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RESEARCH ARTICLE

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Accuracy of LiDAR-based tree height estimation and crown recognition in a subtropical evergreen broad-leaved forest in Okinawa, Japan

Azita Ahmad Zawawi[1, 3, *], Masami Shiba[2] and Noor Janatun Naim Jemali[1]

[1] The United Graduate School of Agricultural Sciences Kagoshima University, 1-21-24, Korimoto, Kagoshima, 890-0065, Japan. [2] Faculty of Agriculture, University of the Ryukyus, Senbaru-1, Nishihara-cho, Okinawa 903-0213, Japan [3] Faculty of Forestry, Universiti Putra Malaysia, 43400, Serdang, Selangor, Malaysia

Abstract

Aim of study: To present an approach for estimating tree heights, stand density and crown patches using LiDAR data in a subtropical broad-leaved forest.

Area of study: The study was conducted within the Yambaru subtropical evergreen broad-leaved forest, Okinawa main island, Japan.

Materials and methods: A digital canopy height model (CHM) was extracted from the LiDAR data for tree height estimation and a watershed segmentation method was applied for the individual crown delineation. Dominant tree canopy layers were estimated using multi-scale filtering and local maxima detection. The LiDAR estimation results were then compared to the ground inventory data and a high resolution orthophoto image for accuracy assessment.

Main results: A Wilcoxon matched pair test suggests that LiDAR data is highly capable of estimating tree height in a subtropical forest ($z = 4.0$, $p = 0.345$), but has limitation to detect small understory trees and a single tree delineation. The results show that there is a statistically significant different type of crown detection from LiDAR data over forest inventory ($z = 0$, $p = 0.043$). We also found that LiDAR computation results underestimated the stand density and overestimated the crown size.

Research highlights: Most studies involving crown detection and tree height estimation have focused on the analysis of plantations, boreal forests and temperate forests, and less was conducted on tropical and/or subtropical forests. Our study tested the capability of LiDAR as an effective application for analyzing a highly dense forest.

Key words: Broad-leaved; inventory; LiDAR; subtropical; tree height.

Abbreviations: DBH: Diameter at Breast Height, CHM: Canopy Height Model, DEM: Digital Elevation Model, DSM: Digital Surface Model, LiDAR: Light Detection and Ranging, YFA: Yambaru Forest Area.

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Correspondence should be addressed to Azita Ahmad Zawawi: azitazawawi@gmail.com

Introduction

Quantitative forest information, such as tree counts, diameter at breast height (DBH), tree heights, crown diameter and biomass are critical for effective forest management. Field measurements and remote sensing represent two primary ways to assess forest inventories. However, the traditional method of field measurements involved a labor-intensive forest inventory, required supplementary work, and was more time-consuming and more applicable to a small area (Avery & Bukhart, 1994; Shivers & Borders, 1996). Therefore, new technologies such as remote sensing and satellite imagery have been introduced and provide an observation for large areas through the application of different types of high resolution sensors, including the most recently used LiDAR (Light Detection and Ranging).

The application of LiDAR in forestry began in the 1980s and the technology keeps on improving throughout the years. Most recently, many GIS softwares have incorporated special analysis tools for LiDAR data processing. New algorithms and important methodological procedures were developed for use with LiDAR from 1999 to 2004 (Tiede *et al*., 2005). Among the pioneers were Aldred & Bonner (1985), who discovered its great potential in assessing various forest characteristics. One of the significant contributions of LiDAR is the ability to extract single tree level information using its high density laser data (Kwak *et al*., 2007). Airborne LiDAR developed to where it can provide good images of vertical profiles of vegetation and bare earth to derive higher precision information and is highly capable when it comes to a wide variety of uses such as topographic mapping, forest height surveying (Koch *et al*., 2006) and modeling stand biomass (González-Ferreiro *et al*., 2013a). Along with the advancement of LiDAR, a variety of algorithms, which allow for the detection of individual trees have been introduced. Popular approaches are local maxima filtering (Wulder *et al*., 2000), image segmentation (Zhao & Popescu, 2007), and marker- control, template matching (Larsen & Rudemo, 1998). To date, González-Ferreiro *et al*., (2013b) in his recent study, has introduced a series of mixed pixel and region based algorithms to locate individual tree positions and height estimations.

The accuracy of tree height and stand density estimations through LiDAR are very important for determining the subsequent analysis of the forest stand such as volume, basal area and biomass. The success of this kind of application will efficiently benefit forest managers in terms of reducing labor time, completing data processing that is not weather dependent and in enacting procedures that are cost effective for long-term monitoring. However, most studies involving crown detection, tree height estimation and high resolution imagery have focused on the analysis of plantations, boreal, and temperate forests. Less study was conducted on tropical forests (Asner *et al*., 2002; Falkowski *et al*., 2006). Several researchers experimented and determined that the accuracy of each developed algorithm depends on its forest structure and stand composition (Stereńczak, 2013). Potential algorithms that are able to improve tree detection and measurements in structurally complex forests such as a subtropical forest would be very beneficial when obtaining forest inventories in those areas.

The main objective of this study is to present a potential approach for estimating tree heights, stand density and crown patch characteristics using LiDAR data in a subtropical broad-leaved forest. A method combining multi-scale filtering and local maxima detection was adapted. The assessment was conducted on up to five sets of CHM derived from LiDAR data captured over the Yambaru subtropical broad-leaved forest. The LiDAR based results were then compared to ground inventory data over the same locations, as well as to segmentation results from the orthophoto image. The accuracy of LiDAR estimation was examined and limiting factors in achieving desirable results were critically discussed. The outcome of this study contributed to a critical and interesting discussion in evaluating the accuracy and capability of LiDAR for various forest types.

Material and methods

Study area

The study was conducted in Compartment 79 within Yona Experimental University Forest, Yambaru Forest Area (YFA), Kunigami village, Okinawa main island, Japan (Fig. 1). The total area of Compartment 79 is 108.6 ha. This area is characterized by a subtropical climate, a highly diversified georelief, and extremely rich in species. The mean annual temperature and amount of rainfall are 22.3°C and 2,827 mm, respectively. Precipitation ranges from 1,900 to 4,000 mm/year with a mean value of 2,745 mm. During the summer season, the subtropical forest receives frequent typhoons and monsoon strength winds. The bedrock is mostly composed of Tertiary sandstone and a red yellow forest soil. YFA is dominated by a secondary forest of subtropical evergreen broadleaf trees, especially *Castanopsis sieboldii,* which almost extends to the coastlines. The forested area has been harvested for fuel wood, especially for charcoal production during World War II, while the lower slope is mostly converted into pine and orange plantations (Yamamori, 1979; Xu *et al*., 2008).

Forest characterization

The forested area on the island is characterized by short-bold trees and larger trees having spreading crowns, forming a close canopy of rounded crowns (Shinohara

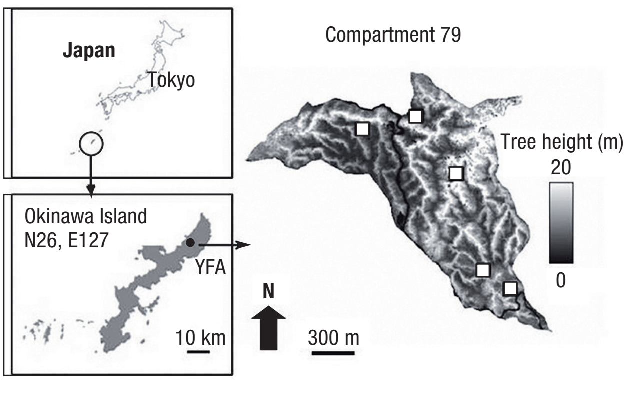


Figure 1. The map shows 5 experimental plots established within Compartment 79 (represented by the tree height map) in YFA.

et al., 1996). Fig.2 shows the distribution of tree species recorded in the study site. The forests are rich in species where 45 species were found within the study site. Based on our field inventory, the mean number of species per plot was 20. The graph highlights the dominant species, which are *Castanopsis sieboldii* and *Daphniphyllum glaucescens*. Table 1 presents stand characteristics of each experimental plot. Generally, the mean canopy height for the five selected plots was 6.9±2.5 m, with a minimum of 3.3 m and a maximum of 20.3 m. Plot 3 recorded the highest value of stand basal area (49.0 m^2ha^{-1}) while Plot 1 recorded the lowest value (21.5 m^2ha^{-1}). The highest number of species was recorded in Plot 5 (30 species), while the lowest number of species was recorded with only 15 species in Plots 1 and 2.

LiDAR data specifications

LiDAR data was recorded on April 2011 using ALTM 3100 (CASI-3). The laser wavelength was 1,064 nm with a scan frequency, pulse repetition frequency, and scan angle of 39 Hz, 70 kHz and ±20°, respectively. The flight altitude was 1,100 m with a beam width of 0.26 mrad. The laser footprint size was about 0.25 to 0.30 m. XY accuracy was 55 cm and elevation accuracy was 15 cm. The LiDAR system recorded up to four echoes per pulse; first return, last return, and two in between. Fig. 3 presents a cross section of some LiDAR point cloud data showing the first return and the last return provided by the data vendor.

Field data and vegetation survey

In this study, five sample plots with individual plots sized 20 x 20 m were randomly selected as representative of the forest area. The criteria for field plot selections were their scattered location, minimum topographical heterogeneity and accessibility. Each selected plot represents the existing range of tree density, high canopy closure, and mixed-species in the

Table 1. Descriptive statistics of DBH range, height range, stand basal area, tree density and number of species in each plot.

Plot/ Variable	DBH (cm)	Height (m)	Stand basal area (m^2ha^{-1})	Density (stems ha^{-1})	No. of spp
1	7.6±5.4	5.7±1.4	21.5	179	15
2	8.8±5.0	6.1±1.3	33.2	205	15
3	15.7±13.4	10.8±4.2	49.4	73	24
4	9.6±5.6	6.8±1.5	33.3	196	22
5	9.3±5.7	7.9±2.1	34.4	161	30

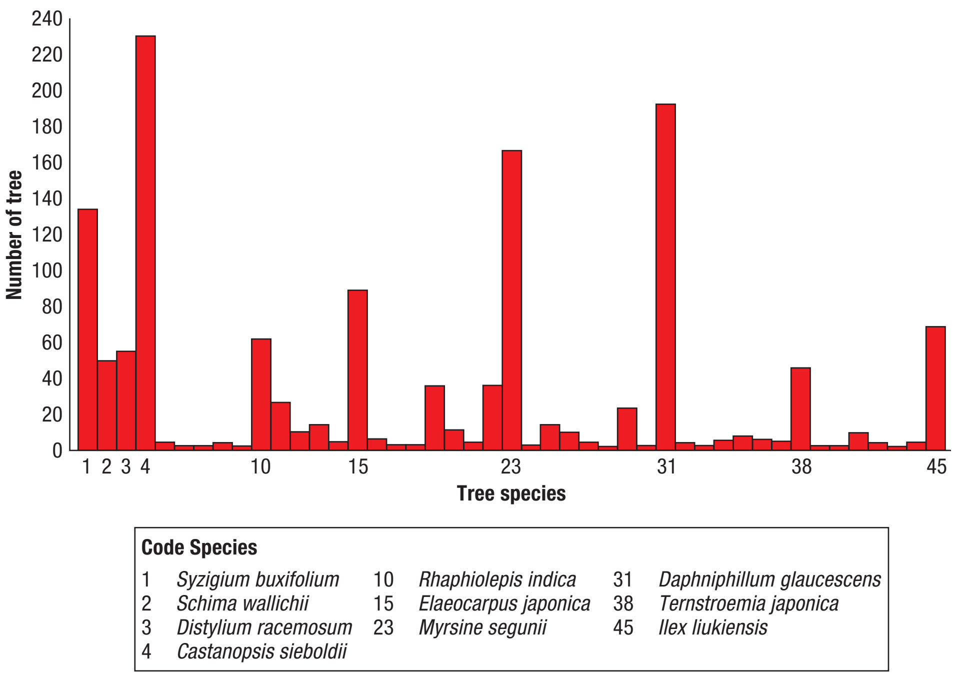


Figure 2. Distribution of tree species recorded in the study site based on stem density.

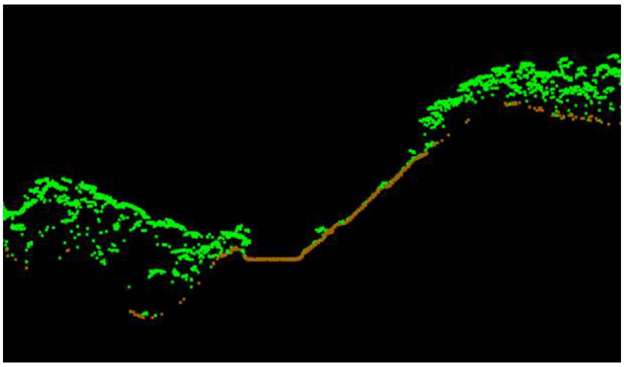


Figure 3. Cross section of LiDAR point cloud data showing three tops (green points) and the ground surface (yellow points).

forested watershed. A small number of plots were selected and correspond to a limited degree of accessibility for ground truth surveys due to topographical characteristics, weather conditions, and labor constraints. All trees with diameters at breast height (DBH) larger than 3.0 cm were recorded and tree species were identified. Tree height was measured for selected trees using a 12 m pole with a scale. In this study, we did not compare locations of individual trees in the field and detected trees in the imaged data (on a tree by tree basis). Individual tree positioning is complicated due to errors influenced by topography and multi-canopy layers as well as insufficient visibility of GPS satellites. Read *et al*., (2003) and Palace *et al*., (2007) also faced similar limitations in their studies of tropical forests. Therefore, a comparison of LiDAR estimations to the referenced data was done on a stand basis (plot by plot). Measurements of the corner points for each experimental plot were taken manually. A Garmin GPS model Oregon 550 with coordinate reference WGS 84 Zone 52N was used for this task.

Orthophoto image

An orthophoto image was used as reference data for stand density and crown assessment. The image was acquired in September 2011 using a Leica RC analoque camera (orthorectified, RGB natural colour, scale: 1/10,000, 25 cm resolution, focal length 153,265 mm, and photography altitude at 1,500 m). However, the optical remote sensing data cannot be used to measure tree height. A watershed segmentation method was applied to all images and crown maps were produced. Data processing was done following similar procedures carried out by LiDAR. For additional information, diameter and fractal dimensions were calculated for each segmented polygon. The diameter was also computed by a determination of the maximum width of the patches and the fractal dimension was calculated following Mandelbrot (1982), where:

$$D = 2^* \text{ (log perimeter) / (log area)}$$

Image processing and data analysis

Fig.4 illustrates the workflow of tree detection and crown segmentation. The generation of CHM, including image filtering algorithms, tree detection procedures and crown segmentation were carried out following a module programmed within SAGA GIS software (Böhner *et al*., 2006). Crown assessment was conducted using Patch Analyst software within ArcGIS 9.3.(Elkie *et al*., 1999).

Height estimation and tree detection

CHM was calculated by subtracting the DTM from the DSM. The extracted CHM was then smoothed using Laplacian of a Gaussian (LoG) function. Gaussians filtering with varying parameters adaptive to height classes was applied following a procedure introduced by Koch *et al*. (2006) and Chen *et al*. (2006). In the Gaussian function, a standard deviation was set at 0.2 with a variance of 0.07. The smoothed image was again re-filtered using the Laplacian function at a standard deviation and radius of 0.4 and 1, respectively. For both Gaussian and Laplacian functions, the standard deviation and radius were determined based on a pre-test assessment of a multi-scale prior to the analysis. The filtering process is important in the edge detection to reduce local height variations and higher frequencies. The delineation process works by detecting the local maxima on the filtered image, from which regions are

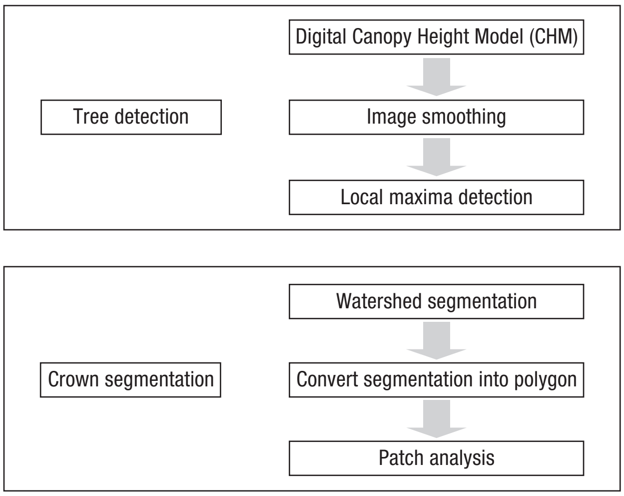


Figure 4. Workflow of tree detection and crown segmentation.

extended until neighboring pixels with similar or lower height values can be seen.

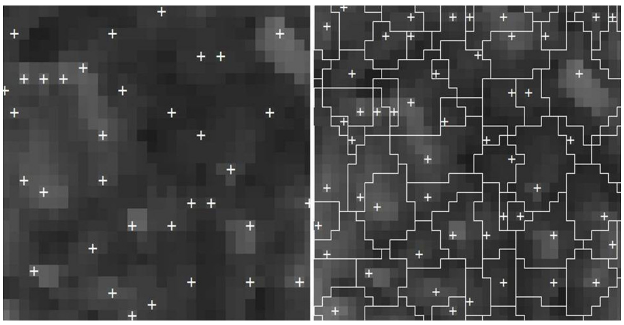
Fig.5(a) shows the grayscale image of the filtered CHM marked by local maxima seeds which are identified as tree tops. The height values for each detected tree top and the mean values for each sample plots were then obtained.

Crown delineation using watershed segmentation approach

The next step was applying the watershed segmentation module to the CHM by following an approach introduced by Gougeon (1995). It uses the assumption of an existence of dark pixels between tree crowns. Bright pixels represent high altitude areas (peak) while dark pixels represent valleys or low altitude areas (Erikson, 2004). In this method, watershed segmentation defines the process of separation of the detected object in the image from its background. The segmentation result was then converted into polygon shapes for crown patch assessments (Fig.5(b)).

Accuracy assessment

Two sources of reference data were used for accuracy assessments and include field measurement data and high resolution orthophoto images. For stand density and individual tree detection, the LiDAR-based result was compared to the ground inventory data. For crown assessments, the delineated crown patches produced from the LiDAR computation was compared to a similar output produced from an orthophoto image at 0.25 m of resolution. Height estimation and extracted crowns were compared from both data sets to determine the percentage of agreement. A comparison of the results was completed using a nonparametric Wilcoxon matched pairs test ($\alpha < 0.05$).



(a) (b)

Figure 5. (a) Grayscale image of the filtered CHM marked by local maxima seeds identified as tree tops (b) Segmented image interpreted as tree crowns derived from the watershed segmentation method.

Results

Height estimation and crown recognition

Table 2 shows mean values and standard deviations of tree heights estimated by LiDAR and the field inventory at each plot level. Plot 3, which is characterized by a higher slope value recorded the highest mean value of tree height in both field inventory and LiDAR estimations. For both datasets, Plot 1 had the lowest estimated mean value of tree height with 5.5±1.5 m for LiDAR and 5.7±1.4 m for the field inventory, respectively.

A comparison of crown density estimated by LiDAR and the orthopohoto image is presented in Table 3. We assumed that each individual crown detected represents individual trees in the plot. We also observed that slope values provide a huge influence to the rate of accuracy where Plot 3 which is characterized with a higher value of

Table 2. The mean values and standard deviation of slope conditions and a comparison of tree height estimated by LiDAR and measured by the field inventory on a plot by plot basis.

Plot/ Model	Slope	LiDAR	Inventory
1	6.7±4.4	5.5±1.5	5.7±1.4
2	8.0±3.5	6.0±1.3	6.1±1.3
3	37.8±15.8	18.2±2.9	10.8±4.2
4	6.9±4.1	6.9±1.1	6.8±1.5
5	22.9±4.8	9.7±1.8	7.9±2.1

Table 3. The accuracy of crown density estimated by LiDAR and orthophoto.

Plot	Tree inventory	LiDAR	Accuracy(%)	Orthophoto	Accuracy (%)
1	179	46	25.7	151	84.0
2	205	44	21.9	153	74.6
3	73	41	56.2	66	89.2
4	196	47	23.9	146	74.5
5	161	45	27.9	151	93.0

N = Number of trees.

a mean slope shows a higher amount of accuracy of individual tree detection for both LiDAR and orthophoto images with accuracy values of 56.2 and 89.2%, respectively.

The segmentation maps for both LiDAR and orthophoto images are presented in Fig.6.

A fractal analysis of the segmented crown of the orthophoto image suggests that the YFA is characterized by an irregular shape of crown patches with an average complexity of 1.4±0.1 and an average crown diameter of 6.08±2.5. The result that were obtained contribute to a critical discussion of the crown structure pattern of the forest stand.

Table 4 shows the Wilcoxon matched pairs t-test results and indicate that the differences of mean tree height from LiDAR data and the ground inventory were not statistically significant ($z = 4.0$, $p = 0.345$), which suggests that LiDAR estimation achieved a satisfactory level and is reliable for representing the mean tree height at plot level. For crown detection that represents stand density, the statistical test shows a very significant difference between the two groups ($z = 0$, $p = 0.043$).

Discussion

Height estimation and tree detection based on plot level assessments

The entire selected series of subsets represent a high canopy closure and multi-storey forest stand. Height estimations from both the field inventory and LiDAR computations were not statistically different. However, when observed individually at plot level, the mean value for LiDAR estimation in Plot 3 was observed to be higher than those presented by the inventory data. When examined thoroughly, Plot 3 is characterized with a high value of a mean slope and a lower tree density. Based on literature reviews, it is mentioned that topographical characteristics and site conditions do have a significant influence on the accuracy rate when estimating heights, where a bias might occur during a calculation due to steep slopes and terrain characteristics (Toutin, 2002; Liu *et al.,* 2007). A forested area that has a dynamic slope and a sharp relief are difficult to filter where LiDAR point outliers might cause errors to the returning pulses. These points have unusually high or low elevation values and must be eliminated during data preprocessing (Meng *et al.,* 2010; Wang *et al*., 2009). The selection of LiDAR first or last returns during ground filtering have also been debated. It is possible that some pulses from the first return may fall over the ground surface and an important proportion of the last return might fall above the canopy, or reach the lower part of other objects rather than the ground surface. Therefore, a pre-treatment procedure to both the raw data of DSM and DTM is appropriate in order to improve the assessment.

In this study, an accuracy assessment was conducted at plot level and an adequate comparison of individual trees was not present. A plot level assessment is popular for dense and close canopy forests and has been widely used by several researchers (Gougeon & Leckie, 1999; Wang *et al*., 2004). These methods, however, provide an insufficient amount of information on tree location accuracy and might result in a misleading report caused by commission and emission errors (Lamar *et al*., 2005). Some researchers discuss that this issue could be overcome by conducting a regression

Table 4. Wilcoxon matched pairs test.

Variables	T	Z	p-level
Tree height	4.0	0.943	0.345
Crown density	0	2.022	0.043*

*Marked tests are significant at $p < 0.05$

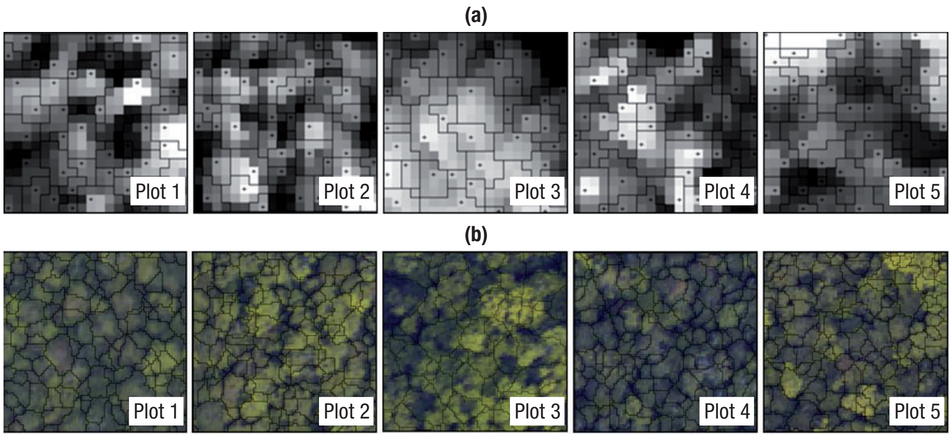


Figure 6. The experimental plots and tree crown segmentation maps of (a) CHM derived from LiDAR data at 1 m resolutions and (b) from orthophoto images at 0.25 m resolution.

analysis between the variables studied, but a more detailed field inventory of the forest stands are required in order to achieve the most desirable results (Holmgren *et al*., 2003; Popescu & Wynne, 2004: Vincent *et al*., 2012). Nevertheless, overall, the height estimation results presented in this study are encouraging, especially when considering that the study area is covered by mixed species and high stand densities. The results could suggest guidelines to forest managers for effective forest planning and management purposes.

Individual crown recognition

The tree crown has a significant role in tree productivity as it is an important part of the physiological process that contributes to forest growth and development. Higher trees usually have larger crown that are predefined by a height-crown equation (Popescu *et al*., 2003). In order to effectively evaluate the results, the numbers of tree crown segments generated by LiDAR were compared to outputs from orthophoto images, as well as to tree densities identified during the field survey. As shown in Table 3, the numbers of detected crowns by LiDAR shows an accuracy percentage of 21.9 to 56.2%. LiDAR computation shows a lower accuracy for the detection of individual trees, while segmentation by orthophoto imagery shows contrasting results with accuracy values more than 70% (Table 4). However, ground data was not recorded for crown diameters. Therefore, the orthophoto image was optimally computed to estimate the crown diameter using a patch analysis. The ability to effectively analyze crown assessment data is important for improving our understanding of the stand structure and for delineating the limiting factors when it comes to achieving a satisfactory level of accuracy. Our observations suggest that accuracy was affected by two factors: forest type and data resolution.

Factor 1: Type of forest

The Yambaru Forest Area consists of heterogeneous, multi-scale branches, dynamic crown widths and tree clusters, with a dense understory and highly diverse set of species. Low accuracy detection might be influenced by a distribution of small, thin branches within the canopy, which give rise to canopy returns. Very small tress with few laser returns are located next to bigger trees and are difficult to detect as single individuals even with multi-scale approaches (Brandtberg *et al*., 2002). Within a single crown, there may be multiple local maxima that result primarily from the irregularity of crowns or from random errors in the process of creating the raster data for CHM. Therefore, over segmentation or missed-segmentation can occur.

Falkowski *et al*., (2008) related that increasing tree canopy cover significantly decreased the accuracy of individual detection rates. Most algorithms performed well in forests with low canopy covers or in plantations that have a high accuracy of tree height measurements and crown diameter estimations. A review by Ke & Quackenbush (2011) stated that there is no research on canopy covers found in tropical forests due to the complexity of the stand structures. Many studies reported that the accuracy rate was higher on even-aged and homogenous stands (Gougeon & Leckie, 2006), where species have uniform heights and crown structures. In open forests with uniform stand ages and less overlapping trees, it is easier to detect all of the trees by their crown shapes and delineations. In a dense, mixed forest, with a tightly interlocked, homogenous canopy, it is difficult to separate two closely standing trees as the crowns are touching each other, as well as detecting young trees in regenerating forests. In this case, more than two crown areas that are connected are misinterpreted as one single tree and results in a smaller number of individual trees identified. This could be further explained by the fractal dimension value estimated in this study. The analysis shows that crown patches in the YFA is characterized by an average complexity of 1.4±0.1, where the highest value recorded was 1.9, which indicated a very complex irregular shape.

Korpela (2004) studied that in the case of a boreal forest, trees with relative heights are detectable in images but 0 ~ 12% of the total stem volumes and nearly all short trees remain unseen. A satisfactory level of accuracy is very hard to obtain, especially in a mixed forest where several species coexist in a stand. Oono *et al.* (2008) studied that with an increase in tree density, the detection accuracy decreases by 10 to 20%, especially within a dense forest stand. Matsue *et al.* (2006) emphasized that stand density and crown shape highly influence tree detection rates, where overlapping crowns cannot be completely differentiated by the filtering process. In most studies, the detected crowns were observed to be the dominant layer, where the understory layer remains unseen.

Factor 2: Data resolution

Previous research has determined that the accuracy rate of tree detection depends on data resolution, where a resolution value of 1 m has an accuracy rate of 50% (Stereńczak *et al*., 2008). Two types of data were used in our study: LiDAR at 1 m of resolution and an orthophoto image of 0.25 m. Our result suggests that LiDAR at 1 m of resolution is not able to capture tree information at an individual level in a subtropical dense forest environment. This is supported by Popescu *et al.* (2002) and Stereńczak & Zasada (2011) who discuss that LiDAR is more suitable for the measurement of upper layer canopies where the focus is on dominant trees. Additionally, there is a possibility that smaller trees are partly or completely obscured in the shadows of larger or dominant tree layers. Schaaf *et al*. (1994) demonstrated earlier that topography and off nadir illumination can significantly alter the amount of shadow captured by optical sensors and cause errors in the accuracy of the data concerning height estimations and single crown recognitions. However, the segmentation results using orthophoto images shows a higher accuracy of crown detection, which is more than 70%. Scarth & Phinn (2000) stated that for a tropical forest, the extraction of its structural properties using remote sensing and satellite imagery is challenging as the image resolution is comparable to the size of the largest crown. Many researchers faced the same challenge where a study by Maltamo *et al.* (2004) detected only 40% of the trees, Heurich *et al.* (2004) with 37.5% detection rate and Tiede *et al.* (2004) who also achieved a detection rate below 50%. In this case, individual tree detection and crown recognition might be difficult, but laser data still have the capability to reveal the vertical distribution of vegetation (Persson *et al*., 2002). However, the accuracy might be improved with the use of a higher point cloud density LiDAR as well as the integration of other supporting data such as a high resolution orthophoto image or TM data (Shataee, 2013).

Conclusions

The results of this study suggest that LiDAR data has the powerful ability to estimate mean tree heights in a subtropical forest environment, but is not able to detect small understory trees and single tree crown delineations. We found that the LiDAR computations underestimated the frequency of trees in a given area, and further, overestimated their crown size. The accuracy and reliability of LiDAR rely on two main factors, which depend on: i) the type and condition of the forest that is recorded and ii) the kind of imagery that is resolved. In this study, low accuracy results are likely due to an inability of LiDAR to capture understory trees and for them to misinterpret multiple crowns as a single crown. We also concluded that at 1 m resolution, an interpretation of the LiDAR data did not sufficiently estimate the distribution of tree crown characteristics in the mixed subtropical forests of Okinawa. However, despite its low accuracy, the results and outcomes of this study indicate interesting and critical discussions when it comes to the utilization of LiDAR technology so that a more adaptive methodology can be applied to widen its application and practicability.

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Annex. List of tree species recorded within the sample plots.

Sp code	Scientific name	Local name
1	*Syzigium buxifolium*	Adeku
2	*Schimawallichii ssp. Liukiuensis*	Iju
3	*Distylium racemosum*	Isunoki
4	*Castanopsis sieboldii*	Itaji
5	*Neolitsea aciculata*	Inugashi
6	*Podocarpus macrophyllus*	Inumaki
7	*Styrax japonica*	Eigonoki
8	*Ilex warburgii*	Oshibamochi
9	*Glochidion acuminatum*	Okinawa ushirogashi
10	*Rhaphiolepis indica var. insularis*	Okinawa Syarimbai
11	*Dendropanax trifidus*	Kakuremino
12	*Vaccinium wrightii*	Gima
13	*Symplocos lucida*	Kuroki
14	*Symplocos prunifolia*	Kurobai
15	*Elaeocarpus japonica*	Kobanmochi
16	*Cleyera japonica*	Sekaki
17	*Rhododendron tashiroi*	Sakura azalea
18	*Camelia sazanqua*	Sazanka
19	*Cinnamomum doederleinii*	Shibanikkei
20	*Randia canthioides*	Shimamisaonoki
21	*Neolitsea sericea*	Shirodamo
22	*Tricalysia dubia*	Shiromimizu
23	*Myrsine segunii*	Taimin Tachibana
24	*Persea thunbergii*	Tabunoki
25	*Ilex goshinensis*	Tsugemochi
26	*Diospyros morrisiana*	Tokiwagaki
27	*Meliosma squamulosa*	Nambunawaki
28	*Rhus succedanea*	Hazenoki
29	*Eurya japonica*	Hisakaki
30	*Tutcheria virgat*a	Hizekakisazanka
31	*Daphniphyllum glaucescens ssp. teijsmannii*	Himeyuzuriha
32	*Schefflera octophylla*	Fukanoki
33	*Schoepfia Jasminodora*	Boroboronoki
34	*Symplacos confusa*	Miyamashirobai
35	*Ilex maximowicziana*	Mutchagara
36	*Microtropis japonica*	Mokureishi
37	*Ilex integra*	Mochinoki
38	*Ternstroemia japonica*	Mokkoku
39	*Osmanthus okinawensis*	Yanagibamokusei
40	*Camellia japonica*	Yagujibaki
41	*Myrica rubra*	Yamamomo
42	*Symplocos okinawensis*	Ryukyuhainoki
43	*Pinus Luchuensis Mayr*	Ryukyu matsu
44	*Osmanthus marginatus*	Ryukyumokuzai
45	*Ilex liukiuensis*	Ryukyu mochi