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The determination of some stand parameters using SfM-based spatial 3D point cloud in forestry studies: an analysis of data production in pure coniferous young forest stands

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Abstract Benefiting from current unmanned air vehicle (UAV) and remote sensing techniques, the present study aims to estimate tree count (TC), tree height (TH), and tree crown cover area (TCCA) in a young Calabrian pine stand via *canopy height model* (CHM). Overlay images obtained using Quadcopter were used to generate two spatial three-dimensional (3D) cloud points in two different qualities. Point clouds were processed using R program in order to produce tree data using CHM. The sensitivity of CHM-based tree data was revealed using 318 tree measurements in 32 different sampling units. Estimation and measurement values were classified based on their *structure from motion* (SfM) quality and cover classes, and the statistical relationships among them were analyzed. Without any classification, R^2 was calculated for TC, TH_{Mean}, and $TCCA_{Total}$ estimations and field measurements. R^2 values were calculated as 0.865, 0.778, and 0.869, respectively, for $SfM_{Highest}$ CHM, while they were calculated as 0.863, 0.736, and 0.843, respectively, for SfM_{Medium} CHM. In addition, sensitivity and performance ranking in different groups were determined based on root mean square error (RMSE) and mean absolute percentage error (MAPE) values. A significant difference was observed among groups in terms of quality and cover for TH, while no significant differences were observed for TCCA. Therefore, it is possible to estimate the properties of SfM CHM–based young coniferous stand. It was understood that tree density, crown shape, and branching influenced the accuracy of the present study. The developed UAV (Drone)-SfM is a promising technique for further small-scale forestry studies.

Introduction

Since ancient times, aerial photogrammetry has been used for natural resources management and planning as well as in the field of forestry. Unmanned air vehicle (UAV) platforms and systems, which have been widely used in almost all engineering operations and have offered a cost-efficient and time-saving solution to cartography operations in recent years, now benefit from photogrammetry with the advent of various technological developments. The variety of data obtained from the studies using UAV photogrammetry (observation, cartography, and three-dimensional (3D) modeling, and etc.) (Nex and Remondino 2014) gained different functional dimensions due to several technological innovations in different fields (Pajares 2015). A newly developing UAV sector offers a number of sensors (such as laser detection and ranging = LiDAR, multispectral, hyperspectral, and

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thermal sensors), and aerial platforms carrying these sensors are commercially offered in the market.

The increasing use of UAV and its systems in both military and civil applications (such as search and rescue, cartography, and 3D modeling) can be attributed to a number of factors. The leading factor is the ability of the systems to offer spatial and temporal flexibility for data production as well as their low cost. As for scientific studies, UAVs can be used along with different sensors depending on the objective of the study, making it possible for researchers to use them as a versatile tool of functional data production (Anderson and Gaston 2013; Pajares 2015). There are various aerial carrying platforms such as UAV, Drone, Delta wing, Multicopter, Hexacopter, and Quadcopter that be adapted to different studies in the existing literature. In addition, these devices can be divided into different categories depending on their technical structure, equipment, and flying properties (Watts et al. 2012). Rather than fully automatic high-altitude UAV types, scientific researches often prefer semi-automatic controlled vehicles (low altitude UAV) for their simple and basic needs in order to capture photogrammetric images based on *structure from motion* (SfM) approach (Akgül et al. 2016; Buğday 2018; Grenzdörffer et al. 2008; Gülci et al. 2017; Pérez et al. 2013).

Widely used in forestry studies, photogrammetry involves mathematical calculations based on 3D images produced by two-dimensional overlay photograph pairs (Yilmaz 2010). Recently developed technologies and image processing algorithms have remarkably increased the number of photogrammetry studies in various disciplines. Nowadays, it is much easier to produce 3D models such as LiDAR via consumer-grade digital cameras thanks to the development of SfM technique (Colomina and Molina 2014; Wallace et al. 2016). The difference between LiDAR- and SfM-based models is the ability of LiDAR to generate 3D points for understory surface, while SfM cannot penetrate into spaces on the canopy cover (Wallace et al. 2016). However, SfM technique usually attracts many researchers and practitioners in the field as it can produce acceptable, accurate, low-cost, and quick surface models (Micheletti et al. 2015; Smith et al. 2016). Yielding considerably successful and effective results in complex surface structures, SfM technique displays a more optimal level of accuracy compared with LiDAR (Akgul et al. 2018; Westoby et al. 2012). As a result, similar to other scientific disciplines, UAV platforms carrying various sensors are also used in the field of forestry because it is a data production tool/device with an acceptable level of accuracy.

UAV offers a more cost-effective solution to image capturing and processing operations in medium- and small-scale areas compared with other widely used conventional platforms (aircraft and satellites). Low-altitude UAVs can provide higher resolution images compared with conventional aerial and satellite photogrammetry (Zhang et al. 2016). It cannot be denied that UAV brings an evident advantage in terms of low cost particularly in small-scale field study (20 ha and less) (Matese et al. 2015). Cost is an important restrictive factor in forestry studies when it comes to field measurement (Goodbody et al. 2017). Therefore, UAV systems are often preferred in various forestry studies not only for their time-saving and cost-effective features but also their spatial flexibility. It is not surprising that UAV photogrammetry, which is used to analyze stand structure, has become a less costly measurement technique in terms of canopy height and cover measurements compared with Airborne LiDAR System (Siebert and Teizer 2014). It can be thus argued that digital data obtained from UAV-based photogrammetry studies have also paved the way for sensitive forestry studies (Zhao et al. 2005). As a result, the use of UAV and related systems enables researchers to take a different approach towards various common problems in the field of forestry, and provide them with a number of new methods, applications, research, and strategies (Pajares 2015).

Dense point clouds obtained from UAV photogrammetry can be spatially and temporally used in sustainable forestry in order to produce data for different studies. In recent years, the use of UAV in various forestry studies in Europe and Asia is summarized under six categories by Torresan et al. (2017) as (1) the estimation of dendrometric information, (2) classification of tree species, (3) the determination of forest spaces, (4) post-fire observation and measurements, (5) forest protection and health cartography, and (6) post-harvest stand damages. Being a new field of study in forestry, UAV-Drone SfM photogrammetry studies have so far been used in various studies in Europe and Asia. In addition to their economical features and temporal flexibility for research purposes, drones are now commonly used for data production due to their acceptable accuracy (Tang and Shao 2015) since the estimation of tree height and crown width using drone-based images is now a

more cost-effective and popular research topic and technique in the field of forestry (Goodbody et al. 2017; Mlambo et al. 2017).

There are numerous commercial and open-source software which can be used to easily obtain and analyze low-cost overlay UAV images for data production in the stand measurement (i.e., Pix4D, Agisoft, and VisualSfM). In today's technology, SfM technique can generate 3D point clouds without any spatial and positional camera information to create 3D models (Baltsavias et al. 2008; Westoby et al. 2012). Canopy height models (CHMs) are produced using 3D point clouds obtained from consumer-grade digital cameras, and used to estimate tree height (Birdal et al. 2017), crown width (Panagiotidis et al. 2017), tree diameter (Fritz et al. 2013), tree location, and count (Mohan et al. 2017). In short, it can be effectively used to identify spatial changes which play an important role in the determination of forest variables in the stand size (e.g., density, canopy cover, stand volume, stand biomass) and estimation of differences between tree growth and efficiency (Guerra-Hernández et al. 2016; Puliti et al. 2015).

In the present study, medium- and high-density points were generated using SfM technique based on the images obtained from a low-cost quadcopter in order to analyze the estimation of stand properties (tree count, average tree height, and tree crown area). These high-density point clouds were analyzed through processing new-generation image processing algorithms in R programming language. The method and parametric values used in order to increase the estimation performance of tree parameters obtained using CHM algorithms were selected through trial and error and based on the existing studies in the literature. As a result, the present study aims to discuss the feasibility of UAV in forestry studies within the framework of precision forestry studies in young Calabrian pine stands. The term UAV is used to refer to drone as an aerial carrying platform in the following sections.

Material and method

Study area

The present study was conducted in the province of Kahramanmaras located in Eastern Mediterranean Region of Turkey. A plantation area with an altitude of 559

m in the main campus of Kahramanmaras Sutcu Imam University was selected as the main study area, which is located at 37° 35′ 06″ N and 36° 48′ 21″ E. Although the study area, which is a young plantation forest area, is largely covered by Calabrian pine trees. Calabrian pines in this study are aged around 15 and 16. The research was carried out in a relatively flat and straight terrain in order to minimize the impact of ground slope on the precision of method used for the estimation of tree data.

Equipment and software

DJI Phantom 4 Drone UAV platform was used for photogrammetric capturing. Its standard camera and other equipment were not modified, and its flight controllers can fulfill fully automatic flight missions thanks to third-party programs. The digital camera (with a 1/2.3″ CMOS sensor) mounted to the carrying platform with a gimbal had a resolution of 12.4 megapixels and a shutter speed of 1:8000 (DJI 2016). UcGS Pro was used as a third-party program in order to plan flights and define flight missions (Universel Ground Control System 2019). Photoscan software based on SfM technique was preferred for spatial 3D point cloud generation (Agisoft 2016). SPSS was used in order to statistically compare tree data and field measurements obtained via SfM CHM (IBM 2012). A UNI-T UT363 anemometer was used for temperature and wind speed measurement. Tree height was determined using a Blume-Leiss, a device which measures ground slope and tree height on a trigonometric basis. It can directly measure tree height at a fixed distance of 15, 20, 30, and 40 m. A Leica Disto D3, steel tape measure, and rope were also used. Land investigation forms were used to record data such as tree diameter (TD) (dbh), tree height, and crown width. SMARTK GNSS was used in order to obtain geographical location data belonging to ground control points (GCPs) and sampling units. A laptop with an Intel Core i7 and 8 GB RAM and a 2-GB graphic card was also used for image processing and storage.

Method

When existing studies on the estimation of canopy height using UAV photogrammetry are analyzed, it can be observed that similar image capturing, processing, and evaluation steps are taken. In the last few years, tree height and crown width measurements are performed using SfM-based spatial point processing

algorithms or through the comparison of digital surface models obtained from 3D point clouds with digital terrain models (Birdal et al. 2017; Mlambo et al. 2017; Mohan et al. 2017; Panagiotidis et al. 2017). In the present study, images obtained from UAV were processed using SfM technique in order to estimate tree data, and spectral data were not used (Lie 2016). The images obtained using consumer-grade camera mounted UAV were converted to point clouds thanks to SfM algorithms. Point clouds of a young stand produced in two different quality levels were used to compare, measure, and analyze CHM-based tree data estimations.

In the present study, data production using UAV photogrammetry in forest studies consists of 9 basic steps as follows: (1) data collection on the area where forestry operations are to be conducted, (2) preliminary land investigation, (3) planning UAV flight plans in the office environment, (4) controlling land feasibility for flight plan and automatic flight for photogrammetric capture, (5) transferring overlay images to the computer following the flight, (6) the determination and measurement of ground control points, (7) generation of point clouds using SfM technique, (8) statistical analysis of estimation data obtained using canopy height model, and (9) accuracy analysis using the data obtained from the study area and parametric comparisons.

Planning prior to flight

Necessary updated software for UAV was accessed on the official website of producing company. IMU, GPS, gimbal, obstacle sensor, and digital camera calibrations were performed for UAV prior to the flight mission. In addition to legal procedures for flight, necessary precautions were taken for flight safety in the given area. In the flight planning, a Windows-based UcGS, which is a user-friendly ground control station (ver. 3.1.871), and an Android-based UgCS, which is a third-party software ensuring connection with UAV via telemetry, were used.

Recommended flight heights (Dandois et al. 2015) and sensor values for UAV-SfM photogrammetry were taken into account, and optimal flight altitude was determined as 78 m. The flight route of carrying platform and capturing altitude of digital camera were determined in parallel with above mean sea level (AMSL) in order to increase the performance of 3D surface model (Universel Ground Control System 2019). In addition, overlaying ratios were set to higher values for a highly sensitive CHM estimation. Gimbal was adjusted in parallel with ground at an angel of 90° in order to capture rare images. WGS84 UTM Zone 37N projection system was used in order to identify and control spatial data. A flight mission of 8.24 min was planned for photogrammetric capturing in an area of 2.63 ha. Flight data for photogrammetric capturing mission are summarized in Table 1.

Prior to the flight, temperature (°C), average wind speed (m/s), and direction were determined using an anemometer. Flight route was planned based on the wind direction, and the whole flight route was (single grid) 2.2 km. Flight mission was planned in the office environment based on the weather conditions. Spatial data were logged in UAV (departure and landing positions and flight route) after they had been determined in the study area. When the image processing was completed, 13 GCPs measured via NRTK (network real-time kinematic) global navigation satellite system (GNSS) (± 2 cm accuracy) were used following to the connection to Turkey CORS (Continuously Operating Reference Station) in order to measure spatial sensitivity of the obtained data.

Photogrammetric flight information

UcGS Pro used in the flight planning has turned low-cost aerial platforms into devices which can capture photogrammetric images. UAV used in the present study successfully completed its planned flight mission. During the flight, air temperature was measured as 14–15 °C, while minimum and maximum average wind speed were measured as 2 and 4 m/s, respectively. The flight route followed a north-west direction, which was also the wind direction. The duration of image capturing via UAV lasted nearly 2 min longer than the actual planned duration. In addition, flight altitude was estimated as 72.5 m by Photoscan even though the planned flight altitude was 78 m. The smart battery, which had been

Table 1 Predefined parameters of flight mission for UAV (DJI Phantom 4)

Flight parameters	
Flight altitude (m)	78
Flight speed (m/s)	5
Ground resolution (cm)	3.33
Forward overlap (%)	80
Side overlap (%)	70
Photo Shot Interval (sec)	3
Camera attitude (^{0})	90

used for 6 different flights before, spent nearly 45% of its energy for this flight. The estimated error for X, Y, and Z coordinates based on digital camera stations of images processed in two different qualities were calculated as 2.30 m, 1.17 m, and 0.27 m, respectively.

Based on the dense point cloud generated using $SfM_{Highest}$, $RMSE_x$, $RMSE_y$, and $RMSE_{xy}$ values of orthomosaic data were calculated as 30 cm, 83 cm, and 88.5 cm, respectively. On the other hand, based on the dense point cloud generated using SfM_{Medium}, $RMSE_x$, $RMSE_y$, and $RMSE_{xy}$ values of orthomosaic data were calculated as 29 cm, 81 cm, and 85.5, respectively. In order to minimize spatial errors, the sensitivity of tree parameter estimation in forestry areas can be enhanced if high-accuracy GPS modules (such as D-GPS or RTK) are mounted on low-cost UAV platforms (DJI 2018). However, despite its reasonable advantages, the use of UAV-SfM in small-scale forestry operations may disturb the balance between research costs and data quality (Puliti et al. 2015). In addition, capturing healthy ground control point images on mountainside areas will contribute to the sensitivity and cost of the study. There are no RTK modules on the aerial carrying platform used for image capturing in the present study. This is because the use of UAV models with RTK modules in the market will bring an additional cost of 6200 US dollars for forestry studies and operations.

Spatial 3D point cloud generation

Following the flight, dense point clouds in two different qualities were generated from images captured via UAV. EXIF (Exchangeable image file format) data were used instead of GCPs in order to create photograph routes and test spatial XY axis sensitivity of the model produced using UAV-SfM. Spatial sensitivity of individually estimated tree was not evaluated. The following steps are taken in this process: (1) The identification of common points and creation of photo plane for block (alignment of photo), (2) point cloud generation, (3) manual removal of unstable point clouds, (4) point cloud export as *.las extension (Agisoft 2016). Parametric and preferred sensitivity values for this process are summarized in Table 2.

CHM generation using point clouds

rLidar (0.1.1) (Silva et al. 2017) and Fusion/LDV 3.80 (release date August 6, 2018) (McGaughey 2018)

Table 2 Preferred image processing parameters

Photo alignment		
Accuracy	Highest	
Pair pre-selection	Generic	
Key point limit	40000	
Tie point limit	4000	
Dense point cloud		
Reconstruction quality	Highest[a]	Medium[b]
Depth filtering	Moderate[a,b]	

[a] $SfM_{Highest}$, [b] SfM_{Medium}

modules, which are compatible with R statistical computing and graphics software (Microsoft R Open 3.5.2) (R Core Team 2019), were used for dense point cloud (*.las extension) reading, processing, and visualization processes. GroundFilter, GridSurfaceCreate, and CanopyModel functions in Fusion/LDV were applied, respectively. The distinction between soil ground and canopy cover was made during the point cloud filtering. Taking topographic structure of the study area into account (Kraus and Pfeifer 1998), the shift value, aboveground offset, and iteration parameters of the model adapted from Kraus and Pfeifer (1998) were defined as 0, 0.5, and 10, respectively (McGaughey 2018). A 0.5-m resolution DTM was generated using GridSurfaceCreate without any filtering. In addition, a CHM at a 0.5-m spatial resolution was generated using CanopyModel. Later, Gaussian filtering function (sigma = 0.6) was applied in order to increase the performance of the generated CHM for the estimation of individual tree parameters.

Tree data estimation

SfM-based CHM, which was generated using Fusion/LDV, was used to estimate tree count and spatial tree data. CHMsmoothing in open-source rLidar package and local maximum algorithm-based FindTreesCHM and ForestCAS were used for tree definition (Silva et al. 2017). Smoothing was performed for CHM using Gaussian function with a 3×3 window in order to optimize the results of tree parameter estimation (Mohan et al. 2017). Given tree count and canopy cover in the study area, maximum crown width in the model was determined as 10 m. Additionally, the limit value of exclusion parameter was set as 0.3 in order to identify neighboring pixels which exceed the maximum height of an individual tree by 30%.

Sampling unit design and measurements

In the present study, coniferous species count (Calabrian pine) (TC), tree height (TH), and tree cover crown area (TCCA) were estimated. The study area was divided into sampling units in order to control the estimated TC, TH, and TCCA values. The dimensions of each sampling unit were determined as 20×20 m (400 m^2), which yielded a total number of 21 sampling units. Canopy cover values were determined beforehand thanks to the ratio of tree crown area to the area of a single sampling unit (Eq. 1). Cover types were divided into 4 categories as very sparse (covered by few trees or without trees by < 10%), sparse (covered by trees by 10–40%), medium (covered by trees by 41–70%), and full cover (covered by trees by > 70%) (Fig. 1).

Canopy cover ratio $(\%)$

$$= \frac{\text{Detected tree cover area } (\text{m}^2)}{\text{Total area of sampling unit}(400 \text{ m}^2)} \times 100 \quad (1)$$

Sampling units were randomly selected by taking canopy ratios into consideration for accuracy analysis and statistical data. Twenty percent area of all sampling units belonging to each cover category was selected randomly. Thus, TC, TH, and TCCA measurements were performed for the area in the randomly selected sampling units. Given the cover ratios of sampling units (Fig. 1), 4 different groups (4 cover categories and 3 different methods) were created for SfM CHM and field measurements. For instance, group I was defined as SfM$_{Highest}$-very sparse (P1), SfM$_{Medium}$-very sparse (P5), and Field-very sparse (P9) (Table 3). The correlation among groups was analyzed for the measured and estimated TH and TCCA values in sampling units.

The following hypotheses will be analyzed in detail in order to limit the findings in the study area and clarify the objective of the present study:

H$_a$: There are significant differences among tree parameters (TC, TH$_{Mean}$, TCCA$_{Total}$) in different cover categories and estimated using point clouds in different qualities.
H$_b$: There are no significant differences among tree parameters (TC, TH$_{Mean}$, TCCA$_{Total}$) in different cover categories and estimated using point clouds in different qualities.

It was later analyzed whether the categorized TH and TCCA data displayed a normal distribution based on normality test (Shapiro-Wilk). Kruskal-Wallis, a non-parametric test, was used to analyze whether there was a significant difference between the estimated TH and TCCA in each group among the sampling units (IBM 2012). In addition, tree data (tree height and crown width) belonging to the models created using CHM were statistically analyzed (Pearson's r correlation analysis). Topography was not taken into account because the ground slope in the study area was nearly flat.

Root mean square error (RMSE) and mean absolute percentage error (MAPE) were used in order to indicate the accuracy of field measurements in the sampling units and tree data produced using SfM-based 3D point clouds (Eqs. 2 and 3). R^2 values were calculated using linear goodness of fit curve for TC, TH$_{Mean}$, and TCAA$_{Total}$ obtained using SfM CHM and field measurements. In addition, X, Y, and XY spatial errors were revealed using RMSE for orthophoto produced via SfM.

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\sum_{i=1}^{n} \frac{ei^2}{n}} \quad (2)$$

$$\text{MAPE} = \frac{1}{n} \sum_{i}^{n} \frac{AE_i}{AD_i} \times 100 \quad (3)$$

where AEi is absolute error and AD is actual observation.

Measurements in the sampling units

The central point of randomly selected square sampling units was determined using GNNS-CORS. A stake was erected on these central points, and edges were found using a rope. Thus, measurements were performed for trees which were located in the area of the sampling unit. After tree measurement values were recorded in the investigation forms, they were transferred to a personal computer. A Blume-Leiss was used to measure the length between root crown and terminal bud at a fixed distance of 15 m. Crown width of an individual tree was calculated based on the mean values of branch measurements on both sides. Measured crown width values were used to calculate TCCA (*pi* value 3.1415926) (Fig. 2).
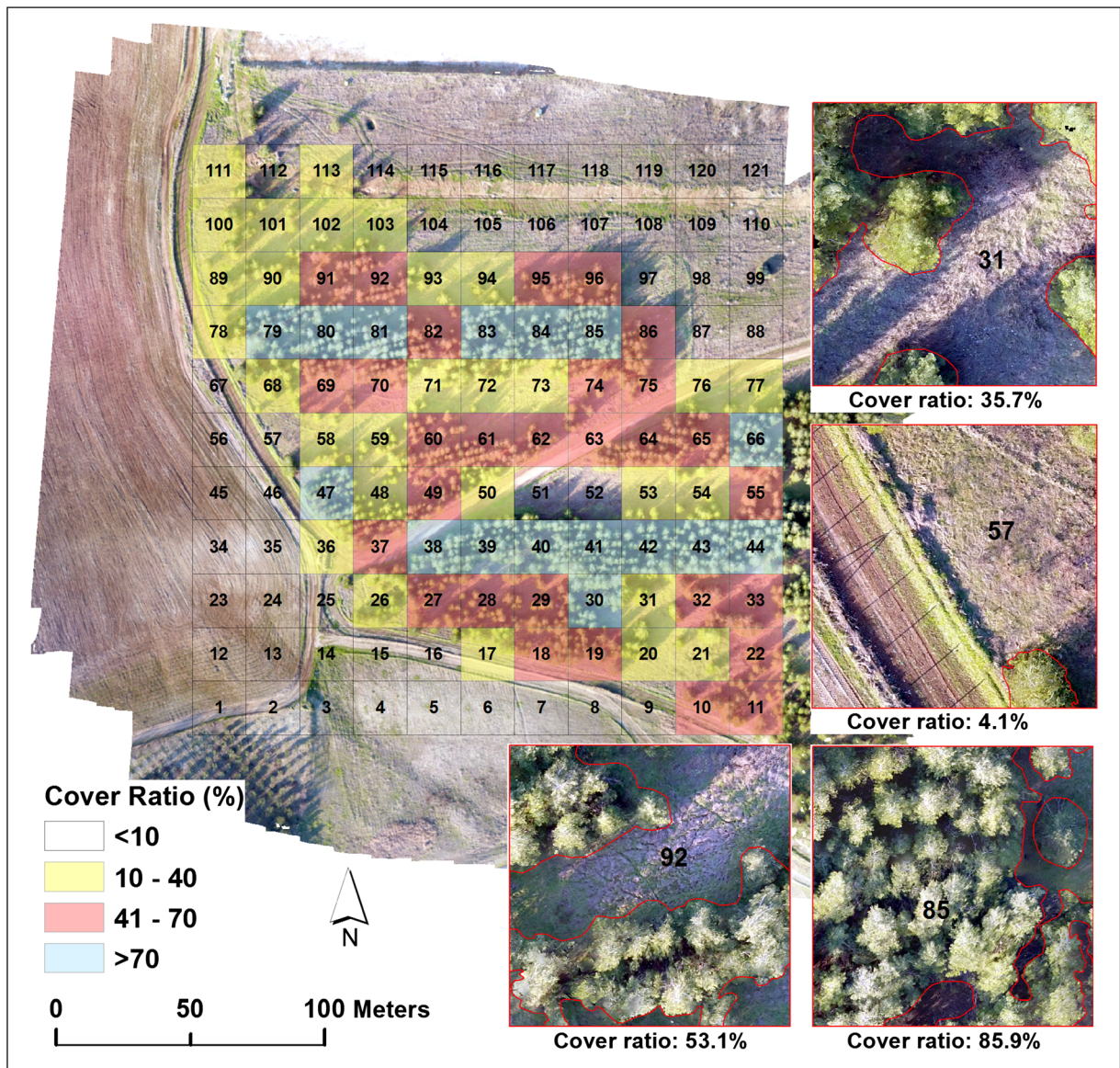
Fig. 1 The distribution of each sampling unit on orthophoto and the numbers assigned to them. Sampling units with very sparse (57), sparse (31), medium (92), and full (86) cover

Table 3 The determination of tree data estimation and measurement groups used for statistical comparisons

Technique	Cover			
	Very sparse (0)	Sparse (1)	Medium (2)	Full (3)
SfM$_{Highest}$	P1	P2	P3	P4
SfM$_{Medium}$	P5	P6	P7	P8
Field	P9	P10	P11	P12
	Group I	Group II	Group III	Group IV

Results and discussion

The analysis of spatial point cloud generated by UAV-SfM

A total of 126 images were captured during the flight, and all of them were processed using Photoscan software. These images were included in spatial 3D point cloud generation, and RMS re-projection error was calculated as 0.78 pixels. It took nearly 32 min to create a
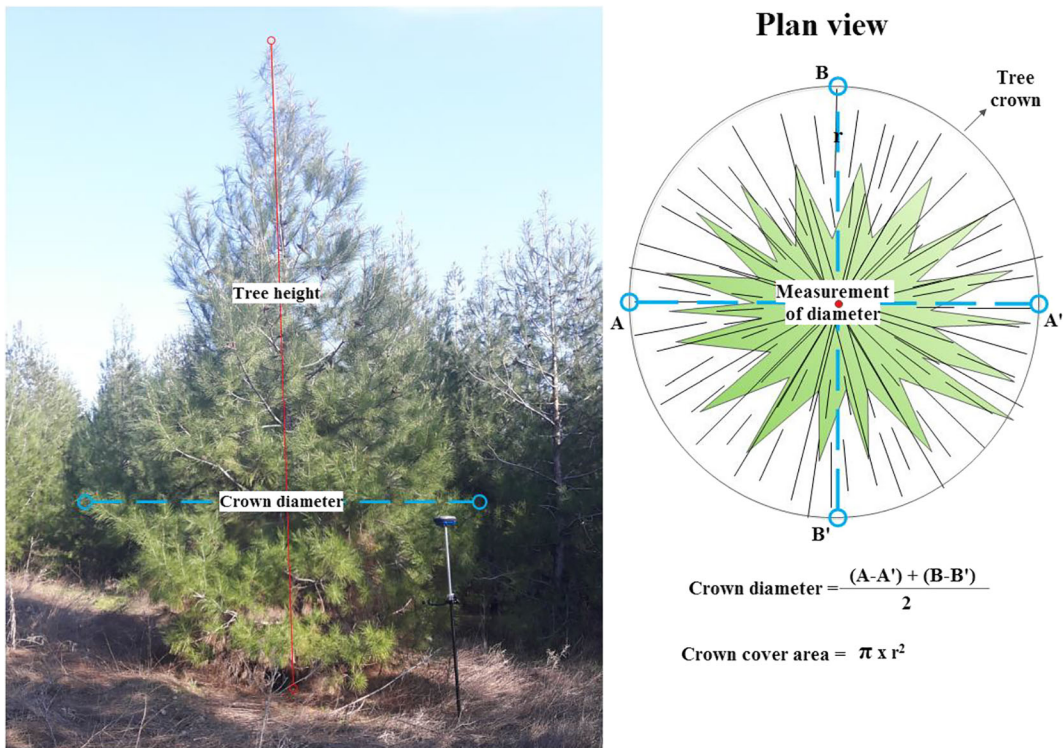
Fig. 2 The method used for tree height and diameter measurement (the height of the range pole next to the tree is 2 m)

route for the images. Nearly 47.874 million and 12.573 million spatial 3D points were generated (Fig. 3) in the highest (images downscaled twice by each side) and medium (images downscaled four times by each side) quality (Table 2), respectively. Image matching and the determination of image capturing stations took 32 min. Additionally, point cloud generation using $SfM_{Highest}$ took 42 min, while the same process took 7.05 min using SfM_{Medium}.

The analysis of data estimation using $SfM_{Highest}$ and SfM_{Medium} CHM

Tree count obtained from point clouds generated using $SfM_{Highest}$ is 1428, and average tree height is 5.53 m. Total tree crown cover area was estimated as 8600.25 m^2. On the other hand, tree count obtained from point clouds generated using SfM_{Medium} is 1383, and average tree height is 4.73 m. Total tree crown cover area was estimated as 10887.75 m^2. Thus, the difference between $SfM_{Highest}$ and SfM_{Medium} in terms of the highest estimated tree heights was 1.81 m (Fig. 4). The cover ratio of the study area was calculated as 17% (sparse) using

$SfM_{Highest}$, while it was estimated as 22.5% (sparse) using SfM_{Medium} (Eq. 1).

The differences between spatial data of trees estimated using CHM and point clouds generated in two different qualities are shown in Fig. 5. Even defoliated trees, withered plants, and bushes were visibly captured in sparse areas thanks to the parameters used in the estimation of tree parameters (see the calculation of tree parameters). It was also observed that the parameters of totally defoliated acacia trees (height and crown area) located in sampling unit 121, which is categorized as very sparse, were partially estimated (Fig. 5). Therefore, tree estimations and data were restricted to coniferous tree types (Calabrian pine).

The statistical differences between tree data generated in different qualities and in the same area (TH and TCCA) are shown below. In both quality categories ($SfM_{Highest}$ CHM and SfM_{Medium} CHM), the parameters of 407 trees were estimated. The difference between tree locations in different sampling units varies between 0.5 and 1 m (Fig. 5).

While a low correlation was found between crown areas of single trees in the same sampling unit, a very high correlation was observed between estimated tree
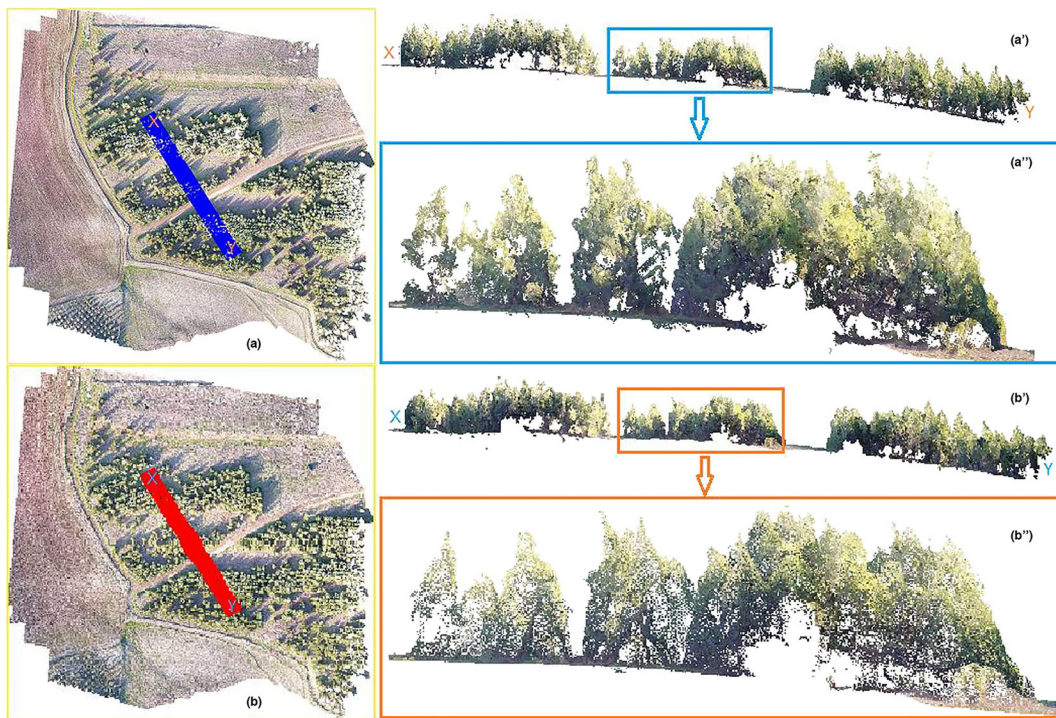
Fig. 3 The comparison of point cloud generation in high quality (a) and medium quality (b). The comparison of high-quality sections (a′ and a″) and medium-quality (b′ and b″) point clouds. The demonstration of differences between spatial 3D point cloud densities of tree (Calabrian pine) groups through sections

heights (Table 4). When the difference among tree heights obtained from field measurements is low, SfM_{Medium} spatial 3D point cloud generation can be preferred instead of $SfM_{Highest}$. Thus, it may be possible to minimize times losses in image processing and analysis.

It can be understood from Table 5 that there are no significant differences between two quality categories when TH and TCCA values estimated in two different qualities are taken into account. RMSE and MAPE values for tree heights ($TH_{Highest}$–TH_{Medium}) were calculated as 1.26 and 24.61%, respectively. Tree crown area ($TCCA_{Highest}$–$TCCA_{Medium}$) was calculated as 3.84 and 69.45%, respectively (Eqs. 2 and 3).

Based on Shapiro-Wilk (SW, $p < 0.05$), it was found out that TH and TCCA values of trees in the same area did not display a normal distribution for SfM quality categories. As for normality correlations among defined groups for TH values, while P1–P5 (SW 0.178, $p > 0.05$) and P2–P6 (SW 0.141, $p > 0.05$) displayed a normal distribution, P3–P7 (SW 0.031, $p < 0.05$) and P4–P8 (SW 0.000, $p < 0.05$) did not display a normal distribution. On the other hand, when it comes to TCCA

values, P1–P5 (SW 0.424, $p > 0.05$) displayed a normal distribution, P2–P6 (SW 0.024, $p < 0.05$) and P3–P7 and P4–P8 (SW 0.000, $p < 0.05$) did not display a normal distribution. Given these normality test results, it can be stated that the differences between estimated TH and TCCA values are directly proportional to cover ratios.

The comparison of SfM CHM–based tree data and field measurements

It was indicated in the study area that 29 sampling units were very sparse, 29 of them were sparse, 29 of them had medium cover, and 19 of them had full cover (Fig. 1). Three hundred eighteen different trees in 32 different sampling units were used as a reference for TC, TH_{Mean}, and $TCCA_{Total}$ values. The measurements were performed in very sparse (sampling unit 15, 16, 25, 46, 51, 52, 57, 67, 87, 98, 107, 112, 114, 117, 121), sparse (sampling unit 21, 50, 71, 77, 89, 93, 102), medium (sampling unit 11, 18, 37, 63, 69, 70, 96), and full cover (sampling unit 38, 44, 84) sampling units (Fig. 1). The mean values of tree data measured in the study area are
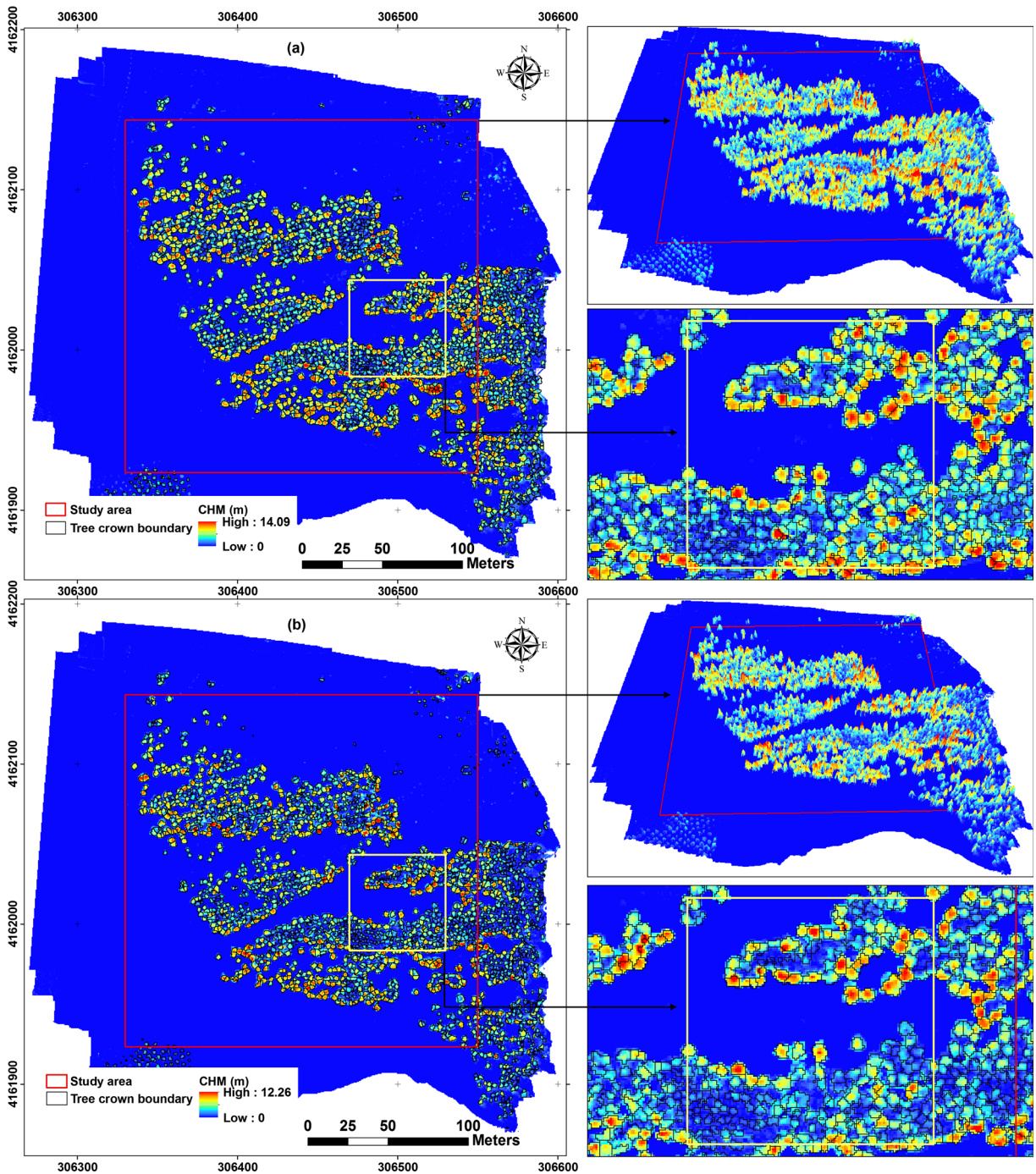
Fig. 4 3D and 2D images of SfM CHM in high (**a**) and medium (**b**) qualities. The illustration of spatial tree crown boundaries and height obtained from "rLidar." The study area highlighted by thick reddish lines in 2D maps was used for tree data estimations and field measurements

given in terms of their cover categories in Table 6. Calabrian pines in the study area are pole-stage trees. As the tree density in the study area decreases, branching forms, tree height, tree diameter, and crown area often vary. In addition, overgrown trees can also be observed in very sparse and sparse areas.

The differences between the estimated values and field measurements (TH and TCCA) in the sampling
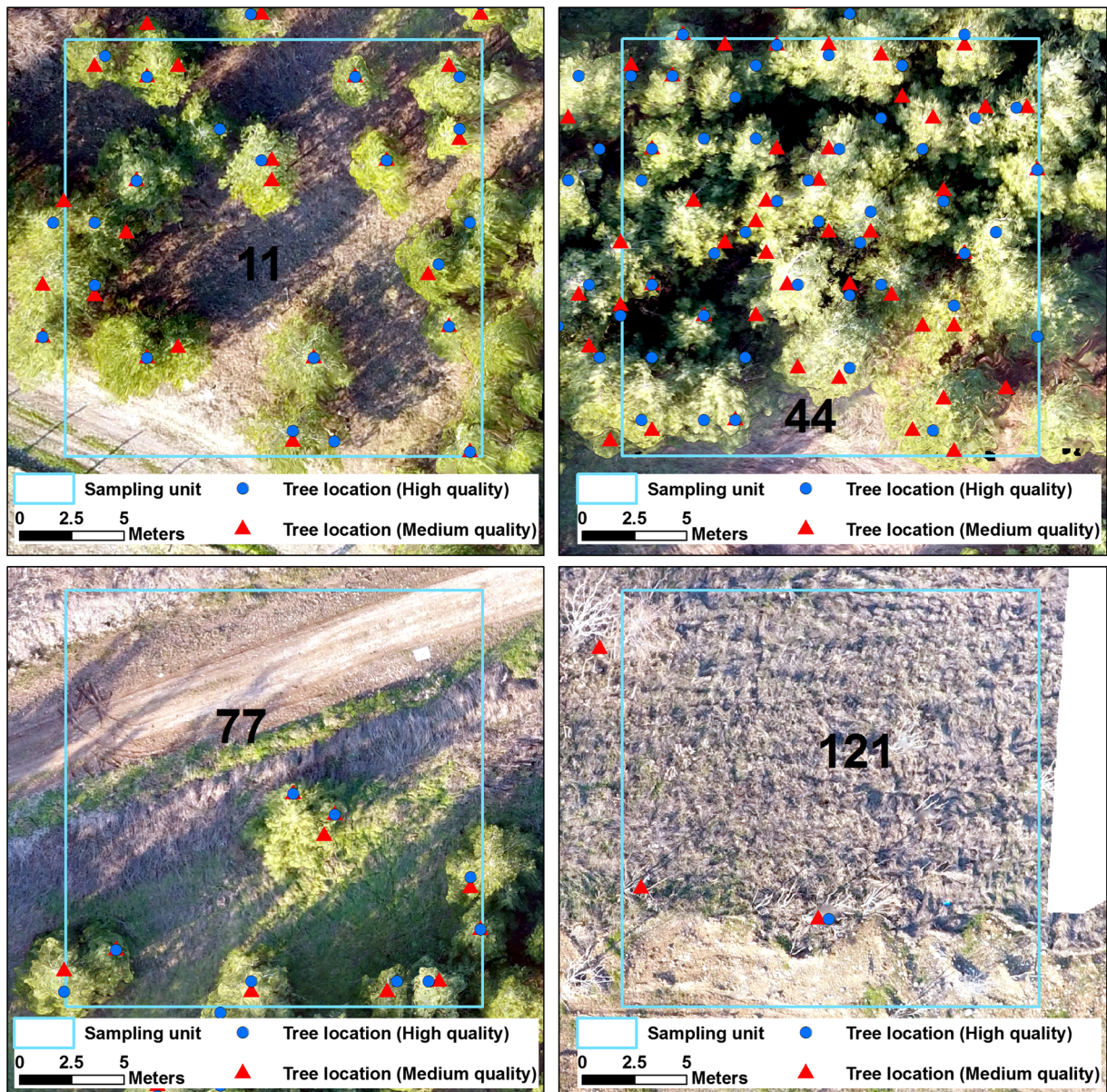
Fig. 5 The comparison of spatial data of trees estimated using SfM-based point clouds in different qualities 11 (2 = medium), 44 (3 = full), 77 (1 = sparse), and 121 (0 = very sparse) (sampling units are shown at a frame of 20 × 20 m). Red triangles and blue dots on these images show trees which can be estimated using SfM_{Medium} and $SfM_{Highest}$ CHM, respectively

units were analyzed based on their respective groups (classified from P1 to P12) (Table 3). The Shapiro-Wilk normality test demonstrated that all four groups (group I, group II, group III, group IV) displayed a not normal distribution in terms of TH and TCCA ($p < 0.05$). On the other hand, it is clear from Kruskal-Wallis test findings that there was a significant difference among groups in terms of TH (χ^2 8.088, $p = 0.044$; $p < 0.05$), whereas no

significant differences were found among groups in terms of TCCA (χ^2 0.358, $p = 0.949$; $p > 0.05$).

Similar to Lie (2016) and Panagiotidis et al. (2017), the present study found out strong direct correlations between the data estimated using SfM CHM and field measurement data. R^2 values for tree count, mean tree height (TC_{Mean}), and total tree crown area ($TCCA_{Total}$) estimated using SfM_{Medium}-based CHM were calculated

Table 4 Pearson's *r* correlation analysis for tree height (m) and tree crown area (m²) based on SfM quality (TH$_{Highest}$ and TCCA$_{Highest}$ are estimated using SfM$_{Highest}$, and TH$_{Medium}$ and TCCA$_{Medium}$ are estimated using SfM$_{Medium}$)

	TH$_{Highest}$ × TH$_{Medium}$	TCCA$_{Highest}$ × TCCA$_{Medium}$
Pearson's correlation	0.868**	0.109*
Sig. (2-tailed)	0.000	0.028
N	407	407

*Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.01 level (2-tailed)

as 0.863, 0.736, and 0.843, respectively. On the other hand, R^2 values for TC, TC$_{Mean}$, and TCCA$_{Total}$ values estimated using SfM$_{Highest}$ CHM were calculated as 0.865, 0.778, and 0.869, respectively. These findings in the present study overlap R^2 values for the estimated tree height and field measurement in other similar studies (Guerra-Hernández et al. 2016; Mlambo et al. 2017). It must also be noted that the correlation between tree height estimation and measurement values using

different SfM-based CHM can be revealed more accurately (R^2 0.94) (Birdal et al. 2017).

Thanks to SfM CHM, TC was estimated with an individual tree sensitivity of RMSE ± 9 and 10 in full cover areas, while it was estimated with a sensitivity of ± 1 and ± 6 in sparse and medium cover areas, respectively. The sensitivity of TC estimated using SfM$_{Highest}$ and SfM$_{Medium}$ was inversely proportional to cover ratio. The lowest error rate in TH estimation using SfM$_{Highest}$

Table 5 The statistical tree height (m) and tree crown area (m²) of 407 trees obtained using SfM$_{Highest}$ and SfM$_{Medium}$ CHM

	CCR*	*N*	Mean	Std. deviation	Std. error	95% confidence interval for mean		Min.	Max.
						Lower bound	Upper bound		
TH$_{Highest}$	0	10	5.0839	1.6363	0.5174	3.9134	6.2544	2.95	7.31
	1	114	5.9740	1.6990	0.1591	5.6588	6.2893	1.80	9.59
	2	158	6.1391	1.7068	0.1358	5.8709	6.4073	1.64	9.45
	3	125	5.2315	1.9549	0.1749	4.8854	5.5775	1.52	13.35
	Total	407	5.7882	1.8226	0.0903	5.6106	5.9658	1.52	13.35
TH$_{Medium}$	0	10	4.5249	1.6496	0.5217	3.3448	5.7050	2.18	6.50
	1	114	5.2558	1.7839	0.1671	4.9248	5.5869	1.52	9.57
	2	158	5.3329	1.7822	0.1418	5.0529	5.6130	0.87	9.54
	3	125	4.2442	1.7874	0.1599	3.9277	4.5606	0.91	8.45
	Total	407	4.9571	1.8415	0.0913	4.7777	5.1365	0.87	9.57
TCCA$_{Highest}$	0	10	4.8000	1.7192	0.5437	3.5702	6.0298	2.25	7.50
	1	114	5.6733	2.0275	0.1899	5.2970	6.0495	1.25	11.50
	2	158	5.6551	2.4385	0.1940	5.2719	6.0383	1.25	14.75
	3	125	6.5360	2.3608	0.2112	6.1181	6.9539	2.00	16.75
	Total	407	5.9097	2.3245	0.1152	5.6832	6.1362	1.25	16.75
TCCA$_{Medium}$	0	10	8.9750	2.6860	0.8494	7.0536	10.8965	5.75	14.75
	1	114	7.7215	2.4674	0.2311	7.2637	8.1793	2.50	14.50
	2	158	7.8165	2.7588	0.2195	7.3829	8.2500	3.00	15.25
	3	125	8.0280	2.5123	0.2247	7.5832	8.4728	3.50	15.25
	Total	407	7.8833	2.6020	0.1290	7.6298	8.1368	2.50	15.25

**CCR* crown cover ratio

Table 6 Descriptive statistical data of tree data (TH, TCCA, TD (dbh)) obtained from measurements in the sampling units in terms of their cover categories

	CCR	N	Mean	Std. deviation	Std. error	95% confidence interval for mean		Min.	Max.
						Lower bound	Upper bound		
TH_{Field}	0	21	7.5786	2.2403	0.4889	6.5588	8.5984	4.5	11
	1	62	8.2226	2.1958	0.2789	7.6650	8.7802	2.0	12
	2	133	7.8481	1.7208	0.1492	7.5530	8.1433	1.4	11.5
	3	102	9.9716	1.5600	0.1545	9.6652	10.2780	6.0	12.5
	Total	318	8.5844	2.0475	0.1148	8.3585	8.8103	1.4	12.5
$TCCA_{Field}$	0	21	8.7148	5.5476	1.2106	6.1895	11.2400	0.5	22.06
	1	62	7.7765	5.5194	0.7010	6.3748	9.1781	0.2	32.17
	2	133	6.4854	4.1546	0.3603	5.7728	7.1980	0.6	19.63
	3	102	6.9760	5.4718	0.5418	5.9012	8.0507	1.1	30.19
	Total	318	7.0417	4.9953	0.2801	6.4906	7.5928	0.2	32.17
TD_{Field}	0	21	16.1905	5.1246	1.1183	13.8578	18.5232	8.0	24
	1	62	16.1613	6.1941	0.7867	14.5883	17.7343	4.0	34
	2	133	15.4737	4.0836	0.3541	14.7733	16.1741	5.0	24
	3	102	17.6176	5.0933	0.5043	16.6172	18.6181	8.0	28
	Total	318	16.3428	5.0097	0.2809	15.7900	16.8955	4.0	34

CHM and SfM_{Medium} CHM was obtained in very sparse and medium cover areas (Table 7). RMSE value of TH_{Mean} was calculated as 1.6 m in very sparse cover, while it reached to a maximum value of 4.95 m in full cover (Table 7). Clark et al. (2004) report in their related study that even RMSE values of sensitive surface models generated using LiDAR in forestry areas with different stand structures (slope, crown cover, closure, etc.) varied between 2.41 and 4.15 m, respectively. Therefore, it can be argued the present study, which benefits from SfM CHM estimations, offers a great potential for further studies on this topic.

Mean MAPE values of $SfM_{Highest}$ CHM and SfM_{Medium} CHM for crown cover area estimation performance in the whole study area were calculated as 29.40% and 30.07%, respectively (Table 7). The performance of total tree crown cover area estimated using SfM CHM relatively decreased due to cover ratios and entangled branches of dense individual trees (Vauhkonen et al. 2012). Furthermore, it was also observed that younger trees under tall and wide trees were another decisive factor. Therefore, lower parts of tree crowns could not be captured, resulting in 3D point cloud generation from crown surfaces. This indicates the difference between the sensitivities of LiDAR- and SfM-based studies (Wallace et al. 2016).

Branching formations and crown deformation of trees were among main reasons for the decreasing sensitivity of TC and TCCA estimation using SfM CHM in the study area (Guerra-Hernández et al. 2016). It was found out that there were some individual trees under large trees particularly in some areas with a higher cover ratio (Vauhkonen et al. 2012). In addition, some overgrown trees in very sparse areas may have resulted in the estimation of a single tree as two different individual trees due to the fact that UAV platform evaluated it as more than one tree crown.

RMSE and MAPE were used to indicate the performance of TC, TH, and TCCA values estimated using CHM in terms of point cloud generation quality and cover category (Table 8). For instance, RMSE findings demonstrated that the estimated TC, TH, and TCCA values of P1 (high quality–very sparse) were more sensitive compared with tree data of P5 (medium quality–very sparse).

Area and stand parameters obtained using LiDAR offer a feasible level of sensitivity for the determination of production technology and system to be used in forestry production (Akay et al. 2009; Becker et al. 2018). However, many researchers prefer UAV-SfM in their modeling studies to the high cost of LiDAR systems (Siebert and Teizer 2014). Stand parameter

Table 7 RMSE and MAPE values of stand parameters estimated using SfM CHM in different qualities in terms of their crown cover categories

CCR	SfM$_{Medium}$						SfM$_{Highest}$					
	RMSE			MAPE (%)			RMSE			MAPE (%)		
	TC[a]	TH[b]	TCCA[c]	TC[a]	TH[b]	TCCA[c]	TC[a]	TH[b]	TCCA[c]	TC[a]	TH[b]	TCCA[c]
0	1	2.04	10.77	34	13.64	22.07	1	1.69	6.37	33	10.92	30.72
1	3	3.27	21.47	22	37.18	28.73	2	2.57	22.10	19	26.28	30.53
2	6	2.56	38.61	28	29.11	39.70	5	2.52	57.54	25	25.30	44.91
3	9	4.07	77.69	19	58.97	27.10	10	4.95	63.98	21	48.63	14.11
Mean	4.75	2.99	37.14	25.8	34.73	29.40	4.50	2.93	37.50	24.5	27.78	30.07

CCR, crown cover ratio; [a] tree counts; [b] mean tree height in the study area (m); [c] total crown cover area (m^2)

estimation using UAV-SfM will offer effective solutions to the problems in the field of production and planning for forestry researchers (Pajares 2015) and bring a new perspective to sensitive forestry studies (Zhao et al. 2005). There is no doubt that photogrammetric flight planning is as important as algorithms in order to increase the stand parameter estimation performance in forestry areas. However, the problems encountered in the estimation of stand parameters using UAV (drone)-based SfM technique in forestry areas should also be solved: These problems are as follows: (1) technical problems such as the lack of qualified staff, high capacity computer hardware, data loss during the modeling process, the role of GCPs in the minimization of spatial errors, and short flight durations due to poor energy supply; (2) political problems such as legislations and strict procedures in the flight area; and (3) social problems such as local people's negative reactions to flight process.

The data of understory in the stand cannot be obtained due to the vegetation covering the land in the present study. Therefore, it seems difficult to estimate stand parameters of high closure forest areas and multi-stratum using the method developed in the present study. The precision of the parametrical values (TC, TH, and TCCA) in the present study is low in dense, very dense, and clustered young Calabrian pine stands. On the other hand, individual tree parameters yielded a higher precision in areas with less canopy cover ratio (10–70%) and clustering (Table 7). Therefore, GCPs should be used in order to increase the precision of measurement values obtained using UAV-SfM technique. In addition to weather conditions, it can be stated various factors such as stand cover, light exposure, and tree density heavily influence tree parameter estimation performance using UAV-assisted SfM CHM (Dandois et al. 2015; Gong et al. 2002; Vauhkonen et al. 2012). In particular, the UAV-SfM method should be integrated

Table 8 RMSE and MAPE (%) values for the performance ranking of tree data estimated using point cloud SfM quality and crown cover categories (between P1 and P8) (Table 3)

RMSE					MAPE (%)		
TC	TH$_{Mean}$	TCCA$_{Total}$			TC	TH$_{Mean}$	TCCA$_{Total}$
P1	P1	P1	High		P2	P1	P4
P5	P5	P5	Sensitivity		P8	P5	P5
P2	P3	P6			P4	P3	P8
P6	P7	P2			P6	P2	P6
P3	P2	P7			P3	P7	P2
P7	P6	P3			P7	P6	P1
P8	P8	P4			P1	P4	P7
P4	P4	P8	Low		P5	P8	P3

into other photogrammetric techniques for stand closure and crown cover estimations (Yurtseven et al. 2019). Thus, it can be concluded that when the forest has low canopy cover and tree density is low, UAV-based SfM technique yields low-cost and comparable results for the determination of forestry production techniques and systems compared with LiDAR-based stand parameters (Becker et al. 2018; Fritz et al. 2013; Goodbody et al. 2017; Tang and Shao 2015; Torresan et al. 2017).

The sensitivity of tree data obtained in the present study can be increased. However, such an attempt will also lead to higher economic costs and longer durations of research in today's conditions in order to increase data quality. It can be observed that the sensitivities of data produced using algorithms for the determination of individual tree parameters in many previous studies do not significantly differ. This is because canopy cover ratio in a forest and tree density should be analyzed in detail in order to reveal the sensitivity of a model used for tree data production (Vauhkonen et al. 2012). High-resolution image capturing yields better results thanks to the capacity of their sensors in photogrammetric image capturing. It is advised to set flight altitude at 40 m or less and plan image overlaying rate over 90% for higher resolution in photogrammetric image capturing (Dandois and Ellis 2013).

Conclusion and suggestions

Within the scope of sustainable forestry studies, stand parameters (tree count, tree height, the estimation of tree crown diameter, and canopy cover) are obtained using low-cost multicopters as a basis of small-scale forestry studies. Tree attributes of young Calabrian pines were estimated using SfM-based CHM. The sensitivity of estimations using $SfM_{Highest}$ was slightly higher compared with SfM_{Medium}. In other words, it can be said that H_a was approved, whereas H_b was disproved. However, there are also some insignificant differences among the accuracy of tree data which were estimated by taking SfM quality and cover ratios into account. Dense point cloud generation using $SfM_{Highest}$ required a longer duration of processing by 53% compared with SfM_{Medium}. Cover ratio and tree growing formation (density, crown cover form, and branching) were decisive factors in the performance of the present study focusing on coniferous young Calabrian pine. There is a number of UAV platforms and image processing

qualities which can be used as a solution to the research problem in question. It can be argued that UAV-SfM-based 3D point cloud system can be offered as an alternative to LiDAR systems for forestry management and planning due to its sensitivity of tree count, tree height, estimation of tree crown diameter, and canopy cover in terms of stand characteristics. Nevertheless, UAV-SfM-based tree parameter estimation still requires newly developed 3D point cloud processing algorithms and techniques to achieve more reliable results. The sensitivity of SfM CHM is influenced by various environment variables (light exposure, wind, species, terrain, etc.). Therefore, it is necessary to conduct further studies on stand types in different slope categories in the future. It is evident that the estimation of stand parameters using UAV-SfM technique will provide forest practitioners with valuable information regarding the estimation and effective planning of production costs in forestry operations. As a result, SfM CHM–based aboveground biomass estimation models can be created as a basis for several studies such as sensitive ecological observation.

References

Agisoft LLC. (2016). Agisoft PhotoScan user manual : Professional Edition, Version 1.3. *User Manuals*.

Akay, A. E., Oğuz, H., Karas, I. R., & Aruga, K. (2009). Using LiDAR technology in forestry activities. *Environmental Monitoring and Assessment., 151*, 117–125. https://doi.org/10.1007/s10661-008-0254-1.

Akgül, M., Yurtseven, H., Demir, M., Akay, A. E., Gülci, S., & Öztürk, T. (2016). İnsansız hava araçları ile yüksek hassasiyette sayısal yükseklik modeli üretimi ve ormancılıkta kullanım olanakları. *İstanbul Üniversitesi Orman Fakültesi Dergisi.* https://doi.org/10.17099/jffiu.23976 [Turkish].

Akgul, M., Yurtseven, H., Gulci, S., & Akay, A. E. (2018). Evaluation of UAV- and GNSS-based DEMs for earthwork volume. *Arabian Journal for Science and Engineering, 43*(4), 1893–1909. https://doi.org/10.1007/s13369-017-2811-9.

Anderson, K., & Gaston, K. J. (2013). Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Frontiers in Ecology and the Environment., 11*, 138–146. https://doi.org/10.1890/120150.

Baltsavias, E., Gruen, A., Eisenbeiss, H., Zhang, L., & Waser, L. T. (2008). High-quality image matching and automated generation of 3D tree models. *International Journal of Remote Sensing., 29*, 1243–1259. https://doi.org/10.1080/0143116070173 6513.

Becker, R. M., Keefe, R. F., Anderson, N. M., & Eitel, J. U. H. (2018). Use of lidar-derived landscape parameters to characterize alternative harvest system options in the Inland Northwest. *International Journal of Forest Engineering., 29*, 179–191. https://doi.org/10.1080/14942119.2018.1497255.

Birdal, A. C., Avdan, U., & Türk, T. (2017). Estimating tree heights with images from an unmanned aerial vehicle. *Geomatics, Natural Hazards and Risk., 8*, 1144–1156. https://doi.org/10.1080/19475705.2017.1300608.

Buğday, E. (2018). Capabilities of using UAVs in forest road construction activities. *European Journal of Forest Engineering, 4*(2), 56–62.

Clark, M. L., Clark, D. B., & Roberts, D. A. (2004). Small-footprint lidar estimation of sub-canopy elevation and tree height in a tropical rain forest landscape. *Remote Sensing of Environment., 91*, 68–89. https://doi.org/10.1016/j.rse.2004.02.008.

Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: a review. *ISPRS Journal of Photogrammetry and Remote Sensing., 92*, 79–97. https://doi.org/10.1016/j.isprsjprs.2014.02.013.

Dandois, J. P., & Ellis, E. C. (2013). High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. *Remote Sensing of Environment., 136*, 259–276. https://doi.org/10.1016/j.rse.2013.04.005.

Dandois, J. P., Olano, M., & Ellis, E. C. (2015). Optimal altitude, overlap, and weather conditions for computer vision UAV estimates of forest structure. *Remote Sensing., 7*, 13895–13920. https://doi.org/10.3390/rs71013895.

DJI. (2016). Phantom 4 specs. *Online Webpage.* https://www.dji.com/phantom-4/info. Accessed 10 Jan 2019.

DJI. (2018). Phantom 4 RTK user manual. https://www.dji.com/phantom-4-rtk/info . Accessed 08 Mar 2019.

Fritz, A., Kattenborn, T., & Koch, B. (2013). UAV-based photogrammetric point clouds—tree stem mapping in open stands in comparison to terrestrial laser scanner point clouds. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences., XL-1/W2*, 141–146. https://doi.org/10.5194/isprsarchives-XL-1-W2-141-2013.

Gong, P., Sheng, Y., & Blging, G. S. (2002). 3D model-based tree measurement from high-resolution aerial imagery. *Photogrammtric Engineering & Remote Sensing., 68*(11), 1203–1212.

Goodbody, T. R. H., Coops, N. C., Marshall, P. L., Tompalski, P., & Crawford, P. (2017). Unmanned aerial systems for precision forest inventory purposes: a review and case study. *Forestry Chronicle., 93*, 71–81. https://doi.org/10.5558/tfc2017-012.

Grenzdörffer, G., Engel, A., & Teichert, B. (2008). The photogrammetric potential of low-cost UAVs in forestry and agriculture. In *International Archives of Photogrammetry*

Remote Sensing and Spatial Information Sciences Vol. XXXVII. Part B1. https://doi.org/10.2747/1548-1603.41.4.287.

Guerra-Hernández, J., González-Ferreiro, E., Sarmento, A., Silva, J., Nunes, A., Correia, A. C., et al. (2016). Using high resolution UAV imagery to estimate tree variables in Pinus pinea plantation in Portugal. *Forest Systems., 25*. https://doi.org/10.5424/fs/2016252-08895.

Gülci, S., Akgül, M., Akay, A. E., & Taş, I. (2017). Using ready-to-use drone images in forestry activities: case study of Çinarpinar in Kahramanmaras, Turkey. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives* (Vol. 42, pp. 51–53). https://doi.org/10.5194/isprs-archives-XLII-4-W6-51-2017.

IBM. (2012). IBM SPSS Advanced Statistics 22. *IBM., 22*, 419–430. https://doi.org/10.1080/02331889108802322.

Kraus, K., & Pfeifer, N. (1998). Determination of terrain models in wooded areas with airborne laser scanner data. *ISPRS Journal of Photogrammetry and Remote Sensing., 53*, 193–203. https://doi.org/10.1016/S0924-2716(98)00009-4.

Lie, H. L. (2016). *Assessing accuracy of using unmanned aerial system in forest inventory.* Ås: Norwegian University of Life Sciences.

Matese, A., Toscano, P., Di Gennaro, S. F., Genesio, L., Vaccari, F. P., Primicerio, J., et al. (2015). Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. *Remote Sensing., 7*, 2971–2990. https://doi.org/10.3390/rs70302971.

McGaughey, R. J. (2018). *FUSION/LDV: software for LIDAR data analysis and visualization. FUSION Version 3.80* (Vol. 123(2)). Seattle: United States Department of Agriculture Forest Service. Pacific Northwest Research Station.

Micheletti, N., Chandler, J. H., & Lane, S. N. (2015). Structure from motion (SFM) photogrammetry. In Clarke, L. E. & Nield, J. M. (Eds.) *Geomorphological Techniques (Online Edition).* https://doi.org/10.5194/isprsarchives-XL-5-W4-37-2015.

Mlambo, R., Woodhouse, I. H., Gerard, F., & Anderson, K. (2017). Structure from motion (SfM) photogrammetry with drone data: a low cost method for monitoring greenhouse gas emissions from forests in developing countries. *Forests., 8*. https://doi.org/10.3390/f8030068.

Mohan, M., Silva, C. A., Klauberg, C., Jat, P., Catts, G., Cardil, A., et al. (2017). Individual tree detection from unmanned aerial vehicle (UAV) derived canopy height model in an open canopy mixed conifer forest. *Forests., 8*. https://doi.org/10.3390/f8090340.

Nex, F., & Remondino, F. (2014). UAV for 3D mapping applications: a review. *Applied Geomatics, 6*(1), 1–15. https://doi.org/10.1007/s12518-013-0120-x.

Pajares, G. (2015). Overview and current status of remote sensing applications based on unmanned aerial vehicles (UAVs). *Photogrammetric Engineering & Remote Sensing.* https://doi.org/10.14358/PERS.81.4.281

Panagiotidis, D., Abdollahnejad, A., Surový, P., & Chiteculo, V. (2017). Determining tree height and crown diameter from high-resolution UAV imagery. *International Journal of Remote Sensing., 38*, 2392–2410. https://doi.org/10.1080/01431161.2016.1264028.

Pérez, M., Agüera, F., & Carvajal, F. (2013). Low cost surveying using an unmanned aerial vehicle. *ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences., XL-1/W2*, 311–315. https://doi.org/10.5194/isprsarchives-XL-1-W2-311-2013.

Puliti, S., Ørka, H. O., Gobakken, T., & Næsset, E. (2015). Inventory of small forest areas using an unmanned aerial system. *Remote Sensing., 7*, 9632–9654. https://doi.org/10.3390/rs70809632.

R Core Team. (2019). *R: a language and environment for statistical computing (R version 3.5.2.)*. Vienna: R Foundation for Statistical Computing http://www.R-project.org/ . Accessed 07 Jan 2019.

Siebert, S., & Teizer, J. (2014). Mobile 3D mapping for surveying earthwork projects using an unmanned aerial vehicle (UAV) system. *Automation in Construction., 41*, 1–14. https://doi.org/10.1016/j.autcon.2014.01.004.

Silva, C. A., Crookston, N. L., Hudak, A. T., Vierling, L. A., Klauberg, C., & Silva, M. C. A. (2017). rLiDAR: an R package for reading, processing and visualizing LiDAR (Light Detection and Ranging) data, version 0.1.1.

Smith, M. W., Carrivick, J. L., & Quincey, D. J. (2016). Structure from motion photogrammetry in physical geography. *Progress in Physical Geography, 40*(2), 247–275.

Tang, L., & Shao, G. (2015). Drone remote sensing for forestry research and practices. *Journal of Forestry Research., 26*, 791–797. https://doi.org/10.1007/s11676-015-0088-y.

Torresan, C., Berton, A., Carotenuto, F., Di Gennaro, S. F., Gioli, B., Matese, A., et al. (2017). Forestry applications of UAVs in Europe: a review. *International Journal of Remote Sensing., 38*, 2427–2447. https://doi.org/10.1080/01431161.2016.1252477.

Universel Ground Control System (UgCS). (2019). Desktop Application Version 3.1 (871) user manual. *UcGS Desktop Application Version 3.1 (871) User Manuel*. https://www.ugcs.com/files/manuals/v.3.1/UgCS_User_manual_3.1_871.pdf. Accessed 19.01.2019.

Vauhkonen, J., Ene, L., Gupta, S., Heinzel, J., Holmgren, J., Pitkänen, J., et al. (2012). Comparative testing of single-tree detection algorithms under different types of forest. *Forestry., 85*, 27–40. https://doi.org/10.1093/forestry/cpr051.

Wallace, L., Lucieer, A., Malenovskỳ, Z., Turner, D., & Vopěnka, P. (2016). Assessment of forest structure using two UAV techniques: a comparison of airborne laser scanning and structure from motion (SfM) point clouds. *Forests., 7*. https://doi.org/10.3390/f7030062.

Watts, A. C., Ambrosia, V. G., & Hinkley, E. A. (2012). Unmanned aircraft systems in remote sensing and scientific research: classification and considerations of use. *Remote Sensing., 4*, 1671–1692. https://doi.org/10.3390/rs4061671.

Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., & Reynolds, J. M. (2012). "Structure-from-Motion" photogrammetry: a low-cost, effective tool for geoscience applications. *Geomorphology., 179*, 300–314. https://doi.org/10.1016/j.geomorph.2012.08.021.

Yilmaz, H. M. (2010). Close range photogrammetry in volume computing. *Experimental Techniques., 34*, 48–54. https://doi.org/10.1111/j.1747-1567.2009.00476.x.

Yurtseven, H., Akgul, M., Coban, S., & Gulci, S. (2019). Determination and accuracy analysis of individual tree crown parameters using UAV based imagery and OBIA techniques. *Measurement, 145*, 651–664. https://doi.org/10.1016/j.measurement.2019.05.092.

Zhang, J., Hu, J., Lian, J., Fan, Z., Ouyang, X., & Ye, W. (2016). Seeing the forest from drones: testing the potential of light-weight drones as a tool for long-term forest monitoring. *Biological Conservation., 198*, 60–69. https://doi.org/10.1016/j.biocon.2016.03.027.

Zhao, G., Shao, G., Reynolds, K. M., Wimberly, M. C., Warner, T., Moser, J. W., et al. (2005). Digital forestry: a white paper. *Journal of forestry, 103*(1), 47–50.