Detection of trees features from a forestry area using airborne LiDAR data

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Abstract: *The impact of anthropogenic actions on the environment and climate has recently increased the need to map the afforested areas. In this context, the three-dimensional (3D) measurement of vegetation structures plays an important role in having an efficient forest inventory and management. Nowadays, the airborne LiDAR (Light Detection And Ranging) system offers high horizontal resolution as well as vertical dimension information, making it possible to estimate both three-dimensional characteristics of individual trees and to identify the distribution of forest resources in the region. This study aims to present a processing approach for the determination of each tree's position (X and Y location, as well as tree height) and its dimensions (crown diameter, area and volume) using geometrically accurate 3D point clouds (data sets were collected in a forested area in Argeș County, Romania). To a better understanding of the forest features and to explore the potential of remote sensing for such analysis, it was further exploited Digital Terrain Model (DTM), Digital Surface Model (DSM), and Canopy Height Model (CHM) derivation.*

Key Words: *Airborne Laser Scanning, Forest Mapping, Digital Terrain Model, Digital Surface Model, Canopy Height Model, Individual Tree Segmentation, Feature Extraction*

1. INTRODUCTION

Climate change represents a real concern both in academic and political terms, namely the increase by 1.53° C of the observed mean land surface air temperature, which already affects food security, changing precipitation patterns, and greater frequency of some extreme events. One of the climate change mitigation measures is represented by the improvement of sustainable forest management [1]. Forests play a key role in the capture and storage of carbon and biomass production in terrestrial ecosystems [2]–[4], which is why all Intergovernmental Panel on Climate Change (IPCC) scenarios for global warming mitigation include activities in the Agriculture, Forestry and Other Land Use (AFLOU) sector. For a sustainable management of forests, the estimation of biomass and carbon content, as well as for the conservation of biodiversity, it is necessary to characterize as accurately as possible the forest species and their spatial distribution, which implies first of all the knowledge of individual tree parameters [5].

Three spatial data characterization technologies – GIS (Geographical Information System), GNSS (Global Navigation Satellite System) and remote sensing have changed how the society perceives, evaluates and manages the natural resources [6]. The georeferenced data provided by remote sensing is easily to integrate into GIS databases, thus creating the possibility of analyzing large areas, which is important for generalizing certain observations or for identifying trends in forest studies.

An effective method of mapping and analyzing forests in detail and their evolution over time is the use of Airborne Laser Scanning (ALS), also referred to as LiDAR (Light Detention and Ranging) [7] [8].

LiDAR technology uses coherent beams of light to indirectly determine the distance between the emitter and the surface that produces the reflection of the beams, in order to accurately position the scanned surface in space.

The advantage of LiDAR technology for determining forest parameters is given by the ability to penetrate the foliage, which allows laser pulses to reach the earth's surface, thus being obtained both the digital terrain model and data on the horizontal and vertical characteristics of trees or forests.

Also, the representation in the LiDAR data of the structural characteristics of a tree through a large number of points makes it possible to identify the tree species with high precision [9]-[12].

Although in recent years the use of airborne LiDAR for individual tree delineation has increased, due to the fact that it provides very high resolution information, both horizontally and vertically, the full exploitation of data and the improvement of procedures for extracting information from it, with high accuracy, remains challenging [13]-[16].

Taking into accounts the current trends seen in forestry research, this paper presents a procedure for determining the parameters of individual trees from LiDAR data. For this purpose, there were performed LiDAR scanning flights over a forested area near Mihăești village (45°06’40’’N, 25°00’30’’E), Argeș county, Romania.

The characteristics of the extracted individual trees were: the geographical coordinates of the position of each tree (x, y), the height of the tree, the diameter of the crown, the area of the crown and the volume of the crown.

To extract this information, the point cloud representing LiDAR data was classified. Also, detailed 3D tree crown structures were generated. As secondary objectives of this analysis, the digital terrain model, the digital surface model, respectively the canopy height model were achieved.

This paper is also a first step in a larger effort to monitor activities in the Land Use, Land Use Change and Forestry (LULUCF) sector that affect carbon stocks and greenhouse gas emissions. This monitoring supports the development of the national greenhouse gas emissions inventory.

2. STUDY AREA AND DATA DESCRIPTION

2.1 Study area

The research area is located in the northeastern part of Argeș County in Romania, between 25.103927 E, 45.130312 N and 25.15804 E, 45.103595 N, occupying around 13 km² (Fig. 1).

The temperate continental climate with transitional influences offers a moderate thermal regime, favorable to agriculture, especially for fruit crops. In terms of topography, the area is hilly, with altitudes ranging between 490 m and 750 m, and presents a degree of afforestation of about 35%, as shown in this study.

In Argeș county, the forests occupy a little over 40% of the county's surface and have a distribution of species characterized mainly by beech (44%), spruce (20%) and oak (17%), followed by other different species of hard or soft essence and coniferous species [17].

2.2 LiDAR data

To investigate the application of LiDAR sensor within forest analyses, a flight mission was performed using the Hawker Beechcraft King Air C-90 GTx aircraft, equipped with a Riegl LMS-Q680i LiDAR system, operated at a wavelength of 1064 nm, and a data link transmission system. This infrastructure was provided by National Institute for Aerospace Research "Elie Carafoli" (INCAS Bucharest).

The airborne LiDAR data was acquired in the leaf-off season on 7 March 2020, with an average lateral overlap between adjacent strips about 35% in order to ensure a seamless and fine resolution with respect to project propose.

The airborne survey was performed in parallel lines (flight legs), trying to maintain a constant altitude and it took approximately 3 hours to complete the research mission. The average flight height was 550 m above the ground and the average flying speed was 70 m/s. Thus, it was collected a dataset having an average point density of 8 points/m².

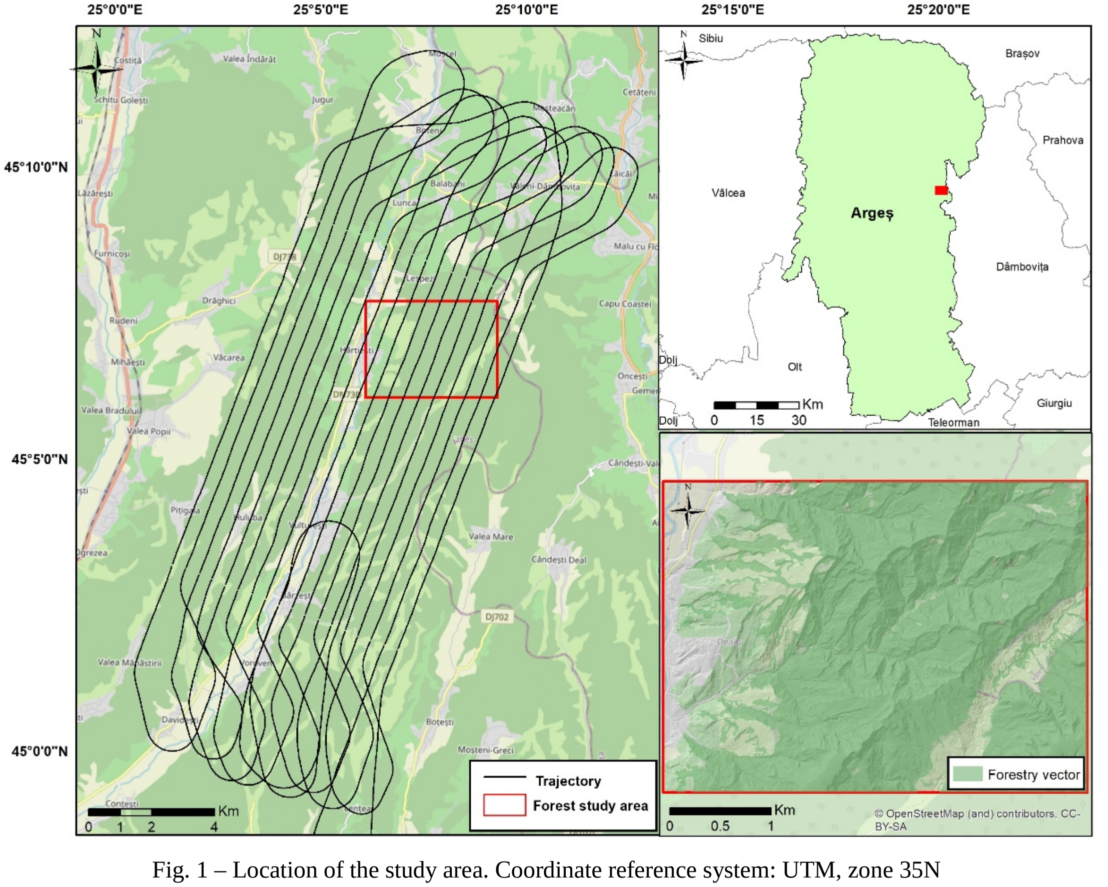


Fig. 1 – Location of the study area. Coordinate reference system: UTM, zone 35N

3. METHODS

The main objective of this research is to determine the position of each tree (X and Y coordinates, as well as tree height) and its dimensions (crown diameter, area and volume) in the study area, using LiDAR data.

To achieve this goal, the paper also explores some methodological steps for data processing that are shown in figure 2, as discussed briefly in the next paragraphs.

As it can be seen in the workflow (Fig. 2), the proposed approach mainly includes two phases:

1. Flight planning and execution of the flight mission and data preparation for deriving digital terrain and surface models (marked in blue);
2. Canopy Height Model derivation and extraction of tree parameters (marked in orange);

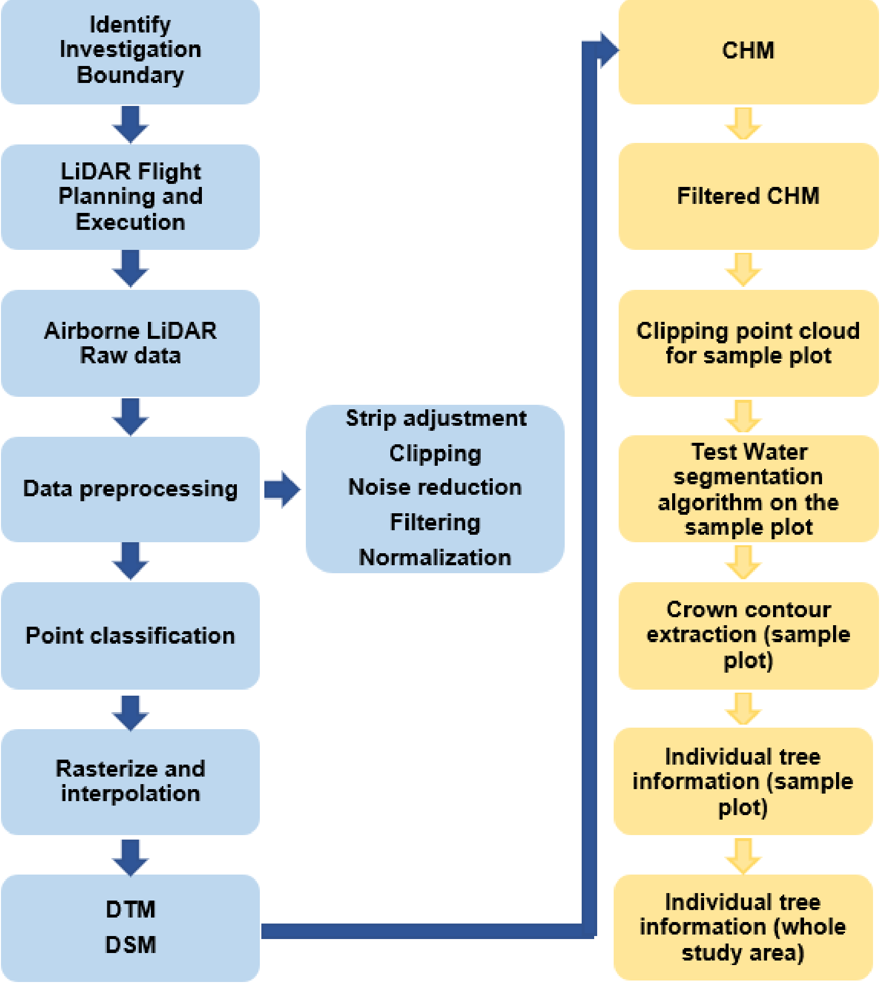


Fig. 2 – Flowchart for individual tree delineation from LiDAR data

Defining the investigation boundary stands at the beginning of such studies, followed by a meticulous flight planning and execution using an ALS – Riegl LMS-Q680i. The result of LiDAR survey consists of a raw point-cloud data whose position relative to the geometric center is determined in a polar coordinate system with respect to scanning instrument.

Transforming the raw data recorded into a final data set involves several processing steps. Thereby, in order to obtain the final products, pre-processing of the raw data sets is deemed to be crucial before any tree parameters could be extracted. Because 18 parallel strips were acquired in the study area and although a good calibration of the system was made, discrepancy between adjacent strips remained. Therefore, the strip adjustment was performed. When working with many large files, it is sometimes helpful to clip the point cloud data to a specific area of interest to save processing time and storage space. In this study, it was used a polygon feature to define the area of data to clip. After delineation of the study area, some data corrections were performed, namely noise (false surface points) reduction, filtering and normalization that will improve the quality of data products and can serves as the basis of forest metrics calculation. Once the pre-processing steps had been completed, the ground points were classified before creating the DTM. In the general context, the classification process consists of a set of methods for finding common properties for objects, which are then grouped into different classes, according to a classification model [18]. The DSM represents the altitudes of the reflecting surface of the upper crown of trees, building roofs and other objects on the ground surface. By filtering the DSM, meaning removal of points that do not belong to the Earth's surface, the DTM can be obtained. DTM, as a mathematical representation of all points on the terrain surface, is one of the most important products of LiDAR data. To obtain it, it is necessary to separate the terrain points from all the point cloud resulting from the scan. In the analyzed area, because of the dense vegetation coverage, the infiltration rate of LiDAR pulses to the ground surface was reduced, thus the classification was quite difficult. After the classification is made, an interpolation method is applied on this dataset in order to model, visualize and analyze the data as a raster format, namely a matrix of cells equal in size to which a singular value for altitude is assigned, within a GIS environment. A universal surface interpolation method for all applications does not exist, each method of generating surfaces having a number of advantages and disadvantages that must be taken into account when choosing it [19]. In this study, following the analysis of the most well-known multivariate interpolation methods [20], the aim was to choose the best interpolation method on the available dataset, namely the natural neighbour interpolation developed by Sibson [21], [22]. The method is based on taking a weighted average over the natural neighbors of a point (x) and the basic equation is [20]:

$$G(x) = \sum_{i=1}^{n} w_i(x) f(x_i) \tag{1}$$

where $G(x)$ is the interpolated function value at the location x, w_i are the weights, and $f(x_i)$ are the known data at (x_i).

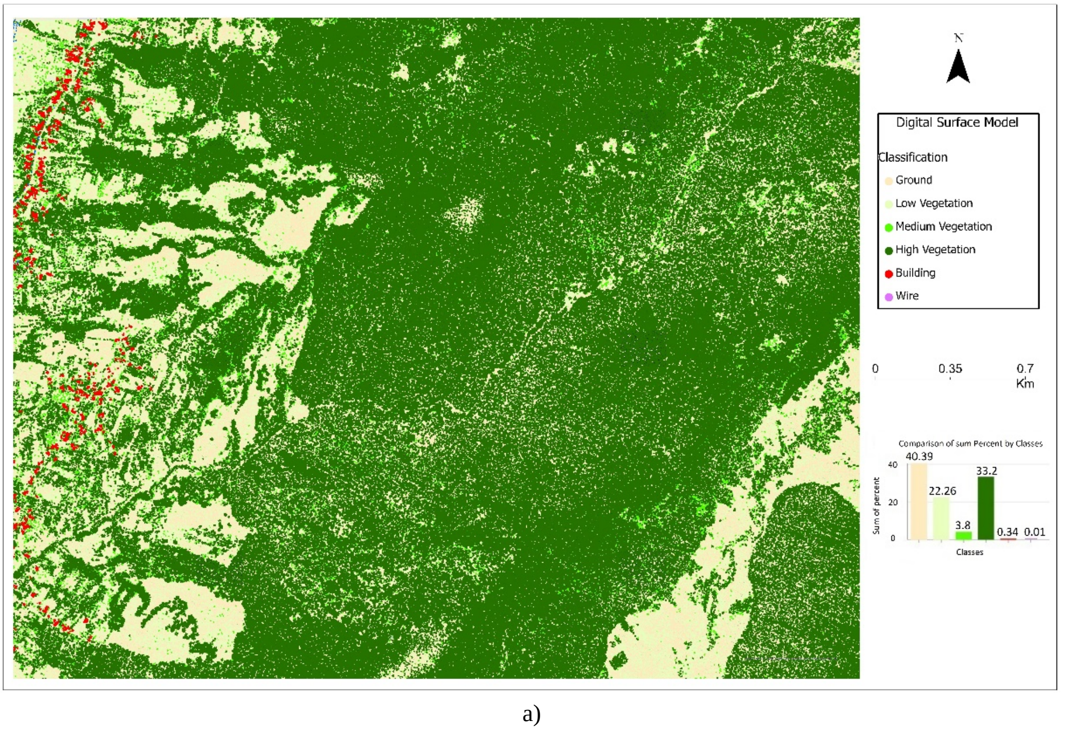
After generating the two digital models (DTM and DSM) from LIDAR data, the canopy height above the ground can be computed and interpolated into a Canopy Height Model (CHM). A standardized CHM can be generated by subtracting the DTM from the DSM, thus creating a raster file in which the pixel values represent the maximum height of the canopy [23]. In other words, the CHM provides the interpolated height of all points in the canopy in the form of a regularly spatial network with a pixel size, being an important indicator in forest management that can provide information of forest structure, biomass and therefore, carbon storage. Since the height variations form pixel-free areas and destroy the smoothness of the model, a filter application is required in order to avoid errors in tree detection and dendrometry measurements [23]. Further, an individual tree segmentation is necessary for LiDAR point cloud, which is an essential step in individual trees parameters extraction, like tree height and crown diameter. According to the relevant published literature [24], [25], [26], there are two main methods for individual trees segmentation: first method is marker watershed segmentation based on CHM and the second one is point cloud segmentation based on the point cloud. Here, the first method was approached and involved a simulation of flooding the entire relief by placing a water source at each lowest point in the CHM, thus generating barriers when different water sources are encountered.

A sample subset of CHM was selected over the study area with a size of 150 m × 100 m over which the aforementioned algorithm was applied. Once the segmentation is completed, a comma-separated values (CSV) file which contains tree location and height and crown diameter and area will result. In addition, a vector data with the crown boundary of individual tree was generated.

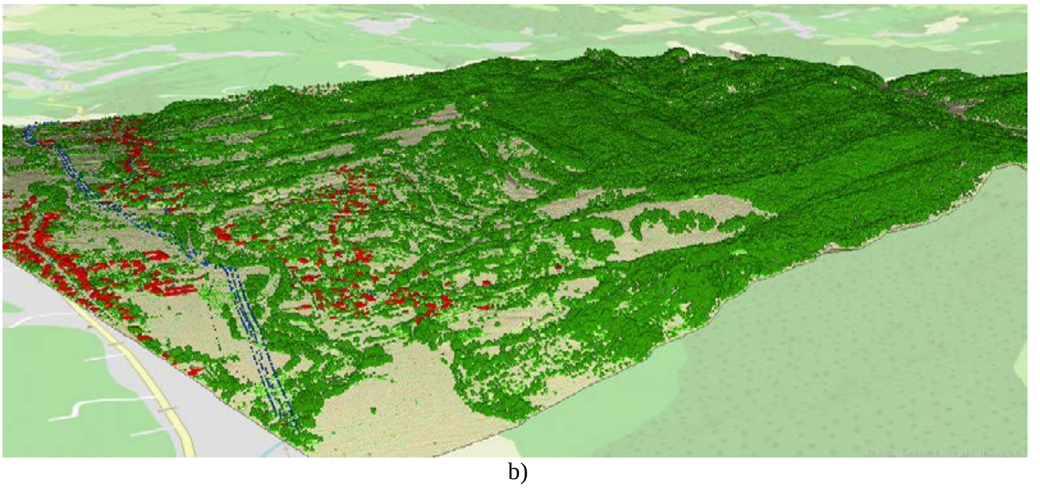
4. RESULTS

Most structural parameters estimated based on LiDAR measurements (e.g. canopy height, height of individual trees) require a priori modeling of the Earth's surface.

The intermediate results obtained in this study, such as DTM and DSM, are also valuable in forestry applications. DTM is very useful for planning and operational activities, while DSM describes the structure of vegetation, and can thus be used in forests roughness understanding. In the conducted research, an algorithm based on an active Triangulated Irregular Network (TIN), carried out in Terramodeler module of Terrasolid software [27], was used to compute a first terrain model using only the ground points from the point cloud data. It should be noted that before applying this algorithm, all points were classified (also called filtered) into non-ground (meaning object above ground level such as vegetation: low, medium, high; building and wires) and ground (Earth's surface) points using Terrascan module (belonging to Terrasolid software as well), resulting the DSM (fig. 3).



a)



b)

Fig. 3 – Digital Surface Model (a. 2D, b. 3D)

Following the application of the TIN algorithm, a 2.5 D surface model resulted, in which each point in the horizontal domain has a single corresponding altitude [28], meaning that the elevation in this surface is a function of the planimetric coordinates (x, y). Due to artifacts occurrence within this 2.5 surface, a manual data corrections was carried out to classify points that have not been properly classified.

On the basis of these filtered points, the interpolation using the Natural Neighbour method [21-22] of DTM surface was made using ArcGIS software [29], having as input data the ground points. The result (fig. 4) was a surface model at 1.0 m spatial resolution.

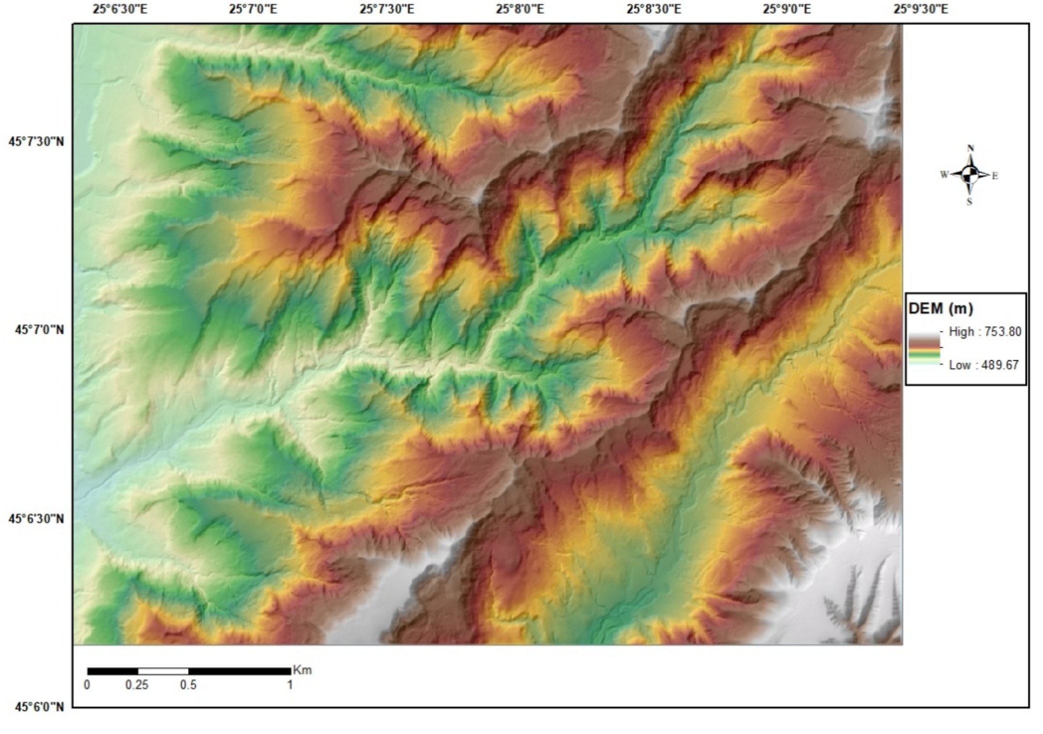


Fig. 4 – Digital Terrain Model at 1.0 m spatial resolution

These two models can be further used to derive the CHM in raster format at 1 m resolution for individual tree crown delineation and tree parameters extraction.

As mentioned in the Methods section, the CHM is computed by the subtraction of the DTM from the DSM.

Because negative values appear in the resulting model due to interpolation errors, CHM had to be cleaned up using the conditional function in ArcGIS Raster Calculator geoprocessing tool. Thus, the values that were less than zero have been returned to zero, resulting a new clean CHM with values greater than or equal with zero, in this case from 0 to approx. 44 m.

The resulting CHM is shown in figure 5.

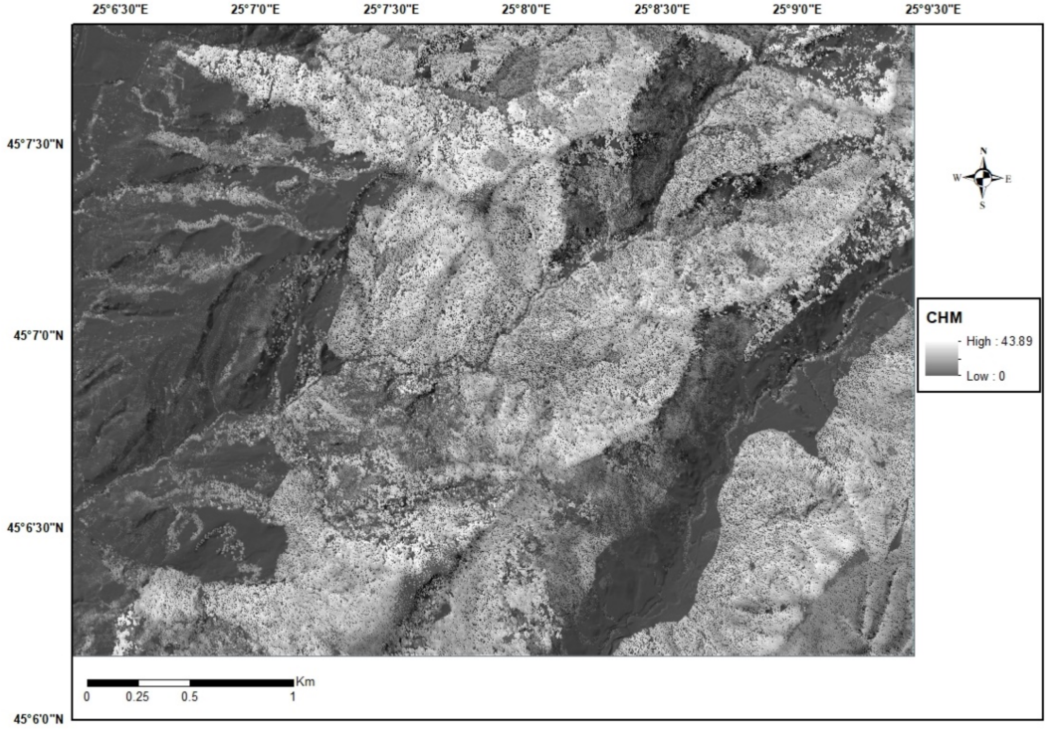


Fig. 5 – Canopy Height Model

Further, the segmentation of CHM was performed in LiDAR360 software [30] through the marker-controlled watershed algorithm by which the individual tree detection is formulated into a gray-scale image segmentation problem, and the success of it is determined by the spatial interpolation where most of the time the 3D information is lost. This segmentation was initially tested on a smaller area (fig. 6), and then it was applied on the entire study area.

The parameters used in this algorithm were set as follows: maximum tree height 80 m, minimum tree height 2.5 m, buffer size 50 pixels, crown base height threshold 0.8 m, radius (pixel) 5, and beside these, the Gaussian smooth box with the Gaussian smoothing factor (sigma) of 1 were checked in order to remove noise effects that appear in the CHM.

This segmentation led to two files: one CSV file that contains the location and dimensions of each tree, and a shapefile with the contour of the crowns (fig. 6).

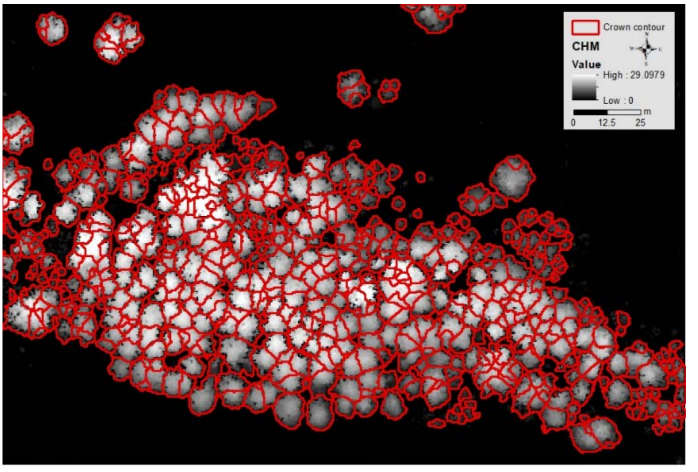


Fig. 6 – CHM segmentation on test plot

The information included within csv file area is shown in table 1.

Table 1. Individual tree segmentation information (test plot)

Tree ID	Tree Location X	Tree Location Y	Tree Height	Crown Diameter	Crown Area	Crown Volume
1	351808.197	4998356	27.306	9.433	69.881	626.381
2	351802.656	4998367	27.866	5.142	20.765	91.287
3	351793.936	4998333	25.837	8.417	55.638	337.807
4	351742.066	4998325	24.841	8.237	53.294	399.543
5	351807.02	4998362	29.313	9.003	63.663	577.481
6	351798.458	4998365	28.72	5.521	23.944	93.953
7	351820.821	4998327	25.742	10.982	94.717	684.379
…	…	…	…	…	…	…

In order to closely examine the segmentation result and to improve the accuracy, the LiDAR point cloud was segmented into individual trees (fig. 7) using the CSV file generated previously.

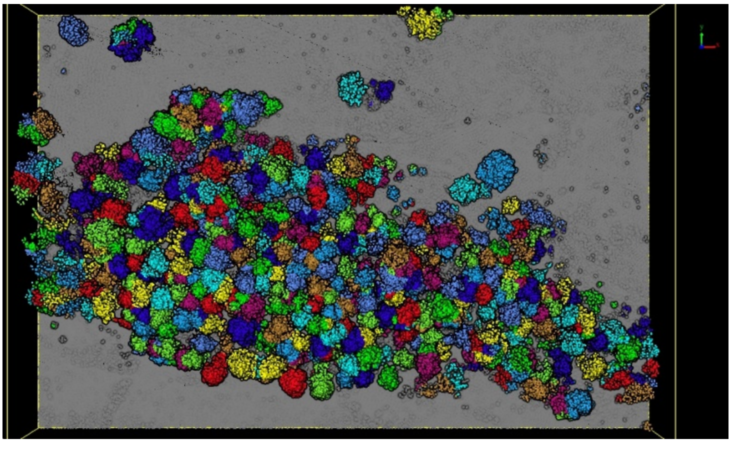


Fig. 7 – Point cloud segmentation

At this point, the errors that may occur in certain locations can be better seen and can be manually corrected directly from CSV file. A hexagonal profile section (fig. 8) is made in order to view the data in 3D view, and editing is performed where trees have a larger or smaller than real crown area due to segmentation algorithm.

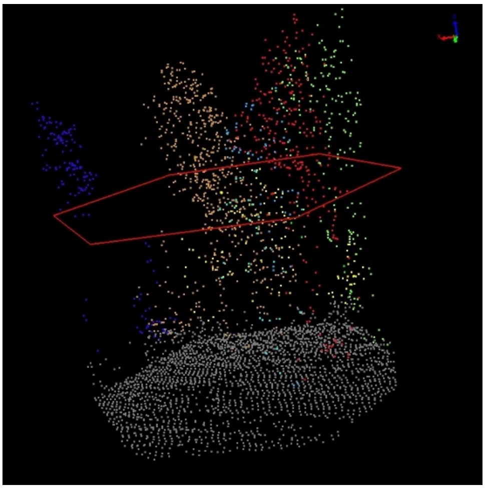


Fig. 8 – Section view: point cloud segmentation

In the final step, after the correction is finished, the CSV file containing the individual tree information is saved, and the segmentation is rerun based on the edited seed points. The result is summarized in table 2.

Table 2. Individual tree segmentation information (whole study area)

	Min	Max
Trees	1	3465
Tree Location X	351732.001	351984.001
Tree Location Y	4998272.749	4998435.249
Tree Height	3.053	28.288
Crown Diameter	0.798	14.636
Crown Area	0.5	168.25

5. CONCLUSIONS

Forests play an important role both in human life and in maintaining balance in nature. For this reason, an accurate knowledge of the forest as a terrestrial ecosystem, as well as the sustainable management of forest resources is essential. In recent years, remote sensing technology has been widely applied in extraction of information about individual trees that is a priority for foresters.

The aim of this study was to extract accurate individual trees information by applying the marker watershed segmentation based on LiDAR-derived Canopy Height Model, in a forested area in Argeș County, Romania.

To achieve this segmentation, certain data processing steps that include derivation of the three models (DSM, DTM and CHM), described in Methods and Results sections, must be followed. Particular attention must be paid during the preprocessing and interpolation of LiDAR point cloud data to help reducing error propagation from raw data to final products.

Another important aspect described in this paper is the application of the Gaussian filter on the CHM due to its significant influence on tree segmentation.

In order to fulfill the aim of this study, commercial data processing software such as ArcGIS, Terrasolid with Terrascan and Terramodeler modules and LiDAR360 were used.

The segmentation method was initially tested on a plot area of 150 m x 100 m resulting 400 trees. For the main arboreal species, namely beech, the method showed average values between 8.23 m and 29.31 m for the tree height parameter and a range of values between 2.33 m and 11.78 m for the crown diameter parameter. After applying the corrections and performing the method over the entire study area, 3465 trees were resulted with average values between 3.05 m and 28.28 m for the tree height parameter and a range of values between 0.79 m and 14.63 m for the crown diameter parameter.

To conclude, this paper has illustrated how the information resulting from the use of these methods could be of great relevance for forest managers in the process of forest inventory and planned management.

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