AUTOMATED HEIGHT MEASUREMENT AND CANOPY DELINEATION OF HARDWOOD PLANTATIONS USING UAS RGB IMAGERY

by

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ALS:	Airborne Laser Scanning
CHM:	Canopy Height Model
CORS:	Continuously Operating Reference Station
DEM:	Digital Elevation Model
DSM:	Digital Surface Model
FN:	False Negative
FP:	False-Positive
GCP:	Ground Control Point
GCS:	Ground Control Stations
GNSS:	Global Navigation Satellite Systems
GSD:	Ground Sampling Distance
INS:	Inertial Navigation System
ITD:	Individual Tree Detection
IWD:	Inverse Watershed Segmentation
MCWS:	Marker Controlled Watershed Segmentation
MLS:	Mobile Laser Scanning
pc:	Precision
PPK:	Post Processing Kinematic
rc:	Recall
RMSE:	Root Mean Square Error
RTK:	Real Time Kinematic
SfM:	Structure from Motion
SIFT:	Scale Invariant Feature Transform
TLS:	Terrestrial Laser Scanning
TP:	True-Positive
UA:	Unmanned Aircraft
UAS:	Unmanned Aerial Systems
UAV:	Unmanned Aerial Vehicle
UI:	User Interface

ABSTRACT

Recently, products of Unmanned Aerial System (UAS) integrated through SIFT algorithm and dense cloud matching using structure from motion has gained prominence with tree-level inventory maintenance in forestry. Various studies have been carried out by using UAS imagery to quantify and map forest structure of simple coniferous stands. However, most of the previous works employ methodologies that require manual inputs and lack of reproducibility to other forest systmes. Manual detection of trees and calculation of their attributes can be a time-consuming and complicated process which can be overcome with an automated technique applied by forest managers and/or landowners is highly desired to take full advantage of the readily available UAS remote sensing images. This study presents a methodology for automated measurements of tree height, crown area and crown diameter of hardwood species using UAS images. Different UAS platforms were employed to gather digital data of two hardwood plantations at Martell, Indiana. The resulting aerial images were used to generate the Digital Surface Model (DSM) and Digital Elevation Model (DEM) for the forest stand from which the Crown Height Model (CHM) was derived. The canopy height model can be inputted to the web platform deployed through shiny server (https://feilab.shinyapps.io/Crown/) to derive individual tree parameters automatically. The results show that this automated method provides a high accuracy in individual tree identification (F-score> 90%) and tree-level measurements ($RMSE_{ht}$<1.2m and $RMSE_{crn}$<1m). Moreover, tree-level parameter estimation for 4,600 trees were calculated in less than 30 minutes based on a post-processed DSM from UAS-SfM derived images with minimal manual inputs. This study demonstrates the feasibility of automated inventory and measure of tree-level attributes in hardwood plantations with UAS images.

Keywords: Tree-level inventory, hardwood species, hardwood forest, automated tree measurement, canopy height model, UAS, drone remote sensing, ForestTools.

CHAPTER 1. INTRODUCTION

In the past decade, ground survey supplemented with recent remote sensing technology has played a major role in capturing, monitoring and analyzing data pertaining to complex forest systems. Across the world, humans have benefitted from forest products utilizing it for food, aesthetics, housing and shelter. Such benefits had resulted in extensive deforestation throughout many countries. Since the early 1990s, forests in several developed countries have undergone a transition from degradation to reforestation (Chen et al. 2019; Liang et al. 2011). During this transition period, remote sensing technology supplied effective tools to study spatial-temporal changes to forest (Liang et al. 2011). Improved understanding of forest structure transition helped in understanding global carbon balance (Bhishma et al. 2010), forest policy implementation (Agriculture, n.d.) and regeneration success.

Recently, remote sensing, combined with conventional ground measurements to supply validation data, has been used extensively for forest inventory management (Liang et al. 2011; Li et al. 2012). In this form of forest management, acquiring an accurate spatial location of individual trees is a crucial parameter for calibrating tree-level inventory and in connecting the reference and measured data (Ganz, Käber, and Adler 2019; Resop, Lehmann, and Hession 2019). Traditional methods based on field measurements are time consuming, labor intensive and limited to a small spatial extent (Liang et al. 2011; Li et al. 2012; Yin and Wang 2019). Forest inventory maintenance has witnessed developments such as phase-based scanners (Němec 2015), employment of unmanned aerial systems (UAS) and terrestrial Light detection and ranging (LiDAR) (Bauwens et al. 2016).

LiDAR has been increasingly employed in forest surveys in the form of airborne laser scanning (ALS), terrestrial laser scanning (TLS) and mobile laser scanning (MLS). Laser scanning technology is considered the most reliable method to measure structures, mainly toward generation of 3D models due to its high accuracy (Němec 2015; Piermattei et al. 2019). ALS is an effective technique with its strong penetrating power to retrieve biophysical variables such as tree height (Ganz, Käber, and Adler 2019), stem volume estimation (Noordermeer et al. 2019), leaf area index (Caruso et al. 2019), measurement of forest growth (Krause et al. 2019) and tree crown volume estimation (Selkowitz et al. 2012). Although, ALS has provided immense contributions in forestry, the efficiency of this technology largely depends on the quality and quantity of field referenced data. Thus, the main limitation of ALSlies in their failure to obtain more detailed structural parameters of trees due to canopy occlusion and low-density point clouds per unit area thereby making it less preferable for forest survey practices (Chen et al. 2019).

Similarly, TLS methods have demonstrated promise in acquiring tree attribute information in forest sample plots in the last two decades (Norbert Pfeifer, Xinlian Liang, Juha Hyyppä 2017). In comparison with ALS data products, TLS point clouds are denser and therefore better suited to determine the exact spatial distribution of trees and capture the whole geometry of each tree with high precision (Chen et al. 2019; Sun et al. 2015). Furthermore, detailed analysis of other variables such as stem volume, stem curvature, stem quality and biomass can be performed by reconstructing the stem model. However, in practice the TLS instrument must be strategically placed in the sample plot thus limiting the mobility of this form of data acquisition. The method is time consuming for large scale plots and requires multiple leads to build point clouds for analysis (Chen et al. 2019; Bauwens et al. 2016).

In order to eliminate the drawbacks of ALS and TLS, foresters transitioned toward to MLS, a powerful tool that overcomes tree occlusion and allows for free movement between trees and therefore greatly reduces survey time and cost (Chen et al. 2019). The point data acquired through MLS are less precise than TLS due to the propagation of positional errors during the survey (Liang et al. 2011; Chen et al. 2019). The level of terrain, dense undergrowth and branch barriers are some terrain constraints that need to be considered before employing MLS for forest surveys. This type of data acquisition requires specialized expensive equipment and highly trained personnel to collect and process the data to derive quality point clouds.

Although laser scanners proved to be an essential tool for forest studies, due to their high cost and complicated experiment design, optical imagery obtained with UAS is gaining prominence in forest surveys (Wallace et al. 2016; Ganz, Käber, and Adler 2019; Selkowitz et al. 2012). UAS inherently consists of a platform integrated with 1-2 image sensors that requires a small crew consisting of a pilot and field observers to operate (Colomina and Molina 2014). A typical UAS mission usually consists of operating a platform (fixed-wing or rotary-wing) of less than 30 kg maximum take-off weight. In the low-altitude, high resolution remote sensing missions related to UAS, the platform typical carries a small or medium-format optical camera, along with other front mounted sensors for First-Person-View (FPV) (Colomina and Molina 2014; Bonnet, Lisein, and Lejeune 2017). The UAS can be operated remotely by a human pilot guiding the aircraft with a transmitting controller, or automatically by pre-programming an autopilot mission based on two navigation technologies, Global Navigation Satellite Systems (GNSS) and Inertial Navigation System (INS). A ground control station (GCS) is an important component to be considered while employing UAS. GCS is a stationary or transportable hardware/software device transportable to monitor the location of the unmanned aircraft (UA) (Everaerts 2009). GCS enables an interface through which any change in the route of the UAS or any positional or geometric error can be viewed and corrected. UAS can be equipped with different sensors such as multispectral cameras, hyperspectral cameras, thermal scanners and laser scanners upon the application needs.

In the past decade, UAS has been increasingly employed for studying forest metrics with diversified processing techniques as the methods for measuring and monitoring forests keep advancing. Although UAS has become a popular geospatial data collection tool in stand-level forest applications (Zarco-Tejada et al. 2014; Selkowitz et al. 2012), much advancement is still needed in improving image collection and processing (Iglhaut et al. 2019) for tree-level information extraction (Dempewolf et al. 2017).

Over the past 5 years, there has been a substantial rise in forestry applications employing UAS (Iizuka et al. 2018; Guerra et al. 2016; Piermattei et al. 2019). UAS imagery has been utilized extensively for studying controlled burns and forest fire outbreaks (Shin et al. 2019). It is also continuously employed for inventorying attributes (e.g., tree height, canopy width, and diameter at breast height (dbh)) that quantify forest structure (Panagiotidis et al. 2017), estimating above ground biomass (Kachamba et al. 2016), and carbon content (Jones et al. 2020). Lately, numerous studies have been carried out by employing new techniques to measure individual tree attributes pertaining to forest management. All the previous individual tree detection and measurement studies using UAS generally employed proprietary image processing software such as Pix4D and Agisoft Photoscan and reconstructed point cloud data using structure from motion (SfM) for further analysis.

1.1 Structure from Motion Workflow

The idea of SfM was developed in 1979 by Ullman. S (Westoby et al. 2012) and the algorithm for it was developed in 1999 by David G. Lowe. SfM derives from traditional stereo-photogrammetric approach which matches corresponding features when the camera height, focal length and the baseline between the images are known (Figure 1.a). It measures the distances between features on the camera image plane and calculates the relative position of the features. SfM mainly uses the Scale Invariant Feature Transform (SIFT) which allows similar features or corresponding features to be matched between different images even with large variation in scale, viewpoint, illumination and occlusion (Lowe 2004).

1.2 SIFT Algorithm

The SIFT algorithm was developed in 1999 and the algorithm for it was developed in 1999 by David G. Lowe. The algorithm consists of four major steps. The first step is to detect the scale-space extrema, where the algorithm searches over all the scale and image locations to identify the potential keypoints using the difference-of-Gaussian function. The second step is keypoint localization where at each location, a detailed model is fit to determine the scale and location and the keypoints are selected based on their stability. The third step is orientation assignment where one or more orientation is assigned to each keypoint based on image gradient directions and all future operations are performed on image data that has been transformed according to the assigned model. This provides invariance to the transformations. The final step is called the keypoint descriptor, where the local image gradients are measured at the selected scale around each keypoint. They are then transformed into a representation that allows the algorithm to identifies the keypoint with significant levels of shape distortion and change in illumination (Lowe 2004; Karami, Prasad, and Shehata 2017; Kuželka and Surový 2018). Although, SfM uses a similar approach akin to stereoscopic photogrammetry to where it matches corresponding features and measures the distance between them on the camera image plane, the SIFT technique to match features despite varying distance makes it efficient (Westoby et al. 2012).

When there are matching location of multiple points on two or more photos, individual camera positions, orientations, focal length and relative position of the features can be calculated in a single step. This step is known as bundle block adjustment. In Figure 1 (b), there are two camera position (*x*, *y*, *z*) and (*x*', *y*', *z*') focusing objects at b and h. We can calculate the camera positions individually, their focal length (*f*, *f*'), orientation (*i*, *i*'), relative position of corresponding features *b* and *h* through bundle block adjustment (Westoby et al. 2012; Lowe 2004)

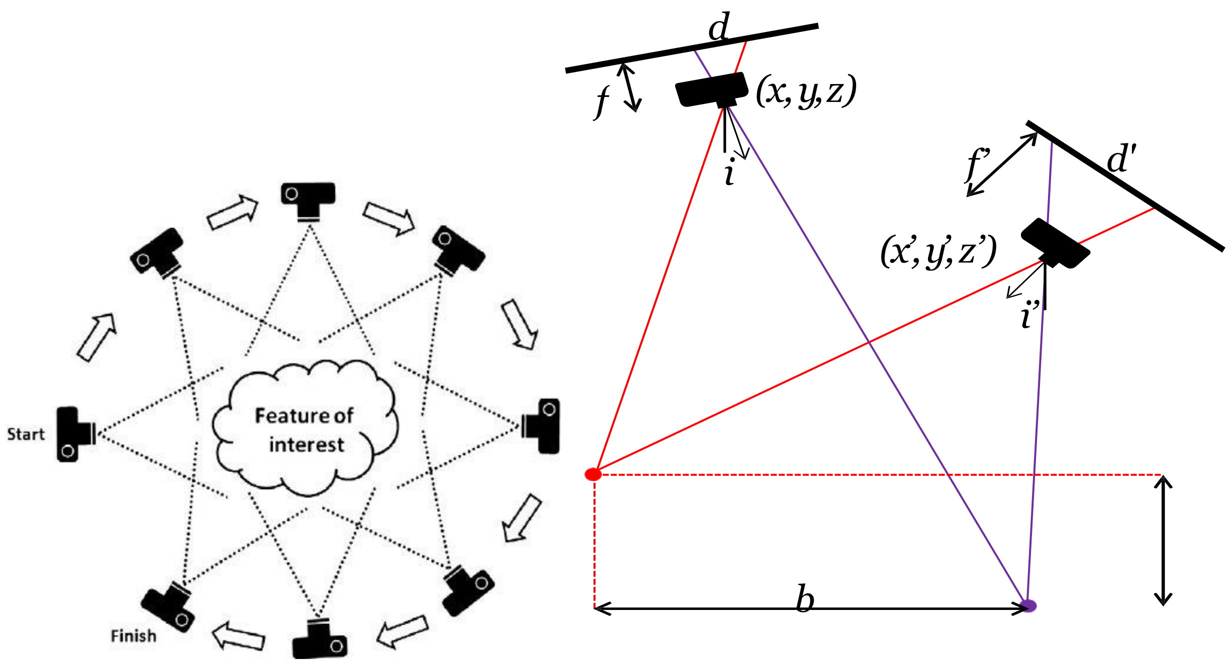


Figure 1. (a) Structure from motion; (b) Illustrating the bundle block adjustment step (Westoby et. al. 2012)

Once the bundle block adjustment is complete, a dense point cloud and 3D surface are determined using the known camera parameters and the SfM points as ground control. Acquiring a 3D surface also happens with the overlap between two images and the corresponding points present in both the images. All the pixels in the image are used to derive a dense model in a similar resolution as the raw images. This step is called multi-view stereo matching. After the stereo-matching step, geo-rectification is carried out. Geo-rectification means converting the point cloud from the arbitrary coordinate system to geographic coordinate system. This step can be achieved in two ways, directly and indirectly. It can be achieved directly by knowing the camera position and focal length or it can be achieved indirectly by incorporating a few ground control points spread throughout the plot with known coordinates.

Once the 3D model is calibrated, we can derive sub-products such as Digital Surface Model (DSM), Ortho-mosaic and Digital Elevation Model (DEM) as well. This new technique can use photos taken many angles and distances with no a priori knowledge of pose or location. It also enables unstructured image acquisition from ground, aircrafts or unmanned platforms such as unmanned aerial vehicles (UAVs). Construction of height models with DEM and DSM is crucial in studying process for many forestry applications

1.3 Individual tree segmentation methods

Researchers have adopted different tree segmentation techniques for detecting and delineating individual trees for forest measurement studies. In most of the previous works, local maxima filtering and inverse watershed delineation have been extensively employed to segment individual tree crowns. This study examined the previous methods and employed an advanced segmentation technique called Marker Controlled Watershed Delineation to derive results for individual trees.

1.3.1 Local Maxima Filtering

The region growing technique employs a local maximum filter to identify seed pixels for expanding on a region. For this technique, the local maximum filter passes a window of a fixed size over the pixels in an image dataset to decide whether the given pixel has the largest spectral value that all other pixels in that window (Wulder, Niemann, and Goodenough 2000; Korpela, Anttila, and Pitkänen 2006). The pixels having the highest digital number in that window is identified as a seed to the tree locations. The brightness of a pixel does not necessarily have to correspond with the treetop, rather it depends on the spectral property and complicated texture of crowns (Wulder, Niemann, and Goodenough 2000), actual sun and sensor angle determined for the survey (Novotný et al. 2011). When a fixed size window progresses over an image, it does not account for trees with varying crown sizes. If the window size is small, errors of omission increases as a result of selecting missing or nonexistent trees or multiple radiance peaks for a single tree crown. The errors of commission increase when the window size is too large (Wulder, Niemann, and Goodenough 2000; Novotný et al. 2011). Identifying the optimal window size poses a huge barrier for accurate determination of tree location.

1.3.2 **Inverse Watershed Delineation**

Inverse Watershed Delineation (IWD) derived from the well-known and explored watershed delineation algorithm that has been extensively used in Civil Engineering projects for identifying catchments. A watershed is an area that separates surface water to a common outlet. The watershed boundary can be delineated using DEMs or contour lines to determine the steepness of the area which is related to the waterflow (Marcu, Stătescu, and Iurist 2017). The procedure used for watershed delineation primarily depends on the contour information generated in a local zone or neighborhood on the Digital elevation model (DEM). For the IWD method, the height raster containing tree information is inverted to treat the inverted tree crowns like watershed catchments and determine the tree peaks using local minima through focal flow approach (Figure 2. a, b). The watershed segmentation approach studies the geometric morphology of trees to determine the structural variances in crowns. The main advantage of this approach is that it preserves the structural variation information while achieving the appropriate tasks. There has been evidences that IWD over-estimates individual trees due to high tree height variation within the topography or crowns shadowed by larger trees.

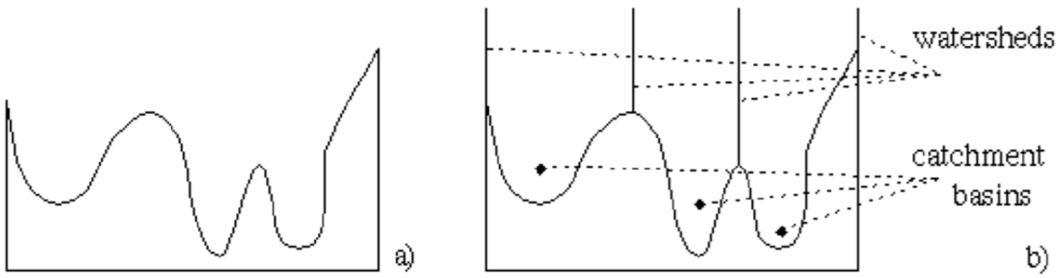


Figure 2. a) Gray level profile of image data. b) Watershed segmentation – local minima of gray level (altitude) yield catchments basins, local maxima define the watershed lines. (Casiana Marcu, Florian Stătescu 2017)

1.3.3 Marker Controlled Watershed Segmentation

The Marker Controlled Watershed Segmentation (MCWS) technique is a step-wise procedure to create individual markers and reconstruct morphological image through a robust and adaptable approach for delineating objects of closed contours with ridged boundaries (Parvati, Prakasa Rao, and Mariya Das 2008). During the marker creation stage, a marker or a seed image, which is a binary image containing seed points of treetops placed inside each crown is supplied for watershed segmentation. Each marker is associated with a specific watershed region; hence the total number of markers or seeds will always equal the number of watershed regions. After segmenting each watershed with their respective markers, the edges are aligned with the ridges without intersecting the neighboring edges. The morphological reconstruction transformation stage extracts the components of the marker image and extends to grey scale reconstruction thereby accomplishing image filtering, domes and basin (Crown) extraction (Figure 3). The MCWS approach employs a variable window and accounts for noise and over segmentation in an image which were the drawbacks of IWD.

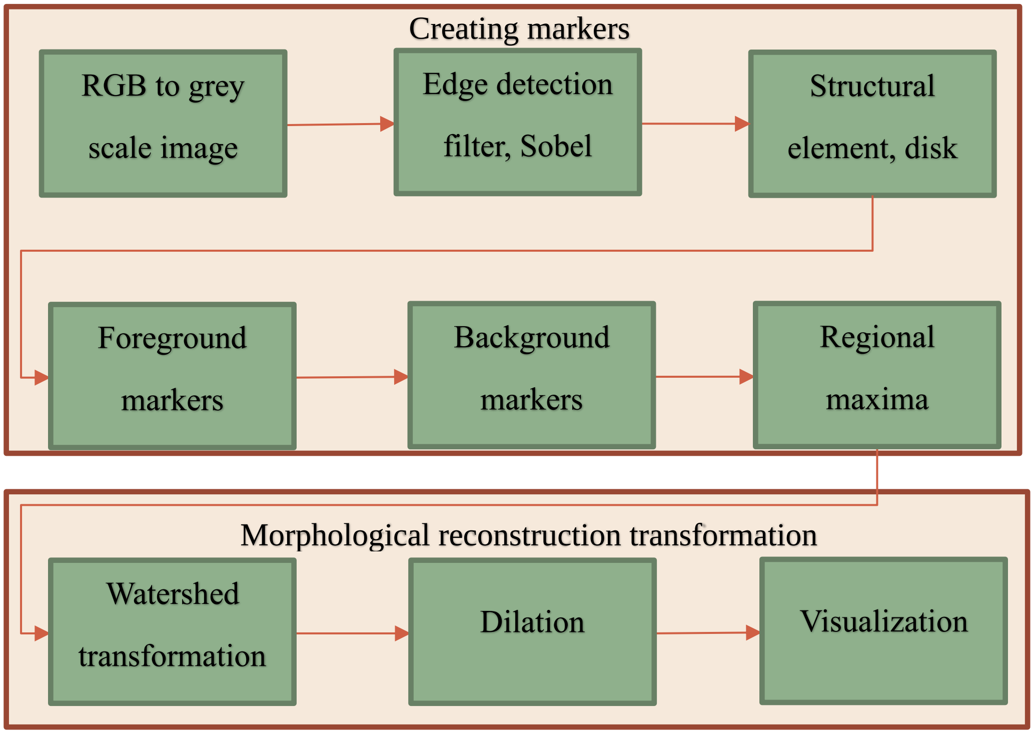


Figure 3. Steps of Marker-Controlled Watershed segmentation algorithm with morphological techniques (Amiri 2014).

1.4 Advantages and challenges regarding UAS deployment

UAS-based data collection and analysis have many advantages over conventional forest monitoring methods. UAS can be used to acquire hyper-spatial and hyper-temporal data (Bonnet et al., 2017; Caruso et al., 2019). The unmanned aerial platform is nimble, easily transportable, can be equipped with customized sensors and requires a minimal crew to operate (Birdal et al., 2017). Data acquisition can average 20-40 minutes to cover multiple hectares of forested area (Birdal et al., 2017; Carr & Slyder, 2018; Caruso et al., 2019; Fankhauser et al., 2018). A UAS platform equipped with consumer-grade cameras and sensors reduces survey costs (Birdal et al., 2017; Tang & Shao, 2015). These advantages make UAS an ideal remote sensing tool in forest applications, especially for regular monitoring and updating of forest growth.

Although UAS has many advantages over traditional forestry methods, there remains the challenge for improving individual tree level data derived from UAS. Previously, Birdal et al. (2017) employed a semi-automated approach for studying individual trees in a coniferous stand with UAS imagery achieving an accuracy of 94%. Bonnet et al. (2017) followed the same approach to detect individual trees using Micmac software. Carr & Slyder (2018) and Dempewolf et al. (2017) studied temperate mixed coniferous stands by manually identifying and segmenting trees, while Mohan et. al. (2017), Fankhauser et al. (2018); Ganz et al. (2019) and Krause et al. (2019) worked on individual tree measurements for mixed conifer stands in boreal forest systems. The previous works employed point clouds generated from images processed through Ground Control Points (GCP) and Real Time Kinematic (RTK) methods to generate virtual tree models and derive tree heights and achieved an RMSE ranging between 0.106 m and 2.92 m. Despite considerable research related to forestry UAS applications, UAS technology has not completely altered forest inventory procedures; current UAS methods have progressed extensively with simple-structured forests or plantations mainly constituting coniferous species (Table 1). UAS derived tree attributes rely on semi-automated data analysis that involve multiple software systems. At present, the methodologies available require manual input and are site-specific. Also, the current UAS data acquisition techniques are reliant on GCP and provide suitable accuracies only when applied to open-canopy forest conditions.

Table 1. Selected previous works on measuring forest metrics with UAS data

Author, year	Application	UAS model	UAS platform type	Software used	Data used and steps	Manual/ Automated	Result accuracy
(Birdal et al., 2017)	Tree height measurement- coniferous trees	SenseFly eBee	Fixed wing	Pix4D-GCP	DSM point clouds and Local maxima filtering	Semi-Automated	R^2:0.94 RMSE: 28cm
(Bonnet et al., 2017)	Individual Tree detection for coniferous stands	Gatewing X10 0	Fixed wing	Micmac	DSM point clouds and Local maxima filtering	Semi-Automated	*R^2: 0.83 RMSE: 1. 39m
(Carr & Slyder, 2018)	Tree segmentation- deciduous forest	DGI Phantom 3	Multi-rotor	Pix4D	Lidar Point cloud	Manual	R^2:0.82 RMSE: 0.106m
(Dempewolf et al., 2017)	Tree height growth- temperate mixed forest	DGI Phantom 3 Pro	Multi-rotor	Agisoft Photoscan	Orthoimages	Manual	-
(Mohan et al., 2017)	Individual tree detection- mixed conifer forest	DGI Phantom 3 Quadcopter	Multi-rotor	Agisoft Photoscan	Point cloud to generate CHM	Semi-automated	Overall tree detection accuracy – 0.85
(Krause et al., 2019)	Tree height measurement- scots pine	OctoXL 6S12 Octocopter	Multi-rotor	Pix4D	Point clouds and ortho mosaics – local maxima algorithm	Semi-automated	R^2: 0.971 RMSE: 0.34m
(Fankhauser et al., 2018)	Forest monitoring (Tree height)- pine trees	3D Robotics Solo	Multi-rotor	Agisoft Photoscan	Lidar point clouds and UAS imagery- local maxima	Semi-automated	R^2:0.82 RMSE: 2.92m
(Noorderme er et al., 2019)	Forest attribute accuracy-boreal forests	Varied systems	-	SURE Aerial	Point clouds	Manual	-
(Ganz et al., 2019)	Tree height – Douglas fir	Gyrocopter	Multi-rotor	SURE Aerial	Lidar and UAV point clouds	Semi-automated	RMSE: 1.09m

* RMSE was converted from cm to meters

Tree-level UAS studies have not explored broad-leaf hardwood stands, in part, because the complex overlapping canopy structure of hardwood species delimits the measurement of tree attributes. Besides, the use of GCPs may not be effective in closed-canopy structure as they may not be visible over dense tree canopies. When working with closed canopies, issues with current image construction using GCPs can be resolved with the Post Processing Kinematic (PPK) system (Dempewolf et al. 2017). PPK is a post-processing technique to achieve sub-centimeter accuracy of image location capture by the camera.

Therefore, this study investigates the applicability of R and its image libraries to derive tree parameters for forest inventory management. I implemented a web-based interactive platform for users to supply input height models and download deliverables such as individual tree location, their height and crown diameter. I hypothesized that individual tree information derived from R will yield results comparable to the ground measurement. I also tested this hypothesis with a different UAS platform and on a different hardwood species. Also, this automated technique will derive tree parameters like tree height and crown diameter with minimal manual input. The procedure is site-independent (centric). The main objective of this study is to realize the automation of measuring individual tree height and crown diameter using an open source software R.

Here, I report the results of an experiment conducted on an oak plantation and a walnut plantation to measure the height and crown diameter of individual trees automatically using R, an open source platform for image and statistical analysis. I used two different types of UAS platform (Bramor and DJI M600) to study the accuracy of the data products. My field experiment was conducted at Martell forest owned by Purdue University in West Lafayette, Indiana, USA. Various elevation models were developed using Structure from Motion (SfM) to derive individual tree height and subsequently measure crown diameter from UAS imagery for this plantation area. Subsequently, I developed a web-based application for researchers and foresters to derive tree parameters from elevation model developed from UAS data.

CHAPTER 2. AUTOMATED MEASUREMENT OF HARDWOOD TREE ATTRIBUTES USING UAS RGB IMAGERY

2.1 Study Area

The research was conducted for planted forests at Martell Forest owned by Purdue University in the city of West Lafayette, Indiana, USA (Figure 4. a). The UAS images covered a 12-year plantation forest consisting of red oak (*Quercus rubra*) and bur oak (*Quercus macrocarpa*) tree species. The imaged area was 7 ha (17 ac). The trees were planted on three plots identified as 112, 115 and 119. Plot 115 and 119 have red oaks bordered by bur oaks planted in 50 rows x 22 columns. These plots have been pruned and well maintained. Plot 112 has not been pruned and has alternating trees of red oak and bur oak in 50rows x 50 columns. The main reason behind using this study area was to experiment on hardwood trees with different canopy overlaps. As the hardwood trees were relatively young, ground measurements were not difficult.

UAS imagery for a nearby plot comprising of Black walnut plantation *(Juglans nigra)* was also taken in order to test the repeatability of the proposed approach (Figure 4.b). The walnut trees were planted in the late 1960s as part of a fertilizer study. As the intent for planting the black walnut seedlings were different, recent height or crown data is not available for this area.

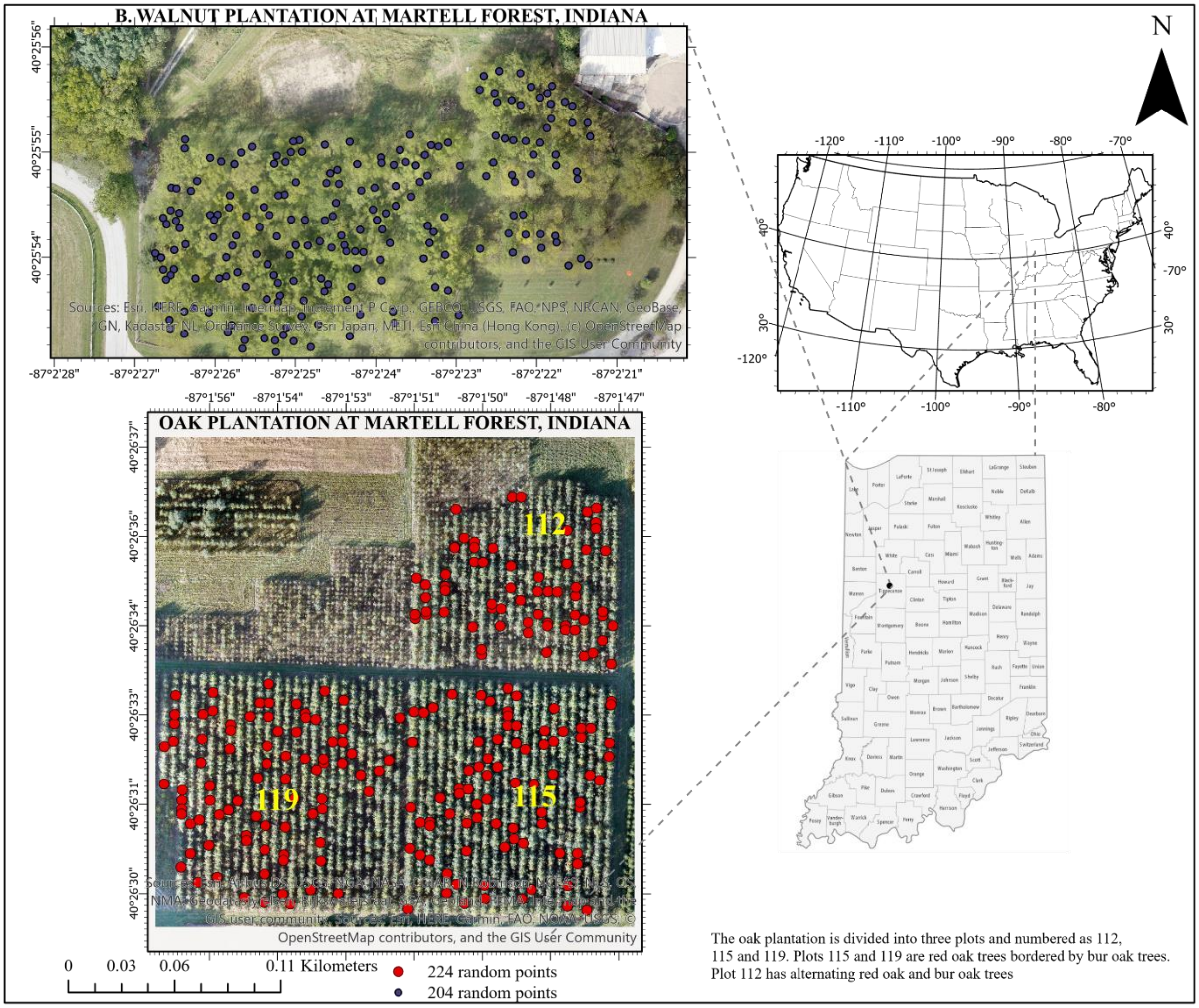


Figure 4. Study site localization and illustration of three oak plantation plots present at the northern region of Martell forest, Indiana.

2.2 Field measurements of tree height and crown width

I selected 224 trees for ground measurements using the random sampling technique in R. Their heights were measured with a Vertex IV hypsometer (Haglöf, www.haglof.se), which provides decimeter accuracy based on measuring distances and angles through ultrasound. This type of hypsometer is extensively employed in forestry to measure tree heights (Watts and Tolland 2005). A crew of four spent 5 hours over the course of two days to conduct field measurements for the randomly selected individual trees (Figure 5). Two crew members measured the crown diameter using the average crown spread technique with a measuring tape (Formula 1). They measured the diameter at the longest crown spread and measured the distance perpendicular to the widest crown spread (cross spread) in order to generate the average crown diameter of the tree. One member measured height with the hypsometer and recorded the measurements. An accompanying forester charged with maintaining the plantation helped with tree identification using row and column information. Tree height ranged from 3.3 m to 15.6 m and crown diameter ranged from 1.69 m to 6.69 m, respectively. The recorded measurements were stored as a point feature class in ArcGIS Desktop 10.6.

$$Average\ crown\ spread = (\text{longest spread} + \text{longest cross spread})/2 \quad (1)$$

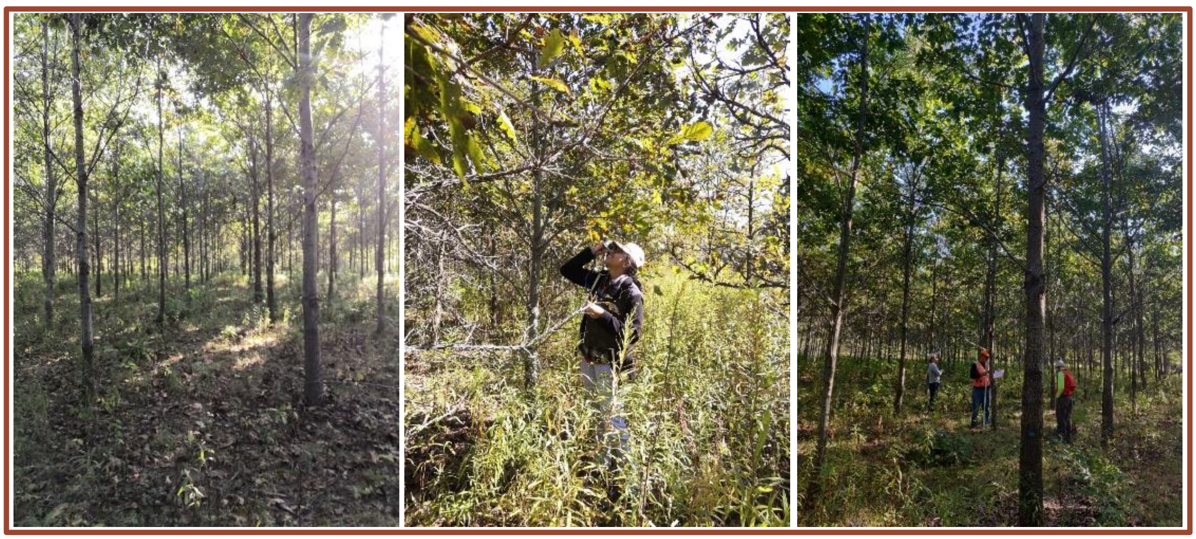


Figure 5. Ground measurements of tree height using Vertex IV hypsometer and crown diameter using a measuring tape.

2.3 UAV platform

In order to assess the accuracy of the results, the red oak plantation was surveyed using two different kinds of UAS platforms, i.e. a fixed wing platform (Bramor) and a multi-rotor platform (DJI M600). Both the platforms were tested to study the efficiency of image capturing, time consumption and workforce requirement. A fixed wing platform can be used for large study areas whereas a multi-rotor platform can be employed on smaller scale plots (Table 2). Depending upon the maximum allowable altitude to fly an UAS and cost limitations, the type of platform can be chosen.

A C-Astral Bramor fixed-wing UAS platform was used to gather imagery over the study site. The Bramor weighs less than 4 kg (including the RGB sensor payload) with a wingspan of 2.3 m. Its cruising speed ranges from 50 to 80 km/h, making it suitable for mapping up to 85 km^2 in 60 minutes. The platform was equipped with a PPK GPS system and Sony RXI RII RGB camera with a 42.4-megapixel resolution sensor that captured images with a relative aperture of f/4.5 and at a shutter speed of 1/1600 s.

The data acquisition mission was planned and executed using the C-Astral C3P ground control software with lateral and longitudinal image overlap set at 80%. The flight was conducted with wind speeds under 10 knots to ensure straight flight paths and ample image overlaps. Cloud cover was zero over the study area during the flight. A total of 1,124 images were taken from a 122 m altitude with a ground sampling distance (GSD) of 2.14 cm/pixel.

We also used a DJI M600 hex-rotor platform to capture images of the red oak plantation due to its vertical takeoff and landing with a relative flight time of 26 minutes when equipped with a full sensor payload, making it ideal for operating in forested environments. The sensor payload consisted of a Field of View Geosnap PPK GPS that was used to trigger a fixed mount RGB digital camera. The Geosnap PPK acts autonomously from the M600, containing its own IMU and GPS, and is responsible for triggering the camera in-flight based on its position and recording each of those events in a rover log file. The Geosnap was configured to gather images at 80% overlap at a 120-meter altitude, which produced a total of 343 images over the 24-minute flight.

Table 2. Specifications of the fixed-wing and multirotor platform, camera and mission parameters for this study

Specifications	Bramor	DJI M600
Platform	Fixed-wing	Multi-rotor
Sensor	Sony RXI RII	Sony A6000
Resolution in MP	42.4	24.2
Focal length	35 mm	21 mm
Aperture	F 4.5	F 3.5
Flight time	25 min	24 min
Maximum payload	3 kg	15 kg
Area Covered in sq. m.	1,331,905.24	207,290
Photo overlap	80%	80%
Images captured	1124	343

2.4 DSM and DEM generation

After collecting the required reference data, the next step was to process the UAS imagery and produce height models that can be further analyzed to derive individual tree height and crown diameter. Because the UAS platform was equipped with PPK technology, no GCP markers were utilized in the study. Image post-processing accuracy was accomplished by correcting the Bramor PPK rover log file with an established fixed location using the Continuously Operating Reference Station (CORS) network through EZSurv software. The resulting corrected imagery was then uploaded into Pix4D software where the parameters for spatial resolution, filtering and outputs were provided based on the characteristic of the study area and the desired output accuracy. Pix4D employs SfM technique to generate a point cloud, and subsequently an orthoimage mosaic (Iglhaut et al., 2019). DSM and DEM were generated from the point cloud data using SfM for the red oak and walnut plantations (Figure 6).

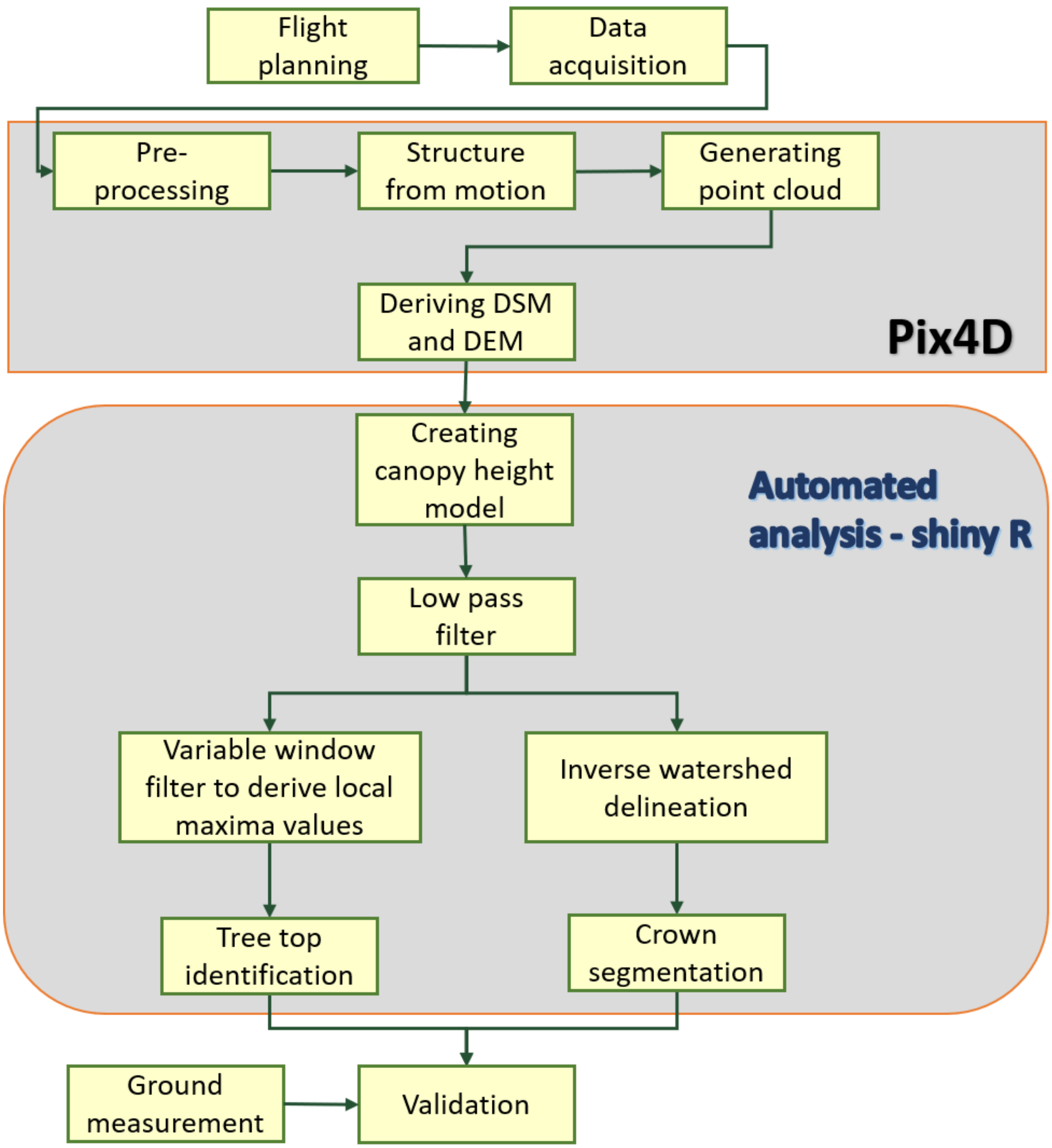


Figure 6. Complete methodology workflow

2.5 Automation with Shiny R

The whole tree identification and measuring process was automated using Shiny, which is an open source package in R used for developing powerful interactive web applications without separate requirement of HTML, CSS and JavaScript. A Shiny app consists of two parts, one is the web application that shows the app to the user and a computer that runs the application in the background. The user interface (UI), server and Shiny app are the three main components that are required to run a web application through the Shiny library. The user interface, which is plainly HTML can be written using Shiny functions, controls the overall appearance of the app and the server function contains the instructions for the computer to build and run the app when the user interacts with the web application. In programming terms, UI controls the front-end of the application and the server function acts as a back-end structure.

As specified above, all Shiny apps follow the same template (figure 7). This template is a minimal working Shiny app that initializes an empty user interface and an empty server, and runs an app using the empty functions. This basic template can be improved and developed further to user’s web application requirements.

```
library(shiny)
ui <- fluidPage()
server <- function(input, output) {}
shinyApp(ui = ui, server = server)
```

Figure 7. Basic Shiny app template

Shiny has been primarily employed for data visualization in different industrial and research arenas. Developers deploy Shiny apps to provide users with a platform to interact with results of research projects thereby making it available on a largescale online platform. Although most Shiny applications are interactive, it has mostly focused on visualization and not on information download. There has not been much advancement with external data inputs and visualization. This app that I developed has a user interactive framework where data can be imported, analyzed online and downloaded for further study by individual users with three mouse clicks.

Here, I used the Shiny library to develop a web portal that will automate individual tree detection and segmentation when supplied with DSM and DEM information (Figure 8). A user can input height models such as DSM and DEM through the interactive user interface provided by Shiny R. Using the ForestTools package in the backend of the Shiny server, the inputs are processed, and the crown delineated shapefile is supplied for download to the user.

The website I created can be accessed at https://feilab.shinyapps.io/Crown/. The user manual for the website can be found in the appendix section, as well as in the web application. The user manual has been created to make the website more accessible and reachable at the user end.

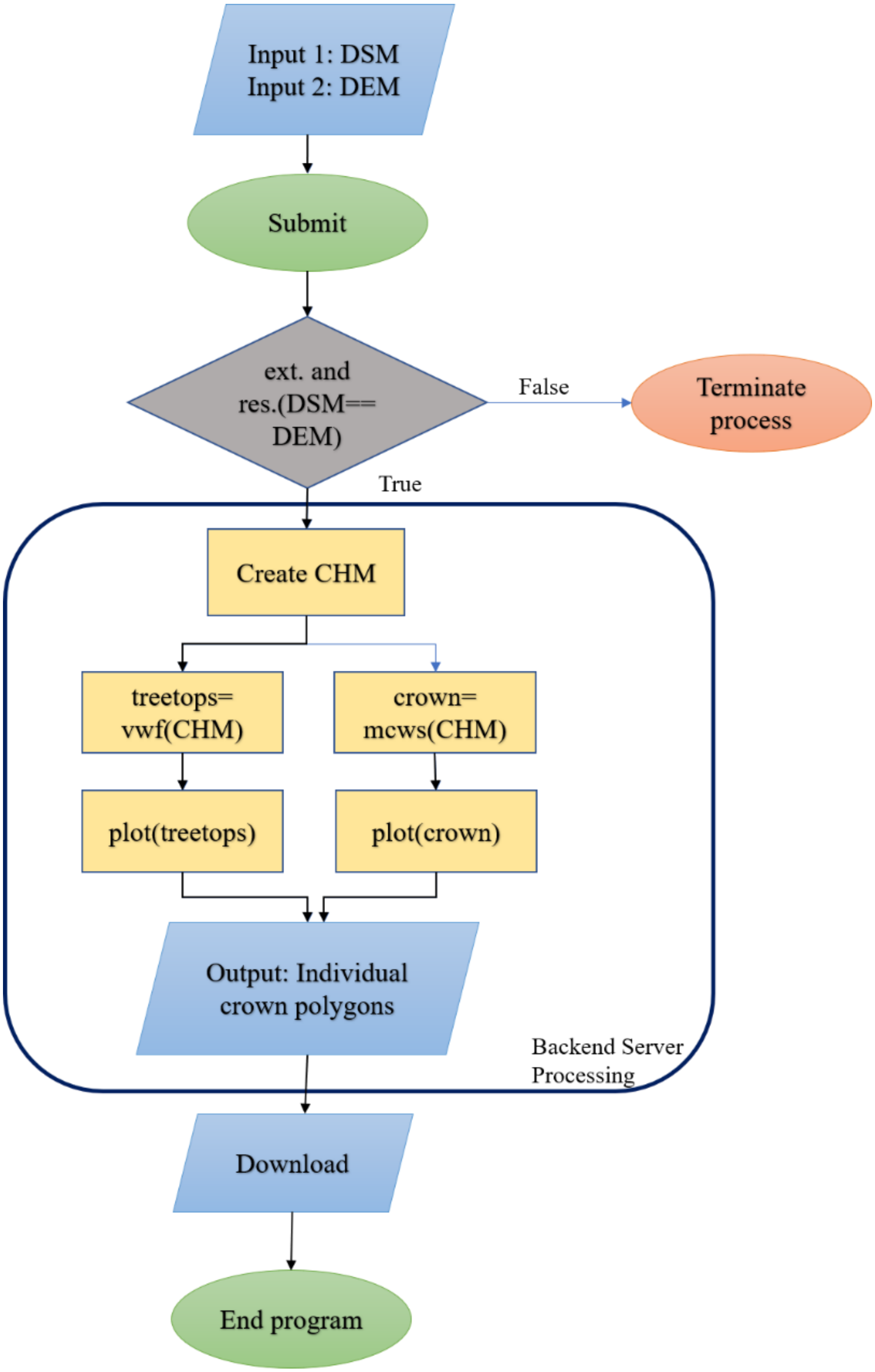


Figure 8. **Shiny app workflow representing the automation of estimating tree parameters**

2.6 R- Individual tree detection and height measurement

With the generated DSM and DEM, Canopy height model (CHM) was extracted by subtracting the DEM from the DSM in R 3.6.2. A canopy refers to the upper layer of a forest formed by tree crowns (Birdal, Avdan, and Türk 2017). The CHM used in this study is a measure of the above-ground height of trees. Various packages like Raster, rgdal and ForestTools were used for the analysis of CHM in R (Table 3). After generating the CHM, extreme values were removed using a low pass filter.

Table 3. Different R packages used in this study

Libraries	**Use in this study**
Raster	Read DSM and DEM data
Rgdal	Read vector data (area of Interest) and subset CHM.
ForestTools	Generating individual tree information
Shiny	Web application

Using the reconstructed CHM, I obtained individual tree-level data by employing a variable window filter function in the ForestTools package. The window size is an important factor for applying the local maxima filter to delineate individual trees. Previous works employed local-maxima filtering using a pre-defined window over the CHM which compared the center cell's value with its surrounding in that window (Birdal, Avdan, and Türk 2017). In this study, the size of the window varies according to the CHM cell value. The output from this filtering procedure is a spatial point file that indicates the location of individual treetops and its corresponding height.

From the treetop location, Marker Controlled Watershed segmentation (MCWS) method delineated individual crowns for the study area. This method assumes a tree crown as an inverted watershed and delineates the boundary. The segmentation depends on the highest point for that window which in this case is the treetop location. Therefore, taller the tree, larger is the crown area assuming that tall trees have longer crown spread and vice versa. The crown diameter was calculated from crown area coverage.

CHAPTER 3. EXPERIMENTAL RESULTS

3.1 Tree count analysis

Automated analysis of UAS data identified 4,449 trees out of the manually counted 4,668 trees in the research plot from the images captured by the Bramor platform. Similarly, the algorithm determined 4,606 trees from the data obtained by DJI M600. Figure 9 is a map representing the tree height and crown diameter of individual trees of the red oak plantation detected from the automated analysis in R. Spatial files were created as outputs from R and the resulting maps were produced from ArcGIS 10.6 for visual interpretation. Using this methodology, 4,668 trees were identified for the plantation which was validated by manually counting trees from the ortho-map. The same approach was conducted at a walnut plantation at Martell to check the repeatability and reliability of this technique. The total number of trees estimated through the prescribed open-source variable window filter approach in R counted 204 walnut treetops (Figure 10).

The minimum and maximum height observed from UAS-Bramor derived algorithm was 3.9 m and 12.9 m. Similarly, the crown diameter ranged from 1.1 m to 6.7 m. The minimum and maximum values of algorithm derived measurements values corresponded well with the ground measurements (Figure 11). The red oak plantation was surveyed using the DJI M600 UAS platform from which the derived tree height ranged from 3.4 m to 10.7 m and the crown diameter ranged from 1.1 m to 6.6 m (Figure 12).

Figure 9. Map of the outputs acquired from employing the R workflow for the red oak plantation at Martell (a). Individual treetop location (b). Individual tree crown cover.

Using the M600 platform, RGB imagery was collected for one plot of walnut plantation in order to check the repeatability of the current methodology. Due to its better accuracy in delineating each tree, the M600 platform was employed for repeating the experiment at the Walnut plantation. It was observed that through this automated technique, 204 trees were identified within five minutes after providing the height models as input. Upon manual inspection of the orthophoto imagery, 213 trees were counted indicating an overall accuracy of 97% through this automated open source methodology.

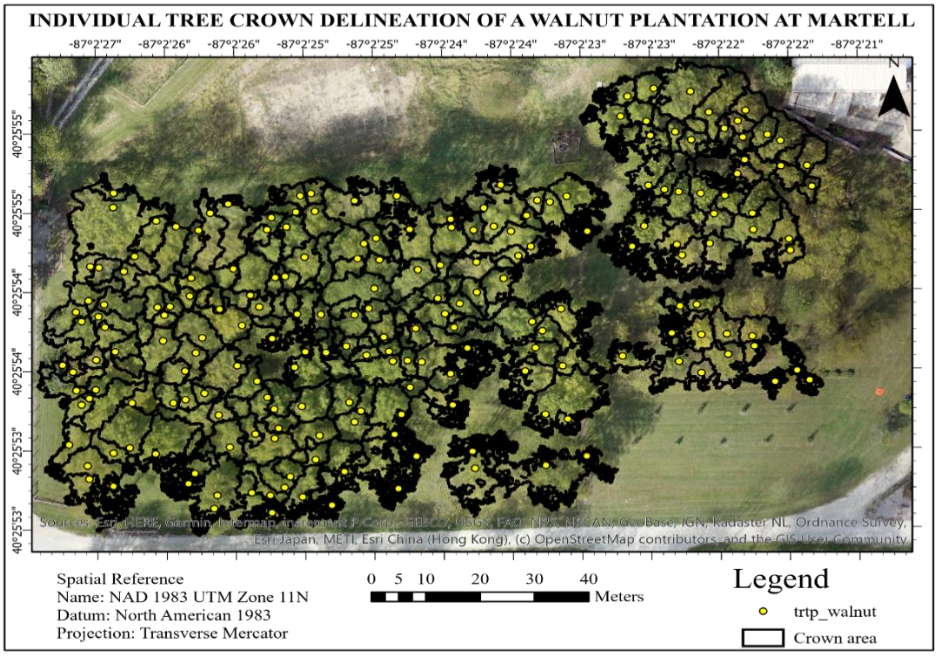


Figure 10. Individual tree detection and crown area delineation of the walnut plantation at Martell using DJI M600.

3.2 Correlation of determination and RMSE

In order to evaluate the reliability of the ForestTools package in R, generated results of tree height and crown diameter were validated using three measures i.e., Correlation coefficient (R^2), Root mean square estimate (RMSE) and Tree detection accuracy.

Figure 11 and 12 show the correlation of ground measured tree height and crown diameter with the algorithm derived tree height and crown diameter respectively measured from the imagery gathered by Bramor and M600 platform. It can be inferred from the graph that the adjusted R^2 for tree height and crown diameter is 0.93 and 0.79 respectively for Bramor, whereas the adjusted coefficient for the tree measures using M600 is relatively low (R^2_{ht} =0.67; R^2_{crn}= 0.78). These R^2 values indicated a high correlation between measured and estimated values for tree height and crown diameter using Bramor than M600. But the measured crown diameter The RMSE observed for tree height is 0.73 m and for crown diameter is 0.43 m measured through Bramor which is also much lower compared to the RMSE of tree height and crown diameter measured through M600 ($RMSE_{ht}$= 1.4 m; $RMSE_{crn}$= 1.2 m).

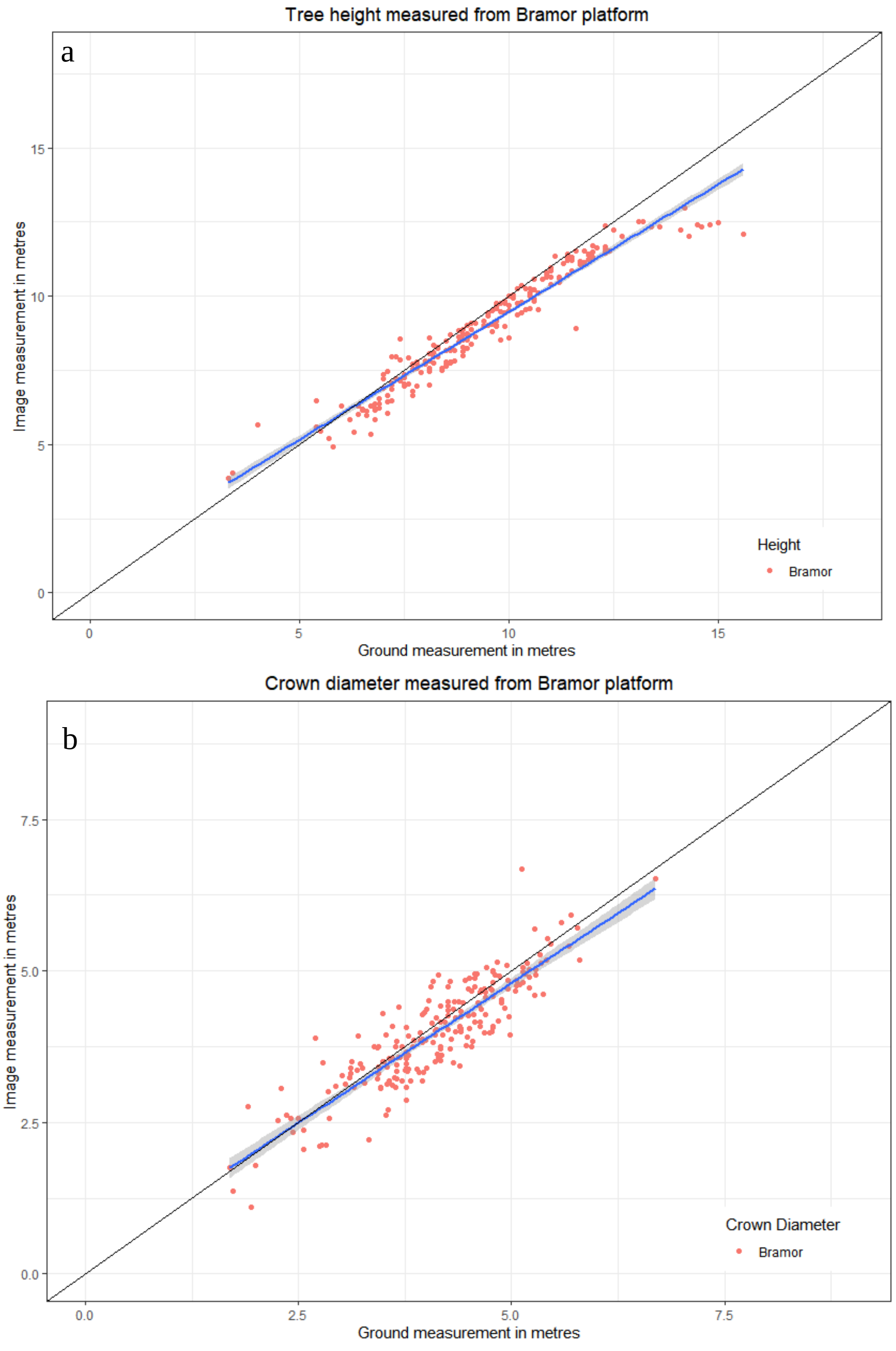


Figure 11. Correlation between ground measured and UAS-Bramor derived (a) Tree height (b) Crown diameter

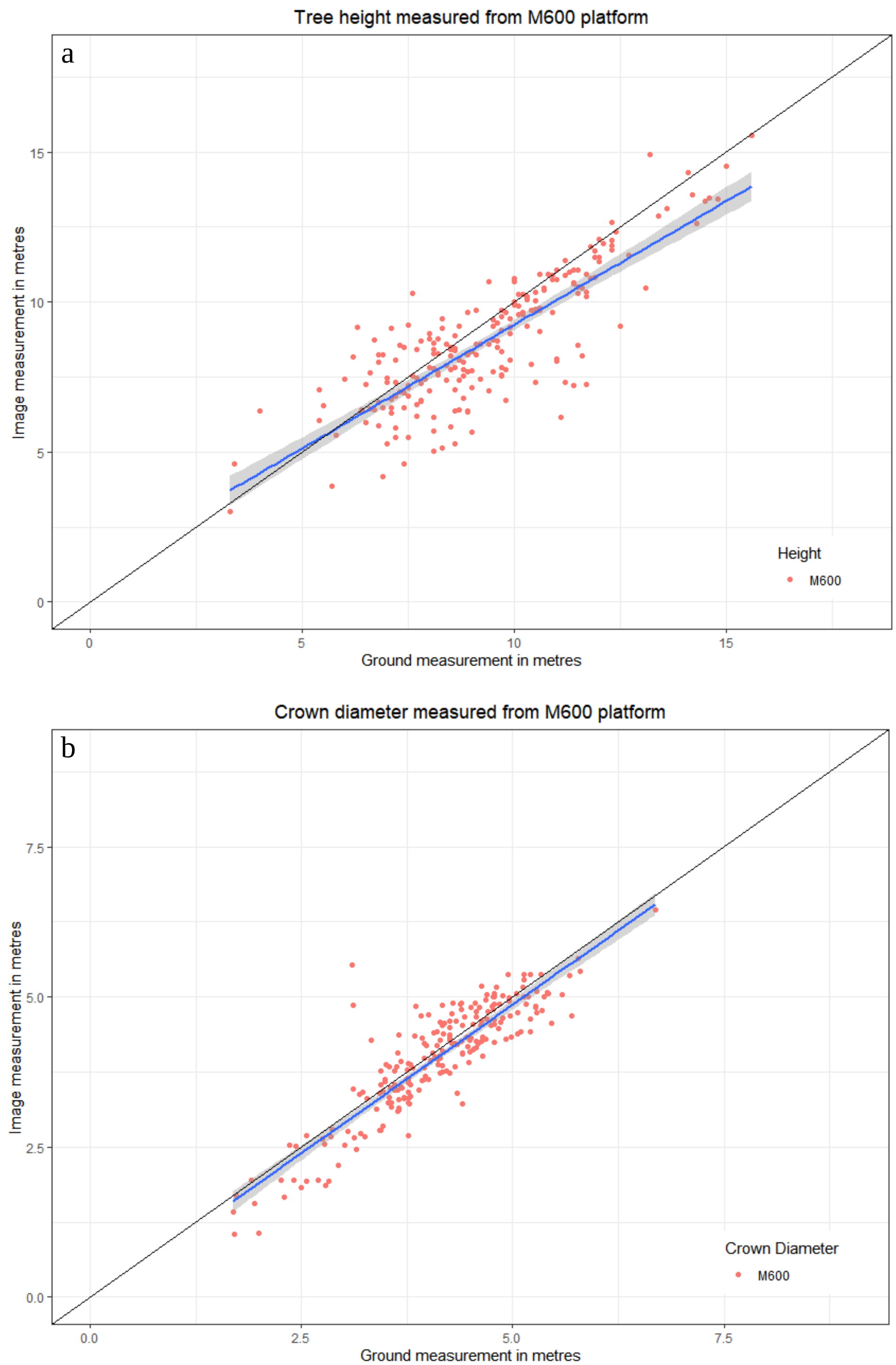


Figure 12. Correlation between ground measured and UAS-M600 derived (a) Tree height (b) Crown diameter

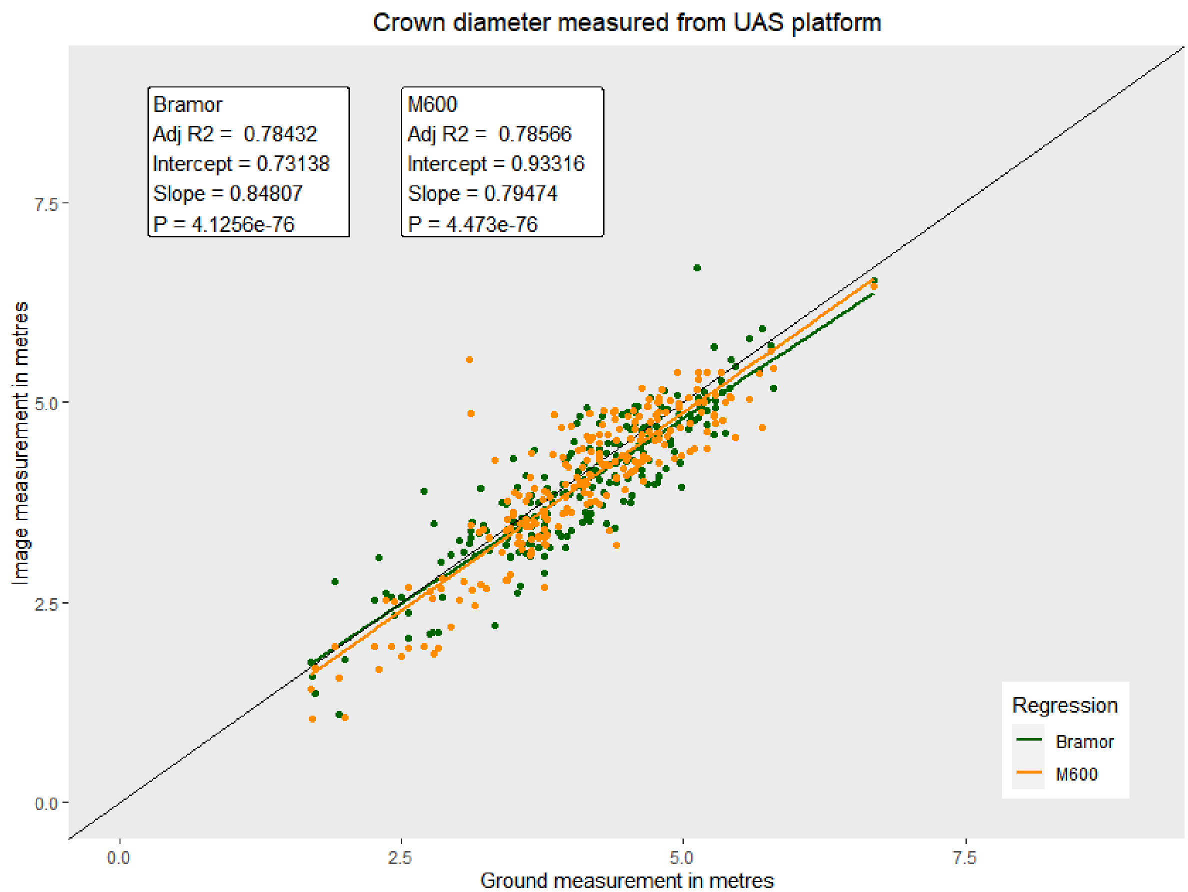


Figure 13. Plots indicating the results of comparison between ground measured and algorithm derived estimates of crown diameter measured using different UAS platform (Bramor and DJI Mavic 600) respectively

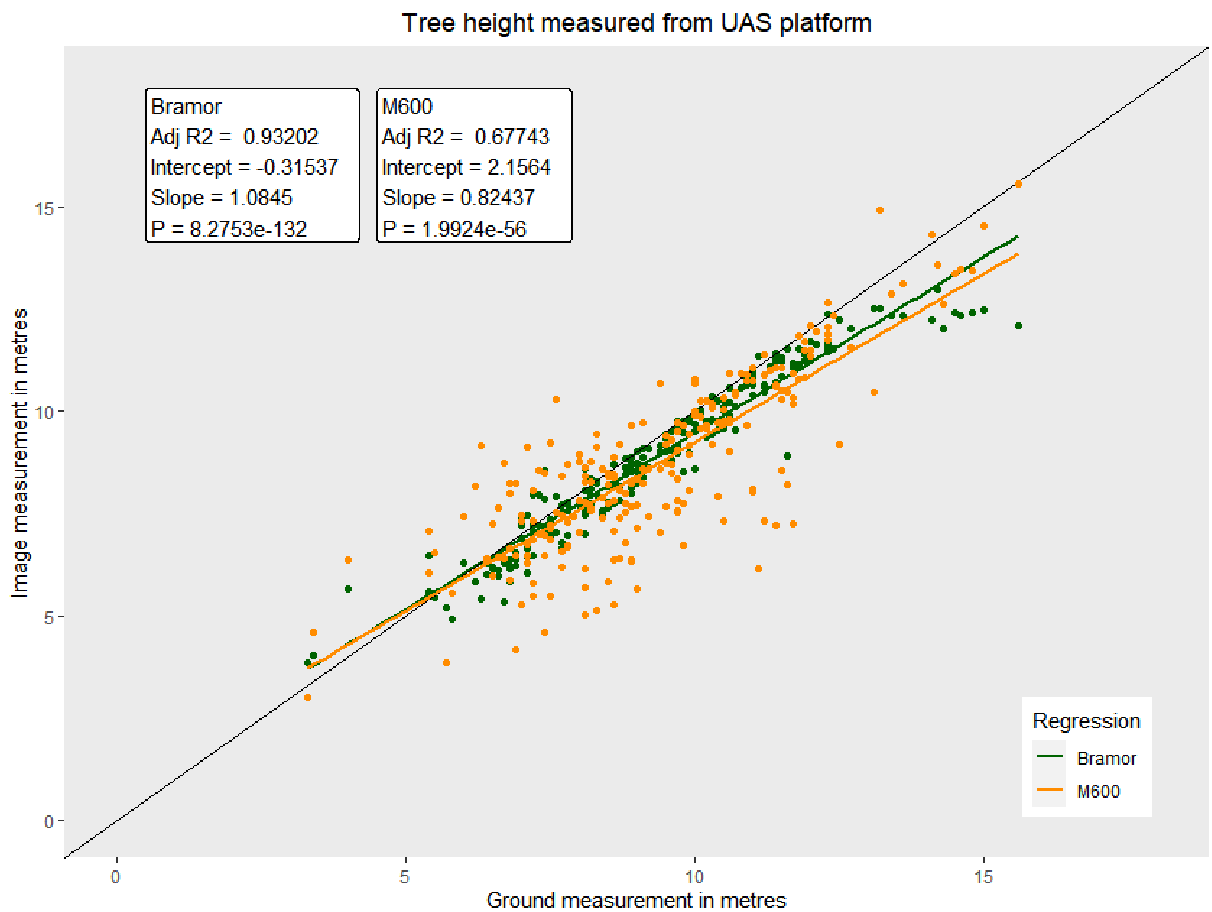


Figure 14. Plots indicating the results of comparison between ground measured and algorithm derived estimates of Tree height measured using different UAS platform (Bramor and DJI Mavic 600) respectively

From figure 13 and 14, it can be inferred that the p-value is extremely low for tree height and crown diameter measured from height models generated using both fixed-wing (Bramor) and multi-rotor (DJI M600) platform indicating high correlation between the ground measured and algorithm derived estimates. But, the slope of tree height measured from Bramor is 1.01 indicating over estimation of algorithm derived estimates in comparison with ground observed height measures.

3.3 Recall, Precision and F-Score

I used multiple metrics to evaluate segmentation accuracy: recall (rc), precision (pr), and F-score, based on the true-positive (*TP*), false negative (FN) and false-positive (FP) detection rates, indicating perfect segmentation, under-segmentation and over-segmentation, respectively (Li et al., 2012; Mohan et al., 2017). (Mohan et al. 2017; Li et al. 2012) employed this technique for validating Individual Tree Detection (ITD) and segmentation. The segmentation accuracy is determined by three factors; true-positive detection (*TP*), false-negative detection (FN), false-positive detection (FP). These factors indicate perfect segmentation, under-segmentation and over-segmentation respectively. The accuracy was evaluated from these factors by calculating recall (rc), precision (pc) and F-score using the following equations 2, 3 and 4 (Goutte and Gaussier 2005; Sokolova, Japkowicz, and Szpakowicz 2006).

$$rc = TP/(TP + FN) \qquad \text{----------------------(2)}$$

$$pc = TP/(TP + FP) \qquad \text{----------------------(3)}$$

$$F - \text{score} = 2 \times (r \times p)/(r + p) \qquad \text{----------------------(4)}$$

Table 4 represents the accuracy assessment of individual tree detection using *TP, FP, FN, r, pc* and F-score for this study It is evident that the overall accuracy of individual tree detection using MCWS method with the M600 platform was higher (F-score = 0.93) than the Bramor platform (F-score = 0.91) and the precision for ITD was relatively high as well (pc_{m600} = 0.9 and pc_{bramor} = 0.88).

Table 4. Accuracy assessment results for individual red oak and Black walnut segmentation at Martell using various parameters like True Positive (TP), false-negative detection (FN), false-positive detection (FP), precision, recall and F-score.

Plantation	UAS platform	*TP*	*FP*	*FN*	*rc*	*pc*	*F*-score
Red Oak (3 Plots)	Bramor	3913	536	219	0.95	0.88	0.91
	M600	4057	442	169	0.96	0.9	0.93
Walnut	M600	203	7	2	0.99	0.96	0.97

Although, the correlation coefficient and root mean square error of the tree measures derived from products using M600 platform was comparatively lower than that of the Bramor platform, overall tree detection accuracy and precision was higher when surveyed with the M600 platform. Therefore, DJI M600 hex-rotor platform was employed to survey one plot of Walnut plantation at Martell due to its vertical take-off and landing. The analyzed results showed high *F*-score and precision (pc = 0.96; F-score = 0.97) indicating the efficiency of M600 platform in providing better results for small plots.

CHAPTER 4. DISCUSSIONS AND CONCLUSIONS

The results of this study demonstrate the ability of using an open source platform (RStudio) for automated estimation of hardwood tree parameters with UAS-derived DSM and DEM. It can be inferred from the results section that this automated technique proves efficient and effective in terms of cost, time and convenience than the traditional semi-automated proprietary procedures.

4.1 Image derived tree parameters vs. ground measurements

According to table 4 and figures 11, 12, 13 and 14, stronger correlation of determination (R^2) and lower RMSE were observed for a fixed wing UAS derived tree height using the Bramor platform for the red oak plantation area at Martell. A similar survey with a hex-rotor platform did not produce similar correlation but identified individual trees more accurately for the red oak plantation. The overall segmentation accuracy of individual tree crown was higher using both the platforms than that observed by a similar study carried out by (Mohan et al. 2017). In the past decade, several studies (Table 1) have highlighted the potential for UAS in studying forest structure. The current methodology shows better results in comparison with the previous studies. Frankhauser et al, (2018) achieved an R^2 of 0.82 and an RMSE of 2.92 m for tree height measurement. Carr et al, (2018) employed a manual approach to segment individual trees and measure tree height where they obtained an R^2 of 0.82 and RMSE of 1.06 m. This study achieved a higher R^2 (R^2_{ht}= 0.93; R^2_{cm}= 0.79 with Bramor). The RMSE is less than a meter for both tree height and crown diameter due to high resolution height models derived from high precision images captured using the PPK system, employment of a variable window filter for segmentation and a simple hardwood plantation system thereby, resulting in better results than previous studies. The observed RMSE is less than a meter for both tree height and crown diameter studied from images obtained using a fixed wing platform (Bramor) indicating better results than previous studies.

Although our study provided acceptable accurate estimations of tree height and crown diameter, other studies have shown even higher accuracies (Birdal et al., 2017; Krause et al., 2019). This study is a pioneer on hardwood systems while Birdal et al., 2017 and Krause et al., 2019 have focused majorly on conifer stands resulting in ease of ground visibility and non-overlapping crown structure for better results. One possible reason could be imperfect field measurement of tree height and crown diameter as a reference data in complex overlapping hardwood systems. We can improve the reliability of field measurement by directly measuring felled trees. Another reason is that tree crowns included in this study were considerably large and overlapping, resulting in some field measurement errors of crown diameter. From table 4, it can be observed that there are higher false-positive numbers indicating over-segmentation, though MCWS method accounts for it. This could be due to the structural complexity of overlying canopies, which could affect photogrammetric reconstruction and spectral resolution of the images after reconstruction. Environmental and UAS platform attributes play a strong role in the accuracy of the obtained dataset.

4.2 R tool

The results obtained from the correlation graphs and the accuracy table indicate that the free open-source platform written in R can be used to measure tree parameters from UAS imagery efficiently. Most studies have employed forms of watershed delineation algorithms in order to identify individual crowns due to their intuitive and computationally efficient features. Due to its high sensitivity to noise and variance in spectral frequency, Marker controlled watershed delineation method is prone to over-segmentation (Gu, Grybas, and Congalton 2020). The MCWS approach adopted in this study overcomes the traditional watershed delineation method by adding marker regions corresponding to one segmented object and employing a variable window filter, i.e. the size of the filter window changes according to the maximum pixel value. The shape of the window is circular, and the size varies with the height of the pixel. MCWS differs from the regularly employed watershed segmentation method in controlling over-segmentation (Longzhe and Enchen 2011). This segmentation technique is also sensitive to noise in an image (Boren, Mao, and Zixing 2012) and can account for wind-swayed treetops which is a common phenomenon while capturing images. The variable window filter used in this study alters future tree measurement studies as the window size varies with the maximum height of the cell. This important factor makes this study repeatable to any plantation or forest system.

4.3 Advantages and disadvantages

This automated technique performs objectively and can be replicated for various tree species and possibly natural forests. It has potential for varied forestry applications such as tree age classification, biomass calculation and timber estimation. A multi-rotor UAS platform (DJI M600) provided better image results from which the overall tree detection accuracy of the automated technique increased from 0.91 to 0.93. The increased accuracy can be a result of the platform type, tree spacing and crown segmentation. The main advantages of this study are that the proposed method is relatively cheap and reliable and provides accurate estimates at individual tree level. It also follows an automated procedure to decrease human intervention that might factor in during the individual tree delineation stage. This method was also tested for repeatability and reproducibility by applying the same procedure on a walnut plantation at Martell successfully. Tree parameters for 4,600 trees were calculated from the CHM in less than 20 minutes in R, indicating the efficiency of this automated technique in measuring thousands of trees within short amount of time. This method provides a supportive basis for accurate remote measurement of trees in the future.

Although our study provided reasonably accurate estimations of tree height and crown diameter, other studies have shown even higher accuracies (Birdal et al., 2017; Krause et al., 2019). This study is based on hardwood systems whereas Birdal et al., 2017 and Krause et al., 2019 have focused majorly on conifer stands resulting in ease of ground visibility and non-overlapping crown structure for better results. One possible reason is the imperfect field measurement of tree height and crown diameter as reference data in complex overlapping hardwood systems. We can improve the reliability of field measurement by directly measuring felled trees. Another reason is that tree crowns included in this study were considerably large and overlapping, resulting in some field measurement errors of crown diameter.

While this study explores automating forest inventory procedures, datasets of consumer grade UAS systems, sensor parameters, optimal overlap accuracy have not been tested for cost efficient and optimal forest management. The web application is also constrained in terms of data size and extent matching. At this point, the application will perform optimally for datasets smaller than 10 MB provided there is an equal input extent between the DSM and the DEM. The DEM is generated through Pix4D due to the ground visibility at both the plantations. In order to obtain accurate DEM for closed canopy forest systems, it is advised to either employ LiDAR DTM or obtain UAS datasets during the leaf-off season. Also, environmental factors such as wind speed, temperature variation and cloud cover (fog, mist, snow) must be considered for preflight mission planning.

Future forest maintenance requires information in computerized format for continuous and repeatable workflow and UAS based data collection offers a promising workflow. Although, the integrative methodology adopted here is an initiative to employ UAS for studying hardwood species in a plantation, it can be extended further to structurally complex mixed forest systems. Based on the findings of this study, future research should direct along automated species identification, estimating other tree-level characteristics like DBH which can be further explored to estimate biomass and stem volume.

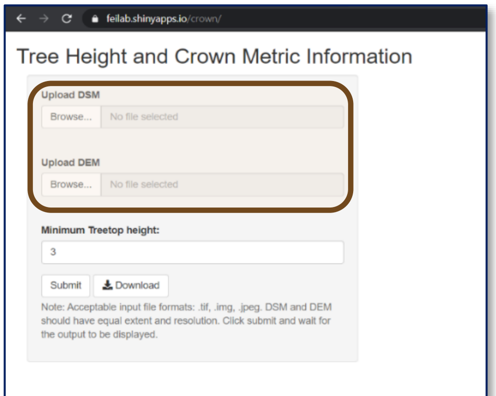
4.4 Conclusions

This study demonstrates the applicability of employing an automated procedure with an open source platform (RStudio) for studying hardwood plantations using UAS derived imagery. DSM and DEM models were produced through photogrammetric point cloud reconstruction in Pix4D. From the derived surface models, CHM was generated. From this product, an automated approach was carried out in R platform to derive tree height and crown diameter. This study experimented both types of UAS platform (Fixed wing and multi-rotor) to test the efficiency of each platform in capturing accurate images of the red oak plantation at Martell. Although the fixed wing platform (Bramor) performed well in terms of correlation with ground measure, the height models derived from images captured using the multi-rotor platform (DJI M600) delineated accurate individual tree location and estimated tree height and crown measures efficiently. The estimated tree height and crown diameter from the algorithm showed a strong correlation with the ground measurements for the Bramor platform. The results from further analysis indicated a high R^2 and meter level RMSE for tree height and crown diameter with 93% accuracy of detecting individual trees using DJI M600. This study illustrates the repeatability and reliability of an automated approach created in R and deployed online for users to benefit further (https://feilab.shinyapps.io/Crown/).

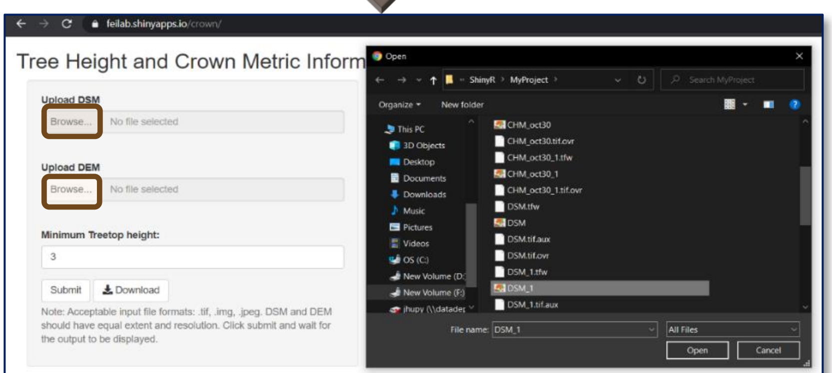
The focus of this study includes specific hardwood species of oak and walnut, but it can be further extended to other plantations as well. The web application was created to bridge the gap between the need for complex computation and readily available data. As this study demonstrated the applicability of an automated procedure for studying different hardwood plantation, it will be better to examine other complex forest structures. The results of this study are promising to extend future work on complex mixed-forest systems. Further research should focus on integrating this technique with deep learning methods for tree species classification in a complex forest system.

CROWN DELINEATOR

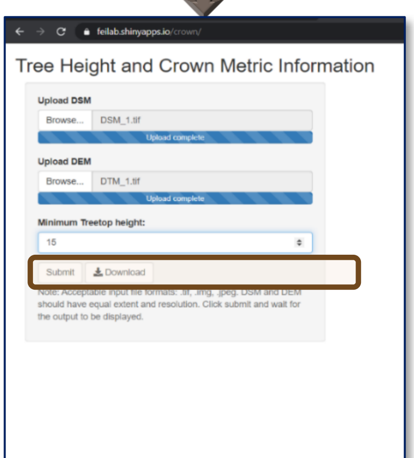
User manual for a simple Three click delineating process



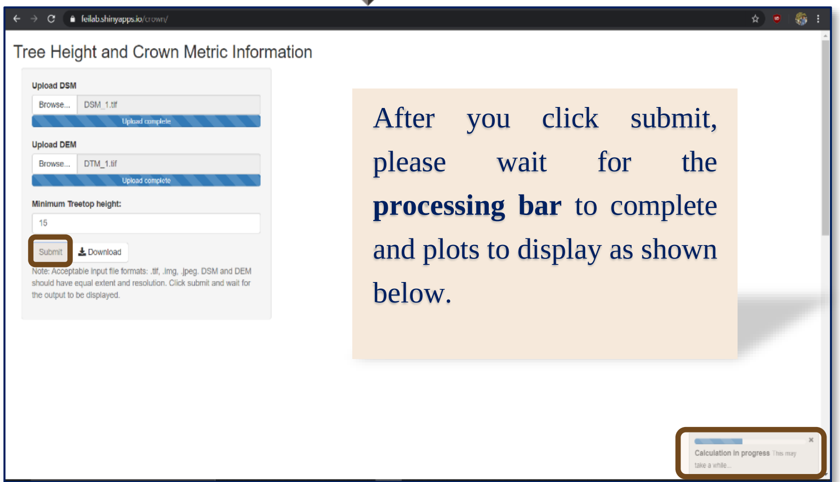
Upload Digital Surface model (DSM) and Digital Elevation model (DEM) generated through **Pix4D, Agisoft, ODM** or other drone image processing software.



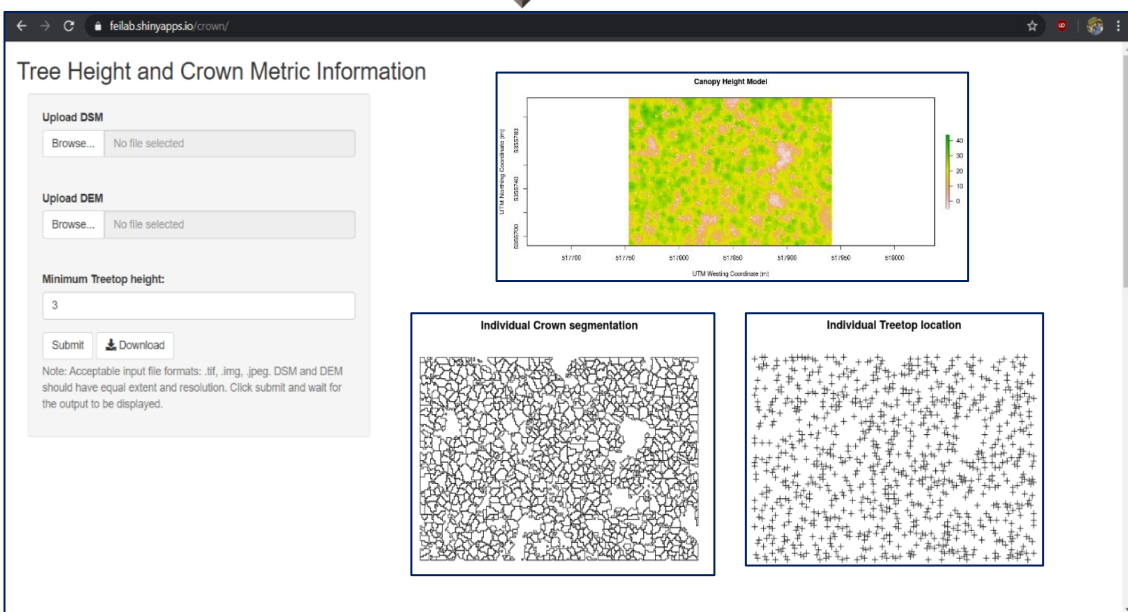
Before uploading, make sure that both DSM and DEM have **same extent, resolution, origin and cell size**. The algorithm will not work if either one does not work.



Once you have uploaded both the image files, you can specify the minimum treetop height. This height value will **delineate any undergrowing shrubs** and plants below that limit for the study area.

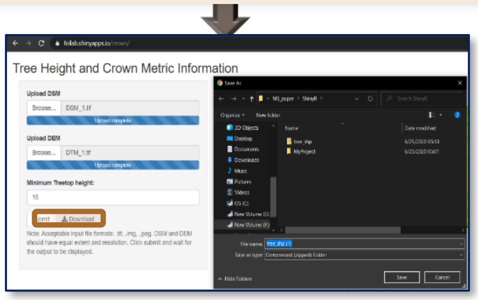


After you click submit, please wait for the **processing bar** to complete and plots to display as shown below.



Once the plots are displayed, **click download** and navigate to your preferred folder for the output to be downloaded.

The output is a **polygon shapefile** containing information about individual tree. The file will contain information on individual tree height and crown area for the uploaded plot.



APPENDIX A. SOURCE CODE FOR DEPLOYING THE SHINY APP

```
# install.packages('rsconnect')
# install.packages("shinyWidgets")
# install.packages("shinyBS")
# install.packages("shiny")
library(rsconnect)
library(shiny)
library(shinyWidgets)
library(ForestTools)
library(raster)
library(shinyBS)

rsconnect::setAccountInfo(name='feilab',
                          token='3D08E932439A362F48F4DCF14D887CCF',
                          secret='xkRIyoBFY+jRGSAFculwQHtK3qW5a978CeLodrAs')    #function    to
deploy the website online

options(shiny.maxRequestSize = 100*1024^2)

ui<- fluidPage(
  titlePanel("Tree Height and Crown Metric Information"),

  sidebarPanel(
    fileInput(inputId = "file1",
              label = "Upload DSM",
              accept = c('image/png', 'image/jpeg','image/jpg', 'image/tif', 'image/img')
    ),

    fileInput(inputId = "file2",
              label = "Upload DEM",
```

```
        accept = c('image/png', 'image/jpeg','image/jpg', 'image/tif', 'image/img')
  ),

  bsTooltip("file1", "Can accept any form of image file (eg. .tif, .img, .jpeg",
        "right", options = list(container="body") ),

  numericInput("Tree_Ht", "Minimum Treetop height:",3, min = 1, max = 20 ),

  actionButton(inputId = "Input_action", label = "Submit"),

  downloadButton(outputId =  "Download", label = "Download"),

  br(),

  a("User Manual",target="_blank",href="Crown_UserManual.pdf"),

  HTML("   "),

  a("Sample Images",target="_blank",href="SampleImgs.zip"),

  helpText("Note: Acceptable input file formats: .tif, .img, .jpeg. ",
        "DSM and DEM should have equal extent and resolution. ",
        "Click submit and wait for the output to be displayed.")

),

mainPanel(plotOutput(outputId = "plot"),
      plotOutput(outputId = "plot1"),
      plotOutput(outputId = "plot2"),
      plotOutput(outputId = "plot3")
)
```

```
)

#Functions that will be used in the server. Always write the functions outside of the server in order
to make it work.
subs<- function(x1,x2){x1-x2}
lin <- function(x){x * 0.05 + 0.6}



server <- function(input, output, session){
  library(raster)
  library(ForestTools)
  library(rgdal)



  inFile<- reactive({
    raster(input$file1$datapath)
  })

  style <- isolate(input$style)

  inFile2<- reactive({
    raster(input$file2$datapath)
  })

  chm1<- observeEvent(input$Input_action, {


    progress <- Progress$new(session, min=1, max=15)
    on.exit(progress$close())

    progress$set(message = 'Calculation in progress',
                 detail = 'This may take a while...')
```

```
    for (i in 1:15) {
      progress$set(value = i)
      Sys.sleep(0.5)
    }
    withProgress(message = 'Step 1',
                 detail = 'This may take a while...', value = 0, {
                 })
    subsVal<-subs(inFile(),inFile2())
    par(mar = rep(0.5, 4))
    output$plot <- renderPlot(plot(subsVal, main= "Canopy Height Model",
                              xlab = "UTM Westing Coordinate (m)",
                              ylab = "UTM Northing Coordinate (m)"
                              ))
    tTop <- vwf(CHM = subsVal, winFun = lin, minHeight = input$Tree_Ht)
    output$plot1 <- renderPlot(plot(tTop, main= "Individual Treetop location"))
    crown<<- mcws(treetops = tTop, CHM = subsVal, format = "polygons", minHeight =
input$Tree_Ht, verbose = FALSE)
    output$plot2 <- renderPlot(plot(crown, main="Individual Crown segmentation"))
    #aish<- c(crown, tTop)
    return(crown)
    })


  # Deploying a download button for users to download the output crown shape file.

  output$Download <- downloadHandler(
    filename = function(){
      paste("tree_shp", "zip", sep = ".")
    },
    content = function(fname){
```

```
      #data1 = chm1
      tmpdir <- tempdir()
      setwd(tempdir())
      print(tempdir())

      writeOGR(crown, tmpdir, "crown", overwrite_layer = TRUE, driver="ESRI Shapefile")

      zip_file <- file.path(tmpdir,"tree.zip")
      shp_files <- list.files(tmpdir,"crown",
                              full.names = TRUE)

      zip(fname,shp_files)
      file.copy(zip_file, fname)

    },
    contentType = "application/zip"
  )
}
shinyApp(ui, server)
```

REFERENCES

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