The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W4-2022
17th 3D GeoInfo Conference, 19–21 October 2022, Sydney, Australia

NOVEL APPROACH FOR FOREST ALLOMETRIC EQUATION MODELLING WITH RANSAC SHAPE DETECTION USING TERRESTRIAL LASER SCANNER

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Commission IV, WG IV/9

KEY WORDS: Allometric equation, Forest, Terrestrial Laser Scanner (TLS), RANSAC, ANOVA.

ABSTRACT:

Forest biomass quantification is highly crucial for the maintenance of global carbon cycle. Hence, the accurate estimation of tree parameters is of utmost requirement nowadays. The hypothesis of this research is to formulate a volumetric equation which will be focussed on the structure of the tree and not the species. To serve this purpose, 13 plots were scanned in the Barkot forest range of Uttarakhand, India, and the plots were scanned using Terrestrial Laser Scanner (TLS). The tree attribute such as radius of the stem and tree height were estimated using Random Sample Consensus (RANSAC) algorithm and line primitive vector, respectively. The correlation was established using multiple linear regression using the TLS derived tree parameters and field estimated tree parameters. The R^2 obtained for field estimated biomass is 0.91 with radius and 0.73 with the tree height. The radius of the stem and tree height were used for the calculation of volume of all the trees and the R^2 value obtained for field estimated volume and TLS derived volume is 0.95. Then the stem volume of the trees were calculated based on the new volume equation. The statistical analysis was done, and ANOVA test was performed indicating high F value (25.4) which shows that the regression model is significant. The predicted biomass correlation coefficient (R^2 = 0.97) was obtained. It represents the significance of the model for the estimation of volume and biomass is high. The equation can be implemented in any forest type irrespective of the forest structure.

1. INTRODUCTION

The ecosystem services monitoring and productivity estimation is important nowadays to regulate the changes in the forest (Huang et al., 2018). Earlier, the regulation of forest changes was done using the traditional methods. The traditional methods were destructive and tedious task. The traditional destructive sampling has subdued by the new emerging techniques of scanning (Ojoatre et al., 2019). One of the most popular instruments used for the terrestrial scanning using LiDAR is Terrestrial Laser Scanner (TLS). TLS is used for validation in the forest inventory information retrieval. The tree attributes such as Diameter at Breast Height (DBH) and tree height are used for the biomass estimation purpose using TLS and it was found that the observed values were very close to the field measuring data (Xi et al., 2016). The application of TLS is not confined to a particular discipline rather it is of wide range (Calders et al., 2015). However, TLS can also be used for accurate DTM generation with different combinations of scan positions in the plot (Kushwaha et al., 2022). Further investigation was done in urban heterogeneous forests and found that the DBH is highly correlate with d than height of the tree (Moskal & Zheng, 2011). TLS was also used for the biomass allometric equation modelling for the mangrove trees (Olagoke et al., 2016). Also, the stem volume estimation was done using a 3D point cloud based technique (Hildebrandt & Iost, 2012). The use of SimpleTree software to automatically correct the parameters provided by users was done based on the TLS Point Cloud Data (PCD) (Hackenberg et al., 2014). Moreover, the identification of stem and other fine structures of the trees was done using two-scale classification method which includes clustering and direction growing algorithm (Xia et al., 2015).

TLS has more dimensions of applications when it comes to the forestry. However, there are still challenges left behind. The tree information can be retrieved using TLS, the research was focussed on the random sample consensus (RANSAC) algorithm for the tree detection and delineation using LiDAR PCD (Tittmann et al., 2011). The stem reconstruction technique was developed using TLS based on self-adaptive cylinder growing method (Wang et al., 2016). To mitigate several issues concerning the forest management the tree attribute information was retrieved and later, volume and biomass was estimated using TLS (Olofsson et al., 2014). RANSAC was also used for the primitive structure formation using TLS which can be represented to automatic shape proxies using Computer Aided Design (CAD) model (Schnabel et al., 2007). Another parameter which is Leaf Area Index (LAI) was estimated using 3D PCD of TLS by converting it to 2D raster image (Zheng et al., 2013). Not only tree attribute information estimation, TLS can also be used for the quantification of post fire effects in the forest (Gupta et al., 2015). Also, TLS can be used to find out

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the leaf orientation using least square fitting approach (Zheng & Moskal, 2012).

The Quantitative Structure Model (QSM) was used for the estimation of Above Ground Biomass (AGB) using species specific wood density equations (Gonzalez de Tanago et al., 2018). The circle fitting and scan mode approach was used for the estimation of stem volume and diameter (Pueschel et al., 2013). Maximum likelihood method was used to improve the accuracy of tree attribute information such as canopy profile, direction of leaf angle, and LAI (Zhao et al., 2015). Thus, different approaches have already been taken to utilise the TLS PCD for the purpose of digging more information of the forest.

It has been proven that TLS can be used both in qualitative and quantitative assessment of tree in diverse aspects. The main aim of this research is to investigate the already established techniques for tree information retrieval and use them to improvise the national forest volumetric equation. The objective is to find out best algorithm for the stem volume and biomass retrieval without inspecting the species of the tree. Also investigate the statistical importance for retrieval of tree attribute information using TLS and the algorithm can be used irrespective of the forest type.

2. STUDY AREA

The study area focussed on this research is Barkot Forest which is located between the latitude of 30°03′52″ to 30°10′43″N and longitude of 78° 09′49″ to 78°17′09″ E. The forest is present along the Dehradun-Rishikesh Road. The forest type is moist deciduous and totally dominated by the *Shorea robusta* (Sal) species, also, the understory vegetation is generally occupied by *Mallotus philippensis* (Rohini). The location of the study area is shown in Figure 1.

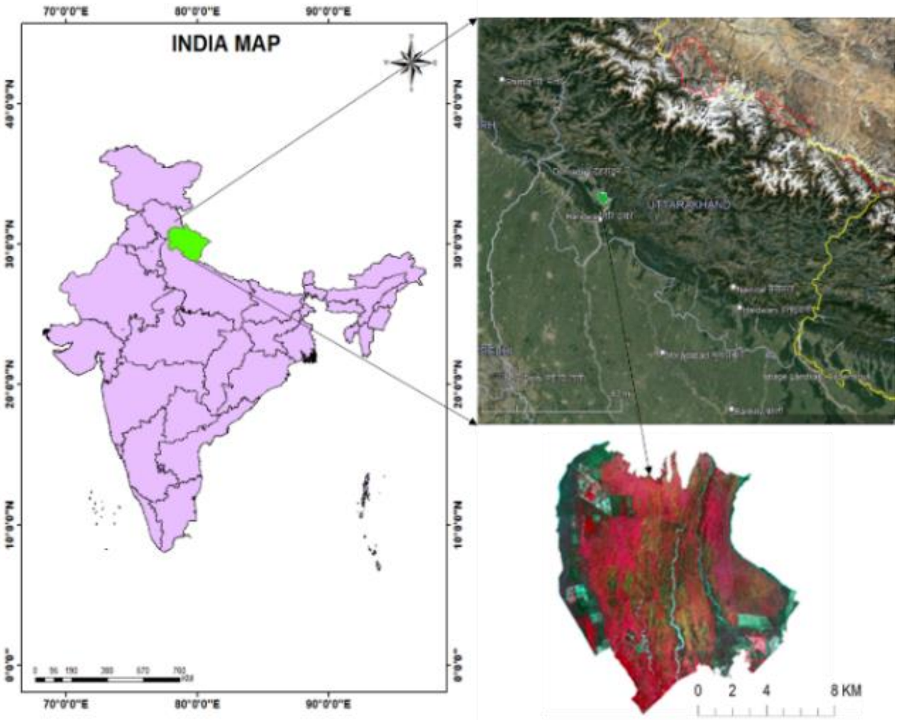

Figure 1: Study area.

3. DATASET USED

The TLS used in this research is Riegl VZ 400 which was extensively used for the scanning of 13 plots of 25 m X 25 m in the forest. The TLS belongs to the Laser class 1 category. The total measurement range varies between 1.5 m to 600 m and with the laser reception rate of 100 kHz. The wavelength used for scanning is near infrared (1050 nm). The angular resolution was kept at 0.03 mrad. The vertical resolution was set between 30° to 130° whereas, horizontal resolution was between 0° to 360°. The ancillary data was used which includes the field estimated tree parameters. The National volume equations were used for the calculation of the stem volume and biomass. The stem volume and biomass were then used for the validation of the TLS modelled volumetric equation. The plot scheme is shown below in Figure 2.

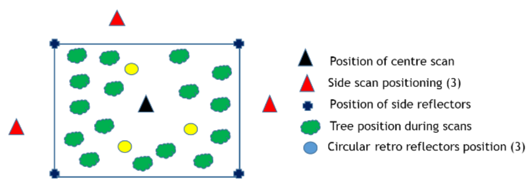

Figure 2: Schematic representation of scanning position in forest plots.

4. METHODOLOGY

The TLS data acquisition was done with the scheme represented in the Figure 2. The scans were done at 4 position using side reflectors and circular retro-reflectors. Before scanning the plot tagging of each tree were done. So, total 13 plots were acquired. The most dominated species of the tree was *Shorea robusta* (Sal). Approximately 10 -13 trees were considered per plot for the estimation of tree parameters in this study. After scanning, registration of scans was performed using the common tie points in all the scans for which retro reflectors were used. Thereafter all the scans were transformed to a common coordinate system since, all the scans were in different local coordinate system. Noise filtering was done to remove all the outliers in the PCD just after the co-registration. Next step was to extract the single tree from the plot in the CloudCompare software. After extracting a plot from the merged PCD, the individual trees were recognised and segmented out. Later, this individual PCD of tree was used for tree attribute retrieval.

The RANSAC algorithm was used for the estimation of DBH and radius of the trees. The algorithm works in the set of parameters for cylinder primitive structure. Firstly, the inliers and outliers of the datasets were characterised and removed. Secondly, Minimal Sample Set (MSS) of points were created based on the input PCD in the first step. Then minimum number of points were estimated from the MSS. The geometrical shape was decided considering the parameters in the algorithm. The workflow of the RANSAC is presented in the following equations.

The center of the circle (x_0, y_0, z_0) was estimated and r, the locus of all points (x, y, z) was calculated using the following equation.

$$r^2 = (x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2 \qquad (1)$$

The plane that contains the non-collinear points were defined by these equations,

$$center,\ c = (x_0, y_0, z_0) \qquad (2)$$

$$Ax_i + By_i + Cz_i + D = 0 \qquad (3)$$

Where, $i = 1,2\ and\ 3$,

Where, r and center, c is obtained by these equations,

$$d(p_1, c) = d(p_2, c) = d(p_3, c) = r \qquad (4)$$

$$d(p_i, c) = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2 + (z_i - z_0)^2}$$

Estimation of error of each point by computing minimum distance between each point and the cylinder axis, p_D was a point of input point cloud dataset.

$$dmin_j = \frac{\bar{|U_n|}\ Xcp_D}{\overrightarrow{|U_n|}} \qquad (5)$$

The error vector was calculated by subtracting the estimated cylinder radius from these minimum distances.

$$E_j = (dmin_j - r) with\ E_j \epsilon\ E = [E_1, E_2 \ldots \ldots E_j, \ldots \ldots E_N), \qquad (6)$$

The height of the trees were calculated using line primitive vector in CloudCompare by allocating the lowest and highest point of the tree PCD. The individual tree extraction was done prior to the estimation of tree height. The individual tree extraction is shown in the Figure 3. The volume of the trees was calculated using the equation of the cylinder as shown below.

$$V = \pi r^2 H \qquad (7)$$

Where, **r** is radius of the stem in meters (m) and **H** is the height of the tree in meters (m).

The volume calculated using TLS was regressed with the field estimated volume using national volumetric equations.A new volume equation was created based on the multiple linear regression with TLS derived parameters such as DBH, radius, and height, and field estimated tree parameters. The volume equation was then used for the calculation of the stem volume as shown below.

$$Volume = C + \beta_1 * r - \beta_2 * H \qquad (8)$$

Where, C is intercept, β_1 is coefficient of radius (r), and β_2 is coefficient of height (H).

The coefficients of radius and height were calculated while derivation of the volume equation. The volume equation mentioned here is the total volume of the stem of the tree. The stem volume of all the trees in the plots were calculated using above mentioned volume equation. The tree volume was calculated for all the trees in the plot and later used for the calculation of biomass using the following equation.

$$Biomass = V * S * 1.59 \qquad (9)$$

Where V is stem volume, S is specific wood gravity, and **1.59** is biomass expansion factor. The biomass is calculated and regressed with the field estimated biomass for all the trees. The workflow of the methodology is depicted in Figure 4.

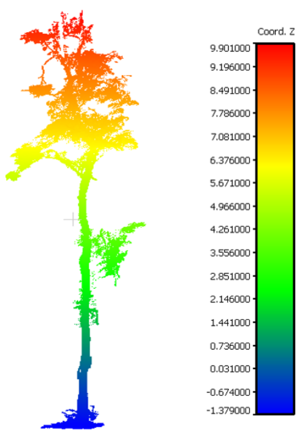

Figure 3: Individual tree extraction from TLS PCD.

The statistical analysis was done using the Analysis of Variance (ANOVA) F test for the significance of the TLS modelled equations to predict the stem volume and biomass of the trees.

The ANOVA F -test is performed for the data which are normally distributed, the variances are homogenous, and the data are independent. The ANOVA F-test establish a linear relation between the independent variables. Here, the independent variable were radius and tree height. The statistical analysis was done to confirm the role of the two tree parameters such as radius and tree height in the estimation of stem volume. Later, the stem volume was used to calculate the biomass of the trees in all the plots.

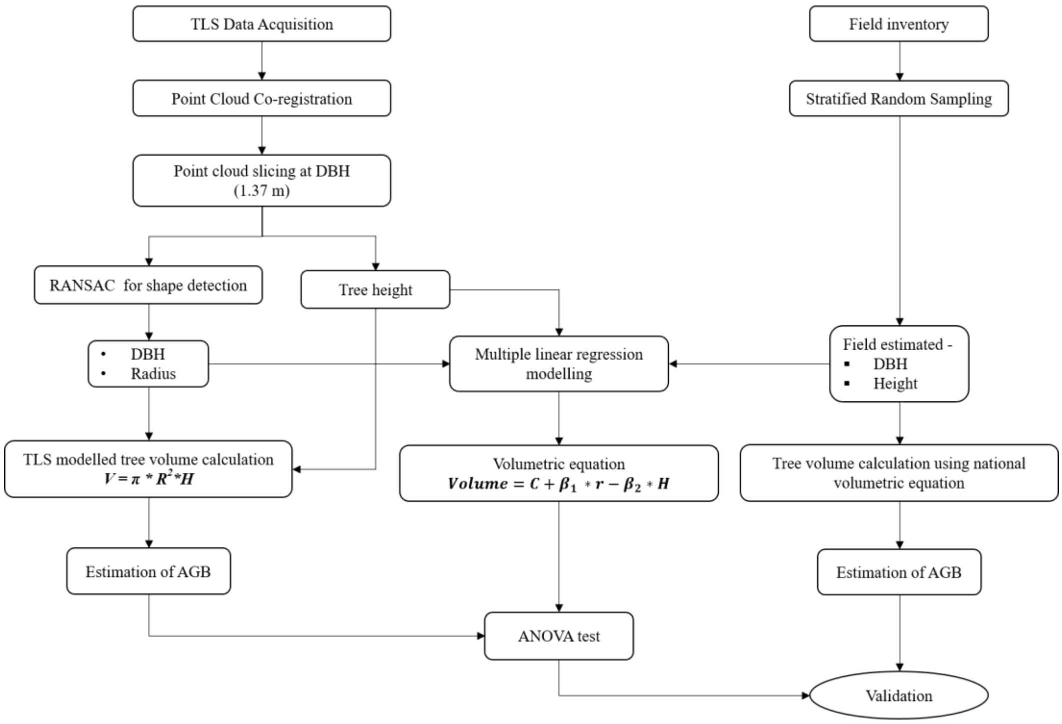

Figure 4: Methodology workflow.

5. RESULTS AND DISCUSSIONS

TLS derived tree parameters were regressed with the field estimated biomass and stem volume. The coefficient of correlation (R^2) obtained for DBH was 0.96 whereas, 0.63 for the tree height.

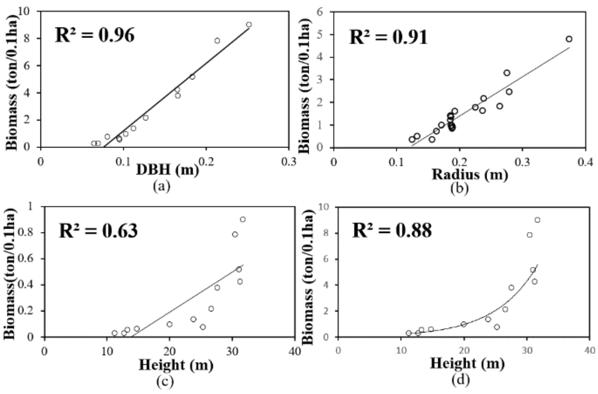

Figure 5: Represents (a) Correlation between DBH and field estimated biomass (b) Correlation between radius and biomass (c) Correlation between height and biomass (d) Log-transformed correlation between height and biomass.

Similarly, the correlation between radius and biomass was found as 0.91. The tree height and biomass regression were log transformed to best fit the model and R^2 was improvised to 0.88. The graphical representation is depicted in Figure 5.

Based on the correlation between the tree parameters derived using TLS and field estimated biomass, the TLS volumetric equation was modelled. The TLS volumetric equation modelling was performed using two parameters namely, radius and height. DBH was not considered even showing high correlation between DBH and field estimated biomass because the equation only focusses on the parameters considered in the RANSAC algorithm.

The volume was calculated using the cylindrical equation and correlation was established between field estimated volume using national volume equation and TLS modelled volume. It has been found that the R^2 obtained was 0.95. Thereafter, based on the regression analysis a new volume equation was used to calculate the volume of the trees in all the 13 plots. This tree volume was then used for the calculation of biomass.

The correlation between the TLS modelled biomass and field estimated biomass was done and R^2 obtained was 0.97. This represents the high correlation between the biomass estimated using the TLS modelled volume equation and field biomass.

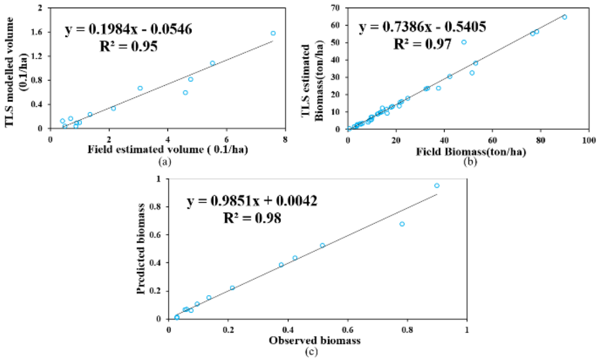

Figure 6: Shows (A) Correlation between field estimated volume and TLS modelled volume, (B) Correlation between field biomass and TLS estimated biomass, (C) Correlation between observed biomass and predicted biomass using TLS modelled volumetric equation.

Using the TLS modelled volume equation, prediction of biomass was done and R^2 obtained was 0.98 between the observed and predicted biomass. The correlation plot is shown in Figure 6. The values obtained using TLS modelled equation is depicted as predicted biomass in the Table 1. The biomass was calculated for every single tree in the plot. The biomass values mentioned in the Table 1 is at plot level.

TLS Plots	Observed Biomass (ton/0.1ha)	Predicted Biomass (ton/0.1ha)
Plot 1	0.074	0.061
Plot 2	0.515	0.524
Plot 3	0.212	0.221
Plot 4	0.376	0.387
Plot 5	0.095	0.108
Plot 6	0.782	0.677
Plot 7	0.899	0.951
Plot 8	0.134	0.151
Plot 9	0.423	0.435
Plot 10	0.026	0.008
Plot 11	0.026	0.015
Plot 12	0.054	0.066
Plot 13	0.059	0.069

Table 1: Showing the predicted biomass using the TLS modelled volume equation and field observed biomass for all the 13 plots.

The regression statistics of the TLS modelled volume equation is represented in Table 2. Where, the multiple R is obtained as 0.98. The R^2 obtained was 0.92, the adjusted R2 was reported as 0.89. The standard error was observed as 0.049. Considering the R^2 value of the multiple regression analysis, the importance of the radius and height for the estimation of stem volume is shown. The correlation between the independent (radius and height) variables and dependent (volume) variable is very high and hence, can be used for the calculation of stem volume.

Regression Statistics	Value
Multiple R	0.96
R Square	0.92
Adjusted R Square	0.89
Standard Error	0.049
Observations	13

Table 2: Represents the regression statistics of TLS modelled volume equation.

ANOVA test was performed to check the significance of the equation in biomass and volume estimation. The F test was performed and found low value as 25.42. This shows the high significance of the equation in the prediction of biomass and volume. The test results are mentioned in Table 3.

	df	SS	MS	F	Significance F
Regression	4	0.246	0.061	25.421	0.00013
Residual	8	0.019	0.002		
Total	**12**	**0.265**			

Table 3: ANOVA test analysis.

6. CONCLUSIONS AND FUTURE SCOPE

We presented a possible solution for the accurate stem volume and biomass estimation using TLS. Also, to minimise the dependency on the national volume equation in the calculation of stem volume and biomass. The proposed volume equation shows the potential to overcome the species-specific equations biasness in the calculation of stem volume and biomass. All together the data acquisition was done for 13 plots and the scanning of 1 plot exhausted at least 3 hours because the point density chosen was high. The acquisition was mainly done in the leaf-off season of the forest. The advantage of TLS is the wide range coverage of the plot. Here, the plots were not dense, so only 4 scans were done to cover the whole 25 m X 25 m plots. The goal of this research was only to focus on the structure of the stem, although, DBH was not considered because the volume equation was modelled using RANSAC algorithm which treated tree stem as cylinder and only utilises radius and height. The stem volume and biomass were calculated for all the trees in the 13 plots. The multiple linear regression was performed to confirm the dependency and variability of the considered tree parameters (radius and tree height).

Overall, TLS again proved to be the best and accurate forest inventory instruments when it comes to terrestrial LiDAR. Also, RANSAC algorithm is one of the most accurate for the estimation of tree parameters.

The authors, would like to extend the work with a greater number of observations in future. It will be taken under consideration that the work with further to test the potential of volume equations in different forest types.

ACKNOWLEDGEMENTS

This research was undertaken as a work of M.Tech. Thesis of the first author of this paper. The author would like to thank the director and dean academics IIRS for their kind support. Also, it was never possible task without the encouragement of the Head of the Department of Forest an Ecology, Dr. Hitendra Padalia and supervisor Dr. Subrata Nandy. Also, would like to the entire FED lab for their support during thesis research.

REFERENCES

Calders, K., Newnham, G., Burt, A., Murphy, S., Raumonen, P., Herold, M., Culvenor, D., Avitabile, V., Disney, M., Armston, J., & Kaasalainen, M. (2015). Nondestructive estimates of above-ground biomass using terrestrial laser scanning. *Methods in Ecology and Evolution*, *6*(2), 198–208. https://doi.org/10.1111/2041-210X.12301

CloudCompare (version 2.12) [GPL software]. (2022). Retrieved from http://www.cloudcompare.org/

Gonzalez de Tanago, J., Lau, A., Bartholomeus, H., Herold, M., Avitabile, V., Raumonen, P., Martius, C., Goodman, R. C., Disney, M., Manuri, S., Burt, A., & Calders, K. (2018). Estimation of above-ground biomass of large tropical trees with terrestrial LiDAR. *Methods in Ecology and Evolution*, *9*(2), 223–234. https://doi.org/10.1111/2041-210X.12904

Gupta, V., Reinke, K. J., Jones, S. D., Wallace, L., & Holden, L. (2015). Assessing metrics for estimating fire induced change in the forest understorey structure using Terrestrial Laser Scanning. *Remote Sensing*, *7*(6), 8180–8201. https://doi.org/10.3390/rs70608180

Hackenberg, J., Morhart, C., Sheppard, J., Spiecker, H., & Disney, M. (2014). Highly accurate tree models derived from terrestrial laser scan data: A method description. *Forests*, *5*(5), 1069–1105. https://doi.org/10.3390/f5051069

Hildebrandt, R., & Iost, A. (2012). From points to numbers: a database-driven approach to convert terrestrial LiDAR point clouds to tree volumes. *European Journal of Forest Research*, *131*(6), 1857–1867. https://doi.org/10.1007/s10342-012-0638-1

Huang, X., Ziniti, B., Torbick, N., & Ducey, M. J. (2018). Assessment of forest above ground biomass estimation using multi-temporal C-band Sentinel-1 and Polarimetric L-band PALSAR-2 data. *Remote Sensing*, *10*(9), 1–15. https://doi.org/10.3390/rs10091424

Kushwaha, S. K. P., Singh, A., Jain, K., & Mokros, M. (2022). Optimum Number and Positions of Terrestrial Laser Scanner To Derive Dtm At Forest Plot Level. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B3-2022(June), 457–462. https://doi.org/10.5194/isprs-archives-xliii-b3-2022-457-2022

Moskal, L. M., & Zheng, G. (2011). Retrieving Forest Inventory Variables with Terrestrial Laser Scanning (TLS) in Urban Heterogeneous Forest. *Remote Sensing*, *4*(1), 1–20. https://doi.org/10.3390/rs4010001

Ojoatre, S., Zhang, C., Hussin, Y. A., Kloosterman, H. E., & Ismail, M. H. (2019). Assessing the Uncertainty of Tree Height and Aboveground Biomass from Terrestrial Laser Scanner and Hypsometer Using Airborne LiDAR Data in Tropical Rainforests. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *12*(10), 4149–4159. https://doi.org/10.1109/JSTARS.2019.2944779

Olagoke, A., Proisy, C., Féret, J.-B., Blanchard, E., Fromard, F., Mehlig, U., de Menezes, M. M., dos Santos, V. F., & Berger, U. (2016). Extended biomass allometric equations for large mangrove trees from terrestrial LiDAR data. *Trees*, *30*(3), 935–947. https://doi.org/10.1007/s00468-015-1334-9

Olofsson, K., Holmgren, J., & Olsson, H. (2014). Tree stem and height measurements using terrestrial laser scanning and the RANSAC algorithm. *Remote Sensing*, *6*(5), 4323–4344. https://doi.org/10.3390/rs6054323

Pueschel, P., Newnham, G., Rock, G., Udelhoven, T., Werner, W., & Hill, J. (2013). The influence of scan mode and circle fitting on tree stem detection, stem diameter and volume extraction from terrestrial laser scans. *ISPRS Journal of Photogrammetry and Remote Sensing*, *77*, 44–56. https://doi.org/10.1016/j.isprsjprs.2012.12.001

Schnabel, R., Wahl, R., & Klein, R. (2007). Efficient RANSAC for point-cloud shape detection. *Computer Graphics Forum*, *26*(2), 214–226. https://doi.org/10.1111/j.1467-8659.2007.01016.x

Tittmann, P., Shafii, S., Hartsough, B., & Hamann, B. (2011). Tree Detection and Delineation from LiDAR point clouds using RANSAC, *Silvilaser 2011*, October 16-19, 1–23.

Wang, D., Hollaus, M., Puttonen, E., & Pfeifer, N. (2016). Fast and robust stem reconstruction in complex environments using terrestrial laser scanning. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *41*, 411–417. https://doi.org/10.5194/isprsarchives-XLI-B3-411-2016

Xi, Z., Hopkinson, C., & Chasmer, L. (2016). Automating plot-level stem analysis from terrestrial laser scanning. *Forests*, *7*(11), 1–20. https://doi.org/10.3390/f7110252

Xia, S., Wang, C., Pan, F., Xi, X., Zeng, H., & Liu, H. (2015). Detecting stems in dense and homogeneous forest using single-scan TLS. *Forests*, *6*(11), 3923–3945. https://doi.org/10.3390/f6113923

Zhao, K., García, M., Liu, S., Guo, Q., Chen, G., Zhang, X., Zhou, Y., & Meng, X. (2015). Terrestrial lidar remote sensing of forests: Maximum likelihood estimates of canopy profile, leaf area index, and leaf angle distribution. *Agricultural and Forest Meteorology*, *209–210*, 100–113. https://doi.org/10.1016/j.agrformet.2015.03.008

Zheng, G., & Moskal, L. M. (2012). Leaf orientation retrieval from terrestrial laser scanning (TLS) data. *IEEE Transactions on Geoscience and Remote Sensing*, *50*(10 PART2), 3970–3979. https://doi.org/10.1109/TGRS.2012.2188533