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Adrien Michez, Léo Huylenbroeck, Corentin Bolyn, Nicolas Latte, Sébastien Bauwens, et al.. Can regional aerial images from orthophoto surveys produce high quality photogrammetric Canopy Height Model? A single tree approach in Western Europe. *International Journal of Applied Earth Observation and Geoinformation*, 2020, 92, pp.102190. 10.1016/j.jag.2020.102190 . hal-02893362

HAL Id: hal-02893362

<https://hal.science/hal-02893362v1>

Submitted on 15 Jul 2022

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Can regional aerial images from orthophoto surveys produce high quality height model in forest context? A single tree approach in Western Europe

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Abstract:

Forest monitoring tools are needed to promote effective and data driven forest management and forest policies. Remote sensing techniques can increase the speed and the cost-efficiency of the forest monitoring as well as large scale mapping of forest attribute (wall-to-wall approach). Digital Aerial Photogrammetry (DAP) is a common cost-effective alternative to airborne laser scanning (ALS) which can be based on aerial photos routinely acquired for general base maps. DAP based on such pre-existing dataset can be a cost effective source of large scale 3D data. In the context of forest characterization, when a quality Digital Terrain Model (DTM) is available, DAP can produce photogrammetric Canopy Height Model (pCHM) which describes the tree canopy height. While this potential seems pretty obvious, few studies have investigated the quality of regional pCHM based on aerial stereo images acquired by standard official aerial surveys. Our study proposes to evaluate the quality of pCHM individual tree height estimates based on raw images acquired following such protocol using a reference field-measured tree height database. To further ensure the replicability of the approach, the pCHM tree height estimates benchmarking only relied on public forest inventory (FI) information and the photogrammetric protocol was based on low-cost and widely used photogrammetric software. Moreover, our study investigates the relationship between the pCHM tree height estimates based on the neighboring forest parameter provided by the FI program.

Our results highlight the good agreement of tree height estimates provided by pCHM using DAP with both field measured and ALS tree height data. In terms of tree height modeling, our pCHM approach reached similar results than the same modeling strategy applied to ALS tree height estimates. Our study also identified some of the drivers of the pCHM tree height estimate error and found forest parameters like tree size (diameter at breast height) and tree type (evergreenness/deciduousness) as well as the terrain topography (slope) to be of higher importance than image survey parameters like the variation of the overlap or the sunlight condition in our dataset. In combination with the pCHM tree height estimate, the terrain slope, the DBH and the evergreenness factor were used to fit a multivariate model predicting the field measured tree height. This model presented better performance than the model linking the pCHM estimates to the field tree height estimates in terms of r^2 (0.90 VS 0.87) and RMSE (1.78 VS 2.01 m). Such aspects are poorly addressed in literature and further research should focus on how pCHM approaches could integrate them to improve forest characterization using DAP and pCHM. Our promising results can be used to encourage the use of

41 regional aerial orthophoto surveys archive to produce large scale quality tree height data at very low
42 additional costs, notably in the context of updating national forest inventory programs.

43 **Keywords:**

44 Photogrammetry, structure from motion, tree height, large frame aerial imagery

45

46 **1. Introduction**

47 Forests cover almost a third of global land area (Keenan et al., 2015). They provide numerous
48 ecosystem services and are of major importance in public policies worldwide. Monitoring tools, like
49 forest inventories (FI), are regularly set up on national scale in order to promote knowledge-based
50 forest management and policies. On such scale, a complete censusing of all trees is prohibitively
51 expensive and subsequently, FI must rely on sample-based approach. In this context, remote sensing
52 techniques can increase the speed and the cost-efficiency of the field operation while increasing the
53 precision and timeliness of estimates (McRoberts and Tomppo, 2007). Remote sensing can also
54 facilitate the construction of 'wall-to-wall' maps of forest attributes covering entire countries.

55 Since the late 90's, airborne LiDAR point clouds (or Airborne Laser Scanning, ALS) have become the
56 state-of-art remote sensing technique to characterize the 3D structure of forest (Michez et al., 2016).
57 ALS forest characterization approaches have been in the focus of research for two decades and are
58 now an important component of operational large-scale FI (Næsset, 2014). As ALS surveys remain
59 expensive, there is a need for alternative technology like Digital Aerial Photogrammetry (DAP). Aerial
60 photography is the traditional source of information for forest characterization which has been
61 completed by satellite imagery since the 80's and by 3D point clouds since the late 90's. The
62 development of DAP renewed the interest for the use of aerial imagery in forest monitoring which
63 has tended to fade in the late 1990s with the advent of ALS. In the context of forest characterization,
64 when a quality Digital Terrain Model (DTM) is available, DAP can produce photogrammetric Canopy
65 Height Model (pCHM) which describes the tree canopy height. Leberl et al. (2010) identified 4 main
66 innovations which eased the implementation of DAP: cost-free increase of overlap between digitally
67 sensed images, an improved radiometry, the development of multi-view matching algorithm and the
68 ability to run the process on Graphics Processing Unit (GPU). These innovations have made DAP
69 workflows very practical and automated, potentially reaching sub-pixel 3D total accuracy. DAP is a
70 cost-effective alternative to ALS, reducing the cost of the survey to one half to one third (Leberl et al.,
71 2010; White et al., 2013) while it presents similarities with ALS in terms of data structure (i.e. point
72 clouds). Nevertheless, the most important difference from ALS is that DAP is limited to characterizing
73 the outer canopy envelope while ALS provides precious information about the sub canopy layers.
74 DAP can be processed from aerial photos routinely acquired for general base maps updates as
75 highlighted by Ginzler and Hobi (2015). As such systematic surveys (ALS and aerial photos) are more
76 and more carried out in many European and North-American countries, DAP could be used to
77 produce 3D data on a national scale at little or no additional cost.

78 DAP and associated pCHM are subject to inaccuracies with specific spatio-temporal patterns which
79 can thus induce additional intra-variability among large-scale surveys. They can be related with the
80 weather condition and the sun position during the survey (Rahlf et al., 2017), the flight plan and the
81 overlap between images (Zimmermann and Hoffmann, 2017), the terrain complexity as well as the
82 characteristics of the studied forest itself (Goodbody et al., 2019). For example, DAP globally fails to
83 reconstruct the canopy of deciduous forest under leaf-off conditions (Huang et al., 2019) but highly
84 heterogeneous forest structure can also challenge the DAP 3D reconstruction, notably in relation
85 with the fine-tuning of the reconstruction parameters (Ginzler and Hobi, 2015). Numerous studies
86 (see Goodbody et al. (2019) for a complete review on the subject) have used DAP to describe forest
87 structure. Most of these studies are using an area based approach (ABA) to characterize forest
88 structure (timber volume, dominant height, basal area, etc.) of boreal forests (mainly from Canada

89 and Northern Europe). In the context of area based forest inventory, Goodbody et al. (2019) found
90 that *“attribute predictions generated using DAP data in an ABA have been found to be of comparable*
91 *accuracy to that of ALS data across a range of forest environments, although inventory attribute*
92 *predictions made using ALS data are consistently more accurate”*. From a practical point of view,
93 DAP and pCHM can thus be used to timely update regional forest 3D structure as aerial images are
94 generally acquired on a regular basis by national or regional mapping agencies. This interest is
95 reinforced as countrywide ALS surveys providing accurate DTMs are occurring more and more
96 frequently throughout the world. Another major interest of using DAP approaches based on stereo-
97 images acquired during regular national campaigns is to value potentially very dense time series
98 which can cover time period which may cover periods prior to the acquisition of data ALS.

99 While the potential of using pCHM build with aerial images regularly acquired by national or regional
100 mapping agencies seems pretty obvious, few studies have investigated the quality of such
101 regional/countrywide pCHM, especially on the single tree scale. Evaluating the 3D accuracy of DAP
102 derived from such regional/national aerial survey is nevertheless an essential topic as such surveys
103 are generally not designed to produced high density 3D point clouds but only orthophotomosaics
104 which typically require less overlap. In this context, Ginzler and Hobi (2015) re-used national aerial
105 surveys to produce countrywide (41285 km²) photogrammetric Digital Surface Model (DSM) and
106 pCHM in Switzerland. They assessed the accuracy of the DSM with topographic field observations as
107 well as the quality of the individual tree height estimates based on field measurements (3109 trees).
108 While they achieved very good results in terms of 3D accuracy of the DSM (sub-metric accuracies),
109 their result in terms of individual tree height estimates were of lower accuracy than those commonly
110 found with ALS CHM ($r^2 = 0.69$). On smaller spatial extent, Zimmermann and Hoffmann (2017) and
111 Hirschmugl et al. (2007) achieved better tree height estimates than Ginzler and Hobi (2015) but on a
112 smaller reference trees set (respectively 51 and 356 trees) even if the lack of harmonized accuracy
113 metrics hampers real accuracy benchmarking. None of the pre-cited studies investigated the
114 relationship between pCHM error at single tree level and the forest characteristics around the
115 considered trees (e.g., stem density, volume, basal area, canopy roughness).

116 In this context, we propose to evaluate the accuracy of individual tree height estimates provided by
117 pCHM build using aerial images acquired in the specific context of countrywide orthophoto survey
118 protocols. To further ensure the replicability of the approach, the pCHM tree height estimates
119 benchmarking only relied on public FI information and the photogrammetric protocol was based on
120 low-cost and widely used photogrammetric software. Moreover, our study investigates the
121 relationship between the pCHM tree height estimates based on the neighboring forest parameter
122 provided by the FI program in a European temperate forest context.

123 **2. Material and Methods**

124 **2.1. Study site**

125 The study site covers the southern region of Belgium, Wallonia (16,902 km²), representing ca. 55 %
126 of Belgium’s area. Wallonia presents contrasted landscapes and can be divided in five natural
127 ecoregions. Forest landscapes cover one third of the study area (5,546 km²). Broad-leaved forests are
128 more frequent than needle-leaved forest (ca. 57% VS 43%). They are largely dominated by beech

129 (Fagus sylvatica) and oaks (Quercus robur and Q. petraea) but other species such as birch (Betula
130 pendula), maple (Acer pseudoplatanus), ash (Fraxinus excelsior), and hornbeam (Carpinus betulus)
131 are also regularly found. Needle-leaved forests are largely composed of spruce (Picea abies) and
132 Douglas fir (Pseudotsuga menziesii) and to a lesser extent, larches (Larix sp.) and pines (Pinus
133 sylvestris and P. nigra). The evergreen stands are mostly managed as even-aged stands and
134 harvested by the means of clear-cuts (Alderweireld et al., 2015).

135 **2.2. Aerial surveys**

136 The regional orthophoto surveys in the study area are achieved by private operators on a regular
137 basis, notably for the sake of controls related to European Union common agricultural policy. They
138 were initially acquired on a triennial basis and since 2015, on an annual basis. The timetable of the
139 regional surveys is driven by the objectives stated above and typically ranges from April to October
140 (Table 1). Such timetable can indeed lead to the acquisition of aerial images of deciduous forest in
141 leaf-off condition. Since the 2009 survey, the targeted Ground Sampling Distance (GSD) is 0.25m in
142 order to allow the photointerpretation of fine landscape features. The entire time series was
143 acquired using Vexcel UltraCam Imaging Sensors (<https://www.vexcel-imaging.com/>) based on flight
144 plan using 60% along-track and 30% across-track overlaps. Such large frame sensors present low lens
145 distortion and provide a multispectral imagery covering the Red, Blue, Green and Near-Infrared
146 spectral ranges.

147 We also used a regional LiDAR survey performed from 12 December 2012 to 09 March 2014. This
148 LiDAR survey was used as a Digital Terrain Model (1m GSD) to compute the pCHMs (photo. DSMs -
149 ALS DTM) as well an ALS CHM (1m GSD, ALS DSM - ALS DTM) to benchmark the 5 pCHMs in terms of
150 single tree height estimates.

151 **Table 1: essential aerial survey parameters of regional orthophoto coverage.**

Survey reference	Images	GSD (m)	Start	End
2006	4532	0.5	10/06/2006	22/04/2007
2009	7070	0.25	23/05/2009	7/07/2010
2012	6501	0.25	14/05/2012	8/07/2013
2015	8208	0.25	9/04/2015	17/06/2015
2016	8358	0.25	10/06/2016	1/11/2016

152 **2.3. Regional Digital Surface Model**

153 **2.3.1. Photogrammetric reconstruction**

154 We used Agisoft Metashape 1.5.4 in network mode for all the photogrammetric reconstruction steps
155 synthesized in Figure 1. Agisoft is one of the most used photogrammetric packages using a multiview
156 matching strategy (Smith et al., 2016). It also allows to handle large images (200 Mpx and more)
157 generated by large frame sensors like the UltraCam in an easy to set up network processing
158 interface. We choose this software for its relatively user friendly GUI as well as its rather low cost (ca.
159 549 \$ for educational license and 3500 \$ for commercial license) compared to other state-of-art

160 photogrammetric package like Trimble Inpho or Imagine Photogrammetry (LPS). These
161 characteristics will ease the reproducibility of the methodology.

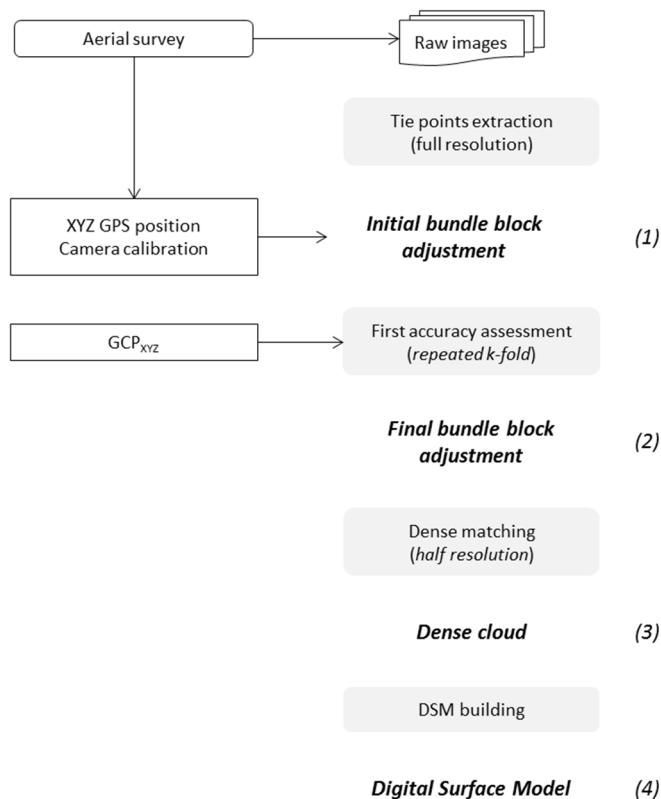
162 We set up a processing network of 3 to 5 (depending on the resources available) computers
163 equipped with GPU processing (NVidia GTX) and 64 Go RAM. The very same photogrammetric
164 protocol was applied to process the raw images of the different regional orthophoto coverages.
165 Based on the GPS positions (metric coordinates system "Lambert 72", EPSG: 31370) and the camera
166 calibration information delivered by the service provider, we realized the tie point extraction in full
167 resolution using the "High" accuracy parameter, "Key points limit" and "Tie point limit" set to 40000
168 and 4000 respectively. To avoid overfitting, we followed the recommendations of James et al. (2017)
169 and used a rather conservative lens calibration strategy. The following lens calibration parameters
170 remained fixed: b1b2 (affinity and skew transformation coefficients), k4 and p3/p4 (additional
171 tangential and radial distortion coefficients). This lens calibration strategy was pursued during the
172 entire photogrammetric processing. This first alignment process resulted in a first 3D reconstruction
173 (sparse point cloud) based on an initial bundle block adjustment (BA) as highlighted in Figure 1-1.

174 Based on this initial result, ground control points (GCP) were easily located on raw images thanks to
175 the pre-positioning performed by the software. Two types of GCP were used to ensure and evaluate
176 the quality of the photogrammetric reconstruction. A first set of GCP is based on a set of GCP
177 network installed by the service provider who produced the orthophoto coverage for the 2012
178 survey. This network is made of 89 black and white circular marks (0.6 m radius) on the ground which
179 can be easily located on the aerial images. All these points were accurately georeferenced on the
180 ground using precision GPS (Figure 3-I). As this network was not available for the entire time series
181 (2006 and 2009 surveys), we used a dense network (1088 units, Figure 3-II) of reference ground
182 marked points provided by the National Geographic Institute which consists of various particular
183 points which can be seen on aerial images and have precisely been georeferenced on the ground
184 with precision GPS (pedestrian crossing, change in road color, ...). The total GCP network represents
185 an important reference dataset covering the entire study area (Figure 3-I and Figure 3-II).

186 The accuracy assessment process is based on a cross-validation using repeated k-fold technique (k=5,
187 repetition = 50) implemented in Agisoft Metashape through python scripting. For each of the 50
188 iterations, the GCP dataset is randomly divided into five folds of GCP and five BA processes are
189 successively run (Figure 2). Each BA process is run based on a set of GCP from one fold as checkpoint
190 (not used in the process, i.e. test set), the other GCP (associated to the 4 other folds) being used as
191 control points (to constrain the BA process, i.e. training set). The XYZ errors associated with the GCP
192 from the test fold are saved and another BA is run, using GCP's from one other fold as checkpoints.
193 Once all the GCP's from the k folds have been successively used as checkpoints (and thus as
194 independent test set), the entire process is repeated over 50 times to ensure the robustness of the
195 cross-validation. Indeed, all the GCPs of the network are used to assess the 3D accuracy of the 3D
196 reconstruction with 50 different neighboring conditions. As the accuracy of the 3D model is
197 subsequently evaluated 50 times for each GCP, the XYZ error values were aggregated by mean. The
198 quality of the photogrammetric DSMs was finally assessed through box-and-whisker plots as they
199 allow to investigating the accuracy (i.e. mean/median error) and the precision (i.e. the deviation of
200 error) as promoted in the guidelines proposed by James et al. (2019). The evenly spatial distribution
201 and the high density of the GCP network (1 GCP / 15 km²) allow avoiding the sampling of a test set of
202 checkpoints within the GCP network and subsequently testing the entire network of ground control

203 points. Once the accuracy assessment has been completed, all the GCP were used to run the final BA
204 process (Figure 1-2) with the GCP accuracy set to 0.01m in the Agisoft interface.

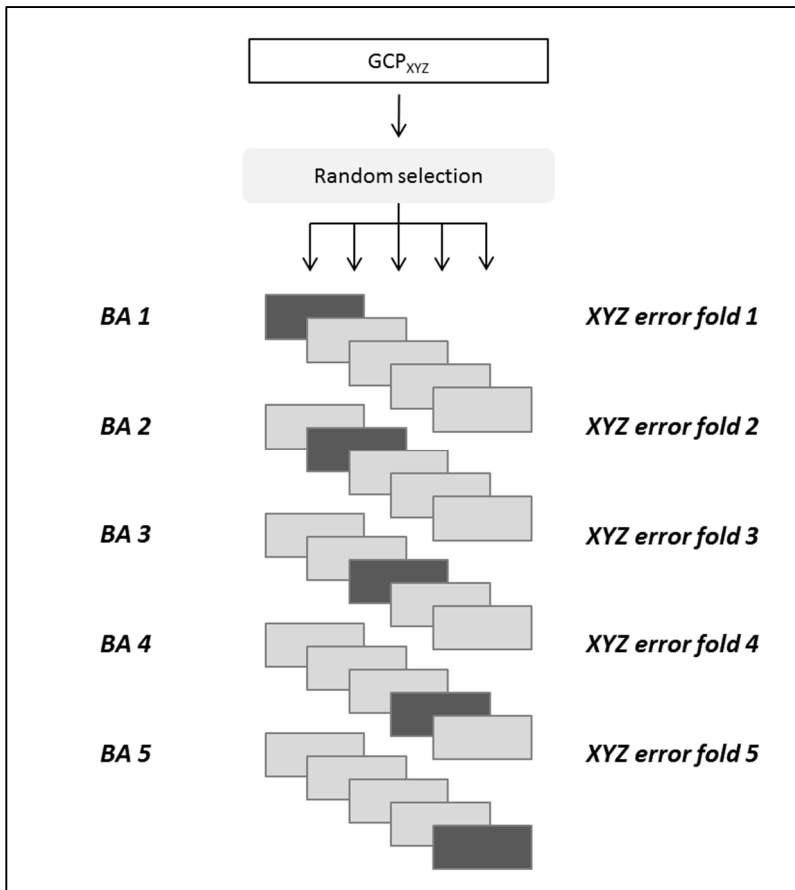
205 The dense matching process was run using aggregated images (aggregation factor of 2, half
206 resolution) as a compromise between spatial resolution and computing time. The “Aggressive” depth
207 filtering strategy was selected to limit the noise in the dense cloud. The final output is a DSM
208 (“Interpolation” enabled) which results in 5 regional DSM in raster format (Figure 1-4, 1m GSD for the
209 2006 and 0.5m for the other).



210

211 **Figure 1: main steps of the photogrammetric workflow implemented in Agisoft Metashape. Data/Input are represented**
212 **in solid white box, processes are in grey boxes and results are bolded, italicized and numbered from (1) to (4).**

213



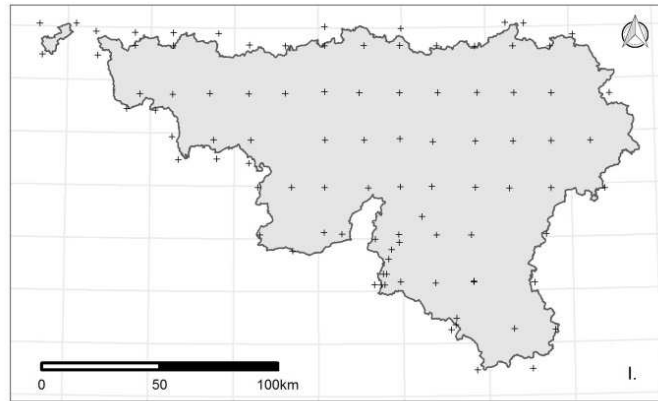
214

215 **Figure 2: k-fold process applied to assess the 3D accuracy associated with the GCP set. GCPs from the light grey folds are**
 216 **used as control points (training set), GCPs from dark greyed fold are use as checkpoints (test set). This process was**
 217 **repeated 50 times with error being aggregated by mean.**

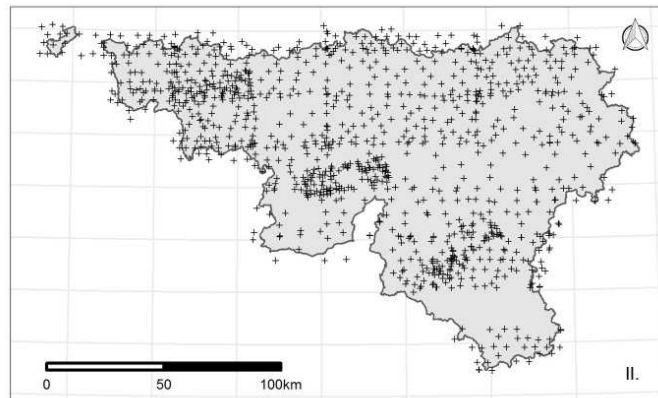
218

219

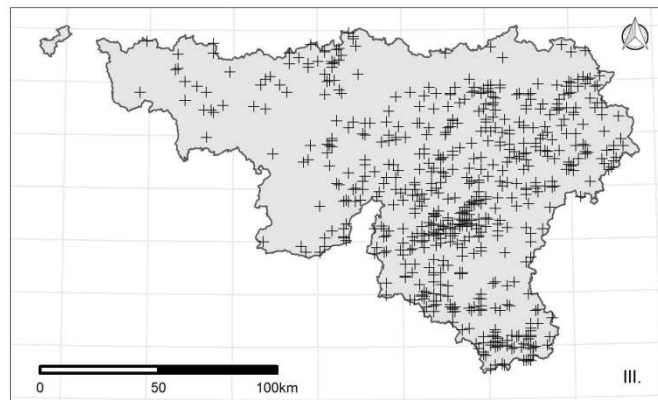
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Figure 3: field reference data used in the different accuracy assessments of the study: I. black and white circular marks GCP (89), II. GCP from reference marked points provided by the National Geographic Institute (1088), III. forest inventory plots (610) used to complete an individual tree height reference database.

227 **2.4. Regional photo Canopy Height Model (pCHM)**

228 **2.4.1. pCHM Processing**

229 The regional photogrammetric DSMs were combined with a regional ALS Digital Terrain Model
230 (photogrammetric DSM - ALS DTM) resampled according to the resolution of the DSM. As the ALS
231 survey occurred from 12 December 2012 to 09 March 2014 (see 2.2 section), we considered the
232 topography as constant during the entire study period. As our study is dedicated to trees located
233 inside forest landscapes, this assumption is reasonable considering the low erosion rate in forested
234 landscape as well as the infrequency in the study area of catastrophic events (e.g. landslide or
235 earthquakes).

236 **2.4.2. Accuracy assessment of tree height estimates from pCHM**

237 A selection of field reference plots from the regional FI program was performed using temporal and
238 spatial criteria. The FI plots collect various parameters such as tree height, diameter above breast
239 height (DBH), tree species, health condition, etc. The measurements of tree height were performed
240 with a vertex ultrasound instrument. Measured trees are spatially located using azimuth and distance
241 relative to the plot center which is georeferenced with off-the-shelf GNSS receivers. In terms of
242 absolute positioning accuracy, a study conducted in a similar context in France (Monnet and Mermin,
243 2014) shows that such GNSS gives a plot positioning accuracy of 9 m (\pm 8.7 m). The field sampling is
244 designed to cover the study area on a yearly basis. The ongoing inventory (second cycle) is a single-
245 phase, non-stratified inventory using a systematic sampling design based on plots located at the
246 intersections of a 1000 m (east-west) \times 500 m (north-south) grid with 11 000 sampling plots located
247 in the forest. Each year 10 % of all plots are assessed. They are selected on a systematic basis to be
248 evenly distributed throughout the region. Sampling plots is composed of concentric circular plots
249 with radius from 4.5m to 18m depending of the dbh class of the trees (Alderweireld et al., 2016).
250 More information about the Walloon FI protocol can be found online (<http://iprfw.spw.wallonie.be>).

251 For every aerial survey, we selected field plots which were measured in the same vegetative year
252 (considering the growing cycle from April to October) in order to minimize errors linked to tree
253 growth and tree removal. The relative position of the individual trees was converted to absolute ones
254 based on the GPS XY position of the plot center. As the plot centers are located using low-quality
255 GNSS receivers, relocation of the field plot was performed in QGIS 3.0 software (QGIS Delopment
256 Team, 2020) by a trained operator. Using reference GIS layers (orthophoto based on photo. DSM and
257 pCHM time series), the operator looked for the best XY shift and applied it to the entire trees of the
258 FI plot. As the tree XY positions are relative to the stem position (at breast height) and not to tree
259 tops, we used the method developed by Eysn et al. (2015). Their approach performs XY and height
260 matching with local maxima detected in the associated pCHM by the tree_detection() function (Imf
261 algorithm, adaptive moving windows based on tree height) of the lidR R package (Roussel and Auty,
262 2019). This approach allows identifying trees from the upper canopy envelope as this information is
263 not recorded during the field measurements of the FI. This results in a database of 1850 reference
264 individual trees (Table 2) from 489 FI plots presenting an evenly spatial distribution in the study area.
265 To avoid 3D reconstruction issues linked to (partial) leaf-off conditions, FI plots were selected only
266 when they were in leaf-on condition during the associated aerial survey. In even-aged forests (mainly
267 spruce and Douglas fir), the field survey of the tree height is limited to few individuals in order to

268 compute the dominant height. As the evergreen forests are mainly managed as even-aged stands,
 269 they occur in a rather low proportion in the reference tree database as compared to deciduous trees.
 270 We performed the same matching between field measured tree heights from FI plots and tree height
 271 estimates extracted from the ALS CHM. This database was composed of 1579 trees from 260 FI plots
 272 (1144 deciduous, 435 evergreen). The Figure 3-III represents the FI plots network used in this study.

273 In order to test the reliability of tree height information provided by pCHM, we performed linear
 274 modelling between field measured tree height (from the reference tree database) and tree height
 275 estimates from local maxima of the 5 different pCHM's. We applied a similar method with ALS
 276 reference dataset to benchmark tree estimates provided by the pCHM with a reference tree height
 277 remote sensing data source.

278

279 **Table 2: reference tree dataset used to assess the accuracy of tree height estimates based on pCHM**

Reference year (aerial survey)	Reference tree		
	Total	Evergreen	Deciduous
2006	95	23	72
2009	380	63	317
2012	510	185	325
2015	246	152	94
2016	619	174	445
Total	1850	597	1253

280 **2.4.3. Drivers of the pCHM tree height estimates error**

281 To investigate the robustness of the pCHM tree height estimates, we compared the impact of various
 282 parameters suspected to have an impact on the 3D reconstruction uncertainties or the tree height
 283 estimate itself (see Table 3). Some parameters are assessed at the scale of the individual tree, others
 284 at the forest inventory plot scale. The mean solar angle of the aerial images is a good proxy for the
 285 light conditions during the surveys. Lower values can be associated to more important cast
 286 shadowing and higher reconstruction uncertainties. The time difference between the aerial images
 287 could also highlight artificial heterogeneity between the aerial images and hamper the
 288 photogrammetric reconstruction. The number of overlapping images used for the photogrammetric
 289 reconstruction is positively linked to the quality of the 3D reconstruction. As the 60% along-tracks
 290 and 30% across-track overlap scheme induces varying image overlap condition, the number of
 291 images used to reconstruct the forest canopy of the FI plot is an interesting parameter. The
 292 uncertainties of the 3D photogrammetric reconstruction of tree canopy can also be linked to the
 293 characteristic of the tree itself as well as its environment. The forest species and its evergreenness
 294 were investigated as well as forest structure. Forest structure was here investigated in terms of stem
 295 densities and tree size within the FI plot with the basal area. The relative DBH allows addressing the
 296 size of the considered tree in relation with the size of the biggest trees in the FI plot (i.e. proxy of the
 297 social status). Lastly, the terrain slope and altitude is also investigated as they can have a significant
 298 impact on the 3D reconstruction but also on the accuracy of the ALS DTM itself.

299 To evaluate the significance of the linear relationship between the selected parameters and the tree
 300 height absolute differences ($\text{abs}(\text{field tree height} - \text{pCHM tree height})$), we used one-way analysis of
 301 variance, (ANOVA) for qualitative factors, and linear regressions for quantitative factors.

302 We ran a best subset regression approach to build a multivariate linear model with the variables
 303 previously highlighted using the *regsubsets* tools from the *leaps* package in R (Miller, 2017). We used
 304 best subsets regression to fit all potential models of pCHM tree height estimate absolute error in
 305 order to highlight the best combination of predictors (using bayesian information criterion, BIC)

306 Finally, we ran a second best subsets regression to test the potential of the highlighted parameters
 307 from Table 3 to improve the tree height estimates with pCHM's data (using BIC).

308

309 **Table 3: parameters and associated explanatory variables used to assess the robustness of tree height from pCHM. The**
 310 **relative diameter is the ratio of the DBH of tree (DBH_{tree}) and the mean DBH of the 100 biggest trees / acre (dominant**
 311 **DBH, $DBH_{dominant}$) for the FI plot.**

Parameter	Symbol	Explanatory variable	Rationale	Scale	Type of parameter
Sun angle during aerial image survey	Sun_{angle}	Mean sun azimuth of aerial images overlapping (angular degree)	Low solar angle induces cast shadow	FI plot	Image survey
Overlapping images	$Overlap_{Im.}$	Number of images overlapping	Higher overlaps improves 3D reconstruction quality	FI plot	Image survey
Time difference	$Time_{dif}$	Max time difference between the survey of the aerial images (day)	Noise induced by varying phenological states	FI plot	Image survey
Aerial survey	Ref_{aerial}	Reference year of the associated pCHM	Test differences among aerial surveys	FI plot	Image survey
Basal area	$Basal_{area}$	Basal area (m^2/Ha)		FI plot	Forest
Stem density	$Stem_{dens}$	Number of stem by hectare	Forest structure is linked to 3D reconstruction uncertainty	FI plot	Forest
Canopy roughness	$Canopy_{rough.}$	Variation Coefficient of associated pCHM (%)		FI plot	Forest
Stem diameter at breast height	DBH	DBH (cm)	Impact of tree size or species characteristics	Tree	Forest
Relative diameter	DBH_{rel}	$\frac{DBH_{tree}}{DBH_{dominant}}$	Trees (understory or with lower leaf amount) are unlikely to be reconstructed in pCHM	Tree / FI plot	Forest
Tree species	$Species_{tree}$	Tree species		Tree	Forest
Evergreenness	$Evergreen$	Deciduousness /Evergreenness		Tree	Forest
Altitude	$Altitude$	Mean ALS DTM altitude	Impact of ecological/geographical context	FI plot	Topo.
Slope	$Slope$	Mean ALS DTM	Impact of slope	FI	Topo.

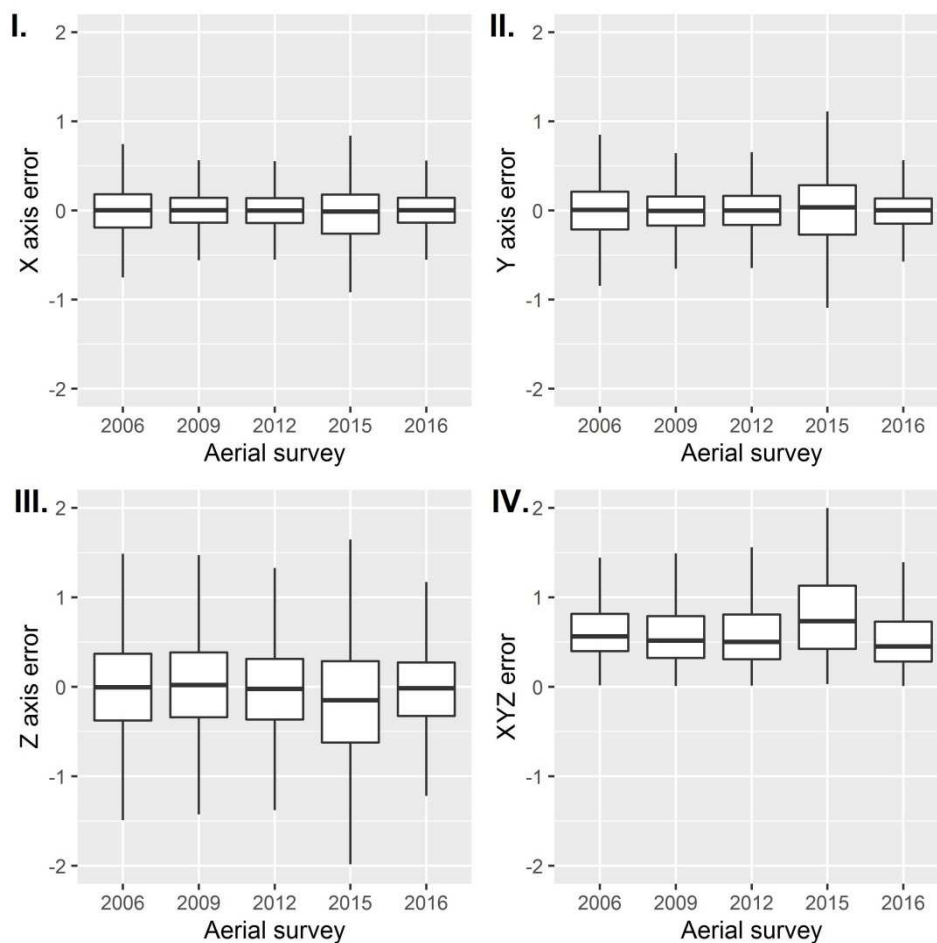
312	slope (%)	plot
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313

314 **3. Results**

315 **3.1. Accuracy assessment**

316 The cross-validation process of the photogrammetric reconstruction highlights very low mean X, Y
317 and Z error values associated with the 3D model of the aerial surveys (Figure 4-I., II., III.). The XYZ
318 error (Figure 4-IV.) which is the root mean square of the X, Y and Z error is quite higher (ca. 0.7 m)
319 but remains acceptable for all the surveys. It is worth mentioning that such low error values are
320 associated to the 3D reconstruction of simple surfaces situated in homogeneous topography (mostly
321 roads). The 3D reconstruction uncertainties are expected to be higher when the algorithms have to
322 deal with complex surfaces like tree canopies.



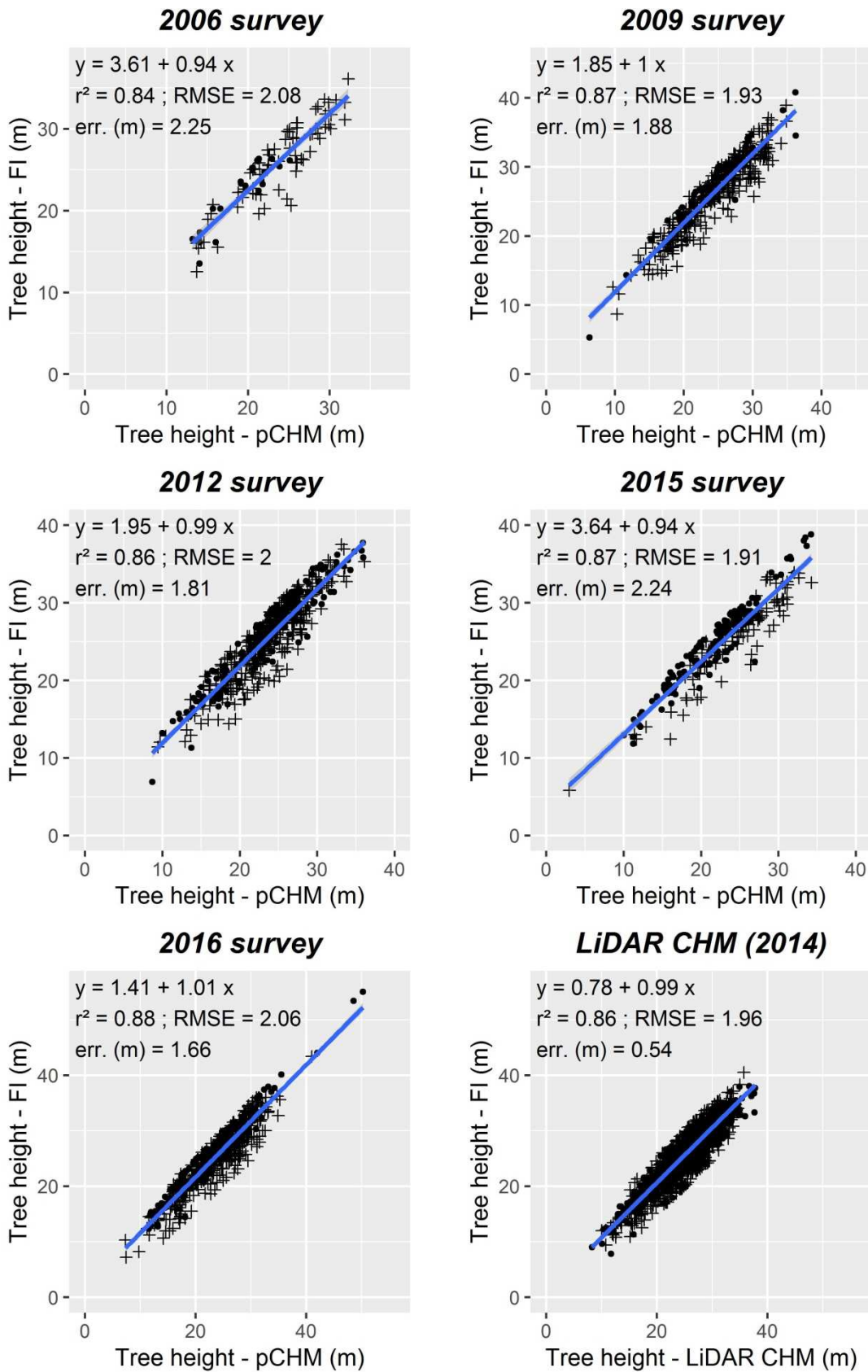
323
324 **Figure 4: boxplot of the X, Y, Z and XYZ error resulting from the cross validation process. The XYZ error is the root mean**
325 **square error of the 3 error components.**

326 The accuracy assessment of the tree height models highlights that the pCHM tree height estimates
327 agreed well with the field tree height estimates (Figure 5). The r^2 values ranges from 0.84 to 0.88
328 with RMSE values ranging from 1.91 to 2.08 m. A global model fitted regardless the aerial survey (not
329 plotted in Figure 5) on the pCHM and the FI tree height estimates reached similar performance with
330 r^2 value of 0.87 and a RMSE of 2.01 m. The quality of the pCHM tree height linear models is in line
331 with the quality reached by the ALS CHM using the same approach ($r^2=0.86$; RMSE=1.96 m). The
332 Table 4 gathers the results of the same modelling approach considering the deciduous and the
333 evergreen species separately. Compared to deciduous species, the r^2 of the models fitted with

334 evergreen species are higher (from 0.83 to 0.95) and the associated RMSE present lower values (from
335 1.4 to 1.7 m).

336 Our results also highlight a clear underestimation of the tree height by pCHM. The same trend is
337 observed to a lesser extent for tree height based on ALS CHM. The mean tree height estimate error
338 (FI tree height - pCHM tree height) ranges from 1.66 to 2.25 m for the pCHM estimates and 0.54 m
339 for the ALS CHM. The mean tree height estimate error is higher for the evergreen species as it ranges
340 from 2.5 to 3 m while it ranges from 0.92 to 2.02 m for deciduous species. The same trend can be
341 observed in the ALS models but again with lower mean error values (< 1 m).

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Figure 5: biplots of tree height estimates from pCHM's and ALS CHM in comparison with FI tree height estimates. Deciduous and evergreen trees are marked using “+” and “.” symbols respectively. The mean error (err.) is computed from the difference between the reference tree height (from FI) and the tree height estimates (provided by pCHM or ALS CHM).

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Table 4: tree height estimates with pCHM and ALS CHM compared to tree estimates from FI.

Aerial survey	Evergreen			Deciduous		
	r ²	RMSE (residuals)	Mean error (y-x, m)	r ²	RMSE (residuals)	Mean error (y-x, m)
2006	0.83	1.68	3	0.83	2.17	2.02
2009	0.92	1.67	2.92	0.87	1.92	1.68
2012	0.91	1.72	2.52	0.83	2.03	1.4
ALS CHM	0.92	1.6	0.6	0.82	2.07	0.52
2015	0.93	1.43	3.05	0.88	1.92	0.92
2016	0.95	1.51	2.76	0.86	2.08	1.23
<i>All photo surveys</i>	0.93	1.59	2.78	0.87	2.01	1.85

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3.2. Drivers of the pCHM tree height estimates error

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Among the 13 potential parameters listed in Table 3, our analysis highlighted 8 variables which present a significant statistical link with the absolute error of the pCHM height estimates (Table 5).

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Except the basal area and the number of trees in the FI plots, all the forest parameters were selected

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as well as the topographic parameters (slope and altitude). In terms of correlation, the slope is the

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only parameter which presents a negative correlation coefficient with the pCHM absolute error.

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The reference year of the aerial survey is the only image parameter which was highlighted by our analysis. As the number of levels in the factor is rather low for this variable, we ran a Tukey Honest Significant Differences implemented in the *TukeyHSD* function in the R basic package. This test highlighted that only the observations from the aerial surveys 2015 and 2016 were significantly different (p-value = 0.011).

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Table 5: parameters and associated explanatory variables used to assess the robustness of tree height from pCHM. For linear model, AHO (acceptation of null hypothesis) stands for no relationship among the variables and for ANOVA models, AHO implies equality of means between the groups.

Symbol	Model	Results DAP
<i>Sun_{angle}</i>	Linear regression	AHO (p = 0.65)
<i>Overlap_{Im.}</i>	Linear regression	AHO (p = 0.12)
<i>Time_{dif}</i>	Linear regression	AHO (p = 0.38)
<i>Ref_{aerial}</i>	ANOVA	RHO (p = 0.004)
<i>Basal_{area}</i>	Linear regression	AHO (p = 0.11)
<i>Stem_{dens}</i>	Linear regression	AHO (p = 0.55)
<i>Canopy_{rough.}</i>	Linear regression	RHO (p = 0.020; r = 0.05)
<i>DBH_{trunk}</i>	Linear regression	RHO (p < 0.001; r = 0.09)
<i>DBH_{rel}</i>	Linear regression	RHO (p < 0.001 ; 0.13)
<i>Species_{tree}</i>	ANOVA	RHO (p < 0.001)
<i>Evergreen</i>	ANOVA	RHO (p < 0.001)
<i>Altitude</i>	Linear regression	RHO (p < 0.001; r = 0.11)
<i>Slope</i>	Linear regression	RHO (p < 0.001; r = -0.08)

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374 Within the set of variables which were proved to have a significant statistical relationship with the
375 pCHM tree height absolute error, we removed the reference year and the tree species factorial
376 variables before running the best subset regression process. This choice was made in order to ease
377 the interpretation (the *Species_{tree}* factor presents 29 levels in our dataset) and the replication of the
378 fitted pCHM error model. Indeed, the aerial survey reference gathers a bunch of environmental
379 parameters at the time of the flight survey (lights conditions, phenology ...) with a rather low interest
380 for understanding the drivers of the pCHM tree height estimates error.

381 The best subsets regression model selected following the BIC a model with 2 variables: the DBH and
382 the evergreenness factor to predict pCHM tree height estimate error. This model presents a rather
383 low r^2 score (0.10) and a RMSE of 1.3 m.

384 Finally, we used the same initial set of variables used to fit the pCHM tree height estimate error
385 model to evaluate their potential income in terms of accuracy improvement of a global model linking
386 the tree height estimates provided with pCHM data (all pCHM used) and the FI tree height estimates.
387 The best subsets regression model selected following the BIC a model with 4 variables to predict the
388 field measured tree height: the pCHM tree height, the DBH, the evergreenness factor and the terrain
389 slope. This model is significantly different (ANOVA test, p-value < 0.001) of the linear model linking
390 pCHM tree height and field measured tree height. It presents a slightly higher r^2 score (0.90 VS 0.87)

391 and a smaller RMSE (1.78 VS 2.01 m). Therefore, the use of these variables in a multiple linear model
392 improved the tree height estimate based on pCHM.

393 **4. Discussion**

394 **4.1. Accuracy of tree height estimates with pCHM**

395 The good agreement between the pCHM and field tree height estimates was clearly highlighted by
396 the fitted linear models. They reached similar performance than ALS tree height estimates model.
397 Globally, pCHM and ALS CHM underestimate the field measured tree height estimate (see Table 4).
398 This was commonly found in literature by various authors like Heurich et al. (2004). Nevertheless, the
399 ALS tree height estimate remains more accurate with mean signed error (field height - CHM height)
400 being submetric (0.54) while pCHM mean signed error being more than three times higher (1.85 m
401 for all pCHM).

402 While the mean difference between pCHM and field tree height estimates is more important for
403 evergreen species than for deciduous ones, the performance of the model fitted with evergreen tree
404 species is better with r^2 values above 0.9 and model RMSE below 2 m. On one hand, the larger
405 difference between pCHM and field tree height estimates for evergreen species can be associated to
406 their higher mean height in the study area. On the other hand, the better model performance is
407 probably related to their simpler canopy structure. These results are in line with a lot of studies
408 having compared the single tree height modeling with CHM (pCHM or ALS CHM) as Ginzler and Hobi
409 (2015) for a pCHM case study.

410 It is worth noting that the 2006 survey presents similar results but with slightly lower model
411 performance and higher mean error values. These results are probably directly linked to the lower
412 spatial resolution of the pCHM (1 m GSD) even if our study design does not permit to further proof it.

413 Our results are in line with those obtained with pCHM approaches at a smaller study area extents by
414 Zimmermann and Hoffmann (2017) or Hirschmugl et al. (2007) even if the lack of harmonized
415 accuracy metrics hampers real accuracy benchmarking. The most similar case studies found in
416 literature is from Ginzler and Hobi (2015) who fitted with pCHM a tree height estimate model based
417 on 3109 field measured trees with r^2 of 0.68. Our slightly better results in terms of
418 accuracy/performance can be linked to the geographical context (mountainous complex landscapes
419 VS lowlands / low mountain landscapes) and the tree top position extraction algorithm (fixed buffer
420 around ground GPS position VS matched position with local maxima) or even the image matching
421 strategy (stereo matching VS multiview matching).

422 **4.2. Drivers of the pCHM tree height estimates error**

423 Our results in Table 5 highlight the significant impact of all the forest parameters except the basal
424 area and the number of trees in the FI plots. This draws attention on a subject poorly addressed in
425 literature: the relationship between forest structure and DAP products quality at the single tree
426 scale. If the impact of leaf abundance is well addressed in literature (see Huang et al. (2019) for a
427 recent case study), our results in Table 5 draw attention on parameters which should be addressed
428 by researchers: the canopy roughness, the tree size (both absolute and relative to its neighbors), the

429 tree species, the deciduousness/evergreenness as well as the topography (slope and altitude). In our
430 results, all of the parameters except the slope are positively correlated with the absolute pCHM tree
431 height estimate error. These results could be synthesized as the bigger the tree is, the bigger the
432 error of its pCHM height estimate is. The positive correlation between the canopy roughness
433 (assessed here through the pCHM coefficient of variation in the FI plot) can be interpreted by the
434 lower ability of DAP to model high slope variation, especially when considering the rather low
435 overlap of our aerial images dataset (60% along-track, 30% across-track) as suggested by Hirschmugl
436 et al. (2007). The altitude is generally considered as a very good proxy of the ecological gradient in
437 various studies in the study area (Brognia et al., 2018; Dufrene and Legendre, 1991; Georges et al.,
438 2019). Beside the link with an ecological gradient, the positive correlation with the absolute pCHM
439 height estimate error can partially be linked to the tendency of evergreen stands to be located in
440 higher altitude while having a higher height. The negative correlation between the absolute pCHM
441 height estimate error and the terrain slope is quite counterintuitive a CHM tends to overestimate the
442 actual tree height (Khosravipour et al., 2015). This overestimation could thus partially counter the
443 general trend to underestimation by pCHM previously highlighted. Subsequently, the surprisingly
444 negative correlation is interpreted as a compensation effect.

445 Among the variables related to the image acquisition, only the reference of the aerial survey was
446 highlighted by our analysis. The absence of impact of the sun light condition during the survey can be
447 related to the rather strict conditions asked to the service provider. Our analysis focused on tree tops
448 from the upper canopy layer, the sun light condition (and associated cast shadows) as well as the
449 images overlap are expected to be of higher importance for studies dealing with canopy gaps for
450 example (Hirschmugl et al., 2007) or when working on lower canopy attributes.

451 Among the parameters underlined in this first analysis, the best subsets regression highlighted the
452 DBH and the evergreenness factor as the best predictors of the absolute pCHM tree height estimate
453 error. This result highlights some interesting potential drivers of the pCHM tree height estimate error
454 but it also highlights that a significant part of its variability was not addressed with these set of
455 parameters. Nevertheless, the use of the same initial set of variables used to fit a model predicting
456 the field measured tree height produced interesting results. The use of these additional variables
457 allows to significantly improving the tree height field measurement model (ANOVA test, p -value <
458 0.001) in terms of r^2 and RMSE.

459 In our study, we considered the field measured tree height as the reference information for the
460 benchmarking of the tree height estimate with the pCHM. Nevertheless, tree height estimates on the
461 ground are both subject to instrumental and measurement errors. As the field height data were
462 collected using ultrasound equipment which tends to have low instrumental errors (if properly
463 maintained), the most important potential errors are suspected to occur in the measurement step
464 itself. Rondeux (1999) highlighted that tree height measurement errors can be considered as
465 random. They are linked to the shape of the tree and its position, the equipment set-up or even the
466 field operator himself. More recently, Wang et al. (2019) highlighted that field measurements tend to
467 overestimate the height of tall trees but also that this trend was more related to non-dominant
468 individuals trees (co-dominant, intermediate, suppressed). Our study design did not allow the
469 evaluation of the field measurement error among pCHM tree height estimate error. Nevertheless,
470 the values of the slope parameter in the different fitted models was close to 1 for the linear models

471 in Figure 5. This result highlights that the differences between field and pCHM tree height
472 measurements tend to remain relatively constant across the tree height range in our datasets.

473 **5. Conclusions**

474 Our results allow highlighting the good agreement of tree height estimates provided by pCHM using
475 DAP with both field measured and ALS tree height data. In terms of tree height modeling, our pCHM
476 approach reached similar results than the same modeling strategy applied to ALS tree height
477 estimates. Our results highlight the interest of re-processing stereo-images acquired during regular
478 national campaigns for orthophotomosaics layers production in order to produce regional pCHM. We
479 tested it at a regional scale (ca. 17,000 km²) using 5 different aerial surveys and a large single tree
480 and FI plots dataset (ca. 3000 trees from 600 FI plots). Our approach presents a great potential as it
481 relies on publically and regularly acquired datasets (aerial images and FI data) and could be thus
482 easily replicated in other countries to build dense time series of pCHM which can even cover time
483 periods prior the ALS survey when the hypothesis of constancy of topography under forest cover can
484 be realized.

485 Our study also identified some of the drivers of the pCHM tree height estimate error and found
486 forest parameters and the terrain slope to be of higher importance than image survey parameters
487 like the variation of the overlap or the sunlight condition in our dataset. In combination with the
488 pCHM tree height estimate; the terrain slope, the DBH and the evergreenness factor were used to fit
489 a multivariate model predicting the field measured tree height. This model presented better
490 performance than the model linking the pCHM estimates to the field tree height estimates in terms
491 of r^2 (0.90 VS 0.87) and RMSE (1.78 VS 2.01 m). As the integration of these environmental
492 parameters is rather straightforward, these results could be further in order to improve forest
493 attributes prediction based on DAP and pCHM. Such aspects are poorly addressed in literature and
494 further research should focus on how pCHM approaches could integrate them to improve forest
495 characterization using DAP and pCHM.

496 Our promising results can be used to encourage the use of regional aerial orthophoto surveys archive
497 to produce large scale quality tree height data at very low additional costs, notably in the context of
498 updating national forest inventory programs.

499

500 **6. Acknowledgment**

501 Authors thank the Belgian National Geographic institute for having shared their reference point
502 database. Authors would also like to thank Alain Monseur, Coralie Mengal and Thibault Delinte for
503 their technical support.

504 Authors express thanks to the Public Service of Wallonia has shared all the dataset and associated
505 expertise from the aerial images (Geomatic Directorate: C. Schenke, N. Stephenne and JC Jasselette)
506 to the forest information from the Forest Inventory program (Forest Resources Department).

507 Finally, authors would like to thanks the funding agencies who provided support to our research: the
508 Stereo program (grants SR/00/347 and SR/12/383) from the Belgian Scientific Policy Department
509 (BELSPO) and the Forest Resources Department of the public service of Wallonia (*accord cadre de*
510 *recherche et de vulgarization forestière 2014-2019*).

511 7. References

- 512 Alderweireld, M., Burnay, F., Pitchugin, M., Lecomte, H., 2015. Inventaire Forestier Wallon-
513 Résultats 1994-2012. SPW.
- 514 Alderweireld, M., Rondeux, J., Latte, N., Hébert, J., Lecomte, H., 2016. Belgium (Wallonia),
515 in: National Forest Inventories. Springer, pp. 159–179.
- 516 Brogna, D., Dufrêne, M., Michez, A., Latli, A., Jacobs, S., Vincke, C., Dendoncker, N., 2018.
517 Forest cover correlates with good biological water quality. Insights from a regional
518 study (Wallonia, Belgium). *J. Environ. Manage.* 211, 9–21.
- 519 Dufrene, M., Legendre, P., 1991. Geographic structure and potential ecological factors in
520 Belgium. *J. Biogeogr.* 257–266.
- 521 Eysn, L., Hollaus, M., Lindberg, E., Berger, F., Monnet, J.-M., Dalponte, M., Kobal, M.,
522 Pellegrini, M., Lingua, E., Mongus, D., others, 2015. A benchmark of lidar-based
523 single tree detection methods using heterogeneous forest data from the alpine space.
524 *Forests* 6, 1721–1747.
- 525 Georges, B., Brostaux, Y., Claessens, H., Degré, A., Huylenbroeck, L., Lejeune, P., Piégay,
526 H., Michez, A., 2019. Can water level stations be used for thermal assessment in
527 aquatic ecosystem? *River Res. Appl.*
- 528 Ginzler, C., Hobi, M., 2015. Countrywide stereo-image matching for updating digital surface
529 models in the framework of the Swiss National Forest Inventory. *Remote Sens.* 7,
530 4343–4370.
- 531 Goodbody, T.R., Coops, N.C., White, J.C., 2019. Digital Aerial Photogrammetry for
532 Updating Area-Based Forest Inventories: A Review of Opportunities, Challenges, and
533 Future Directions. *Curr. For. Rep.* 5, 55–75.
- 534 Heurich, M., Persson, \AA, Holmgren, J., Kennel, E., 2004. Detecting and measuring
535 individual trees with laser scanning in mixed mountain forest of central Europe using
536 an algorithm developed for Swedish boreal forest conditions. *Int. Arch. Photogramm.*
537 *Remote Sens. Spat. Inf. Sci.* 36, W2.
- 538 Hirschmugl, M., Ofner, M., Raggam, J., Schardt, M., 2007. Single tree detection in very high
539 resolution remote sensing data. *Remote Sens. Environ.* 110, 533–544.
- 540 Huang, H., He, S., Chen, C., 2019. Leaf Abundance Affects Tree Height Estimation Derived
541 from UAV Images. *Forests* 10. <https://doi.org/10.3390/f10100931>
- 542 James, M.R., Chandler, J.H., Eltner, A., Fraser, C., Miller, P.E., Mills, J.P., Noble, T.,
543 Robson, S., Lane, S.N., 2019. Guidelines on the use of structure-from-motion
544 photogrammetry in geomorphic research. *Earth Surf. Process. Landf.*
- 545 James, M.R., Robson, S., d'Oleire-Oltmanns, S., Niethammer, U., 2017. Optimising UAV
546 topographic surveys processed with structure-from-motion: Ground control quality,
547 quantity and bundle adjustment. *Geomorphology* 280, 51–66.
- 548 Keenan, R.J., Reams, G.A., Achard, F., de Freitas, J.V., Grainger, A., Lindquist, E., 2015.
549 Dynamics of global forest area: Results from the FAO Global Forest Resources
550 Assessment 2015. *For. Ecol. Manag.* 352, 9–20.
- 551 Khosravipour, A., Skidmore, A.K., Wang, T., Isenburg, M., Khoshelham, K., 2015. Effect of
552 slope on treetop detection using a LiDAR Canopy Height Model. *ISPRS J.*
553 *Photogramm. Remote Sens.* 104, 44–52.
- 554 Leberl, F., Irschara, A., Pock, T., Meixner, P., Gruber, M., Scholz, S., Wiechert, A., 2010.
555 Point clouds. *Photogramm. Eng. Remote Sens.* 76, 1123–1134.
- 556 McRoberts, R.E., Tomppo, E.O., 2007. Remote sensing support for national forest
557 inventories. *Remote Sens. Environ.* 110, 412–419.
- 558 Michez, A., Bauwens, S., Bonnet, S., Lejeune, P., 2016. Characterization of forests with lidar
559 technology, in: *Land Surface Remote Sensing in Agriculture and Forest*. Elsevier, pp.
560 331–362.

- 561 Miller, T.L. based on F. code by A., 2017. leaps: Regression Subset Selection.
- 562 Monnet, J.-M., Mermin, É., 2014. Cross-correlation of diameter measures for the co-
563 registration of forest inventory plots with airborne laser scanning data. *Forests* 5,
564 2307–2326.
- 565 Næsset, E., 2014. Area-based inventory in Norway—from innovation to an operational reality,
566 in: *Forestry Applications of Airborne Laser Scanning*. Springer, pp. 215–240.
- 567 Noirfalise, A., 1988. Les régions naturelles de la Belgique. *G.E.O.* 23, 3:25.
- 568 QGIS Delopment Team, 2020. QGIS geographic information system. Open Source Geospatial
569 Found. Proj.
- 570 Rahlf, J., Breidenbach, J., Solberg, S., Næsset, E., Astrup, R., 2017. Digital aerial
571 photogrammetry can efficiently support large-area forest inventories in Norway. *For.*
572 *Int. J. For. Res.* 90, 710–718.
- 573 Rondeux, J., 1999. La mesure des arbres et des peuplements forestiers. Les presses
574 agronomiques de Gembloux.
- 575 Roussel, J.-R., Auty, D., 2019. lidR: Airborne LiDAR Data Manipulation and Visualization
576 for Forestry Applications.
- 577 Smith, M., Carrivick, J., Quincey, D., 2016. Structure from motion photogrammetry in
578 physical geography. *Prog. Phys. Geogr.* 40, 247–275.
- 579 Wang, Y., Lehtomäki, M., Liang, X., Pyörälä, J., Kukko, A., Jaakkola, A., Liu, J., Feng, Z.,
580 Chen, R., Hyyppä, J., 2019. Is field-measured tree height as reliable as believed—A
581 comparison study of tree height estimates from field measurement, airborne laser
582 scanning and terrestrial laser scanning in a boreal forest. *ISPRS J. Photogramm.*
583 *Remote Sens.* 147, 132–145.
- 584 White, J.C., Wulder, M.A., Vastaranta, M., Coops, N.C., Pitt, D., Woods, M., 2013. The
585 Utility of Image-Based Point Clouds for Forest Inventory: A Comparison with
586 Airborne Laser Scanning. *Forests* 4, 518–536. <https://doi.org/10.3390/f4030518>
- 587 Zimmermann, S., Hoffmann, K., 2017. Accuracy Assessment of Normalized Digital Surface
588 Models from Aerial Images Regarding Tree Height Determination in Saxony,
589 Germany. *PFG—Journal Photogramm. Remote Sens. Geoinformation Sci.* 85, 257–
590 263.

591

592