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# AN AUTOMATED METHOD FOR FORESTRY DETERMINATION USING A UAV LIDAR-MOUNTED PLATFORM

**Maxim ARSENI, Octavian ROMAN, Madalina CALMUC, Valentina-Andreea CALMUC, Adrian ROSU, Stefan-Mihai PETREA, Catalina ITICESCU, Lucian-Puiu GEORGESCU**

REXDAN Research Infrastructure,
"Dunarea de Jos" University of Galati, Faculty of Sciences and Environment,
98 George Cosbuc Street, Galati, Romania

Corresponding author email: maxim.arseni@ugal.ro

***Abstract***

*LiDAR is one of the most promising technologies in the forestry industry. The LiDAR scanning methods help to improve and to drive sustainable forest management. The main purpose of this paper is to apply the UAV LiDAR scanning method, to identify and measure the tree volume calculation along a road section. The flight was made using a UAV octocopter and a LiAir LiDAR system. To determine the forestry volume several steps of postprocessing were applied. Therefore we create a 3D point cloud reconstruction of large forest areas. After the preliminary post-process, we apply a segmentation for the study area and track individual trees, to create an inventory for the detected trees. Determining the tree volume helps to make a correct financial estimation of the elimination of this from a new road or area that changes its destination. On the overhand, automated methods like LiDAR scanning of forestry and terrain, and automated tree volume calculation helps to improve the time spent confronted with traditional taxation methods.*

***Key words***: *LiDAR, UAV, Forestry segmentation, Point cloud classification.*

## INTRODUCTION

The essence of the technology reveals its name: LiDAR from English Light Identification Detection and Ranging - light detection and range determination. It works as follows: the optical system sends a light signal, and based on it receives and processes information about distant objects - and, using this data, creates a three-dimensional image of the scanned object (Burt et al., 2019). The history of the technology began in the 1960s of the 20th century - LiDAR was used to track satellites and military targets(Fryskowska & Stachelek, 2018). Over time, technology has improved and its scope has expanded. For example, today the LiDAR scanner, among other things, is built into the latest iPad Pro model.
One of the most widespread laser scanning technologies has found its way into the forestry industry. Since the early 2000s, LiDAR has been used worldwide as an alternative to traditional forest inventory methods. The advantages of laser taxing over traditional approaches are obvious: the method saves time and therefore money.
Most importantly, laser surveying makes it possible to obtain the most accurate and objective data on the condition of forests, down to tree height and trunk diameter (Kukkonen et al., 2021). The process consists of several stages. The first is information gathering: an aircraft or drone, with a LiDAR scanner installed, flies over a certain territory, scanning it. Penetrating through the forest canopy to the ground, the laser beam encounters many surfaces along the way and is reflected from them. This reflection is captured by the scanner receiver installed on the board of the UAV. Since the scanner is capable of generating from 100 up to 500 thousand laser pulses per second, depending on the used LiDAR model, and also it can provide a very large amount of information that is generated at the end of the scan(Wang et al., 2020).
The next step is decryption. The data collected by the LiDAR scanner is a so-called "point cloud" - a dense field of points located in a three-dimensional coordinate system. Each point in the cloud has its class: soil; undersized vegetation; vegetation of medium height; tall vegetation; noise; water surfaces. To view this

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information and build 3D terrain models based on it, special programs are used. The most accurate results are provided by the additional use of information from external geolocation systems, terrain maps, and GNSS. The data taken from them about roads, lakes, and rivers serve as a kind of reference point for the creation of accurate digital models of the relief, terrain, and canopy of plantations.

The study area was chosen so that there are areas sufficiently covered with trees.

The study area is situated in the western part of Romania, rather than between $22^0 38'30"$ to $22^0 40'30"$ East longitude and $45^0 88'20"$ to $45^0 88'67"$ (Figure 1).

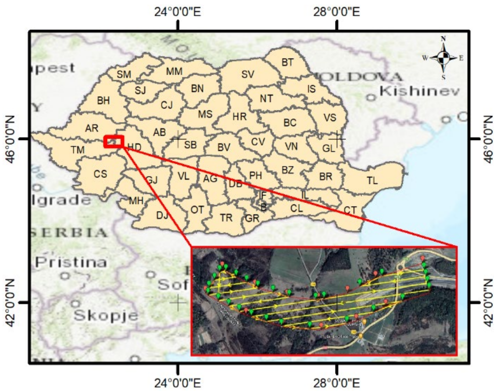


Figure 1. The mission flight path inside the study area

## MATERIALS AND METHODS

To obtain point cloud data from aerial scanning an octocopter UAV with a LiAir V70 LiDAR sensor was used. The LiDAR sensor generates up to 240 000 points for the first strongest return and a total of 720 000 points for a triple return. Additionally, the LiAir sensor has an optical Sony A5100 camera with a 24-megapixel. The range accuracy of the LiDAR unit is ±2 cm with an $70.4^0$ (horizontal) field of view (Figure 2).

The flight plan has 1.7 km long with a 300 m corridor width. The maximum speed allowed for this data collection was 6 m/s. The total flight time was above 50 minutes (Figure 3).

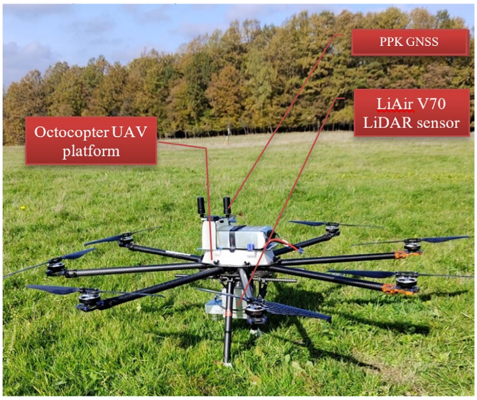


Figure 2. UAV platform and LiDAR sensor used for flight and point cloud data collected


Figure 3. Image footprint and flight path mission created for the aerial survey

Additionally to the UAV platform, in the field was made statical GNSS determinations of ground control points (GCPs). The GCPs were used for the point cloud georeferencing and model calibration. The PPK technology was used to align all the cloud points and trajectory adjustments. The PPK GNSS observation post-processing involves a process of differential correction, which involves comparing the raw GNSS data collected by the receiver with the precise ephemeris data and carrier phase measurements to obtain highly accurate positioning information (Figure 4). The GCP's point was surveyed with a Hiper HR GNSS, produced by Topcon.

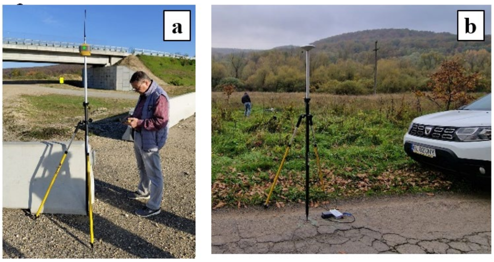


Figure 4. The precision GNSS static survey - image (a). PPK equipment for trajectory adjustment linked to PPK GPS mounted on UAV platform - image (b)

The overlapping of flight paths was 60 x 80%, to have the best accuracy in point cloud coordinate determination (Figure 5) (Arseni et al., 2016). In this case, approximately all the study area was scanned twice, and the confidence level of the data was very high. The UAV flight survey was performed in parallel paths, trying to maintain a constant altitude, by inputting a predefined Digital Elevation Model (DEM) inside the UAV pilot memory. The altitude of the flight was 80 m above the ground.

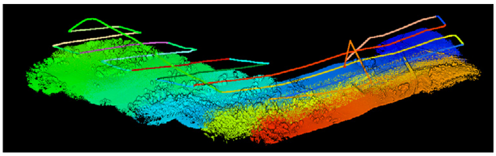

Figure 5. The UAV flight path with 60 x 80 overlapping and displayed by GNSS time mode with applied shading technique to enhance the visual contour effects

Thus, it was collected a dataset having an average point density of 196 points/m². The total covered area was 55.8 hectares with an amount of 191 million points.

To post-process the surveyed point cloud data was made with LiGeoreference software, produced by Green Valley company (Liu et al., 2022). The optional software LiDAR360, also produced by Green Valley was used for the point cloud classification and forestry determination. The ground classification of the point cloud from the collected UAV LiDAR data involves separating the points that correspond to the ground surface from other points such as trees, buildings, and other objects (Zeybek & Şanlıoğlu, 2019). This can be achieved through several techniques, like height thresholding, slope-based filtering, Canopy height model (CHM), or machine learning algorithms. For this study, the ground classification was made by a combination of the height thresholding combined and slope filtering method (Figure 6).

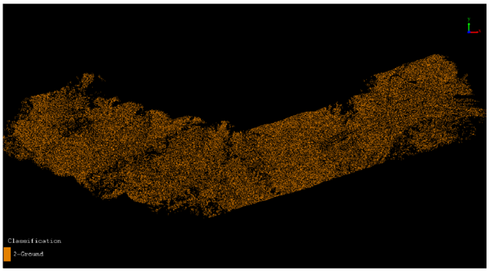

Figure 6. The classification of point cloud data depends on ground points to create a DTM model

To achieve the main purpose of this study, namely to determine the forestry from a point cloud database a flowchart was followed. If we analyze the workflow from Figure 7 the proposed approach includes two main phases: the first step is the flight planning and LiDAR scanning, and the second one is the post-process step and Canopy Height Model (CHM) derivation and extraction of tree parameters.

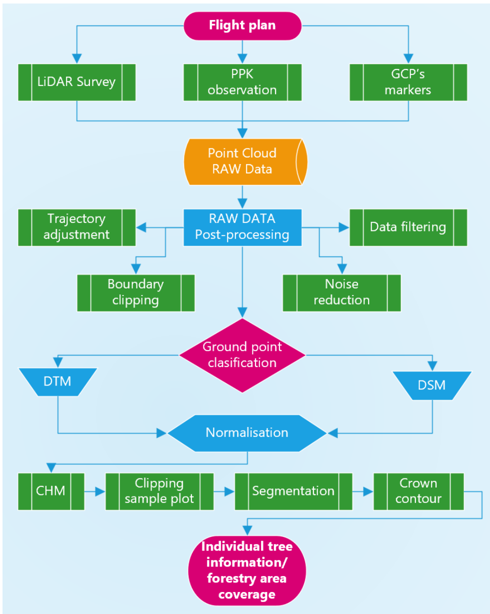


Figure 7. The flowchart of the main steps to automated segmentation and forestry determination from UAV LiDAR data

## RESULTS AND DISCUSSIONS

To achieve the main purpose of this research is necessary to resolve some problems of DTM and DSM creation. These two results serve to estimate the over parameters such as canopy height, individual trees, or crown volume and area. All these data are based on the collected LiDAR measurements. The collected RAW data was pre-processed, by trajectory adjustment, elevation adjustment, and data filtering to obtain a projected point cloud model (Figure 9).
The final result of the point cloud was cleared by removing the outliers. It helps eliminate high-level gross errors and low-level gross errors.

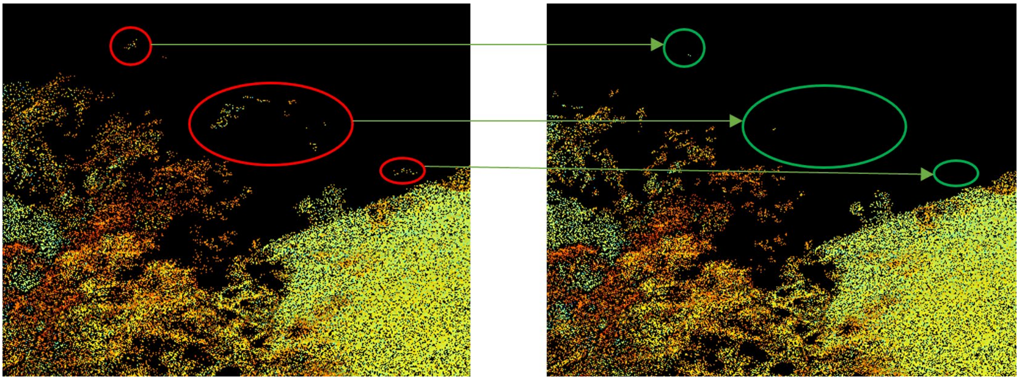

Figure 8. Example of a result obtained by removing the outliers from pre-processed point cloud data

After the point cloud classification by ground point with 20 m maximum building height and $88^0$ maximum terrain angle, the DTM model was created with 0.5x0.5 m pixel dimension. The TIN interpolation method was used to create the DTM model.
Digital Surface Model (DSM) created for the study area refers to the digital representation of the height of the surface including the buildings, bridges, roads, and trees (Selim et al., 2022). Compared to a DEM, a DSM contains more elevation information for buildings, bridges, forests, and other surface objects that don't exist in the DEM. The DSM was created with the same pixel size, by using the TIN interpolation method. DSM is based on DEM and further covers the elevation of surface information other than the ground. As is shown in Figure 9 the DTM profile has only terrain points, while the DSM has forestry information.
An important step for forestry determination from point cloud data is to obtain the canopy height model (CHM) by the subtraction of the DTM from the DSM. Both digital models at 0.5 m spatial resolution will derive to CHM with the same spatial resolution. This resolution is optimal for tree crown delimitation and statistical parameter calculation.

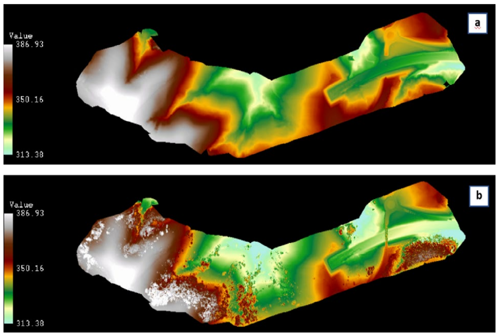


Figure 9. The DTM (a) and DSM (b) at 0.5 m spatial resolution with height variation between 313.38 to 386.93 m reference to the Black Sea Elevation Datum

To eliminate some negative values, the CHM model was normalized by DEM (Figure 10). By normalization, we remove the influence of terrain relief on the elevation value of the point cloud data.
This process is performed by subtracting the corresponding terrain elevation of the DEM from each point's Z value. The height of the CHM model varies between 0 to 35.85 m

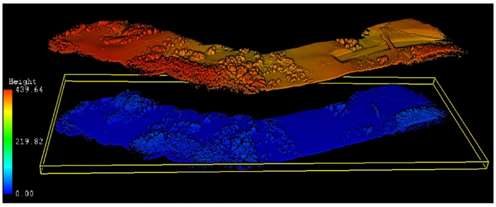


Figure 10. The normalization by DEM of point cloud data makes it easier to identify and separate the ground points from other features in the scene

Extracting forestry information from LiDAR point cloud data involves processing the data to identify and analyze different features of the forest. To make it possible is a need to make a tree segmentation. Tree segmentation from point cloud data is a process of identifying and extracting the point cloud data related to trees in a given environment. It is a crucial task in many fields such as forestry management, urban planning, and environmental monitoring. For this research, it was used a canopy-based segmentation. This method segments trees based on their canopy shape. It assumes that trees have a well-defined canopy shape that can be detected using geometric or statistical methods. The method uses algorithms such as region growing, clustering, or graph-based methods to segment points within the canopy as trees. Canopy-based segmentation step was based on dividing the point cloud data set into tree-like objects based on the characteristics of their canopies (Jakovljevic et al., 2019; Zeybek & Şanlıoğlu, 2019). These basis algorithms used for point cloud segmentation are described by the next equation:

$$P_d x \left(\frac{H_c}{W_c}\right) > T \qquad (1)$$

where:
$P_d$ - the number of points per unit area within the canopy;
$H_c$ - the height of the canopy, typically measured as the vertical distance between the highest and lowest points within the canopy;
$W_c$ - the average width of the canopy, typically measured as the horizontal distance between the leftmost and rightmost points within the canopy;
T - a defined threshold value that determines whether a given cluster of points represents a single tree or not.

To achieve more accurate results is indeed apply the above formula by first identifying clusters of points that represent individual trees based on their proximity to each other. For each cluster, the point density, canopy height, and canopy width are calculated. The formula then evaluates whether the combination of these factors meets a user-defined threshold value. If the threshold is exceeded, the cluster is considered to represent a single tree or tree-like object and is segmented from the rest of the point cloud data (Dai et al., 2022; Nasiri et al., 2021). For point cloud segmentation in this research, a 2 m distance threshold value was used, and a 1.5 m height above ground value was applied to avoid the influence of low vegetation (e.g., grass and shrubs). The result of point cloud segmentation is shown in Figure 11.

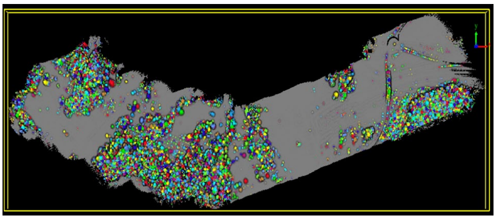

Figure 11. The point cloud segmentation and display by height mode, the grey color represents the above the tree area, under 1.5 m height

To visualize better the obtained segmentation result the crown circle mode representation was run. Each circle represents the crown tree size diameter. Crown diameter is an important metric for assessing the size and growth of individual trees, as well as for estimating forest canopy structure and biomass. Figure 12 shows the result of the crown size diameter classification.

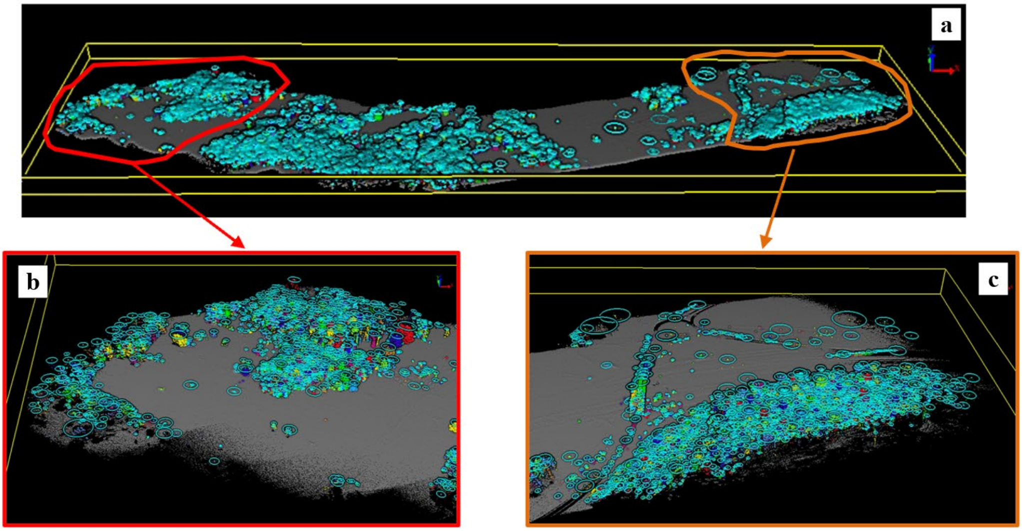


Figure 12. The crown tree representation of the entire area (a - image) and zoom-in clipped sample data from the left (b - image), and the right part (c - image), to visualize the crown size distribution

To identify and adjust the tree segmentation the manual seed identification method was used, The seed point allows selection points within the point cloud that represent the tops of trees and adjust if necessary. Once the seed points have been identified, the ALS seed point editor was used to delineate the individual tree crowns within the lidar data. This is accomplished using algorithms that connect the seed points with neighboring lidar points to create a three-dimensional representation of the tree crown (Schmohl et al., 2022) (Figure 13). The resulting tree crown delineation can be used for a variety of applications, including forest inventory and management, biodiversity assessments, and carbon accounting.

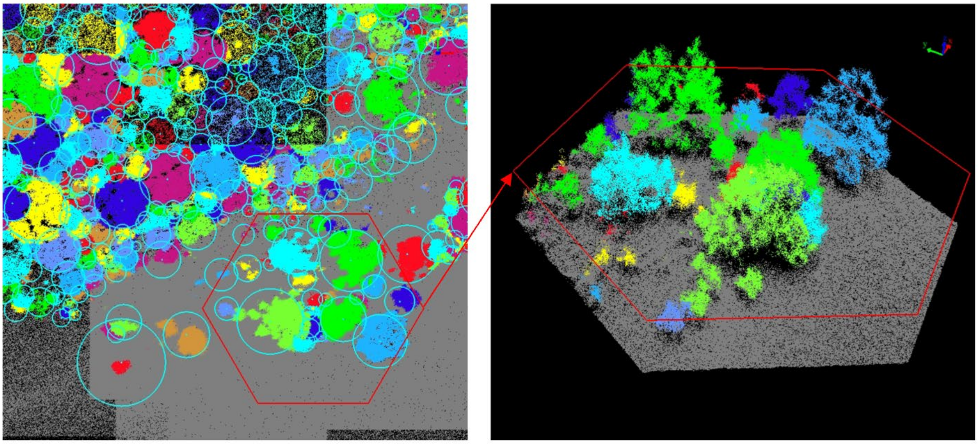

Figure 13. The seed points tool application to represents the 3D model of the tree crown

The total volume of tree crown calculated by point cloud segmentation for the entire surveyed area was amount 300 thousand tons. By applying the segmentation algorithm it was identified 12160 trees. The histogram of height shows that the average tree height is 13.73 m (Figure 14).
The maximum height of the tree was 35.855 m and the minimum was 1.73 m.

Height and crown diameter are two important metrics for characterizing the size and structure of individual trees. The positive and significant results are given by Pearson statistic correlation. The linear relationship between crown diameter and tree height shows that taller trees tend to have medium or smaller crown diameters. Different research studies describe this result as an anomaly, given by the sun missing in the forestry area. So, where the light of the sun is missing the end of the trees is to grow up straight and with minimum crown diameters (Figure 15).

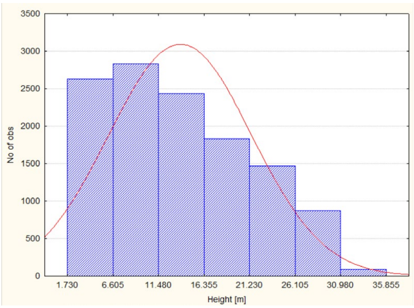


Figure 14. The histogram representation of the height of the tree distributed into 7 classes

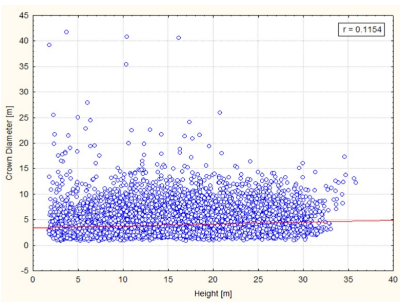


Figure 15. The Pearson correlation between crown diameter and trees height for the entire scanned area

A 3D statistical surface plot is used to represent a three-dimensional graphical surface that is constructed using the crown diameter, crown area, and crown volume parameters. The plot was created by fitting a linear mathematical function to this set of data and then using this function to generate the 3D surface that represents the relationship between the variables in the data set. In Figure 16 can be observed the relationship between the 3 variables. If a tree has a larger diameter then the area and volume also are bigger, and vice versa.

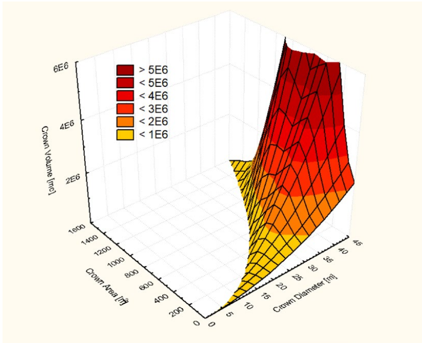


Figure 16. The 3D surface plot representation of dependence between forestry parameters

The forest metrics indicator shows the results of the quantitative measures. This indicator is important to assess various aspects of forest ecosystems, such as their structure, composition, and function. These metrics are used to evaluate the health and condition of forests and to inform management and conservation decisions. The result of the more than 1.5 m canopy cover is presented in Figure 17.

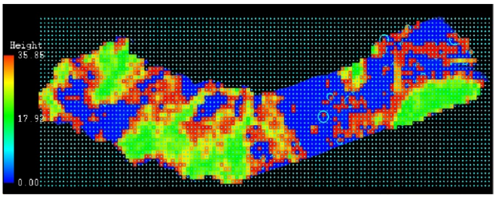


Figure 17. 15 m x 15 m pixel raster representation of canopy cover from the study area

Table 1 shows the summary statistics about the forest from the LiDAR-scanned study area.

Table 1. Summary statistics about forest parameters processed by the CH model

| | Valid N | % Valid obs. | Mean | Sum | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Tree Height [m] | 12160 | 100.0000 | 13.7 | 166968 | 1.7 | 35.9 |
| Crown Diameter [m] | 12160 | 100.0000 | 3.9 | 47527 | 0.8 | 41.7 |
| Crown Area [sqm] | 12160 | 100.0000 | 17.1 | 207335 | 0.5 | 1367.9 |
| Crown Volume [cm] | 12160 | 100.0000 | 69.1 | 839830 | 0.6 | 5498.8 |

## CONCLUSIONS

The practice shows that data collected based on LiDAR not only provides a more accurate estimate of wood stocks but is very useful for statistical assessment and different prediction models for forestry management. The information also allows us to better plan the harvest work, right down to selecting the necessary equipment and its placement. However, LiDAR inventory of forest areas is only one of the applications of laser forest scanning.

Today, the possibilities of LiDAR are increasingly discussed in the context of sustainable forestry. With the help of LiDAR scanning, it is possible to track the growth dynamics of tree trunks, crowns, and their undergrowth, and detect outbreaks of pests and forest diseases promptly. In addition, researchers use LiDAR to measure the amount of carbon that forests in a given area can absorb.

Crown diameter is an important metric for assessing the size and growth of individual trees, as well as for estimating forest canopy structure and biomass. Lidar (Light Detection and Ranging) is a remote sensing technology that can provide high-resolution, 3D point cloud representations of the forest canopy, including the crown of individual trees.

The main purpose of this research was to estimate crown diameter from a lidar point cloud, several methods have been applied, like DEM computation, CH model, or Point Cloud Segmentation. One common approach was to use a point cloud segmentation algorithm to identify individual tree crowns in the point cloud. Once the crown segments have been identified, the diameter can be calculated from various metrics, such as the maximum or average width of the crown segment.

By accurately identifying and measuring individual tree crowns, the ALS seed point editor can help improve our understanding of forest ecosystems and their response to environmental change.

For statistical analysis, the Pearson correlation was used. The R factor shows that the correlation between tree height and crown diameter is ($r = 0.1154$). It shows that the forest from the study area was of high density and the crown is smaller overwise the tree height. However, as mentioned earlier, tree crowns can have different shapes, such as irregular or multi-stemmed, and different formulas or methods may be needed to estimate their volumes accurately. Additionally, tree volume can be affected by many factors such as the tree's age, health, and site conditions, so accurate measurement and estimation of tree volume require careful consideration of these factors. Overwise, the result shows that the canopy coverage is 25% reported to the entire study area.

Overall, lidar point cloud representations offer a powerful tool for accurately and efficiently estimating crown diameter and other important forest metrics. These estimates can be used to inform forest management decisions and assess the health and productivity of forest ecosystems.

## ACKNOWLEDGEMENTS

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