. UAV photogrammetry proved to be a practical and cost-effective alternative to LiDAR for extracting structural metrics from mature *E. grandis* plantations.

The framework presented offers the Uruguayan forestry sector a scalable and operational methodology for evaluating spatial productivity. Future work could focus on validating the model's transferability across different soil types and evaluating, through ablation studies, the independent contribution of each group of variables for volume estimation.

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Supplementary material

Table S1 Candidate allometric models evaluated for estimating individual tree volume (V_i) in *Eucalyptus grandis*. Models include linear and nonlinear formulations based on diameter at breast height (DBH) and total height (Ht).

Equation number	Equation
1	$V_i = \beta_0 \times DBH^{\beta_1}$
2	$V_i = \beta_0 \times ((DBH^2) \times Ht)^{\beta_1}$
3	$V_i = \beta_0 \times (DBH^{\beta_1}) \times (Ht^{\beta_2})$
4	$V_i = \beta_0 + \beta_1 \times DBH^2$
5	$V_i = \beta_1 \times DBH^2 + \beta_2 Ht + \beta_3 DBH^2 Ht + \beta_3 \times DBH^2 \times Ht$
6	$V_i = e^{(\beta_0 + \beta_1 \times DBH + \beta_2 \times DBH^2)}$
7	$V_i = DBH^2 \times \beta_0 + (\beta_1 \times DBH \times Ht)$
8	$V_i = \beta_0 \times DBH + \beta_1 \times DBH^2 + \beta_2 \times DBH \times Ht$
9	$V_i = e^{(\beta_0 + \beta_1 \times \ln (DBH^2 \times Ht))}$

Note. DBH: diameter at breast height; Ht: total height. V_i : individual volume. (Hirigoyen et al., 2021).

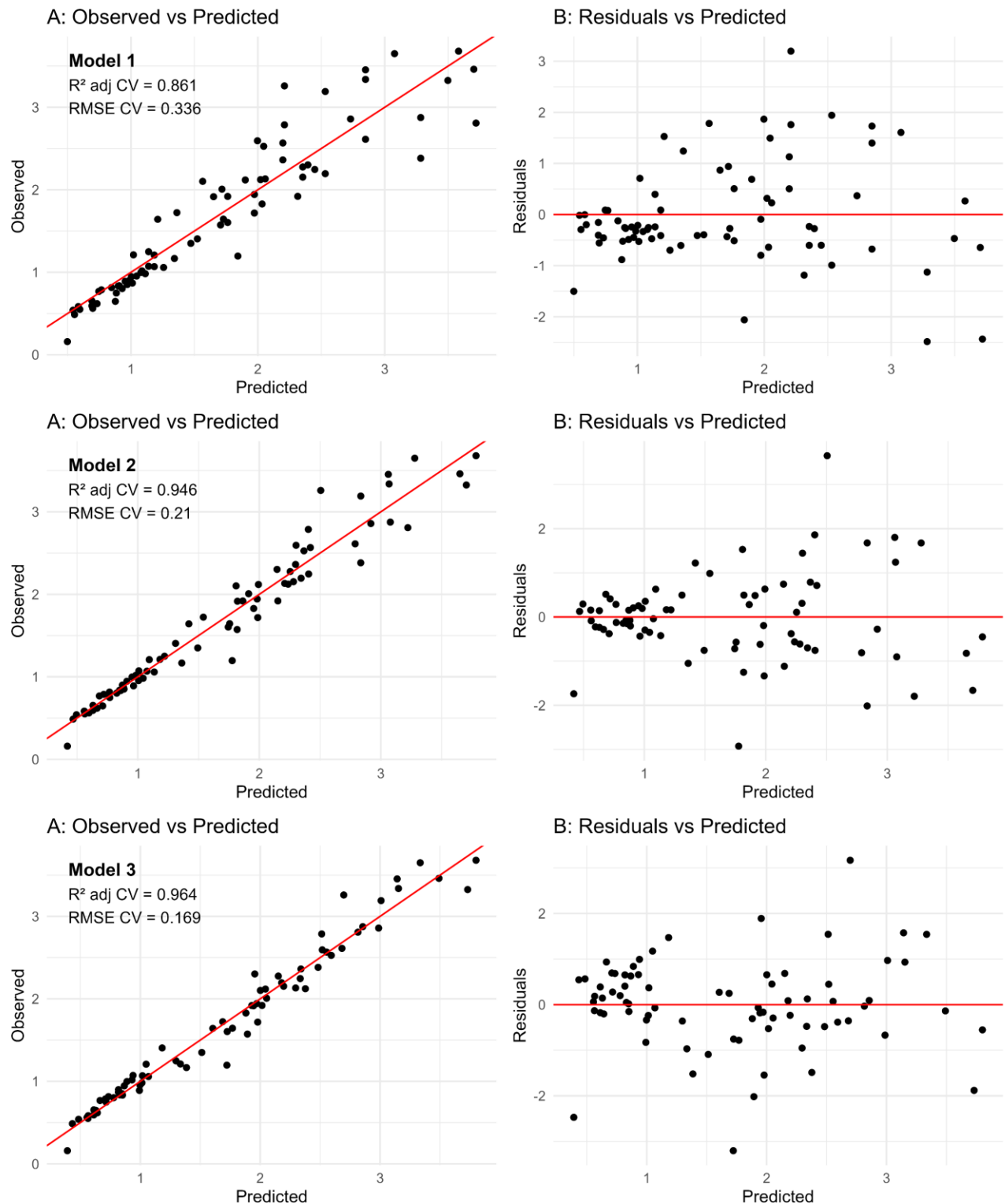


Figure S1. Performance and residual diagnostics of the evaluated allometric models. For each model (Models 1–3), left panels show observed versus predicted values, while right panels present residuals versus predicted values. The red line indicates the 1:1 relationship and zero residual reference, respectively, allowing assessment of model accuracy and bias.

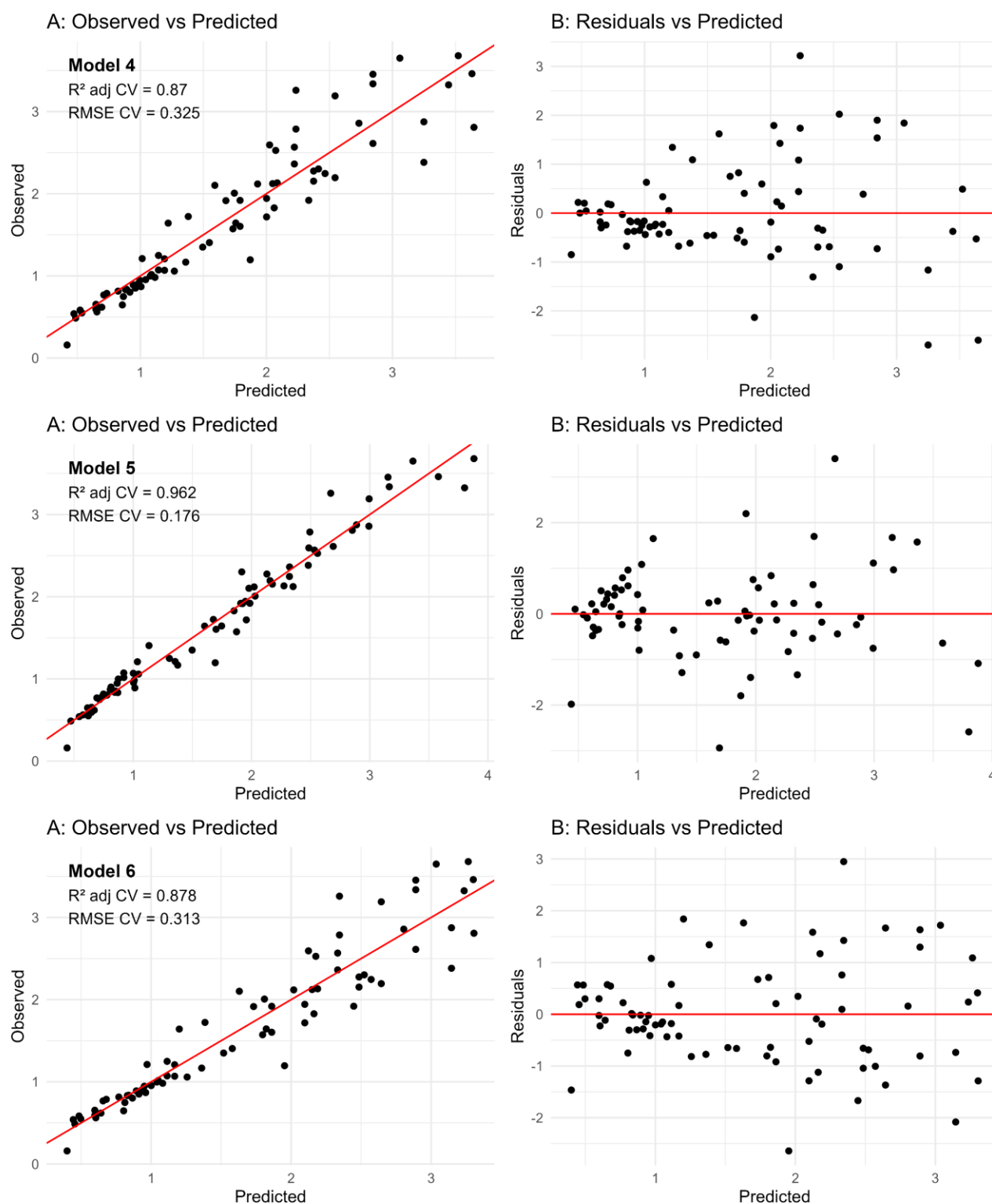


Figure S2. Performance and residual diagnostics of the evaluated allometric models. For each model (Models 4–6), left panels show observed versus predicted values, while right panels present residuals versus predicted values. The red line indicates the 1:1 relationship and zero residual reference, respectively, allowing assessment of model accuracy and bias.

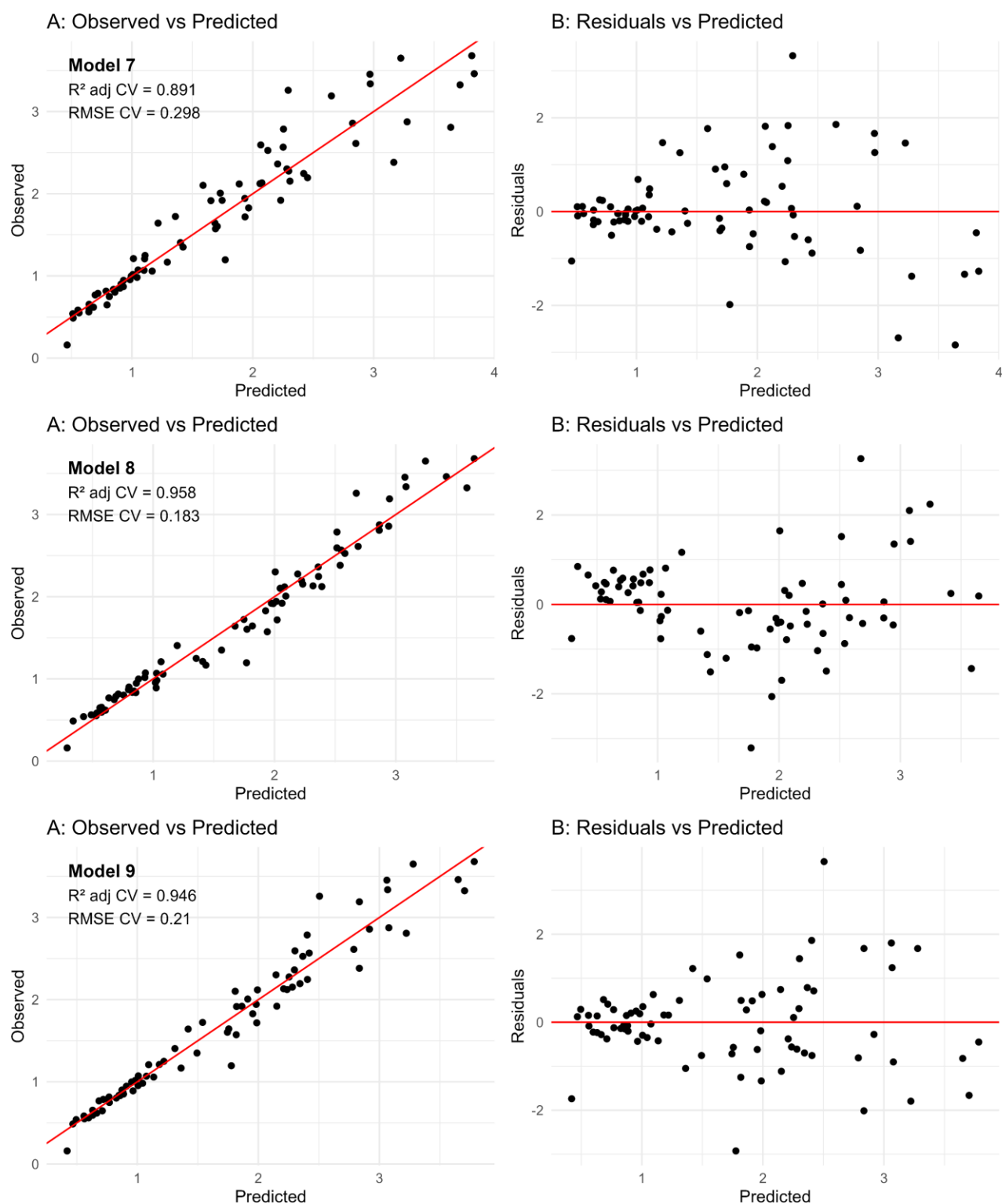


Figure S3. Performance and residual diagnostics of the evaluated allometric models. For each model (Models 7–9), left panels show observed versus predicted values, while right panels present residuals versus predicted values. The red line indicates the 1:1 relationship and zero residual reference, respectively, allowing assessment of model accuracy and bias.