

1 **Estimating the attributes of urban trees using terrestrial** 2 **photogrammetry**

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12 **Abstract**

13 Today, different methods are used to measure two-dimensional (2D) and three-dimensional
14 (3D) attributes of trees. One of these methods, which is considered in recent years is using
15 point clouds and a 3D model extracted from Terrestrial Photogrammetry (TP). This study aims
16 to estimate the 2D and 3D attributes of urban trees at three levels of seedlings, single trees and
17 sample plot using TP. Structure-from-Motion with Multi-View Stereo-photogrammetry (SfM-
18 MVS) method was used to derive the point clouds and the 3D model. Comparing estimated
19 values of diameter at the middle of trunk of seedlings and diameter at breast height (DBH) of
20 trees, using TP with measured values showed that the values of RMSE% were $< 2\%$ at three
21 levels of seedlings, single trees and sample plot. Furthermore, validation of the estimated
22 values of total height and crown height attributes of seedlings and trees at three levels showed
23 that the RMSE% did not exceed 4% and 5%, respectively. Considering the overlap of tree
24 crowns with each other in the sample plot, the average diameter of the crown attribute was
25 estimated only in seedlings and single tree levels with RMSE%= 6.51% and 9.34%,
26 respectively. The validation of estimated values of stem volume of seedlings and trees at three
27 levels showed that the lowest errors were returned from trees within a sample plot with
28 RMSE%=14.37%, whereas the highest rates of errors were achieved for seedlings with
29 RMSE%= 20.99%. As an alternative to approaches such as employing laser scanners, this
30 method is quick, inexpensive, non-destructive, and does not need specialized equipment.

31

32 **Keywords:** Point clouds, 3D model, SfM-MVS, Sample plot, Urban greening

33 **Introduction**

34 According to United Nation's prediction, the urban populations will increase from around
35 47% in 2010 to 60% by 2030 (United Nation, 2020; Van Delm and Gulinck, 2011). This
36 increase in population and subsequent increase in the size of urban areas have led to green
37 space and urban trees to be in the focus of researchers and city managers due to their key role
38 to provide direct and indirect ecosystem services such as biodiversity protection, carbon
39 sequestration, reducing air pollution, preventing the formation of thermal islands, maintaining
40 urban aesthetics, recreational value, reduction of noise pollution, preservation of wildlife
41 habitat, improving environmental quality and reducing storm water (Bolund and Hunhammar,
42 1999; Matyieu and Aryal, 2005; Holopainen et al., 2013; Morgenroth and Gomez, 2014; Lee
43 et al., 2016; Wolf et al., 2020; Song et al., 2020; Gülçin and Konijnendijk van den Bosch, 2021).
44 It was proven that the access to accurate and up to date information on tree attributes, such as
45 DBH, height, crown dimension, basal area, stem volume and aboveground biomass help
46 managers, researchers, governments and environmental organizations for planning and
47 preservation, biophysical process modelling, ecosystem services assessment and quantifying
48 the economic value of the urban greening (Matyieu and Aryal, 2005; Nowak et al., 2008;
49 Morgenroth and Gomez, 2014; Nielsen et al., 2014; Miller et al., 2105; Lee et al., 2016; Mikita
50 et al., 2016; Mokroš et al., 2018).

51 To assess tree attributes, traditional inventory techniques often employ mechanical or
52 optical equipment. However, using these methods is time consuming and expensive, and they
53 do not have the capacity to directly assess tree attributes like volume and biomass (Marzullii et
54 al., 2020). Using allometric equations is one of the methods of estimating the attributes of trees,
55 and estimating 3D attributes with this method is usually associated with error in terms of the
56 different morphology of trees (Marzulli et al., 2020). Therefore, studies were conducted over
57 the last several decades to develop replacements for conventional inventory techniques. Using

58 point clouds data to generate the 3D structure of trees is one of these techniques. Using
59 magnetic motion trackers, laser scanners, or photogrammetric techniques, one may build the
60 3D structure of trees (Surový et al., 2016; Mokroš et al., 2020).

61 Using a magnetic motion tracker is usually time consuming, since this device must move
62 near a tree trunk, and it will usually be difficult to measure the attributes of trees at upper part
63 of the trunk (Mokroš et al., 2020). Regarding the ability of terrestrial laser scanning (TLS) to
64 accurately estimate trees attributes, many researchers have estimated the 2D and 3D attributes
65 of trees, such as DBH, height, crown attributes, aboveground biomass and volume using TLS
66 so far (Moorthy et al., 2011; Moskal and Zheng, 2012; Kankare et al., 2013; Liu et al., 2018;
67 Giannetti et al., 2018). Despite the advantages of TLS, the use of these systems has limitations
68 such as high cost, the requirement for a professional operator and difficulty to move equipment
69 during the inventory (Mikita et al., 2016; Liang et al., 2016; Marzulii et al., 2020). Therefore,
70 by considering the advances in image matching algorithms, cameras and computer hardware,
71 photogrammetry can be considered a cost-effective alternative to laser scanning in the point
72 clouds generation and 3D structures of the trees (Roberts et al., 2019; Akpo et al., 2021).

73 The close-range photogrammetry (CRP) is considered as one of the sub-categories of
74 photogrammetric methods. Hence, the distance of the object from the camera is usually less
75 than 300 meters (Luhmann et al., 2010), and the images can be captured in terrestrial or aerial
76 states.

77 Different methods can be used to derive 3D models; one of which being SfM-MVS method
78 (commonly abbreviated to SfM) (Iglhaut et al., 2019). This method was introduced by Ullman
79 in 1979 and later expanded as a low-cost and fast method for making 3D models (Ullman,
80 1979; Morgenroth and Gomez, 2014; Iglhaut et al., 2019). In this method, overlapping 2D
81 images are taken from different points and angles of view of the object, and are then converted

82 into 3D models (Morgenroth and Gomez, 2014; Miller et al., 2015; Mikita et al., 2016; Marzulli
83 et al., 2020).

84 So far, researchers have conducted various studies on the application of 3D models in
85 estimating different 2D and 3D tree attributes. For example, Sakai et al., (2021) estimated the
86 height, crown diameter and stump diameter of 10 sample plots using the SfM method. R^2 values
87 were 0.81, 0.89 and 0.94 for stump diameter, canopy height and tree height, respectively.
88 Mokroš et al., (2020) used SfM to estimate the annual trunk increments of trees of different
89 species. Comparing estimated perimeters from SfM method with the measured values showed
90 that the RMSE% did not exceed 1% for all tree species. Marzulli et al., (2020) estimated the
91 DBH and stem volume of trees in a sample plot using images taken by a smartphone and the
92 SfM method. The comparison among 3D models and field data showed the RMSE of 1.9 cm
93 and 0.094 m^3 , for DBH and volume, respectively. Miller et al., (2015) estimated the 2D and
94 3D attributes of 30 small potted trees using handheld camera images and SfM-MVS method.
95 They reported RMSE% of 3.74%, 11.93%, 9.6% and 14.76% when estimating the height,
96 crown height, diameter and crown spread using SfM-MVS method, respectively. Besides,
97 Morgenroth and Gomez (2014) concluded that the SfM-MVS method could estimate the
98 diameter of trees with $\text{RMSE}\% = 3.7\%$ as well as height with $\text{RMSE}\% = 2.59\%$ by examining
99 one potted seedling and 2 mature trees. Other studies such as Liang et al., (2014); Forsman et
100 al., (2016); Mikita et al., (2016); Surový et al., (2016); Mokroš et al., (2018); Piermattei et al.,
101 (2019); Mulverhill et al., (2020) and Bayati et al., (2021) have also surveyed the application of
102 TP method in estimating different attributes at the single tree, sample plot and stand levels.
103 These tests revealed that the approach employed in calculating 2D and 3D tree attributes might
104 be an accurate, rapid, low-cost, and non-destructive method. Most of research mentioned in the
105 literature review were done in forests, while several studies were conducted in urban greening,
106 so that 2D and 3D models have been developed only for small potted seedlings and single

107 mature trees. Thus, this study aimed to estimate the 2D and 3D attributes of 74 trees of different
108 species at three levels of seedlings, single trees and trees within the sample plot in urban
109 greening using TP and SfM-MVS methods. Moreover, this research seeks to answer these
110 questions: i) As an alternative to TLS, can the TP and SfM-MVS approaches estimate the 2D
111 and 3D features of urban trees at the seedling, individual tree, and sample plot levels? ii) Does
112 the diminutive size of seedlings relative to mature trees impact the accuracy of calculating their
113 2D and 3D attributes?

114 **Materials and methods**

115 **Materials**

116 The measurements of trees were performed at three levels, including 30 seedlings, 30 single
117 trees and 14 trees located in a sample plot with dimensions of 28×11 meters. Seedlings were
118 selected from urban nurseries and other trees were selected from trees planted in urban green
119 space of Khorramabad and the Faculty of Agriculture and Natural Resources of Lorestan
120 University. Khorramabad is the capital of Lorestan province and with an area of 46.94 km^2
121 ($33^\circ 25' 38''$ to $33^\circ 35' 52''$ N and $48^\circ 18' 29''$ to $48^\circ 23' 39''$ E) in the southwest of Iran. The list
122 of different coniferous and broadleaves species studied in this research is presented in Table.

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Table. 1. List of species examined in the present study

Level	Scientific name	Number
Seedlings	<i>Thuja orientalis</i>	5
	<i>Chamaecyparis lawsoniana</i>	5
	<i>Pinus brutia</i>	5
	<i>Laurus nobilis</i>	5
	<i>Populus alba</i>	5
	<i>Ailanthus altissima</i>	3
	<i>Fraxinus excelsior</i>	2
Single trees	<i>Pinus eldarica</i>	12
	<i>Cupressus arizonica</i>	3
	<i>Melia azedarach</i>	5
	<i>Robinia pseudoacacia</i>	8
	<i>Fraxinus excelsior</i>	2
Sample plot	<i>Pinus eldarica</i>	14

132 **Methods**

133 **Reference data measurement**

134 **2D attributes**

135 2D attributes, including diameter, height, crown height and average diameter of the crown
 136 of seedlings and trees at three levels were measured. Regarding small size of the seedlings, the
 137 diameter at mid-height of trunk was measured instead of the DBH. The DBH of mature trees
 138 and diameter at mid-height of trunk of seedlings were measured using a caliper.

139 The total height and crown height of seedlings were measured using a measuring tape and
 140 these attributes were measured using TruPulse 360 Laser Rangefinder at single trees and
 141 sample plot levels.

142 The crown diameter of seedlings and trees was measured using a measuring tape in two
 143 perpendicular directions, and the average crown diameter of each seedling or tree was
 144 computed using the average of the measured diameters. Because of the closeness of trees and

145 the overlap of tree crowns, it was impossible to compare each tree's crown diameter to the
146 values calculated in the sample plot (no separation in the acquired images).

147 **3D attributes**

148 Seedling volume was measured using Xylometry (Miller et al. 2015), in which the seedlings
149 were cut and divided into small pieces after the photogrammetric imaging. Then, the pieces
150 related to different parts of each seedling were separated, numbered, and packaged. The
151 wooden sections were submerged in water for 48 hours to saturate and prevent them from
152 absorbing water. Finally, the volume of each piece was estimated by inserting it in a graduated
153 cylinder filled halfway with water and measuring the variations in water volume. To accurately
154 calculate the volume of plots, the volume of plastic strips used for packing was calculated
155 separately and the volume of pieces was reduced (Miller et al., 2015).

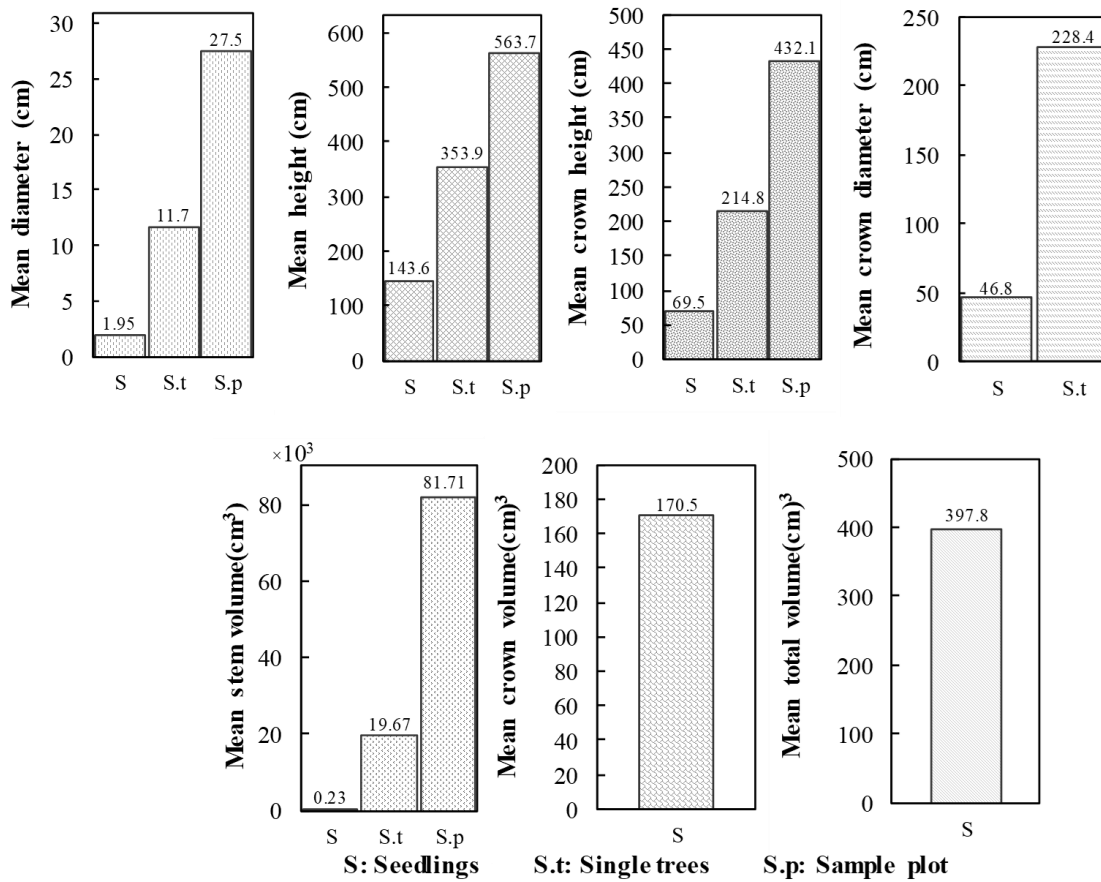
156 Given the impossibility of cutting the trees, the Smalian formula was used to estimate the
157 tree's stem volume based on the morphology of the tree stems (Ahmad et al., 2020). To more
158 accurately estimate the stem volume, the stem length was divided into 65 cm sections using a
159 measuring tape. The total stem volume of each tree was calculated using Equation 1 (Ahmad et
160 al., 2020).

Equation. 1.
$$V = \sum_{i=1}^{i=n} (\pi \times (\frac{d_{base}^2 + d_{top}^2}{8}) \times h_i)$$

161 Where V represents the stem volume of each tree (cm³), h_i denotes the length of each plot
162 of tree stem (cm), d_{base} is the initial diameter of each section of tree stem (cm), d_{top} represents
163 the final diameter of each section of tree stem (cm), π = 3.14 and n: is the number of sections
164 of each stem.

165 The value of tree crown volume was not compared with the values obtained from TP at
166 single trees and sample plot levels, in terms of the inability to accurately measure the volume
167 of tree crowns in terrestrial measurements.

168 The mean values of measured attributes of seedlings and trees at each of the three levels are
 169 presented in Fig.1.



170 Fig. 1. The mean value of the measured attributes of seedlings and trees

171 Image Acquisition

172 Images were captured using a Canon EOS 700D semi-professional camera equipped with a
 173 30 mm EF-S lens. To maintain the camera's stability during shooting, the camera was placed
 174 on a tripod with adjustable height. In order to increase the quality of the images, the photos
 175 were taken using manual settings (shutter speed= 1/180 second, F= 4.5 aperture and ISO=
 176 automatic). The approach suggested by Morgenroth and Gomez (2014) and Miller et al., (2015)
 177 was used to photograph seedlings and single trees. Therefore, two concentric rings were painted
 178 around the trees. Then, photographs of trees were taken around the circumferences of these
 179 circles at regular intervals. The distances among the shooting points were determined so that
 180 the overlap of each image with the next one is > 50%. Scale is needed in the images to create

181 a 3D model in the software environment, therefore, a box with specified dimensions was used
182 when photographing seedlings, while a levelling staff with a height of 3 meters was used during
183 photography of single mature trees. Therefore, after preliminary studies, a combination of the
184 methods proposed by Mokroš et al., (2018) was used in order to obtain the best method of
185 photographing trees in the sample plot. In order to ensure sufficient overlap among the images,
186 photos were taken in different directions, including the perimeter and the two diameters of the
187 sample plot. The distance between the photogrammetric points was approximately 2.5 meters,
188 whereas the overlap between the images was at least 50%. Therefore, the distance among the
189 photogrammetric points of the trees was between 1 and 3 meters, depending on the height of
190 the trees, which in most cases was about 2.5 meters. During imaging, 5 levelling staffs were
191 placed at the four corners and the center of the sample plot to define the scale during image
192 processing.

193 **Image processing**

194 We used Photoscan-professional software for the reconstruction of 3D models (Agisoft
195 LLC, Saint Petersburg, Russia) (Morgenroth and Gomez, 2014). To derive a 3D model of
196 seedlings and trees using the SfM-MVS method, the position and attributes of the camera and
197 sparse point clouds were required to be first derived using SfM method (James and Robson,
198 2012; Miller et al., 2015; Mokroš et al., 2018; Iglhaut et al., 2019). For this purpose, the images
199 were loaded and aligned in the software. Then, the key points were extracted from the
200 overlapping of the images and converted to tie points after matching (Mokroš et al., 2018). The
201 software default values were set to 40000 and 4000 to define the maximum number of key
202 points and tie points, respectively. Using dense image matching methods and the MVS
203 approach, the sparse point clouds retrieved in the previous phase were transformed to dense
204 point clouds in the subsequent step (James and Robson, 2012; Iglhaut et al., 2019). The MVS
205 technique transforms sparse point clouds into dense point clouds by eliminating noisy data and

206 multiplying reconstructed points (Iglhaut et al., 2019). This helps more accurately estimating
 207 the 2D and 3D attributes of trees. Finally, the mesh model of each seedling and tree was
 208 produced using a dense point clouds. Afterwards, 2D and 3D attributes of seedlings or trees
 209 were measured (Miller et al., 2015). To estimate the 3D attributes, unrelated elements such as
 210 pots and ground surface were removed in each model, and the 3D attributes were measured
 211 separately. An example of a 3D model produced for seedlings and trees is shown in Fig. 2 and
 212 Online Resources 1 and 2.

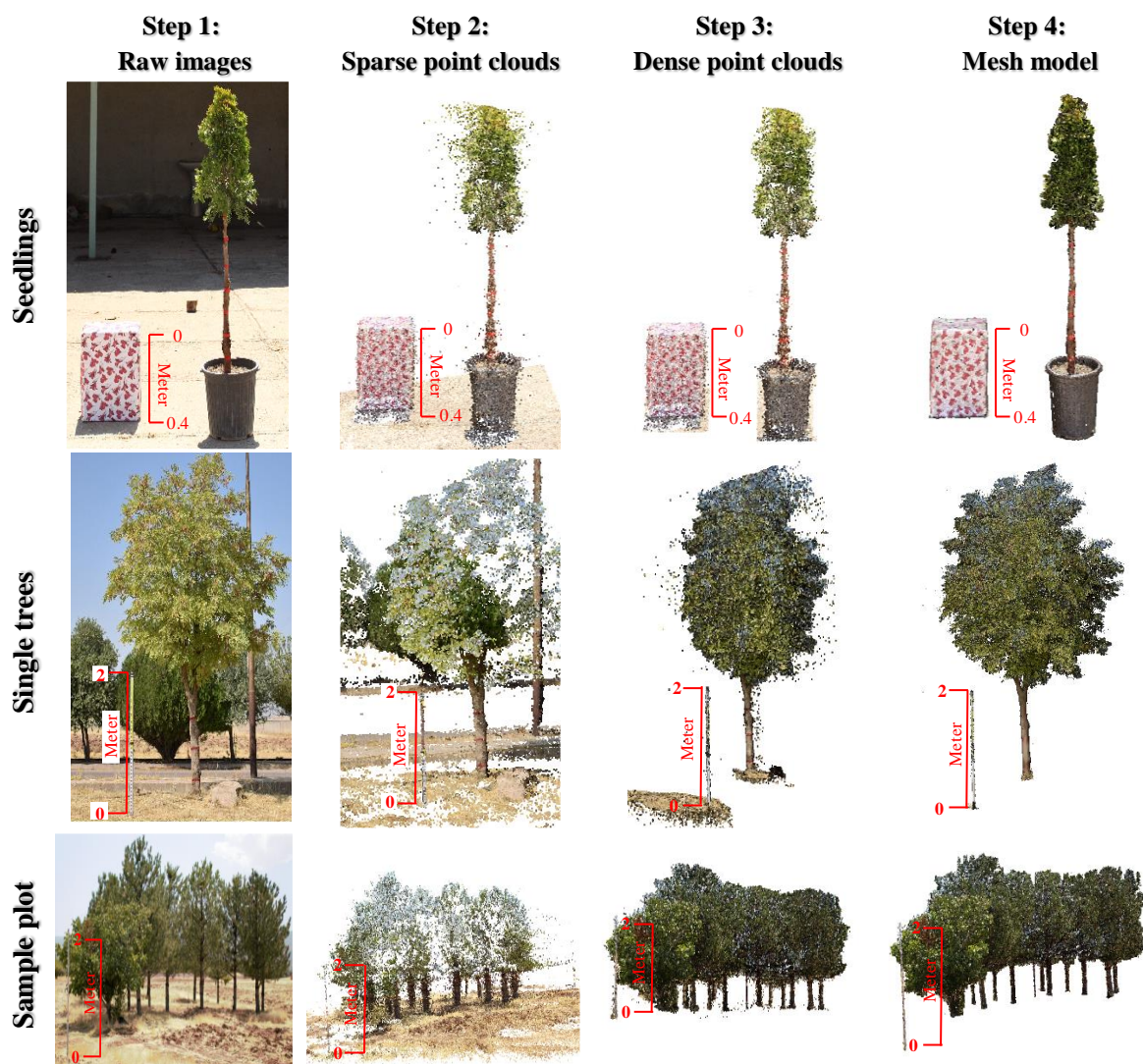


Fig. 2. Different stages of developing a 3D model of seedlings and trees a) raw images, b) sparse point clouds, c) dense point clouds and d) mesh model

213 **Statistical Analysis**

214 To compare the estimated and reference data, statistics of coefficient of determination (R^2)
 215 (Hobart et al., 2020), Root Mean Square Error (RMSE), Root Mean Square Percentage Error
 216 (RMSE %), Bias, relative Bias % (Roberts et al., 2019), Mean Absolute Error (MAE) and Mean
 217 Absolute Percentage Error (MAE%) (Liu and Zhang, 2018) were used (Table. 2). All
 218 relationships and statistical graphs were processed in SPSS statistics 25 IBM and Microsoft
 219 Excel 2016 software. The flowchart of the research steps is presented in Fig. 3.
 220

Table. 2. Statistics formula used to compare estimated and measured data

Name	Equation
Coefficient of determination	$R^2 = \frac{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\left(\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2\right)\left(\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - \bar{\hat{y}})^2\right)}}$
Root Mean Square Error	$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}$
Root Mean Square Percentage Error	$RMSE\% = \frac{RMSE}{\left(\frac{\sum_{i=1}^n \hat{y}_i}{n}\right)} \times 100$
Bias	$Bias = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)}{n}$
Percent Bias	$Bias\% = \frac{Bias}{\left(\frac{\sum_{i=1}^n \hat{y}_i}{n}\right)} \times 100$
Mean Absolute Error	$MAE = \frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $
Mean Absolute Percentage Error	$MAE\% = \frac{1}{n} \sum_{i=1}^n \left \frac{y_i - \hat{y}_i}{\hat{y}_i} \right \times 100$

In the above equations, \hat{y}_i =measured values, y_i = estimated values and n = number of trees or seedlings.

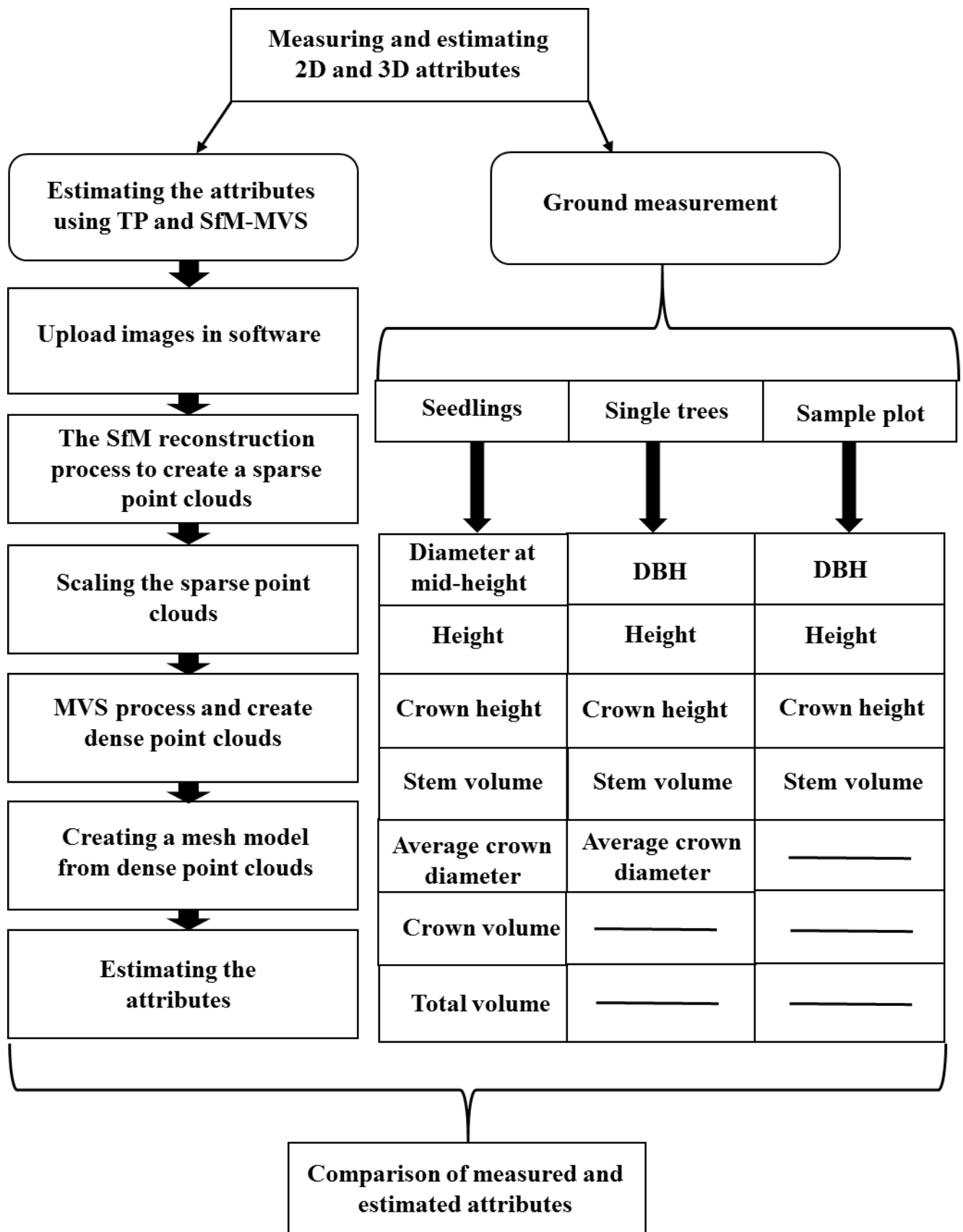


Fig. 3. Flowchart of the study

222 **Results**

223 **Comparison of estimated and measured 2D and 3D attributes of seedlings**

224 Comparing estimated values of 2D attributes of seedlings using TP with values measured in
225 the laboratory showed that the values of RMSE%, Bias% and MAE% for all estimated 2D
226 attributes were < 7%, which indicated high accuracy to estimate the 2D attributes of seedlings.
227 Among 2D attributes, diameter at the middle height of trunk and average crown diameter
228 showed the lowest and highest RMSE% with 1.16% and 6.51%, respectively (Table. 3).
229 Moreover, the scatter plots of estimated and reference values showed a high correlation,
230 suggesting R² of 0.99, 0.98, 0.98 and 0.98 for diameter at middle height of the stem, total
231 height, crown height and average diameter of the crown of the seedlings, respectively (Fig. 4).

Table. 3. Statistics related to comparing estimated and measured 2D attributes of seedlings

Attributes	n	RMSE	RMSE%	Bias	Bias%	MAE	MAE%
Diameter (cm)	30	0.02	1.16	-0.01	-0.70	0.01	1
Height (cm)	30	4.22	2.94	1.20	0.83	1.22	1.11
Crown height (cm)	30	1.96	2.82	0.77	1.11	0.77	1.30
Average crown diameter (cm)	30	3.04	6.51	-0.06	-0.12	1.88	5.01

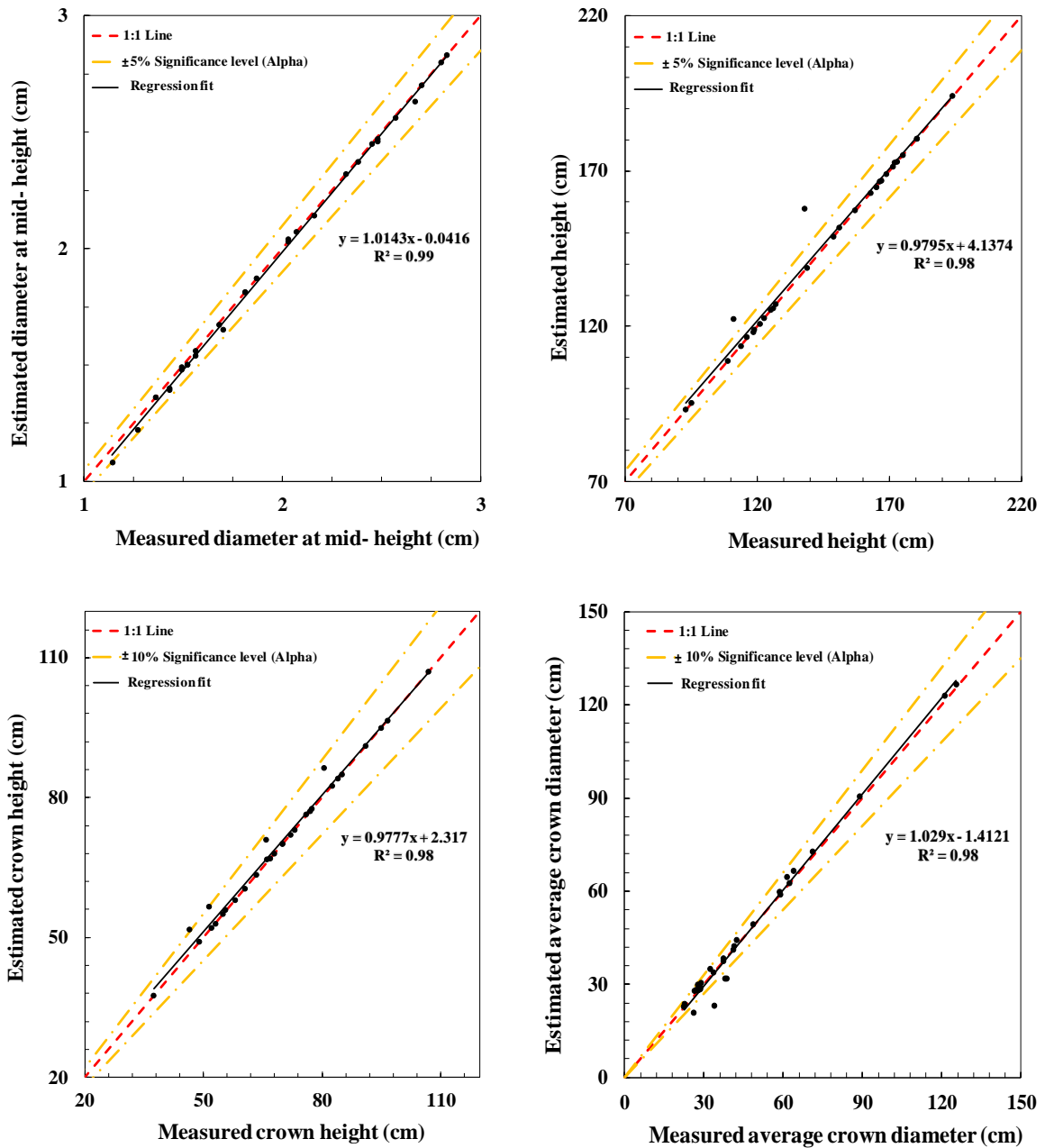


Fig. 4. Scatter plot between estimated and measured values of 2D attributes of seedlings

232 The validation of estimated values of 3D attributes of seedlings showed that the lowest
 233 RMSE%, Bias% and MAE% were returned for stem volume (20.99%, -14.96% and 14.83%,
 234 respectively), whereas the highest rates were achieved for crown volume (30.85%, -18.40%
 235 and 15.42%, respectively) (Table. 4). R^2 values for the stem volume, crown volume and total
 236 volume attributes were 0.90, 0.82 and 0.88, respectively (Fig. 5).

Table. 4. Statistics related to the comparison of estimated and measured 3D attributes of seedlings

Attributes	n	RMSE	RMSE%	Bias	Bias%	MAE	MAE%
Stem volume (cm ³)	30	47.72	20.99	-34	-14.96	65.37	14.83
Crown volume (cm ³)	30	52.60	30.85	-31.36	-18.40	34	15.42
Total volume (cm ³)	30	97.33	24.46	-65.37	-16.43	31.36	14.86

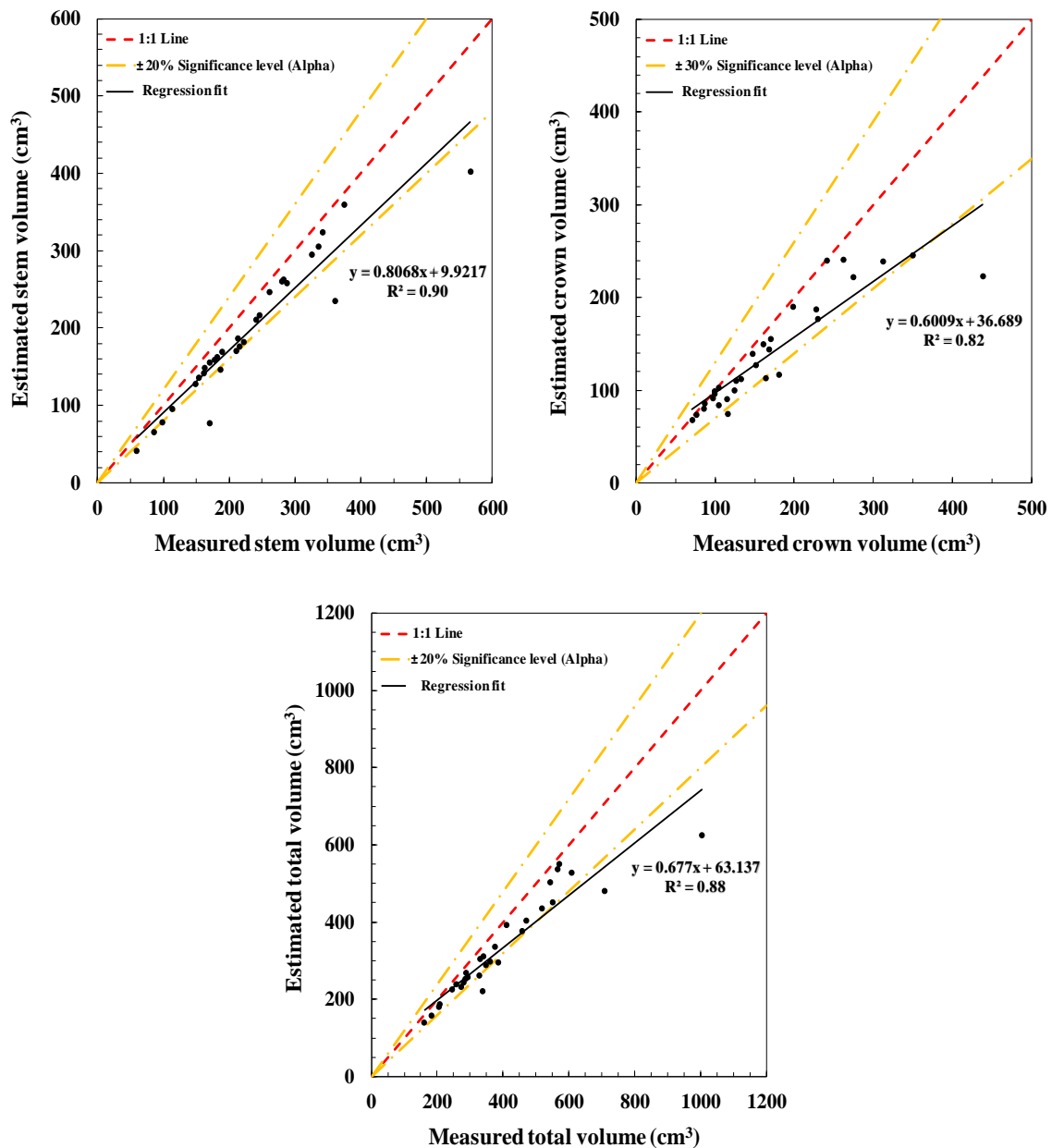


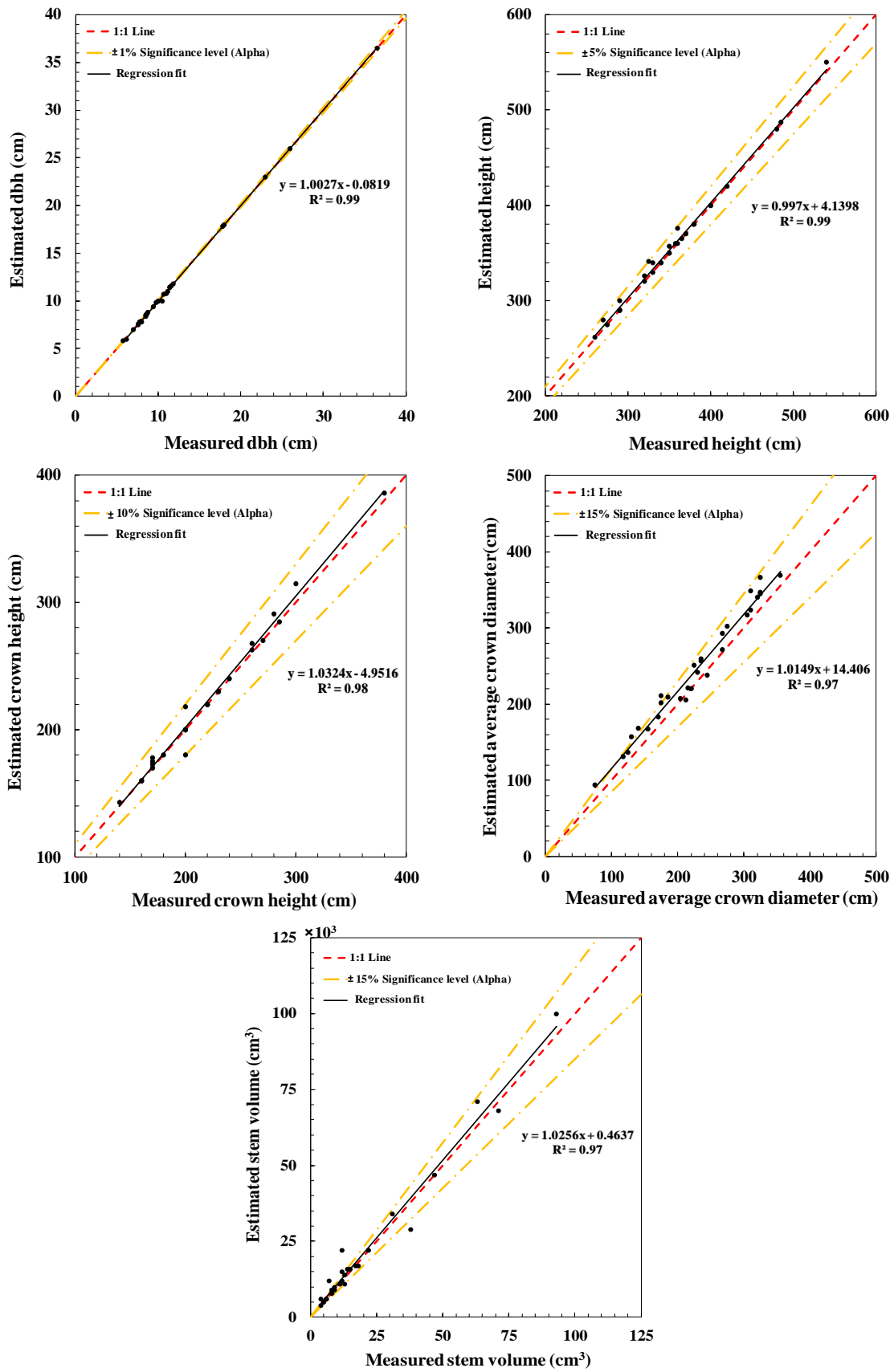
Fig. 5. Scatter plot between estimated and measured values of 3D attributes of seedlings

237 **Comparison of estimated and measured 2D and 3D attributes of single trees**

238 Comparison of the estimated values of single tree attributes with reference values showed
 239 that 2D attributes were estimated more accurately than 3D attributes. Among all attributes, the
 240 lowest RMSE%, and MAE% were returned for DBH (1.02% and 0.55%, respectively).
 241 Whereas, the stem volume with RMSE%= 17.69% and MAE%= 12.03%, showed the lowest
 242 accuracy (Table. 5). The scatter plot of the estimated and reference values for 2D and 3D tree
 243 attributes suggested R² values of 0.99, 0.99, 0.98, 0.97 and 0.97 for DBH, total height, crown
 244 height, average crown diameter and stem volume of single trees, respectively (Fig. 6).
 245

Table. 5. Statistics on comparing estimated 2D and 3D attributes and measured values of single trees

Attributes	n	RMSE	RMSE%	Bias	Bias%	MAE	MAE%
DBH (cm)	30	0.12	1.02	-0.05	-0.43	0.05	0.55
Height (cm)	30	5.81	1.64	3.06	0.87	3.06	0.91
Crown height (cm)	30	6.55	3.05	2	0.93	3.33	1.51
Average crown diameter (cm)	30	21.34	9.34	17.8	7.80	18.66	9.26
Stem volume (cm ³)	30	3.47	17.69	0.96	4.90	1.96	12.03



246

247

Fig. 6. Scatter plot of estimated and measured values of single trees

248 **Comparison of estimated and measured 2D and 3D attributes of trees at sample plot level**

249 The validation results of estimated DBH, crown height, stem volume of trees in the sample
 250 plot are shown in Table. 6 and Fig. 7. Among all attributes, tree DBH showed the lowest error
 251 rate (RMSE% = 1.72% and MAE% = 1.39%) and tree stem volume returned highest error rate
 252 (RMSE% and MAE% of 14.37% and 15.40%, respectively). Further, the bias% values of all
 253 2D and 3D attributes were < 5%. The calculated R^2 suggested a high correlation between the
 254 estimated and the reference 2D and 3D attributes (Fig. 7).

Table. 6. Statistics related to comparison of the estimated and measured values of the attributes of the trees within the sample plot

attributes	n	RMSE	RMSE%	Bias	Bias%	MAE	MAE%
DBH (cm)	14	0.47	1.72	-0.25	-0.91	0.35	1.39
Height (cm)	14	20.54	3.64	19.5	3.46	19.5	3.47
Crown height (cm)	14	20.54	4.75	19.5	4.50	19.5	4.52
Stem volume (cm ³)	14	11.74	14.37	2.57	3.15	9.14	15.40

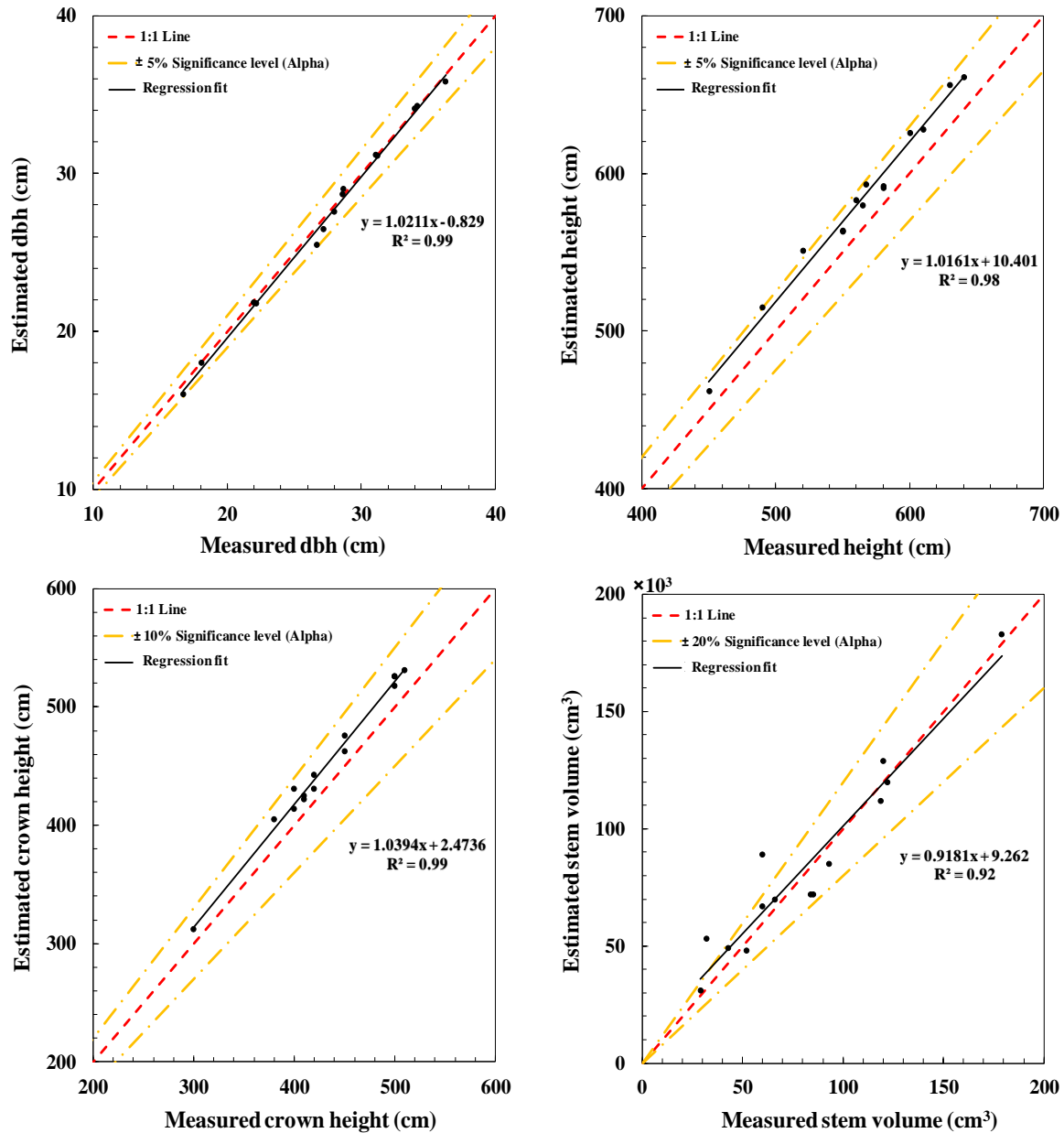


Fig. 7. Scatter plot of the estimated and measured values of trees attributes in the sample plot

255

256 **Comparison of estimated and measured 2D and 3D attributes at three levels**

257 Comparing estimated values of diameter at the middle height of trunk of seedlings and DBH
 258 of trees using TP with measured values showed that the values of RMSE%, Bias% and MAE%,
 259 were $< 2\%$ at all three levels. The height of single trees and trees within a sample plot were
 260 calculated using the lowest and highest RMSE% among the three levels (1.64% and 3.64%,
 261 respectively). However, the crown height of seedlings was assessed with more precision than

262 the other two levels. Considering the overlap of tree crowns with each other in sample plot, the
263 average diameter of the crown attribute was estimated in seedlings and single trees with
264 RMSE%= 6.51% and 9.34%, respectively. The validation of estimated stem volume of
265 seedlings and trees at three levels revealed that trees within a sample plot had the lowest
266 RMSE% and Bias% (14.37% and 3.15%, respectively), but seedlings had the highest rates
267 (20.99% and -14.96%, respectively) (Tables. 3-6).

268 **Discussion**

269 Considering the issues such as population growth, development of urban areas and climate
270 change, sustainable management of urban greening has nowadays increasingly become
271 important in terms of its role to increase the physical and mental health of urban inhabitants.
272 Since the basis of urban sustainable management since access to accurate and up-to-date
273 information is considered as a basis for urban sustainable management, this study aimed to use
274 TP and SfM-MVS methods in estimating 2D and 3D attributes of urban trees at three different
275 levels of seedling, single trees and trees within a sample plot.

276 **Estimation of 2D and 3D attributes of seedlings using TP**

277 Comparing estimated and lab-measured 2D attributes of seedlings using TP and SfM-MVS
278 method suggested high accuracy of estimating the 2D attributes of seedlings. The results of
279 both studies of Miller et al., (2015) and Morgenroth and Gomez (2014) were in line with the
280 results of our research and showed the high accuracy of SfM-MVS method in estimating the
281 2D seedling attributes.

282 When estimating the 3D attributes of seedlings, results showed lower accuracy compared
283 with the 2D attributes. However, the stem volume was more accurately estimate than crown
284 volume. Considering the irregular shape of the tree crown and the empty space between the
285 foliage of the seedlings, the estimated crown volume was different from the actual volume
286 calculated through immersion. Furthermore, since the total volume of each seedling was

287 determined from the total stem and crown volumes, this difference had an impact on the
288 predicted total volume. Due to the narrow diameter of the seedlings, particularly in the region
289 linking the stem to the crown, the volume associated to the terminal parts of the stem was
290 calculated with a minor discrepancy. Among few studies conducted to estimate the volume of
291 seedlings using TP, Miller et al., (2015) can be referred to, in which RMSE% and Bias% of
292 12.33% and -8.2% were reported for stem volume, while -18.53% and -5.56%, were reported
293 for total volume of seedlings, respectively. Finally, in line with the results of our study, they
294 concluded that the accuracy of the TP to estimate 2D attributes is higher those achieved for 3D
295 attributes.

296 **Estimation of 2D and 3D attributes of single trees using TP**

297 RMSE%, Bias% and MAE% values obtained when estimating the 2D tree attributes
298 including DBH, average crown diameter, crown height and height showed that our approach
299 was capable to produce high accuracies. In this regard, Sakai et al., (2021) reported the R^2
300 values of 0.94, 0.89, 0.81 as well as the RMSEs of 0.13 m, 0.33 m and 0.89 cm for estimating
301 the height, crown diameter and stump diameter of trees using TP, respectively. In addition, the
302 results obtained by Bayati et al., (2021) in evaluating the performance of SfM-MVS method in
303 estimating the tree attributes showed $R^2 = 0.98$ for DBH and $R^2 = 0.89$ for tree height. Roberts
304 et al., (2019) estimated the DBH of single urban trees using TP with a RMSE of 10.37%.
305 Results from those previous studies were in line with the results of this study in estimating the
306 2D tree attributes.

307 Comparing stem volume of the by TP and the SfM-MVS method with the volume calculated
308 by the Smalian formula showed relatively high accuracy of our method in estimating the
309 volumetric attributes of single trees. One of the reasons for the lower stem volume estimate
310 accuracy relative to other features seems to be the impossibility of cutting trees, i.e. precise
311 field-based stem volume measurement. To resolve this problem, it was attempted to measure

312 the stem volume within smaller tree sections. However, using formulas which assume the stem
313 shape as cylindrical is associated with drawbacks for different species. Tamaki et al. (2019)
314 pointed out that TP and SfM-MVS methods have the ability and high accuracy in estimating
315 the stem volume of trees. Mulverhill et al. (2019) also stated that there is no significant
316 difference between the stem volume of single trees estimated by TP method and those
317 calculated by allometric equations.

318 **Estimation of 2D and 3D attributes of trees within the sample plot using TP**

319 In the third part of this study, we examined the efficiency of 3D models using TP along with
320 the use of SfM-MVS method to estimate the 2D and 3D attributes of trees at the sample plot
321 level. Due to the overlap of tree crowns with each other and the inability of identifying the
322 precise range of tree crowns, it was not able to estimate the crown spread of each tree, as
323 specified in the Methods section. As a result, the DBH of trees was the most accurate attribute
324 of trees assessed using 3D models. The results showed that the stem volume of trees was
325 estimated with $RMSE\% = 14.37\%$. Comparing estimated stem volume of trees at tree and plot
326 levels suggested that the accuracy was slightly higher at the sample plot level. This was because
327 the trees within the sample plot were entirely from the same species and with an almost
328 "cylindrical" stem shape. However, at the single tree level, tree species were different and thus
329 were associated with different stem shapes. In this regard, previous studies using TP at sample
330 plot and stand levels like Mikita et al., (2016) in estimating the attributes of DBH, height and
331 volume of trees, Forsman et al., (2016), Mokroš et al., (2018), Piermattei et al., (2019) in
332 estimating the DBH, Marzulli et al., (2020) in estimating the DBH and stem volume, Sakai et
333 al., (2021) in estimating the height, crown width and diameter of the tree stumps suggested that
334 the TP method was relatively accurate to estimate the mentioned attributes at the sample plot
335 level. However, they showed slightly different accuracies in predicting DBH, height, and stem
336 volume attributes than we did, which might be because the majority of the researches were

337 done in natural forests. Besides, factors such as photogrammetric method, stand conditions,
338 species type, tree dimensions, tree density, physiographic conditions and floor and shrub
339 coverage can partly influence the results.

340 **The potentials of workflow for practical implementation**

341 2D and 3D attributes of seedlings and trees were estimated using TP and SfM-MVS
342 methods. According to the results, this method can be suggested as a fast, low-cost and non-
343 destructive method that provides accurate estimates of 2D and 3D attributes of seedlings and
344 trees as an alternative to methods such as using TLS and traditional mensuration. As well as,
345 TP method is a hardware low-demanding technique which does not require professional
346 operator. Moreover, this workflow offers potential for application in urban greenings and
347 nurseries inventory.

348 **Technical and practical limitations and bottlenecks**

349 One of the constraints discovered during the conducting of this study was the inability to
350 estimate the average crown diameter attribute of trees within the sample plot due to the high
351 density of trees and the overlap of tree crowns. Another constraint was the assessment of
352 seedling trunk volume, which was less precise owing to the seedlings' tiny trunk diameter. Our
353 review of the relevant literature showed that issues such as image quality, image overlap, and
354 number of images, environmental conditions during photogrammetry, camera settings, as well
355 as the applied hardware and software could affect the quality of output 3D models. The study
356 of the effect of these factors on the quality of 3D output models could be the subject of our
357 future research.

358 **Conclusion**

359 Our results showed that the 3D models that were generated using TP by a semi-professional
360 handheld camera and the SfM-MVS method are capable of accurately estimating 2D attributes
361 of seedlings and urban trees at three levels of seedlings, single trees and trees within a sample

362 plot. According to obtained results, the diameter at the middle height of seedlings and DBH of
363 trees were estimated with $RMSE\% < 2\%$ at three levels.
364 The height of single trees and trees within a sample plot were calculated with the highest and
365 lowest accuracy, respectively, among the three levels. Nonetheless, seedling crown height
366 was more precisely measured than the other two levels. The average diameter of the crown
367 attribute at seedling and single tree levels were estimated with $RMSE\% = 6.51\%$ and 9.34% ,
368 respectively. In this realm, the applied method estimated the stem volume of single trees and
369 trees within the sample plot with practically appropriate accuracy, yet the 3D attributes of
370 seedlings were less accurate ($RMSE\%$ more than 20%). This seems to be due to the small size
371 of the seedlings and the difference in the estimated and measured values of the crown volume
372 of the seedlings.

373 **Data availability**

374 The datasets generated during and/or analysed during the current study are available from
375 the corresponding author on reasonable request.

376 **Conflict of interest**

377 The authors declare no conflict of interest.

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