Research Article

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Tree Height Estimation from Unmanned Aerial Vehicle Imagery and Its Sensitivity on Above Ground Biomass Estimation in Dry Afromontane Forest, Northern Ethiopia

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ABSTRACT

Tree height is a parameter useful for calculating above-ground forest biomass and is mostly measured traditionally by ground survey. On the other hand, measuring the forest tree height and biomass estimation through field survey is labor-intensive and time-consuming. The application of remote sensing for forest above-ground biomass (AGB) estimation without forest destruction is important in order to estimate the carbon sequestration potential of the forest. The unmanned aerial vehicle (UAV) is an elating technology, which can help to estimate tree height and it is evolving at a rapid speed. Moreover, assessing the relationship between estimated and measured tree height is necessary for the future application of estimated tree height on AGB estimation. However, tree height estimation from photogrammetric UAV imagery in the dry Afromontane Forest and its sensitivity to AGB estimation are not investigated. Thus, this study aimed to assess the accuracy of tree height estimated from photogrammetric UAV imagery and the sensitivity of the estimated tree height on AGB estimation. Photogrammetric UAV acquired images and sample trees height measured on the ground were collected in Desa'a dry Afromontane Forest, Northern Ethiopia. Tree height was estimated from photogrammetric UAV acquired images and compared with tree heights measured on the ground. Moreover, the sensitivity of the estimated tree height on AGB estimation was investigated. The estimated tree height explained 89% of the tree height measured in the field. A considerable difference between estimated and measured tree height has an insignificant effect on AGB estimation. Thus, in the dry land Afromontane Forest the application of UAV aerial imagery for tree height estimation is promising to estimate AGB.

Keywords: AGB, Image segmentation, Photogrammetry, Tree height estimation, UAV.

1. INTRODUCTION

Forest has vital role in climate change mitigation through carbon sequestration which minimizes the global temperature (Pan et al., 2011). Forests are a principal element of carbon reserves in the world's ecosystems (Mohren et al., 2012). Tropical dry land forests share more than 40% of the forest ecosystem in tropics (Miles et al., 2006). Above-ground Biomass (AGB) estimation in tropics helps to understand tropical forest contribution on global carbon sink and how to manage forests (Tesfaye et al., 2016). About 11.2% of Ethiopia is covered with forest which contains 219 million metric tons of carbon in its living forest biomass (FAO, 2011). Forest assessment is important for the sustainable use of its resources as well as to assist valuable environmental and

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economic policies (Hailemariam et al., 2013; Krause et al., 2019; Moe et al., 2020). Forest AGB estimation is important to understand its contribution on global carbon sink and for management decisions (Tesfaye et al., 2016). In addition, measurement, reporting, and verification (MRV) of forest carbon stock balance monitoring offers result based reimbursement for REDD adopted countries (Achard and House, 2015). Accurate biomass estimation is the first step of accurate forest carbon stock assessment as 47-50% of the dry biomass is carbon (Solomon et al., 2007). The most accurate but destructive method of forest aboveground biomass estimation is by cutting, drying, and weighing all parts of the trees (Basuki et al., 2009). The destructive method of forest biomass estimation helps to develop allometric equation which corroborate for nondestructive methods of forest biomass assessment (Cunliffe et al., 2020). Different allometric equations need an accurate measurement of forest inventory parameters such as tree height, diameter at breast height (DBH), Crown projection area (CPA) and wood density as an input (Sullivan et al., 2018).

Remote sensing technology is crucial to extract forest variables to estimate aboveground biomass in a nondestructive technique (Brovkina et al., 2017; Nelson et al., 2017; Giannetti et al., 2020). Estimating and measuring forest inventory parameters have been done in numerous studies using different types of remote sensing tools and techniques (Liviu et al., 2016; Brovkina et al., 2017; Næsset et al., 2019). Tree height has a direct relationship to biomass and allows aboveground biomass estimation (Sullivan et al., 2018). Measurement of forest tree height using handheld equipment has a challenge due to occlusion and numerous labor requirements (Saliu et al., 2020). Unmanned Aerial Vehicle (UAV) is an elating tool that able to supply images at high spatial and temporal resolution (Panagiotidis et al., 2017; Puliti et al., 2019). Photogrammetric UAV application for forest assessment is crucial since it keeps the safety of data collectors in harsh and inaccessible places such as forest fire and swamp areas which have risk during ground survey (Stöcker et al., 2017; San Juan et al., 2018). The use of this technology in forest management facilitates estimation of tree height and the REDD-plus strategy (Grenzdörffer et al., 2008; Goodbody et al., 2017). Photogrammetric UAV provides high-resolution image at any moment in time (high temporal resolution), if the weather allows (Messinger et al., 2016). Photogrammetric UAV imagery users have the possibility to adjust the UAV flight time in order to minimize the impact of weather on image quality. Forest AGB assessment using photogrammetric UAV is fundamental to achieve REDD plus MRV goals since it has low cost, light weight and cost diminution on image atmospheric correction (Getzin et al., 2012). Photogrammetric UAV imagery supplements time consuming, expensive, and labour-intensive forest inventory methods (Navarro et al., 2020). Tree variables estimation from photogrammetric UAV image achieved through object-based image analysis (OBIA) and needs high-resolution image for successful image segmentation (Peña et al., 2018).

Tree height is important variable to estimate aboveground biomass using allometric equations (Saliu et al., 2020). Accurate measurement of tree height has a relationship with accurate AGB estimation which supports computing accurate carbon estimation (Phua et al., 2016). But, measuring tree height traditionally is labor-intensive and time-consuming (Krause et al., 2019) as it is tree based and not applicable for large areas. Tree height can be measured in a field using hand-held equipment. But it is difficult to find the peak of each tree and attributed to occlusions of crowns which made the individual tree measurement a big challenge. Offset crowns influence height estimation using traditional approaches (Bragg, 2014; Saliu et al., 2020). Assessing the relationship between estimated and measured tree height is necessary for future application of estimated tree height on AGB estimation. Tree height estimation from photogrammetric UAV acquired aerial imagery in different types of forest has different level of accuracy (Lim et al., 2015; Saliu et al., 2020). However, the accuracy of tree height estimated from photogrammetric UAV imagery and its sensitivity on AGB estimation is not investigated so far in dry Afromontane Forest. Therefore, this study aimed to assess the accuracy of tree height estimated from photogrammetric UAV imagery and its sensitivity on AGB estimation in Desaá dry Afromontane Forest, Northern Ethiopia.

2. MATERIALS AND METHODS

2.1. Description of the study area

2.1.1. Geographic Location

This study was conducted in part of the Desa'a dry land Afromontane Forest environment which encompasses heterogeneous landscapes. It is geographically located between 13°39.88′ to 13°40′ N latitude and 39°46′ to 39°46.37′E longitude as shown in figure 1.

2.1.2. Climate and Vegetation

50% of the Africa Afromontane forests areas are naturally occur in the northern and central parts of the Ethiopian highlands, where a semiarid to sub-humid rainfall regime is prevailing (Reusing, 2000). The study area is characterized as dry single dominant Afromontane Forest type of Ethiopia

(Hishe et al., 2015). This forest area is characterized by arid climate with annual precipitation not exceed 1000 millimeters. The rainfall distribution in a Desa'a forest is unimodal (in the Month of July and August) (Abegaz, 2005; Mokria et al., 2015). The average annual temperature of the study area is about 18.2 degree Celsius (${}_{o}^{C}$). The mean minimum and mean maximum temperatures for the area vary in the range between 9.3 to 14 ${}_{o}^{C}$ and 22.4 to 27.6 ${}_{o}^{C}$, respectively. The natural vegetation had been broadly classified as "dry evergreen Afromontane forest" with *Juniperus procera* and *Olea europaea* subsp. *cuspidata* as the dominant species (Aynekulu et al., 2012).

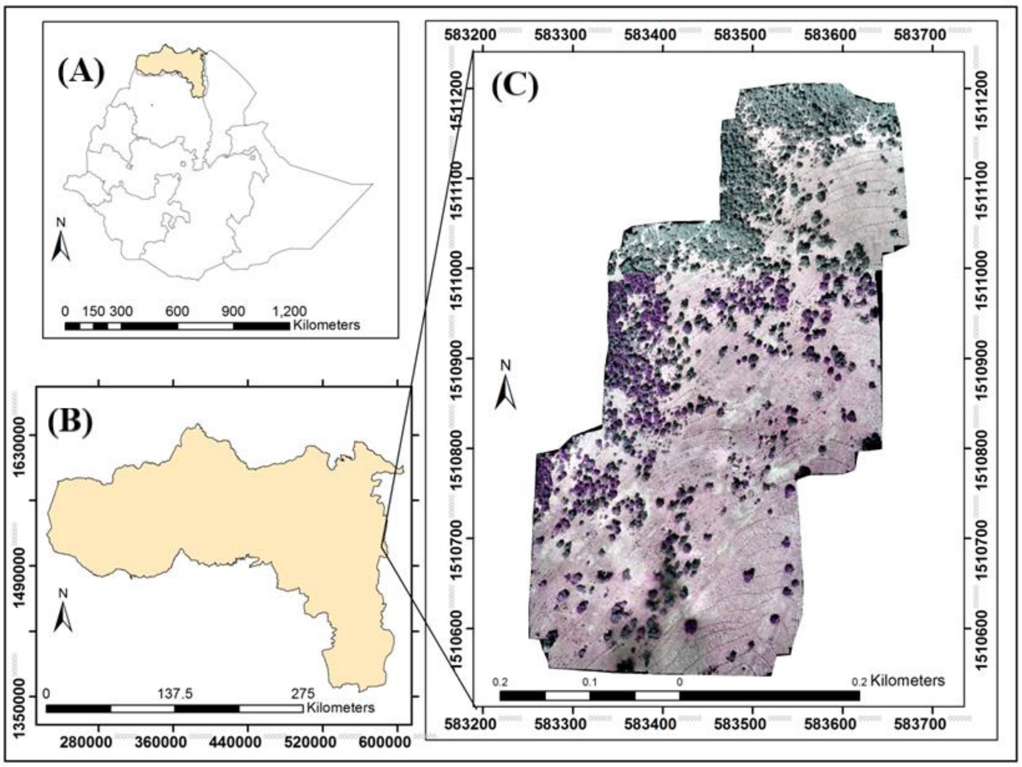

Figure 1. Map of the study area (A = Map of Ethiopia regions, B = Tigray region in Ethiopia and C = Map of the study site that generated by photogrammetric image processing).

2.2. Data Collection and Sampling Method

A stratified random sampling technique was applied in Desaá Afromontane Forest, Northern Ethiopia, to collect the necessary field data (DBH, aerial photos, X Y coordinate and tree height). A stratification of the study site was done using slope class. The field sample collection was done tree-based and inside the UAV flight plan covered area. This method helps to match the measured tree height with the estimated tree height. The sample trees were collected in the UAV flight mission covered area (18.4 hectare) from three slope classes (0-5%, 5-24% and 24-48%). The slope classes were provided from DTM and classified in GIS Arc Map. The selection of UAV flight plans was based on the open space available for marker placement. Two flight plans were established, and fifty-five sample trees were selected randomly from the three slope ranges. The DBH and height of each sample tree were measured using diameter tape and Hypsometer, respectively. The location coordinates of each sample tree were also recorded using Garmin-72 GPS with positional accuracy of three meters.

2.2.1. UAV Aerial Image Acquisition Method

The acquisition of aerial photos using advanced Phantom 4 DJI UAV was conducted in part of Desa'a dry Afromontane Forest, Northern, Ethiopia. Pix4D capture app was used for UAV flight plan preparation with moderate speed, 90^{o} angle, 90% forward-overlap. The side overlaps were adjusted by the software. There are different UAV RGB cameras with different resolution such as Sony A9 (24.2 MP), Canon EOS 5D mark IV (30.4 MP), Nikon D850 (45.7 MP) that highly available in products ranging across different levels of cost (Yao et al., 2019). The phantom 4 types of UAVs have different camera sensors mounted on them such as PHANTOM 4 PRO (camera sensor with 1 inch CMOS and 20 Mega effective pixel), PHANTOM 4 ADVANCED (camera sensor with 1 inch CMOS and 20 Mega effective pixel) and PHANTOM 3 SE (camera sensor with 1/2.3 inch CMOS and 12 Mega effective pixel) (https://www.dji.com/phantom-4-adv). The camera sensor used in this study has CMOS sensor type, 5472*3648 resolution, and 13.2*8.8 mm sensor size. Model of the camera was FC6310 with focal length 8.8 millimeter and ground sample size 1.96 centimeters/pixel. The flight height adjusted 80 meters above ground. Five Ground Controls Coordinate Points (GCCPs) were recorded using a Differential Global Position System (DGPS) with a static approach before flight. The application of DGPS with a static approach has <1 cm accuracy which is important to provide accurately geo-referenced image (orthophoto) and DTM accuracy assessment.

2.2.2. Biometric Data Collection Method

All the selected sample trees DBH measured using diameter tape and recorded in the data collection sheet. The chosen sample trees have greater than 10 centimeters DBH. Because trees with greater than 10 centimeters DBH have a significant contribution to biomass and carbon stock (Brown, 2002). Moreover, during the fieldwork, the x and y coordinates of each sample tree was recorded to match tree height measured in the field with the tree height estimated from UAV-image. Each sample tree height measured using handheld equipment i.e., Hypsometer. Most of the sample trees species were *Juniperus procera*, and *Olea europaea* subsp. *cuspidata*.

2.3. Photogrammetric Aerial Image Processing

Photogrammetric UAV acquire aerial images processed with Agisoft photo scan professional version 1.3.4 Software which was used by Torres-Sanchez et al. (2015). Agisoft Photo scan Professional software works through the principle of structure from motion (SfM). The main steps followed for UAV acquired aerial images processing in agisoft photo scan professional was as illustrated below in figure 2.

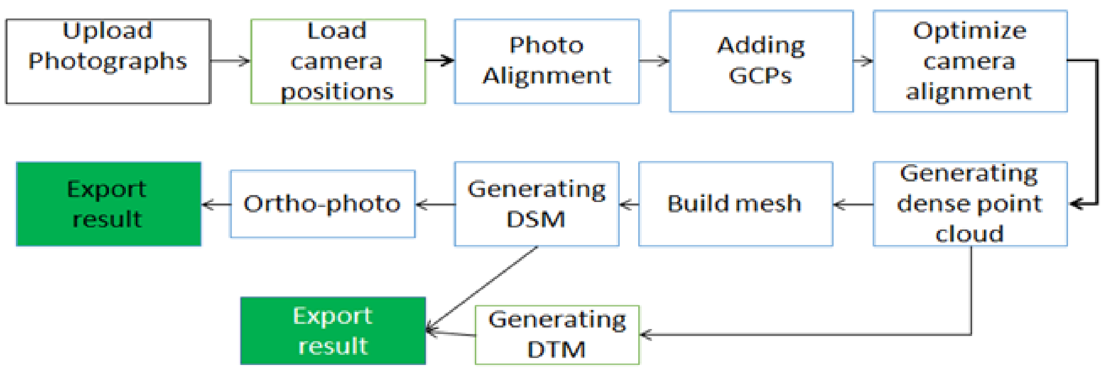

Figure 2. Major UAV image processing steps in Agisoft photo scan professional.

The ground control points (GCCPs) on the images were matched with the DGPS recorded equivalent x, y and z coordinate values to correct possible distortions. The right way of placing the markers supports good camera orientation and possible distortion correction, and a dense point cloud construction. The generated compacted point cloud was used as input for the Digital Terrain Model (DTM), Digital Surface Model (DSM) and orthophoto generation (Lim et al., 2015; Iizuka et al., 2017). The average point density of the photogrammetric image processing point clouds was 162.874 points/square meters. The DSM is a surface model consisting of a regular grid of height values including treetops. The DTM is a regular grid with height values without treetops, i.e. only terrain surface, but these values are the result of interpolation between those pixels which was classified as “ground points”.

The DTM, DSM and orthophoto results were represented in figure 3a, 3b and 3c, respectively. As indicated in figure 3a the height (altitude) of DTM ranges from 2, 377.83 to 2, 417.96 meters while figure 3b, indicates the height of DSM ranges from 2, 377.83 to 2, 421.65 meters. The height of DSM obtained higher than the heights of DTM since the DSM is the height of terrain and objects on the earth's surface while the heights of DTM is only the height of the terrain. The Orthophoto derived from the intermediate output dense point clouds. The generated orthophoto used for individual tree crowns automatic segmentation and manual delineation. The spatial resolution of the generated orthophoto was approximately 2 centimeters. The ground sampling distance (GSD) checked by calculation using relevant formula and it is similar with the GSD from the photogrammetric image processing.

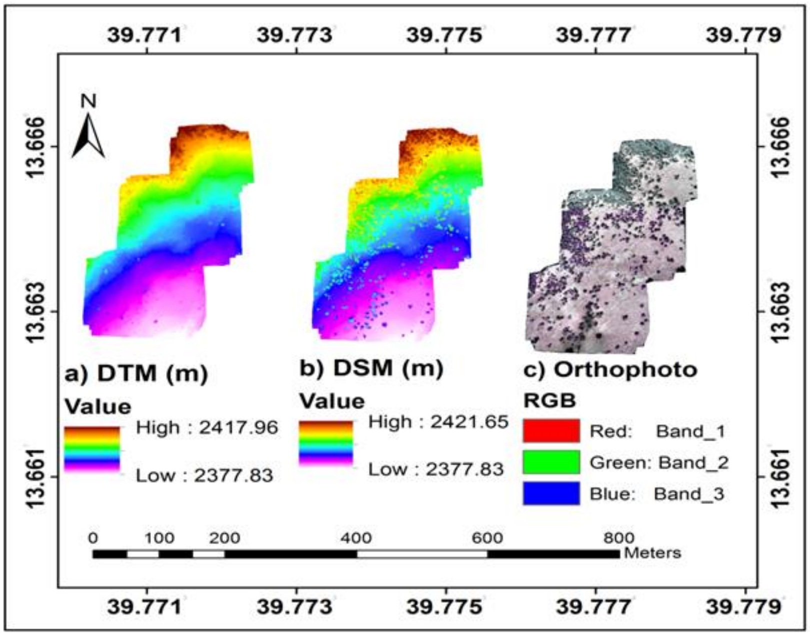

Figure 3. Generated DTM and DSM and Orthophoto (a = DTM, B = DSM and c = orthophoto).

2.3.1. Generating Canopy Height Model

Photogrammetric UAV acquired aerial images processing in agisoft photo scan professional was the initial stage to produce dense point cloud. The generated dense point cloud in-turn used as input to provide DSM and DTM which are input to calculate CHM. The CHM generated from the prepared DSM and DTM in GIS Arc Map using the raster calculator (DSM – DTM) or subtraction (Lim et al., 2015; Iizuka et al., 2017) as shown in figure 4.

Figure 4 shows CHM generated using GIS Arc Map raster calculator and the CHM ranges 2 to 15.7 meters after the pits, and falls were removed. The result indicates the maximum height of individual trees in the study site not exceeding 15.7 meters. A comparison of DTM extracted from UAV aerial images with the altitude measured using DGPS is very important to assess the accuracy of photogrammetry image processing. In addition, DTM accuracy assessment using elevation from the ground truth (DGPS) is crucial and the first step to assess the accuracy of tree height derived from UAV 3-D point cloud. Altitude extracted from UAV aerial imagery accuracy assessed using scatter plot and RMSE (%RMSE).

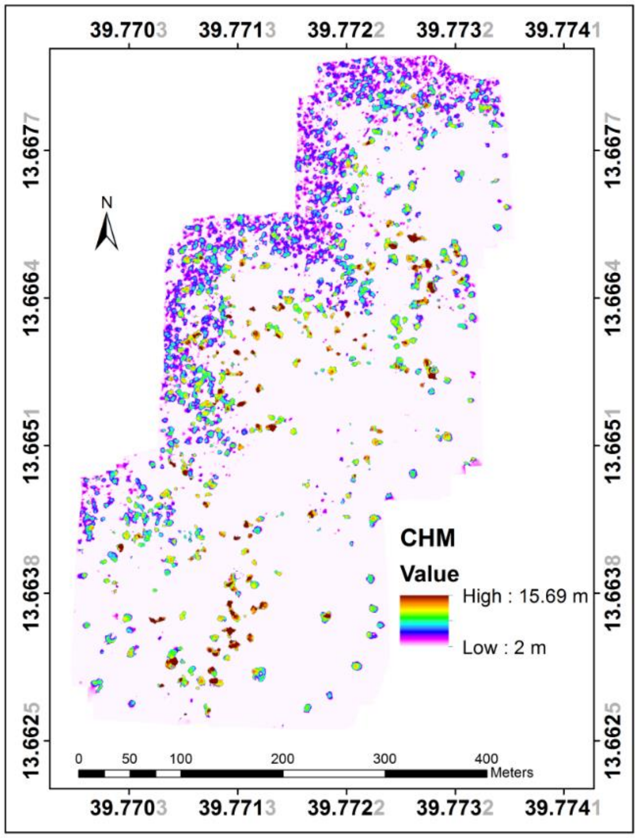

Figure 4. Generated CHM.

2.4. Multiresolution Image Segmentation and Validation

The orthophoto derived from photogrammetric UAV acquired aerial images was segmented automatically in e-Cognition developer 9.01x64 software using the region-based segmentation technique. This segmentation technique helps to classify spatially and spectrally similar pixels to a homogenous area to form an image object. In the algorithm, segmentation started from a single pixel and subsequently grew until a particular tree crown formed (Blaschke et al., 2004). This classification technique was based on homogeneity criteria such as colour, smoothness and compactness parameter which determine segment heterogeneity (Carleer et al., 2005). The homogeneity of segmented tree crowns was maximized using multiresolution image segmentation algorithm (Benz et al., 2004).

To separate a single tree in the aerial image watershed transformation algorithm was applied. To avoid salt-and-pepper problems of extremely high-resolution orthophoto segmentation, the orthophoto resampled from 2 to 30 centimeters (Okojie, 2017). Scale parameter, shape and compactness set by trial and error iteratively until the authors satisfied with the crown projection area (CPA) segmentation. The scale parameter, shape and compactness values used during segmentation and that satisfied the authors were 22, 0.7 and 0.5, respectively.

Segmentation accuracy assessment was conducted by confronting the manually segmented CPAs with the corresponding CPAs in the classified image. The assessment considers the topological and geometrical relationships of the tree crowns (Möller et al., 2007). Topological relationships of tree crowns deal with 'containment' and 'overlap', while the comparison of crown positions assesses geometric relationships. If the automatically segmented crown areas fully enclose the manually digitized crown areas, it is a perfect segmentation. Minimum acceptable accuracy is 50% of reference and automatic segment overlap (Zhan et al., 2005). The value of over and under-segmentation is between values of 0 and 1 while 0 value means that training object is exactly matched with the segments (perfect segmentation) (Clinton et al., 2010). Equation1 below shows the formula for segmentation accuracy assessment.

$$D = \sqrt{\frac{Over\ segmentation^2 + Under\ segmentation^2}{2}} \quad (1)$$

Where, D is the closeness of fit or segmentation goodness; the segmentation goodness or closeness of fit (D) is a measure of the error in segmentation. The accuracy of the segmentation result was assessed using manually digitized tree crown. The manually digitized tree crown is the most accurate since it was digitized following the outermost individual tree crown in the high-resolution orthophoto. The assessment was done by overlaying, observing and calculating the overestimated and underestimated CPA. The accuracy of the automatically segmented tree crowns was evaluated by computing overestimated and underestimated errors. Accordingly, the overall segmentation accuracy was 86.3%, i.e.,13.7 % errors.

2.5. Tree Height Estimation

Tree height estimated by overlaying the segmented shapefile on CHM in GIS Arc Map and run the zonal statistics. The maximum values in the attribute of zonal statistics outputs were the tree heights. Appropriate field data collection and matching with its corresponding image information needed a great attention. For this reason, the DBH data collected in the field should be matched with its corresponding tree height derived from CHM. A spatial joins function has been applied to match the segmented individual polygons and field DBH using recorded coordinates of the trees. The recorded GPS coordinates matched with each sample trees in the image; since the reading was taken close to the stem of the tree and the GPS accuracy was not exceeded the crown diameter of each tree.

2.6. AGB Estimation

The most common nondestructive method of AGB estimation is applying allometric equation (Giannetti et al., 2020) which allows estimating AGB of large forest areas. The allometric equation uses structural forest parameters that regularly measured in the field as input. Even though there are numerous allometric equations for biomass estimation, suitable environment should be considered to select the appropriate equation. In tropical forest which is endowed with species diversity, applying regional or local model is not recommended (Gibbs et al., 2007). Therefore, the AGB calculated using the generic allometric equation (Bao et al., 2016) is widely used for tropical forests. The allometric equation used DBH, tree height and specific wood density as input as shown below in equation 2.

$$AGB = 0.0673 * [(\rho * D^2 * H)]^{(\mathbf{0.976})} \text{ --------------------------------------- } (2)$$

Where,
AGB is the aboveground biomass in kilogram (Kg);
D is DBH in centimeters (cm);
H is tree height in meters and ρ is tree specific wood density in gram per centimeter cube (g/cm^3).

The estimated AGB has been tree based since the tree height, and DBH measurement was based on the number of individual sample trees measured at field. In this study, the estimated tree height and measured tree height based AGB was calculated.

2.7. Sensitivity of Estimated Tree Height on AGB Estimation

In this study, the input tree variables (specific wood density and DBH) for allometric equation in both measured tree height-based and estimated tree height-based AGB computation was common except tree height. So, the expected variation in the computed AGB was due to height difference (tree height measured at field and tree height estimated from photogrammetric image processing). The computed AGB using estimated tree height and DBH measured at the field was compared with measured tree height-based AGB to evaluate their difference and relationship using scatter plot, box plot, paired t-test, correlation and RMSE. The RMSE and percentage of RMSE calculated using equation 3 and 4 below that used by Sherali et al. (2003) to compare the closeness of the measured tree height-based and estimated tree height-based AGB of forest trees.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Yi - \hat{Y})^2}{n}} \text{ -- } (3)$$

$$\%RMSE = \frac{RMSE * N * 100}{\Sigma Yi} \text{ --} (4)$$

Where,
RMSE is the root mean square error;
%RMSE is the Percentage of RMSE;
Yi is the original value of the dependent variable;
$\hat{Y}$ is the predicted value of the dependent variable; and
N is the number of observations.

Finally, the collected and extracted forest variables as well as elevation data analysed by descriptive statistics, scatter plot, RMSE, box plot and paired t-test. The software that was used for data analysis includes, SPSS version 20, R-studio version 3.5 and Microsoft Office excel 2007.

3. RESULTS

3.1. Estimated and Measured Tree Parameters

The minimum, maximum and average tree heights measured in the field were 5, 14, and 8.34 m, respectively, while the estimated tree heights were 4.6, 13.5 and 8.06 m, respectively. The minimum, maximum and mean DBH measured on the ground were 14.5, 103 and 44.73 centimeters, respectively. Descriptive statistics of the estimated and measured tree variables were as shown below in table 1.

Table 1. Descriptive statistics of estimated and measured tree variables.

	Minimum	***Maximum***	***Mean***	***Std. Deviation***
Measured tree heights (m)	5.00	14.00	8.34	2.37
Estimated tree heights(m)	4.60	13.50	8.06	2.33
DBH (cm)	14.50	103.00	44.73	21.03

The accuracy of tree height extracted from photogrammetric UAV aerial image processing was validated by tree height measured using a handheld equipment i.e., Hypsometer at the field. From the 55 sample trees, heights, two trees show relatively outliers. This might be due to the DTM interpolation since these two trees were located close to a mound soil excavated from a trench and the interpolation might start from the mount soil's top. Those tree heights extracted using Photogrammetry obtained shorter than the heights measured using Hypsometer. The difference between measured and estimated tree height did not exceed 2 meters. The altitude derived from UAV aerial image was deviated by 0.37 m (1.5%) from the altitude measured using DGPS. The obtained deviation in altitude might be due to the error created during photogrammetric aerial image processing. The altitude extracted from the UAV explained 99% of the altitude measured using DGPS. The scatter plot of the tree heights extracted from Photogrammetric UAV and measured on the ground was as shown in figure 5. The heights of the trees were distributed along the scatter plot trendline, and their distribution almost equal above and below the trend line.

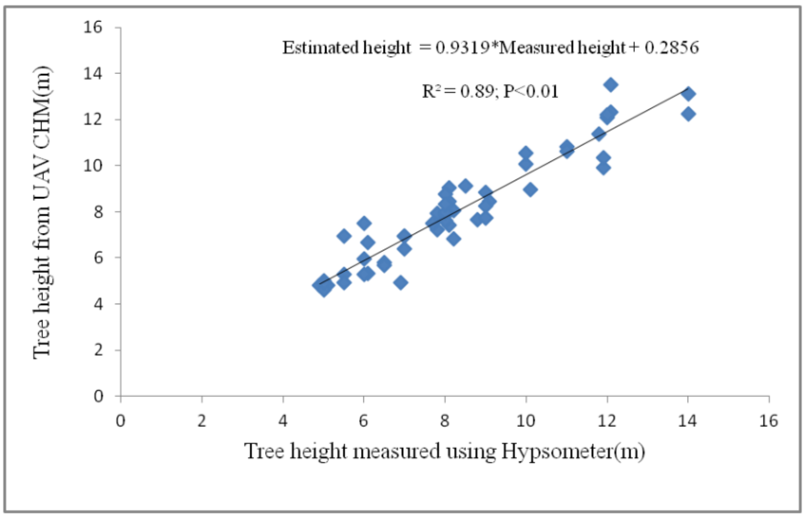

Figure 5. Scatter plot of estimated and measured tree heights.

The RMSE and %RMSE between tree heights extracted from photogrammetric UAV aerial imagery and measured using Hypsometer were 0.76 m (9.45%). The result indicates the mean tree height extracted by photogrammetric UAV aerial image processing has been deviated from mean tree height measured in the field by 0.76 m. The difference between tree height measured in the field and obtained from photogrammetric UAV aerial imagery tested using a paired t-test and the result to be 0.008 (P (T<=t) two-tail). The result indicates a highly significant difference between mean tree heights extracted by photogrammetric UAV aerial image processing and tree height measured using Hypsometer/ Forestry Pro II Laser Rangefinder.

The relationship between estimated and measured tree heights tested using Pearson correlation. The obtained result of the correlation coefficient was 94%, which indicates a strong relationship. Estimated tree height explained 94% of tree height measured in the field. If tree height is estimated using Photogrammetric image processing and used to represent tree height measured at the area, it will have an error of 6%.

3.2. Measured Tree Height-based and Estimated Tree Height-based AGB

The measured and estimated tree height based calculated AGB were 51, 993.46 kg and 50, 048.11 kg, respectively as shown in table 2. This result is obtained from 0.233-hectare area which is covered by the crowns of the sample trees. In the study area approximately 223.15 and 215 Mega grams per hectare (Mg/ha) AGB was estimated using measured and estimated tree heights, respectively. The minimum, maximum and mean measured tree heights based calculated AGBs was 32.81 kg, 5,751.02 kg, and 945.33 kg, respectively. The minimum, maximum and mean estimated tree height based calculated AGB was 32.52 kg, 5, 393.76 kg and 909.96 kg, respectively.

Table 2. Descriptive statistics of estimated and measured tree height based computed AGBs.

	Measured tree height based AGB (Kg)	***Estimated tree height based AGB (Kg)***
Mean	945.33	909.96
Standard Error	154.99	143.50
Standard Deviation	1,149.45	1,064.23
Minimum	32.81	32.52
Maximum	5,751.02	5,393.76
Sum	***51,993.46***	***50,048.11***

The RMSE of estimated and measured tree height based AGB was 107.3 Kg (11.79%). The scatter and box plot of the estimated and measured tree height based AGB is as shown in figures 6 A & B respectively.

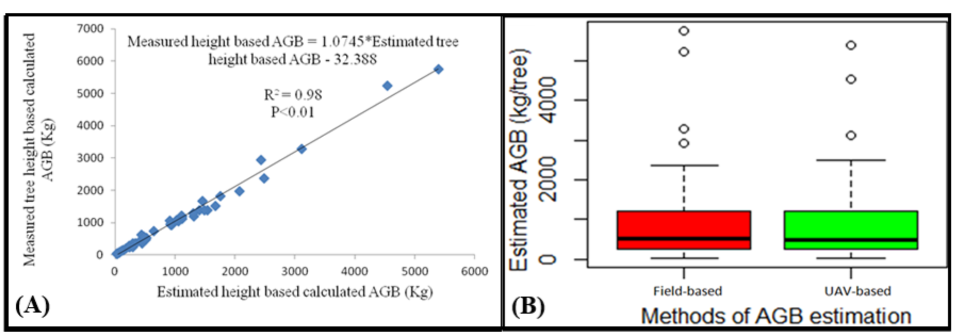

Figure 6. A) scatter plot of estimated and measured tree height based calculated AGB; B) Box plot of field-based and UAV-based AGB.

The equation in the scatter plot of figure 6A indicates the possibility of AGB estimation from estimated tree height based AGB in the study area as well as similar sites. The box plot of the AGB based on tree height extracted from photogrammetric UAV (UAV-based-AGB) and tree height measured in field (field-based-AGB) showed insignificant difference in their median as shown in figure 6B. The median of the two AGBs obtained less than 1, 000 Kg, and there were individual trees (outliers) which have greater than 5, 000 Kg. The RMSE of the AGB indicates that the AGB calculated based on tree height extracted from photogrammetric UAV aerial imagery deviated by 107.36 Kg (11.79%) from AGB calculated using field-measured tree heights. The difference between the mean of field-based and UAV-based AGB is less than the amount of AGB estimated from one big tree. The result indicates insignificant difference between field-based and UAV-based AGB. So, Tree height extracted from photogrammetric UAV image matching and tree height measured in the field has insignificant effect on AGB assessment. In addition to the paired t-test, the relationship between UAV-based and field-based AGB has strong correlation with a correlation coefficient of 99% (r=0.99) which indicates a strong positive relationship. So, it is promising modelling and Mapping field-based-AGB from UAV-based-AGB in the dry Afromontane Forest.

4. DISCUSSION

4.1. Measured and Estimated Tree Height Comparison

In this study, forest tree parameter was estimated using Photogrammetry and multiresolution image segmentation. The estimated tree variable was tree height, which plays a key role in AGB assessment. Different researchers applied different techniques to estimate forest tree variables (Lisein et al., 2013; Wallace et al., 2016; Birdal et al., 2017; Iizuka et al., 2017). Structure from motion method was used to produce the 3-dimensional model (3-D) of the forest tree structure from photogrammetric UAV aerial photos (Wallace et al., 2016; Alonzo et al., 2018). Similarly, Iizuka et al. (2017) estimated forest tree height from multi-rotor UAV aerial photos. In this study, the estimated tree heights range between 3.55 m to 15.68 m while the tree height estimated by Iizuka et al. (2017) ranges between 16 to 24 m. The difference between the ranges of estimated tree heights in these two studies was due to the difference in the nature of the forest environment. The method of tree height estimation was similar in both studies (DSM–DTM). The relationship between estimated and measured tree height achieved R^2 value of 0.98 as shown in figure 6A similar to the result revealed by Birdal et al. (2017); and Dandois and Ellis (2013). Similarly, Lim et al. (2015) applied photogrammetric UAV aerial image segmentation to estimate tree height. In this study, the possibility of tree height estimation was tested in dry Afromontane Forest while study by Lim et al. (2015) confirmed the success on both coniferous and deciduous coniferous trees. The method of tree height estimation was similar to the method used by Iizuka et al. (2017). However, the segmentation techniques were automatic in both studies, this study applied multiresolution orthophoto segmentation in e-Cognition while the study by Iizuka et al. (2017) used the SAGA (System for Automated Geo-scientific Analysis) GIS platform. Thus, this study demonstrated the opportunity of forest parameters estimation in the dry land Afromontane Forest of Ethiopia. The obtained results are similar to areas that applied UAV aerial imagery for forest variables measurement (Næsset, 2002; Magnusson et al., 2007; Tuominen et al., 2014).

The RMSE obtained between altitude from UAV aerial images, and DGPS was 0.37 m with R^2 value of 0.99. The result indicates the extracted UAV DTM deviated by 0.37 m from the ground truth. A similar study done by Jensen and Mathews (2016) that compared altitude derived from UAV aerial imagery and from GPS revealed R^2 value of 0.98. The R^2 value obtained in this study supports the result obtained by Jensen and Mathews (2016). Tree height extracted from UAV CHM and tree height measured on the ground compared by calculated RMSE. The tree height extracted from photogrammetric UAV deviated from tree height measured at field by 0.76 m (9.45%). Similarly, a study conducted by Panagiotidis et al. (2017) revealed 11.42 to 12.62 %RMSE inline to study by Saliu et al. (2020) that revealed 7.1 to 15% %RMSE between tree height measured on ground and extracted from photogrammetric UAV. In this paper estimated tree height obtained smaller than tree height measured on the ground in line with the result revealed by Batistoti et al. (2019); and Laurin et al. (2019).

A study by Dandois and Ellis (2013) achieved RMSE of 2.3 m between estimated and measured tree heights which is higher error compared to the result obtained in this study (RMSE = 0.76 m). The variation between the RMSE could be due to the difference in topographic characteristics (slope, forest density, etc.), flight height, point cloud density and time of data acquisition. The average point density of UAV point cloud data in this study was 162.874 points/square meters while Dandois and Ellis (2013) revealed a point density of 70 points/square meters. A study by Birdal et al. (2017) who compare tree height estimated from UAV-CHM and field-measured tree height in a sparse forest obtained RMSE of 28 cm. The result revealed by

Birdal et al. (2017) has better accuracy compared to the result obtained in this study (RMSE = 0.76 m). In a sparse forest, tree height measured in the field is comparable to tree height extracted from UAV-CHM since DTM interpolation in the forest is from a short distance nearby open space. In a sparse forest canopy, the photogrammetric UAV point cloud has better chance to reach the forest floor and acquire information for accurate DTM generation.

Moreover, better DTM accuracy plays a vital role to obtain a better tree height estimation by photogrammetric image processing. The more open space available inside the forest area shortened DTM interpolation distance and increased the accuracy of extracted tree heights (Lisein et al., 2013). In undulated topography increasing in canopy density increases the effect on DTM accuracy. In this study, the possible reason for estimated and measured tree heights variation is due to the soil and water conservation structures available inside the forest, the uncertainties of tree height measurement on the ground as well as photogrammetric image processing.

4.2. Measured Tree Height-based and Estimated Tree Height-based AGB Comparison

The measured tree height-based AGB obtained more significant than the estimated tree height-based AGB. The difference between the two results is due to the tree height variation. The uncertainty on measurement of tree height affects AGB up to10% (Laurin et al., 2019). Most of the tree heights estimated from photogrammetric UAV imagery obtained short compared to the tree height measured in the field. Tree height measurement by ground techniques lead to overestimation (Laurin et al., 2019).

In this study, the tree variables (specific wood density and DBH) that used as input to the allometric equation were similar in both AGB estimation methods except the tree height. The obtained %RMSE (11.79 %) indicated estimated tree height-based AGB deviated from the measured tree height-based AGB. The measured tree height-based AGB is higher than the estimated tree height-based AGB similar to the result revealed by Batistoti et al. (2019); and Laurin et al. (2019). So, the deviation could be adjusted by the relationship between UAV-based-AGB and field-based-AGB. AGB calculated based on tree height from photogrammetric UAV imagery and tree height measured on ground in a dense tropical forest revealed 360.8Mg/ha and 378.0Mg/ha, respectively (Laurin et al., 2019).

The difference between UAV-based-AGB and field-based-AGB in the dense forest was 17.2 Mg/ha while in this paper obtained 8.15Mg/ha. Although tree height measurement by different techniques lead to variation in the amount of estimated AGB, this study obtained insignificant difference between UAV-based and field-based AGB since simple forest has small effect to tree height measurement on the ground.

The biomass computed using heights measured on ground obtained 11.79 % higher than estimated height based AGB similar to the result revealed by Laurin, et al. (2019) (6.5%). The 5% variation could be due to the uncertainty of height measurement on ground and photogrammetric image processing in a simple and a dense tropical forest. As the %RMSE (9.45%) between measured and estimated tree heights resulted insignificant in the calculated AGB in this study. Similarly, %RMSE revealed by Panagiotidis et al. (2017); Krause et al. (2019); and Saliu et al. (2020) also resulted insignificant when estimated AGB using similar allometric equation.

In this study, the scatter plot of measured tree height-based and estimated tree height-based AGB has R^2 value of 0.98 as shown in figure 6A. The obtained result is comparable to the result obtained by Muti (2017) who has been applied DBH from Terrestrial Laser Scanner, tree height from UAV, DBH measured at field and tree height extracted from LiDAR. Because the study by Muti (2017) was conducted in the tropical rain forest with different vertical canopy strictures (upper and lower) while this study was conducted in a relatively sparse dry land Afromontane Forest. The obtained correlation coefficients between the estimated and measured AGBs of both studies were also similar (r = 0.99) which indicates estimated and calculated AGB has a close relationship.

The tree heights measurement using LiDAR data in the tropical rain forest is to minimize occlusion during tree height measurement using handheld equipment. On the other hand, the result of this study indicates a better relationship than the result obtained by Ediriweera et al. (2014) which was conducted in subtropical eucalyptus forest using airborne and multi-spectral data. The possible reason for the lower relationship (R^2 = 0.81) obtained by Ediriweera et al. (2014) might be due to the difference in methods of tree variables estimation and modelling. The result of this study also indicates a better relationship than the result obtained by Karna et al. (2015) for the reforested tropical forest plots (R^2 =78-94%) using a combination of Worldview-2 high-resolution satellite image and airborne LiDAR. The difference could be due to the use of the same height, but different DBH values to estimate both the modelled and field-based AGB while this study, used field DBH for measured tree height-based and estimated tree height-based AGB calculation.

In this study, the similar input (DBH) in both the UAV-based-AGB and field-based-AGB calculation leads to a strong relationship between UAV-based-AGB and field-based-AGB since the contribution of DBH for biomass estimation is very high (Brown, 2002). Similarly, study by Lawas (2020) revealed a similar result in the tropical rainforest through the integration of airborne LiDAR and Terrestrial Laser Scanner. The result of the paired t-test indicated insignificant difference between measured and estimated tree height based AGBs. The reason for the negligible difference between the two means could be due to the generic allometric equation which used similar tree variables (specific wood density and DBH). Therefore, the difference between tree height measured at field and tree height extracted from photogrammetric UAV imagery have not significant effect on AGB estimation using generic allometric equation in a simple dry Afromontane forest.

5. CONCLUSION

This study has investigated forest tree height estimation and AGB computation using UAV acquired aerial image through digital Photogrammetry and multiresolution image segmentation. The estimated and examined forest tree heights were used as input to compute forest AGB. A general allometric equation was used to estimate AGB. The forest tree heights extracted using Photogrammetry and measured in the field show strong linear relationship. But the relationship needs replication to be valid in similar study areas. This means, photogrammetric technique is an alternative to the costly and routine field survey. In addition, vast and inaccessible areas can be evaluated using photogrammetric UAV aerial imagery. Furthermore, with this approach change in AGB detection could be simplified using estimated tree height. This has a very big implication for development since the recent focus on carbon stocks globally is getting serious attention. It is possible to obtain reasonable AGB by integrating small field survey with photogrammetric UAV aerial imagery.

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7. CONFLICTS OF INTEREST

Authors of this paper declare no conflict of interest.

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