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Comparing airborne and terrestrial LiDAR with ground-based inventory metrics of vegetation structural complexity in oil palm agroforests

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ABSTRACT

Vegetation structural complexity is an important component of forest ecosystems, influencing biodiversity and functioning. Due to the heterogeneous distribution of vegetation elements, structural complexity underpins ecological dynamics, species composition, microclimate, and habitat diversity. Field measurements and Light Detection and Ranging (LiDAR) data, such as airborne (ALS) and terrestrial (TLS), can assess structural characteristics of forest and agroforestry systems at various spatial scales. This assessment is urgently needed for monitoring ecosystem restoration in degraded lands (e.g., in oil palm landscapes), where it is not well-known how structural measures derived from these different approaches relate to each other. Here, we compared the degree of correlation between individual and multivariate datasets of vegetation structural complexity metrics derived from ALS, TLS, and ground-based inventory approaches. The study was conducted in a 140 ha oil palm monoculture, enriched with 52 plots in the form of tree islands representing agroforestry systems of varying sizes and planted diversity levels in Sumatra, Indonesia. Our datasets comprised 25 ALS, five TLS, and nine ground-based inventory metrics. We studied correlations among metrics related to traditional stand summary, heterogeneity, and vertical and horizontal stand structure. We used principal component analysis for data dimensionality reduction, correlation analysis to quantify the strength of relationships between metrics, and Procrustes analysis to investigate the agreement between datasets. Significant correlations were found between ALS and TLS metrics for canopy density ($r = 0.79$) and maximum tree height ($r = 0.58$) and between ALS and ground-based inventory measures of stand heterogeneity and height diversity (r between 0.60 and −0.63). Further, we observed significant agreements between the ordinations of multivariate datasets ($r = 0.56$ for ALS − TLS; and $r = 0.46$ for ALS – ground-based inventory). Our findings underline the ability of ALS to capture structural complexity patterns, especially for canopy gap dynamics and vegetation height metrics, as captured by TLS, and for measures of heterogeneity and vertical structure as captured by ground-based inventories. Our study highlights the strength of each approach and underscores the potential of integrating ALS and TLS with ground-based inventories for a comprehensive characterization of vegetation structure in complex agroforestry systems, which can provide guidance for their management and support ecosystem restoration monitoring efforts.

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1. Introduction

Vegetation structural complexity is an important characteristic of forest and agroforestry systems, supporting microclimatic conditions for different taxa (Ehbrecht et al., 2019; Kovács et al., 2017; Meijide et al., 2018) and influencing ecosystem functionality and biodiversity (McElhinny et al., 2005). Defined as the "three-dimensional distribution of vegetation within an ecosystem" (Coverdale & Davies, 2023), vegetation structural complexity integrates the number and relative abundance of individual vegetation structural attributes (McElhinny et al., 2005) such as heterogeneity, vertical, and horizontal structure (Atkins et al., 2018; Rutten et al., 2015). Greater complexity in forest ecosystems contributes to overall biodiversity by creating heterogeneous structures with varying water and light distribution, microhabitats, and niche occupations for diverse plant and animal communities (de Almeida et al. (2021a); Ehbrecht et al., 2017; Santos et al., 2022). Therefore, studying vegetation structural complexity is essential for understanding ecosystem processes and for the sustainable management of forest and agroforestry systems (Aalto et al., 2023).

Traditionally, vegetation structural complexity has been assessed through ground-based tree inventories (Avery & Burkhart, 2015; Köhl et al., 2006) which are limited to the plot area (McElhinny et al., 2006; Zellweger et al., 2013), and are costly and time-consuming (Zenner & Hibbs, 2000), especially in areas of difficult access. These conventional methods mainly focus on two-dimensional stand-level characteristics (Lines et al., 2022), neglecting the three-dimensional nature of forest stands (Perles-Garcia et al., 2021). In contrast, remote sensing technologies, particularly light detection and ranging (LiDAR), have revolutionised the estimation of vegetation structural complexity (Thers et al., 2019) by enabling a rapid and precise characterization of vegetation, from individual trees to entire forests (Seidel et al., 2019; Stovall et al., 2018). Airborne Laser Scanning (ALS) and Terrestrial Laser Scanning (TLS), as forms of LiDAR, facilitate the estimation of vegetation structural characteristics across multiple forest types, at varying spatial scales and resolutions (Asner & Mascaro, 2014; Næsset, 2002; Nguyen et al., 2023). Hence, LiDAR technologies provide opportunities to evaluate restoration practices at larger scales and characterize tree-based systems such as agroforestry (Camarretta et al., 2020, 2021), especially in tropical areas where the characterization of vegetation structural complexity using different methods remains underdeveloped (Becknell et al., 2018).

While ALS is primarily used for acquiring upper canopy variability data (Hilker et al., 2010) across larger spatial extents in a relatively short time (White et al., 2016), TLS assesses tree form and vegetation distribution under the canopy and at plot level (Calders et al., 2020) (see conceptual Fig. 1). These methods can enhance vegetation characterization when combined, enabling effective monitoring of ecosystem restoration and conservation efforts on a scalable basis (de Almeida et al. (2021a); Camarretta et al., 2020; Coverdale & Davies, 2023). However, both technologies face limitations due to the occlusion effect, caused by obstructive vegetation elements (Crespo-Peremarch et al., 2020). For instance, in ground-based scanning, the occlusion effect in the lower canopy limits the assessment of top-canopy characteristics (Mathes et al., 2023; Wang et al., 2019). Conversely, ALS encounters occlusion from the top of the canopy (Lefsky et al., 1999, 2002), limiting the characterization of below canopy vegetation but proved to be ideal for representing tree heights and top canopy characteristics, thought its accuracy depends on the point cloud and canopy density (Crespo-Peremarch et al., 2020; Ganz et al., 2019).

Agroforestry systems represent a sustainable form of land utilization that integrates a diverse, productive, and resilient land management approach (Wilson & Lovell, 2016). They involve complex vegetation structures (Camarretta et al., 2021; Seidel et al., 2021) as a result of the mixture between vegetation layers including trees, shrubs, and crops on the same land unit (Nair, 1991, 1993). Compared to simplified monoculture farming, these complex structures can enhance plant and faunistic diversity (Manning et al., 2019; Santos et al., 2022), and outyield monocultures when managed effectively (Pretzsch & Schütze, 2016). The complementarity of tree species within these systems facilitates efficient use of resources (e.g., light, water), bringing different ecosystem services and benefits for biodiversity and people (Garrity, 2004; Nair et al., 2008). The adaptability and multifunctionality of

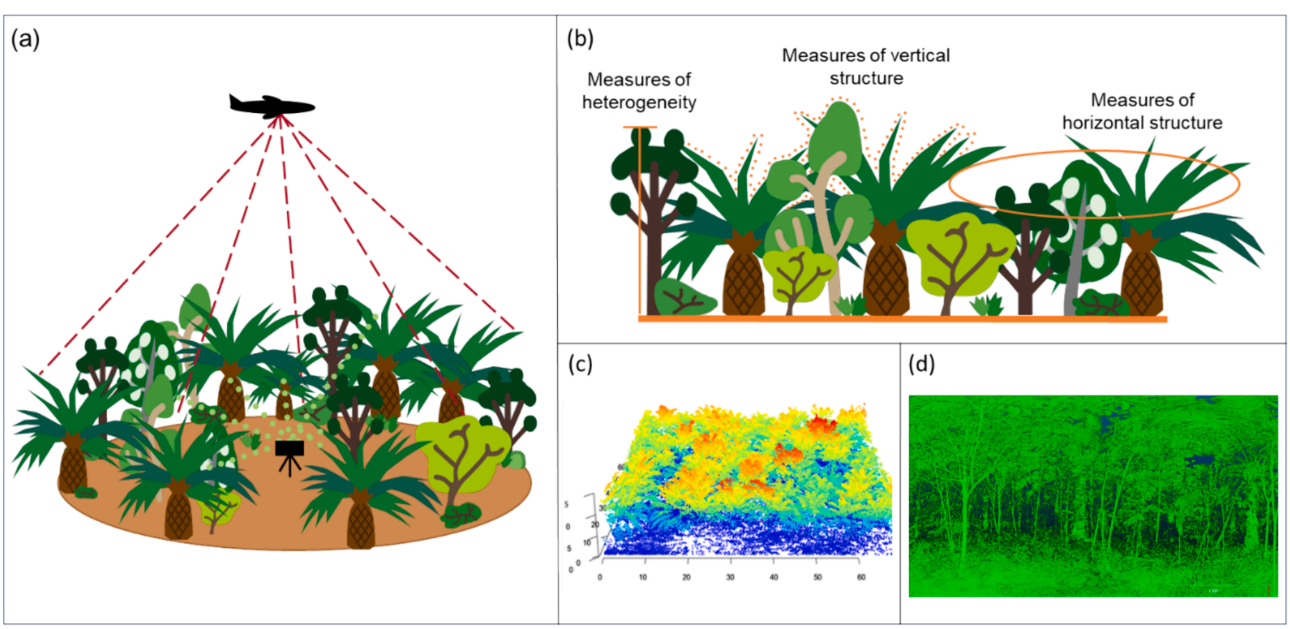

Fig. 1. (a) Graphical representation of an oil palm agroforestry system in which vegetation structural complexity metrics were assessed with ALS (red dashed line) and TLS (green dotted line). ALS emits laser pulses above the canopy, capturing upper canopy surface characteristics and heterogeneity. TLS characterizes under canopy structural diversity. (b) Conceptual side view of the agroforestry system with extracted metrics, including measures of heterogeneity (e.g., entropy or standard deviation of height points), vertical structure (e.g., number of points above a threshold or foliage height diversity), and horizontal structure (e.g., canopy openness and gaps size). A complete list of metrics extracted from the different approaches is described in Table S2. (c) An example of point clouds obtained from ALS and (d) TLS.

agroforestry align with the goals of the UN Decade on Ecosystem Restoration, offering practical solutions to some of the most pressing environmental challenges (UN Decade on Ecosystem Restoration (UN (2021)). Therefore, agroforestry systems are promising, long-lasting, and effective reference models for restoration ecology within agricultural landscapes (Aronson et al., 2017).

Accurate assessment of vegetation structure in agroforestry systems is crucial for effective ecosystem management and restoration, representing a critical area for the utilization of LiDAR technology. However, the advantages and potential limitations of using different LiDAR technologies to characterize vegetation structural complexity in agroforestry systems remain underexplored. In this study, we compared the degree of correlation between individual and multivariate sets of vegetation structural complexity metrics derived from ALS, TLS, and ground-based inventory. While previous studies have explored the relationship between LiDAR metrics from different platforms with ground-based inventory data in forest ecosystems (e.g., Bazezew et al., 2018; Hilker et al., 2010; Jayathunga et al., 2018; Palace et al., 2015), here we provide insights on the applications of LiDAR in characterising vegetation structural complexity in oil palm agroforestry systems. We asked how ALS metrics correlate with ground-based metrics (TLS and ground-based inventory) in characterising vegetation structural complexity in oil palm agroforestry systems. We hypothesised that the degree of correlation among ALS, TLS, and ground-based inventory metrics varies across structural complexity categories of heterogeneity, vertical, and horizontal structure. Specifically, we expected ALS and TLS to demonstrate strong correlations for vertical (e.g., height measures) and horizontal (e.g., canopy gap measures) metrics. Conversely, we expected the correlations between ALS and ground-based inventory metrics to be moderate or low as the dense agroforestry setting might lead to different characteristics from both methods. Finally, in the comparative analysis between multivariate datasets, we hypothesised higher concordance or association between ALS and TLS datasets as both methods can capture vertical and horizontal vegetation variability in three-dimensional space from different positions, compared to ground-based tree inventories.

2. Methods

2.1. Study area

The study was carried out in an oil palm landscape in the estate of Humusindo Makmur Sejati near the Bungku village in Jambi province, Sumatra, Indonesia (1.95° S, 103.25° E; 47 ± 11 m a.s.l.). The lowlands of Jambi are characterized by a humid tropical climate with two peak rainy seasons in March and December and a dryer period from July to August (Drescher et al., 2016). The mean annual precipitation is 2235 ± 385 mm (1991–2011), and the mean annual average temperature is 26.7 ± 1.0 °C (Drescher et al., 2016). Spatial and ground-based data were collected within EFForTS-BEE, a large-scale, long-term Biodiversity Enrichment Experiment in the EFForTS project (Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems, https://www.uni-goettingen.de/efforts). The main aim of EFForTS-BEE is to evaluate the potential of establishing small patches of native trees (i.e., tree islands, representing agroforestry systems) (Benayas et al., 2008) within an industrial oil palm plantation as a restoration measure to enhance biodiversity and ecosystem functioning while still providing socio-economic benefits (Teuscher et al., 2016; Zemp et al., 2023). The experiment was established in December 2013 within a 140-ha oil palm monoculture of 6- to 12-years of age. In the experiment, 52 plots in the form of tree islands were established following a random partition design. The tree islands vary in sizes of 25 m^2, 100 m^2, 400 m^2, and 1600 m^2, as well as the number of tree species planted inside of the island ranging from 0, 1, 2, 3, and 6 native tree species planted (see tree islands information and coordinates in Table S1), with a total of 6354 trees planted. The total area of the tree islands is 2.8 ha, representing less than 5 % of the oil palm monoculture. Before the establishment of the islands, oil palm density was reduced by 40 %, except in the 25 m^2 plots (Teuscher et al., 2016). Manual weeding of the understorey stopped two years after planting, allowing for natural regeneration inside the tree islands. More details of the experimental design and the management are available in Teuscher et al., (2016).

2.2. Data collection

We analyzed three datasets containing vegetation structural complexity metrics obtained from the 52 tree islands. The first dataset was obtained from ALS in January 2020, i.e., six years after the establishment of the experiment. The data was collected with a Riegl LMS-Q780 full waveform scanner (Riegl Laser Measurement Systems GmbH, Horn, Austria), operating at the near-infrared wavelength, mounted on a BN2T fixed-wing aircraft flying at an altitude of 1780 m above ground level (AGL). The waveforms were discretized and rectified with the Riegl software suite (RiProcess, RiAnalyze, RiWorld). The flight line overlap was at least 60 % resulting in a point cloud average density of all points in the studied tree islands was 26.6 points m^{-2}, with a standard deviation of 4.3 points m^{-2} (see an example of the point cloud obtained from ALS in Fig. 1C). The second dataset was obtained from TLS in single-scan mode (Ehbrecht et al., 2017; Seidel et al., 2016) in January 2020 (see an example of point cloud obtained from the TLS in Fig. 1D). A FARO Focus M70 terrestrial laser scanner (Faro Technologies Inc., Lake Mary, USA) was used once at the center of each tree island to capture the 3-dimensional distribution of the stand elements. ALS plot centroids corresponded to the plot's center measured in the field with the help of a Reach RS2 Global Navigation Satellite System (GNSS) receiver. The third dataset was obtained from a ground-based tree inventory carried out between January and February 2020, following Zemp et al., (2019). In each tree island, we inventoried all trees taller than 130 cm (planted or established naturally). Oil palms were not included in the inventory. We recorded tree species' identity, spatial coordinates, and structural attributes (Table 1). Diameter at Breast Height (*DBH,* measured at 130 cm above ground) was measured with a calliper for trees < 6 cm diameter and a diameter tape for larger trees. Tree height was measured with regular tape for trees < 2 m height, a telescopic pole for trees between 2 and 12 m, and a VERTEX for trees > 12 m. Plot centers used for ALS, TLS, and ground-based inventory were carefully aligned to ensure consistent spatial referencing and accurate comparison across datasets, without calibration or adjustment.

2.3. Data processing

ALS point cloud data were processed using the statistical language R (R Core Team, 2021), with the packages *lidR* (Roussel (2022))*, ForestGapR* (Silva et al., 2019), and *leafR* (de Almeida et al. (2021b)) (a complete explanation of the methodology for LiDAR data is described in Camarretta et al., 2021). In total, 25 metrics were extracted from the ALS point cloud (Table 1) in circular plots of five meters radius from the plot center. Next, five TLS metrics were calculated from the TLS point cloud, including top height (*Top.height*), Mean Fractal Dimension (*MeanFrac*), Effective Number of Layers (*ENL*), stand structural complexity Index (*SSCI*) and canopy openness (*Canopy.openness*) (Table 1), following Ehbrecht et al., (2021). Canopy openness is also a measure of canopy gaps, with openness including the sum of all gap sizes. TLS point clouds were processed using the statistical language R (R Core Team, 2021). Finally, with the ground-based tree inventory data, we calculated different measures of dispersion for DBH, height, and basal area, using allometric equations (Table 1).

All metrics from the different datasets describe different vegetation structural characteristics in three-dimensional space and are grouped into four different categories including (1) traditional stand summary measures (including the most common metrics used in remote sensing and ground-based inventories), (2) measures of heterogeneity (upper

Table 1
Categories and list of vegetation structural complexity metrics extracted from ALS and TLS point clouds and ground-based inventory. Adapted from Camarretta et al., (2021). A detailed description of metrics can be found in the supplementary materials Table S2. Metric name abbreviations are listed in parentheses.

Category of measure	ALS metric	TLS metric	Inventory metric
Traditional stand summary	Maximum height within the point cloud (*zmax*), mean height within the point cloud (*zmean*), vegetation cover above 2.5 m (*veg_cover*), total extent of gaps > 2.5 m (*sum_gapArea*), leaf area index (*lai*)	Height of the highest z-coordinate within the point cloud (*Top. height*)	Maximum height per tree island (*max_height*), mean height per tree island (*mean_height*), mean diameter measured at 130 cm length of the stem (*mean_DBH*), total basal area per tree island (*T.BAm2*), mean basal area per tree island (*mean_BAm2*)
Heterogeneity	Entropy of height points (*zentropy*), kurtosis of height points (*zkurt*), skewness of height points (*zskew*), standard deviation of height points (*zsd*), rumple index (*rumple*)	Stand structural complexity index (*SSCI*), arithmetic mean of fractal dimensions of polygons within the point cloud (*meanFRAC*)	Standard deviation of height per tree island (*SD_height*), standard deviation of diameter measured at 130 cm (*SD_DBH*), standard deviation of basal area (*SD_BAm2*)
Vertical structure	Number of points above 2 m height threshold (*pzabove2*), number of points above zmean (*pzabovemean*), percentiles of height returns 25, 50, 75 (*zq25*, *zq50*, *zq75*), foliage height diversity calculated as Shannon evenness (*fhd_shan_eve*) or Shannon diversity (*fhd_shan_div*), effective number of layers (*ENL*), canopy ratio (*cr*)	Effective number of layers (*ENL*),	Height values greater than 95 % of heights in the tree island (*H. Quantile_0.95*)
Horizontal structure	Total number of gaps in the canopy > 2.5 m (*num_gaps*), maximum gap size > 2.5 m (*max_gapArea*), min gap size > 2.5 m (*min_gapArea*), mean gap size > 2.5 m (*mean_gapArea*), median gap size > 2.5 m (*median_gapArea*), number of points classified as ground (*pground*)	Canopy openness (*canopy. openness*)	

canopy and below canopy complexity or heterogeneity), (3) measures of vertical structure (including height measures and vertical complexity), and (4) measures of horizontal structure (canopy cover or canopy gaps measurements) (Camarretta et al., 2021; Kane et al., 2010; LaRue et al., 2020).

2.4. Statistical analysis

We compared correlations between ALS and ground-based (TLS and ground-based inventory) datasets of structural complexity for individual metrics and for multivariate sets of metrics. First, we used principal component analysis (PCA) to study data variation and to reduce data dimensionality in the ALS dataset (25 variables), for which many variables described similar structural attributes. PCA analysis was conducted using the function *PCA()* from the *FactorMineR* R package (Husson et al., 2022). All values were standardised before the analysis to control for the effect of scale and different units. Results were visualised as biplots using the *fviz_pac_biplot()* function from the *factorextra* R package (Kassambara & Mundt, 2020).

Second, we computed a matrix of non-parametric Spearman's r-rank correlation coefficients (r) to investigate the correlation between individual metrics from the different datasets. We calculated correlations in pairs for 1) ALS and TLS metrics and 2) ALS and ground-based inventory metrics. For interpretations, in this study we considered $r \geq 0.7$ as a strong correlation, $r \geq 0.4$ and < 0.7 as a moderate correlation, and $r < 0.4$ as a weak correlation. We calculated Spearman correlations using the function *rcorr()* from the R package *Hmisc* (Frank (2021)). We assessed the statistical significance of the correlation using multiple significance thresholds (p-values, significance level $p < 0.05$, < 0.01, and < 0.001). We used scatterplots to show the highest correlations found in the analysis. We reduced dimensionality in the ALS dataset for the subsequent comparative analysis based on the results of the eigenvalues associated with the first two principal components from the ALS PCA and the correlation analysis. For this, we selected the metrics with the largest possible variances and showing the highest correlation among datasets, making sure to include metrics describing the different vegetation structural categories.

Next, using a Procrustean superimposition approach (Gower, 1971; Peres-Neto & Jackson, 2001), we compared multivariate datasets and tested the agreement between pairs of ordinations for 1) ALS – TLS and 2) ALS – ground-based inventory datasets. Procrustes analysis rotates and rescale the axes of two ordinations in order to find an optimal superimposition, so that the target dataset (e.g., ALS dataset) corresponds as closely as possible to the reference dataset (e.g., TLS or ground-based inventory). The obtained Procrustes sum of squared errors (i.e., m^2) indicates overall dissimilarity between datasets (Peres-Neto & Jackson, 2001). The statistical significance of the Procrustes results was measured with the Procrustes permutation test (Protest) of community environmental concordance (Jackson, 1995) and a correlation coefficient (r) was computed to quantify the correlation between datasets after Procrustes transformation. We performed a Procrustes and Protest test using the functions *procrustes()* and *protest()* from the R package *vegan* (Oksanen et al., 2022). All the analyses were performed in R (R Core Team, 2021).

3. Results

3.1. Principal component analysis (PCA) for the ALS dataset

PCA for the 25 ALS metrics showed that 81 % of the total variance came from the first two axes of ordination (Fig. 2), while PC3, and PC4 only accounted for 10.2 % and 6.8 %, respectively (Table S3). The first principal component (PC 1, accounting for ~ 53 % of the total variance) was mainly associations with measures of vertical structure, including *pzabove2*, *fhd_shan_div*, *cr*, and *zq25*. In the first PC, metrics describing horizontal structure (e.g., *max_gapArea*, *sum_gapArea, pground*) had an inverse relationship with metrics describing vertical structure (e.g., *pzabove2*, *fhd_shan_div*, *zq25*). The second PC (accounting for ~ 19 % of the total variance) was mainly correlated with metrics describing heterogeneity and vertical structure (e.g., *enl*, *zentropy*, *zsd*), indicating tree height variance. Scatter points symbolising tree diversity level (point colour) and tree island size (point size) showed heterogeneous

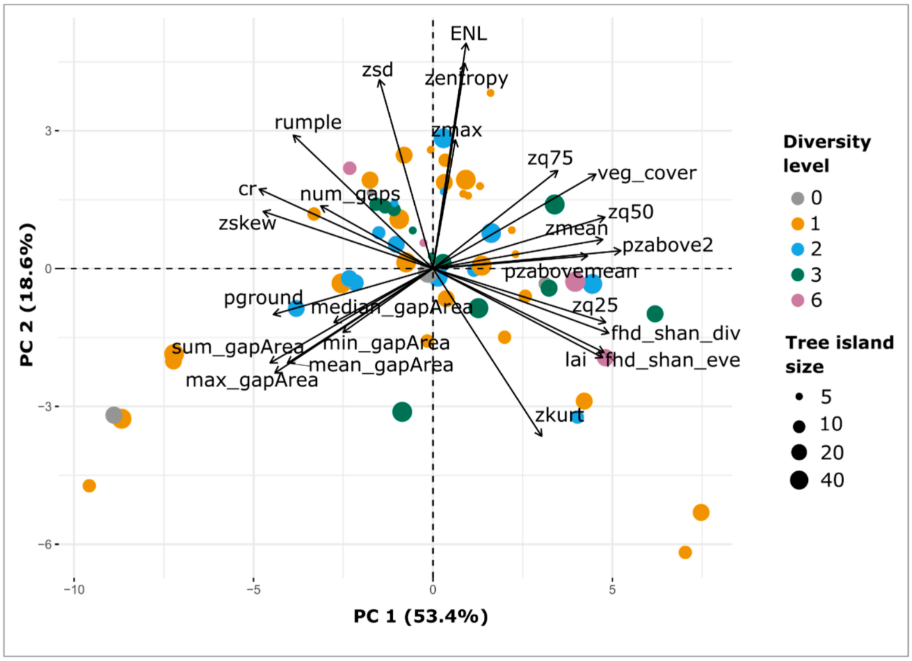

Fig. 2. PCA-biplot for the 25 ALS metrics. The % value shows the explained variance by each axis for the two principal components (PC 1 and PC 2). Metrics are represented with arrows, where arrows length represent the variance of metrics. Points represent the distribution of tree islands where point colour indicate the diversity level and point size represents the tree island size. See the detailed description of metrics in Table S2.

distribution along metrics, indicating no substantial differences among tree islands.

3.2. Correlations between ALS and ground-based (TLS and ground-based inventory) vegetation structural individual metrics and multivariate datasets

Strong positive correlations (Spearman $r > 0.7$) were found between metrics characterising stand summary and horizontal structure. The highest correlation was observed between the ALS *max_gapArea* and the TLS *canopy.opennes* ($r = 0.79$ – Fig. 3A). Other strong correlations were observed between *sum_gapArea*, *veg_cover*, and *mean_gapArea*, with *canopy.openness* ($r = 0.78$, -0.78, and 0.73 respectively – Table 2). The ALS metric *pzabove2* (a measure of vertical structure) also showed a strong correlation with *canopy.openness* ($r = -0.73$). Moderate correlations were found between the ALS vertical structural metrics *zq50* and *pzabovemean* and the TLS *canopy.openness* ($r = -0.66$ and -0.63, respectively). We did not find any significant correlation between the effective number of layers (*ENL,* a measure of vertical structure*)* from ALS and TLS, which was assessed following the same methodology (Table S4). Other moderate correlations were observed between metrics describing height measurements, e.g., between *zmax* and *Top.height* (Fig. 3B) and *zmean* and *canopy.openness* ($r = 0.58$ and -0.59, respectively). Maximum tree height values obtained from ALS varied from 10.4 m to 18.3 m, with a mean and standard deviation of 13.5 m and 1.5 m, while values of top tree height from TLS varied from 11 m to 23 m, with a mean and standard deviation of 14.6 m and 2 m (Figure S1). The correlations between ALS – TLS metrics describing heterogeneity were moderate (r between 0.40 and 0.55).

Correlations between ALS and ground-based inventory metrics showed mainly moderate correlations (r between 0.40 and 0.63 – Table 3). The highest correlation was observed between the ALS *rumple* and *mean_BAm2* ($r = -0.63$ – Fig. 3C). We found many correlations between ALS measures of vertical structure and the ground-based inventory metrics, e.g., between *fhd_shan_eve*, *cr* and mean_height ($r = 0.6$ and -0.60, respectively, Fig. 3D). For stand summary measurements, moderate positive correlations were found between the ALS *lai* and seven of the inventory metrics (r between 0.41 and 0.59). Further, ALS measures of heterogeneity including *zskew*, *zsd*, and *rumple* showed mainly negative moderate correlations with the ground-based inventory metrics (r between -0.32 and -0.63). We found no significant correlations between height measurements from airborne LiDAR and inventory, except between *zmean* and *mean_height* ($r = 0.41$) and *zmean* and *SD_height* ($r = 0.48$). Maximum tree height obtained from the inventory varied from 2 m to 18 m, with a mean and standard deviation of 8.8 m and 3.5 m (Figure S1). Finally, we did not find strong or moderate correlation between ALS metrics of horizontal structure and the inventory metrics, except for the correlation between *pground* and *mean_BAm2* ($r = 0.40$).

Based on the PCA and correlation analysis, we selected the ALS metrics *veg_cover*, *lai*, and *zmax* to describe stand summary measures; *zsd*, *rumple*, and *zskew* to characterize heterogeneity or complexity; *pzabove2*, *fhd_shan_div*, and *cr* as vertical structural metrics; and *max_gapArea*, *mean_gapArea*, and *pground* to characterize horizontal structure for the Procrustes analysis, since they had the highest contribution to the first and second principal component in the PCA and because they showed the highest strong or moderate correlations with the TLS and ground-based inventory metrics.

Procrustes analysis showed closer levels of similarity between the ordinations of ALS and TLS datasets ($m^2 = 0.68$) after Procrustes transformation (rotation, scaling, and translation), compared to the ordinations of ALS and ground-based inventory datasets ($m^2 = 0.78$). While we observed some moderate alignments between the two ordinations (Fig. 4A and B), the correlations after Procrustes transformation were moderately positive ($r = 0.56$ for ALS – TLS and $r = 0.46$ for ALS – ground-based inventory), implying a significant but not perfect overlap in the information captured by the different approaches. Larger residuals from the Procrustes analysis indicated greater discrepancy between the original and aligned position in the observations for both ALS – TLS and ALS – ground-based inventory comparisons (Fig. 4), suggesting a higher degree of variability or disagreement in how these methods characterize certain aspects of vegetation structural complexity.

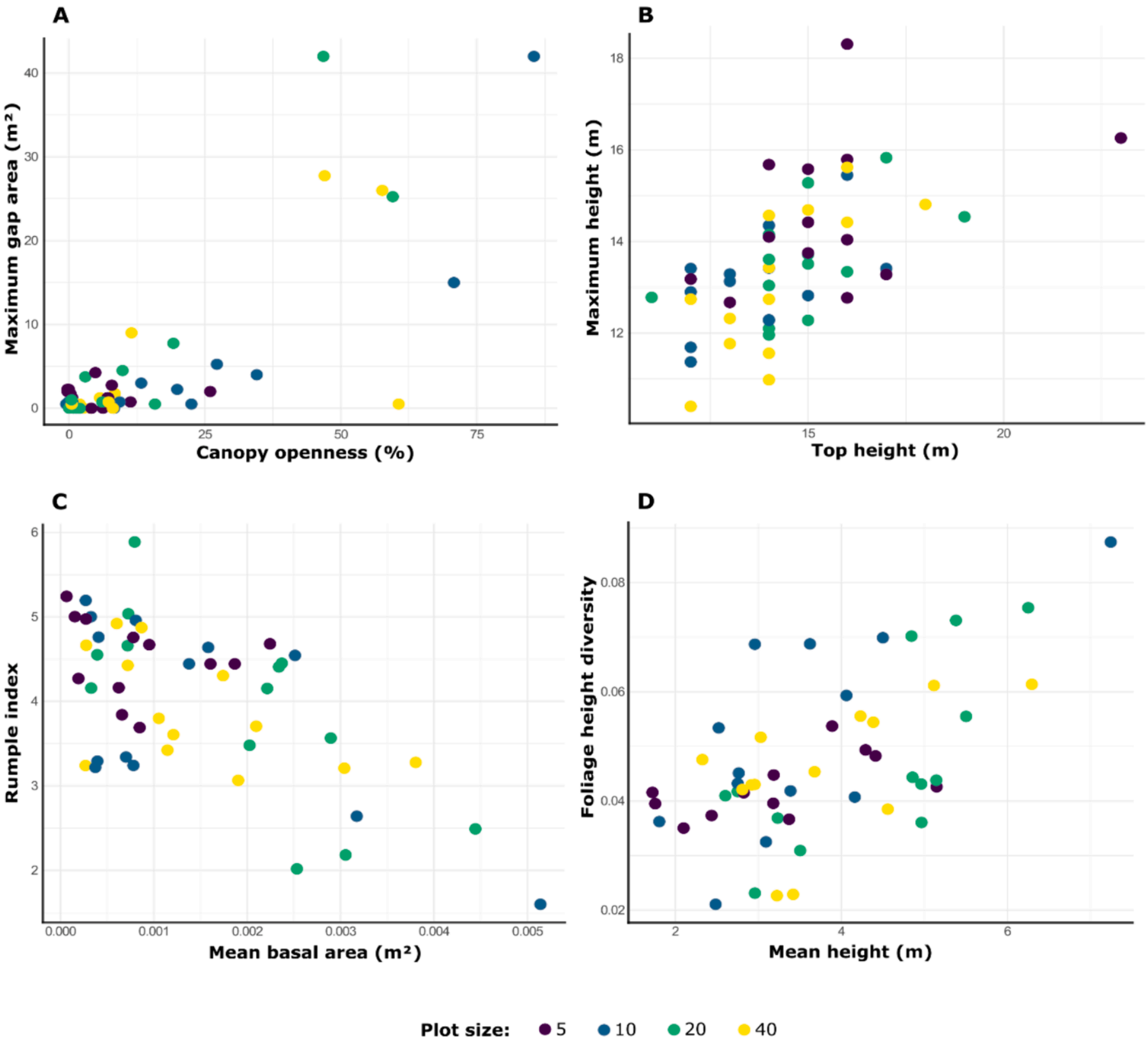

Fig. 3. Scatter plots showing some of the highest correlation found in the analysis. (A) canopy openness (*Canopy.openness)* from TLS and maximum gap area (*max_gapArea)* from ALS, Spearman's rank correlation $r = 0.79$, n = 52; (B) top height (*Top.height*) from TLS and maximum height (*zmax*) from ALS, Spearman's rank correlation $r = 0.58$, n = 52; (C) mean basal area (*mean_BAm2*) from the ground-based inventory and rumple index (*rumple*) from ALS, Spearman's rank correlation r = -0.63, n = 52; and (D) mean height (*mean_height*) from the ground-based inventory and foliage height diversity (*fhd_shan_eve*) from ALS, Spearman's rank correlation $r = 0.60$, n = 52.

4. Discussion

In this study, we compared the degree of correlation among metrics of vegetation structural complexity calculated from ALS, TLS, and ground-based inventory in oil palm agroforestry systems in Indonesia. Our results reveal various relationships across approaches, with strong significant correlations observed between ALS and TLS metrics of vertical and horizontal structure and moderate significant correlations between ALS and ground-based measures of heterogeneity and vertical structure. The analysis of agreement between ordinations of multivariate datasets showed higher similarity between ALS and TLS compared to ALS and ground-based inventory datasets. This comparative analysis highlights the advantages and limitations of ALS, TLS, and ground-based inventory to study structural attributes as well as the potential of data integration for a holistic characterization of vegetation structural complexity patterns in agroforestry systems.

Correlations between metrics describing traditional stand summary and heterogeneity were moderate for ALS, TLS, and ground-based inventory. Consistent with our hypothesis, ALS and TLS metrics describing vegetation height (also a measure of vertical structure) were more closely correlated than ALS and ground-based inventory height values, indicating that ALS and TLS methods provide a similar characterization of height, especially maximum tree height, in oil palm agroforestry systems. Our study obtained consistently lower values for maximum height from ground-based measurements compared to the LiDAR methods. The difference could be due to the limited visibility given the high density of canopy strata inside the tree islands, e.g., resulting from the mixture of trees and palms, and because oil palms were not included in the ground-based measurements. Other studies comparing tree height estimations from field measurements and LiDAR techniques found that height values within the plot varied across different measurement methods (including LiDAR and field measurements), with higher values

Table 2
Correlations (calculated as Spearman's correlation coefficient *r*) between ALS and TLS metrics. Only strong and moderate significant correlations with *r* values >= 0.40 and p-value < 0.05 are shown. Significance levels are indicated as follows: * for p < 0.05, ** for p < 0.01, and *** for p < 0.001. All significant correlations are shown in Table S5. See metrics code and description in Table S2.

Category of measure	ALS metrics	TLS metrics	*r*
Traditional stand summary	*zmax*	*Top.height*	0.58***
	zmax, lai	*ENL*	0.40**, -0.40**
	zmean, veg_cover	*canopy. openness*	-0.59***, -0.78***
	sum_gapArea, lai	*canopy. openness*	0.78***, -0.54***
Heterogeneity	*zsd, rumple*	*Top.height*	0.52***, 0.42**
	zsd, rumple	*ENL*	0.54***, 0.44**
	zskew, rumple	*canopy. openness*	0.55***, 0.40**
Vertical structure	*fhd_shan_eve*	*ENL*	-0.42**- 0.73***, -
	pzabove2, pzabovemean	*canopy. openness*	0.63***- 0.52***, -
	zq25, zq50	*canopy. openness*	0.66***
	zq75	*canopy. openness*	-0.47***
	fhd_shan_div, cr	*canopy. openness*	-0.58***, 0.52***
Horizontal structure	*max_gapArea, min_gapArea*	*canopy. openness*	0.79***, 0.44**
	mean_gapArea, pground	*canopy. openness*	0.73***, 0.59***

obtained from remote sensing techniques (Ganz et al., 2019; Wang et al., 2019). In dense vegetation areas such as agroforestry systems, field-based measurements of tree height can be over or underestimated primarily due to limitations in the visibility of the treetop with errors up to 5 m (Bragg, 2014; Ganz et al., 2019). In contrast, ALS can provide good estimations of heights for dominant trees, but its precision is reduced when it comes to estimating the heights of less prominent trees from intermediate crown classes (Hirschmugl et al., 2023; Wang et al., 2019; Zimble et al., 2003). In large-scale restoration projects, remote sensing technologies like LiDAR can be used to capture stand height over large areas rapidly (Dickie et al., 2023), providing a comprehensive overview of the structure of forest and agroforestry systems, otherwise difficult to access by ground measurements due to time, resource limitations, and vegetation density.

The variation in the correlation between the ALS rumple index and the mean basal area from ground-based inventories, observed as negative in our study and positive in previous research (Kane et al., 2008), underscores the complex interplay between metrics characterising different aspects of forest structure. The discrepancies suggest that some correlations must be interpreted in the context of the specific forest ecosystem under study. In dense, uneven-aged stands such as agroforestry systems, a high canopy complexity might not necessarily be related to a high stand density. Furthermore, while the rumple index was calculated for the whole plot, mean basal area was estimated only for trees, excluding oil palms. Therefore, a comprehensive approach based on the inclusion of multiple metrics describing different aspects of vegetation structure is essential for accurately capturing structural complexity in different forest ecosystems.

We studied measures of vertical structure because they can provide information about height measurements, canopy vertical geometry and complexity, leaf distribution, and stem diameter (Stark et al., 2012; Sullivan et al., 2014). Furthermore, the first component identified in the PCA for the ALS metrics was mainly associated with measures of vertical structure. Most of the correlations for the three different approaches were moderate. Positive correlations between the ALS metrics,

Table 3
Correlations (calculated as Spearman's correlation coefficient *r*) between ALS and ground-based inventory metrics. Only strong and moderate significant correlations with *r* values >= 0.40 and p-value < 0.05 are shown. Significance levels are indicated as follows: * for p < 0.05, ** for p < 0.01, and *** for p < 0.001. All significant correlations are shown in Table S5. See metrics code and description in Table S2.

Category of measure	ALS metrics	Ground-based inventory	*r*
Traditional stand summary	*zmean, lai*	*mean_height*	0.41*, 0.59***
	zmean, lai	*SD_height*	0.48***, 0.43**
	zmean, lai	*H.Quantile_0.95*	0.43**, 0.49***
	lai	*mean_DBH*	0.51***
	lai	*SD_DBH*	0.44**
	Lai	*mean_BAm2*	0.57***
	lai	*SD_BAm2*	0.44**
Heterogeneity	*zkurt, zskew*	*mean_DBH*	0.49***, -0.54***
	zsd, rumple	*mean_DBH*	-0.48***, -0.58***
	zkurt, zskew	*mean_height*	0.58***, -0.61***
	zsd, rumple	*mean_height*	-0.48***, -0.62***
	zkurt, zskew	*H.Quantile_0.95*	0.42*, -0.58***
	zsd, rumple	*H.Quantile_0.95*	-0.40*, -0.54***
	zkurt, zskew	*mean_BAm2*	0.52***, -0.61***
	zsd, rumple	*mean_BAm2*	-0.48***, -0.63***
	zskew, rumple	*SD_DBH*	-0.53***, -0.48***
	zskew, rumple	*SD_height*	-0.59***, -0.43**
	zskew, zsd	*SD_BAm2*	-0.51***, -0.40***
	rumple	*SD_BAm2*	-0.51***
Vertical structure	*pzabove2, pzabovemean*	*mean_DBH*	0.41*, 0.42*
	zq25, fhd_shan_eve	*mean_DBH*	0.44**, 0.52***
	fhd_shan_div, cr	*mean_DBH*	0.48***, -0.51***
	pzabove2, pzabovemean	*SD_DBH*	0.43**, 0.49***
	zq25, fhd_shan_eve	*SD_DBH*	0.45***, 0.47***
	fhd_shan_div, cr	*SD_DBH*	0.44**, -0.49***
	pzabove2, pzabovemean	*mean_height*	0.46***, 0.45***
	zq25, fhd_shan_eve	*mean_height*	0.54***, 0.60***
	fhd_shan_div, cr	*mean_height*	0.57***, -0.60***
	pzabove2, pzabovemean	*SD_height*	0.45**, 0.56***
	zq25, zq50	*SD_height*	0.51***, 0.50***
	fhd_shan_eve, fhd_shan_div	*SD_height*	0.44**, 0.44**
	cr	*SD_height*	-0.52***
	pzabove2, pzabovemean	*H.Quantile_0.95*	0.45***, 0.49***
	zq25, zq50	*H.Quantile_0.95*	0.53***, 0.43**
	fhd_shan_eve, fhd_shan_div	*H.Quantile_0.95*	0.51, 0.49
	cr	*H.Quantile_0.95*	-0.55***
	pzabove2, pzabovemean	*mean_BAm2*	0.46***, 0.48***

(continued on next page)

Table 3 (*continued*)

Category of measure	ALS metrics	Ground-based inventory	*r*
	zq25, fhd_shan_eve	*mean_Bam2*	0.51***, 0.59***
	fhd_shan_div, cr	*mean_BAm2*	0.54***, -0.58***
	pzabove2, pzabovemean	*SD_BAm2*	0.40**, 0.44**
	zq25, fhd_shan_eve	*SD_BAm2*	0.43**, 0.47***
	fhd_shan_div, cr	*SD_Bam2*	0.43**, -0.48***
Horizontal structure	*pground*	*mean_BAm2*	-0.40*

especially between foliage height evenness and all the inventory metrics, indicate that ALS can moderately capture information about vertical forest arrangement (Hirschmugl et al., 2023; McElhinny et al., 2005), especially mean height and basal area, as captured by ground-based inventory. Strong correlations between ALS and TLS measures of horizontal structure (e.g., between *max_gapArea* and *canopy.openness*) suggest that both methods can capture similar patterns in canopy gaps. ALS can be used in agroforestry systems for quantifying variation in canopy density with greater detail (e.g., sum, min, max, mean, and number of canopy gap area, etc.), compared to TLS or ground-based inventory methods, where assessing canopy openness is more challenging due to the occlusion effect (Mathes et al., 2023; Wang et al., 2019). In general, canopy gaps are essential for the regeneration of tree species (Muscolo et al., 2014; Whitmore, 1989), influencing and shaping forest structure and community dynamics (Chen et al., 2023; Jucker, 2022). Therefore, metrics describing horizontal structure, for instance assessed through ALS, allow for large-scale and long-term monitoring of changes in canopy dynamics (Jucker, 2022), useful in forest management and conservation as indicators of forest functioning (Asner & Mascaro, 2014; Atkins et al., 2018; Ehbrecht et al., 2017) and forests restoration (Jucker, 2022; Li et al., 2023).

The moderate but statistically significant alignment between the ordinations derived from ALS – TLS and ALS – ground-based inventory datasets obtained in the Procrustes analysis indicates that while the three approaches capture related aspects of vegetation structural complexity, there are differences in the information content in each dataset. Relatively high differences among individual points in the concordance correlations expressed by tree islands with high residuals may indicate areas where the structural complexity captured by ALS, TLS, or ground-based inventory diverged significantly. These differences could be attributed to the variability in structural complexity development in the different tree islands, subject to different enrichment treatments (Kikuchi et al., 2023) (e.g., varying plot size and planted tree diversity level). Therefore, the specific characteristics of the vegetation and the performance of the LiDAR technology need to be considered while comparing methodological approaches for characterising vegetation structural complexity.

Overall, the significant correlations found between ALS and TLS vegetation structural metrics, in the univariate and multivariate comparative analysis, suggest that ALS has the potential to characterize vegetation structural patterns 1) for measures of horizontal structure and heterogeneity (e.g., vegetation height and canopy gap dynamics) as captured by TLS and 2) for measures of vertical structure and heterogeneity (e.g., mean vegetation height and diameter) as ground-based inventory. Furthermore, in line with our initial hypothesis, we found that ALS and TLS multivariate datasets were more closely correlated than ALS and the inventory dataset in agroforestry systems, highlighting their ability to detect the variability of vegetation in three-dimensional space from different positions. Unexpectedly, we did not find correlations between the ALS rumple index and the TLS stand structural complexity index or the effective number of layers (calculated following a similar methodology). We conclude that the different methods are compatible only to a certain degree. Correlations among metrics will greatly depend on the technology utilised, the position of the LiDAR sensor (Hilker et al., 2010; LaRue et al., 2020), and their capacity to distinguish between upper and lower canopy structural characteristics (Calders et al., 2020; Hilker et al., 2010). Furthermore, vegetation structural complexity can vary with changes in scale, species composition, stand age, canopy disturbances (Hardiman et al., 2011), and in the case of agroforestry systems, on management intensity (Bisseleua et al. (2008); Kessler et al., 2005). We emphasise the importance of combining different LiDAR technologies in different tree-based systems and using different metrics to better describe vegetation structural complexity.

One limitation in our study was the ground-based inventory, which unlike LiDAR data, excluded oil palm height measurements, although oil palm can be generally higher than most recently planted (Zemp, Ehbrecht, et al., 2019) or naturally established trees. Furthermore, the ground-based inventory did not prioritise measures of horizontal structure (i.e., canopy size and gap characteristics), whereas LiDAR captured these structural features. This information gap constrained the characterization of canopy structure and horizontal complexity and limited the comparison with ALS-derived metrics. The characterization of horizontal structure is particularly important in oil palm agroforestry systems where the canopies have a complex structure influenced by the

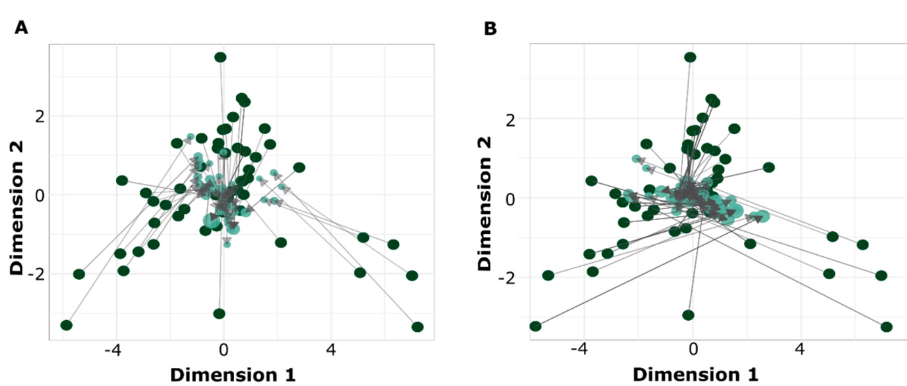

Fig. 4. Comparative alignment of ordinations derived from (A) ALS – TLS and (B) TLS – ground-based inventory. The figure illustrates the spatial correlation and alignment adjustment between dataset pairs through Procrustes analysis. In both panels (A) and (B), dark green points indicate the original position of observation (n = 52), and light green points indicate their position post-alignment. The size of the light green points reflects the magnitude of Procrustes residuals. Grey arrows indicate the adjustments in direction and magnitude required to align each observation with grey opacity indicating the magnitude of the residual. Closer proximity between paired points indicates a higher degree of initial similarity between datasets, requiring minimal adjustment and indicating strong concordance. Conversely, longer adjustment represented by a larger distance between points indicates a lower initial similarity, requiring greater adjustment and suggesting that the compared metrics may represent different aspects of vegetation structure.

different tree species and oil palm mixture, and high densities can lead to occlusion effects from top to bottom and *vice versa*, challenging both airborne and terrestrial scanning techniques. Strategies to generate more integrated descriptions of forest structure as well as to alleviate limitations in data acquisition due to signal occlusion include increasing ALS flyovers (Schneider et al., 2019), integrating multiple-temporal TLS data (Olivier et al., 2017), and combining data from airborne and terrestrial laser scanning (Giannetti et al., 2018). However, applying the mentioned strategies is limited due to practical and logistical constraints (Kushwaha et al., 2023), especially in dense and structurally complex environments. Additionally, expanding the scope of ground-based inventories to include various structural components, such as measures of canopy gaps, will facilitate comparative analysis with LiDAR-derived metrics.

5. Conclusions

The integration of ALS, TLS, and ground-based inventory data can provide a comprehensive understanding of vegetation structural complexity in agroforestry systems, thus enhancing monitoring and management strategies, for example in the context of ecosystem restoration practices. The comparative analysis presented in this study showed the ability of ALS to capture patterns of vegetation structural complexity in oil palm agroforestry systems similar to those captured by TLS and ground-based inventories. Our results revealed that ALS captured stand height and canopy density variations consistent with TLS and can characterize measures of heterogeneity and complexity as measured by ground-based tree inventories. Despite the observed correlations, the different methods provided different characterizations of structural complexity, with discrepancies possibly attributed to the technology used and the characteristics of the studied system. These insights suggest that integrating different methodologies to leverage the strength of each approach can provide a comprehensive understanding of vegetation structure in agroforestry systems. Such an integrated approach holds the potential to improve the knowledge of ecosystem functioning and can contribute to guiding forest management strategies and supporting landscape restoration monitoring efforts in different forest systems and at different scales.

CRediT authorship contribution statement

Vannesa Montoya-Sánchez: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Nicolò Camarretta:** Writing – review & editing, Software, Data curation. **Martin Ehbrecht:** Writing – review & editing, Software, Data curation. **Michael Schlund:** Writing – review & editing. **Gustavo Brant Paterno:** Writing – review & editing, Data curation. **Dominik Seidel:** Writing – review & editing. **Nathaly Guerrero-Ramírez:** Writing – review & editing. **Fabian Brambach:** Writing – review & editing, Data curation. **Dirk Hölscher:** Writing – review & editing. **Holger Kreft:** Writing – review & editing. **Bambang Irawan:** Writing – review & editing. **Leti Sundawati:** Writing – review & editing. **Delphine Clara Zemp:** Writing – review & editing, Supervision, Conceptualization.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.112306.

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