

1 **Unmanned aerial vehicle (UAV) derived structure-from-**
2 **motion photogrammetry point clouds for oil palm (*Elaeis***
3 ***guineensis*) canopy segmentation and height estimation**

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Unmanned aerial vehicle (UAV) derived structure-from-motion photogrammetry point clouds for oil palm (*Elaeis guineensis*) canopy segmentation and height estimation

Abstract

The vast size of oil palm (*Elaeis guineensis*) plantations has led to lightweight unmanned aerial vehicles (UAVs) being identified as cost effective tools to generate inventories for improved plantation management, with proximal aerial data capable of resolving single palm canopies at potentially, centimetric resolution. If acquired with sufficient overlap, aerial data from UAVs can be processed within structure-from-motion (SfM) photogrammetry workflows to yield volumetric point cloud representations of the scene. Point cloud-derived structural information on individual palms can benefit not only plantation management but is also of great environmental research interest, given the potential to deliver spatially contiguous quantifications of aboveground biomass, from which carbon can be accounted. Using lightweight UAVs we captured data over plantation plots of varying ages (2, 7 and 10 years) at peat soil sites in Sarawak, Malaysia, and we explored the impact of changing spatial resolution and image overlap on spatially variable uncertainties in SfM derived point clouds for the ten year old plot. Point cloud precisions were found to be in the decimetre range (mean of 26.7 cm) for a 10 year old plantation plot surveyed at 100 m flight altitude and >75% image overlap. Derived canopy height models were used and evaluated for automated palm identification using local height maxima. Metrics such as maximum canopy height and stem height, derived from segmented single palm point clouds were tested relative to ground validation data. Local maximum identification performed best for palms which were taller than surrounding undergrowth but whose fronds did not overlap significantly (98.2% mapping accuracy for 7 year old plot of 776 palms). Stem heights could be predicted from point cloud derived metrics with root-mean-square errors (RMSEs) of 0.27 m ($R^2=0.63$) for 7 year old and 0.45 m ($R^2=0.69$) for 10 year old palms. It was also found that an acquisition designed to yield the minimal required overlap between images (60%) performed almost as well as higher overlap acquisitions (>75%) for palm identification and basic height metrics which is promising for operational implementations seeking to maximise spatial coverage and minimise processing costs. We conclude that UAV-based SfM can provide reliable data not only for oil palm inventory generation but allows the retrieval of basic structural parameters which may enable per-palm above-ground biomass estimations.

1 Introduction

The oil palm (*Elaeis guineensis* Jacq.) can yield considerably more oil per hectare than any other crop, which explains its large-scale expansion over the last century, to meet the global demand for food and biofuel (Corley and Tinker 2016). As a result the conversion of forest ecosystems to oil palm plantations has been the topic of much international research and also controversy due to concerns regarding its impact on biodiversity, carbon storage and ecosystem services (Fitzherbert et al. 2008; Butler and Laurance 2009; Carlson et al. 2012; Germer and Sauerborn 2008; Koh and Wilcove 2008).

The global demand for oil palm products means that plantations now cover large tracts of land in the tropics – for example, in Malaysia 58,100 km² is taken up by commercial oil palm plantations (as of 1 December 2017, Malaysian Palm Oil Board (MPOB) statistics retrieved from <http://bepi.mpob.gov.my>).

56 Both at national and plantation block scale, remote sensing is a valuable tool both for stakeholders and
57 researchers. To provide an example, remote sensing data offers a means by which plantation
58 management can be performed in a more profitable and arguably more sustainable manner because
59 plantation inventories can be generated to inform targeted fertiliser and pesticide application (Chong
60 et al. 2017). Beyond the commercial sector, remote sensing data have been applied on a state-wide
61 scale to monitor and quantify the impact of the land-use change due to the establishment of new
62 plantations. These analyses are predominantly based on satellite data, and various studies have
63 utilised optical, and radio detection and ranging (RADAR) capabilities to differentiate oil palm from
64 other land cover classes (Morel et al. 2011; L. Li et al. 2015; Koh et al. 2011; Cheng et al. 2018). The
65 challenge with using readily available satellite data for oil palm science is the limited spatial and/or
66 temporal resolution of such data. The demand for finer spatial resolution data is motivated by the
67 ability to resolve individual palm canopies, which can be used as reference data to improve land-cover
68 classifications (Nomura and Mitchard 2018) and allows for automated identification and parameter
69 retrieval to provide information about palm structure and status. These parameters are not only of
70 interest for plantation management but are central to the estimation of plantation carbon stocks, e.g.
71 through the use of allometric equations (Corley and Tinker 2016). Such work is critical from a scientific
72 perspective if the carbon implications of forest conversion to oil palm are to be quantified accurately
73 (Morel et al. 2011), and yet, there are missing examples of such methods in the literature. Furthermore,
74 patterns relating to local soil nutrient deficiency or disease could also be better identified (Shafri and
75 Hamdan 2009).

76 For inventory generation, fine spatial resolution satellite data (e.g. WorldView 4 at 0.31 m spatial
77 resolution) provides fine resolution information, while enabling monitoring over a broad spatial extent
78 and has been successfully used for palm identification (Weijia Li et al. 2016; Srestasathiern and
79 Rakwatin 2014), but is not suitable for estimating structural parameters. For practical considerations,
80 fine spatial resolution satellite data have known limitations, for example – they are financially costly
81 and for countries with frequent cloud cover, acquiring a cloud-free acquisition at the desired time can
82 be challenging. Improved accessibility, low operating costs, and ease of use has recently led to
83 lightweight drone platforms (often called unmanned aerial vehicles or systems (UAV/UAS)) being
84 identified as a useful tool in oil palm plantation management, with major commercial oil palm
85 companies establishing dedicated UAV-teams for the routine acquisition of aerial imagery (pers. comm.
86 Sarawak Oil Palms Berhad, 2018).

87 Currently the primary application of UAV data in oil palm management is the generation of
88 photographic-based orthomosaics for inventory purposes (Rokhmana 2015). Manual identification
89 based on spatial data products is still considered the most accurate and cost-effective method to
90 generate inventories in commercial applications and the selection of training data in recent scientific
91 applications (e.g. Nomura and Mitchard 2018). There are however promising first demonstrations of
92 machine learning techniques on both fine spatial resolution satellite and UAV image data of oil palms
93 and date palms respectively (Weijia Li et al. 2016; Malek et al. 2014) as well as software packages for
94 the operational implementation of object-based segmentation (eCognition, Trimble, California, USA)
95 for palm identification.

96 In these workflows, the third spatial dimension (i.e. height) has to date been completely disregarded
97 for oil palm, however, its inclusion opens up many scientific and operational management possibilities
98 at low opportunity cost. The acquisition of overlapping images from UAV platforms allows the
99 application of a photogrammetric method which automatically solves for the geometry of the scene,
100 camera positions and orientations, known as structure-from-motion (SfM) photogrammetry (Westoby
101 et al. 2012). SfM can be used to generate fine spatial resolution orthomosaics, and point clouds
102 representing the height structure of the scene (Dandois and Ellis 2013). Coupled with precise

103 georeferencing information, resultant point clouds can be used to spatially separate objects and
104 determine their spatial and volumetric dimensions, in much the same way that light detection and
105 ranging (LiDAR) data permit, but at lower acquisition costs. Such methods are now being used
106 extensively to derive canopy metrics of individual vegetation canopies of varying sizes and structure
107 (Puliti et al. 2015; Cunliffe, Brazier, and Anderson 2016; Zarco-Tejada et al. 2014), so it is a natural step
108 to consider the utility of such approaches for oil palm inventory. Doing so would deliver new
109 understanding of the volumetric characteristics of oil palm plantations, which would prove particularly
110 useful for spatial carbon evaluations. Currently such aspects of oil palm plantations lack sufficient data
111 from which to quantify the environmental effects of tropical forest conversion (Kho and Jepsen 2015).
112 Information on palm height and its distribution is desirable as it can be an indicator of palm age and
113 localised growing conditions. Variations due to re-planting of missing palms are expected to be small
114 as this does generally not occur past the first year (Corley and Tinker 2016). More spatially contiguous
115 variations can be the result of unequal fertiliser application or other variations, e.g. in soil nutrient
116 availability. In previous work, UAV based photogrammetry derived top-of-canopy height metrics in
117 other ecosystems were found to be comparable with LiDAR derived heights (Wallace et al. 2016; Thiel
118 and Schnullius 2017), with data acquisition being comparably, more affordable (relying only on
119 consumer grade sensors and platforms) and easy to deploy (so long as the aircraft and payload are
120 lighter than the low weight categories defined by civil aviation classifications (Duffy et al. 2017)). First
121 efforts in applying the UAV-based SfM methodology to palm plantations have demonstrated the
122 potential for palm identification and retrieval of structural parameters (Kattenborn et al. 2014),
123 however further investigation into uncertainties within generated products as well as the influence of
124 acquisition schemes which allow to cover greater area at the cost of data quality is required for the
125 operational implementation of these workflows.

126 Presented in this study is the first investigation of UAV and SfM-derived point clouds for oil palm
127 plantation physical assessment. This application of UAV data extends beyond identification and
128 counting of individual palms and presents a novel workflow for the segmentation of individual palm
129 objects from point clouds to explore their application for retrieving height-related structural
130 parameters, as well as quantify spatially-variable uncertainties. Specific aims of this study are:

- 131 a) To demonstrate a workflow for the retrieval of single palm canopies from SfM point clouds.
- 132 b) To quantify the uncertainties introduced by the acquisition scheme and steps in the SfM-based
133 workflow as well as in the retrieved metrics.
- 134 c) To derive and assess top-frond-height (TFH) and stem height metrics from single palm SfM
135 point clouds.

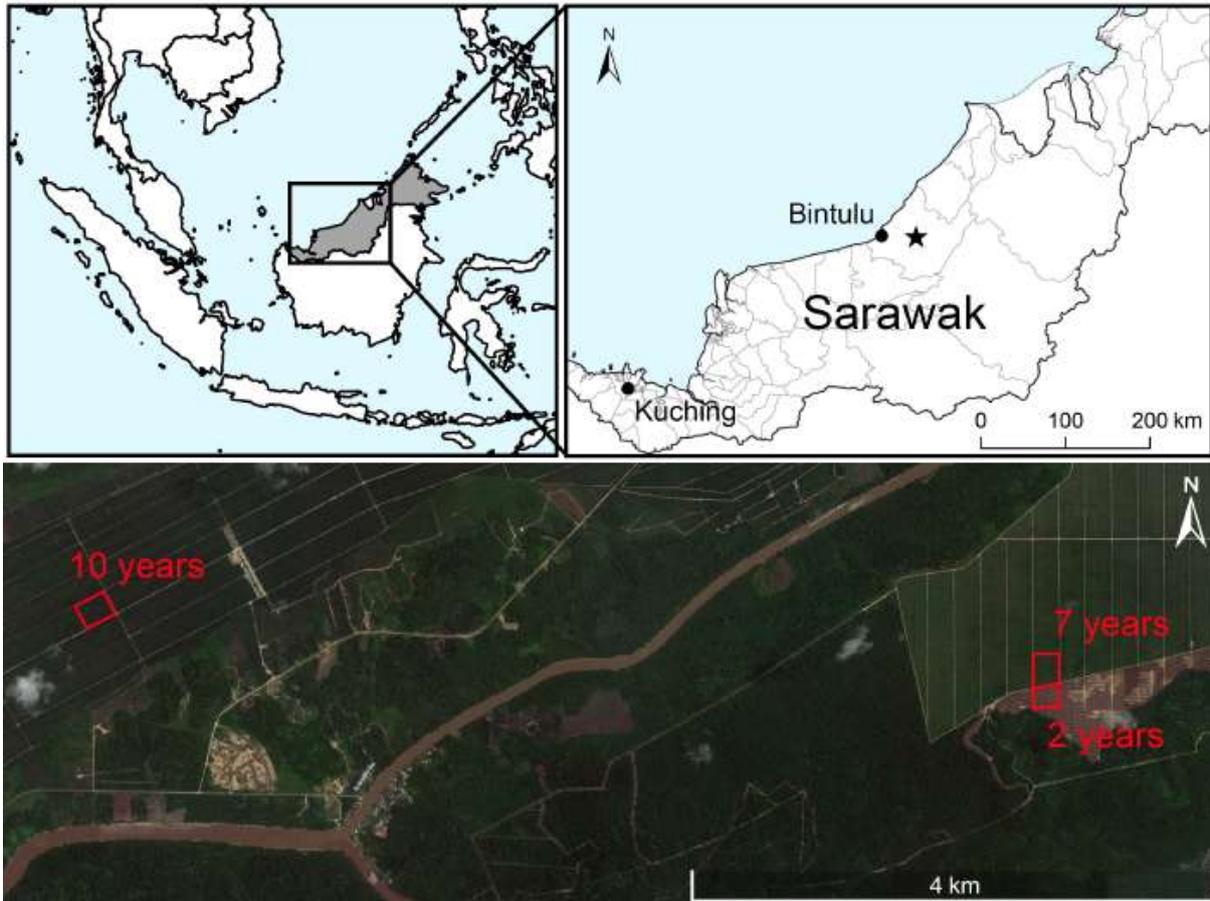
136 Aim b) is key to understanding the potential and limitations of our methodology for oil palm science.
137 This is especially important when considering the possible further usage of the retrieved structural
138 parameters (aim c)) to inform larger scale models, as has been successfully demonstrated for forestry
139 (Puliti et al. 2017), to quantify error propagation. Aim c) provides an important step towards deriving
140 per-palm above-ground biomass (AGB) (Corley and Tinker 2016; Thenkabail et al. 2004).

141 **2 Materials and Methods**

142 **2.1 Study site**

143 The study sites were located in the state of Sarawak, Malaysian Borneo, on the Sarawak Oil Palms
144 Berhad plantations of Sabaju (3°09'40.1"N 113°25'09.1"E) and Sebungan (3°09'58.1"N 113°21'20.2"E).
145 The majority of the plantation area was planted on tropical peat with smaller areas on clay dominated
146 mineral soil. Three peat soil plantation sub-plots of 2, 7 and 10 years of age and covering approx. 4, 6
147 and 6 ha respectively were selected for this study. Plot sizes were chosen based on the maximal area
148 which could be safely covered with one flight battery whilst also fulfilling the desired image acquisition

149 parameters (see section 2.2.2). The locations of the survey plots are depicted in



150
151 Figure 1. These locations were selected to contain two 1 ha carbon sampling plots which are
152 periodically measured by researchers associated with the MPOB. The peat soil plantations possess only
153 slightly varying topography (e.g. <1 m vertically over 100 m horizontal distance). The 2 year old palms
154 consisted mainly of fronds with the above-ground stems being negligible. Besides the young palms,
155 the 2 year old plot also contained stacking rows of woody material which were overgrown by
156 vegetation and were higher than the TFH of the palms. The 7 year old plot contained significant
157 undergrowth and the same heaped rows of timber between every other palm row, though here the
158 palms had grown higher than this topographic variation. In the 10 year old plot there was significantly
159 less undergrowth, likely due to light limitation as the fronds of neighbouring palms begin to overlap,
160 as well as a very high water table due to a difference in local topography. Undergrowth here occurred
161 mainly along drainage channels dug between every other palm row.

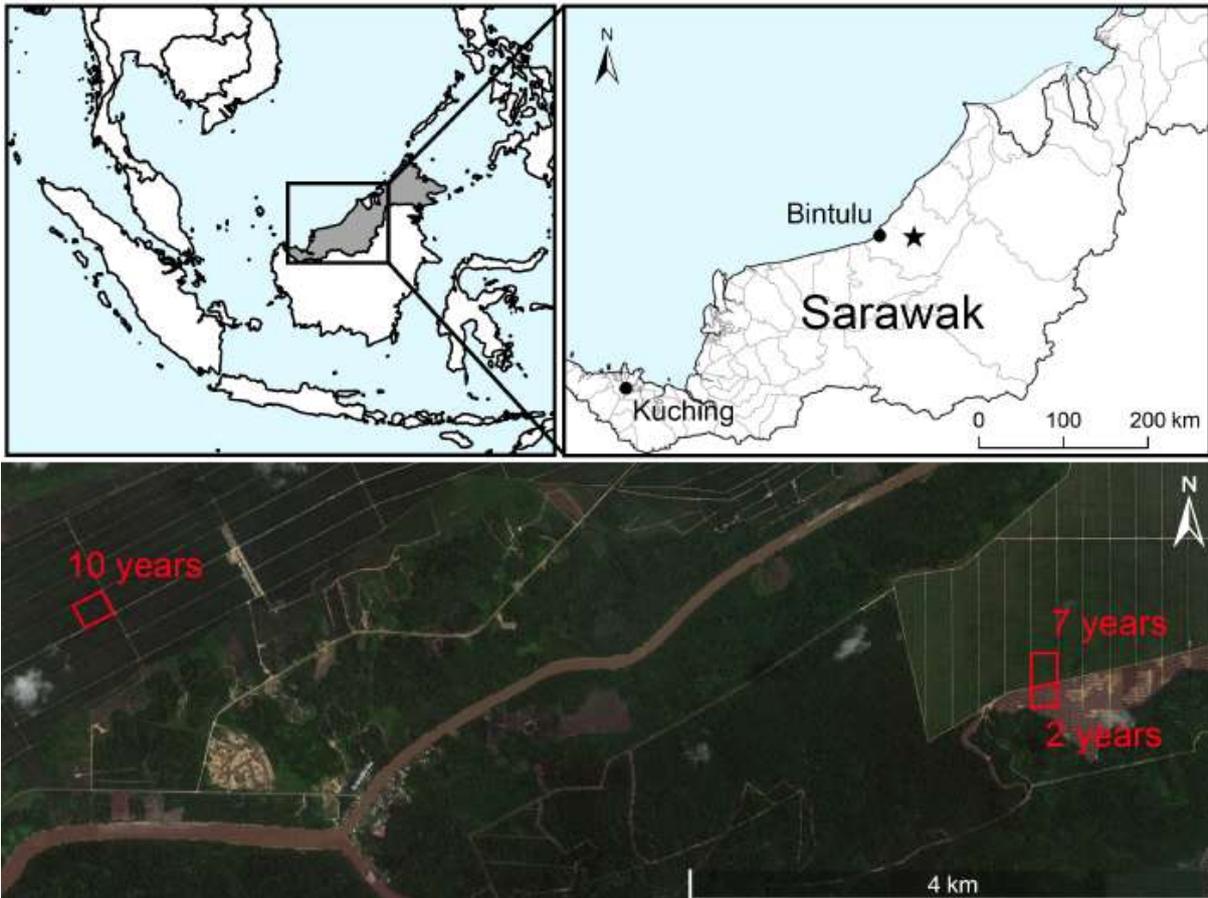


Figure 1: Top: The state of Sarawak in Malaysian Borneo with a star marking the location of the studied plantation (shapefiles from www.diva-gis.org). Bottom: Satellite imagery with the location, extent and age in years of the studied plots (Google Earth).

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167 **2.2 Data acquisition**

168 **2.2.1 Field sampling**

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170 Measurements in the field were conducted on a per-palm basis. Within the boundaries of the existing
 171 1 ha carbon sampling plots, palms were sampled in a grid pattern in accordance with the subdivided
 172 squares of the plot. Outside of carbon plots, palms were sampled following a random sampling scheme.
 173 33, 22 and 37 palms were selected for measurement in the 2, 7 and 10 year old plots respectively, with
 174 the number of samples varying due to sampling time constraints and accessibility of the plots. TFH as
 175 a metric representing canopy height was measured as the distance between the apex of the highest
 176 frond and ground level, to provide a validation for SfM photogrammetry derived heights. The stem
 177 height was also measured as the distance between the petiole base of the lowest intact frond and
 178 ground level (see Morel, Fisher, and Malhi 2012). Due to the size of the older palms, both heights were
 179 consistently measured using a laser rangefinder in all plots. These systems typically possess decimetre
 180 accuracy.

181 **2.2.2 UAV flights and GPS data**

182

183 The UAV used for this study was a 3DR Solo quadcopter containing a pixhawk 2.0 flight controller.
 184 Including payloads it weighs under 2 kg and is capable of approximately 15 minutes flying time on a
 185 single battery. The system was selected due to its ease of use and flexibility. Flights were programmed

186 in the ArduPilot Mission Planner software by drawing a polygon per plot that was reused for all flights.
 187 Flights were conducted at an altitude of 100 m and a speed of 5 m s⁻¹. The minimum frontal and side
 188 overlap was defined as 75%. For the 10 year old plot, a replicate was flown using identical flight
 189 parameters to enable an independent assessment of the photogrammetric reconstruction and derived
 190 parameters as done in previous studies (Dandois et al. 2017). UAV flights were conducted close to solar
 191 noon for all acquisitions when lighting conditions are optimal for later photogrammetric
 192 reconstruction (Dandois, Olano, and Ellis 2015), and wind speeds at ground level were below 4.5 m s⁻¹.
 193 Flight details are summarised in Table 1.

194 The sensor mounted on the UAV was a consumer-grade RGB camera (Ricoh GR11). The ground sampling
 195 distance (GSD) at 100 m altitude was 2.52 cm. The camera was triggered by intervalometer every 2
 196 seconds during the flight – chosen since the flight planning software suggested that this would ensure
 197 the desired 75% front and sidelap (with higher effective frontal overlap of 82%), close to the optimal
 198 overlap of 80% recommended by Dandois et al., (2015) for vegetation SfM photogrammetry workflows.
 199 The focus was set to infinity, white balance to automatic and exposure time (1/1250 s – 1/1600 s) as
 200 well as aperture (f2.8-f3.2) and ISO (100-200) were varied based on the illumination conditions and
 201 site characteristics (direct/diffuse and amount of shadow) but kept constant throughout each flight,
 202 following recommendations from previous studies (Cunliffe, Brazier, and Anderson 2016; O’Connor,
 203 Smith, and James 2017).

204 For georeferencing, a total of 10-15 ground control points (GCPs) and >10 height validation points were
 205 surveyed per site using a Trimble Geo 7x GNSS system coupled with a Zephyr Model 2 antenna and
 206 were post-processed using RINEX data acquired from the Department of Survey and Mapping Malaysia
 207 (JUPEM) to yield 3 cm horizontal and 5 cm vertical precision. These measurements allow SfM
 208 photogrammetry generated digital surface models to be adequately constrained (Tonkin and Midgley
 209 2016) and can be used to validate georeferencing accuracies utilising unused GCPs as check-points.
 210 GCP distribution followed recommendations from previous work on UAV SfM survey accuracies (James
 211 et al. 2017) by ensuring placements around the boundaries of the region of interest as well as close to
 212 the centre of each plot.

213 In addition to the main data acquisition described above, an additional RGB image dataset covering
 214 the entirety of the studied 10 year old plantation block was acquired by the Mapping Unit of Sarawak
 215 Oil Palms Berhad. The system used was a DJI Phantom 4 with integrated camera, flying at 150 m and
 216 11 m s⁻¹ resulting in a GSD of 3.93 cm pixel⁻¹. The programmed flight plan was aimed at acquiring image
 217 data with 60% frontal and side overlap. This acquisition plan allowed for coverage of one entire
 218 plantation block using a single DJI flight battery.

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222 *Table 1:* List of UAV flights used in this study, referred to by an identifier throughout the remainder of the manuscript and
 223 indicating the flight parameters, the palm age plot site (including the replicate for the 10 year old plot) and date of
 224 acquisition.

Identifier	System	Sensor	Altitude (m above ground level)	Speed (m s ⁻¹)	Overlap	Site	Date
HO_2yr	3DR Solo	Ricoh GR11	100	5	>75%	2 year	30 January 2018

HO_7yr	3DR Solo	Ricoh GR11	100	5	>75%	7 year	9 February 2018
HO1_10yr	3DR Solo	Ricoh GR11	100	5	>75%	10 year	2 February 2018
HO2_10yr (replicate)	3DR Solo	Ricoh GR11	100	5	>75%	10 year	2 February 2018
LO_10yr	DJI Phantom 4	Integrated camera	150	11	60%	10 year	5 February 2018

225

226 **2.3 Photogrammetric processing**

227

228 The photogrammetric processing of UAV-acquired images was performed in Agisoft Photoscan
 229 Professional V1.4.2 (St. Petersburg, Russia). There are a number of software options available for
 230 photogrammetric processing and Photoscan was selected here due to its successful use in similar
 231 applications such as forest inventories (Dandois and Ellis 2013; Puliti et al. 2015), and the ability to use
 232 previously developed Python scripts for spatial uncertainty estimation (James, Robson, and Smith
 233 2017). Palms differ considerably from coniferous or broadleaf trees, however no inter-comparison of
 234 software options and algorithms exists for this canopy type. Images per flight and plot were input into
 235 the software, upon which tie-points within images are identified and used for image matching
 236 (algorithms used are proprietary, but a similar method is the scale invariant feature transform (SIFT)
 237 algorithm (Lowe 2004)). An automatic aerial triangulation followed by a bundle block adjustment is
 238 then performed, reconstructing scene geometry while accounting for camera orientation and
 239 distortion. The resulting sparse point cloud representing the tie-points in 3D space is used to generate
 240 a rough mesh of the scene. After this initial processing, GCP coordinates are imported and their
 241 position manually identified within the images. To evaluate the geometric accuracy of the resulting
 242 model, $\approx 25\%$ of measured GCPs per site were omitted from the photogrammetric processing and used
 243 as independent check points. The initial processing was re-run on the highest setting (with key point
 244 limit: 80'000, tie point limit: 8000), followed by depth-map and dense point cloud generation on high
 245 settings. Depth filtering was disabled as even mild depth filtering appeared to remove points of vertical
 246 palm fronds.

247 While geometric uncertainties of the resulting model are reported by the software (see supplementary
 248 information for examples), these only represent errors in relation to the measured GCPs and check
 249 points at ground level, which are clearly identifiable within the image. At the top of the canopy, errors
 250 can be expected to be considerably larger, as the z dimension cannot be adequately constrained by
 251 the measured GCPs and values are more heavily dependent on the non-reproducible tie point
 252 identification. To quantify the precision of the photogrammetric processing as outlined in aim b), which
 253 is impacted by varying camera geometry and GCP uncertainties, we utilised a Monte Carlo (MC)
 254 method developed by (James, Robson, and Smith 2017) to derive point precisions representing the
 255 expected one standard deviation in x, y and z directions by running many simulations of the sparse
 256 point cloud generation including GCP information while randomly varying parameters within reported
 257 accuracy thresholds. Precision estimation is performed based on the sparse point cloud as the dense
 258 matching does not optimise the image network and, while it can introduce additional smaller errors,
 259 does therefore not affect the underlying precision (James, Robson, and Smith 2017). This method was
 260 primarily developed for the assessment of SfM based surveys of non-vegetated landforms but the

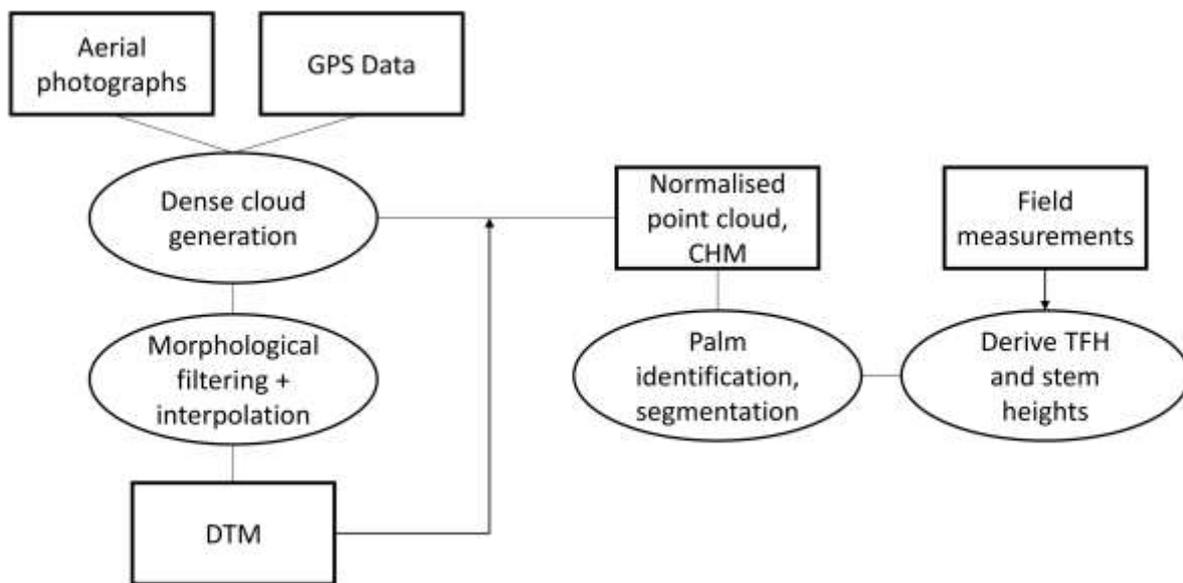
261 precision estimates it generates, we argue, can also prove useful for vegetation focused studies. The
 262 algorithm was originally designed by (James, Robson, and Smith 2017) for time-series change analysis
 263 that accounts for survey-to-survey uncertainties, but can be used stand-alone on single surveys to
 264 highlight areas of higher and lower point precision, in 3 dimensions. 1000 simulations proved sufficient,
 265 assessed by the difference between the MC means and the initial error free values. Per-point precision
 266 estimates in each dimension were generated based on the simulations, using the 'sfm-georef' software
 267 (James and Robson 2012).

268

269 **2.4 Point cloud processing and parameter retrieval**

270

271 The processing workflow for oil palm segmentation and derivation of TFH and stem height is
 272 demonstrated in



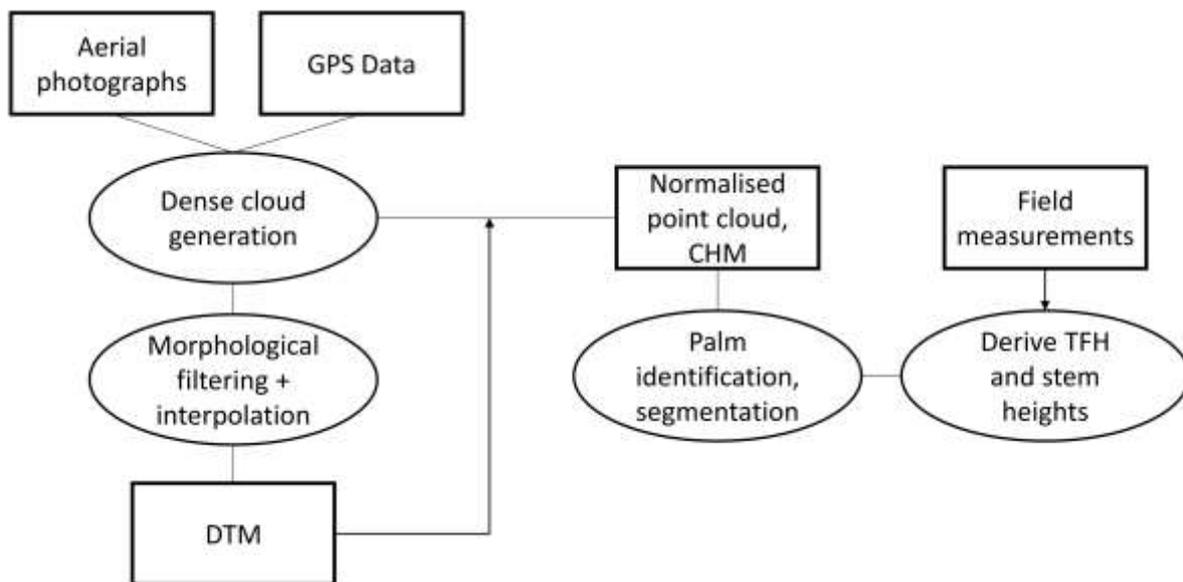
273

274 Figure 2. After generating the dense point cloud representing the volumetric structure of the scene, a
 275 statistical outlier filtering was performed (CloudCompare, V2.9.1), removing points far above or below
 276 the scene which are considered as noise, likely attributed to movements of palm fronds between
 277 images. As most scenes contained water, either as standing water or in drainage channels, this caused
 278 errors in the photogrammetric processing due to reflections and larger negative outlying point clusters
 279 were found, an effect also described by Duffy et al., (2017). The majority of these outliers were
 280 removed by eliminating points below a feasible threshold, informed by GCP heights. A minimal
 281 amount of manual clipping of the point cloud in CloudCompare (V2.9.1) was therefore required.

282 Due to the lack of detailed topographical data of the sites, the digital terrain model (DTM) had to be
 283 derived from the SfM point cloud. Ground points in each plot were classified by excluding the
 284 vegetation through a morphological filtering procedure, originally developed for airborne laser
 285 scanning (Zhang et al. 2003) and implemented in the R lidR package (Roussel and Auty 2018). This
 286 method has previously been applied for SfM-based DTM generation (Dandois and Ellis 2013) and was
 287 selected as it provided more control over the filtering process. It appeared to perform better for sparse
 288 ground points as opposed to PhotoScan's own implementation of ground classification which has been
 289 used for DTM generation in more recent SfM based studies where more ground information was
 290 available (e.g. Cunliffe, Brazier, & Anderson, 2016). It did however require the point cloud to be
 291 subsampled with a 0.1 m distance constraint between points for efficient processing. The parameters
 292 for morphological filtering had to be adjusted for each plot due to the varying height and density of

293 palm crowns. The classified ground points were interpolated using k-nearest-neighbour inverse
 294 distance weighting. The noise filtered original point clouds were normalised using the derived DTM,
 295 yielding height above ground for the remaining vegetation points and canopy height model (CHM). For
 296 palm identification, the CHM was first smoothed using a mean filter after which local-maximum
 297 filtering was applied with a window size informed by the known planting distance between palms
 298 (approx. 9 m, an established planting pattern for oil palm (Chong et al. 2017)). Individual palms were
 299 then segmented from the point cloud using a crown delineation method by Silva et al., (2016) and
 300 adjusted by Roussel and Auty, (2018), using the identified palm points as centroids and the CHM as
 301 input. This particular delineation method was selected due to its suitability for the simple circular
 302 footprint of oil palm crowns and as the impact of overlapping fronds can be reduced by constraining
 303 the buffer radius used. Other methods based on watershed analysis or region-growing (Dalponte and
 304 Coomes 2016) proved to have issues where overlap occurred.

305 The TFH values for each segmented palm were retrieved by selecting the maximum point within the
 306 cloud, the sensitivity to erroneous outliers reduced by the previous statistical outlier filtering. Derived
 307 TFH is assessed against field measured TFH for measured palms. To test the consistency of TFH for two
 308 independent builds, TFH was also derived from a replicate dataset over the 10 year old plot and the
 309 values compared for the same palms.



310
 311 *Figure 2: Processing workflow for deriving per-palm height metrics from UAV data.*

312 Using linear regression, the correlations of different height percentiles (30 to 90% in 10% steps), and
 313 the mean and maximum point height with field measured stem height were assessed for the samples
 314 of the 7 and 10 year old plantation. For the 2 year old palms, the bases of the lowest intact fronds were
 315 at ground level and therefore no stem was measured. Due to a limited number of samples, prediction
 316 accuracy was assessed using leave-one-out cross validation (LOOCV) as used in similar studies (Wang
 317 Li et al. 2016). Two separate models depending on plot age were assessed as the relationship between
 318 point cloud metrics and stem heights can be expected to differ slightly between palms of different age
 319 classes. This does not avoid the issue of younger, re-planted palms within the same plots. The
 320 relationships with highest coefficient of determination (R^2) were then applied to all identified palm
 321 point clouds to derive stem heights.

322

323 **3 Results**

324 **3.1 Photogrammetric dense clouds**

325

326 UAV image data averaged around 350 images per plot and acquisition, from which dense point clouds
327 were generated for each plot through photogrammetric processing. For the 10 year old plot, a replicate
328 dataset using the same acquisition parameters was generated (HO2_10yr), as well as a coarser
329 resolution sparser dataset for the entire plantation block (LO_10yr).

330 Subsets of the point clouds from the three different aged plots are displayed in Figure 3. Initial visual
331 inspections of the generated dense point clouds per plot show reconstructions of individual palm
332 fronds. Noise increased for higher, more vertically-oriented fronds. The point density decreased
333 towards the apical stem as fronds overlapped more. No information on the trunk was captured as it
334 was entirely obscured by fronds in all images. The 10 year old plot contained fewer points from the
335 ground and bottom fronds due to the high canopy density.



336

337 *Figure 3: RGB dense point cloud subsets (33x33 m) of the 2, 7 and 10 year old plantation datasets, resulting from the*
338 *HO_2yr, HO_7yr and HO1_10yr flights.*

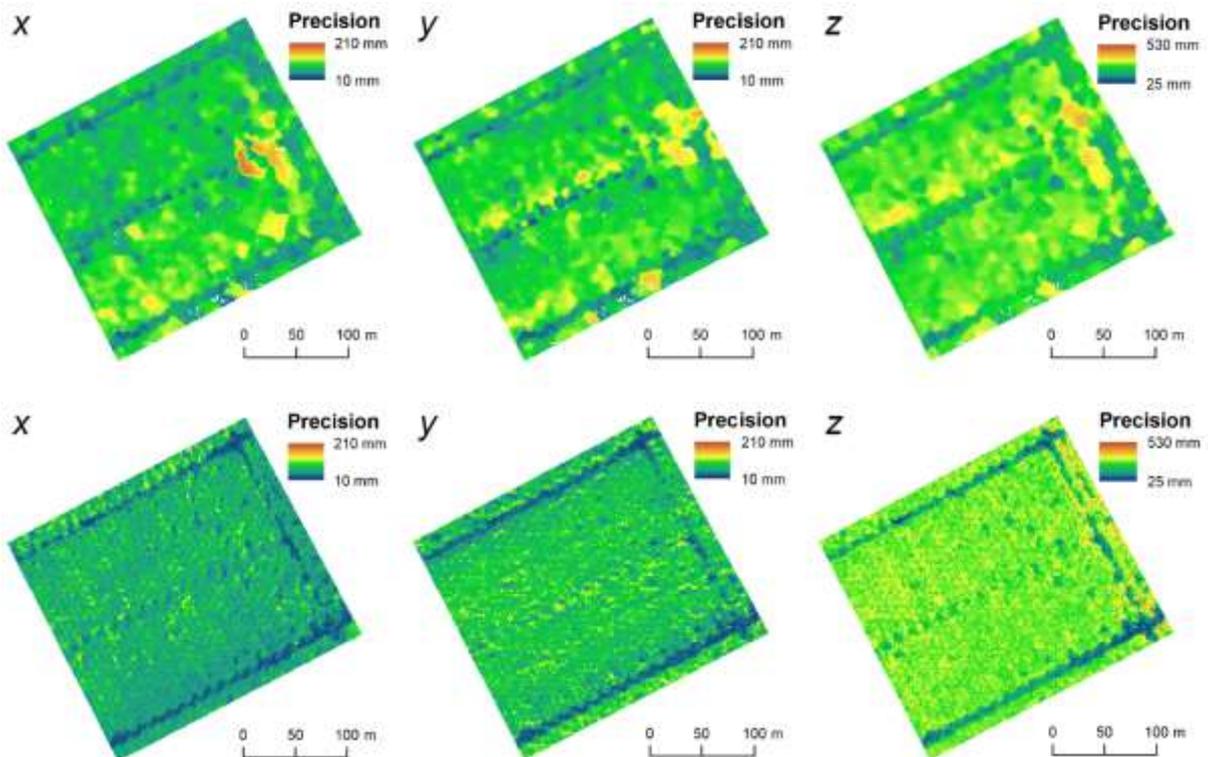
339 The geometric accuracies of the scene reconstructions, assessed by check points which were not used
340 for the photogrammetric processing ($\approx 25\%$ of total GCPs per site), were high with mean horizontal
341 errors (x, y) of 2.29 cm and mean vertical errors (z) of 3.4 cm (see supplementary information for
342 individual processing reports).

343 The LO_10yr dataset showed significantly lower point density (a 1 ha square extracted from the dense
344 clouds contained 10.26 Mio points for HO1_10yr and 1.69 Mio points for LO_10yr) but still appeared
345 to represent finer details and individual fronds of single palms. At the higher altitude and speed of this
346 flight, surface points were imaged 8 times and the ground resolution was 3.93 cm per pixel (for
347 HO1_10yr, points were imaged 44 times on average at 2.52 cm per pixel). The average of 8 images per
348 ground point indicates that the overlap lies slightly below the targeted 60% recommended for
349 photogrammetric surveys (Dandois, Olano, and Ellis 2015). This may have been due to acquisition
350 conditions on the day of the flight, or imperfect flight planning.

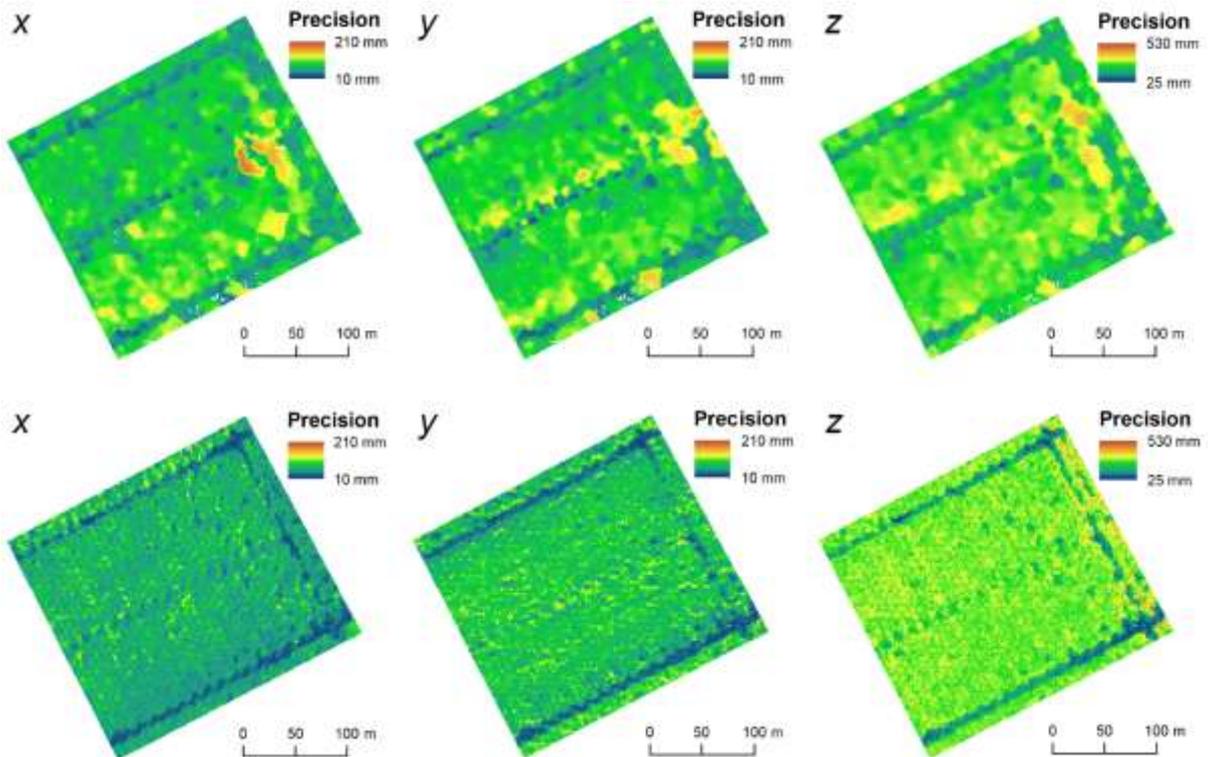
351 Geometric accuracies reported by check points for LO_10yr were lower than the other flights with
352 horizontal error (x, y) of 12.9 cm and vertical error (z) of 39.1 cm.

353 For the generation of maps from the sparse point cloud precision estimates, values were interpolated
354 for the dense point locations using nearest-neighbour inverse distance weighting. It should be noted
355 that due to the reduced overlap for LO_10yr, there were considerably fewer tie points within the
356 sparse point cloud (Table 2, see supplementary information for visual representations). The resulting
357 map therefore includes a higher amount of interpolation and the precision estimates are more poorly
358 resolved spatially. Derived statistics should be treated with caution as there can be expected to be a
359 bias depending on the 3D location of tie points identified during processing, such as a lesser proportion
360 of points found inside the vegetation canopy.

361 The mean precisions do not exhibit large differences between low and high overlap acquisitions.
 362 Horizontal precisions in x and y were very slightly larger for HO1_10yr, while vertical precisions (z) are
 363 slightly lower on average (Table 2). When displaying point precisions spatially
 364 (



365
 366 Figure 4: Maps of interpolated point precisions in x, y and z direction for the 10 year old palm plot. Top
 367 row: Acquisition with $3.93 \text{ cm pixel}^{-1}$ GSD and 60% nominal overlap (LO_10yr). Bottom row: Acquisition
 368 with $2.52 \text{ cm pixel}^{-1}$ GSD and 75% nominal overlap (HO1_10yr).



369
 370 Figure 4), it is apparent that precisions are higher for the flat ground surface on which GCPs were
 371 placed as opposed to points located vertically above the ground, within the vegetation canopy.

372 LO_10yr displays larger patches of lower precision, due to the sparser tie points. Such patches of low
 373 precision may influence the reliability of the derived DTM. For HO1_10yr, precisions are higher for
 374 resolved ground points. Vertical precisions appear lower but more uniform for the vegetation canopy,
 375 with some edge effects at the north-eastern border.

376

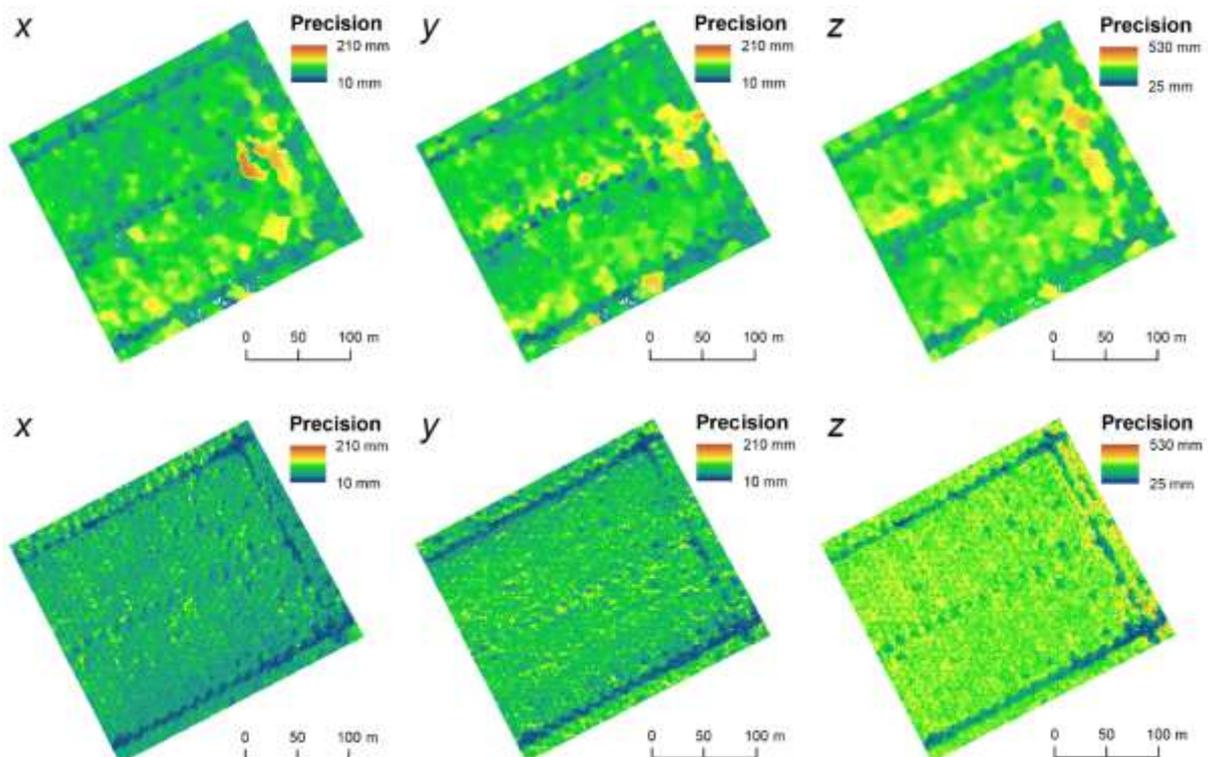
377

378 *Table 2:* Parameters for the two different acquisitions over the 10 year old plot along with mean precision estimates in x, y
 379 and z directions.

Acquisition overlap	GSD (cm pixel ⁻¹)	Tie point density (points m ⁻²)	Mean x precision (mm)	Mean y precision (mm)	Mean z precision (mm)
<60%	3.93	0.05	77.35	89.86	247.90
>75%	2.52	10.28	68.34	80.29	267.39

380

381



382

383 *Figure 4:* Maps of interpolated point precisions in x, y and z direction for the 10 year old palm plot. Top row: Acquisition with
 384 3.93 cm pixel⁻¹ GSD and 60% nominal overlap (LO_10yr). Bottom row: Acquisition with 2.52 cm pixel⁻¹ GSD and 75% nominal
 385 overlap (HO1_10yr).

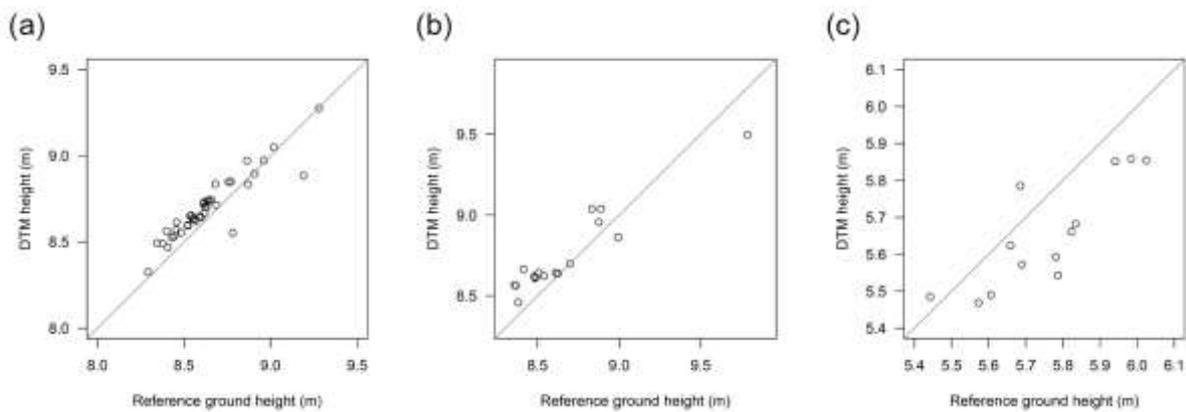
386

387 **3.2 Digital terrain models**

388

389 After filtering out non-ground points the remaining points were interpolated to derive a DTM per site.
 390 The DTM accuracy was assessed using height validation points measured between palms in the field

391 with reported mean measurement horizontal precisions of 3.23 cm and vertical precisions of 5.74 cm.
 392 Mean vertical absolute errors assessed for height validation points were 9.1 cm for the 2 year old
 393 (HO_2yr), 12.4 cm for the 7 year old (HO_7yr) and 12.12 cm for the 10 year old plot (HO1_10yr).
 394 LO_10yr resulted in errors of 31.62 cm. The increase in errors from the 2 year old to the older plots is
 395 due to less visible ground within the imagery and thus non-uniformly distributed ground points within
 396 the dense cloud. For the 2 and 7 year old plots, DTM heights were generally over-estimated (Figure 5).
 397 This overestimation is assumed to be related to undergrowth which obscures the ground beneath.
 398 While there is very little undergrowth present in the 10 year old plot, the reason for the
 399 underestimation of ground height is unclear but likely due to interpolation related uncertainties as
 400 well as the larger amount of drainage channels in this plot.



401
 402 *Figure 5: Interpolated DTM heights above mean sea-level versus GPS measured reference ground heights. (a): 2 year old plot,*
 403 *(b): 7 year old plot, (c): 10 year old plot.*

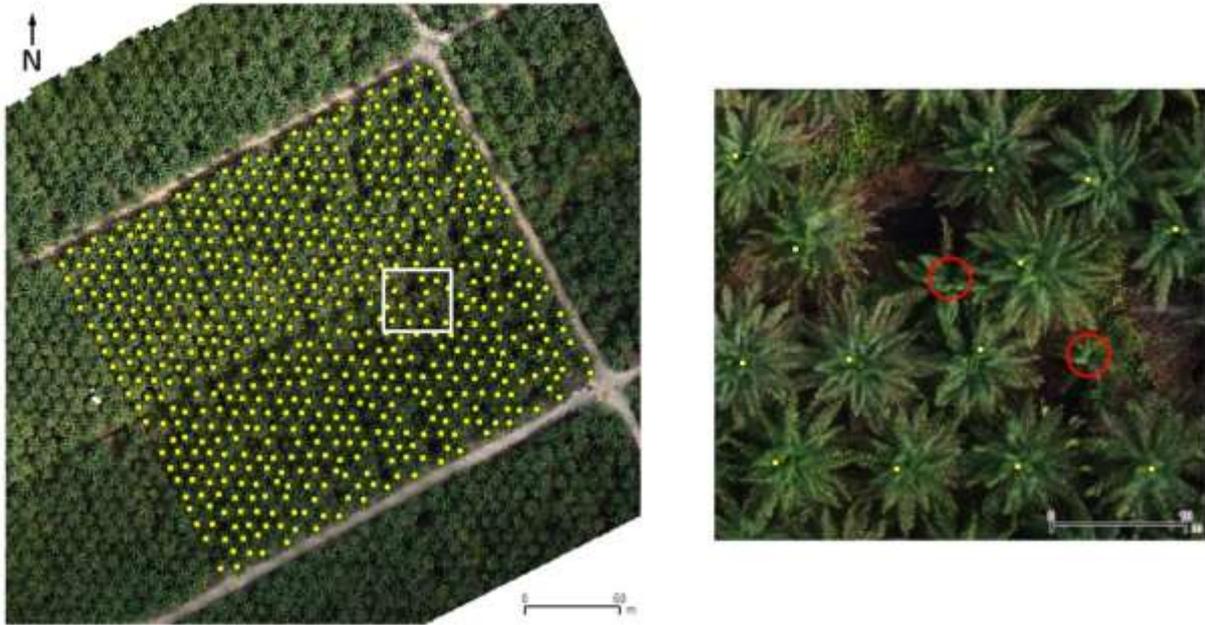
402

403

404 **3.3 Palm identification**

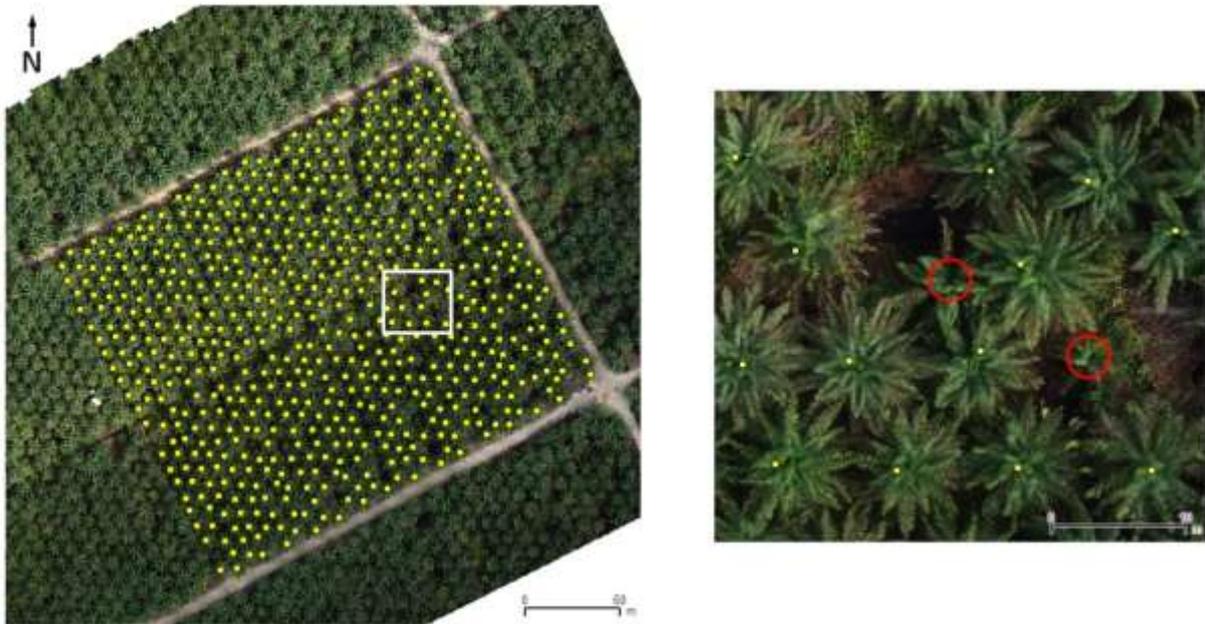
405

406 The local maximum palm identification algorithm performed relatively well for the 7 and 10 year old
 407 palm plots (containing 776 and 654 palms total), with a mapping accuracy (MA: correctly
 408 identified/(true total + commissions)) of 98.2% and 94.9% respectively. The identified palm locations
 409 for the 10 year old plot derived from HO1_10yr are illustrated in



410
 411 Figure 6, along with a subset showing an example of omitted palms. For the 2 year old plot, this method
 412 caused a large amount of omission and commission errors in the vicinity of the overgrown stacks of
 413 woody material between the palm rows, as the vegetation here was higher than the palm canopies.
 414 Neglecting these stacks and immediately adjacent palms, the method showed a MA of 80.4% for 238
 415 palms total.

416 The MA for the same region of the 10 year old plot using LO_10yr is 94.0%.



417
 418 *Figure 6:* Left: Resulting palm locations (yellow points) for the 10 year old plot and subset location (white rectangle), right:
 419 Subset illustrating omitted palms (red circles).

420 **3.4 Height metrics**

421

422 Maximum values of the individual palm point clouds were assessed against the TFH measured in the
 423 field. Results showed relatively large deviations between TFH measurements and maximum point
 424 cloud values with mean absolute errors of 0.383 m for HO_2yr, 0.968 m for HO_7yr and 1.246 m for

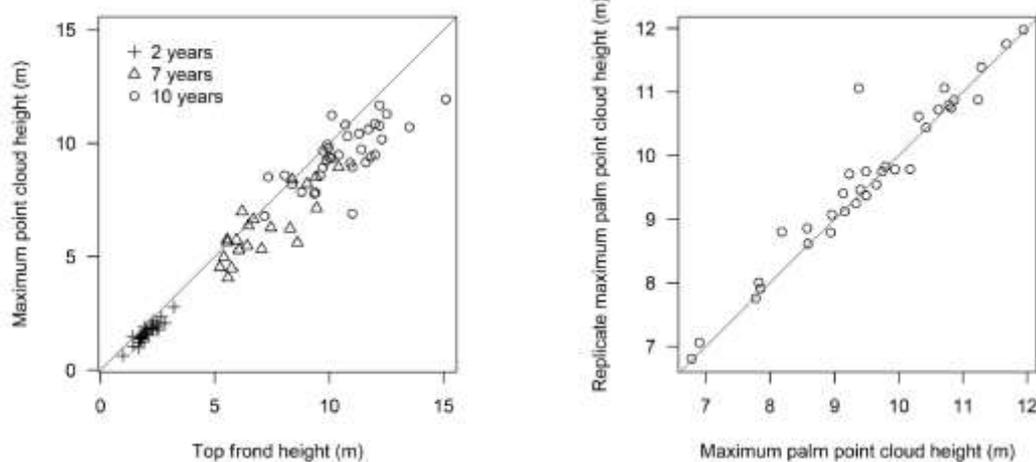
425 HO1_10yr, which represented 18.9%, 13.7% and 11.7% of the mean measured heights respectively
426 (Figure 7). LO_10yr showed lower mean absolute errors of 1.099 m for TFH of the 10 year old plot.

427 When comparing the maximum values between the replicates HO1_10yr and HO2_10yr for the field
428 measured palms (**Error! Reference source not found.**), this resulted in a mean absolute error of 0.199
429 m. Deviations between the values appear independent of field-measured height. One obvious outlier
430 is visible, caused by overlap resulting in a different segmentation of the palm. The magnitude of this
431 deviation between replicates is consistent with values generated by the MC point precision analysis on
432 the sparse point cloud (Table 2).

433 To establish the optimal metrics for deriving stem height from the point cloud it was necessary to
434 establish separate linear relationships between basic point cloud height metrics of the segmented
435 palm point clouds and the structural metric of stem height using LOOCV for different age stands (Table
436 3). For the 2 year old plot, the stem height above ground was negligible and so is not analysed. The
437 strongest relationships (according to R^2 values) with stem heights of the 7 year old plot was shown by
438 the maximum value ($R^2 = 0.63$; Table 3), while for the 10 year old plot the 80th percentile of elevations
439 performed better ($R^2 = 0.69$; Table 3). The MAEs represent 12.2% and 30.9% of mean stem heights
440 respectively. Results for the low overlap acquisition showed overall lower R^2 values compared to the
441 high overlap dataset, but was consistent in showing the best relationship for the 80th elevation
442 percentile ($R^2 = 0.59$).

443 Using these linear models to derive stem heights from the extent of each plot (i.e. using heights derived
444 from the UAV-SfM derived point clouds) for the 7 and 10 year old plots yields the distributions in Figure
445 9. For the 7 year old plot, negative values for predicted stem heights were constrained to 0 which
446 results in high counts for this bin. Despite the errors introduced, these models coupled with the
447 segmented point cloud represent an efficient method for the mapping of stem height and thus
448 provides necessary information for spatially differentiated AGB and carbon retrieval. Fine-grained
449 remotely sensed data thus enables single palm based estimates over spatial extents which would
450 require immense efforts of field-based sampling.

451



452

453

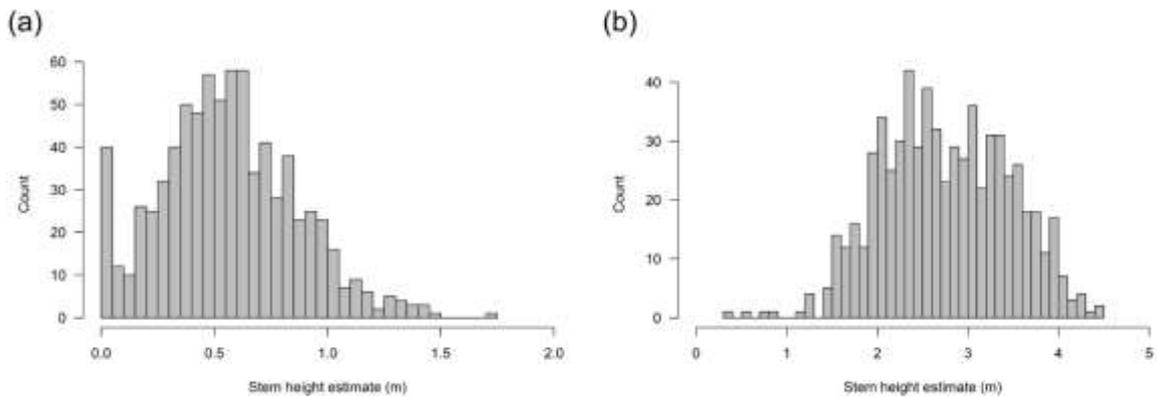
Figure 7: Maximum point cloud heights plotted against field measured TFHs for 2 year, 7 year and 10 year old palms.

Figure 8: Maximum point cloud height compared for the same palms between replicates of the 10 year old plot.

458 Table 3: Linear stem height model strength, root-mean-square errors (RMSE) and mean absolute errors (MAE) for the 30th -
 459 90th point cloud height percentiles as well as the maximum and mean values. Reported for the 7 year old plot and the 10
 460 year old plot with high and low overlap acquisitions. The highlighted rows show the models with the highest R^2 values
 461 which are used subsequently for stem height estimation.

Percentile	HO_7yr, n = 22			HO1_10yr, n = 37			LO_10yr, n = 37		
	R^2	RMSE (m)	MAE (m)	R^2	RMSE (m)	MAE (m)	R^2	RMSE (m)	MAE (m)
30%	0.56	0.30	0.24	0.64	0.48	0.40	0.52	0.50	0.42
40%	0.62	0.28	0.21	0.64	0.48	0.40	0.54	0.49	0.41
50%	0.61	0.28	0.21	0.64	0.48	0.39	0.55	0.48	0.39
60%	0.60	0.29	0.21	0.66	0.47	0.38	0.55	0.49	0.38
70%	0.58	0.29	0.21	0.68	0.45	0.36	0.54	0.49	0.38
80%	0.58	0.29	0.22	0.69	0.45	0.34	0.59	0.46	0.37
90%	0.57	0.30	0.22	0.68	0.45	0.34	0.57	0.47	0.38
Max	0.63	0.27	0.22	0.52	0.55	0.39	0.41	0.56	0.45
Mean	0.61	0.28	0.21	0.48	0.58	0.43	0.54	0.49	0.39

462



463

464 Figure 9: Histograms of estimated stem heights for the 7 year old plot (a) and 10 year old plot (b).

465 4 Discussion

466 This manuscript has presented an operational processing workflow for deriving per-palm height
 467 metrics from UAV image data while quantifying method-inherent uncertainties introduced at different
 468 stages. As demonstrated, it is possible to successfully segment single palms from fine-grained, UAV-
 469 derived SfM based datasets and derive TFH and stem height from point-cloud-derived products.
 470 Subsequent sections of this discussion will address precision estimates and accuracies of the generated
 471 results, and their implications for the application of this method in management and research of oil
 472 palm plantations.

473

474 **4.1 Uncertainties within resulting SfM point clouds**

475

476 Uncertainties resulting from SfM processing were estimated using a method which has not previously
477 been applied to a vegetation focused study. If correctly parameterised, this method may reduce the
478 need for time consuming replicates from independent acquisitions which are commonly advocated in
479 SfM based studies (Dandois et al. 2017; Dandois, Olano, and Ellis 2015). Overall, the precision maps
480 provide a better spatial indication of the SfM method's inherent uncertainties than relying exclusively
481 on values reported by GCPs and check points as a measure of reconstruction quality, which due to the
482 limited number of surveyed GCPs and the lack of GCPs at canopy level cannot adequately represent
483 uncertainties across the scene. However, it must be noted that these precision maps can't account for
484 some systematic errors (e.g. doming) and do not represent accuracy, which can only be assessed using
485 check points (James, Robson, and Smith 2017). Sparse point precisions at ground level were higher
486 (<10 cm) than for the vegetation canopy (20-50 cm). The contrast between precisions of the lower
487 (60%) versus higher (>75%) overlap acquisition highlighted that ground information resulting from
488 higher overlap flights appears more reliable, an observation which has previously been made for
489 forested areas (Dandois, Olano, and Ellis 2015). These uncertainties were confirmed at the dense point
490 cloud level by comparing per palm maximum values from a replicate dataset.

491

492 **4.2 Quality of derived DTMs**

493

494 Retrieving accurate ground elevations from SfM can introduce considerable uncertainties but doing so
495 represents an alternative to time consuming manual surveys when lacking LiDAR coverage of the
496 studied area, for point cloud normalisation and CHM determination. We found that undergrowth
497 caused an overestimation of the elevation of identified ground points, while dense canopies led to the
498 absence of information about the ground position. Interpolating between sparse ground points as was
499 required in this study for the 10 year old plantation was only feasible for regions of very slightly varying
500 topography as is the case for peat-soil plantations which show very subtle changes in topography at
501 landscape extents (Ballhorn, Jubanski, and Siegert 2011). Although the MAE of the measured ground
502 points did not exceed 20 cm for all the studied areas, it can be expected that uncertainties in the DTM
503 remain a major limiting factor in the quality of resulting canopy height metrics. An increase in DTM
504 error resulting from fewer ground points was observed for the lower overlap (60%) acquisition,
505 suggesting that higher overlap is recommended if DTMs must be derived from SfM point clouds alone.

506

507 **4.3 CHM-based palm identification**

508

509 Local maxima based palm identification informed by planting distance performed very well (98.2% MA)
510 for palms of intermediate ages (here 7 years), when they were taller than surrounding vegetation and
511 other topographic variations (e.g. mounds of overgrown timber) and when their fronds did not yet
512 overlap by more than a few decimetres. This mapping accuracy is identical to that reported by
513 Kattenborn et al., (2014) for dense palm stands without overlap. The performance of height based
514 identification of young palms (2 years) was heavily dependent on the plantation structure and
515 undergrowth. Excluding areas with large local topographic variations our approach performed
516 moderately well with 80.4% mapping accuracy, influenced predominantly by false positives from tall
517 undergrowth. In the plot studied here, the application of the method to the entire plot was
518 complicated by the overgrown stacks of organic material which resulted in false positives and

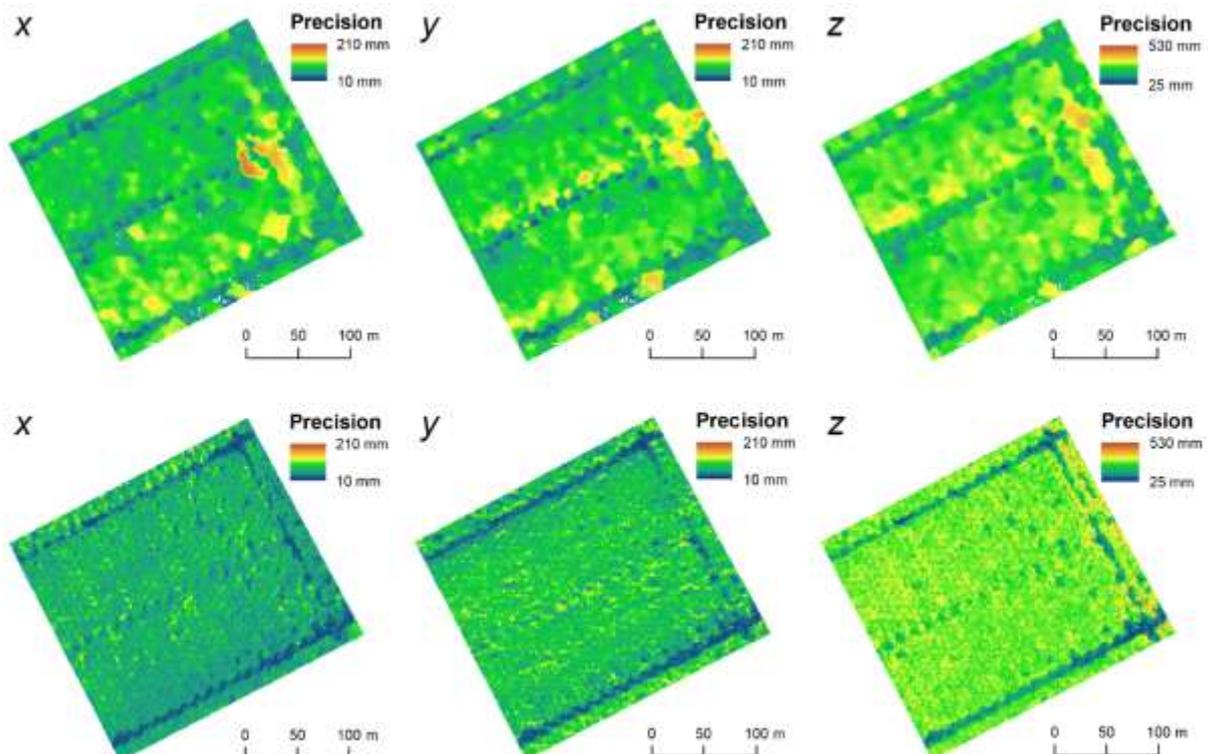
519 sometimes obscured adjacent young palms. We advise that local maximum methods are not
520 appropriate for direct application to plantation blocks with such topographic variations. For older
521 plantations (10 years), the resulting MA of 94.9% was caused by issues with overlap and smaller palms
522 which are surrounded by taller ones not being identified as local maxima. This could be partly
523 addressed by decreasing the window size of the local maximum filtering, which would however
524 introduce more false positives.

525

526 **4.4 Assessing maximum point cloud height against TFH**

527

528 Comparing the maximum point cloud height with field-measured TFH appeared to show a high
529 uncertainty but also an apparent negative bias for the UAV-derived metric (Figure 7). The large
530 deviations between field measurements and point cloud metrics are likely due to biases also in field
531 measurements – e.g. including the manual identification of the highest frond, selection of its highest
532 part and a possible x, y discrepancy between the reference point on the ground and the highest
533 measured frond point. Treating the field validation data as a perfect baseline against which to assess
534 the SfM result is probably a flawed approach, and both datasets should be considered as uncertain.
535 This difficulty of validating SfM-derived height metrics for higher vegetation such as trees has also been
536 encountered in previous studies (Lisein et al. 2013). Here this issue is not solved but addressed by the
537 generation of tie-point precision estimates which provide further insight into the method-inherent
538 uncertainties, which we show to be relatively low (e.g. < 10 cm) for ground points and higher at canopy
539 level, averaging around 30 cm as visible in



540

541 Figure 4.

542 The negative bias apparent in the results (Figure 7) is expected to be independent of the above
543 uncertainties and can be partially explained by the effect of undergrowth on the interpolated DTM
544 surface. For the 10 year old palm plot this is however not consistent with height validation
545 measurements where the DTM values were below the reference. Further bias may originate from an
546 inherent smoothing effect of the dense matching process, observed in previous studies where SfM

547 point clouds were compared to LiDAR reference data (Lisein et al. 2013), but this is contradictory to
548 the fact that LO_10yr produced maximum height values closer to field measured TFH.

549 Overall, the errors resulting for the TFH (or top-of-canopy height) estimation are very close to those
550 reported by other studies applying SfM methodologies to vegetated systems of similar height range
551 (Wallace et al. 2016; Panagiotidis et al. 2017). Better results can be achieved when employing a LiDAR-
552 derived DTM (Lisein et al. 2013; Puliti et al. 2015), though this represents a considerable operational
553 constraint. The inclusion of convergent imagery at non-nadir angles (e.g. 45°) has also been advocated
554 as besides strengthening the image network for reconstruction it can result in more ground points
555 being visible to aid in DTM generation (Cunliffe, Brazier, and Anderson 2016). The latter aspect may be
556 negligible for dense canopy cover but could yield better results for younger palms. The impact on point
557 precisions and DTM error would benefit from further study, especially in relation to the cost of
558 additional acquisitions and processing time.

559

560 ***4.5 Point cloud height metric based stem height estimation***

561

562 Assessing the relationship between different point cloud height metrics and field measured stem
563 height did not show very large differences between the metrics used. Nevertheless, the strongest
564 relationship differed between the two different aged plots analysed, which can likely be attributed to
565 different point cloud characteristics as a result of canopy density. For 7 year old palms where little to
566 no overlap occurs, a greater portion of the fronds were resolved in the point cloud; while for the 10
567 year old palms the lower fronds were completely, or partially obscured. When applying the resulting
568 models to generate estimates of stem height distributions throughout the plots, it is striking that there
569 were relatively large value ranges for plots of the same age, considerably larger than the resulting
570 MAEs. For the 7 year old plot, there were however a considerable number of negative values, which
571 were re-set to zero for the analysis. The two primary causes for this were local DTM errors caused by
572 undergrowth as well as the fact that younger, later planted replacement palms have significantly
573 smaller fronds which results in under-estimation of stem height by the linear model. Due to the
574 amount of palms affected, we advise that a solution should be sought before applying this model for
575 stem height estimations. Given a large amount of field samples across multiple palm ages, it may be
576 possible to identify a robust non-linear relationship which accounts for age-dependent differences.
577 This would allow efficient and accurate retrieval of per-palm trunk biomass from SfM point cloud data
578 using allometric equations, given assumptions about diameter at breast-height (DBH) (Corley and
579 Tinker 2016).

580

581 ***4.6 Implications for oil palm plantation management and research***

582

583 The methods for palm identification, TFH and stem height retrieval presented here are applicable to
584 image data from consumer grade UAV systems, provided such data are acquired with sufficient spatial
585 overlap. Our workflow can thus be of relevance to improved plantation management – because it can
586 deliver maps indicative of plantation status at relatively low financial cost. Repeat acquisitions would
587 further allow the identification of height increments over time and local variations in height could
588 possibly be correlated with oil palm yield, for example by influencing the light regime (Corley and
589 Tinker 2016). The retrieval of height metrics appears to work almost as well for lower resolution, lower
590 overlap acquisitions (LO_10yr) as they do for acquisitions focused on retrieving a higher quality point
591 cloud (e.g. HO1_10yr). This is an important insight when seeking to maximise the spatial coverage of

592 survey flights, whilst also reducing the time required for acquisitions and data processing. A
593 constraining factor regarding both time and cost of UAV acquisitions, following the survey designs
594 presented here, is the reliance on high precision GCP measurements. If the absolute geographic
595 locations are not a necessity, an alternative may be the use of a total station to measure distances
596 between markers. The installation of adequately spaced permanent GCPs would also greatly facilitate
597 repeat acquisitions. Furthermore, with the ongoing development of UAVs that will, in future, carry on-
598 board real-time kinematic GNSS capabilities, immediate high precision georeferencing of the acquired
599 data may become an operational option in the future, minimising the need for ground control (Turner,
600 Lucieer, and Wallace 2014).

601 The demonstrated usefulness of even low overlap acquisitions to derive height metrics and the
602 increased application of UAVs for plantation management means that there may be an untapped data
603 source of interest for research and a potential for a closer collaboration between researchers and
604 innovative palm oil companies. Despite similar results for HO1_10yr and LO_10yr it can be assumed
605 that for deriving information on younger palm canopies and for finer scale structural information such
606 as frond rachis length and number, utilizing advanced point cloud metrics, higher overlap and finer
607 resolution are required. The ability to derive advanced metrics with higher reliability may also prove
608 useful in predicting per palm biomass, given adequate training and validation data derived from
609 destructive harvesting or estimated AGB derived from allometric measurements of stem height, DBH,
610 petiole cross-section and frond number in the field (Corley and Tinker 2016). Coupled with further
611 concurrent field sampling efforts, UAV SfM photogrammetry derived metrics may be robust enough
612 to provide much needed information to address one aspect of the lack of data for oil palm carbon stock
613 estimates and the impact of the conversion of different land cover to oil palm plantations (Kho and
614 Jepsen 2015).

615 Emerging work by Malek et al. (2014) and Manandhar, Hoegner, and Stilla (2016) indicates the
616 potential of computer vision and object based detection for automated oil palm identification and
617 counting. Further work is needed to develop and demonstrate the robustness of these methods in
618 complex plots with larger undergrowth. It stands to reason that object based and height based
619 detection possess a number of contrasting advantages and that a hybrid approach including height
620 information and image-based segmentation may yield the most accurate solution. As a DSM typically
621 results from the workflow for orthomosaic generation, no additional data acquisition is required.
622 Therefore this would be a promising direction for future research aiming at developing palm
623 identification methods with sufficient accuracy for commercial application.

624 **5 Conclusions**

625 This study demonstrated the use of SfM point clouds derived from UAV imagery for the identification
626 of single palm canopies and the retrieval of basic structural information based on height metrics from
627 segmented palms. In plantation plots with flat topography as studied here a DTM interpolated from
628 classified SfM ground points proved sufficiently accurate (~10 cm for high overlap acquisitions) for
629 height based studies of oil palm without requiring LiDAR based information, which is key for the
630 operational implementation at similar sites. Employing an MC approach for generating point cloud
631 precision estimates allowed a spatially resolved assessment of SfM data quality which can be used to
632 inform a quantitative assessment of point cloud robustness and suitability for vegetation structure
633 related studies. Local maximum methods for CHM based palm identification performed best for
634 intermediate palm ages (7 years) but show more errors where large undergrowth and overlapping
635 between palm canopies is common. Further it was shown that reliable inventories of the number of
636 palms per plantation block could be generated with acquisition plans which favour coverage over high

637 overlap, which provides an important benchmark for applying this methodology while maximising the
638 efficiency of data acquisition. However, more highly resolved per-palm point clouds allowed for better
639 estimation of stem height using height percentiles, and enabled the generation of stem height
640 distributions for the studied plots. Due to the amount of detail resolved, it can be assumed that more
641 complex point cloud based metrics could be identified which correlate with other aspects of palm
642 structure and therefore warrant further research. These derived per-palm metrics, besides giving
643 detailed information on plantation status, may prove useful for predicting per-palm AGB and
644 ultimately mapping oil palm carbon stocks, providing an affordable and widely applicable method for
645 carbon accounting.

646

647

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655 **7 Declaration of interest statement**

656 The authors declare no conflicts of interest.

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