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Mapping tree height in agroforestry system using Landsat 8 data

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ABSTRACT

Agroforestry is a land use management-system represents unique vegetation characteristics among tree vegetation types. Tree height is a vegetation variable used to characterize vertical structure, including mixed vegetation structure in agroforestry. Estimation of tree heights with multispectral imagery is a relatively new application and is dependent on integrating synoptic coverage optical data with samples of height data, often from LiDAR-derived reference data. In this study, multispectral Landsat 8 data, Unmanned Aerial Vehicle (UAV)-based LiDAR height data and a log-linear regression model were used to estimate tree height for agroforestry land use in western part of Java Island, Indonesia. We generated a Canopy Height Model (CHM) directly from height-normalized LiDAR points and used as reference data in modeling the key height variable in the multispectral bands of Landsat 8. The analysis showed that red band was the best band to estimate tree height in agroforestry land use, followed by swir band. The log-linear regression algorithm of red band accurately reproduced the LiDAR-derived height training data using Landsat 8 data with overestimate 1.46 m in estimating tree height < 5 m and underestimate 7.79 m for tree height > 20 m.

Keywords: Reflectance metric, Canopy Height Model, LiDAR, Landsat 8, Agroforestry

1. INTRODUCTION

Agroforestry is a land use management system, which represents unique land use practices with mixed vegetation types; combines trees, shrubs, palms and crops. These flexible combinations tailored to the needs of landowners[1]. Some previous studies emphasize that agroforestry has an important role to maintain carbon (C) sequestration in agricultural lands as it provides higher carbon density than annual crops or pasture[2,3,4]. The Intergovernmental Panel on Climate Change (IPCC) recognized the role of agroforestry for C sequestration[5]. Consequently, a vegetation monitoring system in agroforestry land use is required to adjust agroforestry as an effective strategy for C sequestration.

The mixed vegetation characterizes the canopy structure of agroforestry land use, which refers to the shapes of various plant organs (e.g. leaves, stems) and different tree height. Canopy structure is a vegetation variable used to characterize vertical structure, including mixed vegetation structure in agroforestry[6].

LiDAR remote sensing technology provides relatively accurate and effective datasets to estimate and monitor the vegetation structure, which will refer to the biomass and C stock of different vegetation types[7]. One of the main advantages of LiDAR is that it can penetrate through the small canopy gaps for detecting vertical structure and extracting ground elevation. The height information derived from LiDAR data is strongly related to biomass for most tree species[8,9].

Estimation of tree heights with multispectral imagery is a relatively new application and is dependent on integrating optical-sensor data with samples of height data from LiDAR-derived reference data[10]. Several studies applied an integration of the LiDAR data with optical-sensor data, for example, characterizing forest structure[11], quantifying forest biomass at a sub-national scale[12], estimating change in vertical structure[13], and creating global forest height maps[14]. This paper evaluates the spectral characteristics of Landsat 8 in correlation with the height datasets from airborne-based LiDAR data to estimate the tree height attribute of agroforestry land use in western part of Java Island. We generate a

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canopy height model (CHM) directly from height-normalized LiDAR cloud points and used as the reference data in modeling the key height variable of Landsat 8.

2. METHODOLOGY

2.1 Study area

This study encompassed agroforestry land use in Cidanau Watershed, which is located on the western part of the Java Island (06°07'30"S 105°49'00"E to 06°18'00"S 106°04'00"E) (Figure 1). The study site lies at an elevation from 192 to 400 m above sea level (asl) and the majority of areas have very steep slope. The several rivers that originate in the surrounding hills flow to the main river, the Cidanau River.

Agroforestry land use in the study site consists of 6 dominant agroforestry types, namely: Sengon (*Paraserianthes falcataria*), Clove (*Eugenia aromatic*), Melinjo (*Gnetum gnemon L*), Cacao (*Theobroma cacao*), Coffea plant (*Coffea arabica*) and complex mixed plants agroforestry. Complex agroforestry is dominant agroforestry type in Cidanau Watershed as the trees are very diverse[15].

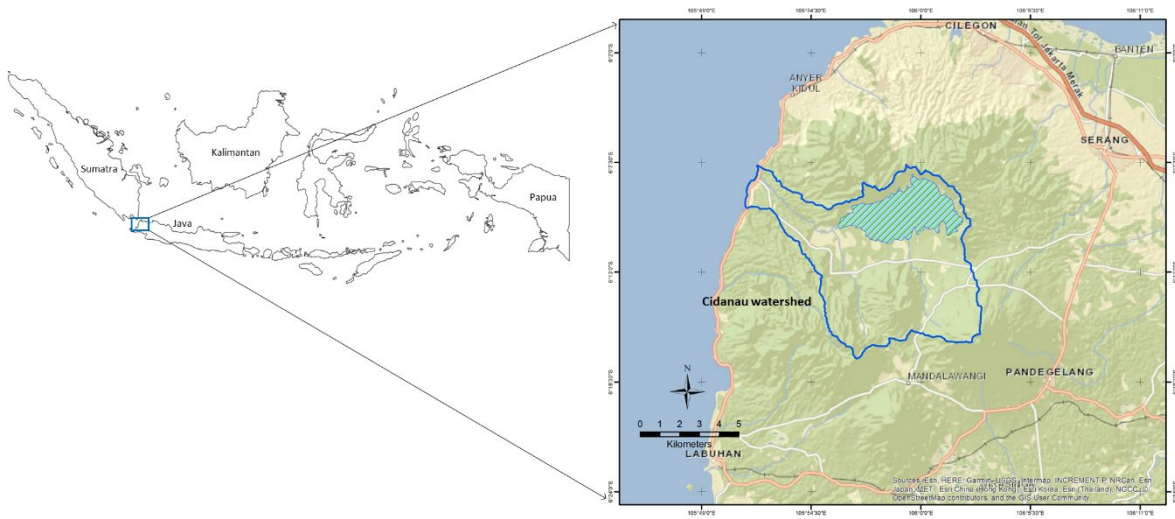


Figure 1. The study site

2.2 Landsat 8 data

Landsat 8 image over our study area (path/row: 123/064) for August 27, 2017 was acquired from the United States Geological Survey (USGS) Landsat archive (http://earthexplorer.usgs.gov). That data had already been systematically corrected for terrain and converted to top of atmosphere radiance (L1T data product). However, due to topographic variations of study area, we applied illumination algorithm to correct the reflectance from terrain effect[16]. In this study, longer wavelength red (0.630–0.680 μm), near infrared (0.845–0.885 μm) and shortwave infrared (1.560–1.660 μm) bands were used as inputs. Meanwhile, the shorter wavelength of blue and green bands were not used in this study, due to persistent atmospheric contamination and scattering effects[17].

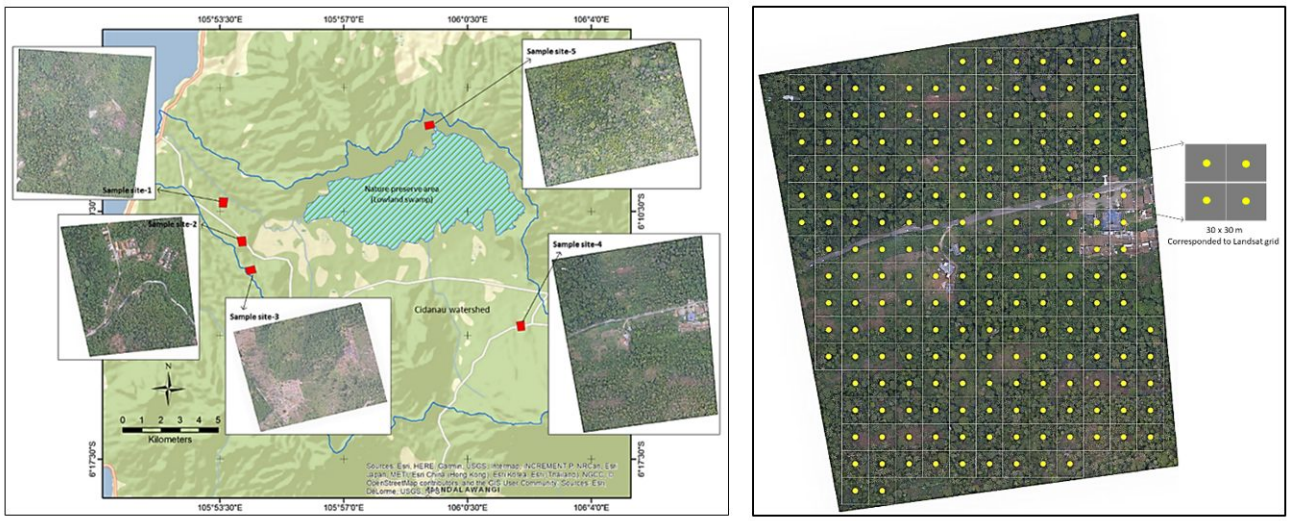
2.3 LiDAR data

LiDAR data were acquired on 11 September 2017 using YellowScan LiDAR system (YellowScan Mapper) on a hexacopter platform (DJI Matrice 600). In order to provide a higher point density, we set flight parameters of the LIDAR scanning as follows: flying height – 70 m above ground, laser time gap – 2 s, drone speed – 6-8 m/s, point cloud density – 12-18 points / m^2, vertical accuracy – 10-15 cm, horizontal accuracy – 2x vertical accuracy and flight side lap - 50%. Moreover, we preformed initializing inertial measurement unit (IMU) to determine the attitude of the aircraft while the sensor taking measurements. These are recorded in degrees to an extremely high accuracy in all three dimensions as roll,

pitch and yaw - the vertical and horizontal movements of the aircraft in flight. From these two datasets, the laser beams exit geometry was calculated relative to the Earth's surface coordinates based on two instruments; transmitter RTK GNSS LiDAR antenna and TOPCON GR 5.

The LiDAR points cloud data were processed using the lidR package in R (https://github.com/Jean-Romain/lidR). Using the lidR package, we created the CHM directly from height-normalized LiDAR points with a 2-m pixel size image. Rasterizing canopy height model in detail can be seen in https://github.com/Jean-Romain/lidR/wiki/Rasterizing-perfect-canopy-height-models.

To capture the variability of the study area, five locations were selected based on stratification of difference landscape (Figure 2-a). Each location was overlaid with a 30 m fishnet corresponding to the pixels of the Landsat 8 data (Figure 2-b). This procedure provided the height data-derived from the LiDAR data within the corresponding Landsat pixels, and used as a reference data to evaluate the spectral characteristics of Landsat 8. The final number of grid samples in the reference dataset was 981 grids.



a) b)

Figure 2. a) The 5-sites selected as LiDAR data sampling, b). 30 m-grid correspond to the pixel size of Landsat 8

2.4 Correlation model of canopy height and multispectral Landsat 8 data

Considering simple bivariate linear model, we used the log-linear regression model log $Y_i = \alpha + \beta * X_i + \varepsilon_i$, to estimate tree height from a key height variable of multispectral bands of Landsat 8, where Y represents the Landsat-estimated height and X is the reflectance metrics of Landsat. In the log-linear model, the literal interpretation of the estimated coefficient β is that a one-unit increase in X will produce an expected increase in log Y of β units. Logarithmically transforming variables in a regression model is very common way to handle situations where a non-linear relationship exists between the independent and dependent variables. For assessing the accuracy of Landsat-estimated height data, we applied a mean absolute error (MAE) of the result and LiDAR-derived height in several sampling data by using a formula below:

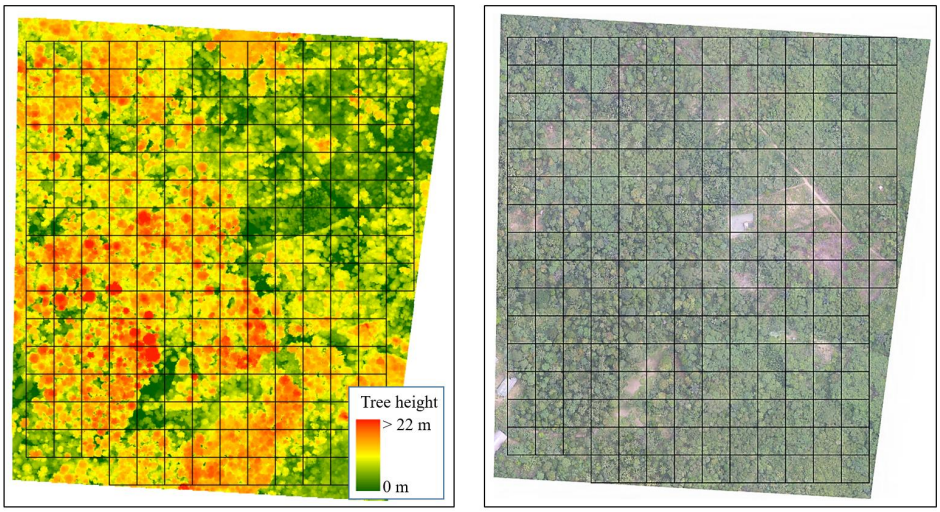
$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{1}$$

where y is the Landsat-estimated height data, and x is the LiDAR-derived height data.

3. RESULTS AND DISCUSSION

3.1 Canopy Height Model

Canopy Height Model (CHM) is typically raster representations of the tree canopy. Figure 3 shows the result of LiDAR-height derived in a study site overlaid with the 30-m grid of Landsat. The figure indicates that there is a disparity between the average patch size of the canopy height and the Landsat pixel size (30-m grid). It revealed to the mixed height-pixel issue in agroforestry land use.



a) b)

Figure 3. a) Canopy Height Model derived from LiDAR data, b) RGB orthophoto image. The black line represents the grid for 30-m Landsat pixel

3.2 Height variable of the multispectral metric

The analysis showed that, for mapping tree height in agroforestry land use, red band was found to be the best band, followed by swir band. Meanwhile, nir band was not significantly correlated with the tree height attribute. The red, swir and nir reflectance metrics accounted for 59.4%, 53.7% and 0.04% of Landsat log-linear models. Figure 4 illustrates the relationship between each reflectance metric and LiDAR-derived tree height over 981 sample grids. Estimated tree heights from red reflectance metric is shown in Figure 5. This result conformed to a study in Sub-Saharan Africa by Hansen et al (2016) that red reflectance was the most important variable in estimating tree height.

3.3 LiDAR-derived height versus Landsat-estimated height

Mean absolute error (MAE) is a measure of difference between two continuous variables between Landsat-estimated height and LiDAR-derived height data. The results show a near-functional equivalency for each input data set as shown in Table 1. Mean absolute errors were highest in the tree height >20 m. These results indicate a likely lack of sensitivity of Landsat, as a mean of underestimate in the tree height >20 m and overestimate in the height <5 m. A lack of signal to differentiate taller canopies is a likely reason, as shown in Figure 4-a. Meanwhile, overestimates in the tree height <5 m were likely due to the presence of poor quality LiDAR retrievals of low cover conditions.

Table 1. Mean absolute errors from LiDAR-derived height and Landsat-estimated height by the log-linear model

LiDAR tree height (CHM)	Errors from Landsat 8-estimated height
0 – 5 m	1.46
5 – 10 m	0.61
10 – 15 m	-1.63
15 – 20 m	-4.94
> 20 m	-7.99

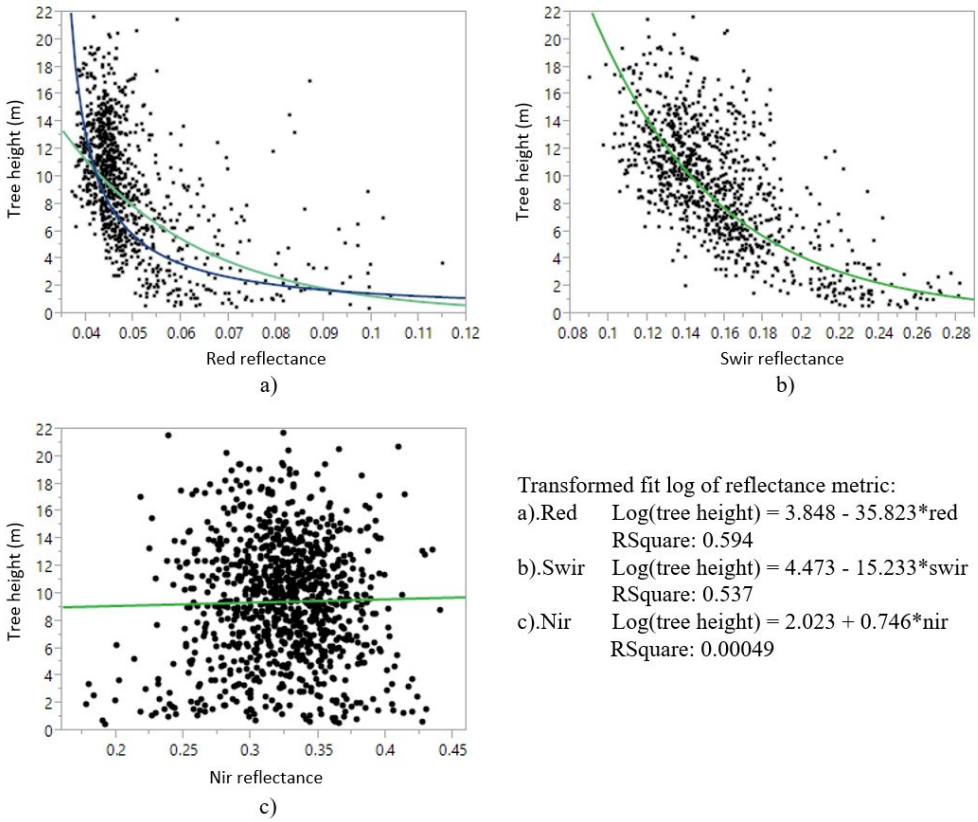
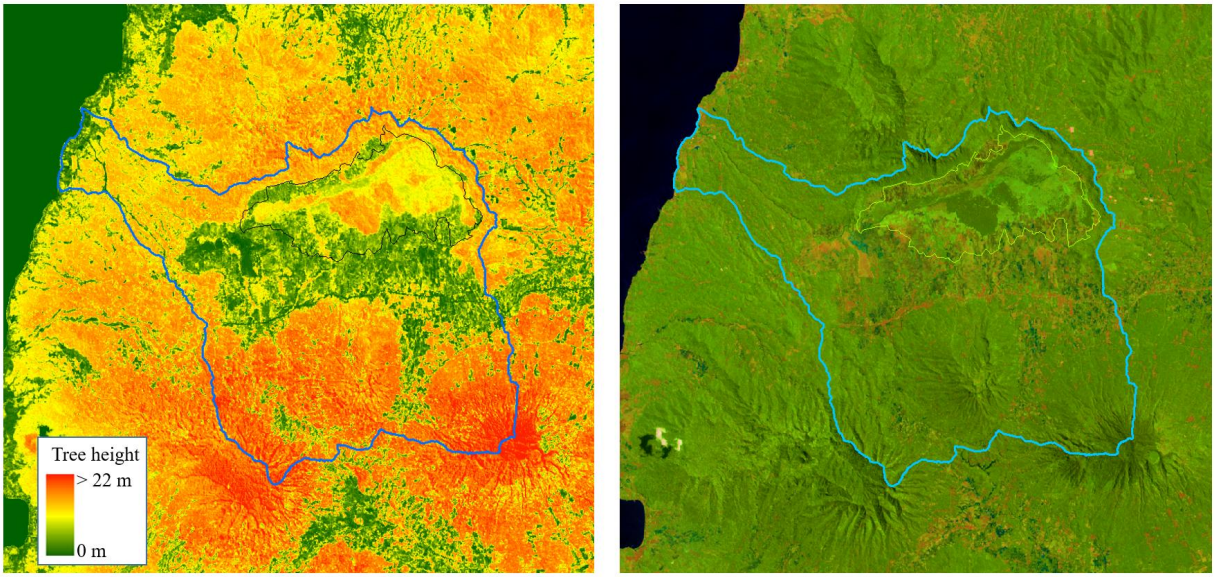


Figure 4. Correlation model between red reflectance of Landsat 8 and LiDAR-derived height in 5–selected sampling sites



a) b)

Figure 5. a) Estimated tree height from red reflectance of Landsat, b) Landsat image (RGB: 6-5-3)

Moreover, the results of LiDAR height and Landsat 8-estimated height data are plotted in Figure 6.

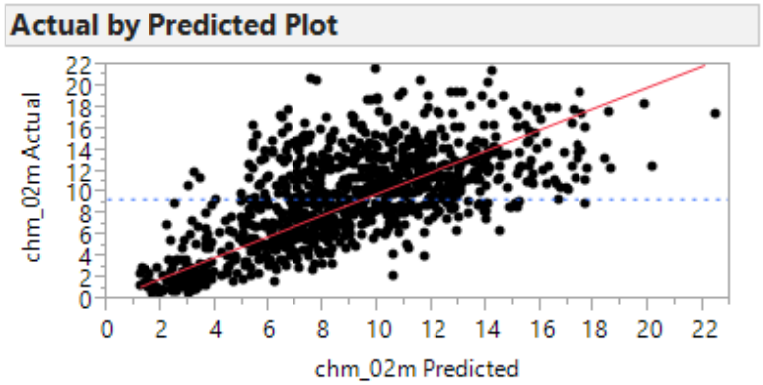


Figure 6. Plot of difference between LiDAR height data and Landsat-derived height

4. CONCLUSIONS

Estimation of tree heights with multispectral imagery is dependent on integrating synoptic coverage optical data with samples of height data, often from LiDAR-derived reference data. This study estimated tree height for agroforestry land use using multispectral Landsat 8 data, LiDAR-derived height data and a log-linear regression model. We generated a Canopy Height Model (CHM) directly from height-normalized LiDAR points and used as reference data in modeling the key height variable in the multispectral bands of Landsat 8. The analysis showed that red band was the best band to estimate tree height in agroforestry land use, followed by swir band. Meanwhile, nir band was not significantly correlated with the tree height attribute. The red, swir and nir reflectance metrics accounted for 59.4%, 53.7% and 0.04% of Landsat log-linear models. The log-linear regression algorithm of red band accurately reproduced the LiDAR-derived height training data using Landsat 8 data with overestimate 1.46 m in estimating tree height < 5 m and underestimate 7.79 m for height > 20 m.

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REFERENCES

[1] Peters, S. M. [Agroforestry: An integration of land use practices], ed. S. S. Hodge. Columbia: University of Missouri Center for Agroforestry (2000).
[2] Sharrow, S. H., Ismail, S., “Carbon and nitrogen storage in agroforests, tree plantations, and pastures in western Oregon, USA”. Agrofor. Syst. 60, 123–130 (2004).
[3] Kirby, K. R. and Potvin, C., “Variation in carbon storage among tree species: Implications for the management of a small-scale carbon sink project”, For. Ecol. Manag. 246, 208–221 (2007).
[4] Nair, P. K. R., “Carbon sequestration studies in agroforestry systems: A reality-check”. Agrofor. Syst. 86, 243–253 (2012).
[5] Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Haberl, H., Harper, R., House, J., Jafari, M., et al., [Agriculture, Forestry and Other Land Use (AFOLU)]. In Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change; Edenhofer, O., Pichs-Mdruga, R., Sokana, Y., Minx, J.C., Farahani, E., Kadner, S.,

Seyboth, K., Adler, A., Baum, I., Brunner, S., et al, Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA (2014).

[6] Chen, Q., Lu, D., Keller, M., dos-Santos, M. N., Bolfe, E. L., Feng, Y., and Wang, C., "Modeling and mapping agroforestry aboveground biomass in the Brazilian Amazon using airborne Lidar data", Remote Sens. 8 (1), 1-17 (2012).

[7] Thapa, R. B., Watanabe, M., Motohka, T., Shiraishi, T., and Shimada, M., "Calibration of aboveground forest carbon stock models for major tropical forests in central Sumatra using airborne LiDAR and field measurement data". IEEE J. Sel. Top. Appl 8, 661–673 (2015).

[8] D'Oliveira, M.V., Reutebuch, S.E., McGaughey, R.J., and Andersen, H.E., "Estimating forest biomass and identifying low-intensity logging areas using airborne scanning Lidar in Antimary State Forest, Acre State, Western Brazilian Amazon". Remote Sens. Environ. 124, 479–491 (2012).

[9] Andersen, H. E., Reutebuch, S. E., McGaughey, R. J. D'Oliveira, M.V., and Keller, M., "Monitoring selective logging in western Amazonia with repeat Lidar flights". Remote Sens. Environ. 2014, 151, 157–165 (2014).

[10] Hansen, M. C., Potapov, P. V., Goetz, S. J., Turubanova, S., Tykavina, A., Krylov, A., Kommareddy, A., and Egorov, A., "Mapping tree height distributions in Sub-Saharan Africa using Landsat 7 and 8 data", Remote Sens. Environ, 185, 221-232 (2016).

[11] Hudak, A. T., Lefsky, M. A., Cohen, W. B., and Berterretche, M., "Integration of lidar and Landsat ETM+data for estimating and mapping forest canopy height". Remote Sens. Environ. 82, 397–416 (2002).

[12] Asner, G. P., Clark, J. K., Mascaro, J., Galindo García, G. A., Chadwick, K. D., Navarrete Encinales, D. A., Paez-Acosta, G., Cabrera Montenegro, E., Kennedy-Bowdoin, T., Duque, Á., Balaji, A., von Hildebrand, P., Maatoug, L., Phillips Bernal, J. F., Yepes Quintero, A. P., Knapp, D. E., García Dávila, M. C., Jacobson, J., and Ordóñez, M. F., "High-resolution mapping of forest carbon stocks in the Colombian Amazon", Biogeosciences, 9, 2683–2696 (2012).

[13] Ota, T., Ahmed, O. S., Franklin, S.E., Wulder, M.A., Kajisa, T., Mizoue, N., Yoshida, S., Takao, G., Hirata, Y., Furuya, N., Sano, T., Heng, S., Vuthy, M., "Estimation of airborne Lidar-derived tropical forest canopy height using Landsat time series in Cambodia" Remote Sens. 6, 10750–10772 (2014).

[14] Simard, M., Pinto, N., Fisher, J. B., and Baccini, A., "Mapping forest canopy height globally with spaceborne Lidar", J Geophys Res, 116, G04021 (2011).

[15] Khairiah, R. N., Setiawan, Y., Prasetyo, L. B., and Permatasari, P. A., "Leaf Area Index (LAI) in different type of agroforestry systems based on hemispherical photographs in Cidanau Watershed". IOP C Ser Earth Env, 54, 012050 (2017)

[16] Hudjimartsu, S., Prasetyo, L. B., Setiawan, Y., and Suyamto, D., "Illumination Modelling for topographic correction of Landsat 8 and Sentinel 2A imageries". EMS2017: European Modelling Symposium. Manchester, United Kingdom, November 20-22 2017

[17] Vermote, E. F., El Saleous, N. Z., and Justice, C. O., "Atmospheric correction of MODIS data in the visible to middle infrared: First results", Remote Sens Environ 83, 97–111 (2002)