Automated *Eucalyptus* Inventory: Comparison of Manual, CHM and LiDAR Methods

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Abstract. Traditional forest inventory requires substantial manual effort and resources for measuring dendrometric parameters. This study compares field-based inventory with two automated remote-sensing approaches in *Eucalyptus urograndis* plantations: Canopy Height Model (CHM) analysis and direct LiDAR point cloud processing. Both methods employ robust preprocessing pipelines including statistical outlier filtering (median + 3 MAD), multi-scale peak detection, and watershed segmentation for individual tree delineation. CHM processing utilises morphological operations and dynamic Gaussian smoothing, whilst LiDAR analysis applies DBSCAN clustering on height-normalised point clouds. Evaluation across two commercial stands revealed that CHM slightly overestimated mean tree height (+10.5% and +1.6%), whereas LiDAR underestimated (–4.6% and –4.2%), both remaining within acceptable operational tolerances (±10%). Volume estimates achieved high precision, with maximum deviation of 6.7% from manual measurements. Tree density was consistently underestimated by 10% across both methods. Despite these systematic biases, both approaches demonstrated operational viability for commercial forest inventory, offering substantial improvements in efficiency and spatial coverage whilst maintaining accuracy comparable to traditional sampling methods.

Keywords: Forest Inventory · Biomass · LiDAR · Remote Sensing · *Eucalyptus* · Watershed Segmentation

1 Introduction

Traditional forest inventory through systematic plot sampling, whilst established and reliable, is constrained by high labour requirements, limited spatial coverage,

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and measurement errors, particularly for tree height [4,5]. These limitations are increasingly problematic for the Brazilian forestry sector, which requires precise quantification of timber stocks and carbon sequestration across extensive plantations [9].

Airborne LiDAR has transformed forest measurement by providing three-dimensional structural data enabling accurate derivation of tree height, crown dimensions, density, volume, and biomass with complete spatial coverage [7,10]. This capability is particularly valuable for fast-growing *Eucalyptus urograndis* plantations, where rapid growth rates and structural variability challenge traditional inventory methods [3].

Recent advances include machine learning approaches such as DBSCAN clustering [2], multi-source data fusion [13], and combined terrestrial-UAV scanning [6]. However, rigorous validation against traditional methods remains essential for specific regional conditions and plantation types.

This study directly compares forest parameter estimates from traditional manual inventory, Canopy Height Model (CHM) processing, and LiDAR point cloud analysis in commercial *Eucalyptus urograndis* plantations, evaluating their precision, consistency, and operational viability for Brazilian commercial forestry.

2 Materials and Methods

2.1 Study Area Characterisation

The study was conducted in two adjacent commercial stands of *Eucalyptus urograndis* (clone 2361), aged between 9 and 10 years at the time of data acquisition. The stands are located within the Tela Branca Farm, situated in the municipality of Águas de Santa Bárbara, São Paulo State, Brazil. The total evaluated area comprised approximately 51.4 hectares, specifically 27.55 ha in Stand 1 and 23.02 ha in Stand 2.

2.2 Traditional Forest Inventory

The traditional forest inventory was conducted using a systematic sampling methodology involving permanent monitoring plots. Within these plots, key dendrometric parameters were directly measured. The measured parameters included:

- Diameter at Breast Height (DBH): Measured at 1.30 m above ground using a calliper.
- Total height (H): Measured for a sample of trees using a digital clinometer.

For trees where direct height measurement was not feasible, a local hypsometric model (Henriksen model: $h = b_0 + b_1 \log(\mathrm{DBH})$[1]) was fitted to estimate total height based on measured DBH values.

[1] $b_0 = 22.1116, b_1 = 5.75306$.

Individual tree biomass (Bs, in kg) was estimated using a species-specific allometric equation previously developed for similar eucalyptus plantations in the region [17]:

$$\text{Bs (kg)} = \exp(-2.977 + \ln(\rho \times \text{DBH}^2 \times H)) \quad (1)$$

where ρ represents the basic wood density (adopted as $0.5\,\text{g/cm}^3$ based on manual report data), DBH is the diameter at breast height in cm, and H is the total tree height in meters. Total biomass, including root systems, was calculated by applying an expansion factor of 1.2 to the above-ground biomass, a value commonly used for eucalyptus plantations and adopted from the manual report [8].

The results from this traditional inventory served as the reference dataset for evaluating the accuracy and performance of the automated methodologies.

2.3 LiDAR Data Acquisition and Pre-Processing

Airborne LiDAR data were acquired using a DJI Zenmuse L1 sensor flown at approximately 100 m above ground level. The sensor operated at 160 kHz pulse frequency with a 70.4° (horizontal) × 4.5° (vertical) field of view, achieving a nominal point density of 377 points/m^2 with 55% flight strip overlap. Positional accuracy was estimated at 10 cm horizontally and 5 cm vertically at 50 m altitude.

The automated processing pipeline utilised classified LiDAR point clouds (.las format), Digital Surface Model (DSM), Digital Terrain Model (DTM), area perimeter boundary (KMZ), and orthomosaic imagery. Raster datasets were provided in SIRGAS 2000/UTM zone 22S coordinate reference system (EPSG:31982) at 0.414 m/pixel resolution.

Pre-processing comprised three stages. First, flight strips were aligned using the Iterative Closest Point (ICP) algorithm. Second, points were automatically classified following American Society for Photogrammetry & Remote Sensing (ASPRS) LAS specification standards [1]: Class 2 (ground) and Class 5 (high vegetation). Ground points were identified using the Adaptive Triangular Irregular Network (ATIN) algorithm, whilst vegetation points were distinguished based on height above the interpolated terrain surface. Third, noise removal was performed via Statistical Outlier Removal (SOR) filtering, eliminating points beyond defined statistical thresholds.

To manage computational resources for large datasets (up to 6 GB), a chunked processing approach was implemented, dividing point clouds into blocks of approximately 2,000,000 points. This strategy maintained processing efficiency without compromising spatial continuity or analysis integrity. Forest structure analysis primarily utilised Class 5 (high vegetation) points, with non-ground points serving as supplementary data when vegetation classification was incomplete.

Terrain model generation followed established photogrammetric principles. The DTM was constructed from Class 2 (ground) points through Triangular Irregular Network (TIN) interpolation to a regular grid, refined with moving average filtering. The DSM was similarly generated from first-return points using TIN-based linear interpolation, with median filtering applied to reduce artefacts from isolated high points.

The high-density LiDAR acquisition captured detailed three-dimensional forest structure, enabling precise characterisation of individual tree crowns and vertical stratification. Figure 1 demonstrates the point cloud representation of vegetation, with elevation-coded colouring revealing both terrain variation (approximately 5 m relief) and canopy height heterogeneity across the sample area. This three-dimensional data formed the basis for both the CHM generation and direct point cloud clustering approaches, preserving structural information that would be lost in traditional two-dimensional analysis.

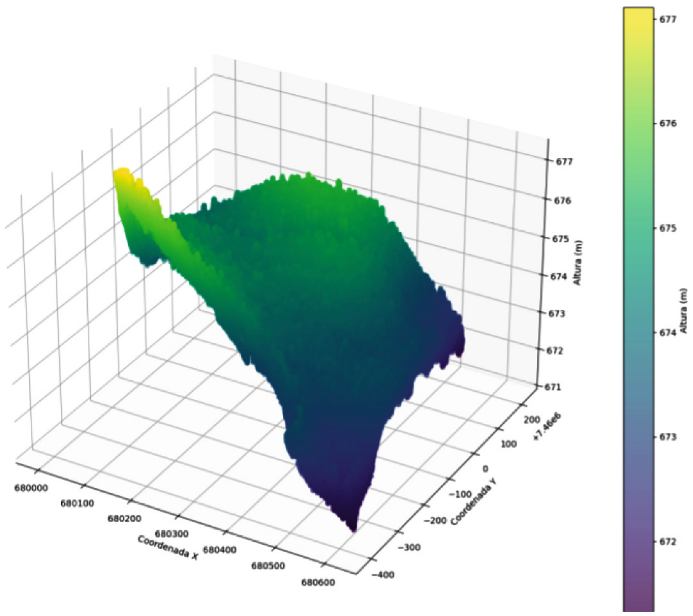

Fig. 1. Three-dimensional LiDAR point cloud of vegetation (Class 5) coloured by elevation (672–677 m), showing the vertical structure and canopy surface variation across a sample area. Point density: 377 points/m^2.

2.4 Canopy Height Model (CHM) Generation

The Canopy Height Model (CHM) represents a fundamental remote sensing product for forest structure assessment, providing spatially continuous measurements of vegetation height above ground level [12]. In operational forestry, CHM serves as the primary input for individual tree detection algorithms and stand-level inventory parameters, offering cost-effective analysis compared to direct point cloud processing [11]. The rasterised nature of CHM enables integration with established image processing techniques and facilitates rapid operational deployment across large forest estates.

CHM generation follows the normalised difference approach, whereby vegetation height is derived by subtracting the Digital Terrain Model (DTM) from the Digital Surface Model (DSM): CHM = DSM – DTM.

Input data comprised pre-processed raster products: the DSM representing the uppermost surface captured by first-return LiDAR pulses, and the DTM interpolated from ground-classified points (Class 2). Both models were derived from the LiDAR point cloud through TIN-based interpolation as described in Sect. 2.3. To ensure spatial alignment, the DTM was reprojected to match the DSM's resolution (0.414 m/pixel), extent, and coordinate system using bilinear resampling.

Data quality control involved three stages. First, pixels containing invalid values in either input model were masked. Second, negative height values—typically arising from classification uncertainties at terrain discontinuities—were set to zero. Third, statistical outlier filtering was applied using the Median Absolute Deviation (MAD) approach: $\mathrm{CHM}_{\mathrm{filtered}} = \min(\mathrm{CHM}, \mathrm{median} + 3 \times \mathrm{MAD})$.

Additionally, an absolute maximum threshold of 45 m was enforced, based on known growth limits for 10-year-old *Eucalyptus urograndis* in the region. Final smoothing employed Gaussian filtering with adaptive kernel size proportional to expected crown dimensions, preserving crown morphology whilst reducing high-frequency noise.

2.5 Tree Detection and Parameter Estimation

Two fundamentally different approaches were implemented for automated forest inventory, each with distinct data sources and processing pipelines (Table 1):

Table 1. Fundamental differences between automated inventory methods

Aspect	CHM Method	LiDAR Point Cloud
Data source	2D raster (0.414 m pixels)	3D points (377 pts/m^2)
Height extraction	Pixel value at crown peak	Mean of cluster points
Tree detection	Watershed segmentation	DBSCAN clustering
Vertical structure	Lost in rasterisation	Fully preserved
Processing speed	Fast (minutes)	Slower (hours)
Memory requirement	Low (<2 GB)	High (>8 GB)
Understorey handling	Filtered by height mask	Analysed separately

CHM-Based Tree Detection. Individual tree detection from the CHM employed a seven-stage processing pipeline optimised for uniform eucalyptus plantations:

1. **Morphological Masking:** Binary classification of pixels exceeding 2 m height threshold, eliminating understorey vegetation whilst preserving canopy structures.
2. **Gaussian Smoothing:** Adaptive noise reduction with kernel size determined by:
$$\sigma = \frac{d_{\text{expected}}}{p \times k} = \frac{2.14\ \text{m}}{0.414\ \text{m/pixel} \times 1.5} \approx 3.4\ \text{pixels} \tag{2}$$
where d_{expected} is the expected crown diameter based on column spacing (2.14 m), p is pixel resolution, and k is an empirically-derived smoothing factor balancing noise suppression against crown boundary preservation.
3. **Multi-Scale Peak Detection:** Local maxima identification using variable window sizes corresponding to crown size variability within the plantation:
$$W_{60\%} = 1.3\ \text{m (suppressed trees)} \tag{3}$$
$$W_{80\%} = 1.7\ \text{m (intermediate crowns)} \tag{4}$$
$$W_{100\%} = 2.14\ \text{m (expected size)} \tag{5}$$
$$W_{120\%} = 2.6\ \text{m (dominant trees)} \tag{6}$$
These scales capture the natural crown heterogeneity arising from competition and microsite variation in even-aged stands.
4. **Peak Validation:** Confirmation of genuine tree apices through neighbourhood analysis, evaluating height gradients and local maxima characteristics within a validation radius of 0.5 m.
5. **Watershed Segmentation:** Crown boundary delineation using validated peaks as markers, with segment boundaries following CHM gradient watersheds.
6. **Centroid Calculation:** Determination of tree positions from crown segment geometric centres.
7. **Non-Maximum Suppression:** Elimination of redundant detections within radius $r = 0.95 \times 2.14$ m, retaining only the highest peak per neighbourhood.

Parameter Calibration Protocol: Initial parameters derived from planting geometry (3.86 m × 2.14 m spacing) underwent iterative refinement through comparison with field inventory. Calibration adjusted detection sensitivity until automated counts approximated manual density within ±10%. For stands where detection fell below 80% of expected density, a correction algorithm generated synthetic trees using spatial statistics (mean height and standard deviation) from detected trees, compensating for systematic under-detection in dense canopy conditions (Fig. 2).

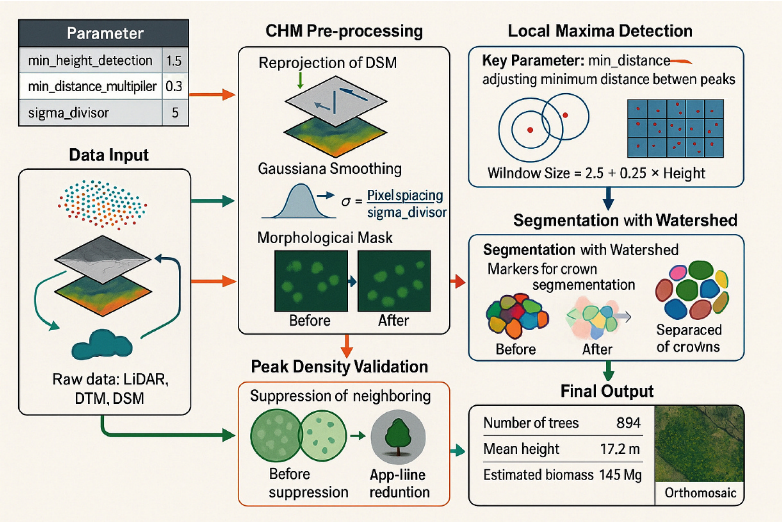

Fig. 2. Parameter-driven tree detection workflow based on CHM, showing the seven-stage processing pipeline from initial height model through to validated tree positions.

LiDAR Point Cloud-Based Tree Detection. Direct point cloud analysis bypassed rasterisation, preserving three-dimensional forest structure. After height normalisation using the DTM, vegetation points exceeding 2 m height were retained. Tree identification employed DBSCAN clustering on points above the 70th height percentile, focusing computational effort on canopy tops where crown separation is maximal.

DBSCAN parameters were derived from plantation geometry:

- ε (neighbourhood radius) = 2.3 m (75% of mean tree spacing)
- MinPts (minimum cluster size) = 3 points

This parameterisation prevented over-segmentation of individual crowns whilst maintaining sensitivity to closely-spaced trees. When clustering yielded <50% expected tree count, population was estimated from point density relationships calibrated against manual inventory.

Parameter Estimation. For each detected tree, mensuration parameters were computed:

- **Height:** CHM pixel value at tree location (CHM method) or mean of clustered canopy points (LiDAR method)
- **DBH:** Stand mean from field inventory (19.04 cm for Stand 1, 20.45 cm for Stand 2), acknowledging current limitations in aerial DBH prediction

– **Volume:** Individual tree volume calculated using cylindrical form adjusted by species-specific form factor:

$$\text{Volume (m}^3\text{)} = \pi \times \left(\frac{\text{DBH (cm)}}{200}\right)^2 \times \text{H (m)} \times 0.5 \tag{7}$$

where 0.5 is the form factor for eucalyptus.
– **Biomass:** Both traditional (volume × wood density × expansion factor) and logarithmic (Eq. 1) methods, with wood density = 0.5 g/cm^3 and expansion factor = 1.2

Population-level metrics were computed by scaling individual tree values by detected stem density (trees/ha).

2.6 Comparison and Validation

The results obtained from the CHM and LiDAR point cloud processing were systematically compared against the reference data from the traditional manual inventory for both Stand 1 and Stand 2. The key parameters evaluated were tree population density (trees/ha), mean tree height (m), volume per hectare (m^3/ha), and biomass per hectare (Mg/ha) using both calculation methods. The comparison focused on quantifying the differences (absolute and percentage) between the automated methods and the manual inventory. The aim was to validate the precision of the automated approaches and understand systematic biases or variations inherent to each method. Parameter calibration for tree detection was guided by the need to achieve population densities similar to the manual inventory. The distribution of biomass by diameter class from the traditional inventory was also compared against patterns observed in the automated methods.

3 Results and Discussion

3.1 Dendrometric Characteristics of the Stands

The traditional forest inventory provided reference data illustrating the structural characteristics of the two studied stands. Stand 1 and Stand 2 exhibited differences in mean DBH, mean height, volume, and biomass per hectare, as summarised in Table 2.

These differences can be attributed to site-specific factors such as subtle variations in soil conditions, microclimate, understorey density, and past management or disturbance events, such as the incidence of fire mentioned in the upper portion of Stand 2. Stand 2 notably presented a higher mean DBH, mean height, volume, and biomass compared to Stand 1, consistent with lower potential interspecific competition from understorey vegetation.

Table 2. Dendrometric characteristics of stands obtained by traditional inventory.

Parameter	Stand 1	Stand 2
Area (ha)	27.55	23.02
Population (trees/ha)	1,211	1,246
Mean DBH (cm)	19.04	20.45
Mean Height (m)	28.73	29.87
Volume (m^3/ha)	499.70	549.47
Biomass (Logarithmic, Mg/ha)	385.41	475.77

3.2 Comparison Between Methodologies

The comparison between the traditional manual inventory and the automated methods (CHM and LiDAR point cloud processing) for both stands is presented in Tables 3 and 4[2].

Table 3. Comparison of forest parameters obtained by different methodologies for Stand 1 (Area: 27.55 ha).

Parameter	Manual	CHM	Difference (%)	LiDAR	Difference (%)
Area total (ha)	27.55	27.55	0.0%	27.55	0.0%
Population (trees/ha)	1,211.00	1,089.87	–10.0%	1,089.90	–10.0%
Number total dof trees	33,363	30,026	–10.0%	30,026	–10.0%
Average DBH (cm)	19.04	19.04	0.0%	19.04	0.0%
Average height (m)	28.73	31.76	+10.5%	30.05	+4.6%
Volume (m^3/ha)	499.70	492.60	–1.4%	466.05	–6.7%
Traditional biomass (t/ha)	–	295.56	–	279.63	–
Total biomass (t)	–	8,142.68	–	7,703.76	–
Logarithmic biomass (Mg/ha)	385.41	426.05	+10.5%	403.07	+4.6%
Total biomass log. (Mg)	10,617.90	11,737.60	+10.5%	11,104.70	+4.6%

The automated methods (CHM and LiDAR point cloud) showed results that are consistent with each other and generally close to the manual inventory results for both stands.

Analysis of Stand 1 Results. For Stand 1, the automated methods consistently underestimated the tree population density by approximately 10% (1,090 trees/ha vs 1,211 trees/ha manually). Mean height estimation varied, with the CHM method superestimating height by 10.5% (31.76 m vs 28.73 m) and the

[2] Biomass traditional manual not provided.

Table 4. Comparison of forest parameters obtained by different methodologies for Stand 2 (Area: 23.02 ha).

Parameter	Manual	CHM	Difference (%)	LiDAR	Difference (%)
Area total (ha)	23.02	23.02	0.0%	23.02	0.0%
Population (trees/ha)	1,246.00	1,121.38	–10.0%	1,121.40	–10.0%
Number total de árvores	28,685	25,816	–10.0%	25,816	–10.0%
DBH médio (cm)	20.45	20.45	0.0%	20.45	0.0%
Altura média (m)	29.87	30.34	+1.6%	28.61	–4.2%
Volume (m^3/ha)	549.47	558.81	+1.7%	526.92	–4.1%
Traditional biomass (t/ha)	–	335.29	–	316.15	–
Total biomass (t)	–	7,718.83	–	7,278.33	–
Logarithmic biomass (Mg/ha)	475.77	483.31	+1.6%	455.72	–4.2%
Total biomass log. (Mg)	10,953.00	11,126.60	+1.6%	10,491.40	–4.2%

LiDAR point cloud method showing a smaller superestimation of 4.6% (30.05 m). Volume per hectare was underestimated by both automated methods, with a difference of –1.4% for CHM and –6.7% for LiDAR compared to the manual inventory. These volumetric differences are well within acceptable margins for forest inventories, typically considered to be around 10%. Logarithmic biomass estimates followed the pattern of height variations, with CHM showing a +10.5% difference and LiDAR a +4.6% difference.

Analysis of Stand 2 Results. In Stand 2, similar to Stand 1, both automated methods underestimated tree population density by approximately 10% (1,121 trees/ha vs 1,246 trees/ha manually). Height estimation in Stand 2 showed less superestimation by CHM (+1.6%, 30.34 m vs 29.87 m) compared to Stand 1, while the LiDAR point cloud method actually underestimated height by 4.2% (28.61 m). Volume per hectare estimations were close to the manual value, with CHM showing a slight superestimation of +1.7% and LiDAR a slight underestimation of –4.1%. These results demonstrate precision for automated methods in estimating volume. Logarithmic biomass estimates also closely followed the height variations, with CHM showing a minimal +1.6% difference and LiDAR a –4.2% difference.

Key Findings. Both methods exhibited consistent patterns across stands:

- **Tree density:** Systematic 10% underestimation, indicating detection sensitivity requires adjustment for dense eucalyptus canopies
- **Height estimation:** CHM overestimated (+1.6 to +10.5%), LiDAR showed mixed results (–4.2 to +4.6%), reflecting fundamental differences in how canopy surface is characterised
- **Volume precision:** Maximum 6.7% deviation demonstrates operational viability for both methods

– **Method comparison:** LiDAR's conservative estimates suggest better handling of canopy gaps and edge effects

The systematic biases are correctable through calibration, whilst maintaining the efficiency advantages of automated inventory.

3.3 Advantages and Limitations of Methodologies

Each methodology presents a distinct set of advantages and limitations for forest inventory:
Traditional Inventory:

– Advantages: Well-established and validated methodology; allows for direct observation and measurement of individual tree attributes (including DBH, health status, presence of pests/diseases); provides data for calibrating allometric equations and validating remote sensing methods.
– Limitations: Requires significant time and human resources for field work; limited spatial coverage (sampling); susceptible to measurement errors; difficult in areas with dense understorey or difficult terrain; data acquisition is slower, limiting frequency of monitoring.

Automated Methods (CHM and LiDAR Processing):

– Advantages: Provide complete spatial coverage of the area; data acquisition is rapid, allowing for frequent monitoring; generate three-dimensional models of forest structure; significantly reduce field work effort and time; scalable to large areas; non-destructive.
– Limitations: Dependence on robust algorithms and calibrated parameters for indirect estimation of attributes; difficulty in reliably detecting suppressed or understory trees fully obscured by the canopy; require initial high investment in data acquisition (LiDAR sensor); need for field validation for calibration and accuracy assessment; processing large datasets can be computationally intensive (though mitigated by chunking); results can be influenced by data quality, acquisition parameters, and stand structure complexities.

4 Operational Implications

The validated accuracy of both automated methods (volume estimates within 6.7% of manual inventory) enables immediate operational deployment in commercial eucalyptus plantations. Key benefits include:

– **Efficiency gains:** Complete stand coverage in hours versus weeks for manual sampling
– **Monitoring frequency:** Annual or bi-annual inventories become economically feasible
– **Spatial precision:** Identification of within-stand variability for targeted silvicultural interventions

– **Scalability:** Methodology validated on 50+ ha directly applicable to estates of thousands of hectares

The consistent 10% underestimation of tree density requires species-specific calibration but does not compromise volume estimates due to compensating height measurements. Integration with reduced field sampling for calibration represents the optimal operational strategy, balancing accuracy with efficiency.

5 Conclusions

This study validated CHM and LiDAR point cloud methodologies against traditional inventory in *Eucalyptus urograndis* plantations, achieving volume estimates within 6.7% of manual measurements—well within operational tolerances. Despite systematic 10% underestimation of tree density, both methods demonstrated immediate operational viability through complete spatial coverage, rapid acquisition, and scalability to commercial estates.

The fundamental difference between methods—CHM's 2D rasterised approach versus LiDAR's 3D point analysis—resulted in complementary height estimation biases (CHM overestimating, LiDAR conservative), suggesting potential for combined workflows. Current limitations in understorey discrimination and suppressed tree detection require species-specific calibration but do not compromise commercial deployment.

Future development should prioritise adaptive parameterisation algorithms and multi-source data integration. However, the demonstrated accuracy already supports transition from labour-intensive sampling to automated inventory in Brazilian eucalyptus plantations, advancing precision forestry practices globally.

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