

Article

Effective UAV Photogrammetry for Forest Management: New Insights on Side Overlap and Flight Parameters

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Abstract: Silvicultural operations such as planting, pruning, and thinning are vital for the forest value chain, requiring efficient monitoring to prevent value loss. While effective, traditional field plots are time-consuming, costly, spatially limited, and rely on assumptions that they adequately represent a wider area. Alternatively, unmanned aerial vehicles (UAVs) can cover large areas while keeping operators safe from hazards including steep terrain. Despite their utility, optimal flight parameters to ensure flight efficiency and data quality remain under-researched. This study evaluated the impact of forward and side overlap and flight altitude on the quality of two- and three-dimensional spatial data products from UAV photogrammetry (UAV-SfM) for assessing stand density in a recently thinned *Pinus radiata* D. Don plantation. A contemporaneously acquired UAV laser scanner (ULS) point cloud provided reference data. The results indicate that the optimal UAV-SfM flight parameters are 90% forward and 85% side overlap at a 120 m altitude. Flights at an 80 m altitude offered marginal resolution improvement (2.2 cm compared to 3.2 cm ground sample distance/GSD) but took longer and were more error-prone. Individual tree detection (ITD) for stand density assessment was then applied to both UAV-SfM and ULS canopy height models (CHMs). Manual cleaning of the detected ULS tree peaks provided ground truth for both methods. UAV-SfM had a lower recall (0.85 vs. 0.94) but a higher precision (0.97 vs. 0.95) compared to ULS. Overall, the F-score indicated no significant difference between a prosumer-grade photogrammetric UAV and an industrial-grade ULS for stand density assessments, demonstrating the efficacy of affordable, off-the-shelf UAV technology for forest managers. Furthermore, in addressing the knowledge gap regarding optimal UAV flight parameters for conducting operational forestry assessments, this study provides valuable insights into the importance of side overlap for orthomosaic quality in forest environments.

Keywords: UAV; SfM; *Pinus radiata*; silviculture; individual tree detection; orthomosaic quality; thinning



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1. Introduction

Thinning is a crucial forestry operation that improves the growth and health of the final crop, and minimises the potential for negative impacts caused by pests or diseases [1]. Post-thinning assessments in operational forestry are critical components of sustainable forest management, enabling forest managers to modify their strategies while ensuring optimal productivity levels [2]. Post-thinning assessments are vital for determining the success of thinning operations in achieving optimal stand density and reducing competition between individuals for sunlight, water, and nutrients, which could be considered as optimising the allocation of growing space [3]. Given the extensive nature of commercial forestry operations, foresters traditionally use subsampling approaches that combine field-based plotting with mathematical and statistical methods to reduce costs and estimation variability

when calculating metrics such as stand density, or forecasting growth and yield [4,5]. However, field-based assessment of stand density is time-consuming, costly, and can be challenging due to remote locations, hindrances, and steep terrain [6,7]. Subsampling generally makes assumptions about the spatial distribution of trees, which can create a bias in stand density predictions if the actual distribution is different [8].

Remote sensing can complement and enhance field-based methods, providing foresters with more accurate and efficient means of monitoring and evaluating their forest resources [9]. Foresters can overcome the limitations of field-based surveys through the use of unmanned aerial vehicles (UAVs), which can cover large areas, by attaining comprehensive and continuous stand-level assessments for stand density [4]. UAVs also overcome many of the shortcomings of other remote sensing techniques, including satellite and conventional manned aircraft captures, which struggle with cloud cover or can be costly when required over smaller areas due to fixed costs or minimum area limits [10]. The ability to capture data flexibly with minimal weather constraints and higher spatial resolutions has made UAVs a popular remote sensing tool in various fields such as agriculture, forestry, mining, and the natural environment [11]. In forestry, UAVs have been applied to a multitude of applications including estimating stockpile volumes [12], mapping forest canopy structures and spectra [13], conducting forest inventories [14,15], identifying invasive plant species [16], fuel characterisation [17], and monitoring insect pests and diseases [18].

Accurate individual tree detection (ITD) is arguably the foundation of forest inventorying and management, yet detection and segmentation of individual trees proves to be quite complex in heterogeneous, multi-layered, and complex forests [19,20]. ITD is integral to an array of forest management and research tasks, including conducting forest inventories [13,21], measuring trials [22], and estimating carbon sequestration [23]. Furthermore, it is crucial to precision forestry, enabling a shift towards an individual-tree-based inventory system [24]. Metrics such as diameter at breast height (DBH), tree height, and volume [25] can be extracted using ITD techniques, yielding valuable information for foresters that helps to determine timing of silvicultural operations such as pruning and thinning.

Laser scanning, also referred to as light detection and ranging or LiDAR, techniques are widely regarded as the optimal method for assessing forest structure. Laser scanners are active sensors, combining multiple measurements of scanned environments to create a point cloud that can be used to derive tree- and stand-level measurements and different structural elements [26]. Airborne laser scanning (ALS) and UAV laser scanning (ULS) enables the scaling of assessments for stand density and tree height to the stand- or forest-level. While ALS can scale forest assessments over significant areas, it is more suited to captures with economies of scale, such as forest-level captures [15]. High costs and capture complexity make ALS less suited to quality control applications for forestry operations at the stand level, where timeliness is crucial [27,28]. ULS enables more timely captures, but despite recent advances in low-cost commercial-grade sensors [25], still has a considerable entry cost for equipment.

UAV structure from motion photogrammetry (UAV-SfM) has emerged as a cost-effective, versatile, and user-friendly method for gathering data on forest structure [27] and inventorying, garnering an increased research interest for both airborne and terrestrial applications [29]. Early research in this field utilised UAV-SfM to produce a dense point cloud of the forest canopy [30], modelling biophysical attributes of a forest, including vegetation spectral dynamics [13] and reconstruction of canopy height models (CHMs; Ref. [31]). In the subsequent years, UAV-SfM techniques have been evaluated for assessing tree height, stem density, basal area, and timber volume derived from UAV-SfM-derived CHMs in homogenous stands of managed boreal forests [14,32].

Although UAV-SfM is an affordable alternative to laser scanning, SfM is a passive sensing technique which is dependent on high-quality input imagery to generate accurate spatial outputs that can provide reliable forest metrics [33]. Factors necessary for successful UAV-SfM data captures in forestry include capturing with sufficient overlap between images, ensuring that features are discernible in sufficient images for optimal

reconstruction, maintaining constant lighting conditions, and avoiding data captures in windy conditions [29]. These considerations underscore the complexity and requirements of effectively applying UAV-SfM photogrammetry to forestry.

Despite the wealth of studies that have assessed the performance of UAV-SfM in forestry, very few studies have been focused on devising the optimal flight parameters for forestry data capture [34–39]. Coniferous plantations provide a homogenous landscape, which can pose challenges for the photogrammetric process [40]. Amongst various capture parameters, the role of ground sampling distance (GSD) and image overlap have previously been highlighted as critically important in this field [34,36]. In Aotearoa, New Zealand (NZ), post-thinning stand density assessments are emerging as an important application for UAV-SfM; however, no research could be identified that has systematically evaluated optimal parameters for this application.

This study had two objectives: (1) The primary objective was to determine the optimal flight parameters for a prosumer-grade UAV; namely, the forward overlap, side overlap, and flight altitude required to create accurate UAV-SfM outputs of a recently thinned stand of *Pinus radiata* D. Don. To this end, a site was sought that would demonstrate the technology in a typical production forestry setting. (2) A secondary objective was to evaluate the performance of a commonly utilised ITD algorithm applied to the optimal UAV-SfM data, as determined by objective one. The resulting stand density was then compared to a reference dataset, derived from ULS, which represents current best practice.

2. Materials and Methods

The study site selected was a 30 ha stand of *P. radiata* in Mohaka Forest, managed by Pan Pac Forest Products Ltd. in Hawke's Bay, NZ (Figure 1). This site was chosen for its steep terrain and its location within a homogenous, monoculture plantation, which is characteristic of a radiata plantation in NZ. Mohaka Forest has a mean annual rainfall of 1365 mm [41], which peaks between May and September, prior to the time that UAV data were acquired. Elevation of the site ranged between 314 m and 454 m above mean sea level, with mean slope values of 22.5°, ranging from 0 to 63.2°. Prior to data acquisition, the stand was thinned using a mixture of the waste thinning (trees felled manually and left in situ to improve the value of the remaining trees; Ref. [42]) and production thinning (trees mechanically felled and extracted for commercial products; Ref. [43]) techniques, depending on the slope class. No field inventory data were collected and thus reference data were obtained from the ULS data by manually cleaning individual tree detections derived from the point cloud (see Section 2.3.2). From the ULS data, 8452 trees were counted, with a mean height of 22.5 m, and a height range of 12.4–30.6 m.

2.1. Data Acquisition

2.1.1. Ground Control

To ensure the accuracy of the three-dimensional (3D) photogrammetric reconstruction, nine ground control points (GCPs) were established across the study site comprising seven physical GCPs and two synthetic GCPs. Physical GCPs were made from 1 m² plastic targets covered with four highly contrasting, retro-reflective squares for maximum visibility in both the ULS and UAV-SfM datasets (Figure 2). For safety reasons, synthetic GCPs in the form of tree stumps that were clearly visible in the ULS and UAV-SfM point clouds were employed in steep and inaccessible parts of the site. Due to poor global navigation satellite system (GNSS) reception under the forest canopy, GCP centre coordinates were extracted from the ULS point cloud. The reported post-processed precision of the position for each point in the ULS point cloud resulted in a route mean square error (RMSE) of 0.6, cm for the X and Y values and 0.04 cm for the Z values. In the context of the GCP centre coordinates extracted from the ULS point cloud, these values represent the relative error between the GCP centres and the ULS base station position.

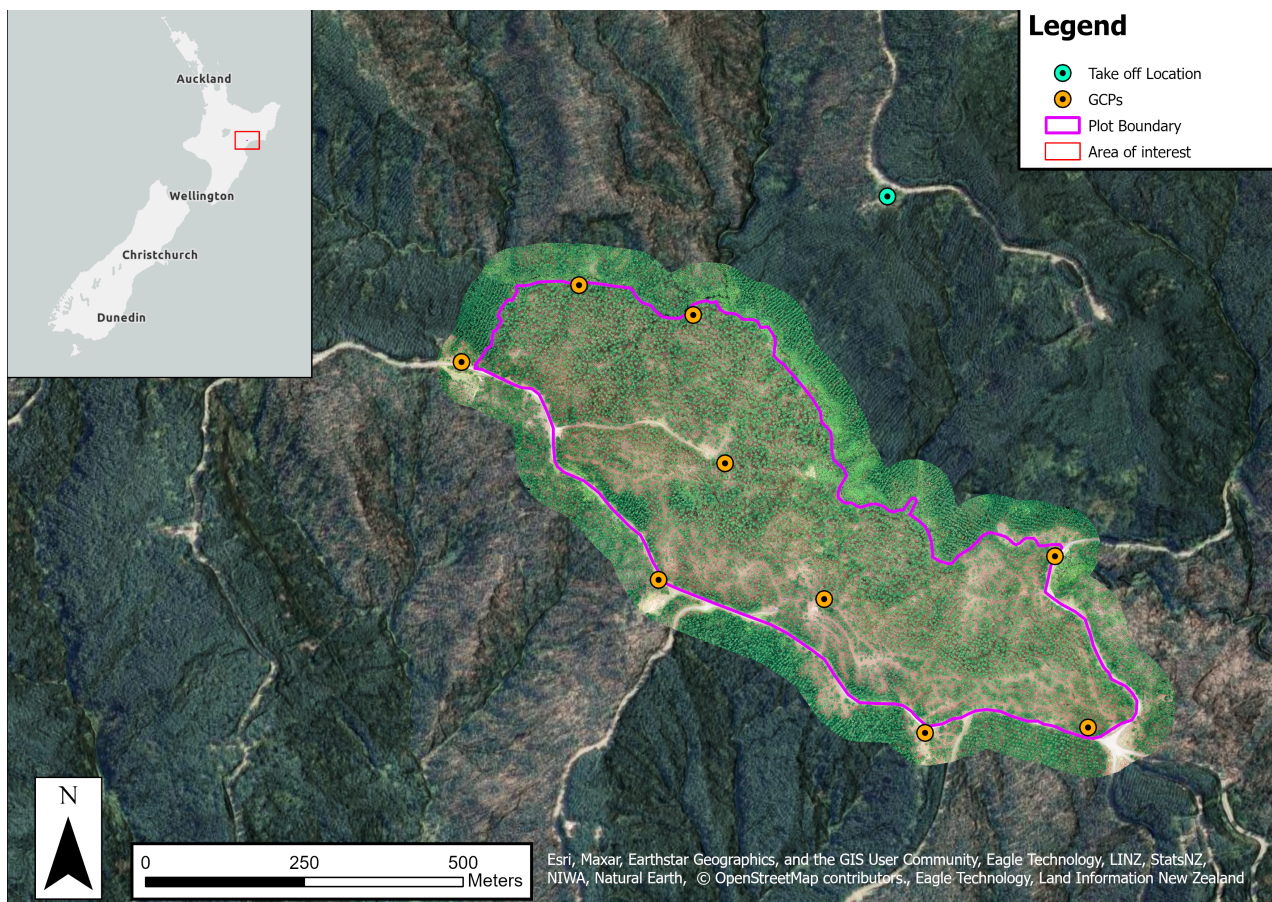


Figure 1. Location of the study site within NZ (insert), with the optimal orthomosaic overlaid on a mixed topographic/aerial image of the region. The stand boundary is indicated by the purple line, GCP locations are in orange, and the take-off location is in cyan.



Figure 2. Image of a GCP coated with reflective material and painted in a high contrast pattern for identification in the ULS and UAV-SfM datasets.

2.1.2. UAV-SfM

High-resolution visual (red, green, blue/RGB) imagery in this study was obtained in two separate visits to the site between 27 September and 8 October 2022 with a DJI Phantom 4 Pro (P4 Pro; DJI Ltd., Shenzhen, China; Figure 3a). This prosumer-grade UAV extensively

used in the forestry industry features a 1-inch 20-megapixel camera. The flight planning and control were carried out using the Map Pilot Pro software version 5.4.8 (Drones Made Easy, San Diego, CA, USA) using a 1 m digital terrain model (DTM) of the study site which was provided by the forest manager. Maintaining visual line of sight (VLOS) in forested environments presents several difficulties, often necessitating the use of high vantage points for UAV operations [44]. As in many other countries, the NZ Civil Aviation Authority (CAA) has implemented VLOS rules for UAV operations in order to maintain the safety of other airspace users, as well as the public and property. A Mobile Elevated Work Platform (MEWP) was therefore employed in order to maintain VLOS during UAV data captures for this study (Figure 3c).



Figure 3. Images of the UAVs utilised in this study: (a) the DJI Phantom 4 Pro; (b) the DJI Matrice 300 RTK with a DJI L1 sensor. (c) Shows the flight crew operating UAVs from an MEWP to maintain VLOS.

To assess the impact of GSD/altitude and image overlap, 18 flight missions with different image overlap combinations were flown at two altitudes (80 m and 120 m above ground level (AGL), producing spatial products with GSDs of ~2.2 cm and ~3.2 cm, respectively. These altitudes were selected as the 120 m (400') AGL is the typical maximum altitude for UAV operations without seeking regulatory approval in most jurisdictions [44] and operationally, foresters may fly at lower altitudes to optimise GSD. The 80 m AGL was considered to be a typical altitude that would improve GSD, whilst maintaining safe canopy clearance and accommodating undulating terrain. Previous research has demonstrated the importance of forward overlap for 3D modelling, with an optimal forward overlap of 95% being reported by multiple studies [34,36,45]. However, prior studies observed significant increases in flight time [36], data processing time [34,45], and a negative impact on positional accuracy [34,35] when conducting flights above 90% forward overlap. As this study was focused on determining the optimal flight parameters for operational forestry, 90% was set as the upper limit for forward overlap. Following the recommendations of Torres-Sánchez et al. [45], we used a minimum overlap of 80% as our lower boundary for forward overlap to achieve model completeness and tree height accuracy. Side overlap has received very little consideration in the literature since it has previously been demonstrated to have minimal impact on 3D model reconstruction [34]. No literature could be found with recommendations for side overlap settings for deriving accurate two-dimensional (2D) spatial products. Therefore, as this study was focused on the impact of flight parameters on 2D orthomosaics, a forward overlap range between 80% and 90% was assessed for both forward and side overlap. Flights were conducted at speeds of 4 m/s and 5 m/s for the

80 m and 120 m AGL flights, respectively, to optimise capture speed, whilst minimising the impact of motion blur. All images were captured with the camera aligned in the nadir position. Flight parameters can be found in Table 1.

Table 1. Overview of flight missions detailing image overlap settings, GSD, altitude, and the quantity of images per dataset.

Mission ID	Planned GSD (cm/px)	Actual GSD (cm/px)	Altitude (m AGL)	Forward Overlap (%)	Side Overlap (%)	No. of Images
1	2.19	2.34	80	80	80	975
2	2.19	2.32	80	80	85	1489
3	2.19	2.29	80	80	90	2265
4	2.19	2.27	80	85	80	1464
5	2.19	2.24	80	85	85	1856
6	2.19	2.28	80	85	90	2747
7	2.19	2.23	80	90	80	2047
8	2.19	2.29	80	90	85	2758
9	2.19	2.29	80	90	90	4199
10	3.2	3.43	120	80	80	804
11	3.2	3.4	120	80	85	920
12	3.2	3.35	120	80	90	977
13	3.2	3.35	120	85	80	710
14	3.2	3.33	120	85	85	930
15	3.2	3.41	120	85	90	1266
16	3.2	3.23	120	90	80	975
17	3.2	3.33	120	90	85	1229
18	3.2	3.32	120	90	90	1875

2.1.3. ULS

ULS data were collected at the site on 18 September 2022 using a DJI Matrice 300 (M300) RTK (DJI Ltd., Shenzhen, China) equipped with a DJI Zenmuse L1 (DJI Ltd., Shenzhen, China) laser scanner (Figure 3b). The DJI Zenmuse L1 is a solid-state scanner with a detection range of up to 260 m and comprises a 20-megapixel RGB camera with a 1-inch CMOS sensor, capable of capturing high-resolution imagery for colourising the point clouds. This assembly was flown over the study area at 80 m AGL, with flight line spacing and speed calculated to ensure 85% forward and side overlap for the integrated RGB camera, improving the quality of point cloud colourisation. DJI Pilot version 1.1.5 (DJI Ltd., Shenzhen, China) was used for flight planning and operations. DJI Terra version 3.6.6 (DJI Ltd., Shenzhen, China) was subsequently used for processing the raw LiDAR data into a point cloud in LAS format. The final point density of the ULS point cloud was 1970 ppm².

2.2. Data Processing

2.2.1. Photogrammetric Processing

The images from all flight campaigns were processed in Pix4Dmapper software v4.8.1. (Pix4D, Lausanne, Switzerland) with spatial outputs processed to the NZGD2000/New Zealand Transverse Mercator 2000 (EGM 96 Geoid) coordinate system. GCPs were utilised and marked in at least 20 images for each GCP and subsequently more through the Automatic Marking function in Pix4D. All data were processed on an Intel® Core™ i9-7940X CPU (3.10 GHz; Intel Corporation, Santa Clara, CA, USA), equipped with 256 GB of RAM and an NVIDIA™ GeForce RTX 3090 GPU (NVIDIA Corporation, Santa Clara, CA, USA). Processing within Pix4D followed these three basic stages: 1. Initial processing, in which

keypoint matching and camera model optimisation is performed, with a sparse point cloud being created; 2. Point cloud and mesh generation, in which the point cloud is densified, enhancing the 3D reconstruction accuracy, with a dense point cloud being output at this stage in the LAS format; 3. Digital surface model (DSM) orthomosaic and index generation, in which a DSM is created from the 3D reconstruction, and an orthomosaic is generated. From this final stage, an orthomosaic in the TIFF format was the only output. The standard settings for each stage were only deviated from in the following places: in Phase 1, geometrically verified matching was turned on and, in phase 2, the minimum number of matches was set to two. Using the SfM workflow described above, 18 orthomosaics and their corresponding points clouds were produced.

2.2.2. Point Cloud Processing

Point clouds derived from UAV-SfM and ULS were processed in R version 4.2 [46] using the *lidR* package version 4.0.3 [47]. As the *lidR* package is capable of parallel computing, the point clouds were first tiled, then the tiles were read into R as an *LAScatalog*. A 10 m virtual buffer was included around each tile to mitigate edge effects in the subsequent processing steps and *LAX* files were generated for each stage to index the *LAS* dataset and enhance speed of parallel processing. A processing workflow was then implemented in *lidR* with the following steps. First, the point cloud was denoised using an Isolated Voxel Filtering (IVF) algorithm, ground points were classified using Cloth Simulation Filtering (CSF; Ref. [48]). Ground points were then interpolated into a DTM using a Triangulated Irregular Network (TIN) algorithm. A resolution of 1 m was settled on through a process of trial and error, as it was observed that finer resolutions increased noise in the resulting DTM. A LiDAR-derived DTM is generally considered more accurate than an SfM-derived DTM over mature forests. This is due to the increased canopy penetration, continuous ground coverage, and reduced occlusion effects of LiDAR point clouds compared to photogrammetric point clouds [49]. In addition, it is a known fact that a majority of operational foresters now have access to high-resolution LiDAR terrain models for their estates. Therefore, the ULS-derived DTM was utilised to normalise the ULS and UAV-SfM point clouds. A pit-free canopy height model (CHM; Ref. [50]) with a resolution of 0.1 m was produced from each normalised point cloud by using the *pitfree* algorithm implemented within the *lidR* package. The resulting CHMs were then post-processed to smooth the surface, removing any noise, negative values, and filling no data values.

2.3. Data Analysis

2.3.1. Orthomosaic Quality Analysis

Orthomosaics were loaded into a geographic information system (GIS) platform. Artefacts, such as blurred or distorted areas caused by the misalignment of pixels resulting from the orthomosaic generation process [51,52], were then manually demarcated as polygons in each orthomosaic, based on visual interpretation. Examples of the artefacts encountered are displayed in Figure 4. The combined area, in ha, of the polygons representing orthomosaic errors was then calculated for each orthomosaic. This was expressed as the area clear of artefacts, from which the percentage of total area clear of artefacts was calculated and represented as the measure of orthomosaic quality. As production of the 2D orthomosaic relies on the 3D surface from the dense point cloud, its quality is dependent on the quality of the sparse and dense cloud stages of the photogrammetric process [51]. For this study, it was deemed that assessing errors in the orthomosaic would provide a simple means for assessing the quality of both the 2D and 3D products from each dataset. The point cloud dataset associated with the orthomosaic that was determined to be the most complete and captured in an optimal flight time was then utilised for further 3D data analysis.

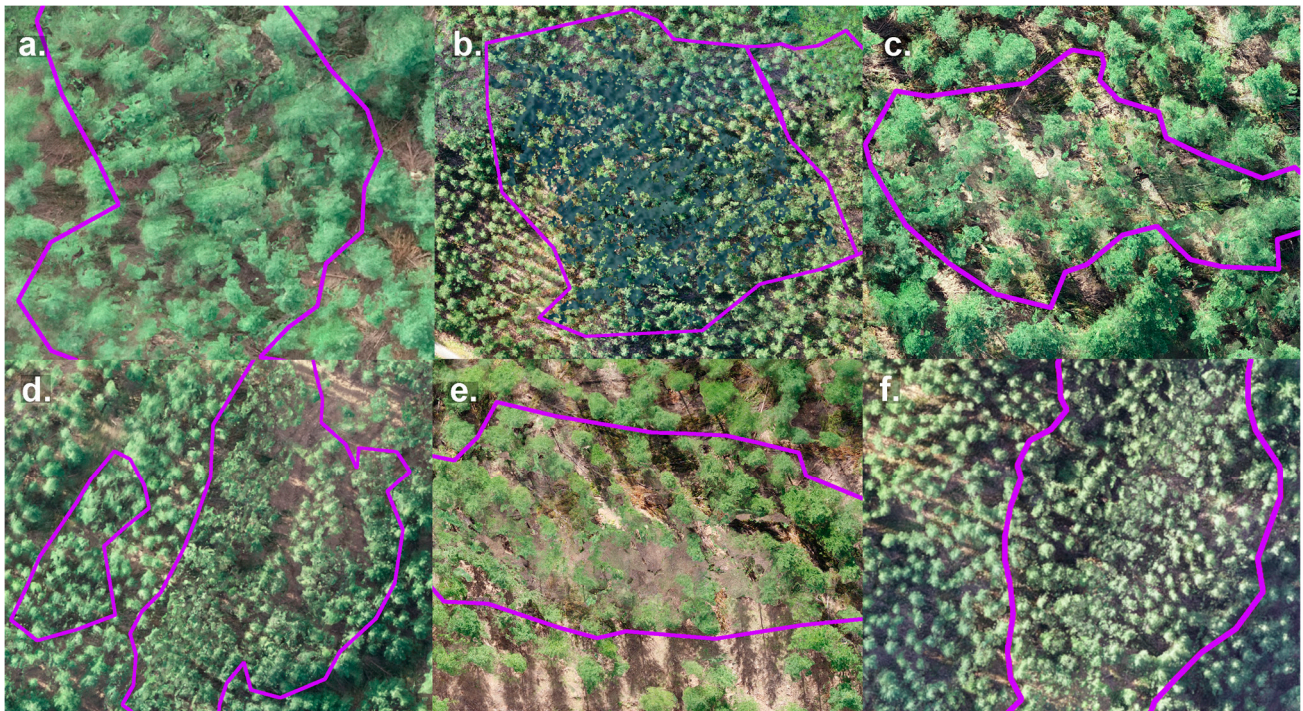


Figure 4. Examples of image artefacts encountered when annotating the orthomosaics: (a,d,e) “blurring” and “smudging” effects; (b,d) “tearing” or “breaking” discontinuities within the image; (c,e) “ghosting”, in which the displacement of ground and canopy pixels results in transparent tree canopies; (d,f) in some areas tree canopies were fragmented into smaller chunks.

2.3.2. Individual Tree Detection

Tree peaks were detected on the CHMs derived from both ULS and the optimal UAV-SfM model through a local maxima filtering (LMF; Ref. [53]) approach, implemented within *lidR* utilising a variable window size. A custom variable window size function was written in R and applied with the *find_trees* function of *lidR*. The window size was increased by 1 m for every 10 m of height starting at 3 m at ground level and increasing to a maximum of 6 m when the search was at 30 m. Due to the even-aged nature of the stand, trees were assumed to be of approximately even height, therefore a minimum tree height of 12 m, below which the algorithm did not perform detection, was set to reduce erroneous detections. The detected tree peaks were then written to a shapefile for further analysis.

Detected peaks were compared to a reference dataset that was created by manually cleaning the results of the peak detection on the ULS-derived CHM. This entailed visual assessment of the detected tree peaks in a GIS platform, removing any false positive detections and manually inserting any false negatives. The total number of trees recorded in the reference dataset was 8452. This dataset served as the comparative benchmark for evaluating the accuracy of automatic peak detection in CHMs derived from both the UAV-SfM and ULS data.

2.4. Statistical Analysis

The results of the peak detection were statistically analysed by calculating recall (R ; 1), precision (P ; 2), and F-score (3) using the following equations:

$$R = \frac{TP}{TP + FN} \quad (1)$$

$$P = \frac{TP}{TP + FP} \quad (2)$$

$$\text{F-score} = 2 \times \frac{r \times p}{r + p} \quad (3)$$

where TP (true positives) is the number of trees correctly detected, FN (false negatives) is the number of actual trees that were not detected by the ITD algorithm, and FP (false positives) is the number of trees falsely detected by the ITD algorithm that do not exist on the ground. F-score is the harmonic mean of recall and precision. All three metrics range between zero and one, with values closer to one representing higher accuracy.

3. Results

3.1. Orthomosaic Quality

The results of the assessment for artefacts in the various orthomosaics produced in this study reveal that the overall quality of the spatial products was high, with little variation, ranging from 83% to 100% free from artefacts (Table 2). Image quality was higher overall for the 120 m AGL datasets, with the area free of artefacts ranging from 87.3%–100%, compared with 83%–100% for the 80 m AGL datasets (Table 2).

Table 2. The results of the orthomosaic quality assessment, showing areas clear of artefacts for each of the flight plans in ha and as a percentage of the total area, along with the flight duration.

Overlap (Fwd:Side)	Area Clear of Artefacts (ha)		Area Clear of Artefacts (%)		Flight Duration (mins)	
	80 m AGL	120 m AGL	80 m AGL	120 m AGL	80 m AGL	120 m AGL
80:80	24.9	26.18	83	87.3	98	58
80:85	27.47	28.99	91.5	96.6	150	84
80:90	29.65	30	98.8	100	213	118
85:80	29.75	26.82	99.2	89.4	98	58
85:85	30	29.65	100	98.8	150	84
85:90	30	30	100	100	213	118
90:80	30	27.21	100	90.7	134	60
90:85	27.55	30	91.8	100	187	87
90:90	28.76	30	95.9	100	270	111

Results for the 120 m AGL datasets display a clear increase in orthomosaic quality in line with an increase in image overlap (Figure 5). The increase in side overlap clearly demonstrated a greater influence over image quality than forward overlap, with a range in orthomosaic quality for each forward overlap group of 9.3%–12.7%, compared with 0%–3.4% for the side overlap groups (Table 3).

For the 80 m AGL datasets, the trend is not as distinct (Figure 5). The lowest quality orthomosaic was produced by the flight plan with the lowest overlap (80:80) and the highest quality orthomosaics were produced by orthomosaic with a minimum side overlap of 85%. There is a general trend for the quality to increase as the side overlap increases, which is demonstrated well by the 80% forward overlap datasets. There are anomalies, however, with the 85% and 90% forward overlap datasets. Both had an increase in quality from a side overlap of 80% to an 85% side overlap, but then had more artefacts for the 90% side overlap datasets.

Table 3. Matrix showing the accuracy for each combination of forward and side overlap for the 120 m AGL datasets, and the range found within each overlap group.

Forward Overlap	Side Overlap			
	80%	85%	90%	Range (%)
80%	87.3	96.6	100	12.7
85%	89.4	98.8	100	10.6
90%	90.7	100	100	9.3
Range (%)	3.4	3.4	0	-

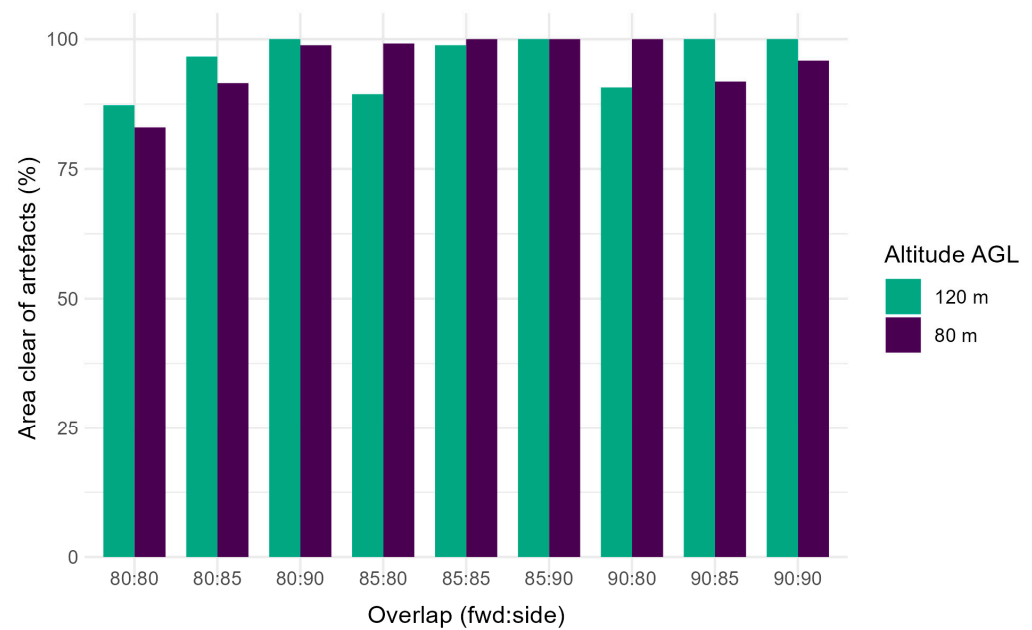


Figure 5. Bar graph plotting the percentage area of each orthomosaic free from artefacts for each flight plan, coloured by altitude. The missions are arranged by overlap with the lowest on the left and highest on the right.

Several overlap combinations created orthomosaics that were devoid of artefacts, including 85:85, 85:90, and 90:80 at 80 m, and 80:90, 85:90, 90:85, and 90:90 at 120 m (Table 2). The optimal results balancing data quality with capture efficiency were achieved with a 90% forward and 85% side overlap at 120 m, with the shortest flight duration to attain a dataset devoid of artefacts being 87 min (Table 2 and Figure 6). The point cloud from this model is further evaluated in Section 3.2. Correlations between forward and side overlap with image quality were significantly higher for side overlap than forward overlap, with R^2 values of 0.81 and 0.04, respectively (Figure 7).

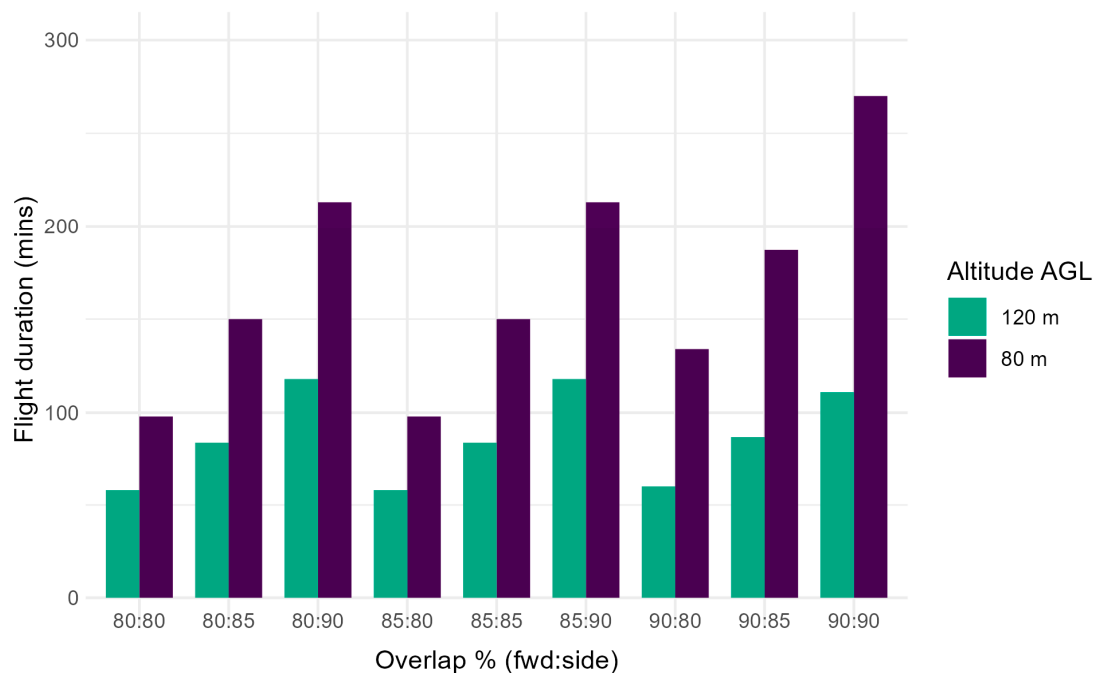


Figure 6. Comparison of flight time duration between different overlap flight missions, coloured by altitude.

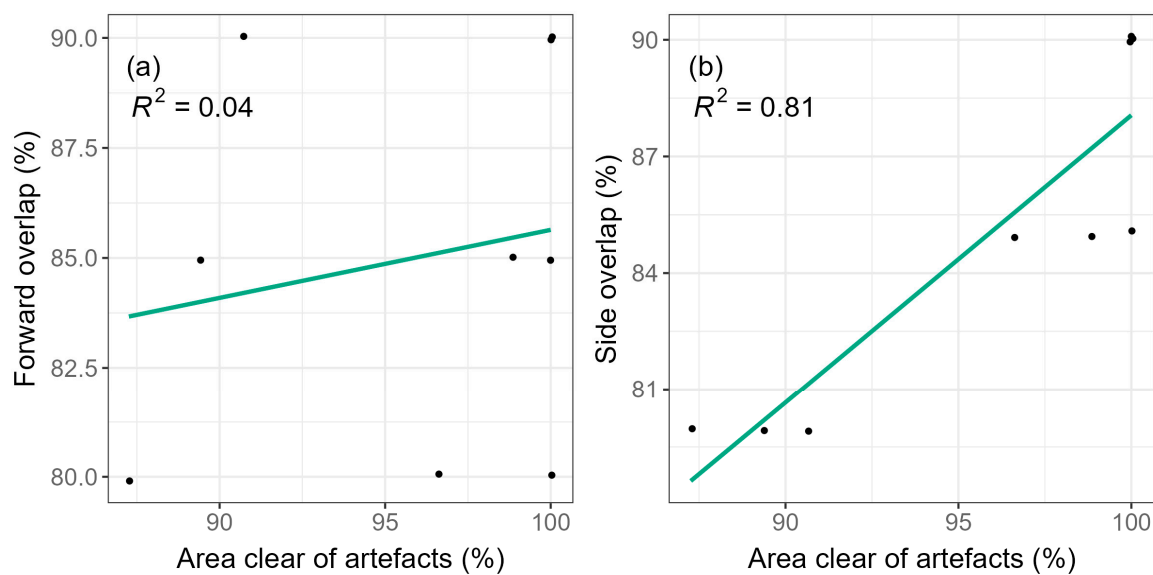


Figure 7. Correlations between (a) forward overlap and (b) side overlap with the area of each orthomosaic that was clear of artefacts. The teal line represents the linear model between variables, and point locations are jittered so that multiple points with the same value are visible.

3.2. Performance of Individual Tree Detection (ITD)

Peak detection from the UAV-SfM-derived CHM yielded high values for recall (0.85), precision (0.97) and F-score (0.91; Table 4). The ULS-derived CHM provided higher levels of recall (0.94) and F-score (0.94); however, lower precision (0.95; Table 4). ITD performed well for both technologies, although ULS performs slightly better.

Table 4. The results of the ITD algorithm after a manual clean-up process on the UAV-SfM-derived CHM (90:85 at 120 m) and ULS-derived CHM.

	TP	FP	FN	Recall	Precision	F-Score
UAV-SfM	7203	207	1249	0.85	0.97	0.91
ULS	7921	439	531	0.94	0.95	0.94

4. Discussion

4.1. UAV-SfM Orthomosaic Quality

Overall, the quality of the orthomosaics obtained from the UAV-SfM data was high, with the lowest quality datasets displaying 83% of the area of interest free from artefacts. This matches findings in the literature that have demonstrated that a minimum of 80% forward overlap is required for the creation of accurate 3D photogrammetric products of trees. Forward overlap has been demonstrated to be a crucial component for 3D reconstruction of forest scenes, with studies recommending a 90%–95% forward overlap as the optimal setting for 3D modelling [34–36,45]. The results of this study support this, particularly for the 120 m AGL datasets, finding a positive association between forward overlap and image quality. However, in this study, a significantly stronger correlation was observed between side overlap and image quality (Figure 7). Previously, the literature has demonstrated a minimal impact of side overlap on 3D modelling results [34,35], although another study found that the number of tie points between images increased exponentially with side overlap [39].

Central perspective images, such as those captured by the P4 Pro feature several distinctive geometric distortions; namely relief displacement, and radial and tangential (de-centering) distortions [54]. Relief displacement results in objects nearer to the camera being displaced away from the principal point of the image, which results in an outward-leaning appearance, most pronounced for tall objects distant from the principal point. The effect of relief displacement is especially prominent in forest scenes, where treetops are closer

to the sensor and are therefore displaced further away from the principal point. Relief displacement is inherent to central perspective images and its magnitude (d) is a function of the height above the datum (typically the ground plane) of features imaged in the scene (h), the radial distance of those features from the image principal point (r), and the flying height of the aircraft (H). Relief displacement (d) can be calculated using the following equation:

$$d = \frac{r \times h}{H} \quad (4)$$

In accordance with Equation (4), the magnitude of relief displacement increases radially from the principal point, where it is equal to zero, and is greatest at the outer margins of the image [54]. The concept of relief displacement is furthermore demonstrated in Figure 8. While correcting for relief displacement is a fundamental objective of the photogrammetric processes of orthorectification and orthomosaic generation, severe relief displacement may act to impair key steps of photogrammetric processing. Specifically, the generation of tie points that facilitate the relative orientation of the image block, and stereo-matching that facilitates dense point cloud extraction during aerial-triangulation. These two steps are likely to perform sub-optimally when severe relief displacement means that coincident points are not recognised across overlapping images or become completely occluded. When the magnitude of relief displacement is large, and the view of tall objects in the image is increasingly oblique, the potential for blunders in the tie point extraction process increases [55,56]. This effect may be convoluted with and amplified by radial distortion arising from camera lens design and imperfections, particularly barrel distortion which also results in an outward displacement of objects from their true location. Barrel distortion commonly affects the cameras carried aboard prosumer-grade UAVs.

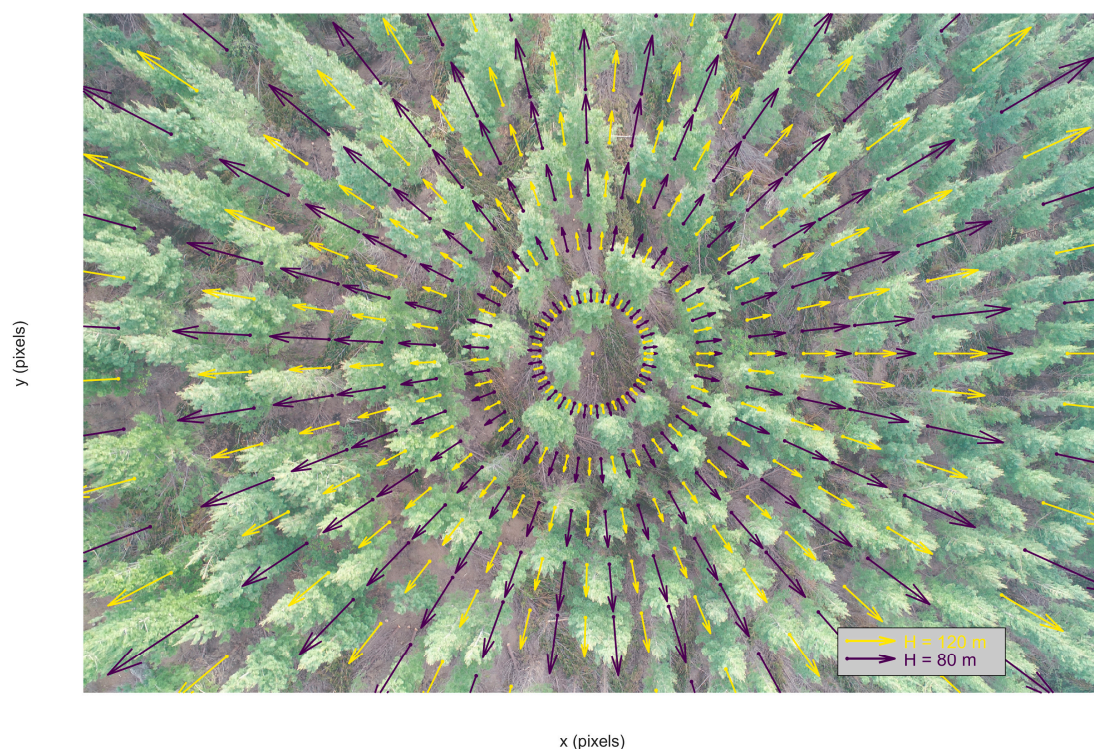


Figure 8. Calculated relief displacement for an object (e.g., a tree) of height (h) 20 m, within imagery captured at a flying height (H) of 80 m (purple vectors) or 120 m (yellow vectors) above ground level. The displacement vectors in the legend are scaled to an image distance of 100 mm. Relief displacement vectors are plotted on an image captured at ~80 m AGL and at image radial distances of 0, 100, 200, 300, 400, 500, 650, and 900 mm from the principal point, which for this illustration is assumed to coincide with the image centre.

The imaging sensor carried aboard the P4 Pro, like many comparable UAV sensors, features a rectangular aspect ratio, causing a larger magnitude of relief displacement across the X axis (width) than along the Y axis (height) of the image frame. This creates a circular region with a near-nadir viewing geometry within the image centre, with increasingly oblique, and for some targets occluded, views towards the image edges (Figure 8). A greater percentage of the image width is outside of this region than the image height, consequently, the same overlap values would move the near-nadir region further sideways than forward, resulting in less overlap of near-nadir features (Figure 9). Therefore, it is reasonable to assume that side overlap would have a greater impact than forward overlap on orthomosaic quality. This would result in fewer tie points between images, as demonstrated in Seifert et al. [39]. As side overlap could be paramount to ensuring sufficient features for the feature matching algorithms to effectively match images, future research could explore the relationship between feature matching and flight parameters. The choice of software has previously been proven to contribute to the quality and accuracy of these outputs [57] and, given that the software used in this study (Pix4D) employs proprietary algorithms, exploration of open-source alternatives like MicMac [58] might enhance understanding in this field.

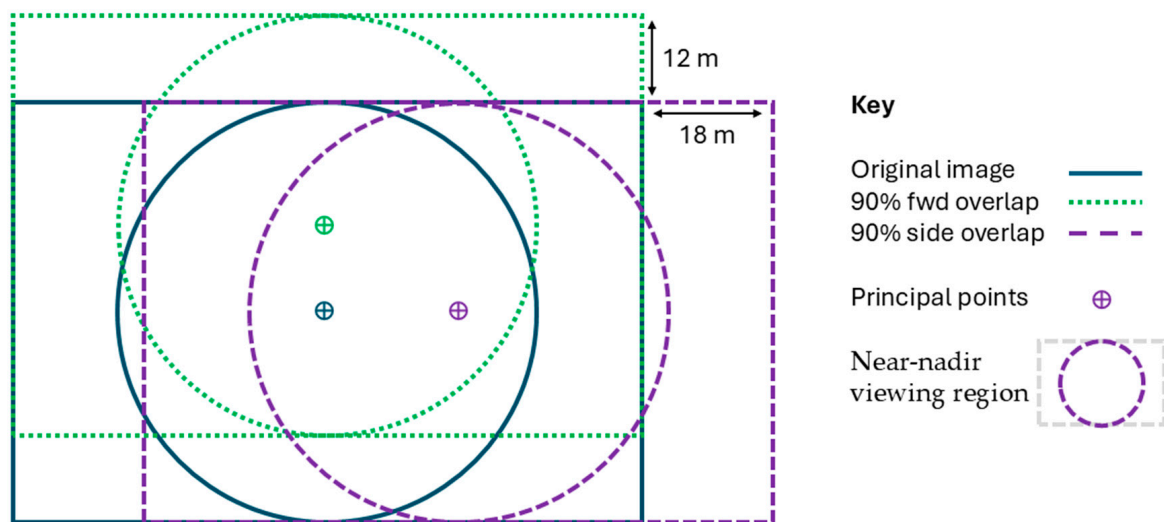


Figure 9. Demonstration of the greater impact of side (dashed purple line) than forward (dotted green line) overlap on movement of the near-nadir viewing region of an image (solid teal line). Movement values are based on P4 Pro camera at a height of 120 m, with an image footprint of 180×120 m.

The datasets captured at 120 m AGL displayed a clear positive correlation between orthomosaic quality and image overlap; however, this pattern was not so obvious with the 80 m AGL datasets. The results for the 80 m AGL datasets, overall, produced slightly more anomalies than the 120 m AGL datasets of the same overlap combinations. Forests are complex and dynamic ecosystems, and the repetitive pattern of trees in a plantation forest stand, the uniform texture of the canopy, and potential for tree movement makes feature matching difficult [40]. Flying at a greater altitude leads to the better performance of the feature matching algorithms as a greater number of tree crowns, and therefore, unique patterns and features, can be determined from the imagery. Flying higher over forested areas also decreases the effect of relief displacement. This in turn increases the number of common features between adjacent images to match, leading to a higher number of keypoints, and consequently more automatic 3D tie points. This directly impacts the quality of the dense point cloud, and the resulting orthomosaic. Our results generally support this with the 80 m AGL datasets overall being of lower quality than the 120 m AGL datasets. There were, however, a few anomalies observed in the 80 m AGL datasets with 85% and 90% forward overlap, where the fewest anomalies were not produced from flights with the highest side overlap. This pattern deviates from the trends observed in flights conducted at

120 m under the same overlap settings. Possible reasons for these anomalies include the increased flight durations at lower altitudes, the time of day, and the impact of missing images due to a triggering error in the craft. Although the affected areas were re-flown to cover this, a mismatch in flight line spacing potentially caused larger gaps between images and subsequently errors in the orthomosaic generation process. The 80 m AGL 90:85 and 90:90 overlap flights were the longest and fourth longest flight lines with durations of 270 and 187 min, respectively. These longer flights both had extensive flight windows stretching from ~8 am to midday.

Weather is another factor that is known to impact on orthomosaic quality [59]. The weather conditions for the data capture period varied from sunny to overcast, and shadows were observed in the orthomosaics resulting from the 80 m AGL 90:85 and 90:90 flights (Figure 10). Although efforts were made to conduct flights under consistent weather conditions, these two missions had long flight durations, leading to uneven conditions over time and resulting in the observed shadows. The presence of occlusion and shadow within forest landscapes can lead to uneven illumination across captured images, compromising image quality and reducing the accuracy of information that can be extracted from these images [33]. The presence of shadows has a negative impact in many image processing tasks such as image classification and causes detection inaccuracies in various computer vision applications [60]. Inconsistent illumination also affects the transfer of spectral information from the matching of image features to the 3D ATPs [34]. Thus, varying illumination conditions should be avoided as far as possible. As no data were collected on lighting conditions in this study, it cannot be verified that lighting conditions did cause the anomalies seen in the data. Future study should be focused on assessing the impact of lighting conditions, particularly the interplay between shadow, solar angle, and light intensity [34], and their effect on the creation of 2D and 3D photogrammetric products in plantation forests to address this crucial gap in the research.

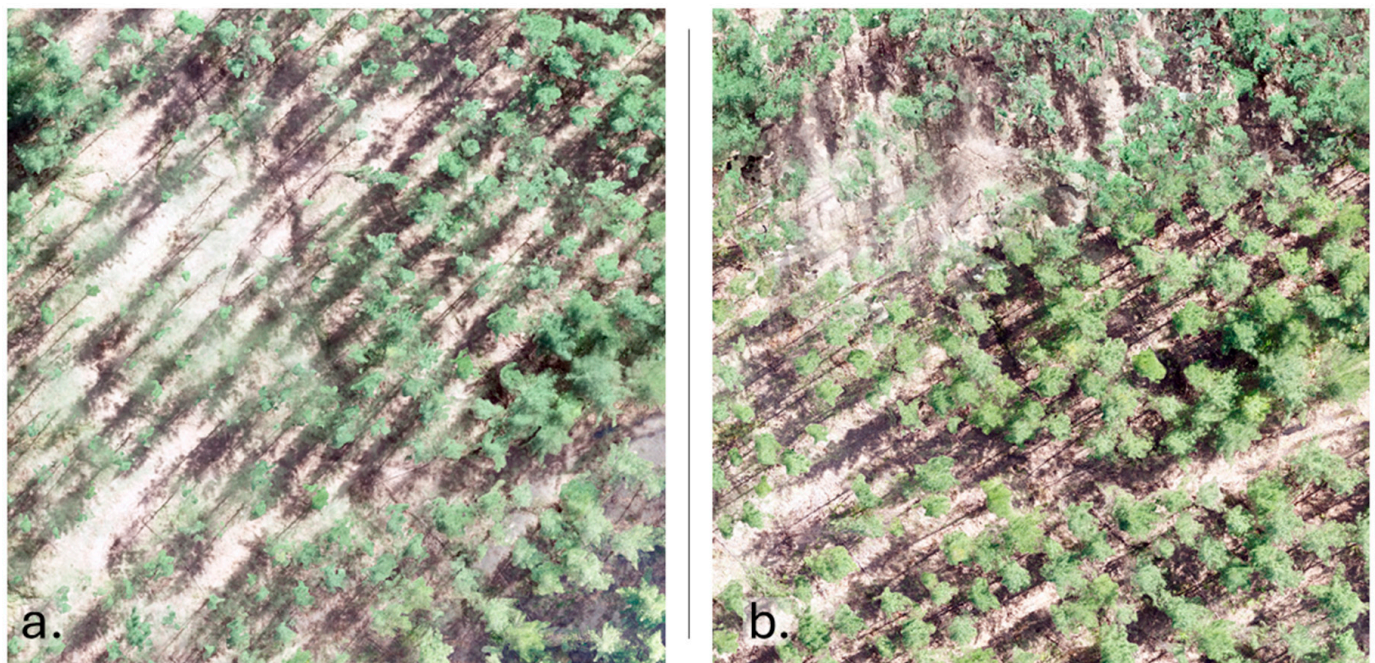


Figure 10. The effects of shadow and occlusions in the orthomosaics produced by flights flown at overlap of 90:85 at 80 m (a) and 90:90 at 80 m (b).

In countries where weather and illumination conditions are highly changeable, such as in NZ, it is not always possible to fly under optimal conditions. The results from this study have demonstrated that flying at a higher altitude significantly decreases the flight duration, requiring less flight lines to cover the same area, thereby minimising the

changes in illumination. This not only decreases the flight time and the additional labour of swapping the batteries more often, but also decreases the number of images in each dataset, significantly reducing data processing time, data storage requirements, and general operational costs. The findings of this study determined that the flight with an overlap of 90:85 at 120 m AGL provided an optimal mixture of flight time and orthomosaic quality for an operational homogenous forestry setting. The data from this flight were subsequently utilised to create a point cloud to conduct a post-thinning stand density assessment.

4.2. Tree Detection Accuracy

Our results for the ITD show that ULS had a higher recall, meaning that it was better at finding actual trees; however, UAV-SfM had a slightly higher precision, meaning that it identified fewer false positives (Table 4). ULS also had a higher F-score (harmonic mean of recall and precision), indicating a better balance between precision and recall (Table 4). Overall, ULS proved to be the more balanced technology, providing a high level of positive identifications, with a relatively low level of false positives. Although UAV-SfM excelled at positively identifying trees, it missed more trees than ULS. However, this reduction in performance should be weighed against the accessibility of the two technologies. ULS offers superior accuracy with enhanced canopy penetration, higher point density, and the ability to provide a more detailed account of terrain, forest structure, and understory. Despite all these benefits, ULS is still relatively cost-prohibitive for many forest management companies, whereas the DJI Phantom 4 Pro is an affordable craft that is commonly used by foresters. The results of this study have demonstrated that foresters can anticipate similar accuracy levels for post-thinning stand density assessments using UAV-SfM, provided they have an accurate DTM available and adhere to the recommended flight parameters.

The ITD results from this study compare favourably with other studies in the literature. The trend in the literature is for ULS to perform the best, with an average F-score of 0.88 (min = 0.81, max = 0.968; Refs. [19,22,61,62]), followed by ALS with an average F-score of 0.84 (min = 0.64, max = 0.966; Refs. [20,63–65]), and with UAV-SfM performing least well with an average F-score of 0.76 (min = 0.54, max = 0.86; Refs. [19,63,64,66]). The trees in this study were in an even-aged, monoculture stand that had recently been thinned and had crowns with a clear apical dominance, presenting an optimal geometry for tree detection. The results from this study for UAV-SfM perform significantly better than these other UAV-SfM studies, which comprised mixed species stands, mature stands with complexed canopy structures, or hardwood plantation stands with un-thinned tall trees. This supports the contention that raster-based ITD methods work better on coniferous trees, and that suppressed trees and overlapping crowns are more prone to errors [62]. For the ULS results, the only ULS-based study identified from the literature with higher results was for another plantation forestry study featuring 1.5-year-old *P. radiata* and *Pinus Pinaster* Ait [22]. These sites would have an even less complex canopy structure, adding more weight to this argument.

The accuracy metrics of the ITD method attained with the two technologies demonstrated satisfactory and comparable results. Recent advances in deep learning have indicated that deep learning techniques applied directly to orthomosaics can achieve high levels of precision and recall for detecting seedlings [67] and mature trees [68]. Future study should focus on comparing these deep learning results with ITD outcomes on UAV-SfM point clouds to assess their performance and potential for increasing the performance of UAV-SfM in line with ULS.

When assessing the literature, it was observed that the number of trees and the area used for this study of 8452 trees across a 30 ha site was unusually large for an ITD study, thus categorising this work as a large-scale study of ITD. The majority of the studies found in the literature used plots for their comparisons, and the largest reference dataset that was found comprised 4470 juvenile *P. radiata* trees across an area of ~5 ha [22], followed by 1277 trees in an Australian savanna environment [63]. Through selecting a typical operational forestry site for this study, the results have further highlighted the scalability of

the proposed approach for more forestry applications beyond stand density assessment. Furthermore, it is hoped that this large-scale study in challenging conditions will give foresters confidence in the methodology and the potential efficiency gains of integrating remote sensing into everyday forestry operations.

4.3. Operational Recommendations

The findings of this study indicate that the flight parameters to attain the best quality photogrammetric data in the optimal time with a prosumer-grade UAV are as follows: a flight altitude of 120 m, a forward and side overlap of 90% and 85%, respectively, and a flight speed of 5 m/s. Please refer to Sections 2.1.2, 3.1 and 4.1 for more details on the methodology, the results, and the discussion, respectively.

The recommendation for the choice of sensor to use for ITD depends on the preference of the user. ULS performed better overall than the UAV-SfM (see Sections 3.2 and 4.2 for results and discussion), and the sensor also inherently characterises the ground better, meaning that a DTM and CHM could be generated from the same dataset (see Section 2.2.2). However, ULS sensors are an order of magnitude more expensive than the prosumer-grade SfM UAV assessed in this study. Therefore, if the user has access to an accurate DTM and would like a more cost-effective solution, then our results have demonstrated that a comparable level of ITD accuracy can be achieved (see Sections 3.2 and 4.2).

5. Conclusions

This study evaluated nine distinct image overlap combinations at two flight altitudes to determine the optimal flight parameters for conducting post-thinning stand density assessments using UAV-SfM. The UAV-SfM workflow produced high-quality outputs across all overlap combinations with side overlap, a parameter previously underexplored in the literature, demonstrating a significantly higher impact on orthomosaic quality than forward overlap or altitude. Manual delineation of artefacts in the resulting orthomosaics arising from the SfM process identified optimal flight parameters of a 90% forward and 85% side overlap at an altitude of 120 m.

The optimal dataset was then compared to data from an industrial-grade ULS through a procedure that derived a CHM and detected individual trees with an algorithm based on local maxima filtering with a variable window size. Both technologies demonstrated high accuracy, with the ULS performing slightly better at reducing false negatives. Despite this, UAV-SfM demonstrated superior precision in making positive identifications. This study enhances the literature around the impact of flight parameters on the photogrammetric process, notably around the importance of side overlap. It also provides a large-scale test of the equipment over operational forestry conditions. Despite the marginally lower performance of the UAV-SfM system, this study demonstrates that UAV-SfM is an affordable and viable approach to ULS for improving operational forest management assessments at large scales.

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