Can iPhone/iPad LiDAR data improve canopy height model derived from UAV?

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Abstract. Aerial images resulting from unmanned aerial vehicle (UAV) are widely used to estimate tree height. The filtering method is required to distinguish between ground and off-ground point clouds to generate a canopy height model. However, the filtering method is not always perfect since UAV data cannot penetrate canopies into the forest floor. The release of iPhone/iPad devices with built-in LiDAR sensors enables the more affordable use of LiDAR for forestry study, including the measurement of local topography below forest stands. This study investigates to what extent iPhone/iPad LiDAR can improve the accuracy of canopy height model from the UAV. The integration of UAV and iPhone/iPad LiDAR data managed to increase the accuracy of tree height model with a mean absolute error (MAE) of 2.188 m, compared to UAV data (MAE = 2.446 m). This preliminary study showed the potential of combining UAV and iPhone/iPad LiDAR data for estimating tree height.

1 Introduction

Three-dimensional arrangement of individual trees within a forest has a significant impact on ecosystem functions as well as nutrients, water, and carbon cycles [1]. Tree height has been widely used to describe tree volume, biomass, and carbon stock, which are important for forest management [2,3].

Traditionally, tree height is measured using tangent method by means of survey tools that can quantity angles, such as clinometer [4]. The more recent terrestrial method employs laser rangefinders to directly measure tree height using laser technology [5]. However, this conventional approach takes intensive labour and time and is limited when implemented in dense and tall canopy forests [4,6,7].

The use of photogrammetry technique from aerial photos taken by unmanned aerial vehicles (UAVs) to calculate tree height has been commonly used these years [8,9]. UAV image captured the height of surface; thus, to obtain information on tree height commonly called canopy height model, the terrain conditions need to be eliminated using filtering method [10,11]. Despite filtering method implemented, in some cases, an inaccurate canopy height model may occur since aerial image cannot penetrate canopies.

Light detection and ranging (LiDAR) sensor has the ability to penetrate the gaps within tree crowns and capture the middle part of stands and even the forest floor [12,13]. Nonetheless, the use of LiDAR technology is costly in current. Alternatively, a low-cost Hand-held Laser Scanning (HLS) has been introduced by Apple in 2020 by releasing iPhone and iPad products with a built-in LiDAR sensor [14]. Although the measurement range is far below traditional LiDAR sensor (maximum distance of 5 m), iPhone/iPad LiDAR can precisely measure objects [15]. This device has been explored for forest inventory and reported to provide reliable information comparable to terrestrial and mobile laser scanner [16,17].

As iPhone/iPad LiDAR scans objects on the ground, it offers an opportunity to be integrated with UAV-based surface model to generate canopy height mode (CHM). Thus, this present study investigates the feasibility of apple lidar to improve CHM generated by UAV.

2 Methodology

2.1 Study area

Our study area is located in Wanagama I Education Forest or simply called Wanagama Forest. Wanagama Forest is situated in Yogyakarta, Indonesia with a total area of 622.25 ha. This study focused on the teak stands (*Tectona grandis*) in Plot 13 of Wanagama Forest with an extent between 110.5286°–110.5334° E and 7.8968°–7.9066° S or 448041–448565 mE and 9127080–9125999 mN (UTM Zone 49M) (Figure 1). The teak stands comprise two different types, i.e., Mega-clone type and conventional type. The Mega teak stands were planted in 2004 with a planting distance of 6 × 2 m [18]. Compared to conventional teak, Mega teak has superior growth characteristics in diameter, height, and stem alignment [19].

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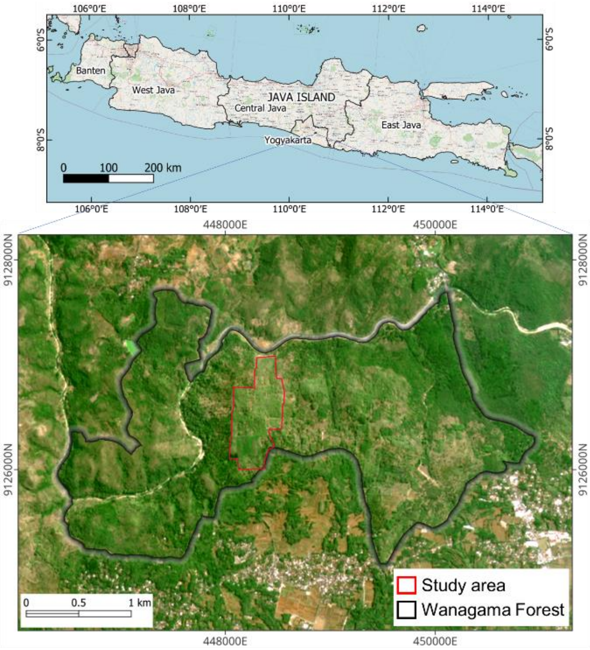

Fig. 1. Study area located in Wanagama I Education Forest, Yogyakarta, Indonesia.

2.2 Materials and methods

This study compared tree height estimates derived from UAV and the integration between UAV and LiDAR data. The flowchart is illustrated in Figure 2, while the detailed methods are provided in the following sub-sections.

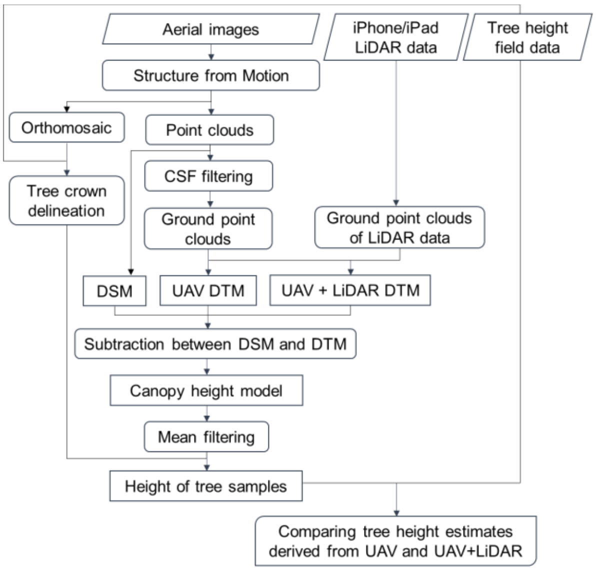

Fig. 2. Flowchart of the present study.

2.2.1 Aerial images

Aerial images were taken by deploying three quadcopter drones simultaneously to minimise the time difference in capturing the study area. We used DJI Mavic 2 Pro with an autopilot according to the planned flight paths programmed on DroneDeploy. The flight height was 150 m from the ground at the base station, while the overlap and sidelap were set to 80%. The aerial images were processed in Agisoft Metashape using Structure from Motion (SfM) algorithm to generate georeferenced orthomosaic and 3D data in the form of point clouds [20]. The resulted orthomosaic has a spatial resolution of 4 cm (Figure 3a).

2.2.2 iPhone/iPad LiDAR data

The Apple products equipped by a LiDAR sensor are iPhone 12 Pro, iPad Pro 2020, and the latest Pro version of those models. This study utilised iPhone and iPad mobile devices to record the point clouds of the ground surface using the LiDAR sensor operated with ForestScanner application [15].

The iPhone/iPad LiDAR scanning system was operated by holding the devices at the breast height (±1.3 m) while walking along the transects. The transects were designed to with a minimum distance of 40 m and considers the variability of topography. There were 11 transects within the teak plantation areas (Figure 3b).

2.2.3 Canopy height model

The point clouds generated from SfM processing contain X and Y coordinates, and Z value which represents a relative height to the ground of all surface objects. A filtering method was implemented to distinguish off-ground from ground objects. We used a cloth simulation filtering (CSF) approach by inverting the Z plane before a simulated cloth drops the surface to cover the inverted surface then performing a re-inversion [21].

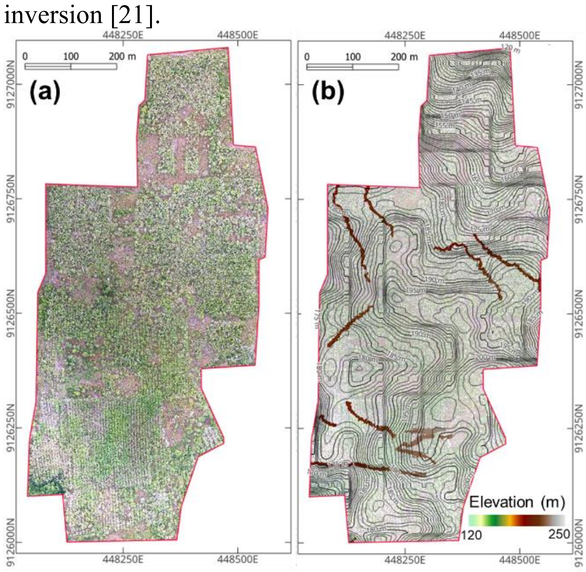

Fig. 3. (a) Aerial images captured from UAV and (b) visualization of filtered LiDAR point clouds measured showing the elevation of the terrain condition captured by iPhone/iPad.

The point cloud processing was conducted in CloudCompare software. CSF algorithm was applied on UAV point clouds with user-defined parameters. Cloth resolution, maximum iteration, and classification threshold were set to 1.2, 500, and 0.5, respectively, and a slope factor was set to “Relief” terrain condition. Subsequently, point cloud noise elimination was performed. CSF method was also implemented for the iPhone/iPad LiDAR data to eliminate tree stems and other non-surface objects which were recorded during the scanning. The parameters selected to filter iPhone/iPad LiDAR data are cloth resolution = 0.8, maximum iteration = 500, and classification threshold = 0.5.

Using the Rasterize tool in CloudCompare, the off-ground UAV point clouds were transformed into digital surface model (DSM) with a resolution of 4 cm. Similarly, the ground UAV point clouds were rasterized to produce digital terrain model (DTM). We also combined the ground UAV point clouds with filtered iPhone/iPad LiDAR data to generate DTM. Canopy height models (CHMs) were generated by a subtraction between DSM and DTMs with and without the integration with LiDAR data. A mean filtering was applied to the CHMs using a 3 × 3 window to minimise the extremely different values.

2.2.4 Tree height data

The ground truth data of tree height were measured using Nikon Forestry Pro II laser rangefinder with 2-points measurement mode. The tree height here refers to Larjavaara and Muller-Landau [4], who defined it as the vertical distance between the topmost of the tree (either living or dead part) and the base of the tree. We measured the tree height within approximately 20 × 20 m plots with a total of 6 sample plots. The measured tree locations were recorded using the iPhone/iPad LiDAR devices.

The tree height data were derived from the CHMs by calculating the maximum height value within the crown of the corresponding trees. The tree crowns were delineated visually from the orthomosaic. In total, there are 148 tree height data for the analysis (Figure 4).

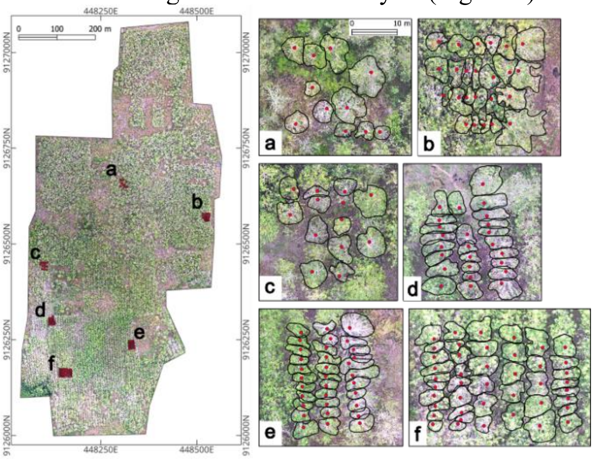

Fig. 4. Orthomosaic of the teak plantation area and the distribution of tree height samples collected in the field.

2.2.5 Data analysis

One-way analysis of variance (ANOVA) ($\alpha = 0.05$) was carried out to test the significant differences of tree height and CHMs generated from UAV and UAV + iPhone/iPad. In addition, Pearson's correlation analysis was conducted between tree height data and both CHMs, separately. Further, a linear regression analysis was performed with the ground truth data as the independent variable. We randomly divided the tree height data into two groups, i.e., training (104 samples) and validation (44 samples). The accuracy assessment was conducted by calculating the mean absolute error (MAE).

3 Results and discussion

CSF algorithm was intended to separate between the ground and off-ground surface of the point clouds generated from UAV data. The point clouds containing off-ground surface were used to produce digital surface model as shown in Figure 5a. The digital terrain models were derived from the UAV point clouds only and the combination of UAV point clouds and iPhone/iPad LiDAR. As depicted in Figure 5, visually, there are no significant differences between both resulted DTMs. While the profiles plotted as shown in Figure 6, the discrepancy is quite clear, where local terrain conditions below the teak stands varied as shown by the DTM from UAV + iPhone/iPad LiDAR. It can be seen that DTM derived from UAV + iPhone/iPad is smoother following the local topography compared to DTM from UAV that interpolated area between ground points indicated by the plain terrain as shown in Profile A. However, some errors were also recorded using iPhone/iPad, showing the rough topography and extreme slopes. This might be due to an imperfect filtering method in excluding the off-ground points.

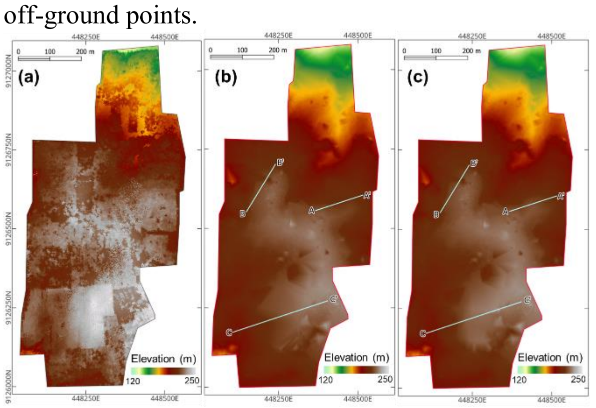

Fig. 5. Rasterization results of point clouds: (a) digital surface model, (b) digital terrain model derived from UAV, and (c) digital terrain model derived from the combination of UAV and iPhone/iPad LiDAR.

Canopy height models (CHMs) were generated from the subtraction results between DTMs and DSM, thus resulting in CHM from UAV and CHM from UAV + iPhone/iPad (Figure 7). At a glance, the UAV CHM shows higher values than UAV + iPhone/iPad CHM, particularly in the southern part of the study area.

The ANOVA test showed a significant difference between three populations (tree height, CHM from UAV, and CHM from UAV + iPhone/iPad) with a *p*-value smaller than 0.001. We plotted scatterplots to see the relationship between CHMs and tree height data. Figure 8 shows that both CHMs are overestimated, particularly for CHMs' values of more than 15 m. The MAE values are 5.24 and 4.05 m, while the correlation values are 0.542 and 0.601 for UAV and UAV + iPhone/iPad CHMs, respectively.

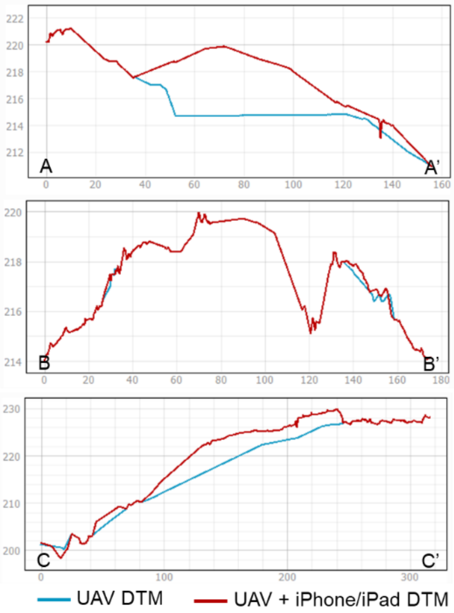

Fig. 6. Profiles showing the differences between DTMs from UAV and UAV + iPhone/iPad.

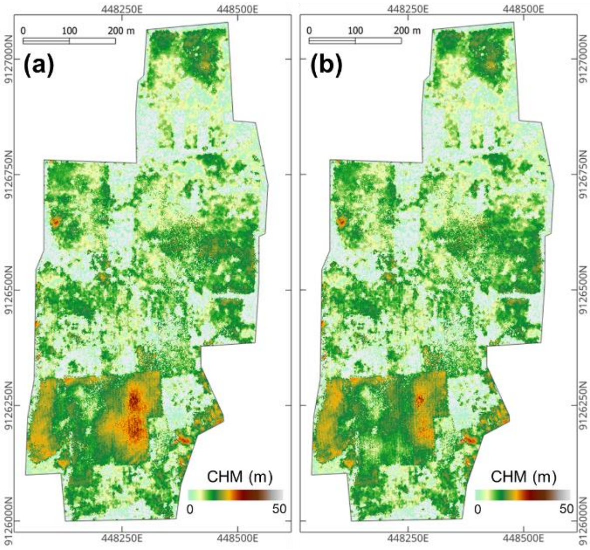

Fig. 7. Canopy height models derived from (a) UAV and (b) UAV + iPhone/iPad combined.

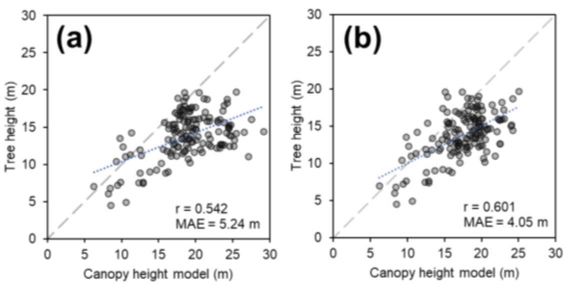

Fig. 8. Scatterplots between tree height and CHMs derived from (a) UAV and (b) UAV + iPhone/iPad.

This study extracted the maximum value of the CHMs within the corresponding tree crowns [9]. From above, UAV can capture the condition of the object's surface so that the maximum height can be easily detected. In contrast, the field measurement using laser rangefinders can lead to erroneous since the topmost of the tree might be obscured by the leaves and branches, especially in the dense coverage as reported by Larjavaara and Muller-Landau [4].

As the correlation values are significant (p-values < 0.05), we modelled the tree height based on the CHMs to correct the overestimation. The total samples are 148, of which 104 samples are for constructing linear regression model. The linear regression plots are illustrated in Figure 9. As observed, the coefficients of determination (R^2) are 0.3082 for UAV only and 0.3761 for UAV + iPhone/iPad CHMs.

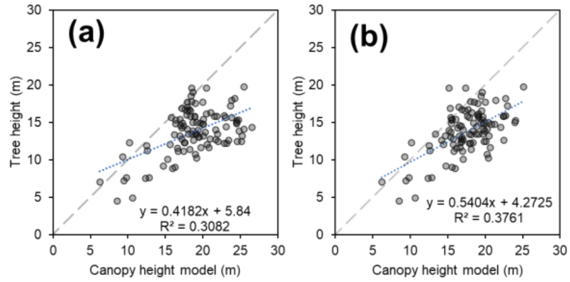

Fig. 9. Linear regression plots between tree height (y-axis) and CHMs (x-axis) derived from (a) UAV and (b) UAV + iPhone/iPad.

The regression equations were then applied to CHMs to produce tree height models from UAV and UAV + iPhone/iPad (Figure 10). Subsequently, we assessed the accuracy using the validation samples. Using the MAE metric, we found that the tree height estimated using the UAV + iPhone/iPad managed to produce a slightly higher accuracy (MAE = 2.188 m) compared to UAV only (MAE = 2.446 m). This improved accuracy is observed due to the local topography correction as the terrain conditions below teak stands were measured by iPhone/iPad.

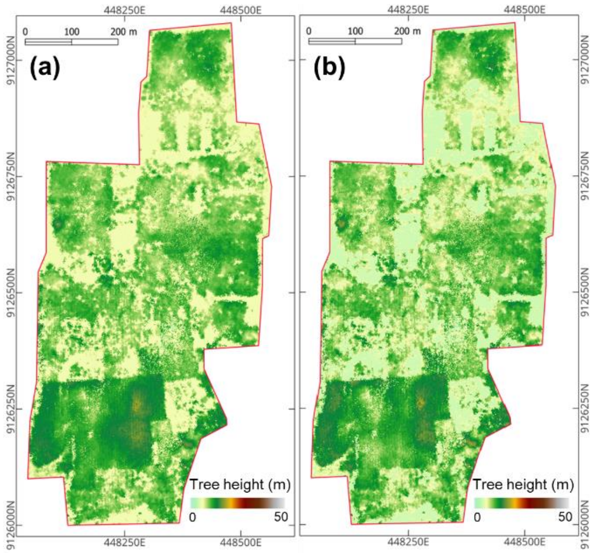

Fig. 10. Tree height modelled from canopy height models derived from (a) UAV and (b) UAV + iPhone/iPad combined.

Although the accuracy increased by 0.258 m, this preliminary study shows the potential of iPhone/iPad LiDAR to be integrated with UAV to generate a more accurate a tree height model. The slight increase is also due to the sparse iPhone/iPad LiDAR measurement transects. Future studies should consider denser and more systematic transects to cover the high variability of local topography.

4 Conclusion

This study demonstrates LiDAR data measured using the advanced iPhone/iPad devices to be integrated with UAV data to generate canopy height model (CHM). CHMs resulting from UAV and UAV + iPhone/iPad show overestimation compared to field data. Linear regression analysis was used to model tree height from CHMs. We found that the combination of UAV and iPhone/iPad can improve the accuracy of the tree height model, showing an MAE of 2.188 m, compared to the UAV-only result (MAE = 2.446 m).

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