

# LiDAR-based assessment of above-ground biomass and carbon stocks in coffee agroforestry systems: Implications for climate mitigation and smallholder livelihoods at different elevations

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## ABSTRACT

Coffee agroforestry systems (CAS) mitigate climate change, but their structural complexity hinders accurate carbon quantification. We combined aerial LiDAR and field data to assess vegetation height, aboveground biomass (AGB), and carbon stocks across three altitudinal strata (1277–1710 m a.s.l.) in six CAS plots (comprising 1559,858 LiDAR-derived observation cells) in northern Peru. Mean canopy height (2.47–8.79 m), AGB (1.55–40.59 Mg ha<sup>-1</sup>), and carbon (0.73–19.08 Mg C ha<sup>-1</sup>) varied widely; coefficients of variation often exceeded 100%, reflecting high heterogeneity. A mixed-effects logarithmic model (LiDAR-derived height as a fixed effect; farm as a random effect) revealed a significant positive height-biomass relationship ( $\beta_1 = 2.400$ ;  $p < 0.001$ ). The model's estimated parameters provide quantitative evidence of the importance of farm-level random effects. While the global fixed-effect slope for the height-biomass relationship was 2.400, the mixed-effects framework allowed this scaling rule to deviate by farm. For instance, the model quantified a distinct random slope of 3.065 for one specific farm. This represents a 27.7% increase in the rate of biomass accumulation per unit of canopy height compared to the global average. This quantitative divergence in allometric scaling across farms provides direct evidence that local conditions significantly alter biomass dynamics, justifying a random-effects structure over traditional fixed-effect models. Random effects captured local variations driven by management and species composition, with one farm showing distinct accumulation dynamics ( $\beta_1 = 3.065$ ). Because of partial dependence between LiDAR metrics and field-calibrated biomass estimates, model performance reflects internal structural consistency rather than independent predictive validation. Consequently, LiDAR height should be interpreted as a robust structural indicator rather than an entirely independent indicator. Nevertheless, LiDAR-derived height reliably indicates AGB in CAS, though model transfer requires farm-scale calibration. This non-destructive, spatially explicit approach strengthens carbon monitoring in tropical agroforestry. By reducing the costs and uncertainties of Measurement, Reporting, and Verification (MRV), this workflow lowers the barriers for smallholder integration into carbon markets and REDD+ programs, directly linking accurate carbon accounting to improved livelihood incentives.

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## 1. Introduction

Coffee agroforestry systems (CAS) are complex, productive landscapes that combine agricultural production with important ecological functions such as conserving biodiversity (Mayorga et al., 2022), regulating the microclimate (Schmidt and Bunn, 2021), and sequestering carbon (Solis et al., 2020). In mountainous tropical regions, these systems play a key role in mitigating climate change. They do this by storing carbon in both above-ground biomass and soil, while supporting the livelihoods of millions of small-scale farmers (Siles et al., 2022; Salgado Veramendi et al., 2025). In Andean countries such as Peru, a significant proportion of coffee is cultivated using agroforestry systems. The interaction between shade trees, coffee plants, and topographic conditions in these systems results in high structural heterogeneity (Arellanos et al., 2025).

To translate the ecological potential of coffee agroforestry systems into tangible climate and economic benefits, a clear conceptual pathway must be established. Vegetation structure (specifically the three-dimensional arrangement of shade canopies and coffee understories) drives the rate of biomass accumulation (Atalaya-Marin et al., 2025). This accumulated biomass represents the quantifiable carbon sequestration that underpins climate mitigation strategies, such as REDD+ and voluntary carbon markets (Murphy and Yong, 2026). However, the success of these mitigation programs relies entirely on the ability to accurately and affordably measure that carbon at the farm scale (Petropoulos et al., 2025). When measurement fails due to structural complexity, smallholder farmers are excluded from these financial mechanisms, undermining their livelihoods. Therefore, accurately capturing vegetation structure is not merely a technical remote sensing exercise; it is the critical foundational step required to link ecosystem carbon dynamics directly to smallholder economic resilience.

However, the intensification of coffee cultivation and transition to full-sun systems in recent decades has substantially reduced the provision of ecosystem services, particularly carbon storage and canopy structural complexity (Vallejos-Torres et al., 2024; Salgado Veramendi et al., 2025). This structural simplification compromises the resilience of production systems to climate change (Bracken et al., 2023), and increases uncertainty in regional estimates of biomass and carbon associated with coffee landscapes (Gonzalez et al., 2014; Ehrenbergerová et al., 2016; Harvey et al., 2021). In this context, precisely quantifying above-ground biomass and carbon stocks in coffee agroforestry systems has become a priority for scientific research and environmental management.

In countries such as Peru, coffee agroforestry systems serve not only as ecological reservoirs but also as the economic foundation for millions of smallholder farmers who depend on these landscapes for their livelihoods (Arellanos et al., 2025). However, advancing sustainable land management and conserving shade-grown coffee requires well-defined economic incentives. Precise, location-specific measurement of carbon stocks is essential for integrating these farms into national REDD+ initiatives, carbon markets, and government payment-for-ecosystem-services programs. LiDAR-based monitoring offers a high-resolution, non-destructive alternative to costly and complex field assessments (Atalaya-Marin et al., 2025). This technology can reduce barriers to entry, enabling smallholders to participate in financial mechanisms that recognize and reward their contributions to climate change mitigation.

In addition, forest biomass plays a vital role in environmental and climate modeling (Thompson et al., 2011; Reichstein and Carvalhais, 2019). Standing forest biomass plays an active role in the global carbon cycle (Powers and Marín-Spiotta, 2017). Efforts to mitigate climate change through reducing emissions from deforestation and forest degradation (REDD) depend on mapping and monitoring the carbon stocks and emissions of tropical forests across vast geographic areas (Haya et al., 2023). Traditionally, biomass estimation in agroforestry systems has relied on field inventories (Goñas et al., 2022) and allometric models (Ehrenbergerová et al., 2016). While fundamentally necessary, these conventional approaches are constrained by high

operational costs, destructive sampling requirements, and, most importantly, a critical inability to capture the continuous, fine-scale spatial variability of complex, multi-strata canopies across entire landscapes. Although these approaches have led to significant advances, they are substantially limited in highly heterogeneous systems such as SAFCs due to their high operational costs (Uttaruk et al., 2026), limited spatial representativeness, and difficulty in capturing canopy structural variability (Sharma et al., 2023). These limitations are severely exacerbated along tropical altitudinal gradients, where elevation acts as a master environmental variable driving complex eco-physiological responses. As altitude increases, temperature decreases and solar radiation intensifies, which directly alters coffee plant physiology and forces farmers to adapt their management strategies (Jawo et al., 2023). Consequently, altitude dictates fundamental shifts in shade-tree species composition, planting densities, and pruning regimes. This management adaptation, in turn, radically transforms the three-dimensional vegetation structure (Wang et al., 2025); for instance, lower elevations may exhibit sparser, taller canopies to mitigate heat stress, while higher elevations often feature denser, highly stratified canopies to buffer against colder temperatures and wind exposure. Because this altitudinal modulation of canopy architecture directly controls the rates of biomass accumulation and carbon storage, traditional, uniform biomass models fail in these landscapes (Chemeda et al., 2022; Rajput et al., 2024). Therefore, the research recommends specific protocol improvements likely to yield more accurate carbon stock estimates, as well as recommendations for future research in areas requiring further investigation (Haya et al., 2023).

Unlike natural forests, which develop relatively predictable vertical stratification, or monoculture plantations, which exhibit uniform canopy structures, coffee agroforestry systems represent a unique and complex structural challenge (Arellanos et al., 2025). They consist of a dense, low-lying shrub layer (coffee plants) beneath a highly heterogeneous, discontinuous overstory of scattered shade trees. This severe vertical discontinuity creates significant 'occlusion' effects that render passive optical sensors incapable of accurately capturing the lower strata. Furthermore, the structural architecture in CAS is not driven solely by natural succession, but by highly variable human management practices (e.g., selective pruning, varying shade tree densities, and species selection) (Grandez-Alberca et al., 2025). Consequently, CAS require specifically tailored LiDAR-based approaches capable of resolving this multi-layered, anthropogenically modified 3D complexity (Jawo et al., 2023). In this context, Light Detection and Ranging (LiDAR) technology has emerged as a robust tool for three-dimensional characterization of vegetation structure and for estimating biomass and carbon (Tafur et al., 2022; Coops et al., 2025; Veneros et al., 2025). LiDAR sensors provide high-resolution data on canopy height, the vertical distribution of vegetation, and structural complexity. This overcomes the limitations of conventional optical sensors in systems with dense and stratified tree cover (Maeda et al., 2025).

Although ground-level biomass estimates can be derived from LiDAR data with high precision, little is known about estimates of biomass components (Ma et al., 2023). Furthermore, combined estimates using allometric formulas are often employed, but they do not always accurately reflect the dataset, as these formulas are specific to individual trees (Liao et al., 2022; Torre-Tojal et al., 2022). Furthermore, while some literature suggests the need for integrating terrestrial and aerial platforms to capture the full vertical profile, this approach is often logistically unfeasible for smallholder landscapes in steep Andean terrain. For the specific objective of assessing above-ground biomass—which is overwhelmingly concentrated in the dominant shade tree overstory—high-density aerial UAV-LiDAR provides the most scalable, cost-effective, and spatially exhaustive data source without introducing the spatial sampling limitations inherent to terrestrial scans (Liang et al., 2025; Donev et al., 2026).

While LiDAR technology has proven highly effective for biomass estimation, its application in agroforestry has suffered from methodological oversimplifications inherited from traditional forestry studies. For instance, while previous LiDAR research in natural forests (Shao

et al., 2024; Chen et al., 2025b) and homogeneous plantations (Chung et al., 2022) has successfully utilized canopy height metrics, these approaches typically assume a continuous and uniformly stratified canopy architecture. When such frameworks are uncritically applied to coffee agroforestry systems (which are defined by extreme vertical discontinuity between a low-lying coffee shrub layer and a highly irregular, scattered overstory of shade trees) they fail to capture the true structural complexity (Liao et al., 2022; Torre-Tojal et al., 2022). Furthermore, the limited number of LiDAR studies that have targeted agroforestry systems have treated the height–biomass relationship as a static, landscape-level constant. Critically, they have failed to account for how localized anthropogenic drivers (such as differential pruning regimes and highly variable shade-tree species assemblages) modulate this allometric scaling at the micro-level. Consequently, previous LiDAR assessments in these landscapes have lacked the methodological nuance to distinguish whether observed spatial variations in biomass are driven by broad environmental gradients or by farm-specific management decisions. Previous LiDAR-based biomass assessments in agroforestry have demonstrated the utility of canopy height metrics; however, these studies have largely treated agroforestry landscapes as structurally homogeneous, relying on traditional fixed-effect regression models at regional or global scales. This methodology overlooks the significant influence of localized farm management practices, distinct shade-tree assemblages, and micro-topography, all of which are highly variable in mountainous tropical regions such as the Andes. As a result, a critical research gap persists: the extent to which the allometric height–biomass relationship varies not only across broad altitudinal gradients but also at the micro-level of individual farms with differing management regimes remains unknown. The present study addresses this gap by moving beyond a uniform predictive framework. A mixed-effects modeling approach is employed to evaluate LiDAR-derived height as a structural proxy, while isolating and quantifying farm-level random effects that influence biomass accumulation in these complex systems.

Despite these limitations, LiDAR technology can improve biomass estimation in complex agroforestry systems (Mekonen et al., 2025). However, a critical methodological limitation persists: most previous LiDAR studies rely on traditional fixed-effect models that force a single, static height–biomass regression line across entire landscapes (Bredinbach et al., 2007; Ortiz-Reyes et al., 2024). This 'one-size-fits-all' approach fails in smallholder agroforestry, where unmeasured, highly localized management decisions (such as differential canopy pruning, variable shade-tree densities, and specific species selections) cause significant farm-to-farm variations in biomass accumulation for any given canopy height. The primary novelty of this study lies in addressing this limitation by shifting from a landscape-level fixed-effect paradigm to a farm-level mixed-effects framework (Beth Kucherov, 2010). By incorporating the farm as a random effect, the model allows the baseline biomass intercept to fluctuate based on localized management signatures, while maintaining the overarching allometric scaling of height as a fixed effect (McNicol et al., 2015). This approach isolates structural variability, providing a significantly more nuanced and accurate estimation of biomass than traditional LiDAR regressions (Ye et al., 2025).

The expectation that LiDAR-derived height alone can serve as a robust indicator of above-ground biomass (AGB), despite high species and management heterogeneity, is firmly rooted in both the structural composition of coffee agroforestry systems and fundamental allometric scaling principles. In shaded coffee systems, the coffee shrub layer contributes negligibly to total AGB compared to the dominant overstory shade trees. Therefore, LiDAR-derived canopy height inherently acts as a direct proxy for the stratum that holds the vast majority of the system's carbon. Furthermore, according to metabolic scaling theory, plant height scales predictably with biomass regardless of species identity or specific wood density variations. In these highly heterogeneous agroforestry mosaics, vertical canopy extension acts as a "structural integrator" it captures the cumulative ecological outcome of localized factors such as tree density, age, and microsite fertility into a single,

quantifiable 3D metric. Taking into account these fundamental principles... it can be hypothesized that canopy height derived from LiDAR is a robust and consistent indicator of AGB in coffee agroforestry systems along the altitudinal gradient.

Therefore, it can be hypothesized that canopy height derived from LiDAR is a robust and consistent indicator of AGB in coffee agroforestry systems along the altitudinal gradient, but that the magnitude of this height–biomass relationship is modulated by structural heterogeneity and management conditions at the farm scale. To test this, this study aimed to evaluate the structure of vegetation, aboveground biomass, and carbon stocks in coffee agroforestry systems across an altitudinal gradient in northern Peru. This was achieved by integrating high-density aerial UAV-LiDAR data with field measurements. Specifically, we analyzed the allometric relationship between LiDAR-derived canopy height and aboveground biomass, while accounting for the farm as a random factor to capture structural heterogeneity related to management, species composition, and canopy architecture. This approach paves the way for more accurate and scalable biomass estimates, strengthening carbon monitoring systems in tropical agroforestry landscapes and providing valuable scientific evidence for climate change mitigation strategies based on sustainable agriculture.

## 2. Materials and methods

### 2.1. Study area and sampling design

The study was conducted in coffee agroforestry systems in the northern Peruvian regions of Amazonas and Cajamarca. Six plots (each  $\geq 1$  ha) were selected across three altitudinal strata: low (1277–1373 m a.s.l.), medium (1349–1521 m a.s.l.) and high ( $>1525$ –1708 m a.s.l.) (Fig. 1). The specific altitudinal classes for the selected plots were defined using the natural interval method (Jenks) to minimise intragroup variance and maximise intergroup differences (Snyman et al., 2024; Gui et al., 2025).

All plots consisted of productive coffee plantations (aged 4–7 years) with shade trees. . Selecting six physical farms, while limiting broad regional generalizability, was a deliberate methodological choice driven by the logistical constraints of acquiring high-density UAV-LiDAR data in steep, remote Andean terrain, where rapid cloud cover changes severely restrict flight windows. Rather than pursuing a broad, low-resolution sampling design, this study adopted an intensive, deep-dive approach. The six plots (each  $\geq 1$  ha) were specifically chosen to maximize the capture of structural variability across the altitudinal gradient, representing the distinct management regimes and canopy architectures found at low, medium, and high elevations. This design prioritized data depth over geographic breadth to thoroughly test and calibrate the novel mixed-effects modeling framework. To explicitly clarify the hierarchical structure and sample size of the dataset for the subsequent statistical analyses, the nested sampling design is structured across three levels: (1) Altitudinal strata (three levels: low, medium, and high); (2) Farms/Plots (six level-2 units, where each farm corresponds to one plot of  $\geq 1$  ha); and (3) LiDAR observation cells (level-1 units). Because the LiDAR point clouds were rasterized to extract continuous structural metrics (see Section 2.4), the actual sample size (N) for the biomass modeling consists of spatially explicit LiDAR observation cells strictly nested within their respective farm plots. In total, the analysis is based on 1,559,858 valid raster cells (excluding NoData cells), distributed hierarchically as follows: Farm HSP1 (n = 188,067), HSP2 (n = 337,462), MSP1 (n = 250,350), MSP2 (n = 267,249), LSP1 (n = 237,084), and LSP2 (n = 279,646). Additionally, for farm-level model calibration, we subsampled 2 circular field subplots per farm, yielding 112 georeferenced shade trees nested within the six plots (Table 1).

#### 2.1.1. Structural and management characteristics of the plots

We conducted field characterizations for each of the six selected coffee agroforestry systems to contextualize the LiDAR-derived structural parameters. All plots contained *Coffea arabica* var. *typica* and *caturra* plants aged 4–7 years. Notable differences in shade management and species composition were observed across the altitudinal strata:

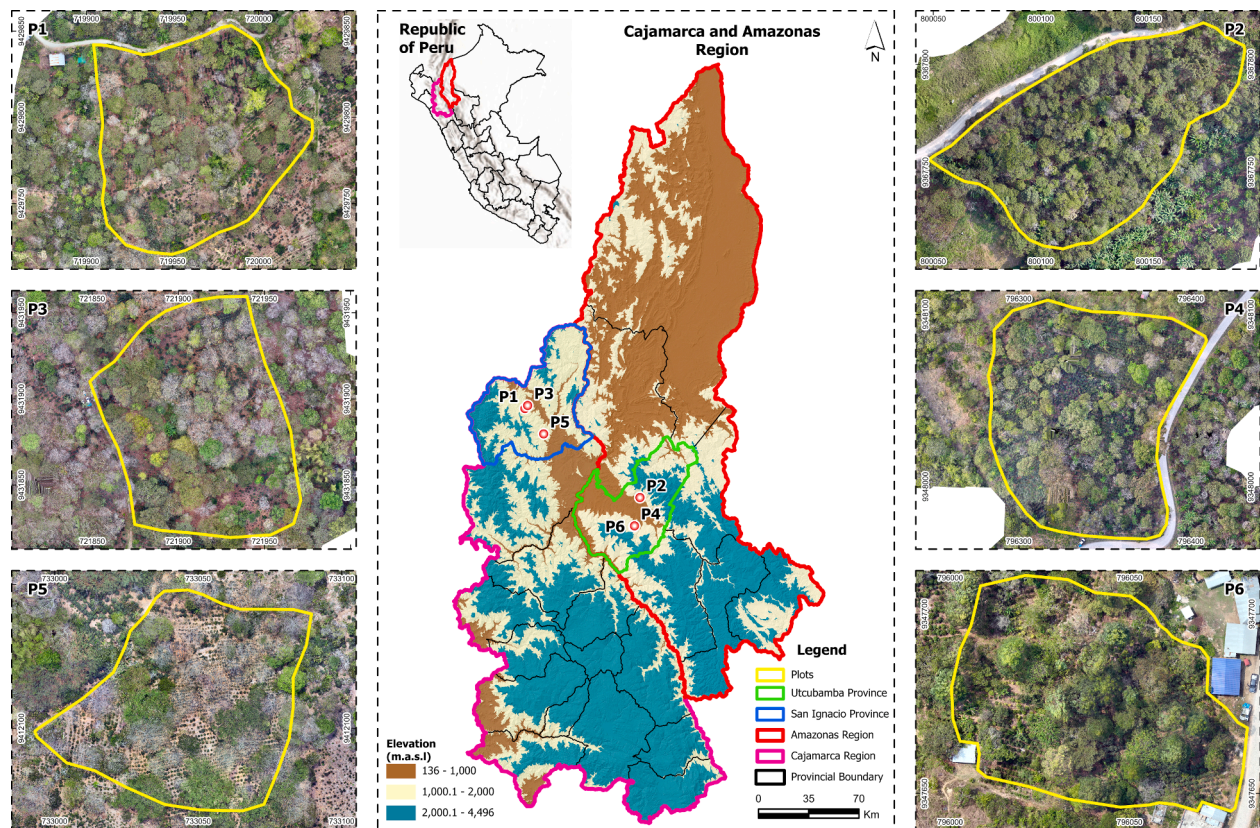


**Fig. 1.** Location and spatial extent of the study area, showing the boundaries of the analysed coffee agroforestry systems superimposed on a high-resolution orthophoto and topographic map. This map defines the spatial framework used for LiDAR data acquisition and subsequent structural analysis.

**Table 1**  
Information on the plots selected for the study.

| Code | Strata | District  | Latitude m | Longitude m | Elevation m a.s.l. |
|------|--------|-----------|------------|-------------|--------------------|
| HSP1 | High   | Chirinos  | 734003     | 9411492     | 1634.21 - 1709.80  |
| HSP2 | High   | Chirinos  | 731976     | 9412653     | 1525.62 - 1578.28  |
| MSP1 | Medium | El Palmo3 | 796361.2   | 9348072     | 1349.63 - 1415.73  |
| MSP2 | Medium | El Palmo  | 795974.5   | 9347677     | 1458.53 - 1521.00  |
| LSP1 | Low    | Jaén      | 739213     | 9365160     | 1287.52-1373.01    |
| LSP2 | Low    | La Union  | 800171     | 9367848     | 1277.22 - 1352.31  |

Low stratum (LSP1, LSP2): This stratum was characterized by intensive pruning and low shade density, with an estimated shade tree density of 80–120 trees ha<sup>-1</sup>, with 32 species recorded, predominantly *Mangifera indica*, *Psidium guajava*, *Pinus patula*, and *Ilex guayusa*, distributed across 21 families. Fabaceae was the most diverse family (8 species), followed by Myrtaceae (3) and Malvaceae (2). The dominant shade tree species produced a relatively open and discontinuous canopy cover.

Mid-altitude stratum (MSP1, MSP2): This stratum exhibited an intermediate management regime with a moderate density of 150–220 trees ha<sup>-1</sup>. The upper canopy was dominated by Sapotaceae and Myrtaceae species, resulting in a more continuous but irregular canopy layer. Researchers recorded 25 plant species, primarily *Inga striata*, *Theobroma cacao*, *Persea americana*, and *Eucalyptus saligna*, from 16 families, including Fabaceae and Malvaceae.

High-canopy plots (HSP1, HSP2): These plots exhibited the most complex structural configuration, with minimal recent pruning and the

highest shade density (250–350 trees ha<sup>-1</sup>). A highly diverse assemblage of native trees, such as *Colubrina glandulosa*, and shade trees, including *Musa x paradisiaca*, *Acnistus arborescens*, *Ananas comosus*, *Annona muricata*, and *Cordia alliodora*, contributed to a dense, multi-layered vertical architecture. This structure matched the high canopy heights observed in these plots, as confirmed by LiDAR data.

2.2. LiDAR data acquisition

A multi-platform LiDAR approach was implemented to capture vegetation structure at different spatial scales (Fekry et al., 2021; Jin et al., 2025).

2.2.1. LiDAR data collection using UAVs

Aerial LiDAR data was collected using a DJI Matrice 350 RTK platform (<https://enterprise.dji.com/matrice-350-rtk>) equipped with a Zenmuse L2 sensor (<https://enterprise.dji.com/zenmuse-l2>), operated via DJI Pilot 2 software (<https://www.dji.com/downloads/djiapp/dji-pilot>). Flights were conducted in terrain-following mode at an altitude of 70 m above ground level, at an average speed of 4 m per second. Flight planning included a double-grid pattern with crisscrossing flight paths to ensure 80% forward and 70% side-to-side overlap (Wu et al., 2025). Flights were conducted in terrain-following mode to maintain a constant height relative to the terrain, ensuring consistent spatial resolution across plots with variable topography (Maes, 2025).

2.2.2. Georeferencing

To ensure the accuracy of the data, ground control points (GCPs) were established using a GNSS RTK system (SOUTH G3) with PPK processing support. These GCPs were then used to achieve high horizontal and vertical accuracy and to align the aerial and ground datasets.

### 2.3. LiDAR data processing

The raw LiDAR point clouds were processed using a standardised workflow. Individual scans were merged by plot and georeferenced using ground control points (GCPs). Noise filters and classifications were then applied to distinguish between ground and vegetation echoes (Dharshan Shylesh et al., 2023). The digital elevation model (DEM) was then used to normalise the point clouds by subtracting terrain elevation values, enabling the derivation of vegetation height metrics (Chen et al., 2022; Liao et al., 2024). A canopy height model (CHM) was then derived from the difference between the normalised LiDAR surface and the DEM. Vegetation height and vertical structure metrics were extracted from the CHM and the normalised point clouds, as well as the spatial variability of canopy attributes (Chen et al., 2025a; Yao et al., 2025). All structural metrics derived from LiDAR were subsequently integrated with field inventory data to estimate biomass and assess carbon stocks (Atalaya-Marin et al., 2025).

### 2.4. Extraction of structural parameters

The vegetation structure was characterised using parameters derived from normalised point clouds and the Canopy Height Model (CHM) (Chen et al., 2025b). These parameters included mean and maximum height (Bento et al., 2025), standard deviation (SD), coefficient of variation (CV) and height percentiles (e.g. P50 and P95). These parameters were used to quantify the vertical structure and spatial heterogeneity within the plots. The LAS Dataset to Raster tool in ArcGIS Pro version 3.6 (<https://www.esri.com/en-us/arcgis/products/arcgis-pro/resources>) was used for this purpose, with the maximum height value per cell selected as the statistic.

### 2.5. Biomass estimation

Above-ground biomass (AGB) was estimated using a logarithmic allometric model based on tree height, as measured by LiDAR and combined with field inventory data. This was done to calibrate and apply previously validated allometric models for shaded coffee agroforestry systems, where tree height is a strong indicator of biomass in structurally heterogeneous environments. An allometric height–biomass model was fitted by treating the farm as a functional unit (non-linear). This model was formulated on a logarithmic scale (Chave et al., 2014), and adapted accordingly.

#### 2.5.1. Justification of the logarithmic mixed-effects modeling approach

The selection of a logarithmic mixed-effects model over alternative modeling frameworks (e.g., raw power-law, generic nonlinear, or machine learning algorithms) was driven by theoretical, statistical, and interpretability factors. Theoretically, metabolic scaling theory indicates that biomass scales as a power function of height; applying a logarithmic transformation linearizes this relationship, allowing the slope to represent the fundamental biological scaling exponent. Statistically, raw biomass data exhibit severe heteroscedasticity (variance increases with canopy height), which violates the assumptions of ordinary least squares; the log transformation inherently stabilizes this variance. Furthermore, structurally, a simple log-log regression was insufficient because the spatial autocorrelation among LiDAR cells within the same farm violates the assumption of independent residuals. Incorporating the farm as a random effect resolved this by modeling the unmeasured, farm-specific management signatures (e.g., localized pruning or species assemblages) as a baseline shift (random intercept), while keeping the biological scaling rule constant (fixed slope).

Alternative approaches were deliberately excluded. Machine learning algorithms (e.g., Random Forest, Neural Networks) were considered inappropriate for this study due to their "black-box" nature, which obscures the allometric relationship we aimed to quantify, and their high susceptibility to severe overfitting given our sample size of six

physical farms, despite the large number of LiDAR observation cells. Similarly, complex non-linear models (e.g., high-order polynomials) were rejected because they introduce coefficients that lack biological interpretability and are mathematically unstable when extrapolating beyond the observed height ranges. The chosen logarithmic mixed-effects framework thus provided the optimal balance between statistical rigor, theoretical alignment with allometric scaling laws, and ecological interpretability.

A random farm effect was included to capture differences associated with management, species composition, and canopy architecture. Thus, vegetation height was treated as a fixed effect, while variability between plots was incorporated via a random term, given the high structural heterogeneity observed in the altitudinal strata. These models enabled us to estimate biomass at the dataset level for each plot, eliminating the need for destructive sampling (Equation 1).

$$\ln(B_{ij}) = \beta_0 + \beta_1 \cdot \ln(H_{ij}) + u_{\text{finca}_j} + \varepsilon_{ij}$$

where:  $\ln(B_{ij})$  = natural logarithm of the estimated above-ground biomass for observation  $i$  within plot  $j$ ;  $i$ : observation (LiDAR cell, raster point);  $j$ : plot (parcel); Biomass  $\beta_0$  (beta zero) = Global intercept of the model;  $\beta_1$  (beta one) = Slope of the model representing the fixed structural effect of height; If  $\beta_1 > 1$ : biomass increases faster than height; If  $\beta_1 \approx 2.4$ – $2.5$ : there is a strong allometric response.  $H_{ij}$ : canopy height;  $u_j$  = represents the random effect of the farm.

The model accounts for structural heterogeneity across farms and enables scalable estimation of biomass from LiDAR data. This approach enabled a non-destructive (Tsoulas et al., 2023), spatially explicit, and scalable assessment of biomass and carbon storage across altitudinal gradients.

Above-ground biomass (AGB) used for calibration was estimated using the allometric equation proposed by Chave et al. (2014), which incorporates trunk diameter (DBH), total tree height, and wood density as covariables. To ensure absolute transparency, the specific pantropical equation applied was (Equation 1):

$$AGB = 0.0673 \times (\rho \times D^2 \times H)^{0.976}$$

Where AGB is above-ground biomass in kg,  $\rho$  is wood specific gravity in  $\text{g cm}^{-3}$ ,  $D$  is diameter at breast height in cm, and  $H$  is total tree height in m.

The selection of this specific equation was driven by the highly diverse species composition documented in our field inventory (Section 2.5.1), which included both broadleaved species (e.g., *Inga spp.*, *Calycophyllum spruceanum*, *Erythrina edulis*) and conifers (e.g., *Pinus patula*). Because these species exhibit drastically different wood densities, using a generic equation without a density modifier would introduce severe bias. The Chave et al. (Chave et al., 2014) model is highly suitable for this Andean agroforestry context because it explicitly incorporates wood density ( $\rho$ ) as a multiplicative scalar, allowing us to accurately account for the specific gravimetric characteristics of each species, rather than relying on an assumed average. Furthermore, this model has been extensively validated across tropical Latin American regions and is explicitly recommended by the IPCC guidelines for ecosystems with complex species assemblages (Eggleston, 2006; Tan et al., 2025).

Consequently, an inherent degree of structural dependence exists between the LiDAR-derived canopy height (indicator) and the field-estimated AGB (response), as both share a common height component. To mitigate this tautological effect, it is crucial to distinguish the nature of both variables: field-measured height represents an intrinsic physiological dimension at the individual stem level, whereas LiDAR-derived height captures the spatially explicit three-dimensional canopy volume and vertical complexity at the plot/cell level. Therefore, in this study, LiDAR height is not treated as a strictly independent indicator of AGB, but rather as a semi-independent structural proxy. Model performance metrics ( $R^2$ , MAE, RMSE) should be interpreted as indicators of internal structural consistency and allometric scaling, rather than as absolute measures of independent predictive accuracy.

### 2.5.2. Field inventory procedures

To calibrate the LiDAR-derived models, we conducted traditional forest inventories within the boundaries of the six 1 ha plots before the UAV flights (Demol et al., 2024). Because measuring every individual shade tree across a full hectare is logistically prohibitive in complex terrain, we applied a stratified sub-sampling design. Within each 1 ha plot, we systematically distributed 2 circular sub-plots with a 10 m radius (314 m<sup>2</sup> each) to capture internal variability, achieving a sampling intensity of approximately 6.3%.

Within each sub-plot, we measured Diameter at Breast Height (DBH) for all shade trees with DBH  $\geq$  5 cm using standard forestry calipers, measured strictly at 1.30 m above the ground on the uphill side of the tree to avoid buttress roots. We measured and georeferenced 112 shade trees (excluding coffee shrubs) across all six plots. Local botanists identified tree species in the field. The dominant shade species included *Inga* spp. (*I. striata*, *I. edulis*, *I. lineata*), *Calycophyllum spruceanum*, and *Erythrina* spp., alongside companion species such as *Theobroma cacao*, *Psidium guajava*, and *Pinus patula*. We then matched each identified species to its corresponding wood density (WD) values using the Global Wood Density Database (Zanne et al., 2010). The high variability in wood densities among these documented species further reinforced the need to use the Chave et al. (Chave et al., 2014) formulation, which dynamically adjusts biomass estimates based on species-specific  $\rho$  values, rather than applying a uniform regression.

To ensure precise spatial alignment between field data and remote sensing data, we recorded the exact geographic coordinates of each measured tree using a sub-centimeter GNSS RTK receiver (Atalaya-Marin et al., 2025). We did not manually measure total tree height (H) for the field inventory because dense canopy occlusion and terrain slope made it difficult; instead, we extracted it directly from the high-resolution LiDAR Canopy Height Model (CHM) by taking the maximum LiDAR height value within a 1.0 m radius of each tree's field coordinates.

### 2.5.3. Estimation of carbon reserves

Carbon stocks were estimated by converting above-ground biomass values to carbon content using a biomass-to-carbon conversion factor of 0.47 (IPCC, 2019; Gatew and Zerihun, 2025; Jirakajohnkool et al., 2025), which is widely used in forest and agroforestry carbon assessments (Joshi et al., 2025; Rahman et al., 2025). This conversion assumes that 47% of dry biomass corresponds to carbon.

### 2.5.4. Integration across altitudinal zones

Biomass and carbon estimates were aggregated at the plot level and then grouped by altitude (low, medium, and high) (Gónas et al., 2022). This stratification enabled assessment of the effects of altitude on biomass accumulation and carbon sequestration capacity in coffee agroforestry systems. The resulting biomass and carbon datasets formed the basis of subsequent statistical analyses to identify significant differences among altitudinal strata and to evaluate the relationship between vegetation height, as derived from LiDAR, and biomass accumulation.

## 2.6. Statistical analysis

Descriptive statistics were calculated for the dataset, which consisted of 1,559,858 LiDAR observation cells nested within six plots, for structural and functional variables, including minimum and maximum values, means, standard deviation, and coefficient of variation, for each plot and altitudinal stratum (García et al., 2024). We assessed differences in elevation, LiDAR-derived vegetation height, aboveground biomass, and carbon between plots and across altitudinal strata using linear mixed-effects models with the plot as a random factor. Differences between altitudinal strata were evaluated using a one-way ANOVA, after verifying the assumptions of normality and homogeneity of variances. When significant differences were found ( $p < 0.05$ ), post hoc pairwise comparisons were performed using the Tukey HSD test (Veneros et al., 2023). Although the underlying distribution of individual LiDAR cells is

highly skewed and non-normal (as detailed in Section 3.2), the use of parametric ANOVA is justified by the extremely large sample size ( $N = 1,559,858$ ). According to the Central Limit Theorem, with such a large  $N$ , the sampling distribution of the means approaches normality, making parametric tests highly robust. Furthermore, non-parametric alternatives (e.g., Kruskal–Wallis) on datasets of this magnitude yield statistically significant  $p$ -values for biologically meaningless differences, whereas parametric tests provide interpretable mean differences required for carbon accounting.

Spearman's correlation was used to evaluate the relationship between canopy height and aboveground biomass (AGB). Model performance was evaluated using the mean absolute error (MAE), which quantifies the mean absolute difference between the observed and predicted aboveground biomass values derived from LiDAR canopy height; the coefficient of determination ( $R^2$ ); and the root mean square error (RMSE), which quantifies the average magnitude of prediction errors (Atalaya-Marin et al., 2025). The  $p$ -value of the Spearman correlation represents the probability of obtaining a test statistic as extreme as or more extreme than the observed value under the null hypothesis (Blanchard et al., 2023; Pisano et al., 2025).

To ensure the statistical validity of the logarithmic mixed-effects model, rigorous diagnostic checks were performed on the model's conditional residuals. Normality was assessed through visual inspection of Quantile–Quantile (Q–Q) plots and statistically evaluated using the Shapiro–Wilk test (applied to a randomized sub-sample of residuals due to the large dataset size of  $>1.5$  million observations). Homoscedasticity (constant variance) was tested by examining the scatterplot of standardized residuals versus fitted values for any systematic patterns or fan-shaped structures, and was further corroborated using the Breusch–Pagan test. Finally, to confirm that the inclusion of the farm as a random effect successfully resolved spatial dependence, we checked for residual spatial autocorrelation (Veneros et al., 2023; Atalaya-Marin et al., 2025).

To assess the model's robustness and avoid overfitting, the  $k$ -fold cross-validation method ( $k = 5$ ) was applied. The dataset was randomly divided into five subsets. Four of the subsets were used for model training, and one subset was used for validation in an iterative process. This procedure enabled the evaluation of the model's predictive performance on independent data. Additionally, a "leave-one-farm-out" (LOFO) cross-validation was performed to evaluate the model's ability to be transferred to different agroforestry systems. Given our total of six farms, this approach consisted of six iterative iterations. In each iteration, the model was calibrated using the LiDAR cells from five farms, and the remaining single farm was excluded from calibration and used entirely as the validation dataset. Fig. 2 illustrates the integrated methodology of this study.

## 3. Results

### 3.1. Elevation

The elevation of the evaluated plots revealed clear spatial and structural differences among the coffee agroforestry systems. These differences allowed the systems to be grouped into three well-defined altitudinal strata: low (1277.22–1352.31 m a.s.l.), medium (1349.63–1521.09 m a.s.l.), and high (1525.62–1709.80 m a.s.l.). Fig. 3 shows these strata. Elevation analysis using LiDAR data revealed statistically significant differences in most paired comparisons between plots in different strata. Notably, comparisons between plots in the low and middle strata, as well as between the low and high strata, exhibited high  $t$ -values and extremely significant levels of significance ( $p < 0.001$ ), confirming a pronounced altitudinal separation between these agroforestry systems.

In the low-elevation stratum, the plots exhibited significant differences, reflecting internal altitudinal variability associated with local topography. However, some comparisons within the stratum, particularly between plots at the same elevation, showed no significant differences

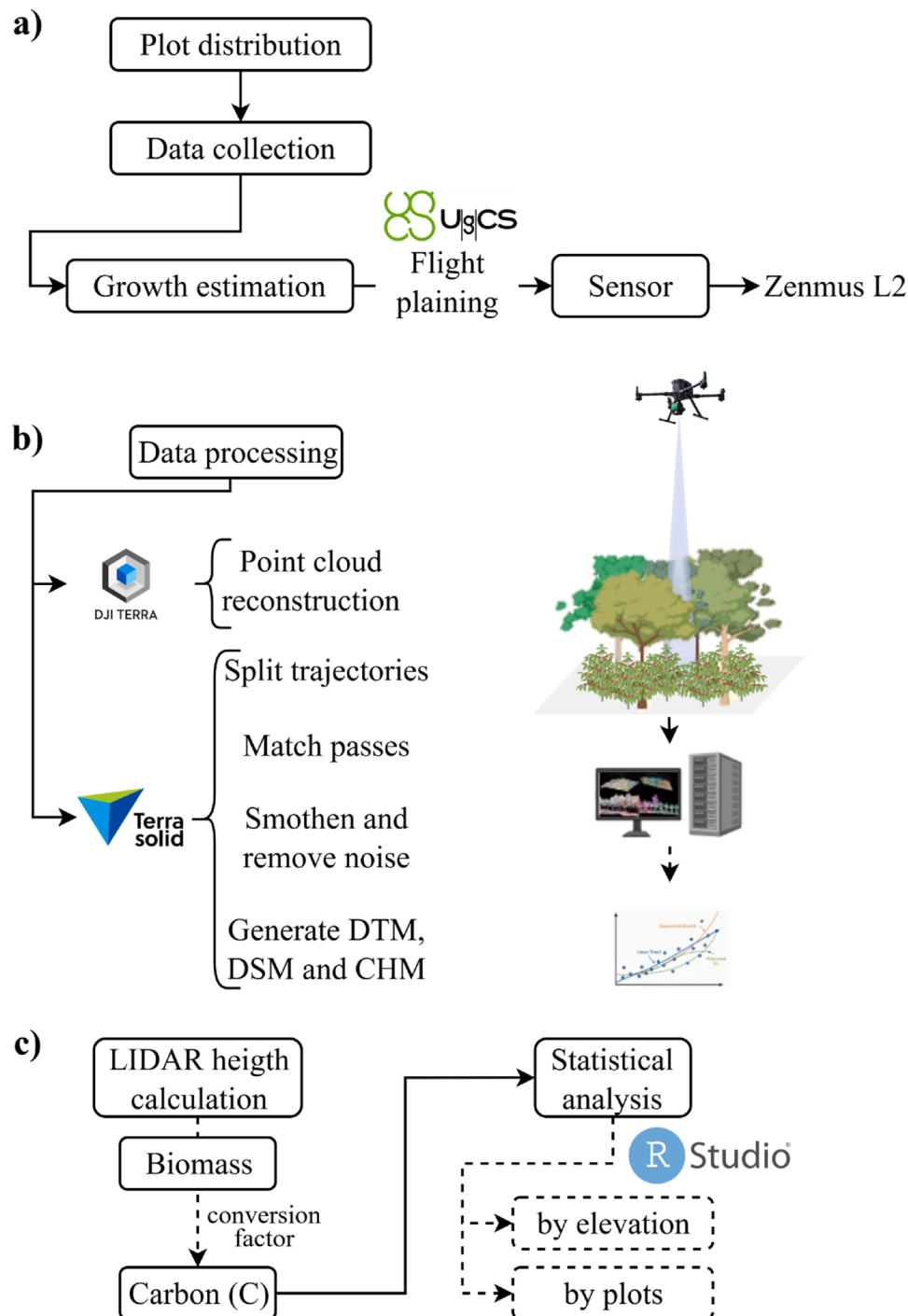


Fig. 2. An integrated cross-platform LiDAR workflow for structural characterization and biomass modeling in coffee agroforestry systems.

( $p > 0.05$ ). This suggests relative altitudinal homogeneity within specific elevation ranges. In the middle stratum, altitudinal differences between plots were highly significant in both internal and external comparisons. This stratum exhibited a transitional position on the altitudinal gradient, acting as an intermediate point between lower- and higher-elevation systems. This is relevant for interpreting subsequent structural and functional patterns. There were no statistically significant differences in comparisons between plots located within the stratum, indicating greater altitudinal uniformity in the higher-elevation areas. However, when compared to plots in the low and middle strata, the differences were highly significant ( $p < 0.001$ ), confirming the presence of a clear altitudinal gradient. Overall, the results confirm that elevation is strongly

associated with the structural characteristics of the evaluated coffee agroforestry systems. While we acknowledge that other factors (such as management practices, species composition, and stand age) also drive this variability, the pronounced altitudinal differentiation observed justifies using elevation as a key stratification variable in subsequent analyses of vegetation structure, aboveground biomass, and carbon sequestration estimated using LiDAR sensors.

### 3.2. Distribution of vegetation height derived from LiDAR

Estimated tree height from LiDAR data showed clear and consistent differences along the evaluated altitudinal gradient (Table 2). Normalizing

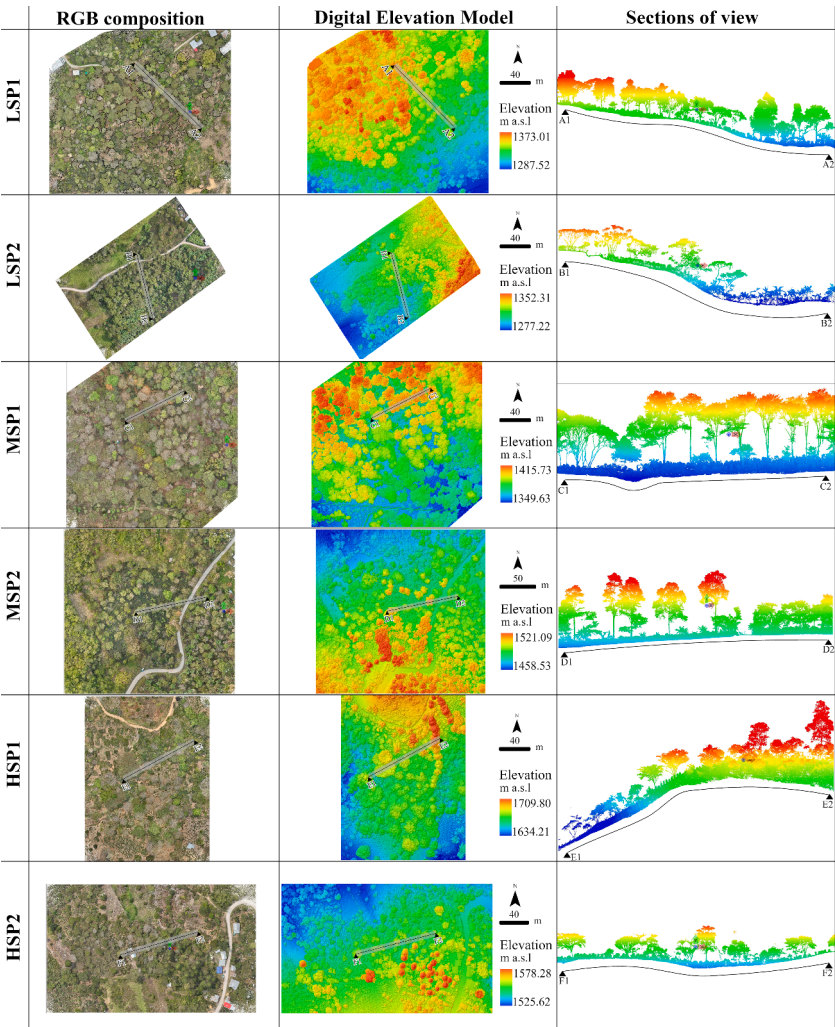


Fig. 3. Digital Elevation Model (DEM) of the evaluated farms.

the LiDAR point cloud using the digital elevation model (DEM) yielded a canopy height model (CHM), which enabled the estimation of actual tree heights in the analyzed coffee agroforestry systems. Contrary to a simple monotonic increase with elevation, the LiDAR results revealed significant farm-level deviations from the altitudinal gradient. While HSP1 exhibited high mean canopy height (7.81 m) consistent with high-altitude environments, LSP2 (low stratum) exhibited the highest mean canopy height overall (8.79 m), driven by the presence of very tall, isolated individuals (max 29.23 m). Conversely, HSP2 (high stratum) showed a surprisingly low mean canopy height (2.47 m).

The frequency distribution of vegetation height derived from LiDAR showed clearly asymmetric and contrasting patterns between plots and altitudinal strata (Fig. 4), reflecting high structural heterogeneity in the evaluated coffee agroforestry systems. In plots in the high stratum (HSP1 and HSP2), distributions were strongly right-skewed with high

frequencies of low-height values and long tails extending above 20 m. The pronounced tail in HSP1 indicates the coexistence of a dominant matrix of low-to-medium vegetation and tall trees, suggesting a complex vertical structure associated with well-developed shade trees. In HSP2, positive asymmetry is maintained; however, the distribution shows a lower relative frequency of tall heights. This indicates a simpler canopy structure and lower contribution from tall individuals (Table 2, Fig. 4).

The plots in the middle stratum (MSP1 and MSP2) exhibited broader and more balanced distributions with a higher proportion of intermediate height values. MSP1 exhibited a broad distribution with a plateau in the intermediate height range (5–15 m), indicating greater diversity in vertical strata and more complex canopy architecture. In contrast, MSP2 exhibited a distribution concentrated toward low-to-medium values with a progressive decrease in frequency at higher heights. This reflects a less developed vertical structure and lower presence of dominant trees (Table 2, Fig. 4).

Table 2  
Vegetation height values (m), derived from the point cloud of the LiDAR dataset.

| Code Strata | Strata | Minimum Value | Maximum Value | Mean | Standard deviation | Coefficient of variation |
|-------------|--------|---------------|---------------|------|--------------------|--------------------------|
| HSP1        | High   | 4.31          | 23.33         | 7.81 | 2.94               | 3.77                     |
| HSP2        | High   | 0.0083        | 23.94         | 2.47 | 2.79               | 112                      |
| MSP1        | Medium | 0.0083        | 20.53         | 3.5  | 3.13               | 89.3                     |
| MSP2        | Medium | 0.0111        | 23.82         | 3.64 | 3.19               | 87.6                     |
| LSP1        | Low    | 0.0083        | 19.48         | 3.17 | 3.23               | 102.1                    |
| LSP2        | Low    | 1.33          | 29.23         | 8.79 | 4.58               | 52                       |

In the lower stratum (LSP1 and LSP2), the distributions were dominated by low height values with pronounced peaks in the lower intervals and infrequent long tails. LSP1 showed a strong concentration of values below 5 m, suggesting a predominantly low canopy and limited vertical stratification. LSP2, on the other hand, exhibited a slightly broader distribution with a higher frequency of intermediate heights and a longer tail. This indicates greater structural heterogeneity compared to

LSP1 and is possibly associated with local differences in management and species composition (Table 2, Fig. 4).

Overall, the histograms demonstrate that vegetation height data derived from LiDAR does not conform to a normal distribution in any of the plots. Rather, it exhibits pronounced asymmetries and long tails, which are typical of complex agroforestry systems. These patterns justify using nonparametric statistical approaches and logarithmic allometric

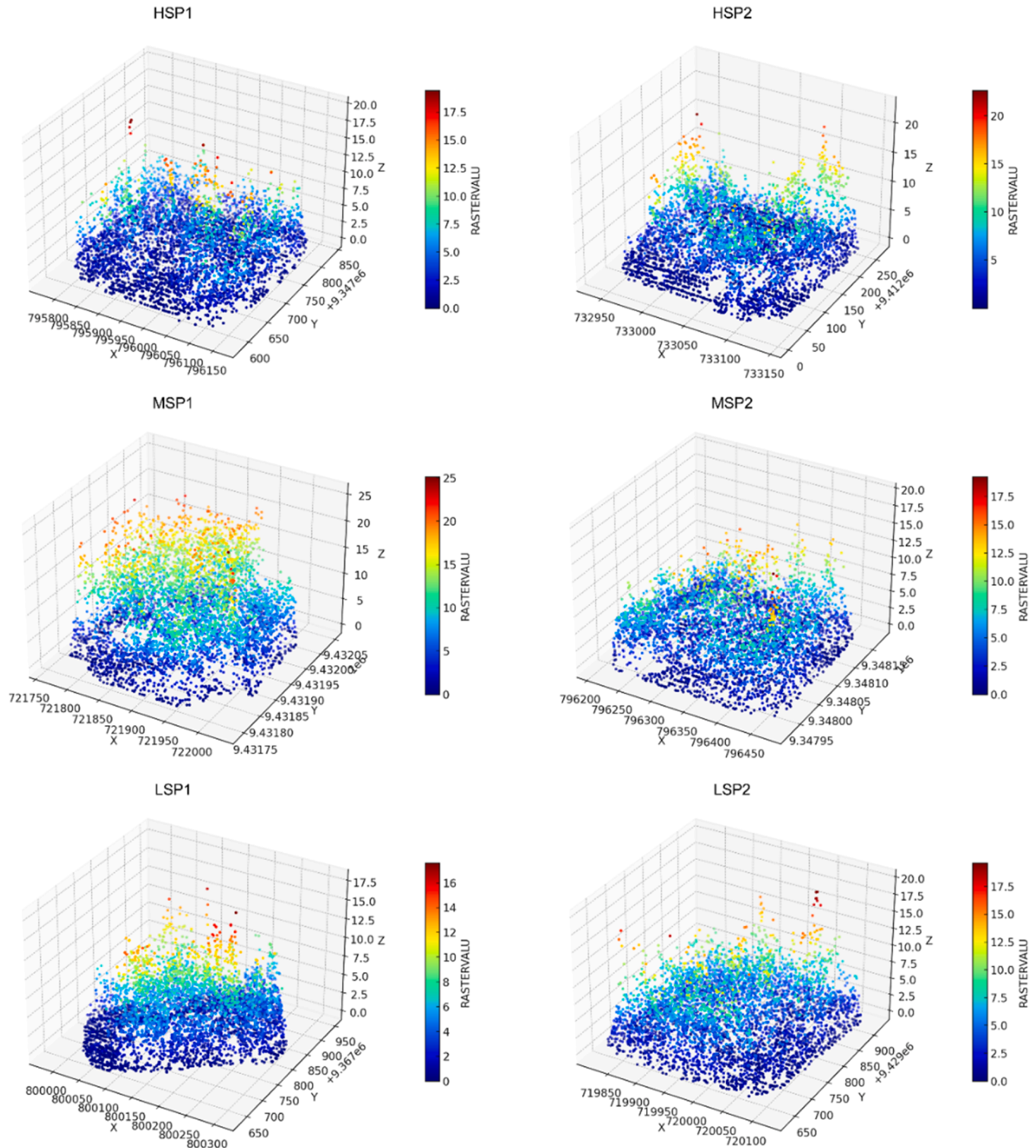


**Fig. 4.** Three-dimensional representation of the canopy structure derived from LiDAR point clouds across three altitudinal ranges of coffee agroforestry systems showing spatial and altitudinal variability in vegetation height. Each panel corresponds to an assessed plot. The points represent LiDAR returns normalized to the digital elevation model (DEM), and the color scale indicates vegetation height in meters.

models to analyze the relationship between canopy vertical structure and above-ground biomass. Similarly, the variability observed among plots emphasizes the importance of incorporating random effects at the farm scale to accurately capture structural heterogeneity in biomass and carbon estimates (Table 2, Fig. 5).

### 3.3. Canopy height comparison derived from LiDAR across plots

Table 3 summarizes the results of the paired comparisons of the vegetation height derived from LiDAR among the evaluated agroforestry plots. The analysis reveals that there are statistically significant

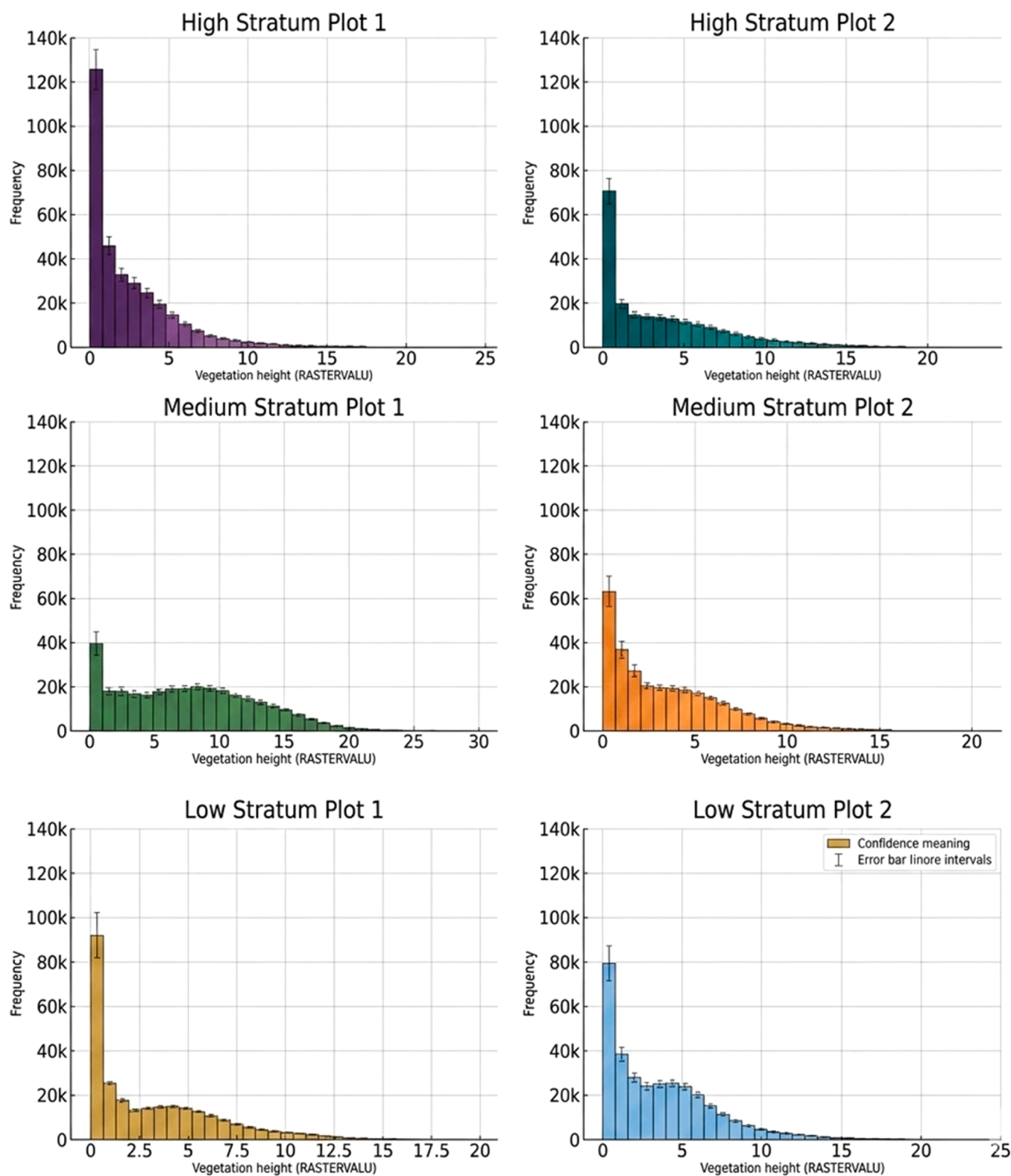


Fig. 5. Histograms showing frequency distribution of vegetation height derived from LiDAR. These histograms illustrate the structural heterogeneity of the canopy between plots and across altitudes.

differences in canopy height between most plot pairs. This indicates that there is marked structural heterogeneity associated with the altitudinal gradient, local management conditions, and canopy composition.

Comparisons between plots in different altitudinal strata mostly showed high *t*-statistic values and highly significant levels of significance ( $p < 0.001$ ). Plots in the low stratum (LSP1 and LSP2) had notably lower canopy heights than plots in the middle (MSP1 and MSP2) and high (HSP1 and HSP2) strata. This confirms a progressive increase in vegetation height with elevation. The largest *t*-statistic values were observed in comparisons between the low and middle strata, as well as between the low and high strata. This indicates a clear structural separation between these agroforestry systems.

A differentiated pattern was observed across the altitudinal strata. In the low stratum, the comparison between LSP1 and LSP2 was highly significant ( $p < 0.001$ ), suggesting internal structural variability associated with local differences in canopy architecture. In the middle stratum, the comparison.

Fig. 6 clearly illustrates these patterns, showing a progressive increase in median canopy height from the lower to the upper stratum. Plots in the lower stratum exhibit distributions concentrated at low height values. In contrast, plots in the middle and upper strata show higher medians and greater dispersion of values, especially in MSP1 and HSP1. The overlap of individual points also reveals high intra-plot variability, a characteristic of complex agroforestry systems.

The agreement between the statistical results in Table 3 and the graphical representation in Fig. 6 confirms that vegetation height derived from LiDAR effectively distinguishes structural differences between plots and altitudinal strata. It also constitutes a robust indicator of canopy vertical organization in coffee agroforestry systems. This structural differentiation provides the basis for explaining subsequent observations of above-ground biomass and carbon stock estimation patterns.

### 3.4. Biomass and carbon determination

Table 4 summarizes the descriptive statistics for aboveground biomass (AGB) and estimated aboveground carbon derived from LiDAR data for the evaluated plots, revealing significant structural variability among and across plots and altitudinal strata. Above-ground biomass values generally exhibited highly dispersed distributions, with coefficients of variation exceeding 80% in all plots and reaching values

**Table 3**

Paired comparisons of vegetation height derived from LiDAR among the evaluated plots.

| Place 1 | Place 2 | t-stat   | p-value  | significance |
|---------|---------|----------|----------|--------------|
| LSP1    | LSP2    | -15.0375 | 1.02E-34 | ***          |
| LSP1    | MSP1    | -19.4345 | 6.68E-48 | ***          |
| LSP1    | MSP2    | -26.4499 | 6.46E-68 | ***          |
| LSP1    | HSP1    | -11.6903 | 1.77E-24 | ***          |
| LSP1    | HSP2    | -17.0001 | 4.08E-41 | ***          |
| LSP2    | MSP1    | -10.0837 | 8.2E-21  | ***          |
| LSP2    | MSP2    | 0.705772 | 0.480869 | ns           |
| LSP2    | HSP1    | 6.707157 | 8.63E-11 | ***          |
| LSP2    | HSP2    | 6.617318 | 1.88E-10 | ***          |
| MSP1    | MSP2    | 11.3956  | 3.63E-24 | ***          |
| MSP1    | HSP1    | 14.84189 | 7.92E-36 | ***          |
| MSP1    | HSP2    | 14.86466 | 3.69E-35 | ***          |
| MSP2    | HSP1    | 8.680695 | 1.08E-16 | ***          |
| MSP2    | HSP2    | 9.206745 | 2.13E-18 | ***          |
| HSP1    | HSP2    | -0.7834  | 0.433896 | ns           |

The *t*-statistic, *p*-value, and significance level are reported (\*\*  $p < 0.001$ ; \*  $p < 0.01$ ; \*  $p < 0.05$ ; ns: not significant). The *t*-statistic indicates the magnitude and direction of the difference. Statistical significance is assessed using the *p*-value associated with the *t*-statistic.

Note: The box plots show the median and interquartile range of the vegetation height derived from LiDAR for each plot. The points correspond to the values of individual raster cells. The lines above indicate paired comparisons using *t*-tests, along with their corresponding *p*-values.

above 190% in several cases. This reflects the high structural heterogeneity characteristic of coffee agroforestry systems. The plots in the high stratum showed notable contrasts. HSP1 had the highest mean aboveground biomass ( $40.59 \text{ Mg ha}^{-1}$ ) and mean aboveground carbon content ( $19.08 \text{ Mg C ha}^{-1}$ ), which is associated with the presence of large shade trees and a more developed vertical structure. In contrast, HSP2 had a considerably lower mean biomass ( $1.55 \text{ Mg/ha}$ ) and the lowest estimated carbon value ( $0.73 \text{ Mg C/ha}$ ), accompanied by the highest coefficient of variation (281.7%), indicating a heterogeneous canopy structure dominated by low biomass values with a few instances of high accumulation.

In the middle stratum, plots MSP1 and MSP2 exhibited intermediate aboveground biomass values, albeit with distinct variation patterns. MSP2 had relatively high average biomass ( $13.47 \text{ Mg/ha}$ ) and carbon content ( $6.33 \text{ Mg C/ha}$ ), while MSP1 had lower average biomass ( $2.49 \text{ Mg/ha}$ ) and estimated carbon content ( $1.17 \text{ Mg C/ha}$ ). Both sites exhibited coefficients of variation greater than 100%, indicating complex canopy architecture and the presence of strata of varying heights and densities.

The low-stratum plots (LSP1 and LSP2) had the lowest average biomass ( $2.32$  and  $2.66 \text{ Mg ha}^{-1}$ ) and relatively low carbon content ( $1.09$ – $1.25 \text{ Mg C ha}^{-1}$ ). However, both plots showed very high coefficients of variation ( $>190\%$ ), indicating considerable structural heterogeneity despite the lower average canopy height due to local differences in management, tree density, and species composition (Table 4, Fig. 7).

Overall, the results confirm that LiDAR-based estimates of aerial biomass and carbon reserves show high spatial variability in coffee agroforestry systems, even within the same altitude stratum. This heterogeneity supports the use of random-effects allometric models at the farm scale and justifies the integration of structural metrics derived from LiDAR to adequately capture the complexity of the canopy and improve the estimation of carbon sequestration in tropical agroforestry landscapes (Table 4, Fig. 8).

These exceptionally high cell-level coefficients of variation are not indicative of model instability or outliers, but rather an expected mathematical consequence of analyzing agroforestry systems at high spatial resolutions ( $1 \text{ m}^2$  cells). At the pixel scale, the dataset inherently combines a continuous matrix of near-zero biomass pixels (coffee shrubs, bare ground, and low vegetation) with discrete, extremely high-biomass pixels (dominant shade tree crowns). This highly skewed, bimodal distribution mathematically inflates the standard deviation relative to the mean, resulting in CVs  $> 200\%$  that accurately reflect the extreme structural heterogeneity of the system."

### 3.5. Comparison of LiDAR-derived AGB biomass across plots and strata

Fig. 9 illustrates the variation in above-ground biomass (AGB) estimated using LiDAR along the altitudinal gradient. Table X summarizes the results of paired comparisons between plots and strata. Together, these results demonstrate statistically significant differences in AGB among most evaluated agroforestry systems, reflecting notable structural heterogeneity related to altitude, local management conditions, and canopy architecture.

Comparisons between plots in different altitudinal strata revealed high *t*-statistic values and highly significant levels of significance ( $p < 0.001$ ) in nearly all instances. Plots in the low stratum had notably lower AGB values than plots in the middle and high strata, confirming an increase in AGB with elevation. This pattern aligns with the greater canopy height and structural complexity observed in the upper strata, which is a result of the presence of larger shade trees.

Significant differences were also observed within the altitudinal strata. In the low stratum, the comparison between the two plots was highly significant ( $p < 0.001$ ), indicating substantial local differences in biomass accumulation despite their similar altitudes. The middle stratum plots showed significant differences from one another ( $p < 0.001$ ),

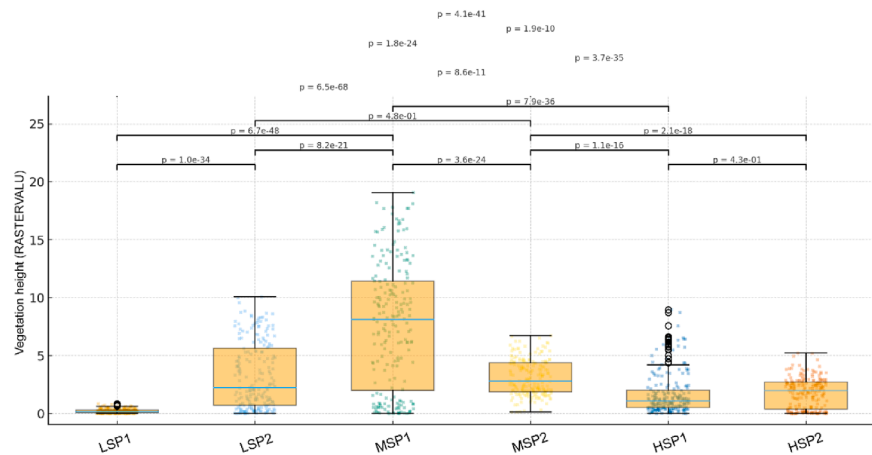


Fig. 6. Distribution and paired comparisons of vegetation height derived from LiDAR among agroforestry plots with coffee at different altitudes.

Table 4

Descriptive statistics for above-ground biomass (AGB) (Mg ha<sup>-1</sup>) and estimated carbon (Mg C ha<sup>-1</sup>) based on LiDAR data in coffee agroforestry systems.

| Code strata | Strata | Minimum biomass (Mg ha <sup>-1</sup> ) | Maximum biomass (Mg ha <sup>-1</sup> ) | Mean biomass (Mg ha <sup>-1</sup> ) | Standard deviation (Mg ha <sup>-1</sup> ) | Coefficient of variation % | Interpretation                | Mean carbon (Mg C ha <sup>-1</sup> ) |
|-------------|--------|----------------------------------------|----------------------------------------|-------------------------------------|-------------------------------------------|----------------------------|-------------------------------|--------------------------------------|
| HSP1        | High   | 0.0009000                              | 220.69                                 | 40.59                               | 34.15                                     | 84.10%                     | high variance                 | 19.08                                |
| HSP2        | High   | 0.0000005                              | 102.11                                 | 1.55                                | 4.36                                      | 281.7                      | high variance                 | 0.73                                 |
| MSP1        | Medium | 0.0000005                              | 70.61                                  | 2.49                                | 4.78                                      | 192.2                      | high variance                 | 1.17                                 |
| MSP2        | Medium | 0.1000000                              | 164.8                                  | 13.47                               | 14.58                                     | 108.2                      | high coefficient of variation | 6.33                                 |
| LSP1        | Low    | 0.0000005                              | 62.22                                  | 2.32                                | 4.53                                      | 194.9                      | high coefficient of variation | 1.09                                 |
| LSP2        | Low    | 0.0000010                              | 100.83                                 | 2.66                                | 5.06                                      | 190                        | high coefficient of variation | 1.25                                 |

reflecting variations in canopy structure and density associated with management and species composition. In contrast, the comparison between the two plots in the upper stratum was not statistically significant ( $p > 0.05$ ), suggesting greater structural and functional homogeneity in agroforestry systems at higher elevations.

Fig. 9 clearly reflects these patterns, showing a gradual increase in median above-ground biomass from the lower to the upper stratum. Plots in the upper stratum exhibit substantially higher median and maximum biomass values, as well as greater data dispersion. This indicates the coexistence of low-biomass areas and isolated pockets of high biomass accumulation associated with dominant trees. In contrast, plots in the lower stratum show distributions concentrated at low biomass values with less canopy development.

Overall, the consistency between the statistical results (Table 5) and the graphical representation (Fig. 5) confirms that LiDAR-derived above-ground biomass responds consistently to the altitudinal gradient, but is also strongly modulated by structural heterogeneity at the plot scale. These differences justify the use of allometric models with random effects at the farm level and reinforce the role of LiDAR-derived canopy height as a key indicator of above-ground biomass in coffee agroforestry systems.

3.5.1. Relationship between vegetation height derived from LiDAR and aboveground biomass

Fig. 10 shows the distribution of mean aboveground biomass as a function of canopy height ranges (defined as the mean  $\pm$  one standard deviation) derived from LiDAR for each evaluated plot. Across all plots and altitudinal strata, a systematic increase in aboveground biomass is observed as canopy height increases. This indicates that height clearly controls biomass accumulation in coffee agroforestry systems.

Plots in the high stratum (High Stratum 1 - P8 JAMALCA01-T and High Stratum 2 - P12) exhibited the highest biomass values in the upper height ranges, reaching maximums of over 120 Mg/ha in classes with

the greatest structural development. This pattern reflects the presence of large shade trees and a more complex vertical architecture, which is associated with a greater capacity for biomass accumulation.

In the middle stratum (P6 SAN-IGN-C and P5), above-ground biomass values were concentrated in intermediate height ranges, with maximums notably lower than those in the upper stratum. Nevertheless, the positive relationship between height and biomass remained consistent, suggesting that canopy height remains a key indicator of above-ground biomass even with less developed vertical structure.

The plots in the low stratum (P16 UNION and P4) exhibited the lowest aboveground biomass values, primarily due to reduced height ranges. However, even in these systems, an increase in biomass with canopy height was observed, confirming a common structural response along the altitudinal gradient.

The variability observed within each height range, as reflected by the dispersion of biomass values, was particularly high in the upper and middle strata plots. This suggests that there is greater structural heterogeneity associated with local differences in management, species composition, and canopy architecture. Standardizing the scales across all panels enables direct comparisons between plots and reinforces the consistency of the height-biomass allometric pattern observed in all evaluated systems.

Standardizing the scales on the X and Y axes (Fig. 10) enables direct comparison of the plots, confirming that although biomass levels differ across altitudinal strata, the positive relationship between canopy height and above-ground biomass remains consistent across all evaluated systems. This visual pattern corroborates the results of correlation analyses and allometric models, which identify LiDAR-derived height as a reliable indicator of above-ground biomass in coffee agroforestry systems. Together, these findings provide strong visual evidence that LiDAR-derived canopy height is a reliable indicator of above-ground biomass in coffee agroforestry systems, justifying its use as a primary structural variable in subsequent allometric models.

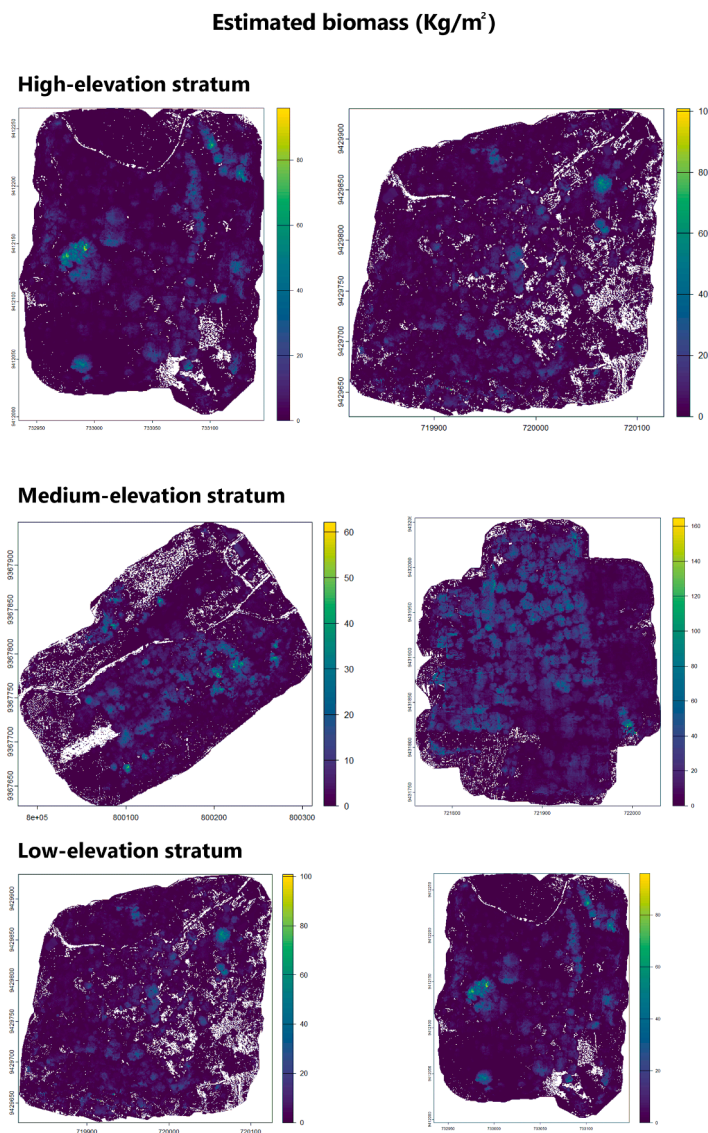


**Fig. 7.** Spatial patterns of aboveground biomass estimated from LiDAR-based height-biomass models across altitudinal gradients.

### 3.5.2. Assessment of the model's performance and constraints

Due to the non-normal distribution of the data and the high structural heterogeneity observed between the plots, the relationship between the canopy height derived from LiDAR and the aboveground biomass (AGB) was evaluated using Spearman's rank correlation.

Model performance was evaluated using the coefficient of determination ( $R^2$ ), the absolute error (MAE), and root mean square error (RMSE) on a logarithmic scale (Table 6). However, it is crucial to emphasize that because the field-calibrated AGB estimates were derived from allometric equations that incorporate tree height, a partial mathematical dependence exists between the indicator (LiDAR height) and the response variable (AGB). Consequently, the metrics reported in Table 6 should not be interpreted as absolute measures of independent predictive error in  $\text{Mg ha}^{-1}$ . Instead, they serve as robust indicators of internal structural consistency, demonstrating that the LiDAR-derived canopy height successfully tracks the allometric scaling of biomass within these complex agroforestry matrices.

Therefore, metrics such as MAE and RMSE should be interpreted as indicators of internal consistency rather than as independent measures of predictive accuracy. The model provides an evaluation of non-independent structural consistency, as biomass estimates are calibrated using allometric equations based on field data, while LiDAR metrics act as structural indicators.

Despite these limitations, the strong monotonic relationship observed between canopy height and biomass (Spearman's rho) indicates that LiDAR-derived height captures key structural patterns associated with biomass distribution in coffee agroforestry systems.

These findings highlight that biomass variability in agroforestry systems is strongly influenced by structural heterogeneity, supporting the use of mixed-effects models and the inclusion of additional LiDAR-derived metrics to improve predictive performance. Future studies should incorporate independent ground-based biomass measurements to fully validate the predictive capacity of LiDAR-derived models. The extremely low mean absolute error (MAE) and high  $R^2$  values observed in some plots are due to the strong structural dependence between the LiDAR-derived height and biomass estimates and should not be interpreted as indicators of perfect predictive performance (Table 6, Fig. 11).

## 4. Discussion

### 4.1. The relationship between height and biomass in coffee agroforestry systems

The close relationship observed between canopy height, as measured by LiDAR, and above-ground biomass (AGB) reflects a fundamental allometric principle: taller vegetation tends to accumulate greater

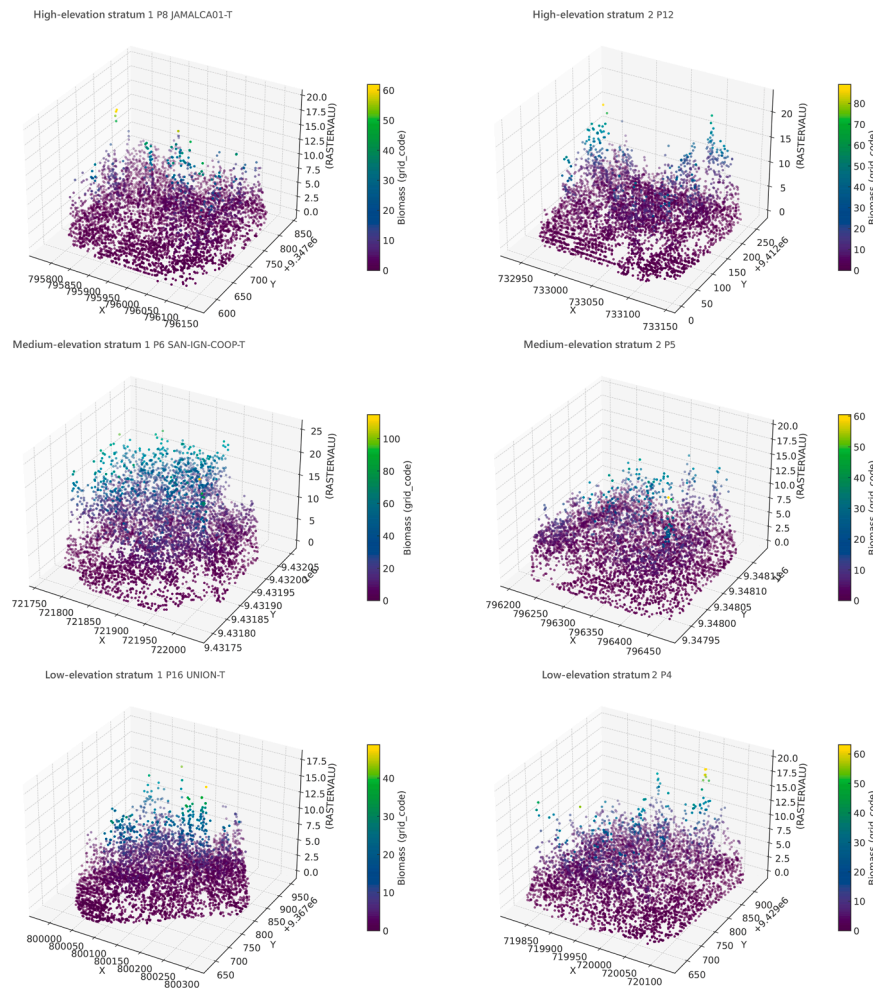


**Fig. 8.** Three-dimensional distribution of above-ground biomass estimated using LiDAR in coffee agroforestry systems along an altitudinal gradient. Each panel corresponds to an assessed plot. The points represent raster cells derived from the height-biomass allometric model, and the color scale shows the estimated above-ground biomass (megagrams per hectare  $\text{Mg ha}^{-1}$ ).

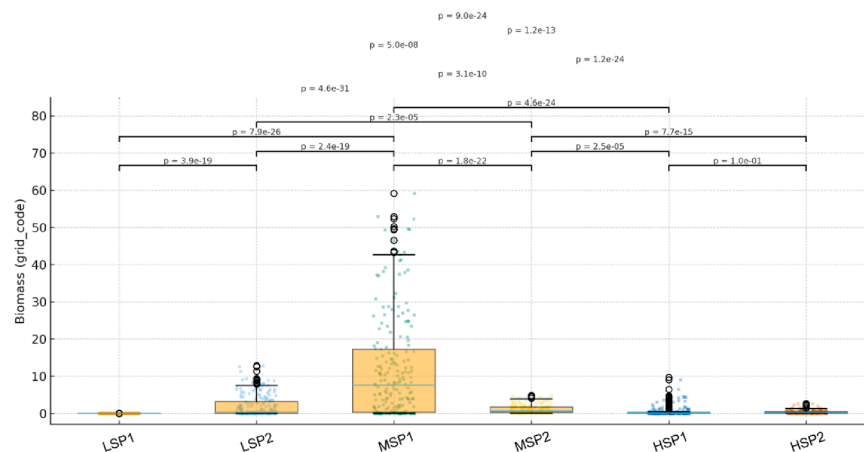


**Fig. 9.** Variation in above-ground biomass estimated using LiDAR along the altitudinal gradient.

biomass due to increased stem volume and canopy expansion (Zhou et al., 2021). In agroforestry systems, the presence of shade trees primarily determines this relationship, as they dominate the vertical structure and contribute disproportionately to total biomass (Schroth, 1999). However, this relationship is neither strictly linear nor universal. In coffee agroforestry systems, for example, canopy height only

represents the upper structural layer, while biomass is distributed among the understorey vegetation and coffee plants (Somarriba et al., 2024). However, in terms of total above-ground biomass (AGB) accumulation, the contribution of coffee shrubs is ecologically minimal (typically estimated at <10% of total plot AGB) compared to the dominant shade-tree overstorey. Consequently, the strong LiDAR-height

**Table 5**

Paired comparisons of LiDAR-derived above-ground biomass (AGB) across altitudinal strata.

| Place 1          | Place 2          | t-stat   | p-value     | Significancia |
|------------------|------------------|----------|-------------|---------------|
| Lower Stratum 1  | Lower Stratum 2  | -9.93014 | 3.94312E-19 | ***           |
| Lower stratum 1  | Middle stratum 1 | -12.1681 | 7.93199E-26 | ***           |
| Lower stratum 1  | Middle stratum 2 | -13.8735 | 4.62782E-31 | ***           |
| Lower stratum 1  | Upper stratum 1  | -5.66831 | 5.01372E-08 | ***           |
| Lower stratum 1  | Upper stratum 2  | -11.491  | 9.00601E-24 | ***           |
| Lower stratum 2  | Middle stratum 1 | -9.91713 | 2.42764E-19 | ***           |
| Lower stratum 2  | Middle stratum 2 | 4.317201 | 2.26052E-05 | ***           |
| Lower stratum 2  | Upper stratum 1  | 6.52578  | 3.08486E-10 | ***           |
| Lower stratum 2  | Upper stratum 2  | 7.944412 | 1.17854E-13 | ***           |
| Middle stratum 1 | Middle stratum 2 | 11.04182 | 1.79818E-22 | ***           |
| Middle stratum 1 | Upper stratum 1  | 11.55687 | 4.60473E-24 | ***           |
| Middle stratum 1 | Upper stratum 2  | 11.77458 | 1.21641E-24 | ***           |
| Middle stratum 2 | Upper stratum 1  | 4.265187 | 2.52345E-05 | ***           |
| Middle stratum 2 | Upper stratum 2  | 8.237725 | 7.68938E-15 | ***           |
| Upper stratum 1  | Upper stratum 2  | 1.629705 | 0.104447482 | ns            |

relationship observed in our study is driven almost entirely by shade-tree accumulation. This means LiDAR's inability to fully penetrate the shrub layer has a negligible impact on total AGB estimates, even though it underestimates total vegetative volume..

In the context of this study, measurements taken at the top of the canopy (RH 98) exhibited relatively high accuracy ( $R^2 = 0.76$ ,  $RMSE = 5.33$  m).

However, data accuracy decreased further down the canopy (RH 50:  $R^2 = 0.54$ ,  $RMSE = 5.59$  m). Although simulated geolocation correction yielded marginal improvements, the decline in accuracy was consistent despite all error reduction measures (East et al., 2024). These findings align with those of other studies using Lidar data (He et al., 2013).

From an empirical perspective, the LiDAR-derived AGB values observed in our plots (1.55–40.59  $Mg\ ha^{-1}$ ) align closely with the broad spectrum reported for tropical coffee agroforestry systems under varying management. Our low-stratum values (e.g., LSP1) are consistent with the reduced carbon stocks reported in intensively managed or simplified agroforestry systems (Mekonen et al., 2025). Conversely, the higher biomass values in our mid- and high-altitude plots fall within the range documented for diverse, structurally complex shade coffee systems in Latin

**Table 6**

Internal consistency metrics of the LiDAR-based structural model.

| Strata          | $\rho$ (Spearman) | p-value | $R^2$ pseudo | MAE   | RMSE   |
|-----------------|-------------------|---------|--------------|-------|--------|
| High 1w = HSP1  | 0.98              | <0.001  | 1.00         | >0.00 | 0.0002 |
| High 1 = HSP2   | 0.85              | <0.001  | 0.70         | >0.00 | 2.39   |
| Medium 1 = MSP1 | 0.87              | <0.001  | 0.76         | >0.00 | 2.32   |
| Medium 2 = MSP2 | 0.86              | <0.001  | 0.75         | >0.00 | 2.51   |
| Low 1 = LSP1    | 0.88              | <0.001  | 0.78         | >0.00 | 2.12   |
| Low 2 = LSP2    | 0.91              | <0.001  | 0.88         | >0.00 | 5.01   |

Note: Model performance metrics ( $\rho$ ,  $R^2$ , MAE, RMSE) were calculated on the logarithmic scale. Because field-estimated aboveground biomass (AGB) was derived using the Chave et al. (2014) equation, which incorporates tree height as a covariate, there is an inherent structural dependence between the LiDAR-derived height (indicator) and AGB (response). Consequently, these metrics reflect internal structural consistency and allometric scaling rather than independent predictive accuracy in absolute units ( $Mg\ ha^{-1}$ ). A near-zero log-scale MAE indicates minimal residual structural noise in the allometric relationship, rather than an absence of real-world predictive error.

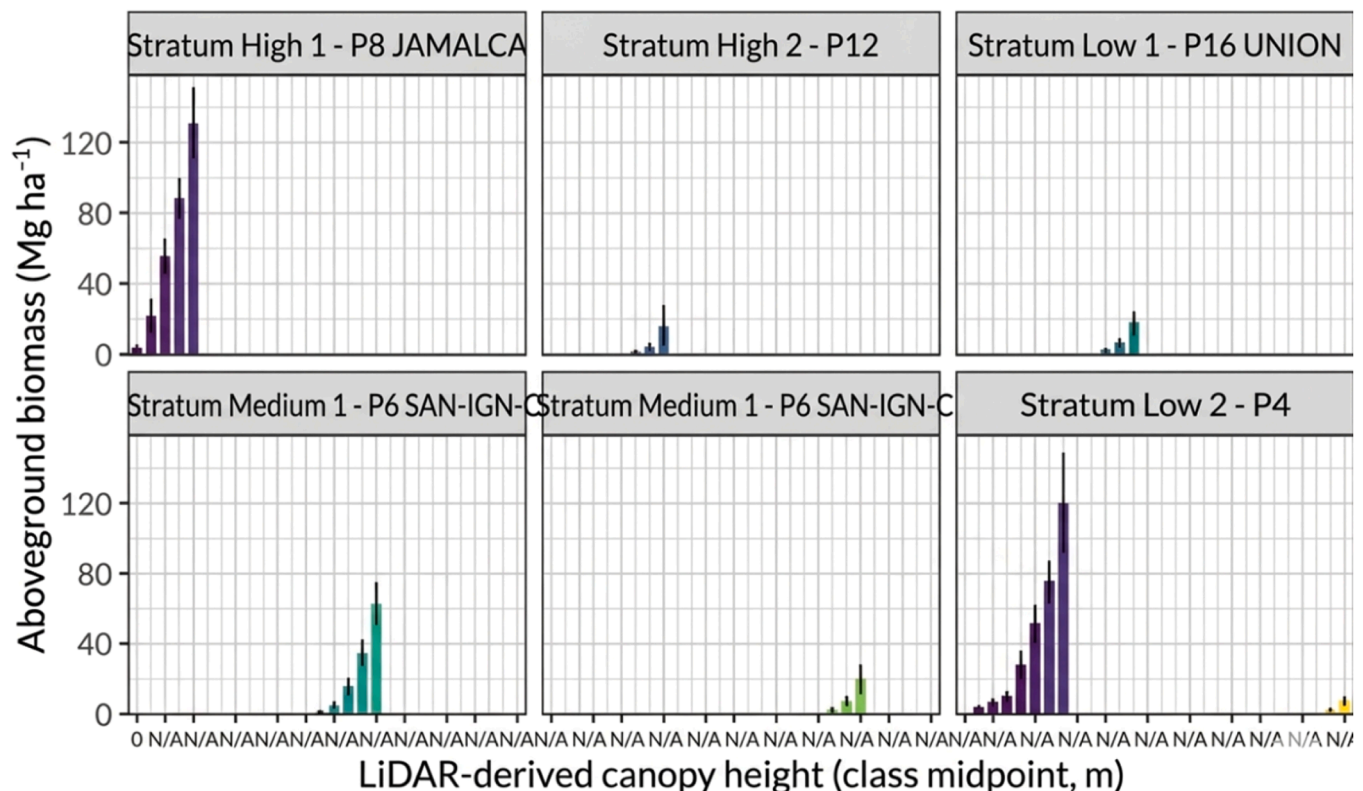


**Fig. 10.** Distribution of Average Above-Ground Biomass as a Function of Canopy Height Ranges Derived from LiDAR in Coffee Agroforestry Systems. The bars represent the average above-ground biomass per canopy height range (midpoint of each class), and the error bars indicate one standard deviation. Each panel corresponds to an evaluated plot, and the axis scales are consistent, allowing comparison across altitudinal strata.

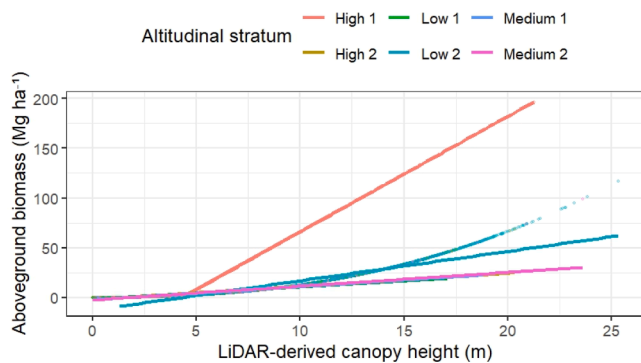


**Fig. 11.** Distribution of mean aerial biomass along canopy height ranges derived from LiDAR (mean  $\pm 1$  standard deviation) for each evaluated plot. The bars represent the mean biomass per height range and the error bars indicate  $\pm 1$  standard deviation. The values on the X-axis correspond to the midpoint of each height range. All panels share common scales on the X and Y axes to facilitate comparison between plots and altitudinal strata.

America (Zhu et al., 2026), though they remain lower than the maximum potentials observed in old-grown tropical agroforests (Yates, 2024). This empirical alignment confirms that our LiDAR workflow captures realistic biomass gradients and serves as a spatially explicit tool that mirrors findings from traditional, but spatially limited, field inventories.

#### 4.2. Structural heterogeneity and its influence on biomass estimation

The high structural variability observed in the plots is a direct consequence of the multi-layered nature of agroforestry systems (Seidel et al., 2021; Raj et al., 2024). Unlike monoculture forests, coffee systems comprise shade trees, coffee shrubs, and sometimes secondary vegetation, creating vertically complex canopies (Mohann Kumar et al., 2021; Somarriba et al., 2023; Arellanos et al., 2025).

This heterogeneity arises from several interacting factors, including differences in shade management intensity, species composition, planting density and stand age (Worku et al., 2015). Plantations with diverse shade tree species tend to have irregular canopy structures with variable crown sizes and gaps, leading to greater variation in height and biomass coefficients.

The application of mixed-effects models in this context represents a methodological advance over traditional fixed-effect LiDAR regressions (Breidenbach et al., 2007). By treating the farm as a random effect, the model successfully absorbed the 'noise' created by heterogeneous anthropogenic management (Addo and Salhofer, 2022). Instead of forcing all plots to conform to a single global intercept (which would systematically overestimate biomass in heavily pruned farms and underestimate it in densely shaded ones) the random effect allowed the model to establish independent, farm-specific baselines (Innocent et al., 2017). This localized calibration significantly reduces unexplained variance in the residuals, demonstrating that accounting for the 'human factor' (management) as a statistical random variable is just as critical as measuring the physical canopy structure when estimating biomass in smallholder landscapes. From a LiDAR perspective, this structural complexity impacts the interaction between laser pulses and vegetation (Lefsky et al., 2002; Bergen et al., 2009). The multiple layers of the canopy generate heterogeneous return signals, meaning that single metrics, such as average height, are insufficient to fully describe biomass distribution (Nasiro, 2024). Multi-metric approaches, which incorporate percentiles and variability indices, are therefore more effective at capturing the vertical organization of biomass (Anaya et al., 2009; Fischer et al., 2019).

#### 4.3. Effect of farm-level variability on model performance

The significant contribution of random effects at the farm level suggests that local ecological and management conditions strongly

influence biomass accumulation (Omeja et al., 2012). Agroforestry systems are shaped by human decisions such as pruning, shade management, and species selection, all of which influence canopy architecture (Isaac et al., 2024).

In farms with intensive shade management, canopy height can be reduced artificially, while biomass remains relatively high due to increased stem density (Tschamtkke et al., 2011). Conversely, in less managed systems, taller trees may predominate with lower overall biomass density (Rytter, 1995). These contrasting configurations weaken the direct relationship between height and biomass, explaining the observed variability due to random effects. Furthermore, species-specific traits, such as wood density and growth form, introduce additional variability in the height-biomass relationship that LiDAR structural metrics alone cannot capture (Osunkoya et al., 2007). Since the Chave et al. (2014), allometric equation explicitly incorporates wood density as a covariable, two trees of similar height but different species (e.g., a high-density timber shade tree vs. a low-density leguminous shade tree) will yield substantially different above-ground biomass values. While the farm-level random effect in our model partially absorbs this species-composition variability, LiDAR's inability to directly measure wood density is a fundamental biophysical constraint. Consequently, LiDAR-derived height acts as a robust proxy for canopy volume and structural dominance, but it cannot fully substitute the physiological and compositional nuances captured by field-based allometric equations. Two trees of similar height may differ significantly in biomass depending on their species, contributing to the observed dispersion in the height-biomass relationship (Mutwiri et al., 2017).

The apparent inconsistencies in the altitudinal gradient (such as LSP2 exhibiting higher mean height than high-altitude plots, or HSP2 showing extremely low height and biomass) perfectly illustrate why traditional fixed-effect models fail in smallholder agroforestry. In LSP2, the high mean height likely reflects an open canopy with a few scattered, tall remnant trees rather than a densely stocked, high-biomass system. Conversely, the low structural metrics in HSP2, despite its high altitude, likely result from recent, intensive selective pruning, a common management practice at higher altitudes to reduce humidity and coffee leaf rust (*Hemileia vastatrix*) incidence. These outliers confirm our initial hypothesis: altitudinal environmental gradients set a broad boundary, but localized anthropogenic management (captured by the farm-level random effect in our model) dictates the system's actual structural expression and biomass accumulation. Similarly, the divergence observed between MSP1 and MSP2 within the same mid-altitude stratum further illustrates this point; despite sharing similar elevational boundaries, differences in localized species dominance (e.g., the proportion of fast-growing timber trees vs. complex multi-strata native shade) and subtle variations in recent thinning or pruning regimes likely drive their distinct biomass allocations.

#### 4.4. Limitations of the model and implications for LiDAR-based biomass estimation

Although LiDAR effectively captures the vertical structure of the canopy, it has limited capacity to estimate biomass because it is less sensitive to internal plant properties, such as wood density and branch architecture (Xu et al., 2021). This limitation is particularly relevant in agroforestry systems, where species diversity is high.

Furthermore, the partial dependence between LiDAR-derived structural metrics and biomass estimates limits the interpretation of the model (Borsah et al., 2023; Li et al., 2025). While the model exhibits strong internal consistency, its predictive capacity may decrease when applied to systems with different structural configurations or species compositions.

These limitations underscore the importance of interpreting LiDAR-derived height as an indicator of structural organization rather than a direct measure of biomass (Yao et al., 2011). Furthermore, a critical limitation of relying solely on aerial UAV-LiDAR is the physical 'occlusion' of the understory by the overstory. While this understory omission had a negligible impact on total AGB in our specific systems (where

shade trees overwhelmingly dominate carbon stocks), in other agroforestry configurations with dense, mid-canopy crops (e.g., mature multi-strata cacao or fruit tree systems), aerial LiDAR's inability to penetrate the upper canopy would lead to a severe underestimation of total biomass. This underscores that our approach is specifically optimized for overstory-dominant shaded coffee, but may be fundamentally limited in systems where understory vegetation contributes substantially to total biomass. Therefore, it is necessary to incorporate additional structural and ecological variables to improve the model's generalizability.

#### 4.5. Limitations and future research directions

First, the small number of physical farms ( $N = 6$ ) inherently limits the broad regional generalizability of our specific parameter estimates. As noted in Section 2.1, this was a deliberate trade-off: prioritizing data depth and methodological calibration over geographic breadth, which is a necessary constraint when acquiring high-density UAV-LiDAR in remote Andean terrain. Consequently, our mixed-effects framework should be viewed as a robust methodological blueprint that requires local farm-scale calibration, rather than a universally transferable predictive equation.

The limitations identified in this study suggest several avenues for future research. First, incorporating independent, field-based biomass measurements would enable robust external validation and enhance the reliability of the model. This is particularly important for capturing species-specific variability and refining allometric relationships. Second, future models should integrate LiDAR-derived metrics that better represent vertical structure, such as canopy density profiles and foliage height diversity. These metrics can capture biomass distribution across canopy layers, thereby improving predictive performance in heterogeneous systems. Third, integrating LiDAR data with spectral information from multispectral or hyperspectral sensors could improve biomass estimation by incorporating information on vegetation composition and physiological status.

Finally, scaling analyses using multiple spatial resolutions could provide insight into how structural patterns influence biomass estimation at different scales. This would contribute to the development of transferable models for agroforestry systems.

#### 4.6. Practical implications for MRV and climate-smart agriculture

Beyond methodological advances, these findings have direct practical implications for carbon accounting and climate-smart agriculture (CSA) in smallholder landscapes. For monitoring programs and MRV (Measurement, Reporting, and Verification), our results prove that applying generic, landscape-level biomass equations leads to significant estimation errors. Instead, carbon projects must adopt farm-specific baseline calibrations (facilitated by affordable UAV-LiDAR) to ensure fair and accurate carbon credit quantification. For agroforestry management, the ability of LiDAR to spatially map the 'invisible' random effects (such as the biomass loss caused by intensive pruning in high-altitude farms like HSP2) provides farmers and technicians with a powerful tool to visualize how specific management decisions impact their carbon stocks. Ultimately, integrating this workflow into CSA programs allows smallholders to quantitatively demonstrate their role as climate mitigators, directly linking sustainable canopy management to tangible economic incentives without the prohibitive costs of traditional forestry inventories.

### 5. Conclusions

This study evaluated the potential of UAV-LiDAR to characterize vegetation structure and estimate above-ground biomass (AGB) in coffee agroforestry systems along an altitudinal gradient in the northern Peruvian Andes. Our results revealed substantial quantitative variability across the evaluated strata, with mean canopy height ranging from 2.47 to 8.79 m, which translated into highly heterogeneous AGB (1.55–40.59 Mg ha<sup>-1</sup>) and carbon stocks (0.73–19.08 Mg C ha<sup>-1</sup>). Despite this extreme structural

variability (with coefficients of variation often exceeding 100%), we showed that LiDAR-derived canopy height consistently indicates AGB patterns. By showing that UAV-LiDAR can effectively track these specific, quantifiable carbon gradients, we close the critical conceptual gap between complex 3D canopy architecture and the actionable carbon data required to sustain both climate mitigation targets and smallholder livelihoods.

However, the findings also show that biomass in coffee agroforestry systems is not determined exclusively by broad environmental gradients such as elevation, nor by canopy height alone. Instead, localized factors (specifically management practices, species composition, and stand structure) exert a stronger, modulating influence on biomass accumulation than elevation alone. The high structural heterogeneity introduced by these farm-level factors creates significant variability, limiting the use of models based on a single structural or topographic. In this context, the inclusion of random effects at the farm level was essential to capture local variability and improve the representation of allometric processes.

From a methodological perspective, the results suggest that the model's performance metrics primarily reflect internal structural consistency rather than independent predictive validation, because LiDAR-derived variables depend on biomass estimates. Therefore, canopy height should be interpreted as a structural proxy for biomass rather than a completely independent indicator.

Despite these limitations, LiDAR provides a robust framework for characterizing the spatial structure of vegetation in complex agroforestry systems. This approach enables the identification of structural variability patterns relevant to carbon estimation and constitutes a valuable tool for non-destructive monitoring in tropical landscapes.

Beyond technical efficacy, our findings hold direct and actionable implications for climate mitigation frameworks, particularly REDD+ and voluntary carbon markets. The high costs and logistical difficulties of traditional ground inventories in structurally complex terrains, combined with the use of generic regional carbon averages, often exclude smallholder farmers from equitable participation in carbon finance, leading to under-compensation. The UAV-LiDAR workflow demonstrated here provides a scalable and cost-effective Monitoring, Reporting, and Verification (MRV) solution tailored for mountainous tropical agroforestry. Crucially, our results demonstrating significant altitudinal and farm-level variability in carbon stocks underscore that "one-size-fits-all" baseline assessments are inadequate. By enabling precise, farm-specific carbon quantification that accounts for local management and topography, LiDAR technology can ensure that smallholders receive fair and transparent payment for the ecosystem services they provide. Ultimately, adopting these advanced remote sensing tools can transform shade-grown coffee from a single-commodity crop into a dual-income strategy, simultaneously safeguarding environmental resilience, contributing to national climate commitments, and securing the economic sustainability of smallholder livelihoods in the Andes.

Finally, this study underscores the importance of integrating supplementary structural metrics derived from LiDAR, such as height percentiles and vertical canopy distribution, as well as incorporating independent field data for robust external validation. Furthermore, future research should explore multi-metric approaches and fusion with spectral data to improve the predictive capacity and transferability of models in highly heterogeneous agroforestry systems. However, given the limited number of plots and the specific geographical context of this study in the northern Peruvian Andes, these findings should be interpreted as a methodological blueprint rather than a universally transferable predictive equation, requiring local calibration before broad application.

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## CRediT authorship contribution statement

**Malluri Goñas:** Writing – review & editing, Visualization, Resources, Investigation, Conceptualization. **Ligia García:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Conceptualization. **Manuel Oliva:** Validation, Supervision, Methodology. **Jhonsy O. Silva-López:** Writing – original draft, Validation, Methodology. **Darwin Gómez-Fernández:** Software, Data curation. **Nilton Atalaya-Marin:** Software. **Ever Tarrillo:** Validation. **Pedro A. Torres-Herrera:** Formal analysis. **Daniel Tineo:** Validation. **Nilton B. Rojas-Briceño:** Writing – original draft, Validation, Methodology. **Alexander Cotrina-Sanchez:** Formal analysis. **Jaris Veneros:** Visualization, Software, Methodology, Investigation, Formal analysis, Data curation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

Data will be made available on request.

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