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Canopy gap monitoring in Central African tropical forests using pocket drones: Reliability depends on scale

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Abstract

Canopy gaps play a fundamental role in shaping light regimes, regeneration dynamics, and carbon stocks in tropical forests. Yet, the high cost and logistical constraints of monitoring 3D forest structure at large scales severely limit our understanding of gap structure and dynamics in Central Africa. We evaluated the performance of pocket-drone (~ 250 g, ~ 500 USD and Passive optical RGB sensor) derived digital surface models (RGB-DSM) against airborne LiDAR-derived canopy height models (LiDAR-CHM), used as a reference, over the Lileko site (~240 ha) within the Yangambi forest landscape located in the Democratic Republic of the Congo (DRC). Results revealed a consistent scale-dependent pattern in gap estimation performance relative to airborne LiDAR reference data. Agreement between methods increased with canopy height, yet local-scale spatial correspondence remained limited across all vertical strata, indicating persistent uncertainty in the precise delineation of individual gaps. However, at plot scale, estimates of gap area per 1-ha plot converged between sensor instruments, suggesting that local over- and under-estimations compensate each other when aggregated. This compensatory effect was more pronounced in structurally heterogeneous old-growth mixed forests than in monodominant *Gilbertiodendron dewevrei* forests, highlighting the role of forest structural complexity in shaping cross-sensor agreement. These results confirm that Pocket drones provide a low-cost, spatially consistent proxy for LiDAR-derived canopy structure despite a systematic bias. Although this bias limit fine-scale individual gap delineation, they reliably estimate plot-scale total gap area, supporting applications in gap dynamics, carbon accounting, REDD+, and canopy monitoring in LiDAR-scarce Central African forests.

Keywords. Canopy gap, Disturbances, Remote sensing, photogrammetry, Unmanned Aerial Vehicle, Airborne Laser Scanning, Congo Basin forests

1. Introduction

Canopy gaps arise from natural disturbances such as tree mortality, wind events, and branch falls, but also from anthropogenic pressures including tree felling, plays a fundamental role in the structure and dynamics of tropical forests [1–3]. These localized disturbances regulate light availability, alter microclimatic conditions, and drive regeneration processes that shape species composition and structural heterogeneity [4]. In old-growth forests, the size, frequency, and spatial distribution of canopy openings influence regeneration pathways and contribute to maintaining biodiversity across vertical forest strata [5]. Particularly, in structurally complex tropical forests, many disturbances do not immediately result in large surface openings but instead propagate gradually through multiple canopy layers, generating vertically structured gaps whose ecological significance extends well beyond what surface-based metrics can capture [6]. Understanding both the spatial and vertical distribution of canopy gaps is therefore critical for assessing forest resilience, disturbance regimes, and long-term ecosystem dynamics. These considerations are particularly acute in the dense tropical forests of Central Africa, where gap dynamics drives the regeneration of commercially and ecologically significant species yet remain poorly characterized at landscape scale, with direct consequences for biodiversity conservation, silvicultural management, and carbon accounting [7,8].

Traditionally, canopy gaps have been investigated through field-based approaches, including ground surveys and long-term monitoring plots. While these methods provide detailed ecological insights, they are inherently labor-intensive and spatially limited, particularly in dense and structurally complex tropical forests [9]. For example, on the 50-ha Barro Colorado Island (BCI) plot in Panama, canopy height measurements have been collected annually since 1983 on a 5 × 5 m grid, representing approximately 20,000 field measurements each year [10]. Implementing such a monitoring program in the Congo Basin, where access to forests is often hampered by dense vegetation, limited transportation infrastructure, and the remoteness of sites [11] requires considerable time and financial investments, involving repeated surveys conducted by large teams of trained personnel over multiple decades. These operational constraints considerably limit the spatial extent and temporal repetition of field-based approaches for monitoring tropical forest dynamics and canopy structural changes over large areas [12].

Remote sensing technologies have substantially expanded the capacity to characterize forest structure and detect canopy disturbances across larger spatial extents [13]. Among these, airborne LiDAR has become the benchmark for three-dimensional forest structure characterization, enabling accurate measurements of canopy height, vertical vegetation profiles, and canopy openings at fine spatial resolution [14,15]. However, despite its high accuracy, LiDAR acquisition remains financially costly and logistically demanding, limiting its operational deployment across many tropical regions where technical and economic resources remain constrained. This limitation is particularly acute in Central Africa, where airborne LiDAR coverage across the Congo Basin remains extremely sparse (CANOBS Network, <https://canoobs.net/network>, accessed 22 March 2026), with most acquisitions restricted to a limited number of experimental or research sites [16]. Therefore, the development of consistent regional three-dimensional structural baselines for Congo Basin forests remains severely constrained [17].

Pocket drone, an unmanned aerial vehicle (UAV) weighing less than 250 g equipped with RGB cameras (passive sensors) offer a cost-effective alternative, with demonstrated potential to estimate key forest structural attributes at high spatial resolution [17,18]. However, the detection of canopy gaps from UAV RGB imagery is highly sensitive to methodological choices, canopy structural complexity, shadow effects, and terrain variability [19]. Existing approaches increasingly rely on spectral contrasts and deep learning techniques, notably convolutional neural networks, to identify canopy openings [19,20]. Although these methods can achieve high detection performance under controlled conditions, they require extensive annotated training datasets, careful model calibration, and computationally intensive workflows that substantially limit their transferability and operational applicability in data-scarce tropical environments [21]. Furthermore, they remain sensitive to variations in illumination conditions and canopy reflectance; if not adequately corrected, these factors can introduce substantial uncertainty in gap delineation, particularly under the dense and structurally heterogeneous canopies characteristic of Central African old-growth forests [20,22].

In contrast, elevation-based approaches building on Digital Surface Models (DSM) derived from UAV photogrammetry provide a more direct and physically meaningful representation of forest structure [23,24]. By analyzing the three-dimensional geometry of the reconstructed canopy surface rather than its spectral properties, these approaches offer greater transparency, reduce computational requirements, and improved transferability across forest types and geographic contexts [25]. These advantages are particularly relevant in tropical environments where annotated datasets and high-performance computing infrastructure are scarce [25]. Importantly, single-date structural metrics derived from elevation-based models avoid the uncertainties associated with multi-temporal approaches that detect gaps by analyzing surface changes between acquisition dates [24]. While multi-temporal methods are effective for capturing disturbance events and monitoring gap dynamics over time, they require repeated acquisitions and precise co-registration of datasets acquired under varying canopy and atmospheric conditions, increasing both operational complexity and uncertainty [22]. Single-date elevation-based approaches are therefore particularly well-suited to tropical forest contexts, where repeated UAV acquisitions may be constrained by logistical and climatic conditions [22].

Several studies have begun evaluating the reliability of UAV-derived products against LiDAR references for canopy structure characterization. In dense tropical forests of the Congo Basin, Zhang et al. [18] demonstrated that low-cost UAV photogrammetric point clouds, combined with machine learning, can produce canopy height models broadly comparable to LiDAR-derived CHMs at the Yangambi forest landscape, though with site-specific limitations linked to sub-canopy occlusion and georeferencing accuracy [18]. For canopy gap detection specifically, Chen et al. [19] showed that UAV RGB imagery can reliably identify gaps in species-rich subtropical forests. But persistent limitations in structurally complex canopies are highlighted due to shadow effects and high spectral variability [19]. Comparisons between UAV-derived digital surface models and LiDAR canopy height models for gap characterization have further shown that photogrammetric approaches systematically underperform LiDAR, particularly for small gaps and in structurally complex strata while achieving broadly comparable gap fraction estimates at the plot scale under certain structural conditions [20,21,26]. Critically, Franz et al. [21] demonstrated that this performance gap can be

partially bridged through a cross-technological approach fusing LiDAR-derived reference data with photogrammetric products within a deep learning framework [21]. Overall, however, these studies have focused primarily on the horizontal representation of canopy gaps from a surface-based perspective, quantifying gaps using two-dimensional metrics such as area, density, or spatial distribution at the canopy, without explicitly evaluating the extent to which low-cost optical photogrammetry can capture the vertical organization of canopy gaps.

Canopy gap dynamics are fundamentally driven by vertical structural processes, including height growth within gaps and lateral crown closing gaps across canopy layers, which cannot be captured by surface metrics alone [6,15]. This limitation is particularly critical in dense tropical forests, where disturbances frequently propagate through multiple forest layers without immediately forming large surface gaps, and where the vertical organization of gaps encodes ecologically distinct regeneration environments at each stratum [6]. This vertical dimension has recently been highlighted in the Congo Basin using airborne LiDAR, where Nguba et al. [27] showed that plot scale canopy gap area distributions vary systematically along the vertical canopy profile and differ markedly between compositionally contrasting old-growth forest types in the Yangambi forest landscape. These findings emphasize that canopy gap characterization should extend beyond the canopy surface to encompass its full vertical organization. Consequently, whether low-cost RGB photogrammetry can recover this plot scale canopy gap area distributions at different canopy height strata, however, remains largely unknown, particularly for pocket drones operating in the structurally complex old-growth forests of Central Africa.

Although LiDAR has substantially advanced the understanding of canopy gap dynamics, most validation studies have focused on individual gap detection rather than plot-scale gap metrics [19,20]. Because individual gap comparisons inherently combine commission and omission errors, whereas plot-scale gap area integrates these local errors, statistical equivalence may emerge through error compensation even when individual gap correspondence is imperfect [28,29]. Similar scale-dependent error attenuation has long been recognized in tropical forest biomass estimation [30–32]. Assessing plot-scale gap areas across canopy height strata therefore represents a distinct and operationally relevant validation target for forest monitoring, carbon assessment, and REDD+ applications.

Here, we propose a methodological framework to derive vertical canopy gap profiles from high-resolution photogrammetric models (12.3 cm spatial resolution) generated using a Pocket drone. Rather than focusing solely on canopy openings visible at the forest surface, our approach examines the distribution of canopy gaps across discrete canopy height strata, enabling characterization of how disturbances are vertically structured within forest stands. By leveraging the very high spatial resolution of UAV photogrammetry and avoiding spectral classification or multi-temporal acquisition requirements, this framework provides an accessible and cost-effective alternative for analyzing forest structural heterogeneity in physically and logistically constrained tropical environments.

To evaluate its robustness, we compare UAV-derived gap metrics with those obtained from simultaneous airborne LiDAR acquisition, applying both methods to two contrasting old-growth forest types in Central Africa: monodominant forests dominated by *Gilbertiodendron dewevrei*

(*G.dewevrei*) and structurally diverse mixed-species forests, which exhibit marked differences in functional structure, canopy architecture, disturbance regimes, and regeneration dynamics [27,33–35]. These forest types represent an ecological gradient from structural homogeneity to complexity that allows direct testing of how canopy architecture mediates the reliability of UAV-based gap detection. Specifically, we test two hypothesis addressing performance at progressively broader spatial scales: (H1) RGB pocket drone-derived DSM gap detection produces no significant difference and statistically equivalent plot-scale total gap area estimates relative to LiDAR CHM across canopy height strata, despite systematic divergence in individual gap spatial co-localization and geometry; (H2) The reliability of UAV RGB photogrammetric canopy gap detection increases with canopy height stratum, with stronger regression performance closer to the canopy. This compensation is more robust in structurally heterogeneous mixed old-growth forest than in structurally homogeneous monodominant forest.

2. Materials and Methods

2.1. Study area

The methodological framework was developed in ~240 ha of forest at the Lileko site (24.349°E; 1.088°N); located about 47 km north of the town of Yangambi, within the Yangambi Biosphere Reserve (YBR) landscape (Fig. 1), which is part of the UNESCO Man and the Biosphere (MAB) Program. The YBR is located approximately 100 km west of Kisangani; in the Tshopo Province of the Democratic Republic of the Congo (DRC) (Fig.1). The region is characterized by a humid tropical climate, with a mean annual precipitation of about 1,800 mm and an average annual temperature of 25.1 °C [36,37].

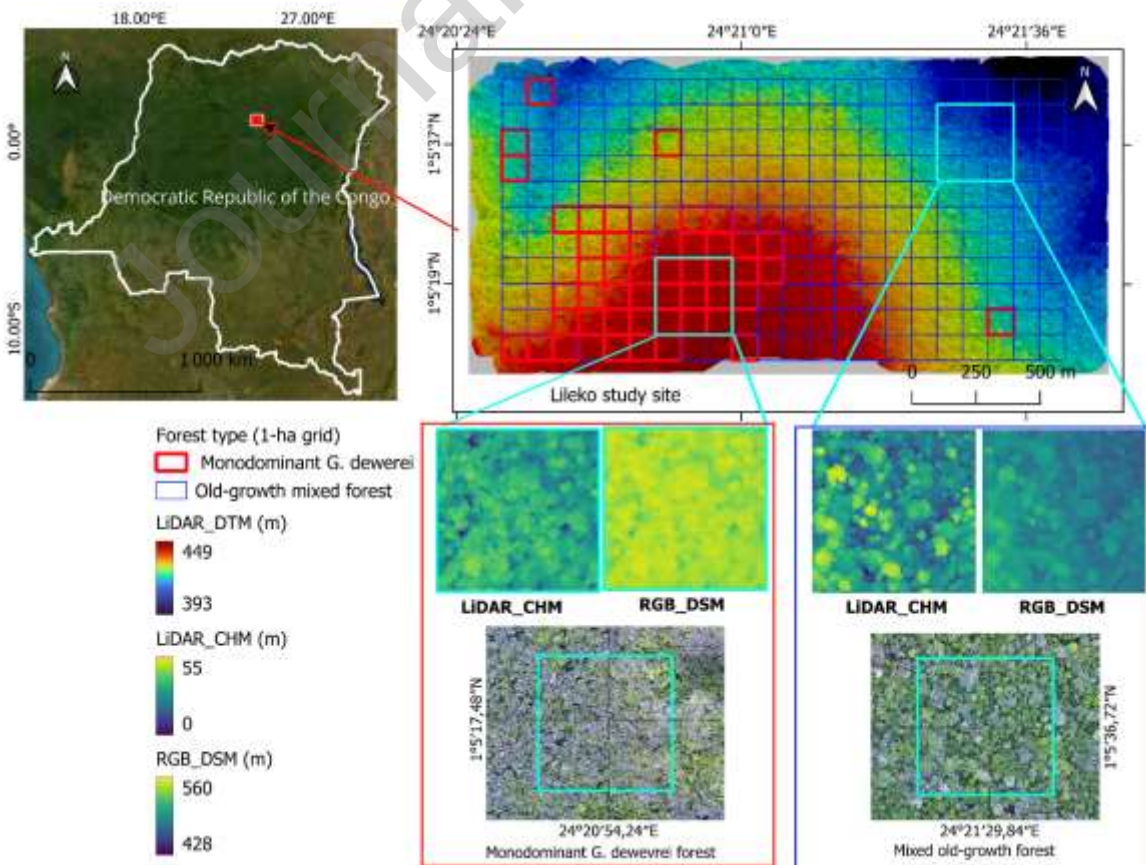


Figure 1. Location of the ~240-ha study site of Lileko within the Yangambi forest landscape. The insets (green rectangles) show the locations of the two forest type areas: monodominant *G. dewevrei* (left panels, 1-ha red grid cells) and mixed old-growth forest (right panels, 1-ha blue grid cells); as well as the corresponding elevation data sources (LiDAR-derived DTM and CHM; RGB-derived DSM) and distinct RGB-derived orthomosaic pattern.

The forest landscape of Yangambi is dominated by two major types of old-growth forests. The first consists of mixed-species moist semi-deciduous forests, characterized by high floristic diversity and variability, although *Scorodophloeus zenkeri* Harms is widely distributed and often locally dominant. The second corresponds to evergreen monodominant forests, primarily dominated by *Gilbertiodendron dewevrei* (De Wild.) J. Léonard [38]. These contrasting forest types exhibit marked differences in functional community and canopy structure [33,39] making them particularly suitable for evaluating the performance of canopy gap detection methods across varying structural conditions.

2.2. Methodological workflow for evaluating canopy gap area and comparing Pocket drone and LiDAR models

Figure 2 presents the integrated methodological framework used to evaluate the performance of canopy gaps derived from pocket drone-based RGB digital surface models (DSMs) against those derived from airborne LiDAR canopy height models (CHMs), serving as the reference.

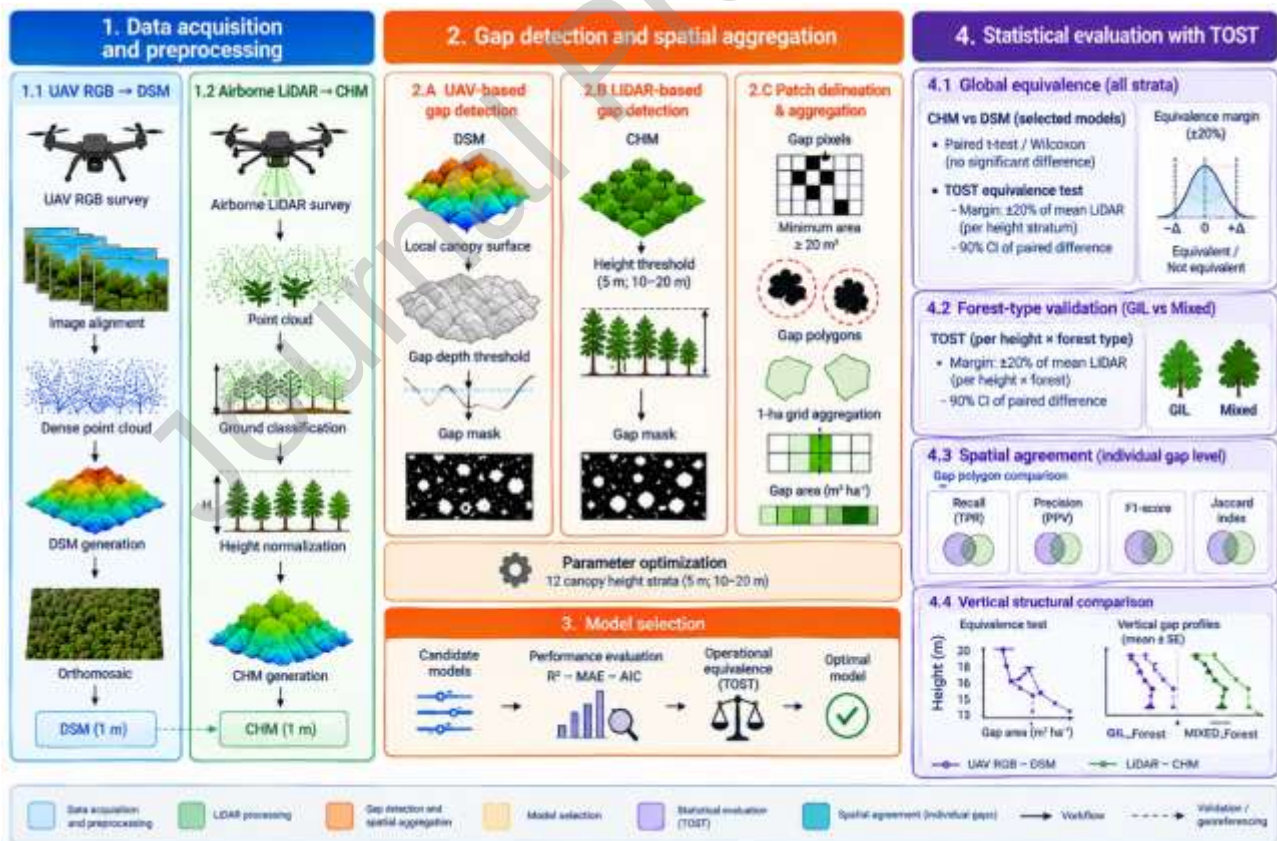


Figure 2. Methodological workflow for evaluating canopy gap area and comparing Pocket drone and LiDAR. (1) Data acquisition and processing: (1.1) UAV RGB imagery acquired with a consumer-grade drone and processed through structure-from-motion photogrammetry to generate a Digital Surface Model (DSM) at 1 m resolution, georeferenced using ground control points derived from LiDAR; (1.2) airborne LiDAR point cloud processed through ground classification, height normalization, and pit-free algorithm to

generate a Canopy Height Model (CHM) at 1 m resolution. (2) Gap detection and spatial aggregation: (2.A) UAV-based gap detection using a local depth approach, different window sizes and aggregation statistics; (2.B) LiDAR-based gap detection using 12 canopy height thresholds (at 5 m and each meter from 10 to 20 m); (2.C) gap delineation, minimum area filtering ($\geq 20 \text{ m}^2$), and aggregation to 233 one-hectare grid cells with border effect correction. (3) Model selection across 2,436 parameter combinations based on R^2 , MAE, AIC, and operational equivalence. (4) Model evaluation: (4.1) Global equivalence based on Two One-Sided Tests (TOST) procedure; (4.2) Forest type validation per height and forest type; (4.3) spatial agreement at the individual gap polygon level (Recall, Precision, F1-score, Jaccard index); (4.4) statistically difference and equivalence vertical structural comparison across different canopy height strata within monodominant *G. dewevrei* and old-growth mixed forests.

2.2.1. Digital Aerial Photographs acquisition and DSM generation processing

Digital Aerial Photographs (DAPs) were acquired between 9 and 16 October 2023 using a DJI Mini 2 RGB UAV as Pocket drone, covering a total of 240 hectares of undisturbed old-growth forest across the study area (Fig.1). Six flight missions were planned and executed using the DJI Fly and DroneLink mobile and web applications. Each individual flight covered approximately 40 ha and was launched from large canopy gaps to ensure optimal GPS signal reception and unobstructed take-off visibility. Flights were conducted at an altitude of approximately 210 m above ground level, with forward and side image overlaps of 75% and 80%, respectively, and a constant flight direction of 90° (eastward) at a cruise speed of 32 km h^{-1} .

Photogrammetric processing was performed in Agisoft Metashape Professional following a standard structure-from-motion (SfM) workflow comprising photo alignment, dense point cloud (DPC) generation, surface model construction, and orthomosaic generation.

A total of 818 RGB images were acquired, for which 800 were successfully aligned. Photo alignment was performed at high quality with no key point limit. Dense point cloud generation used high-quality parameters with aggressive depth filtering to balance reconstruction completeness and artefact suppression. The surface model was generated at a native spatial resolution of 12.3 cm in the UTM Zone 35N projection (WGS84 horizontal datum) and exported in GeoTIFF format at 1 m spatial resolution.

2.2.2. LiDAR data acquisition and CHM generation

We acquired LiDAR data over the Lileko during the same time with UAV RGB data using a DJI Matrice 300 RTK UAV equipped with a Zenmuse L1 sensor. The flights used a terrain-follow mode with a lateral overlap exceeding 50% and triple-echo recording, resulting in an average point density of approximately 500 pts/m^2 . Raw point clouds were extracted via DJI Terra using GNSS data from a DJI D-RTK2 mobile station. The base station position was corrected using the Precise Point Positioning (PPP) method to ensure a positioning error below 1 cm horizontally and 10 cm vertically. This step was essential to guarantee spatial consistency between the different flights performed over the study area. Raw point clouds from both sites followed a common processing workflow implemented in the R environment using the lidR package [40]. Ground points were classified using the Cloth Simulation Filter algorithm (resolution 1 m, rigidity 2, threshold 1.2 m) with slope smoothing enabled. Following classification, point heights were normalized utilizing a Triangulated Irregular Network (TIN) interpolation of ground points, with nearest-neighbor inverse distance weighting applied for edge extrapolation. Finally, a Canopy Height Model (CHM) was generated at a 1-m resolution using the pit-free algorithm to eliminate data pits while preserving natural canopy gaps.

This method employed triangulation across a series of height thresholds (0 to 60 m) to ensure a robust representation of the upper canopy surface.

2.2.3. Co-registration of the RGB-derived DSM with the LiDAR reference

To ensure spatial consistency between the RGB-derived Digital Surface Model (RGB-DSM) and the LiDAR-derived Canopy Height Model (CHM), the RGB-DSM was geometrically co-registered to the LiDAR-CHM reference using ground control points (GCPs) derived from corresponding canopy features. Georeferencing was performed in QGIS 3.40.7 on the rasterized DSM at 1 m spatial resolution using a first-order polynomial (affine) transformation with nearest-neighbor resampling in the local WGS 1984 UTM Zone 35N coordinate reference system.

Six GCPs ($n = 6$) were established by visually identifying the crown apices of morphologically distinctive, spatially isolated emergent trees that could be unambiguously recognized in both the RGB-DSM and the LiDAR-CHM. These emergent crown apices were selected because they represent stable, structurally prominent and geometrically well-defined canopy features, thereby minimizing ambiguity during manual co-localization. The GCPs were distributed across the entire ~240 ha study area to reduce interpolation error during the affine transformation. Their reference coordinates were extracted directly from the LiDAR-CHM, whose geometric accuracy was established during acquisition through Precise Point Positioning (PPP) correction of the DJI D-RTK2 mobile base station, providing sub-centimeter horizontal accuracy (<1 cm) and vertical accuracy better than 10 cm. The affine transformation resulted in a mean residual error of 3.57 m and an overall RMSE of 3.74 m (Supplementary Table S1).

The LiDAR-derived coordinates were used exclusively for geometric alignment and were not used to calibrate or modify the RGB-derived canopy height values, gap detection parameters, or subsequent gap estimates. This co-registration step was intended to minimize residual positional offsets between the two sensing modalities so that subsequent comparisons reflected differences in canopy representation rather than avoidable geometric misalignment.

Because the RGB-derived DSM and the LiDAR-derived CHM represent canopy structure differently and crown apexes are not perfectly homologous between the two sensing modalities, an independent object-based validation was conducted to assess the effective spatial consistency of the co-registration beyond the six GCPs. Twenty pairs of corresponding emergent tree crowns were manually delineated from both datasets and used as external validation objects distributed throughout the study area (Supplementary Fig.S1). For each crown pair, spatial agreement was quantified using the Intersection over Union (IoU) and Dice similarity coefficient, whereas positional agreement was assessed from the centroid displacement (ΔX , ΔY), Euclidean centroid distance and Hausdorff distance between crown boundaries.

The mean IoU was 0.758 (SD = 0.088), the mean Dice similarity coefficient was 0.860 (SD = 0.060), the mean centroid displacement was 1.50 m (RMSE_{XY} = 1.73 m; 95th percentile = 2.64 m), with mean offsets of 0.109 m in the east–west direction (ΔX) and –1.04 m in the north–south direction (ΔY). The co-registration was therefore considered sufficient for the subsequent comparative analyses, while

the potential influence of residual positional uncertainty on individual gap-level spatial agreement was explicitly considered during validation.

2.2.4. Gap detection, patch delineation and spatial aggregation

Canopy gaps were detected from UAV-derived digital elevation models using a multi-scale and multi-threshold approach (Fig. 2) inspired by [23]. Canopy gap candidates were detected from the UAV RGB-derived DSM using a single-date, elevation-based approach that identifies local surface depressions relative to the surrounding canopy height, without requiring spectral classification or multi-temporal data.

Canopy gaps were computed from UAV-derived DSM and from airborne-LiDAR CHM respectively following formula detailed below:

Formula 1. (UAV RGB DSM local depth):

$$Gap_{px} = H_{max(local),W_i} - H_{px_i}$$

Formula 2. (RGB-DSM-derived gaps):

$$DSM_Gap \text{ pixel} = \mathbb{1}[Gap_{px} < th] = \begin{cases} 1 & \text{if } Gap_{px} < th \text{ (closed canopy / vegetation)} \\ 0 & \text{if } Gap_{px} \geq th \text{ (gap detected)} \end{cases}$$

Formula 3. (LiDAR-CHM derived gaps):

$$CHM_Gap \text{ pixel} = \mathbb{1}[H_{px_i} < th] = \begin{cases} 1 & \text{if } H_{px_i} > th \text{ (closed canopy / vegetation)} \\ 0 & \text{if } H_{px_i} < th \text{ (gap detected)} \end{cases}$$

Where, Gap_{px} : the local depth at the DSM focal pixel (m) or the central pixel of a moving neighborhood window, defined as the difference between the generalized canopy surface and the elevation of the focal pixel H_{px_i} . $H_{max(local),W_i}$: generalized canopy surface (m), computed by applying one of three spatial aggregation functions (mean, median, or max) within a moving window i of size $w \times w$ pixels over the DSM, then resampled to the original 1 m resolution by bilinear interpolation. w : moving window size (pixels); controls the spatial scale of the generalized canopy surface estimation. Larger windows smooth over fine-scale surface variation and capture broader canopy structures, while smaller windows are more sensitive to local topographic detail. Seven window sizes were tested: $w \in \{15,18,21,24,27,30,33\}$ pixels. H_{px_i} : elevation of the focal pixel i in the original DSM (m). th : depth threshold (m) in formula 1 refers to the vertical distance from the top of the forest canopy toward the forest floor and canopy height threshold (m) in formula 3 refers to the vertical distance from the floor to top of the forest canopy toward the forest; minimum local depth or eight required for a pixel to be classified as a gap. In formula 1 for Gap_{px} from mean and median aggregation functions, 9 threshold levels were tested at 1 m intervals over the range $th \in [3,11]$ m. For the max aggregation function, 11 threshold levels were tested at 1 m intervals over the range $th \in [8,18]$ m, reflecting the greater dynamic range of local maxima relative to central tendency metrics. In formula 2 for LiDAR-CHM derived gaps, 12 threshold levels were tested, at 5 m and each 1m from 10 to 20 m. $\mathbb{1}[\cdot]$: indicator function, pixels satisfying $Gap_{px} < th$ were assigned a value of 1 (closed canopy or vegetation); pixels satisfying $Gap_{px} > th$ were assigned a value of 0 (gap detected) for UAV-RGB-DSM and pixels satisfying $H_{px_i} > th$ were assigned a value of 1 (closed

canopy or vegetation); pixels satisfying $H_{pxi} < th$ were assigned a value of 0 (gap detected) for LiDAR-CHM.

Both RGB-DSM and LiDAR-CHM derived contiguous gap pixels were aggregated into distinct patches using 8-neighbor connectivity (connected components labeling). Finally, the area-based filter was applied to retain only gap patches within the specific size range, excluding isolated artifacts. We applied a minimum gap area of 20 m² across all thresholds combinations because canopy gaps typically result from disturbances such as branch breakage or treefall [41]. This value is assumed to represent the minimal crown area of a canopy tree with a DBH of at least 10 cm [42] as the standard minimum threshold used in floristic inventories of tropical forests [43].

For each threshold combination, the segmented raster outputs were vectorized into gap polygons. These polygons were then intersected with a grid of 233 1-ha plots (100 m × 100 m), each associated with forest type attributes. According to the classification established for the same study area (Besisa et al., 2026, in review), 187 grid cells correspond to mixed-species forest and 46 to monodominant *G. dewevrei* forest (GIL). To ensure consistency with dense forest conditions, grid cells not fully covered by LiDAR data, as well as those exhibiting a gap fraction greater than 50%, were excluded from the analysis. For the remaining grid cells, gap area was computed on a per-hectare basis, allowing direct and standardized comparison between UAV- and LiDAR-derived estimates.

2.2.4. Model selection framework

The full parameter grid-search generated 2,436 unique LiDAR-CHM~RGB-DSM model pair combinations, computed as the product of the number of window sizes (7), local statistics (3), DSM depth threshold values (9;9;11 levels respectively for mean, median and maximum statistic), and LiDAR CHM height thresholds (12) [$2,436 = (7 \times 9 \times 12) + (7 \times 9 \times 12) + (7 \times 11 \times 12)$] (Fig. 2). For each combination, the correspondence between RGB-DSM and LiDAR-CHM derived gap area per hectare across the 233 grid cells was evaluated using three complementary regression metrics. (1) R^2 (coefficient of determination): measuring the proportion of variance in LiDAR gap area explained by the RGB-DSM predictor; (2) MAE (mean absolute error): quantifying the average absolute difference between RGB-DSM and LiDAR-CHM gap area estimates in m² ha⁻¹; and (3) AIC (Akaike Information Criterion): penalizing model complexity to identify parsimonious predictor configurations.

The optimal model pair for each of 12 LiDAR CHM height stratum was selected as the RGB-DSM parameter combination $R^2 \geq 0.3$ and the lowest MAE as the primary criterion, and the lowest AIC as the secondary criterion, subject to two additional conditions that mean total gap area per hectare was not significantly different (paired t-student/Wilcoxon test, p-value > 0.05) and statistically equivalent (TOST test, 90% confidence intervals; p-value < 0.05, margin range from 10 to 25% of the mean gap area derived from the LiDAR CHM) between RGB-DSM and LiDAR-CHM estimates. This dual criterion optimizing regression fit while requiring plot-scale area equivalence, ensured that the selected models accurately reproduced both the strength and consistency of the relationship between RGB-DSM and LiDAR-CHM derived gap estimates and the absolute magnitude of gap area across the study area.

2.2.5. Model evaluation

2.2.5.1. Regression performance across canopy height strata

Scatter plots of LiDAR-CHM gap area versus RGB-DSM gap area per 1-ha grid cell were produced for each of 12 LiDAR-CHM height strata at 5m and each meter from 10 to 20 m to visually assess the nature and extent of the LiDAR-CHM ~ RGB-DSM relationship, including the slope of the regression line relative to the 1:1 identity line and the presence of systematic bias at high gap area values.

2.2.5.2. Individual gap spatial overlap metrics

To evaluate the spatial co-localization of individually detected gaps between RGB-DSM and LiDAR-DSM methods, four best validated binary classification overlap metrics were computed for a subset of representative strata, treating LiDAR gap polygons as the reference. Metrics were computed at the gap's polygon pixel level. The Jaccard index was considered the primary spatial overlap metric, as it penalizes both commission and omission errors simultaneously without the asymmetric weighting inherent in F1-score.

Table 1. Individual gap spatial overlap metrics (TP = true positives (gap pixels detected by both methods), FP = false positives (UAV gaps not confirmed by LiDAR), and FN = false negatives (LiDAR-CHM gaps missed by RGB-DSM)).

Metric	Formula	Interpretation
Recall	$TP / (TP + FN)$	Proportion of LiDAR gaps also detected by UAV
Precision	$TP / (TP + FP)$	Proportion of UAV detections corresponding to real LiDAR gaps
F1-score	$2 \times (Precision \times Recall) / (Precision + Recall)$	Harmonic mean of precision and recall
Jaccard index	$TP / (TP + FP + FN)$	Intersection over union; strictest spatial overlap measure

2.2.5.3. Plot-scale equivalence testing and vertical gap profiles

For each optimal model pair identified through the grid search, mean total gap area per plot (m^2 per 100×100 m grid cell) was calculated across the same 233 plots (Fig. 1) and compared between RGB-DSM and LiDAR-CHM estimates. Both model selection and subsequent equivalence assessment were therefore conducted on the same plots as part of a comparative evaluation, with the grid search identifying the DSM configuration that best approximated the LiDAR-derived gap-area reference rather than fitting a predictive model with estimated parameters. No significant difference was assessed using a paired Wilcoxon signed-rank test or a paired t-test, selected on the basis of the Shapiro-Wilk normality test applied to the distribution of plot-level differences (RGB-DSM), with a minimum sample size threshold of $n \geq 20$ observations required for the normality test to have adequate statistical power. The result of $p\text{-value} > 0.05$ was interpreted as evidence of no significant difference between instruments at the plot scale.

To further assess the operational equivalence hypothesis, the models with no-significant difference were subjected to an additional equivalence analysis using the Two One-Sided Tests (TOST) procedure [44]. At each canopy height, equivalence was assessed using a predefined margin range from 10 to 25% of the mean gap area derived from the LiDAR CHM, together with a 90% confidence interval for the paired difference between LiDAR- and RGB DSM-derived estimates. The result of TOST test derived $p\text{-value} < 0.05$ was interpreted as evidence of plot scale gap area equivalence

between instruments. The height-dependent results of the equivalence analysis were used to identify the operational bounds of RGB pocket drone-based gap monitoring.

Vertical canopy gap profiles were reconstructed by plotting mean total gap area per plot ($\text{m}^2 \text{ha}^{-1}$) as a function of canopy height stratum (m) on the y-axis, separately for UAV DSM and LiDAR CHM estimates and for each forest type. This representation directly mirrors the vertical organization of forest structure, enabling visual comparison of how gap areas are distributed across sub-canopy, intermediate, and upper canopy strata. Mean $\pm$ SE profiles were computed across all grid cells within each forest type and stratum combination to quantify uncertainty in the vertical gap area estimates. Results were visualized as paired vertical profiles with results of statistical difference tests (significance level) annotated at each stratum and display the equivalence intervals by forest type alongside the 90% confidence intervals of the RGB-DSM estimates, allowing direct visual assessment of the equivalence criterion and the operational limits of the approach for each stratum and forest type combination.

Each of 233 1-ha (100×100 m) grid cell was manually assigned to a forest type through visual interpretation of high-resolution RGB imagery acquired simultaneously with the airborne LiDAR data (Fig.1). The interpretation was supported by field knowledge gained during the UAV survey campaign and by forest inventory plots used as ground reference. A grid cell was classified as monodominant *G. dewevrei* (GIL) forest when the characteristic dark-green, closed canopy of *G. dewevrei*, with relatively few distinguishable individual crowns (Fig. 1), occupied more than 50% of the cell area. Cells in which mixed-species canopy patterns predominated over more than 50% of the visible surface were classified as mixed forest (Fig. 1). Cells lacking a clear dominance of either forest type, including those dominated by palm stands or affected by edge effects or incomplete data, were excluded from the analysis. In total, 242 grid cells were photo-interpreted, of which 187 were classified as MIXED forest, 46 as GIL forest, and 9 were excluded.

3. Results

3.1. Performance of UAV RGB DSM-derived gap area relative to LiDAR CHM across height strata

The grid-search evaluation of 2,436 parameter combinations identified a subset of sixteen optimal UAV–LiDAR model pairs, each corresponding to a specific canopy height stratum (Appendix A Table A1). These best-performing combinations reflect a consistent selection of intermediate window sizes (typically 15–24 m), combined with either mean or maximum based local statistics and stratum-specific depth thresholds. The poor performance was observed at low canopy height strata (Appendix A Table A1; canopy strata ≤ 12 m).

For lower canopy strata (< 16 m) of the best-performing combinations, the optimal models predominantly relied on mean-based aggregation (Appendix A Table A1). In contrast, for higher strata (≥ 16 m), maximum-based statistics metrics systematically outperformed mean metrics, capturing sharper vertical discontinuities associated with larger and more structurally distinct canopy gaps.

Across all canopy strata, a consistent structural pattern emerged in the relationship between RGB-DSM and LiDAR-CHM derived gap areas. At low gap values ($<200\text{--}300\text{ m}^2\text{ ha}^{-1}$), both approaches showed reasonable agreement, with observations clustering near the 1:1 line. However, as gap area increased, the RGB-DSM estimates systematically underestimated LiDAR-CHM derived gap area values, producing a fan-shaped dispersion that widened with increasing gap size (Fig.3).

A clear vertical gradient in model performance was observed. In lower strata (5–12 m), RGB-DSM-based estimates showed weak relationships with LiDAR-CHM ($R^2 \approx 0.30$) and significant deviations from statistical difference (Paired T-student/Wilcoxon test; $p\text{-value} < 0.05$) and equivalence (TOST test, $p\text{-value} > 0.05$) (Appendix A Table A1), indicating a structural decoupling between the two datasets. In intermediate strata (13–15 m), model performance improved progressively (R^2 up to ~ 0.40), and no significant difference (Paired T-student/Wilcoxon test; $p\text{-value} > 0.05$) and equivalence (TOST test, $p\text{-value} < 0.05$) was first achieved, marking a transition zone where RGB-DSM derived gap estimates begin to capture meaningful canopy structure (Fig.3).

A key inflection point occurred at 16 m, where the shift from mean- to max-based aggregation resulted in the strongest agreement observed ($R^2 \approx 0.50$). In upper strata (17–20 m), this pattern persisted, with relatively high R^2 values (up to 0.52) and consistent statistical equivalence, despite increasing MAE (up to $\sim 400\text{ m}^2\text{ ha}^{-1}$).

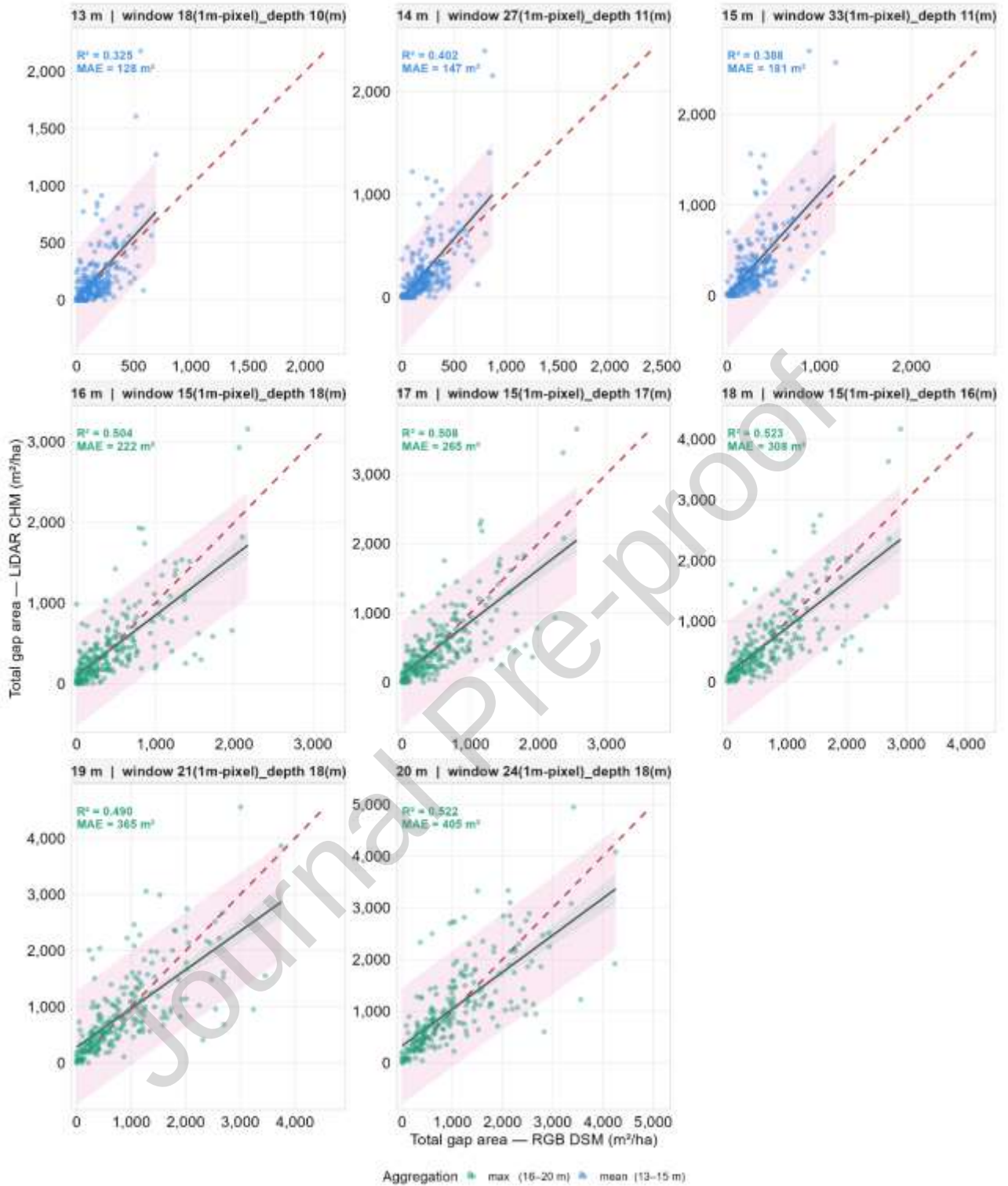


Figure 3. Plot-scale regression of total canopy gap area estimated by LiDAR-CHM against pocket drone RGB DSM for the eight statistically equivalent predictor pairs validated through the grid-search (2,436 pairs combinations tested across 233 1-ha grid cells). Each panel corresponds to one validated canopy height stratum (13–20 m) with its optimal RGB-DSM predictor (window size and depth threshold). Blue points = mean aggregation strata (13–15 m); green points = max aggregation strata (16–20 m). Solid black line = $\ln(\text{CHM} \sim \text{DSM})$ regression; dashed red line = 1:1 identity line; grey shading = 95% confidence interval of the regression; pink shading = 95% prediction interval. R^2 and MAE reported per stratum. MAE = mean $(|\text{CHM} - \text{DSM}|)$, computed as the raw instrument-to-instrument discrepancy without model calibration.

3.2. Individual gap detection: spatial co-localization and overlap between RGB DSM and LiDAR CHM

At the individual gap level, spatial co-localization between RGB-derived DSM and LiDAR CHM remained limited across all canopy strata, with a clear dominance of omission and commission errors (Fig. 4, Appendix A Table A2). LiDAR-only detections (false negatives) and RGB-only detections (false positives) consistently represent substantial portions of the gap population, while true overlaps remain comparatively lower (Fig. 4). Across strata, overlapping gaps tend to exhibit intermediate sizes, whereas LiDAR-only gaps include the largest openings and RGB-only gaps are predominantly small. The aggregated gap area analysis further highlights this imbalance (Fig. 5). While total gap area increases with canopy height, a large proportion of this area is partitioned between LiDAR-only (omission) and RGB-only (commission) components, with overlap accounting for a moderate but consistent share. Notably, omission errors dominate in upper strata, whereas commission errors contribute substantially across all strata due to the proliferation of small false detections (Fig. 4).

The spatial patterns illustrated in Figure 4 further emphasize the contrast between forest types and canopy strata. In monodominant *G. dewevrei* forests (Fig.4, left panels), gap occurrences are sparse and highly fragmented, with limited spatial overlap between UAV and LiDAR detections across all strata. Most detections are isolated pixels or small patches, and the proportion of overlapping gaps remains low even at higher canopy levels. In contrast, mixed forests (Fig.4, right panels) exhibit a much higher density and spatial continuity of canopy gaps, particularly in intermediate and upper strata (16 m & 20 m). In these conditions, the degree of spatial overlap between UAV and LiDAR detections increases visibly, with larger contiguous patches partially shared between both datasets. However, even in these more dynamic systems, discrepancies remain evident: LiDAR-only gaps tend to correspond to larger, well-defined openings, while RGB-only detections are more fragmented and dispersed, highlighting persistent commission and omission errors. The progressive increase in F1-score (0.42 to 0.58) and Jaccard index (0.21 to 0.40) with canopy height confirms that spatial agreement improves in upper canopy layers (Appendix A Table A2), where photogrammetric reconstruction more reliably captures canopy structure.

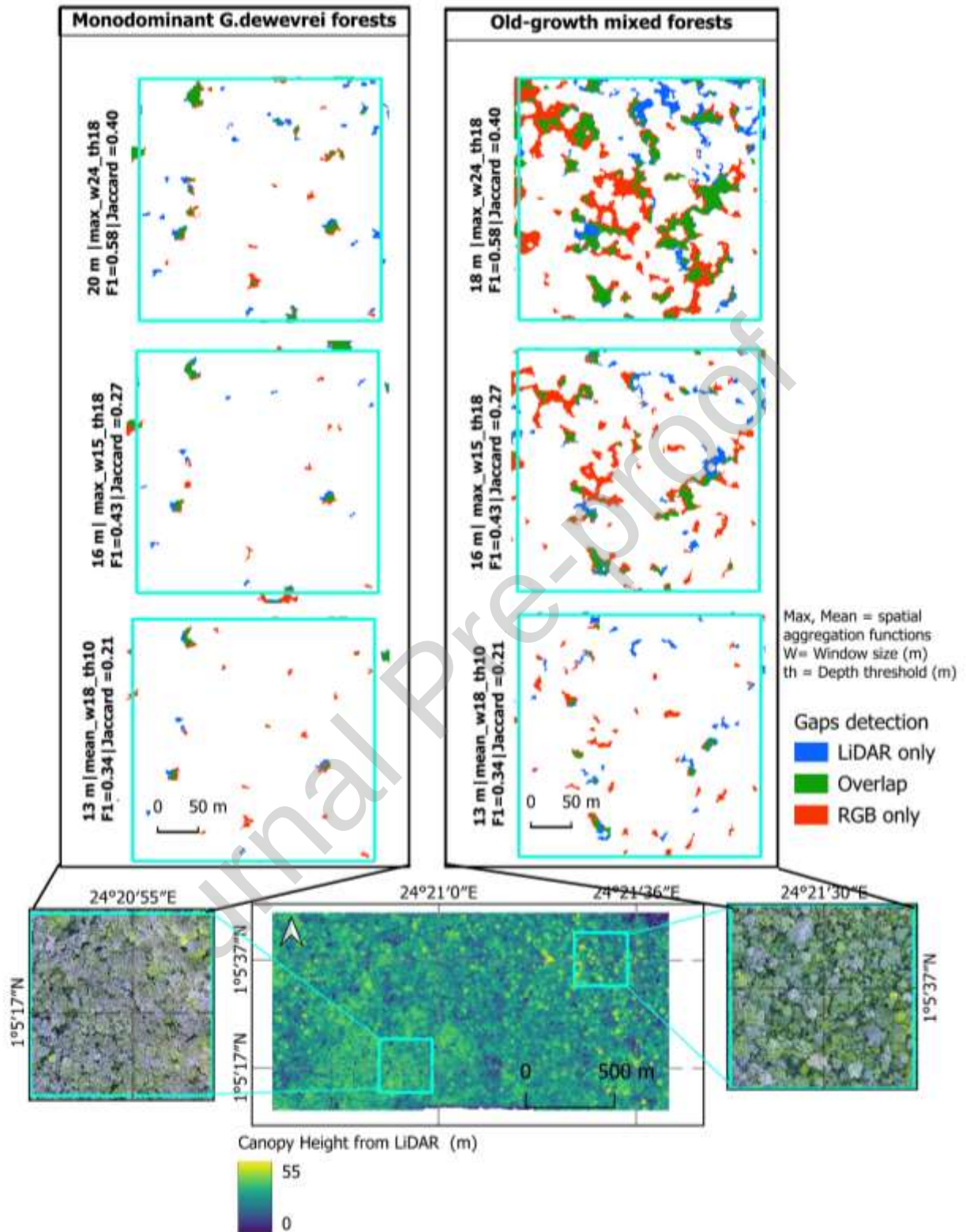


Figure. 4. Spatial co-localisation of canopy gaps detected by LiDAR-CHM and RGB-DSM across three validated canopy height strata (13, 16 and 20 m) in monodominant *G. dewevrei* (left panels) and mixed old-growth forest (right panels) at Lileko study site in Yangambi forest landscape located in the Democratic Republic of Congo. Detection categories: green = co-detected gaps (Overlap, true positives); blue = LiDAR-CHM-only gaps (omission errors, false negatives); red = RGB DSM-only gaps (commission errors, false positives). F1-score and Jaccard index per stratum are shown above each column. Zoom areas are indicated on the LiDAR-derived Canopy Height Model (lower center panel).

3.3. Plot-scale equivalence comparison of mean total gap area per hectare across forest types and height strata

Figure 5 presents the mean total gap area per plot ($\pm$ SE) for LiDAR CHM (dark green) and RGB DSM (orange) across the eight validated canopy height strata (13–20 m), separately for monodominant *G. dewevrei* forest (left panel) and mixed old-growth forest (right panel). In mixed forest stands, the mean total gap area estimated by the UAV RGB DSM is statistically no significant from the LiDAR CHM at all eight validated strata for which five are statistically equivalent (16–20 m). But, in *G. dewevrei* forest stands, the mean total gap area estimated by the UAV RGB DSM is statistically no significant from the LiDAR CHM at five of eight validated strata for which only three are statistically equivalent (at 16 m and 19–20 m).

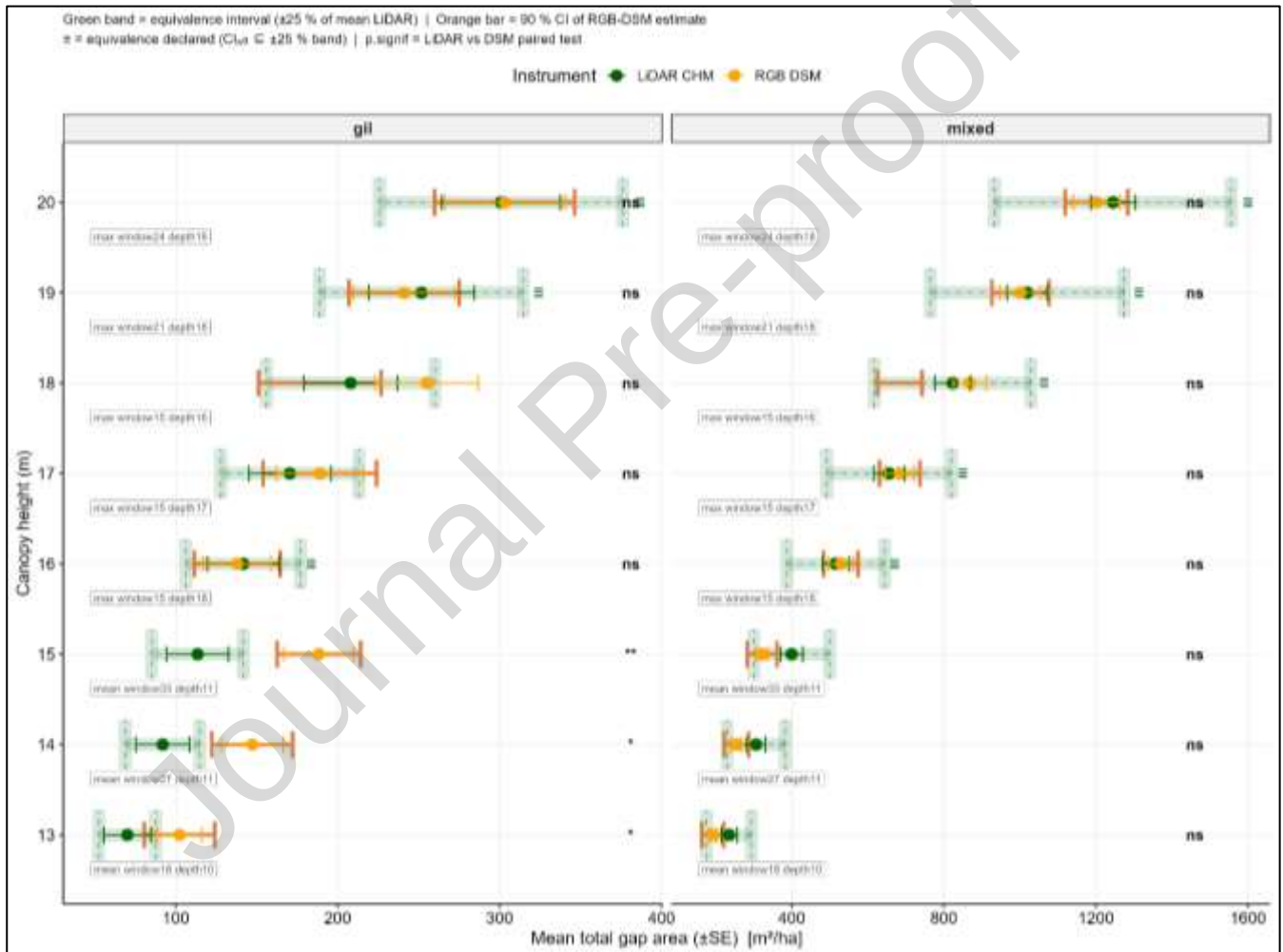


Figure 5. Mean total gap area per plot ($\pm$ SE) for LiDAR CHM (dark green) and RGB DSM (orange) across eight validated canopy height strata (13–20 m), separately for monodominant *G. dewevrei* forest (left panel) and mixed old-growth forest (right panel). Each validated stratum (13–20 m) is associated to its correspondent optimal DSM predictor (aggregation stat, window size and depth threshold). Results of the paired statistical difference test (Wilcoxon signed-rank or paired t-test, p -value > 0.05 = ns) are shown for each stratum and forest type. Green band = equivalence interval [$\text{mean_lidar} \times 0.75$; $\text{mean_lidar} \times 1.25$]; Orange bar = 90% CI of the RGB-DSM estimate; Equivalence is declared when the orange CI falls entirely within the green band.

In the mixed forest panel, the two profiles track each other with remarkable fidelity across the full canopy height range, from approximately 230 m^2 per plot at 13 m to 1,250 m^2 at 20 m, with all eight difference tests returning ns (Wilcoxon signed-rank or paired t-test, p -value > 0.05). Standard errors

overlap at every stratum, and the two profiles cross repeatedly at intermediate strata (16–18 m), where neither instrument consistently overestimates the other.

In the *G. dewevrei* forest, both instruments show lower absolute gap areas than in the mixed forest, consistent with the denser, more homogeneous canopy of monodominant *G. dewevrei* stands, ranging from approximately 70 m² at 13 m to 300 m² at 20 m. The profiles overlap throughout most of the height range, but the equivalence is less symmetric than in the mixed forest. At low stratum < 15 m (Wilcoxon signed-rank or paired t-test, p-value < 0.05, *), the Wilcoxon test reaches significant difference, and the RGB DSM derived profile lies visibly to the right of the LiDAR CHM derived profile, indicating that, at lower stratum RGB DSM overestimates canopy gap area per plot particularly in monodominant *G. dewevrei* forest stand.

4. Discussion

4.1. Plot-scale equivalence despite individual gap-level divergence

No significant difference (paired T-student/Wilcoxon test, p-value > 0.05) and statistically equivalent (TOST test, 90% confidence intervals; p-value < 0.05, margin ranging from 10 to 20% of the mean gap area derived from the LiDAR CHM) between RGB DSM and LiDAR CHM mean total gap area per hectare across all canopy height strata and both forest), particularly in old-growth mixed forests, provides the strongest evidence that pocket drones can produce plot-scale gap area estimates comparable to airborne LiDAR-derived CHM in Central African dense tropical forests (Fig.3, Fig.5, Appendix A Table A1). However, this plot level with no significant difference, and equivalence coexists with systematic individual gap-level bias (Fig.4, Appendix A Table A2). Pocket drone DSMs simultaneously overdetect small artificial gaps beneath closed canopies due to occlusion and surface interpolation artifacts, while underdetecting the extent of large genuine canopy gaps, especially in upper strata [45]. Although each error source is individually biased, their opposing effects compensate when aggregated at the 100 m × 100 m plot scale. This convergence reflects two well-established statistical principles. Firstly, the Central Limit Theorem (CLT), whereby aggregation across numerous gap detections stabilizes mean plot-level estimates despite individual errors [28,29], and secondly, spatial averaging, which reduces the influence of localized commission and omission errors across structurally heterogeneous plots [30–32].

These findings have important methodological and operational implications. Previous studies comparing UAV photogrammetry with LiDAR for forest gap detection have predominantly focused on individual gap metrics: area, perimeter, shape indices and concluded that UAV RGB photogrammetry is insufficiently accurate for operational use [19,20,23]. Our results suggest that this conclusion, while valid at the individual gap level, may not extend to the plot scale, the primary operational unit for forest inventory, carbon stock assessment, and disturbance monitoring [15,31]. A direct parallel can be drawn with above-ground biomass estimation, where allometric prediction errors are very large at the individual tree or very small plot size level but cancel substantially when aggregated to the large plot size and stand scale [31], a well-established property of spatially aggregated ecological estimates that the present study demonstrates applies equally to photogrammetric gap detection. The studies cited above [19,20,23] were not designed to test this

scale dependency, as none explicitly evaluated aggregate gap area metrics at the plot or stand level, nor validated their findings against plot-scale inventory benchmarks. The transferability of their conclusions to operational monitoring at the plot scale and in forests with contrasting canopy structures is therefore inherently limited by the spatial scale at which model performance was assessed. This distinction has been underappreciated in the remote sensing literature on UAV-RGB based forest canopy structure characterization, even though it fundamentally determines the operational conclusions drawn from it [17].

However, our results on individual gap detection performance of the RGB-DSM based on local canopy surface statistics aggregated within a moving window size using either mean or maximum statistics and the local-depth, and validated against airborne LiDAR-CHM (Appendix A Table A2, omission: 43 to 69%; commission: 41 to 63%; F1-score: 0.34 to 0.58; Jaccard: 0.21 to 0.40) was broadly consistent with the unsupervised DAP-based CHM thresholding approach of [19], supporting the view that threshold-based photogrammetric methods represent a lower bound for individual gap detection accuracy. Although supervised and deep learning approaches achieve substantially higher performance, they typically require field-labelled training data, CHM inputs, or computational infrastructure unavailable in low-cost consumer UAV applications. Direct comparison across studies should nevertheless be interpreted cautiously. Our validation relied on LiDAR-CHM rather than field observations, potentially underestimating co-localization accuracy, while the dense multi-layered tropical canopy of Central African forests could be more subject to photogrammetric occlusion than the subtropical and temperate forests [45] investigated by Chen et al. [19] and Htun et al. [20]. Moreover, the reduced performance of transfer learning reported by Htun et al. [20] highlights the limited transferability of supervised models of DSM-derive individual gaps detection across forest types and the need for site-specific calibration. To address these limitations, our results show that, for some ecological applications, a more accurate assessment of UAV-DSM performance in mapping canopy gaps should instead be based on no statistical difference and equivalence observed at the plot scale of a statistical aggregation rather than on the precise detection of each gap.

4.2. Stratum-dependent performance

Regression performance improved consistently with canopy height stratum, with R^2 increasing from 0.31 at 13 m to 0.52 at 18–20 m, and spatial overlap metrics following the same trajectory (Jaccard: 0.21 at chm13 to 0.40 at chm20) (Fig. 3, Fig. 4, Appendix A Table A2). A structurally meaningful transition occurred at the 16 m stratum (Appendix A Table A1), where the optimal RGB-DSM predictors shifted systematically from mean- to maximum-based local statistical aggregation function. This transition likely reflects the increasing reliability of photogrammetric reconstruction toward the upper canopy. In lower strata (<16 m), the reconstructed DSM remains influenced by occlusion from overlying crowns, reduced image redundancy, and local matching uncertainty, making mean-based aggregation advantageous by smoothing small-scale reconstruction artifacts and stabilizing estimates of canopy depressions. Conversely, in the upper canopy (≥ 16 m), where the directly visible crown surface is better resolved, maximum-based aggregation preserves localized height extremes and sharper canopy discontinuities associated with larger gaps, improving predictive performance. Similar vertical limitations of Structure-from-Motion photogrammetry have been reported in previous studies, which consistently show reliable reconstruction of exposed

canopy surfaces but decreasing structural accuracy with increasing occlusion in lower layers [45,46]. These results confirm that the predictive capacity of RGB-derived canopy models increases with canopy height, although the increasing MAE at upper strata reflects the larger magnitude and variability of canopy openings rather than reduced model reliability.

The height-dependent shift in optimal statistical aggregation strategy (mean or maximum) further indicates that gap detection parameters should not be considered vertically invariant in complex tropical forests. Below 16 m, the canopy surface is dominated by overlapping sub-canopy and intermediate crowns, where three-dimensional complexity increases reconstruction uncertainty and favors spatial smoothing through larger-window mean aggregation (w21–w30) (Fig. 5). Above this threshold, emergent crowns and stronger vertical contrasts between crown tops and gap interiors allow smaller-window maximum aggregation (w15–w21) to better capture localized canopy discontinuities (Fig. 5). This vertical adjustment is conceptually consistent with the depth-from-surface approach of Betts et al. [23], who demonstrated that canopy gap detection depends on the relationship between detection-kernel size and the spatial scale of gap-forming processes. While their study focused on structurally simpler temperate forests using airborne photogrammetry, the underlying principle extends here to dense Central African old-growth forests, where optimal detection parameters vary according to canopy position and forest structural complexity. The present results therefore suggest that vertical stratification should be explicitly incorporated into UAV-based canopy gap monitoring rather than relying on a single set of parameters across the entire canopy profile.

The relationship between canopy height stratum and estimation reliability warrants careful methodological interpretation. Regression performance improved consistently with canopy height, with R^2 increasing from 0.31 at 13 m to 0.52 at 20 m of canopy height (Appendix A Fig. A1, blue labels), indicating that the ordinal ranking of gap areas across plots becomes increasingly reliable toward the upper canopy, consistent with improved photogrammetric reconstruction of the canopy surface. In contrast, absolute MAE increased from 128 m² at 13 m to 405 m² at 20 m of canopy height (Appendix A Fig. A1, orange dashed line). This apparent divergence does not indicate a deterioration in instrument performance but reflects a predictable scale effect. Mean LiDAR-derived gap area per plot increased more than fivefold across the same height range, from 152.7 m² at 13 m to 773.0 m² at 20 m of canopy height (Fig. 5), because canopy openings become progressively larger and more spatially extensive in the upper strata. Therefore, larger absolute prediction errors are expected even when the proportional agreement between methods improves. This is confirmed by the relative MAE, obtained by normalizing MAE by the mean gap area of each stratum, which decreased monotonically from 83.8% at 13 m to 52.4% at 20 m of canopy height (Spearman $r_s = -1.00$, $p < 0.001$; Fig. A1, green line). The combined interpretation of R^2 , absolute MAE and relative MAE therefore reveals a consistent increase in estimation reliability with canopy height: both the relative ranking of plots and the proportional accuracy of gap-area estimates improved, whereas the increase in absolute MAE simply reflects the broader distribution and larger magnitude of gap areas at higher canopy strata. This highlights the importance of jointly reporting complementary performance metrics in remote sensing studies, as R^2 alone would suggest improving performance, whereas MAE alone could misleadingly suggest the opposite [47,48].

These findings are also broadly consistent with the pioneering work of Betts et al. [23], who established that DEM-based gap detection in temperate forests achieves acceptable performance when detection parameters are adapted to local canopy structure, and with subsequent studies in temperate and boreal forests showing that photogrammetric CHM quality also degrades with increasing canopy closure and forest structural complexity [49]. The present study extends this pattern to the vertically stratified canopy architecture of Central African old-growth tropical forests, where the additional dimension of canopy height stratification introduces a systematic parameter shift, from mean to max statistical aggregation at 16 m that has no direct analogue in the canopy surface analyses typical of temperate previous forest studies [20,23]. The shift from mean to max statistical aggregation at 16 m identified here may reflect the local canopy architecture of the Lileko site and the surrounding Yangambi forest landscape specifically, where intermediate strata correspond to dense sub-canopy dominated by shade-tolerant species and mean top of canopy of about 30 m [27,50,51] and should at this stage, be treated as a site-specific rather than universal parameter pending validation across other tropical forest landscapes.

4.3. Forest type modulates UAV–LiDAR agreement

Agreement between RGB-DSM and LiDAR-CHM was stronger and more consistent in structurally heterogeneous mixed old-growth forest than in *G. dewevrei* forest. In mixed forest, mean total gap area estimates were not significantly different and equivalence respectively at all eight and five of selected validated strata, with LiDAR-CHM and RGB-DSM profiles tracking each other closely across the full canopy height range and standard errors overlapping at every stratum (Fig. 5). In the *G. dewevrei* forest, while no significant difference and equivalence was maintained respectively at five and three of eight strata (Fig. 5), the RGB-DSM significantly overestimated total gap area relative to LiDAR at < 15 m (t-student/Wilcoxon, p-value < 0.05), with the RGB-DSM-derived profile lying visibly above the LiDAR-CHM derived profile at these heights and standard error bands showing no overlap (Fig. 5).

The spatial distribution of individual gap polygons provides a mechanistic explanation for this contrast (Fig. 4). In the *G. dewevrei* forest, individual gap polygons are sparse and dominated by isolated RGB-only polygons, particularly at 13–15 m, indicating numerous commission errors relative to the LiDAR reference. These false-positive detections likely arise from shadowed depressions formed beneath the tightly interlocking crowns of *G. dewevrei*, which SfM reconstruction cannot reliably distinguish from true canopy openings.

A contrasting spatial organization is observed in the mixed forest. From approximately 16 m onward, gap polygons become larger, denser and more spatially interconnected, with RGB-only, LiDAR-only and jointly detected gaps occurring in close proximity (Fig. 4, right panels). This spatial complexity reflects the greater heterogeneity of crown architecture, canopy height and natural disturbance patterns characteristic of mixed old-growth forest [27], creating numerous opportunities for local commission and omission errors to compensate within plots.

This interpretation is further supported by the supplementary spatial autocorrelation analysis of CHM–DSM residuals based on Moran's I test (Supplementary Fig.S2). In *G. dewevrei* forest, residuals remained spatially random across all validated strata ($I = 0.023\text{--}0.135$; $p \geq 0.051$), indicating that

local over- and under-estimation errors occurred independently in space. In contrast, residuals in mixed forest became significantly clustered from 15 m canopy height onward ($I = 0.136\text{--}0.378$; $p \leq 0.004$), with the strength of clustering increasing toward the upper canopy. Because both forest types were surveyed under identical acquisition conditions, flight parameters, processing workflow and georeferencing procedure, this within-site contrast is unlikely to reflect methodological artifacts. Instead, it is consistent with the contrasting canopy organizations documented independently from the same LiDAR dataset by Nguba Besisa et al. [27]. Despite these contrasting residual patterns, plot-scale statistical equivalence between RGB-derived and LiDAR-derived gap-area estimates was maintained across all validated strata ($p > 0.05$). This indicates that compensation between local commission and omission errors remains effective whether residuals are spatially random or moderately clustered, although additional validation across other tropical forest types will be required to determine the broader generality of these patterns.

The implication for operational monitoring is then significant. The pocket drone-derived DSM is particularly well suited for plot-scale gap-area estimation in structurally heterogeneous old-growth forests, where agreement with LiDAR remained robust across a large portion of the canopy profile. In monodominant *G. dewevrei* forests, however, the overestimation observed at intermediate canopy strata (13–15 m) (Fig. 5) should be explicitly considered when interpreting RGB-derived gap metrics. To our knowledge, this forest-type dependency and notably its counterintuitive direction, with greater uncertainty in the structurally simpler forest type has not previously been reported in UAV-based RGB canopy-gap studies and represents an important contribution to defining the conditions under which low-cost photogrammetry can reliably characterize tropical forest structure.

4.4. Operational implications for Central African forest monitoring and forest management

Overall, our findings suggest that the Pocket drones-derived DSM is an effective tool for plot-scale canopy gap area monitoring in Central African dense tropical forests, subject to clearly defined structural and scale boundary conditions. The most appropriate operational applications include landscape-scale gap fraction estimation [52], monitoring of logging intensity and forest degradation for REDD+ reporting [53,54], and carbon stock assessment [16,55]. These applications operate at the plot scale, where the compensation between commission and omission errors ensures robust aggregate estimates despite limited individual gap-level accuracy.

Canopy opening has been demonstrated to be a good indicator to monitor forest structural changes and upscale logging intensity in central Africa [54]. Therefore, demonstrating that pocket drone (< 500 USD) can provide estimates of gap area through simple automated approaches that are statistically equivalent gap area estimates to LiDAR at the plot scale represents a meaningful step toward democratizing three-dimensional forest structure monitoring across the vast Central African forests that currently lack any baseline structural information.

This is particularly more relevant for Central African context where, airborne or UAV LiDAR coverage remains extremely sparse, with most existing acquisitions concentrated in a small number of research sites [16], and the financial and logistical barriers to systematic LiDAR deployment across the region remain prohibitive for national forest monitoring programs [11]. The pocket drone,

regulatory simplicity in many Central African jurisdictions, and minimal logistical footprint make it deployable by local forest government forest administration, research institutions and forest management agencies and forest logging companies in the Democratic Republic of Congo, Cameroon, Gabon, and the Republic of Congo, countries where national REDD+ programs require cost-effective and reproducible canopy structure monitoring at landscape scale but currently lack the remote sensing infrastructure to deliver it through conventional airborne methods [56–58].

Conversely, the individual gap-level limitations documented in this study confirm that spatially explicit gap characterization remains beyond the operational envelope of consumer-grade UAV photogrammetry in these forests. Therefore, LiDAR remains indispensable for applications requiring precise gap geometry, including gap-phase regeneration dynamics, microclimate modelling within individual gaps, or species-level recruitment analysis linked to gap size and shape. And, the pocket drone-derived DSM should therefore be positioned as a scalable complement to LiDAR in research programs where both plot-scale monitoring and gap-level spatial analysis are required: it provides reliable aggregate estimates at the monitoring scale relevant to carbon accounting and disturbance reporting, while LiDAR retains its irreplaceable role in studies demanding structural precision at the individual gap level.

4.5. Limitations and perspectives

Several limitations of the present study warrant acknowledgement. First, the compensation mechanism documented here was experimented at only one local scale site of Lileko in the Yangambi forest landscape, where canopy disturbances are predominantly natural and forest structure is relatively homogeneous. Although this setting provides an appropriate benchmark for a first validation of pocket-drone photogrammetry across contrasting mature forest types, its applicability to more heterogeneous landscapes, including logged, secondary, fragmented or edge-affected forests remains to be demonstrated. Second, the 12.3 cm spatial resolution achieved with the pocket drone under favorable flight conditions may not be consistently reproducible under various operational conditions. Wind, illumination variability, complex topography and canopy motion may reduce image quality and modify the balance between omission and commission errors. Third, although the grid search explored 2,436 combinations of statistic aggregation, window sizes and depth thresholds, the optimal parameterization was calibrated for the structural conditions encountered in Yangambi and should therefore be re-evaluated before application to other tropical forest ecosystems.

A further limitation concerns the interpretation of object-level validation metrics. The relatively low spatial overlap observed for individual gap polygons (Jaccard: 0.20–0.37; F1: 0.34–0.54) results from two complementary sources of disagreement: (i) the intrinsic inability of passive RGB photogrammetry to reconstruct canopy openings hidden beneath the closed canopy surface and (ii) residual spatial misregistration between the RGB-derived DSM and the LiDAR-derived CHM. The crown-based geometric validation presented in Section 2.3 quantified this latter component, with negligible east-west bias (mean $\Delta X = 0.109$ m) and only a slight systematic southward displacement (mean $\Delta Y = -1.04$ m). Because many canopy gaps identified in this study are of comparable dimensions, even a residual displacement of approximately 1–2 m can substantially reduce polygon

overlap despite both sensors detecting the same disturbance. Consequently, Jaccard and F1 scores should not be interpreted solely as indicators of photogrammetric detection performance but rather as the combined outcome of sensing limitations and residual geometric uncertainty.

Importantly, this positional uncertainty has little influence on plot-scale estimates, where gap area is aggregated within 100×100 m plots. At this spatial scale, residual positional errors affect only a small proportion of boundary pixels [59] and generate largely compensatory over- and under-estimation, consistent with the statistically equivalent total gap area obtained from RGB-DSM and LiDAR datasets. The apparent discrepancy between modest object-level overlap and robust plot-level agreement therefore reflects the different sensitivities of these validation metrics to residual positional uncertainty rather than a contradiction in method performance.

Another limitation concerns the operational scalability of gap area monitoring based on the UAV-derived DSM approach developed here. Although the pocket drone used here represents a low-cost platform (<500 USD), extending pocket-drone surveys beyond local scale studies would require substantial logistical investment in field deployment, battery management, transport to remote forest locations and flight time. In addition, centimeter-resolution imagery generates large datasets whose SfM processing requires Graphics Processing Units (GPUs)-enabled computing infrastructure that remains scarce in many Central African research institutions [45,60]. Rather than exhaustive mapping, we therefore envisage pocket-drone surveys as a sampling tool. Clustered or systematic-random sampling strategies covering representative subsets of landscape units would maintain operational feasibility while preserving statistical inference at landscape scales [61]. Under such designs, the demonstrated agreement between RGB-derived and LiDAR-derived plot-scale gap area estimates supports the integration of pocket-drone measurements into existing forest inventory, carbon monitoring and REDD+ frameworks. Cloud-based processing may further alleviate computational limitations, although data transfer and internet connectivity remain important constraints in remote tropical forests.

The poor performance observed at the lower canopy height strata (Appendix A Table A1; $R^2 < 0.32$; paired test $p\text{-value} \leq 0.05$ for strata ≤ 12 m) reflects an inherent limitation of passive optical photogrammetry. RGB sensors mounted on pocket drones capture only the uppermost illuminated canopy surface, and SfM reconstruction cannot penetrate a closed canopy to resolve sub-canopy or intermediate canopy structure. Consequently, gap estimates derived using low CHM thresholds represent depressions in the reconstructed photogrammetric surface rather than true structural openings at those canopy heights, leading to increasing divergence from LiDAR-derived estimates as the analysis extends into occluded canopy layers. Accordingly, for the study region of Yangambi forest landscape, the present study restricts the operational application of the proposed framework to the validated canopy height range (13–20 m), where UAV-derived estimates showed statistical equivalence with LiDAR.

Future research should focus on extending the geographical, ecological and temporal scope of the proposed framework. Multi-site validation across the Congo Basin should assess its robustness under contrasting forest structures, species compositions and disturbance histories, including selectively logged forests, secondary forests and forest–savanna transition zones. Repeated drone

acquisitions should also be evaluated to determine whether the compensation mechanism observed for single-date surveys remains valid for monitoring canopy-gap dynamics through time. Finally, integrating pocket-drone-derived structural metrics with long-term forest inventory networks may help improve biomass estimation and reduce uncertainty in plot-based carbon accounting.

5. Conclusion

By validating a consumer-grade platform costing less than USD 500, this study provides a practical pathway toward more accessible canopy structure monitoring. Such systems could support local research and practitioner teams, as well as national forest monitoring and REDD+ initiatives, across the Congo Basin and the broader Central African forest landscape. Across canopy height strata, canopy gaps estimated from RGB-derived DSMs using local canopy surface statistics within moving windows and a local-depth criterion provides a structurally biased but plot-scale-consistent and operationally viable proxy for LiDAR-based gap monitoring of canopy gaps. This approach is particularly relevant to forest inventories, carbon stock assessment, and disturbance monitoring under REDD+. However, the spatially explicit delineation and geometry of individual gaps still require LiDAR-quality data. Forest-type-specific boundary conditions must also be incorporated into operational protocols, particularly the overestimation bias observed at intermediate canopy strata in monodominant *G. dewevrei* forests.

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Declaration for generative AI and AI-assisted technologies in the writing process

We acknowledge the use of OpenAI ChatGPT 5.5 and Anthropic Claude 4.6 to assist with text condensation, refinement of R code structure, and the graphical layout and rendering of the workflow chart. The AI-assisted graphical work was based exclusively on the workflow design, methodological framework, analytical concepts, and detailed instructions developed by the authors. All AI-generated suggestions were critically reviewed, adapted, and validated by the authors to preserve scientific accuracy and intended meaning. The conceptualization of the study, methodological development, data analysis, interpretation of results, and final manuscript content, including all figures and scientific conclusions, remain entirely the work and responsibility of the authors.

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Appendix A

Table A1. Optimal UAV RGB-derived DSM predictors of LiDAR-CHM canopy gap area per height stratum, selected from a grid-search of 2,436 parameter combinations (12 CHM thresholds $\times$ 203 DSM configurations). Selection criteria: $R^2 > 0.30$ and minimum MAE. Retained pairs are no-significant difference (paired T-student/Wilcoxon test, p-value > 0.05) and statistically equivalent (TOST test, 90% confidence intervals; p-value < 0.05 , margin of $\pm 20\%$ of the mean gap area derived from the LiDAR CHM) to LiDAR in both forest types Aggregation function: local statistics applied within the detection window. Window: spatial kernel size (pixels- $\times$ 1m). Depth threshold: minimum local depression depth (m) required for gap detection.

5	mean_dem_w27_th11	mean	27	11	0,3	215,	2352,	2.49e-	[-232; -				
					18	21	80	38	198]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
10	mean_dem_w21_th11	mean	21	11	0,3	102,	2910,	1.30e-	[-75; -				
					14	46	96	16	46]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
10	mean_dem_w18_th10	mean	18	10	0,3	120,	2912,	5.89e-	[-101; -				
					09	59	73	22	72]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
10	mean_dem_w27_th11	mean	27	11	0,3	162,	2882,	1.35e-	[-160; -				
					93	30	59	31	130]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
10	mean_dem_w21_th10	mean	21	10	0,3	164,	2912,	1.19e-	[-159; -				
					11	36	10	30	127]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
10	mean_dem_w30_th11	mean	30	11	0,3	189,	2904,	2.15e-	[-194; -				
					32	82	99	34	159]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
11	mean_dem_w21_th11	mean	21	11	0,3	101,	3002,	2.11e-	[-47; -				
					18	01	90	08	14]	9.67e-01	8.94e-01	7.46e-01	5.29e-01
11	mean_dem_w18_th10	mean	18	10	0,3	115,	3003,	7.25e-	[-73; -				
					16	44	74	14	39]	1.00e+00	1.00e+00	9.99e-01	9.95e-01
11	mean_dem_w27_th11	mean	27	11	0,4	146,	2969,	2.75e-	[-131; -				
					10	13	34	26	98]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
11	mean_dem_w21_th10	mean	21	10	0,3	150,	3001,	3.60e-	[-131; -				
					23	86	06	24	96]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
11	mean_dem_w30_th11	mean	30	11	0,3	171,	2989,	1.45e-	[-165; -				
					56	93	70	29	128]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
12	mean_dem_w21_th11	mean	21	11	0,3	108,	3092,	2.44e-					
					14	21	57	02	[-14; 26]	2.16e-01	7.65e-02	1.93e-02	3.42e-03
12	mean_dem_w18_th10	mean	18	10	0,3	116,	3091,	1.16e-					
					19	48	02	05	[-39; 0]	6.36e-01	3.83e-01	1.72e-01	5.60e-02
12	mean_dem_w27_th11	mean	27	11	0,4	139,	3056,	2.45e-	[-97; -				
					13	17	28	16	60]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
12	mean_dem_w21_th10	mean	21	10	0,3	144,	3086,	2.02e-	[-97; -				
					32	68	64	15	57]	1.00e+00	1.00e+00	1.00e+00	9.99e-01
12	mean_dem_w30_th11	mean	30	11	0,3	157,	3073,	4.43e-	[-130; -				
					67	74	94	22	90]	1.00e+00	1.00e+00	1.00e+00	1.00e+00
13	mean_dem_w21_th11	mean	21	11	0,3	124,	3180,	4.57e-					
					13	23	45	02	[30; 78]	9.89e-01	9.47e-01	8.20e-01	5.87e-01
13	mean_dem_w18_th10	mean	18	10	0,3	127,	3176,	6.58e-					
					25	99	26	01	[4; 52]	7.08e-01	4.36e-01	1.93e-01	5.84e-02
13	mean_dem_w24_th11	mean	24	11	0,3	130,	3184,	7.11e-					
					00	52	89	02	[-10; 38]	3.38e-01	1.33e-01	3.60e-02	6.52e-03
13	mean_dem_w27_th11	mean	27	11	0,4	136,	3142,	2.96e-					
					16	62	50	07	[-53; -9]	7.82e-01	5.08e-01	2.29e-01	6.70e-02
13	mean_dem_w21_th10	mean	21	10	0,3	141,	3170,	5.57e-					
					42	95	50	07	[-52; -6]	7.29e-01	4.58e-01	2.06e-01	6.26e-02
14	mean_dem_w27_th11	mean	27	11	0,4	147,	3231,	3.47e-					
					02	25	64	01	[4; 57]	6.05e-01	2.92e-01	8.71e-02	1.52e-02
14	mean_dem_w21_th10	mean	21	10	0,3	153,	3257,	4.27e-					
					32	00	57	01	[4; 61]	6.39e-01	3.38e-01	1.18e-01	2.54e-02
14	mean_dem_w30_th11	mean	30	11	0,3	154,	3243,	4.68e-					
					72	15	14	03	[-28; 26]	6.25e-02	1.01e-02	9.59e-04	5.44e-05
14	mean_dem_w18_th10	mean	18	10	0,3	156,	3265,	2.76e-					
					09	14	36	05	[61; 118]	1.00e+00	9.98e-01	9.81e-01	9.09e-01
14	mean_dem_w33_th11	mean	33	11	0,4	160,	3229,	2.21e-					
					07	84	52	06	[-58; -5]	6.28e-01	3.10e-01	9.41e-02	1.66e-02
15	mean_dem_w33_th11	mean	33	11	0,3	181,	3321,	9.86e-					
					88	44	52	01	[15; 80]	7.50e-01	4.21e-01	1.42e-01	2.61e-02
15	mean_dem_w27_th11	mean	27	11	0,3	183,	3324,	4.68e-					
					79	23	89	05	[77; 143]	1.00e+00	9.98e-01	9.80e-01	8.85e-01

15	mean_dem_w30_th11	mean	30	11	0,3	184,	3333,	3.16e-02	[45; 112]	9.85e-01	9.07e-01	6.82e-01	3.54e-01
15	mean_dem_w15_th8	mean	15	8	0,3	189,	3344,	6.31e-01	[26; 94]	8.94e-01	6.64e-01	3.43e-01	1.09e-01
15	mean_dem_w21_th10	mean	21	10	0,3	190,	3346,	3.38e-05	[77; 146]	1.00e+00	9.98e-01	9.80e-01	8.91e-01
16	max_dem_w15_t_h18	max	15	18	0,5	221,	3354,	9.76e-01	[-47; 26]	6.44e-02	6.25e-03	2.69e-04	5.31e-06
16	mean_dem_w27_th10	mean	27	10	0,4	224,	3396,	2.86e-02	[64; 141]	9.93e-01	9.39e-01	7.29e-01	3.70e-01
16	mean_dem_w33_th10	mean	33	10	0,4	227,	3393,	9.17e-02	[-15; 60]	1.73e-01	2.88e-02	2.22e-03	8.03e-05
16	mean_dem_w33_th11	mean	33	11	0,3	229,	3414,	4.15e-07	[106; 186]	1.00e+00	9.99e-01	9.91e-01	9.29e-01
16	mean_dem_w30_th10	mean	30	10	0,3	230,	3407,	7.79e-01	[24; 102]	7.89e-01	4.49e-01	1.45e-01	2.38e-02
17	max_dem_w15_t_h18	max	15	18	0,4	263,	3436,	7.91e-07	[67; 150]	9.80e-01	8.30e-01	4.40e-01	1.04e-01
17	max_dem_w15_t_h17	max	15	17	0,5	264,	3431,	3.50e-01	[-69; 17]	1.26e-01	1.37e-02	5.74e-04	9.56e-06
17	max_dem_w18_t_h18	max	18	18	0,4	273,	3436,	3.45e-02	[-117; -25]	7.04e-01	3.22e-01	7.26e-02	7.30e-03
17	mean_dem_w33_th10	mean	33	10	0,3	276,	3480,	6.48e-04	[95; 187]	9.99e-01	9.79e-01	8.50e-01	5.14e-01
17	mean_dem_w27_th9	mean	27	9	0,4	280,	3471,	5.17e-01	[40; 130]	8.54e-01	5.14e-01	1.64e-01	2.34e-02
18	max_dem_w18_t_h18	max	18	18	0,5	306,	3503,	4.19e-04	[21; 120]	5.04e-01	1.24e-01	1.05e-02	2.87e-04
18	max_dem_w15_t_h16	max	15	16	0,5	308,	3495,	8.99e-02	[-95; 4]	2.05e-01	2.33e-02	8.47e-04	1.01e-05
18	max_dem_w15_t_h17	max	15	17	0,5	309,	3498,	1.15e-05	[68; 163]	9.41e-01	6.38e-01	1.94e-01	1.93e-02
18	max_dem_w18_t_h17	max	18	17	0,5	321,	3504,	5.54e-03	[-147; -41]	7.70e-01	3.61e-01	7.39e-02	5.75e-03
18	mean_dem_w33_th9	mean	33	9	0,4	326,	3537,	7.82e-02	[70; 175]	9.50e-01	7.06e-01	2.87e-01	4.80e-02
19	max_dem_w18_t_h17	max	18	17	0,5	353,	3563,	3.83e-03	[16; 128]	3.32e-01	4.48e-02	1.62e-03	1.59e-05
19	max_dem_w15_t_h16	max	15	16	0,5	354,	3557,	1.22e-04	[66; 174]	8.46e-01	3.81e-01	5.24e-02	1.74e-03
19	max_dem_w15_t_h15	max	15	15	0,5	358,	3553,	9.43e-03	[-128; -16]	3.28e-01	4.26e-02	1.44e-03	1.28e-05
19	max_dem_w21_t_h18	max	21	18	0,4	364,	3573,	2.10e-01	[-45; 77]	2.74e-02	1.04e-03	1.29e-05	5.62e-08
19	max_dem_w18_t_h16	max	18	16	0,5	368,	3558,	1.23e-04	[-189; -71]	8.84e-01	4.94e-01	1.10e-01	7.66e-03
20	max_dem_w15_t_h15	max	15	15	0,5	397,	3616,	2.91e-03	[58; 181]	6.41e-01	1.45e-01	6.81e-03	6.06e-05
20	max_dem_w18_t_h16	max	18	16	0,5	398,	3619,	4.31e-02	[-2; 125]	1.23e-01	5.84e-03	5.76e-05	1.32e-07
20	max_dem_w24_t_h18	max	24	18	0,5	405,	3621,	1.09e-01	[-32; 101]	3.87e-02	1.14e-03	8.28e-06	1.70e-08
20	max_dem_w21_t_h17	max	21	17	0,5	407,	3625,	8.23e-01	[-64; 70]	5.83e-03	7.66e-05	2.70e-07	2.99e-10
20	max_dem_w15_t_h14	max	15	14	0,5	417,	3613,	2.53e-04	[-173; -47]	5.42e-01	1.01e-01	4.13e-03	3.50e-05

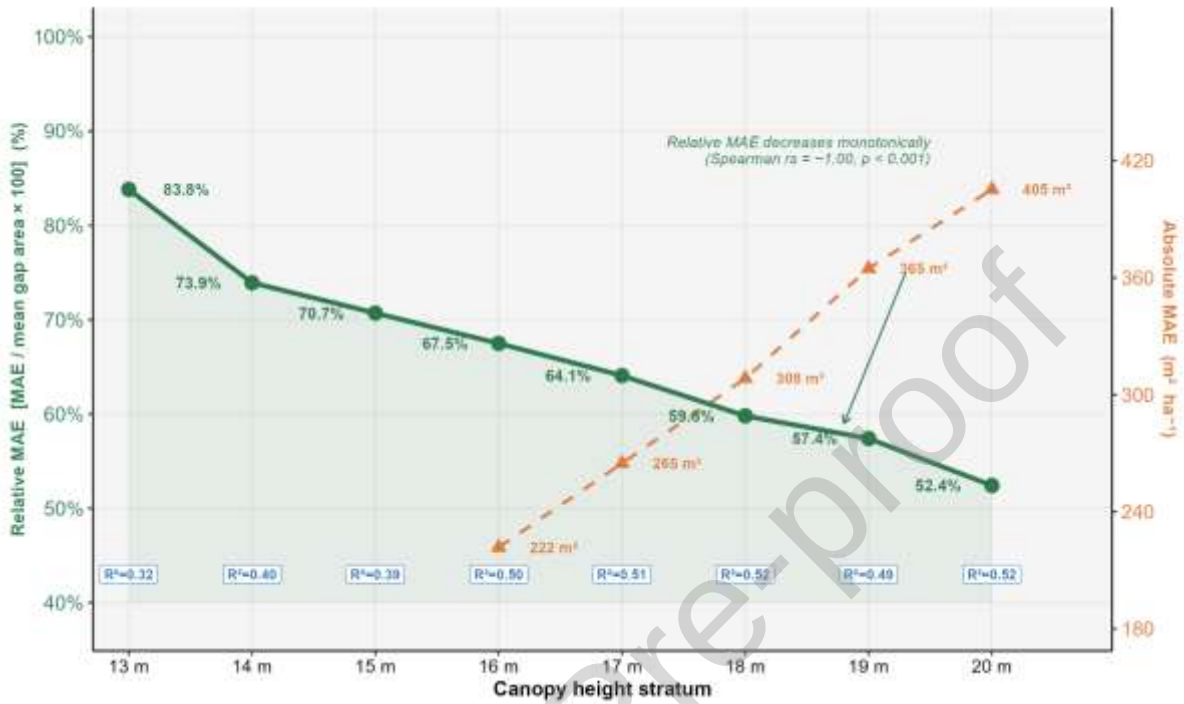


Figure A1. Scale-dependent reliability of RGB-derived DSM canopy-gap area estimates across canopy height strata. The green line (left axis) shows the relative MAE, calculated as the ratio of absolute MAE to the mean LiDAR-CHM gap area for each canopy height stratum, which decreases monotonically from 83.8% at 13 m to 52.4% at 20 m (Spearman $r_s = -1.000$, $p < 0.001$), indicating a progressive improvement in proportional estimation accuracy with canopy height. The orange dashed line (right axis) shows the absolute MAE ($\text{m}^2 \text{ha}^{-1}$), which increases from 128 to 405 m^2 because gap areas become progressively larger in the upper canopy. Blue labels indicate the coefficient of determination (R^2) of the linear regression between RGB-DSM and LiDAR-CHM gap area estimates for each stratum.

Table A2. Pixel-level spatial co-localisation metrics between LiDAR-CHM and UAV RGB-DSM gap detections for all statistically equivalent predictor pairs across canopy height strata (13–20 m). Accuracy, Precision, Recall, Jaccard index, and F1-score computed from binary confusion matrices at 1 m resolution. Accuracy = $(TP + TN) / N$; Precision = $TP / (TP + FP)$; Recall = $TP / (TP + FN)$; Jaccard = $TP / (TP + FP + FN)$; F1 = $2TP / (2TP + FP + FN)$. LiDAR CHM = reference; RGB DSM = predicted. Gap detection threshold: $\geq 20 \text{ m}^2$. In RGB-DSM predictor: max, mean = spatial aggregation functions; W= Window size (m); th = Depth threshold (m).

Height (m)	RGB-DSM predictor	Accuracy	Precision	Recall	Jaccard	F1-score
13	mean_dem_w18_th10	0,98	0,37	0,32	0,21	0,34
13	mean_dem_w24_th11	0,98	0,39	0,36	0,23	0,37
14	mean_dem_w21_th10	0,97	0,40	0,35	0,23	0,37
14	mean_dem_w27_th11	0,97	0,45	0,40	0,27	0,42
15	mean_dem_w15_th8	0,96	0,38	0,31	0,21	0,35
15	mean_dem_w33_th11	0,97	0,50	0,43	0,30	0,47
16	max_dem_w15_th18	0,95	0,42	0,43	0,27	0,43
16	mean_dem_w30_th10	0,96	0,52	0,44	0,31	0,48
16	mean_dem_w33_th10	0,96	0,50	0,48	0,33	0,49
17	max_dem_w15_th17	0,94	0,44	0,46	0,29	0,45
17	mean_dem_w27_th9	0,95	0,53	0,45	0,32	0,48
18	max_dem_w15_th16	0,93	0,47	0,50	0,32	0,48

18	mean_dem_w33_th9	0,94	0,58	0,48	0,36	0,52
19	max_dem_w21_th18	0,92	0,54	0,53	0,36	0,53
20	max_dem_w21_th17	0,91	0,56	0,56	0,39	0,56
20	max_dem_w24_th18	0,91	0,59	0,57	0,40	0,58

List of Figures

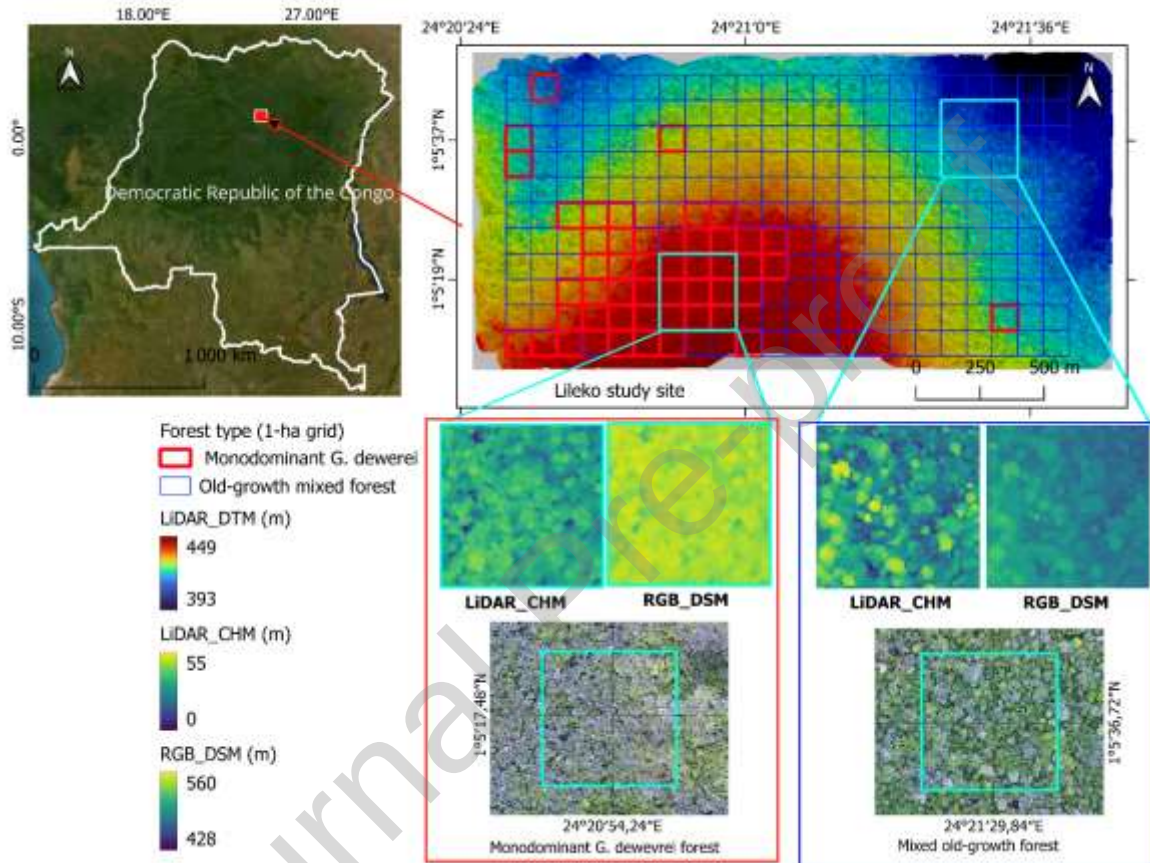


Figure 1. Location of the ~240-ha study site of Lileko within the Yangambi forest landscape. The insets (green rectangles) show the locations of the two forest type areas: monodominant *G. dewevrei* (left panels, 1-ha red grid cells) and mixed old-growth forest (right panels, 1-ha blue grid cells); as well as the corresponding elevation data sources (LiDAR-derived DTM and CHM; RGB-derived DSM) and distinct RGB-derived orthomosaic pattern.

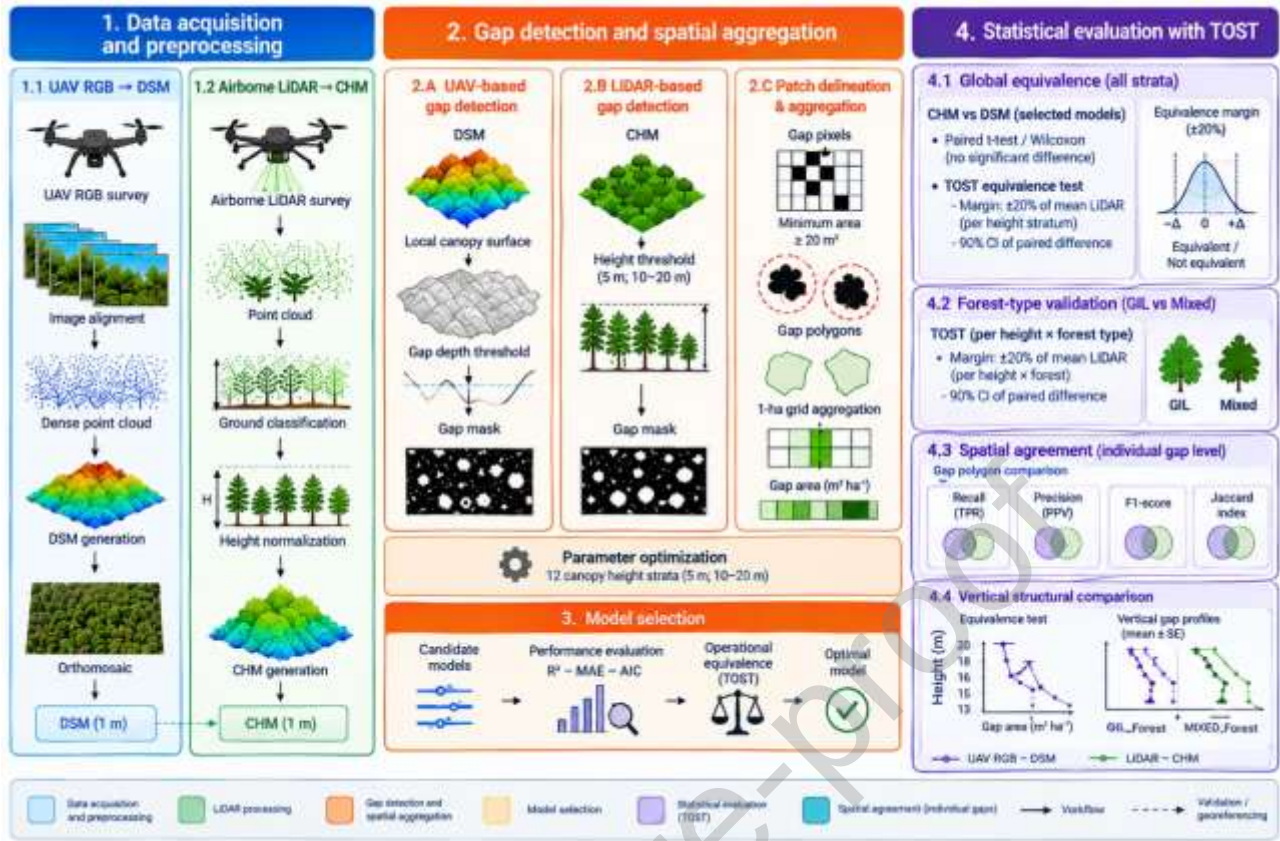


Figure 2. Methodological workflow for evaluating canopy gap area and comparing Pocket drone and LiDAR. (1) Data acquisition and processing: (1.1) UAV RGB imagery acquired with a consumer-grade drone and processed through structure-from-motion photogrammetry to generate a Digital Surface Model (DSM) at 1 m resolution, georeferenced using ground control points derived from LiDAR; (1.2) airborne LiDAR point cloud processed through ground classification, height normalization, and pit-free algorithm to generate a Canopy Height Model (CHM) at 1 m resolution. (2) Gap detection and spatial aggregation: (2.A) UAV-based gap detection using a local depth approach, different window sizes and aggregation statistics; (2.B) LiDAR-based gap detection using 12 canopy height thresholds (at 5 m and each meter from 10 to 20 m); (2.C) gap delineation, minimum area filtering ($\geq 20 \text{ m}^2$), and aggregation to 233 one-hectare grid cells with border effect correction. (3) Model selection across 2,436 parameter combinations based on R^2 , MAE, AIC, and operational equivalence. (4) Model evaluation: (4.1) Global equivalence based on Two One-Sided Tests (TOST) procedure; (4.2) Forest type validation per height and forest type; (4.3) spatial agreement at the individual gap polygon level (Recall, Precision, F1-score, Jaccard index); (4.4) statistically difference and equivalence vertical structural comparison across different canopy height strata within monodominant *G. dewevrei* and old-growth mixed forests.

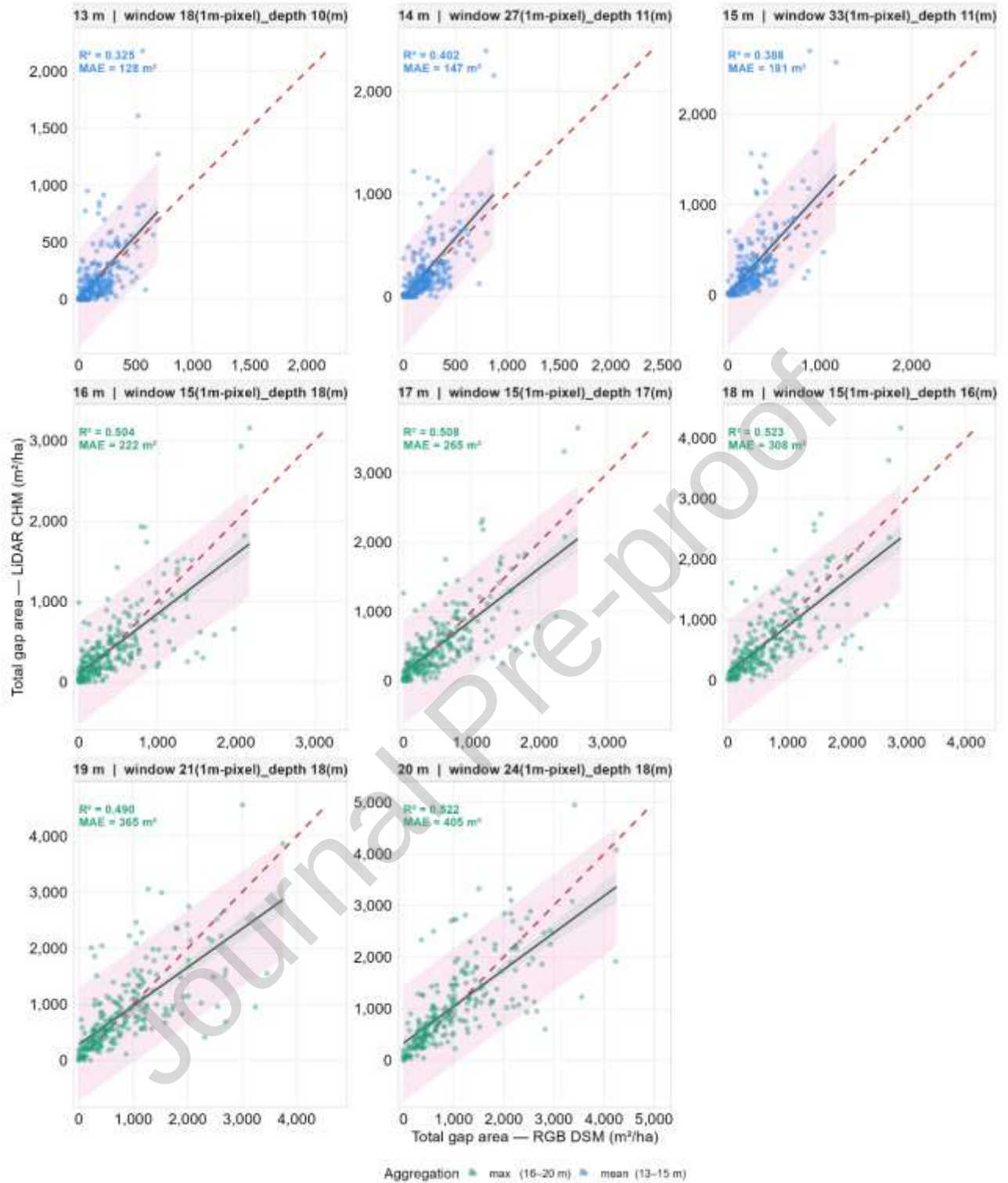


Figure 3. Plot-scale regression of total canopy gap area estimated by LiDAR-CHM against pocket drone RGB DSM for the eight statistically equivalent predictor pairs validated through the grid-search (2,436 pairs combinations tested across 233 1-ha grid cells). Each panel corresponds to one validated canopy height stratum (13–20 m) with its optimal RGB-DSM predictor (window size and depth threshold). Blue points = mean aggregation strata (13–15 m); green points = max aggregation strata (16–20 m). Solid black line = $\ln(\text{CHM} \sim \text{DSM})$ regression; dashed red line = 1:1 identity line; grey shading = 95% confidence interval of the regression; pink shading = 95% prediction interval. R^2 and MAE reported per stratum. MAE = mean ($|\text{CHM} - \text{DSM}|$), computed as the raw instrument-to-instrument discrepancy without model calibration.

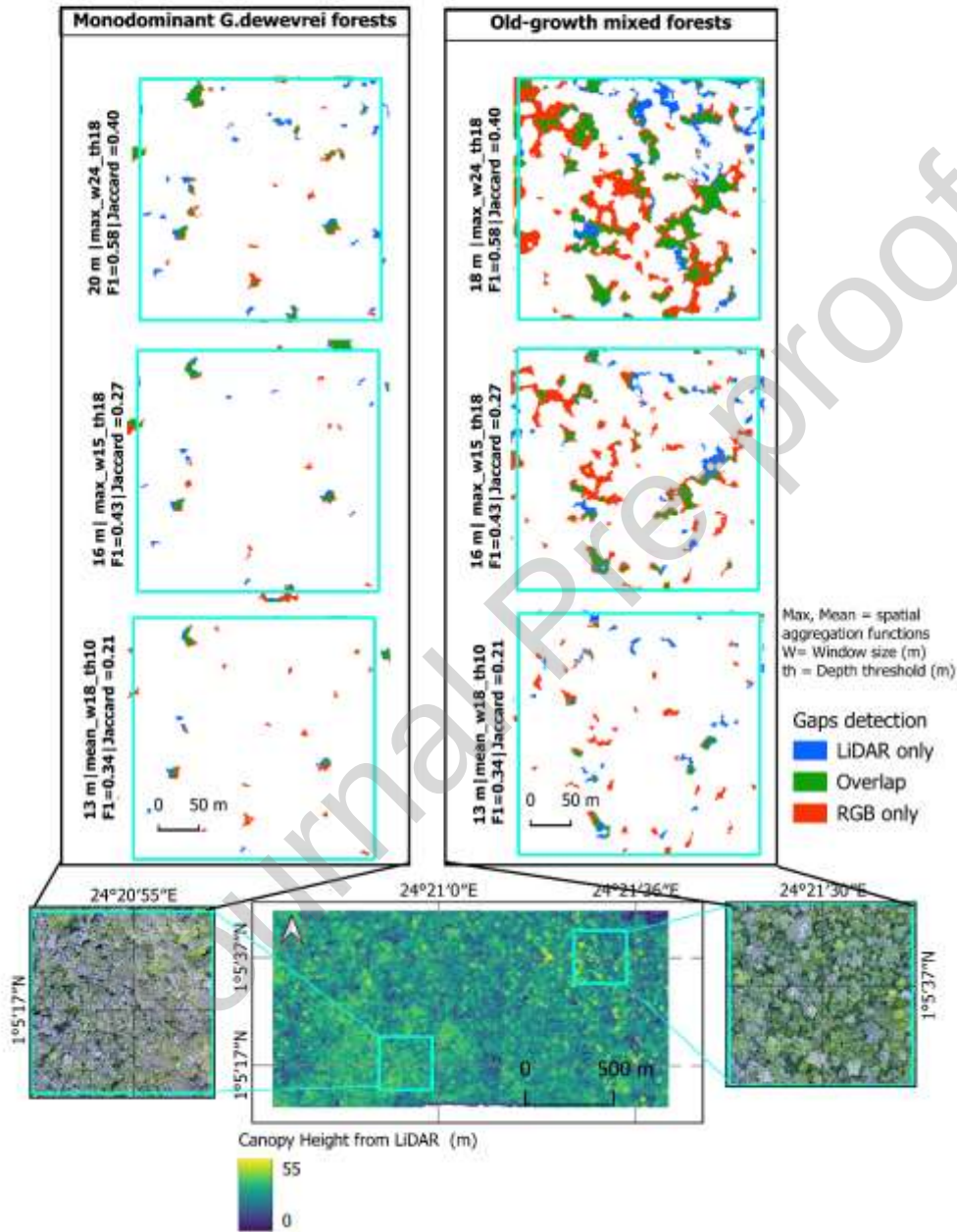


Figure. 4. Spatial co-localisation of canopy gaps detected by LiDAR-CHM and RGB-DSM across three validated canopy height strata (13, 16 and 20 m) in monodominant *G. dewevrei* (left panels) and mixed old-growth forest (right panels) at Lileko study site in Yangambi forest landscape located in the Democratic Republic of Congo. Detection categories: green = co-detected gaps (Overlap, true positives); blue = LiDAR-CHM-only gaps (omission errors, false negatives); red = RGB DSM-only gaps (commission errors, false positives). F1-score and Jaccard index per stratum are shown above each column. Zoom areas are indicated on the LiDAR-derived Canopy Height Model (lower center panel).

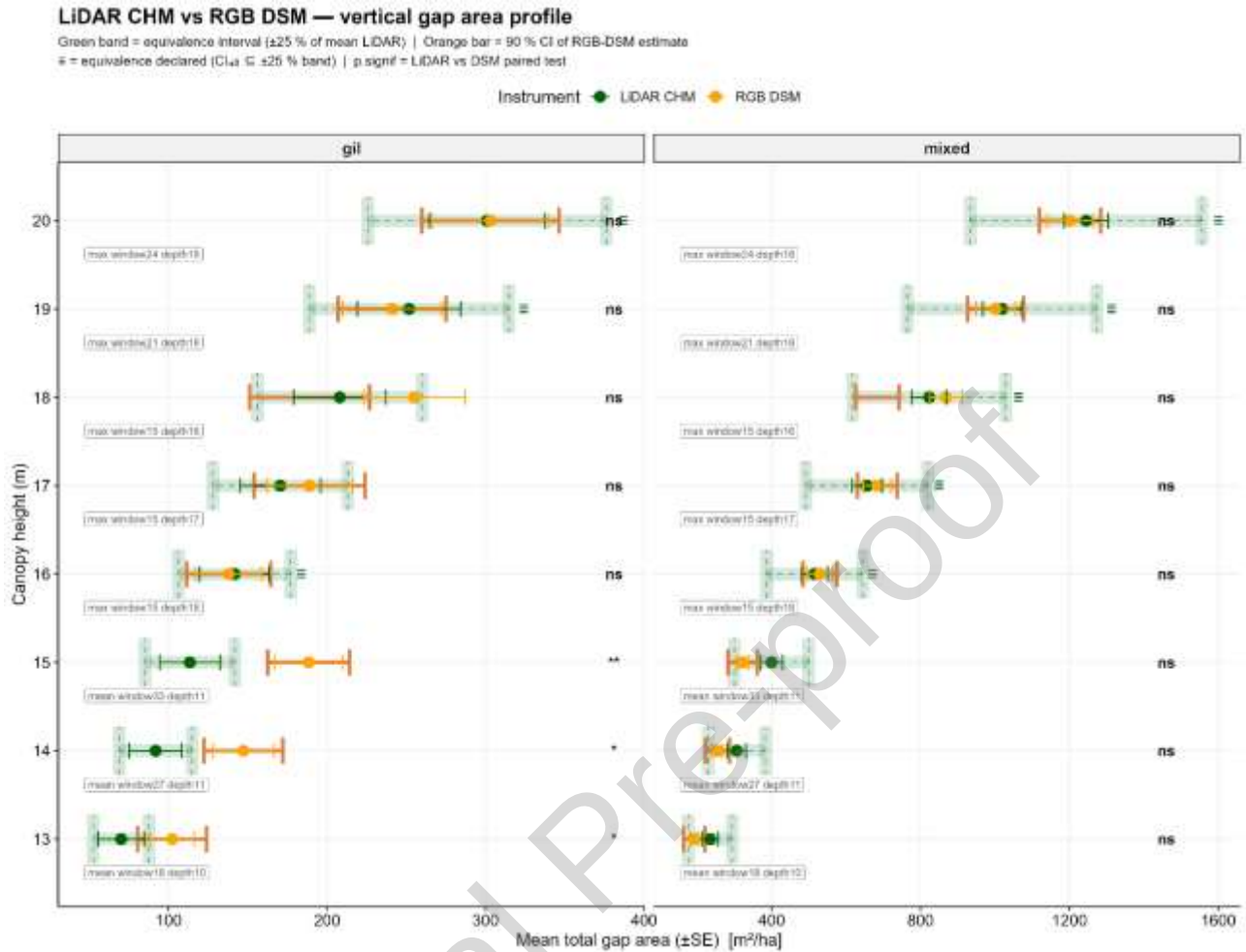


Figure 5. Mean total gap area per plot ($\pm$ SE) for LiDAR CHM (dark green) and RGB DSM (orange) across eight validated canopy height strata (13–20 m), separately for monodominant *G. dewevrei* forest (left panel) and mixed old-growth forest (right panel). Each validated stratum (13–20 m) is associated to its correspondent optimal DSM predictor (aggregation stat, window size and depth threshold). Results of the paired statistical difference test (Wilcoxon signed-rank or paired t-test, p-value > 0.05 = ns) are shown for each stratum and forest type. Green band = equivalence interval [$\text{mean_lidar} \times 0.75$; $\text{mean_lidar} \times 1.25$]; Orange bar = 90% CI of the RGB-DSM estimate; Equivalence is declared when the orange CI falls entirely within the green band.

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.

Highlights

- Pocket drones (<250 g) reliably estimate plot-scale canopy gap area in tropical forests
- Individual gap delineation remains poor across all canopy height strata
- Regression fit improves with canopy height, but absolute errors increase monotonically
- Mixed old-growth forests show stronger RGB–LiDAR compensation than monodominant stands
- Sub-500 USD RGB drones support vertical forest structure and carbon stock and REDD+ monitoring in data-scarce forests.