EXTRACTING TREE COUNT AND INDIVIDUAL TREE CROWN FROM LIDAR-DERIVED CANOPY HEIGHT MODEL USING OBJECT-BASED IMAGE ANALYSIS

Matthew V. Malabanan[1], Enrico C. Paringit[1], Gio P. Zaragosa[1], Carlyn Ann G. Ibañez[1], Regine Anne G. Faelga[1], Reginald Jay L. Argamosa[1], Mark Anthony V. Posilero[1], Fe Andrea M. Tandoc[1], Anjenneth Palmon[1], Aeron Adrian R. Maralit[1]

[1] Phil-LiDAR 2, Project 3: Forest Resources Extraction from LiDAR Surveys, University of the Philippines – Training Center for Applied Geodesy and Photogrammetry, Diliman, Quezon City, 1101, Metro Manila, Philippines
Email: malabanan.matt@gmail.com, paringit@gmail.com

KEYWORDS: Tree Count, Individual Tree Crown, Canopy Height Model, OBIA

ABSTRACT: Tree count and individual tree crown delineation are common for forest resource inventory and assessment. This study attempts to derive a process tree to extract tree count and delineate individual tree crown using available LiDAR data for forest plantations. Two-hectare plot from a Broadleaf and a Coniferous Plantation Forest were established and undergone field inventory. Using the LiDAR derived Canopy Height Model (CHM) or the Normalized Digital Surface Model (nDSM) of each sample plot, Object-based Image Analysis (OBIA) is applied using a software. The general OBIA workflow involves image segmentation, classification, finding local extrema, and region growing. A tree top was determined by getting the local maxima with a specific search range, and then tree crown was individually delineated through region growing algorithm which is also assumed to be equivalent to individual trees. The accuracy of the results was determined by comparing the total number of tree count estimates with the actual number of trees in the field and by looking onto the accuracy of the location of the tree top, comparing the estimates with field measured location of the trees using different sub-plot sizes (5 by 5 meters, 10 by 10 meters, and 20 by 20 meter sub-plots). Results show that the estimated tree count has percent difference of 0.98% and 1.33% for Broadleaf and Coniferous plantation forest, respectively. Tree tops were more effectively counted in Coniferous plantation forest with 0.91 R^2 and RMSE of 3 trees in the 20-meter resolution.

1. INTRODUCTION

Accurate and up-to-date accounting of forest resources is becoming a more important step towards reversing the dwindling trend of these resources. Reduction in forest cover and biomass said to be the primary cause of global warming and therefore climate change. Characterizing forest resources include accounting for their biophysical parameters such as biomass and carbon stock. Accurate assessment of these parameters are essentially and conventionally dependent with direct measurements of the forest structure particularly characterized by the inventory data derived locally (Ferraz et al., 2016).

Scott & Gove (2002) explained that “forest inventory is the accounting of trees and their related characteristics of interest over a well-defined land area”. It includes tree count within the land area and other information such as tree volume, value, growth and species composition. Forest inventory is considered to be quite intensive and challenging, especially to the Philippines which majority of its forest is considered as tropical rainforest. Vegetation of tropical rainforests is tedious and diverse in nature which makes the inventory of these forests very challenging (PTFCF, 2015).

Because of the forest inventory being challenging and tedious, there are a number of technologies that can be used as an alternative and as an aid for the exhaustive methods forest inventory and assessment. LiDAR is one of the technologies that has been widely used in different fields, one of these field or industry is Forestry. LiDAR provides data for forest canopy and terrain that helps forest managers and decision makers do their tasks (Esri, 2010). For this study, Object-based Image Analysis (OBIA) was used. OBIA is “a sub-discipline of GIScience devoted to partitioning remote sensing (RS) imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale” (Hay & Castilla, 2006).

DENR (no date) relates Plantation Forest or Forest Stand or sometimes interchangeable with the term Industrial Forest Plantation with the process of afforestation or reforestation specifically through seeding or planting. Industrial Forest Plantation on the other hand is defined as area of land that has purpose of producing forest resources, timber being the major resource but also includes secondary forest resources such as the non-timber forest products (e.g. bamboo, rattan), to supply the needs of the processing plants for raw materials. Forest plantation which trees has planned tree spacing can also be classified based on the species composition of the stand, either broadleaf or coniferous and if the canopy is considered closed (more than 10% cover) or open (less than 10% open).

Furthermore, to explain how an image is being segmented and what parameters are being considered in the classification of the delineated objects, as defined, grouping of pixels of an image in a given resolution which formed or represents linear and polygonal features on the ground and is assumed to depict same pixel values, is called segmentation. After the pixels were grouped and the objects were delineated from the image, classification process is the second phase which follows the principle of class membership. Image segments or objects are being assigned to classes by per-pixel classification. The pixel grouping is based from the analysis of the majority of pixel values present hence the grouping into segments/objects. A discriminant factor is being used or a membership function classifier which is taking into account the statistical measures of the frequency distribution of the pixel values (e.g. measures of central tendency, image brightness, color, texture and etc.). This is the principle behind the assignment of specified classes per delineated segment of the image (Fischer & Getish, 2010).

The goal of the study is to develop an effective method to extract tree count and to delineate the individual tree crown with the use of Object-based Image Analysis. Hence developing a process tree applicable for Broadleaf Coniferous Plantation Forests. This will be achieved through:

a. Application of the general workflow of OBIA to detect individual tree tops and crown delineation;
b. The use of LiDAR-derived Canopy Height Model (nDSM) as primary input to the OBIA; and
c. Modification of the custom OBIA workflow applicable specifically to BPF and CBF for robust implementation.

The study documented the implications of the application of OBIA to Broadleaf Plantation Forest (BPF) and Coniferous Plantation Forest (CPF), which are different as far as the structure is concerned as well as the type of management over the two areas. Tree count estimate could give a good information that could help foresters/researchers for forest management and utilization, as well as to tree crown. In addition, tree crown is also related to above-ground biomass investment with consideration of light interception of trees (Selaya et al., 2006), which can be beneficial to further forest resource assessment.

2. DATA AND METHODS

2.1. Site Description

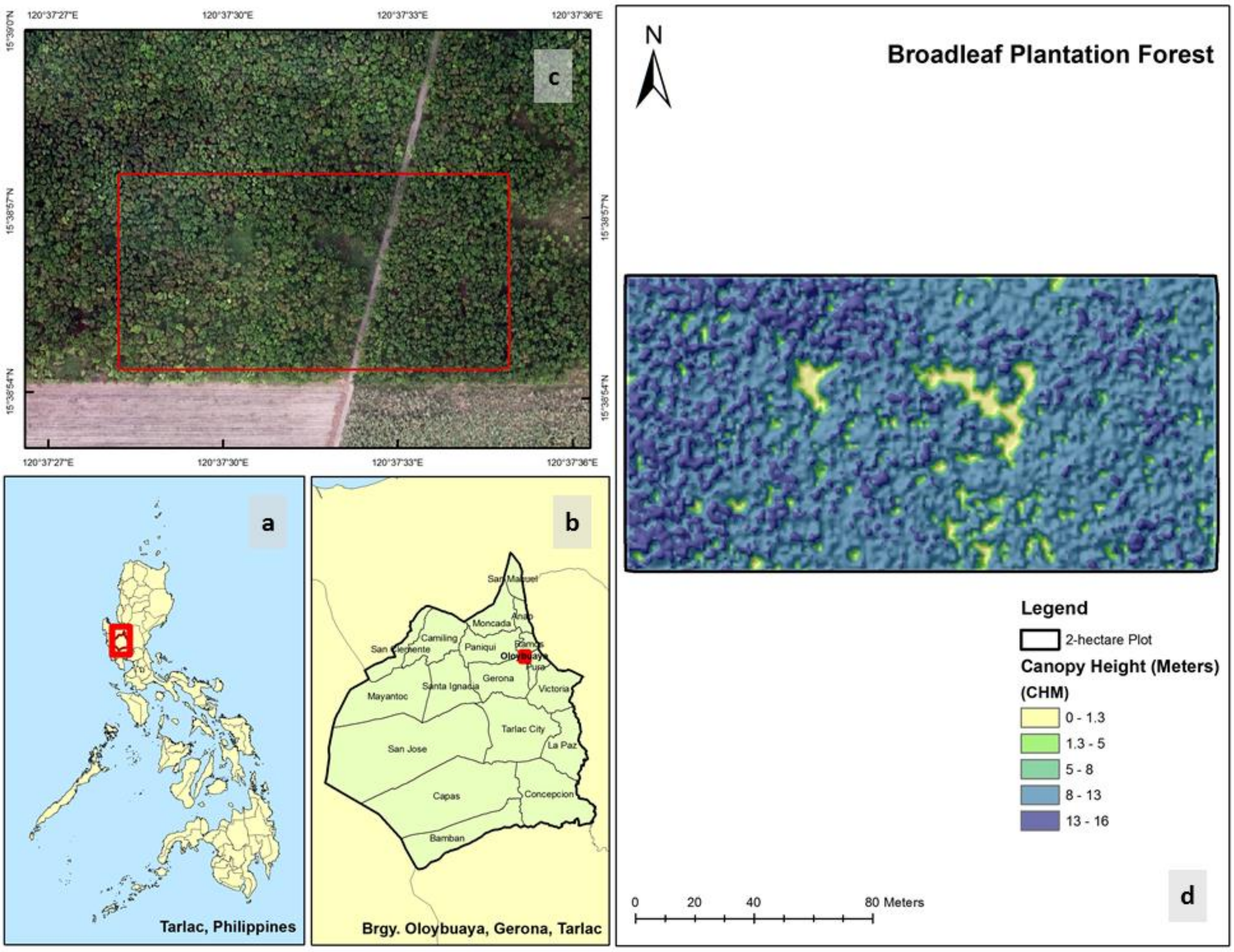


Figure 1. Location Map of (a) Tarlac, Philippines and (b) Brgy. Oloybuaya in Municipality of Gerona; View of two (2) – hectare plot of Broadleaf Plantation Forest in (c) LiDAR Ortho-photo and (d) LiDAR-derived Canopy Height Model

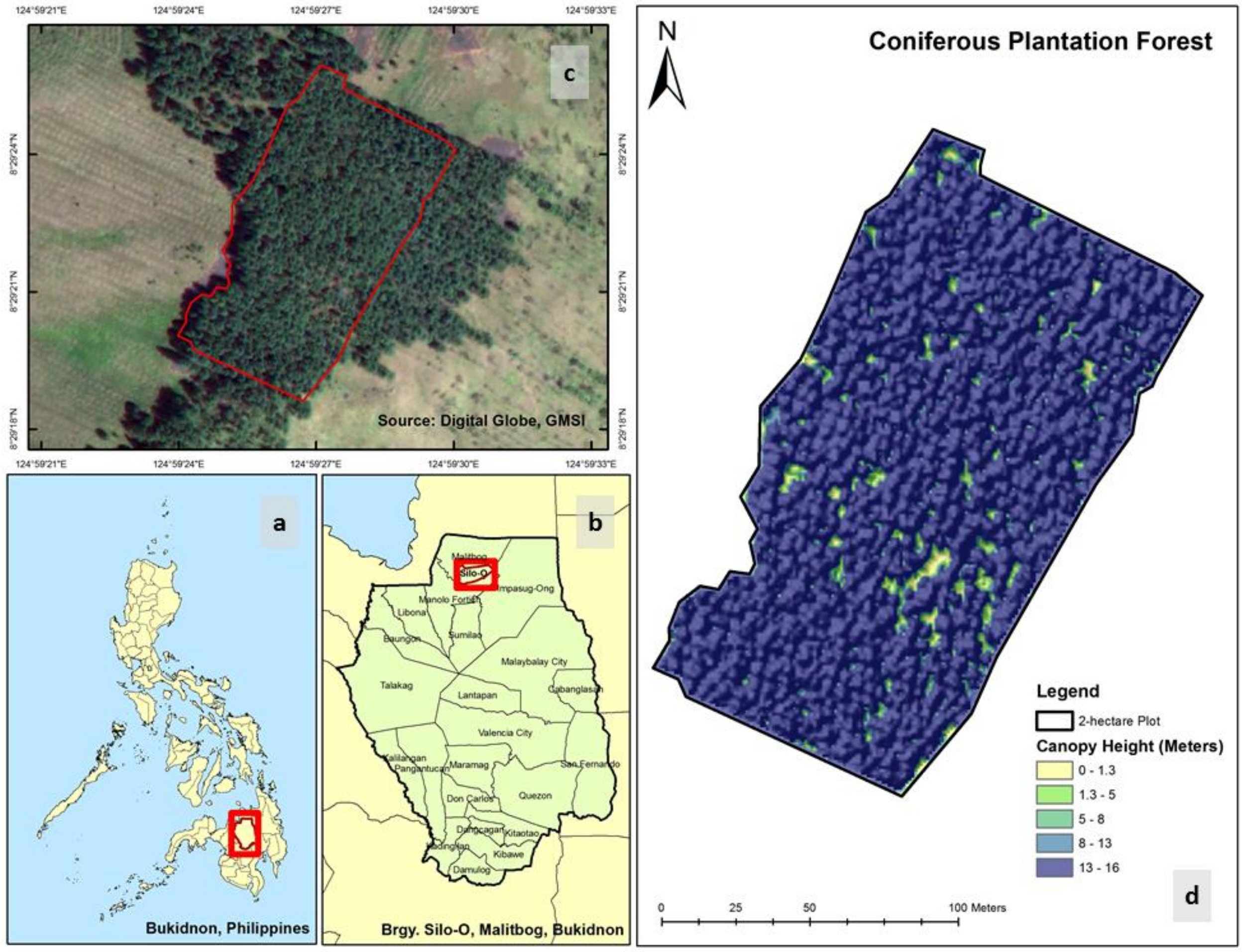


Figure 2. Location Map of (a) Bukidnon, Philippines and (b) Brgy. Silo-O in Municipality of Malitbog; View of two (2) – hectare plot of Coniferous Plantation Forest in (c) LiDAR Ortho-photo and (d) LiDAR-derived Canopy Height Model

For this study, a Broadleaf Plantation Forest (BPF) and a Coniferous Plantation Forest (CPF) were considered as study sites. The study sites are located in the province of Tarlac and province of Bukidnon, respectively. The BPF is composed of Big-leaf Mahogany (*Swietenia macrophylla*) with a 2.5 by 5-meter spacing. On the other hand, CPF is composed of Caribbean Pine (*Pinus caribaea*) with a 3 by 5-meter spacing. Figure 1 and 2 shows the location map of broadleaf plantation and coniferous plantation forests, respectively.

2.2. Field and LiDAR Data

A two-hectare plot was established in each plantation sites for field inventory. Direct measurements of the diameter-at-breast height (dbh), tree height, individual tree geo-tagging, and canopy cover using Digital Hemispheric Photography (DHP) were conducted during field validation. The BPF in Tarlac was surveyed on June 2015 while CBF in Bukidnon was surveyed on February 2015. There are total of 1409 trees and 985 trees inventoried in BPF and CPF respectively.

The airborne LiDAR data for BPF was acquired on January 2013, while for CBF was acquired on August 2013. LiDAR point cloud data was processed to produce normalized Digital Surface Model (nDSM) and create Canopy Height Model. The algorithm used to generate a LiDAR pit-free CHM is from the method of Khosravipour et al, (2013).

2.3. Methodology

The modified general algorithm patterned from OBIA is found in Figure 3. The study patterned the workflow after Tiede and Hoffman (2006) in detecting individual trees. Fisher & Getis (2010) had compiled explanations tackling the emerging Geographic Object-based Image Change Analysis (GeOBICA) which is based from Geographic Object-based Image Analysis or simply GeOBIA or OBIA. These image analyses follow the custom OBIA paradigm which starts from the forming of segments or the so-called objects through image segmentation. From these segmented objects from the image, classification or grouping of these objects follows. In the study, the segments between vegetation and gap were delineated. Features belong to the vegetation that have Canopy Height above 1.3 meters, and the gap from the height values below 1.3 meters. Afterwards, the study suggested to add, from the custom process of OBIA, the chessboard segmentation, generation of the local maxima, and then treating the local maxima as seeds for the region growing algorithm. Added refinements of the results is applied throughout the process such as the merge region and removal of small objects. Merge region algorithm as explained by Peng et al. (2010), is basing the merging or grouping of obtained objects or segments from a homogeneity criterion. This criterion is based on statistical properties, graph properties, or from spatio-temporal similarity of the group of pixels belonging to the formed objects from the segmentation. Distance and uniformity from each object were the primary criterion in merging segments. Region merging is considered as second level in grouping the pixels. First level is the grouping of the pixels into an object or segment in the segmentation process and then the second level which is the grouping of this said segments into a larger region. Merge region was used to merge special cases with 2 to 3 detected tree top and also adjacent to each other. These adjacent local maxima are assumed to be in only one tree or treated as one tree individual. While removal of small objects is done to remove some errors or noise in local maxima detection. These small objects are objects with less than the threshold area of an average tree in BPF and CPF, which are considered outliers.

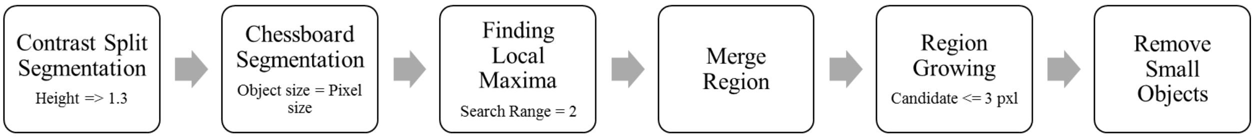


Figure 3. Developed algorithm based from the general OBIA workflow in eCognition Developer software.

Furthermore, with the use of the LiDAR-derived CHM as an input, the process tree starts with the segmentation process of the image and then classification of the segmented objects for the assumed tree area. The threshold for upper vegetation is height value greater than or equal to the height of the tree from the ground where the DBH is measured (1.3 meters). This part of the process also excludes the gap from the vegetation. The gap depicts the ground in the image which will not be considered in detection of tree top or local maxima. In the segmentation process, multiresolution segmentation algorithm is often used, but for this study, contrast split segmentation algorithm is applied since the chosen algorithm is primarily giving more value to the contrast feature of the image in the segmentation. This algorithm differentiates bright object versus dark objects (Trimble, 2014). Bright objects are classified as upper vegetation or tree area, while dark objects are left unclassified for it is also considered as gaps or open spaces.

The classified tree area is then segmented into smaller objects with the application of the Chessboard segmentation. Using this algorithm, the classified object tree area from earlier is segmented into squares or pixels (Blaschke, et. al, 2008). In this part of the process, we assume that the gaps were no longer considered since segments/objects with canopy height values below the 1.3 meters. The square sizes are set to the value of one (1) meter. This resulted to the same size as the resolution of the input CHM which is one meter. The aim of this algorithm is to arrive at an object size that could represent a single point/object for the detection of local maxima. Then, using find local extrema, local maxima is determined using a specific search range. For the case of two plantation forest, search range is equal to two (2) pixels or meters, since LiDAR CHM used has a resolution of one (1) meter. Tree spacing of the plantation is first considered in setting of the search range. Both plantations have almost three-meter spacing at a certain orientation. The search range was experimented on different search ranges to see which would result in a reasonable count value. Local maxima are assumed as tree top which represents individual trees (Blaschke, et. al, 2008).

Using region growing algorithm, individual tree crown was delineated. Region growing starts with as single object, called seed points, and it grows as it merges neighbor objects that fits the characteristics to candidate classes and threshold (Blaschke, 2008). In this case, detected tree tops were used as seed points. Region grows from the seed points up to the edge of the tree crown. This assumption delineates the individual tree crown at its maximum range considering the tree spacing.

Removal of small objects is done because of some erroneous in tree top detection and region growing. Some objects are too small to be considered as trees. Therefore, some threshold has been applied to limit and remove errors. Different threshold is applied per forest type.

3. RESULTS AND DISCUSSION

3.1. Tree Count and Individual Tree Crown

Tree count and individual tree crown were extracted from LiDAR derived CHM. For Broadleaf plantation, 1,423 trees were detected, while 972 trees in Coniferous plantation. Both tree count estimates have acceptable percent difference to the actual tree count, shown in Table 1.

On the test run, value of as search range is tested, but the result is not as good as compared to using the value of two as search range. Therefore, this study arrived at using the value of two (2) pixels as the search range for the two plantations, showing relatively promising results.

Table 1. Results of tree count estimation in Broadleaf Plantation and Coniferous Plantation

2-hectare Plot	Actual Tree Count	Estimated Tree Count	Percent Difference	Remarks
Broadleaf Plantation	1,409	1,423	0.98%	Over-estimated
Coniferous Plantation	985	972	1.3%	Under-estimated

As seen in Figure 4, the delineated individual tree crown has visually promising results. The result of the individual tree crown delineation using OBIA needs to be smoothened using a tool in ArcGIS software which is calculated by the Polynomial Approximation with Exponential Kernel (PAEK) algorithm. Improving the aesthetics and the cartography quality of the delineated crown is the essence of smoothing the sharp angles in the vector file produced in OBIA (Esri, 2010).

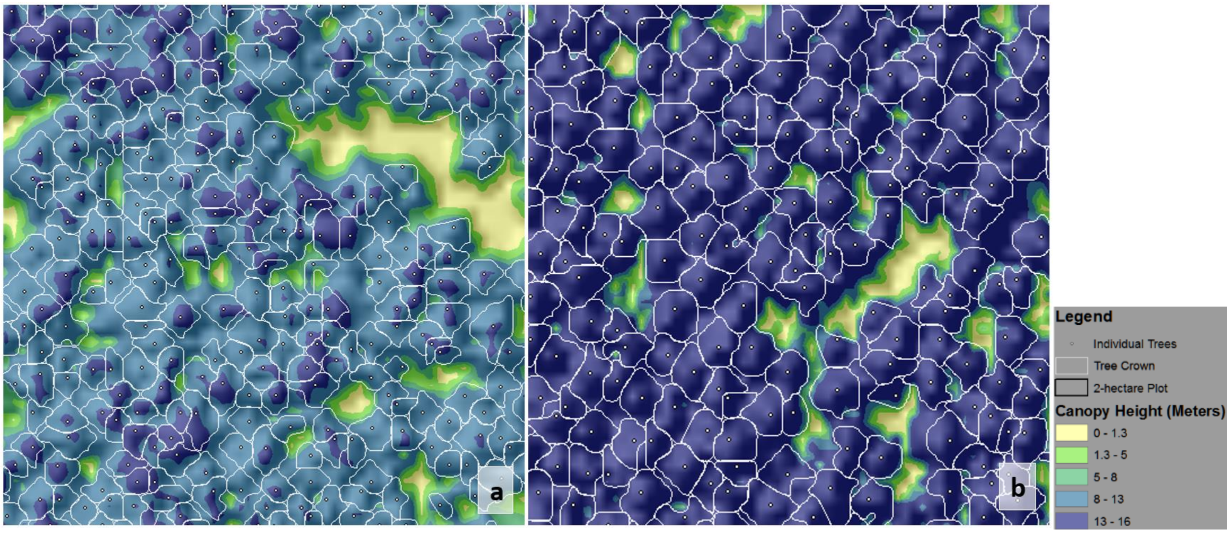


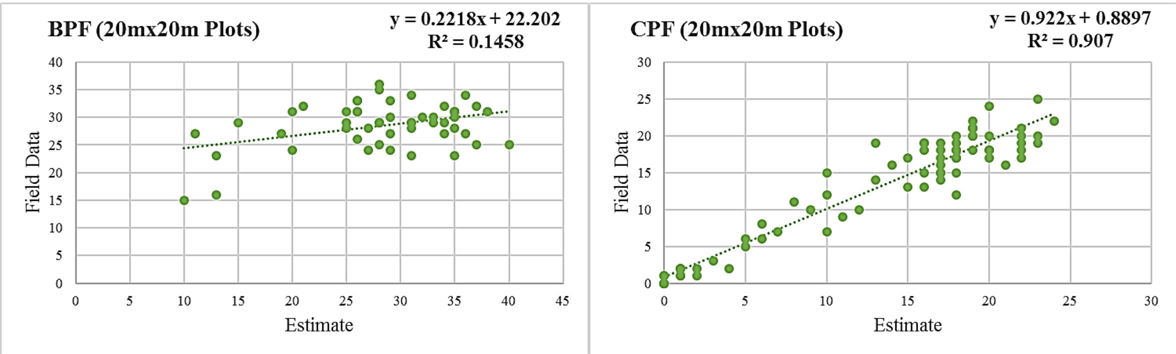
Figure 4. Portion of the 2-hectare plot with properly delineated individual tree crown of the broadleaf plantation forest (a) and coniferous plantation forest (b), overlaid on the Canopy Height Model.

3.2. Accuracy Assessment

To test whether the trees counts and positions are consistently estimated, the 2-hectare plots were subdivided into different subplot sizes (5 by 5 meter, 10 by 10 meter, and 20 by 20 meter subplots) Both plantations site have good linear relationship between estimated and actual tree count in the 20 by 20 meter subplots. Table 2 shows the correlation coefficient and root mean square error (RMSE) for each sub-plot resolution in BPF and CPF. In both plantation types, the best correlation of the estimates is observed in larger grid size/lower resolution. It can be seen from Table 2 that in the 30-meter resolution, the r-squared is 0.70 and 0.97 for BPF and CPF respectively. In the case of the RMSE, the values for the lower grid size were normalized relative the 30 by 30 - meter grids. It then shows that the highest resolution also gave the highest accuracy and lowest relative error, having an error of around 12 and 3 trees for BPF and CBF respectively. The normalization of the RMSE was done to have fair comparison of errors per subplot resolution. The scatter plots for 20 by 20 meter subplots and 30 by 30 meter subplots are shown in Figure 5 and 6 for Broadleaf and Coniferous plantation forest, respectively.

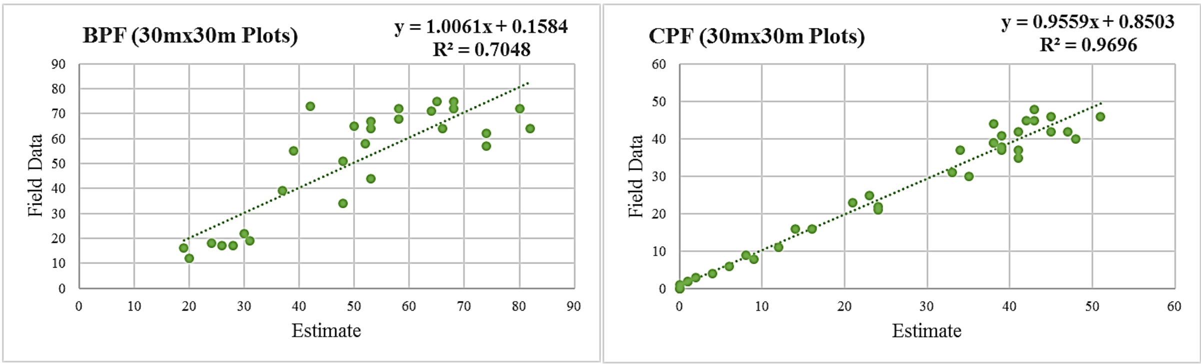
Table 2. Summary results of accuracy assessment in each sub-plot resolution.

Analysis	Broadleaf Plantation Forest				Coniferous Plantation Forest			
	5m by 5m	10m by 10m	20m by 20m	30m by 30m	5m by 5m	10m by 10m	20m by 20m	30m by 30m
No. of sub-plots	800	200	50	28	920	250	74	37
R^2	0.02	0.07	0.14	0.70	0.25	0.53	0.91	0.97
RMSE	1.35	2.93	6.74	11.86	0.79	1.43	2.32	2.99
Normalized Error	49	26	15	12	28	13	5	3



(a) (b)

Figure 5. Scatter plot of the comparison of tree count estimate and actual tree count in 20 by 20 meter subplots of Broadleaf (a) and Coniferous (b) Plantation Forest.



(a) (b)

Figure 6. Scatter plot of the comparison of tree count estimate and actual tree count in 30 by 30 meter subplots of Broadleaf (a) and Coniferous (b) Plantation Forest.

Comparing the two plantations, the tree count estimates in Coniferous Plantation has better results both in tree count estimation and correlation between actual tree location and detected tree tops. Figure 7 shows the histogram of errors for 20 by 20-meter plot for BPF and CPF, and Figure 8 for 30 by 30 meter subplots. This graph shows the frequency per range of errors in counting the tree individual per plot. It can be observed from figure 8 that the graphical representation of errors in estimating the tree count in (b) CBF is generally symmetrical. While in (a) BPF, the histogram follows a bimodal to multimodal pattern in the 20 by 20 and 30 by 30, respectively. Estimation of tree count per plot (20 and 30 m^2) in CBF can be described as random. On the other hand, poor observation of the error plot in BPF can be caused by the doubling of canopies which were considered as one tree in the local maxima determination, hence overestimation.

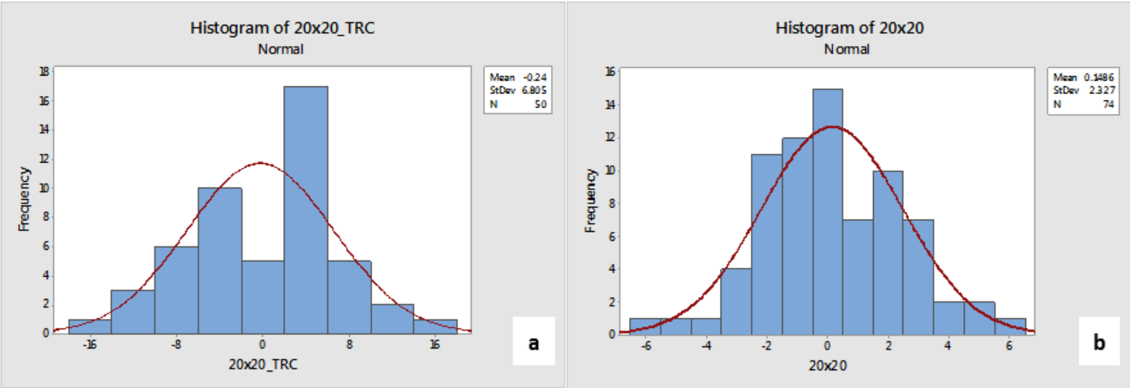


Figure 7. Histogram of count errors for 20 by 20-meter plots in (a) Broadleaf and (b) Coniferous Plantation Forests.

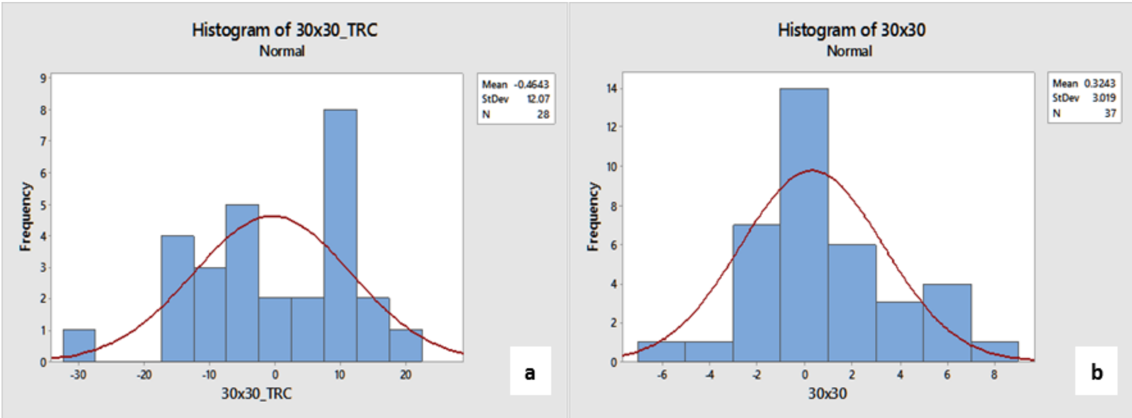


Figure 8. Histogram of Errors for 30 by 30-meter plots in (a) Broadleaf and (b) Coniferous Plantation Forest

The errors observed can be caused by the morphological differences of the species present in the plantation site. The result of both estimation of tree count for CBF and BPF yielded an acceptable result as based from the r-squared as well as to the RMSE. But results for CFP is better than that of the BFP. The primary reason for the less favorable outcome for BPF is the fact that broadleaf species tend to have two or more canopies per individual tree. The ratio of the number of canopies per tree is impossible to be observed on a broadleaf tree species. In nature, broadleaf tree structure tends to have double canopies, an umbrella-shaped canopy and have no distinct top. This is in contrast to a tree in CFPs which has cone-shaped canopy structure is and has relatively pointed top/tip. This form of conifers makes tree top detection more possible. Also, conifers usually only have one canopy top. That being said, species composition (which is between coniferous and broadleaf trees in this study) of the area is a great factor that can affect the detection of tree top and tree crown delineation. Another explanation could be the discrepancy with the time of acquisition of the LiDAR data (2013) and the date the local field survey/inventory was done (2015). The more or less two-year discrepancy could affect the composition and physical structure of both plantations hence a possible cause for the decrease or increase of the number of trees physically present on both plots during the field inventory.

It should also be noted that the accuracy of this study is limited only to tree count. There is no field data that could be used to assess the accuracy of individual tree crown delineation.

4. CONCLUSION

Using OBIA, tree count and individual tree crowns was extracted in LiDAR-derived CHM for broadleaf and coniferous forest plantations. Detection of tree top and individual tree crown results were found to be satisfactory and able to represent each tree in the area. For both plantation forest sites, estimated tree count was comparable to actual tree count. With reference to the accuracy of the position of points which gave the idea of how well OBIA estimated the tree count into different sub-plot sizes, more favorable results were obtained from the estimation of the coniferous plantation forest. In 20-meter resolution, OBIA effectively estimated the tree count, locate the tree top and furthermore tree crown delineation for the Coniferous Forest Plantation. Given that the structure of the trees in the plantation forms a more likely cone shape and that less manifestation of overlapping tree crowns and doubling of crowns per tree. It can be said that a larger grid size or lower resolution or, OBIA is effective in estimating the tree count hence in the tree crown delineation.

5. ACKNOWLEDGEMENT

This research is funded by the Department of Science and Technology (DOST) under the Nationwide Detailed Resource Assessment Using LiDAR (Phil-LiDAR 2), Project 3: Forest Resource Extraction from LiDAR Surveys (FRExLS). Utmost acknowledgement is given to the Disaster Risk and Exposure Assessment for Mitigation (UP DREAM) and Phil-LiDAR 1 for the LiDAR data of the study site. Due recognition is also given to the Central Luzon State University (CLSU) and J & E Development Corporation, Central Mindanao University (CMU) and Bukidnon Forest Incorporated (BFI) for their assistance the field works.

6. REFERENCES

Department of Environment and Natural Resources (DENR). No date. Philippine official reference for forest-related terms and definitions. A PDF file retrieved from www.forestry.denr.gov.ph on August 2016

Esri. 2010. LiDAR Analysis in ArcGIS 9.3.1 for Forestry Applications. 380 New York Street, Redlands, CA 92373-8100 USA. Retrieved from https://www.esri.com/library/whitepapers/pdfs/lidar-analysis-forestry.pdf

Fischer M., Getis A. 2010. Handbook of Applied Spatial Analysis. Springer Heidelberg Dordrecht London New York

Hay, G. J. & Castilla, G. 2006. Report on the Joint ISPRS Commission IV “Object-based Image Analysis: Strengths, Weaknesses, Opportunities, and Threats (SWOT)”, Canada. http://www.isprs.org/proceedings/XXXVI/4-C42/Papers/01_Opening%20Session/OBIA2006_Hay_Castilla.pdf

Peng B., Zhang L., & Zhang D. 2010. Automatic Image Segmentation by Dynamic Region Merging. A PDF file retrieved from https://arxiv.org/abs/1012.1193 on September 2016

Philippine Tropical Forest Conservation Foundation (PTFCF). 2015. Status of Philippine Forests. A PDF file retrieved from http://www.ptfcf.org on August 2016. pp. 3-5

Scott, C. T. & Gove, J. H. 2002. Forest Inventory. Volume 2. John Wiley & Sons, LTD, Chichester. Retrieved from http://www.fs.fed.us/ne/durham/4104/papers/Gove18.pdf. pp. 814-820

Selaya, N. G. et.al. 2006. Above-ground Biomass Investments and Light Interception of Tropical Forest Trees and Lianas Early in Succession. Annals of Botany 99. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2802976/pdf/mcl235.pdf. pp. 141-151

Tiede, D. & Hoffmann, C. 2006. Report on 3D Remote Sensing in Forestry, “Process oriented Object-based Algorithms for Single Tree detection using Laser Scanning”. Center for GeoInformatics, Salzburg University, Austria. Retrieved from https://www.researchgate.net/publication/228851631_Process_oriented_object-based_algorithms_for_single_tree_detection_using_laser_scanning

Blaschke, T., Lang, S., & Hay, G. J (Editors). 2008. Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications. Springer-Verlag Berlin Heidelberg. Pp. 29-42. Retrieved from https://www.researchgate.net/publication/216266255_Object-based_Image_Analysis

Khosravipour, A., Skidmore, A. K., Isenburg, M., Wang, T., & Hussin, Y. A. 2013. Development of an algorithm to generate a LiDAR pit-free Canopy Height Model. SliviLaser 2013. Beijing, China. Retrieved from http://www.riegl.com/uploads/tx_pxpriegldownloads/khosravipour_SilviLaser2013.pdf

Trimble. 2014. Reference Book: eCognition Developer. Trimble Germany GmbH. Munich Germany. pp. 32-34