FOREST MODELING AND INVENTORY ESTIMATION USING LIDAR DATA

B. Farajelahi[1], F. F. Eya[2 *], and H. Arefi[1,2]

[1] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Iran

[2] Hochschule Mainz, University of Applied Sciences, Mainz, Germany

Commission IV, WG IV/3

KEY WORDS: Individual Tree Segmentation, Statistical Information, Filtering, Classification, Point Cloud, Digital Surface Model (DSM), Digital Terrain Model (DTM), Canopy Height Model (CHM)

ABSTRACT:

Aerial laser scanners find rapidly growing interest in photogrammetry and remote sensing as an efficient tool for reliable three-dimensional extraction and modelling of forest inventory information. In addition to interactive measurements in 3D point clouds, techniques for automatic extraction of objects and determination of geometric parameters form a high and important research issues (Maas, Bienert et al. 2008). This paper presents a novel approach on the extraction and modelling of individual trees from the Idaho National Forest in the USA and calculation of the statistical estimation for each extracted segment for future analysing. Lidar point cloud contains three-dimensional structure information which is used to estimate the statistical information for each tree segments. In this study, we worked on the raster surface made directly from the LiDAR point cloud and two main models, namely the digital terrain model (DTM) and the digital surface model (DSM), are generated when the point clouds are processed by the filtering method. Then we have used the segmentation techniques to extract the tree segments which is a triggering process that facilitates the extraction of statistical information such as crown diameter, eccentricity, and other additional attributes. The proposed individual tree segmentation method results in 73% correctness, 92% completeness and 81% F1-score.

1. INTRODUCTION

Forests contain a large portion of renewable resources and have a main and important role in creating balance and sustainable environmental development. Therefore, forest management and protection are the main and most efficient strategies that guarantee its sustainability by providing an overview of the forest's condition. For this reason, we have worked on the extraction and modelling of individual trees and the calculation of the statistical estimation for each extracted segment for analysis. The Lidar point cloud contains three-dimensional structure from the vertical structure of forests from the ground to the top of the canopy height model. Aerial Laser Scanner data is usually used to gain digital terrain elevation characterization and present accurate information about forests such as composition, distribution, and the forest's condition (Douss and Farah 2022), (Silva, Hudak et al. 2016). The extraction of individual trees and modeling of forest parameters using ALS data have recently gained great importance in the monitoring and sustainable management of forests, since they provide highly precise and spatial information about the forest properties (Douss and Farah 2022). The most accurate method to estimate the tree's statistical attributes is to physically sample the trees in the field. However, it has still been impractical to measure the individual tree over large areas as they might contain other objects or the tree might not be extracted properly (Silva, Hudak et al. 2016). The accurate prediction of tree statistical attributes depends on the methods used to detect and extract the individual trees (Kankare, Liang et al. 2015). To detect the individual trees, a LiDAR-derives Canopy Height Model (CHM) can be used (Popescu, Wynne et al. 2003). This study focuses on the extraction and modelling of individual trees from the Idaho National Forest in the USA. Point clouds acquired by LiDAR remote sensing were made available in a LAS format through the online portal Open Topography. In this analysis, the processing of point clouds by the CSF method generates two main models, namely the digital terrain model (DTM) and the digital surface model (DSM). By interpolating the DTM and DSM, the point clouds are converted into a raster image using the normalization process. The Canopy Height Model (CHM) is created by subtracting the DSM and the DTM. Segmentation of the objects is the triggering process that facilitates the extraction of statistical information such as crown diameter, eccentricity, and other additional attributes. The use of morphological operations is very important to make the objects contained in the image easily analysable. To extract all the characteristic properties of each tree, the Regionprops function was used (MATLAB, 2019). The statistical information about each tree segment is used to model and analyse each tree.

In this paper, a hierarchical methodology is used to detect and extract the individual trees in order to model the trees and calculate the statistical attributes for each individual tree. The remainder of this paper is as follows: Section 2 describes materials and methods. Section 3 outlines the proposed approach used in this study. Section 4 includes the evaluation and results, and section 5 presents the conclusion of the methodology.

2. MATERIALS AND METHODS

The procedure for analyzing and processing point clouds from LiDAR remote sensing shows the different methods for extracting and modelling individual trees in the large forest of Idaho in the United States. However, in order to better expand the scope of work in this study, four main phases are divided. The first part deals with the classification of point clouds by the CSF filtering method. This made it possible to generate a digital terrain model and a surface model. The interpolation of the two models is an important process in the realization of raster images. The initiative is to create the crown height models based on the results of the raster images stored in the Geotiff format. It should be noted that one cannot speak of interpolation without mentioning segmentation. Various studies demonstrate the importance of segmentation in binary image processing (Rohs 2005.). Due to its importance, therefore, it becomes essential to extract information such as height, volume, area, and many others. After applying segmentation by the procedure of subtracting a fixed height from the choices, the importance of morphological operators was demonstrated. By combining these results, it was concluded that the MATLAB software contains important functions, such as Regionprops, that provide statistical properties (MATLAB, 2019). The realization of the different models will be possible thanks to this information to perform an analysis and obtain results.

2.1 Study Area

The study area is a part of the St. Joe's National Forest located in the United States (47 °10' 08" north, 115∘ 40' 08" east) and is one of three forests that are aggregated into the Idaho Panhandle National Forests. It has a total area of 3,512 km^2 which is covered by a dense vegetation. The data set is generated by a national, standardized method of photogrammetry, namely aerial remote sensing. The information presented was recorded by a LiDAR system in ASCII format. The sample that enabled the data processing was made available in LAS format on an online portal (Open Topography) for lidar images and data (Open Topography, 2003)

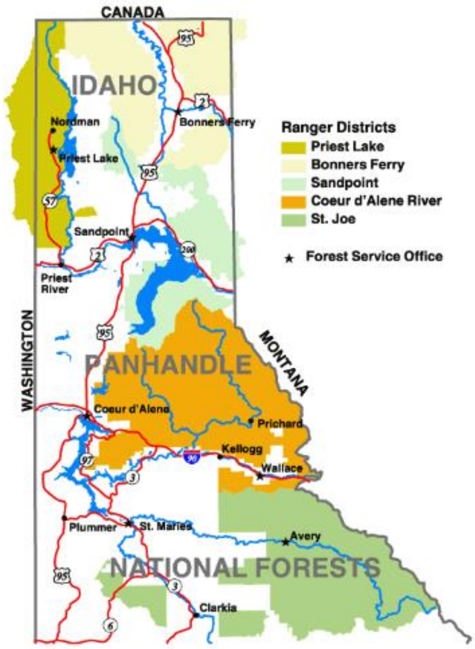

Figure 1. Map of Canadian Forest Districts (Ralph 2005).

2.2 Data Foundation

To create a digital terrain model, a terrain surface model, and an elevation model, certain data from the Idaho National Forest in the USA was collected and stored in the form of a point cloud. In cooperation with the data provider, the forest authority wanted to try out new processing methods and evaluations of the LiDAR technology for the target forest area. The above-mentioned Open Topography website offers free access to the point clouds provided in LAS format and classified (the classification of these points is explained below) thanks to the site administration's permission. The coordinates of the terrain are given in a UTM coordinate system, zone 11 N. The data set has a point density of 0.70 points/m². The LiDAR data was imported into a Leica ALS40 on July 23, August 11 and September 22, 2003. The data recorded as 3D point clouds includes a total of 388,531,920 points measured over a total area of 557 km² (Open Topography 2012). The first and last feedback, as already mentioned, were divided into five different classes (Open Topography 2012):

• Point class 0: never to be assigned (340,078,360)
• Point class 1: unclassified points (4,454)
• Point class 2: ground point (43,185,078)
• Point class 3: low vegetation (5,264,028)

2.3 Preprocessing and Acquisition of LiDAR Data

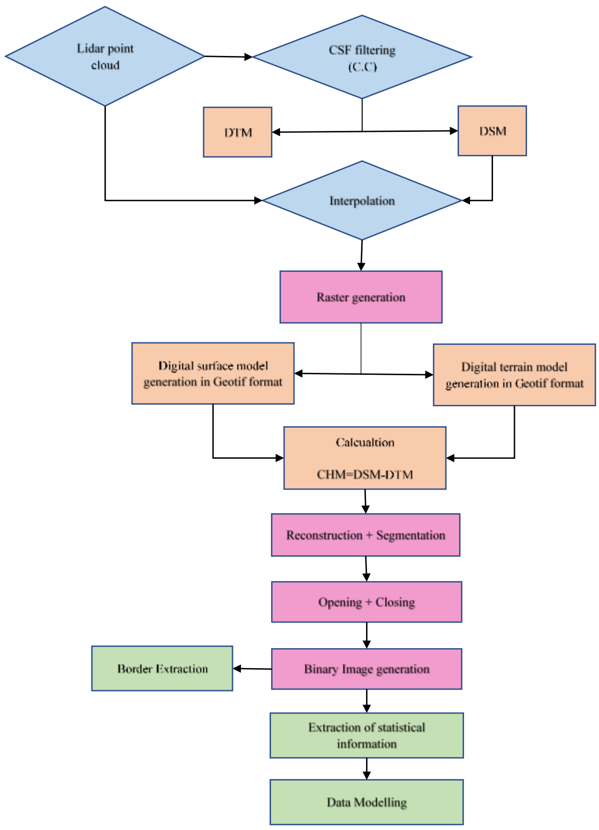

Figure 2. Flow chart of the process of individual tree extraction and modelling.

3. THE PROPOSED APPROACH

3.1 Classification of the LiDAR Point Cloud

There are two types of classification, namely numerical and syntactic. These two methods transform the original data and use the supervised and unsupervised classifiers. All the LiDAR data discussed here was classified using automatic classification. Classification of 3D point clouds acquired with LiDAR is a critical operational task for photogrammetry and cartography today. Many applications, such as the one used in this work, deal with the identification of point clouds and their properties. Therefore, automatic classification allows the categorization of points into two classes, namely: vegetation and soil. Although most software systems focus on the discrimination of available sites, automatic extraction could be made possible thanks to the (Cloud Compare, 2022) software and its CSF tool. Thus, the classification of individual points could be simplified by iteration based on the assigned value for the segmentation of soil and open space points (Lehmann, Oberschelp et al. 1997).

3.2 Generation of DTM and DSM by Filtering

There are many different approaches and more basic tools that can be used to filter point clouds. The goal then becomes to create a DTM and a DSM. The method used in this study is the CSF filter. In fact, filtering allows removing or separating tissue layers from the laser data. In some cases, it can also be called segmentation, given the intended goal.

3.3 Cloth Simulation Filter

CSF is a method based on the 3D fabric simulation used in the Cloud Compare computer software (Cloud Compare, 2022). This flexible fabric stretches and takes on an elastic shape depending on the density, weight, and gravity of the sand grains. The pattern formed is a DSM. After turning the fabric inside out, all the sand is stored, and the fabric returns to its original shape. The final model obtained is the DTM. Thus, the basic principle of the technical operation of the CSF, which is responsible for the extraction of the above patterns, can be deduced. In this process, the LiDAR point cloud is inverted according to the principle already mentioned, and the rigid mesh used for the surface is overlaid with points. At this point, an interaction between the nodes of the mesh and the corresponding LiDAR points can be observed to produce an approximate ground surface (Cloud Compare, 2022). The LiDAR point cloud can be extracted, and the regenerated result can be compared to the original point cloud. Relief was chosen as the operator to develop the LiDAR point cloud filtering. It was used to collect the point cloud by segmenting it into two different classes: on-ground points and off-ground points. With the advantage of not deleting points, it is used to distinguish bare ground from objects overlaid on the earth's surface. It was concluded that the number of points in the cloud, which was initially selected as the operator to perform the filtering, remains unchanged after the filtering of the chosen option. The parameters used are three. The resolution is the first parameter that offers the possibility to specify the size of the grid without changing the unit of the point cloud. It should be noted that the higher the resolution, the better the density of the digital terrain model is observed. In this work, a resolution of 0.8 m was used. The maximum iteration, which is the second parameter, is set according to a maximum time, so the default value is 500 for obtaining the threshold of a better classification of the terrain. The third parameter, which is the classification threshold, depends on the distance between the point cloud and the simulated terrain to be obtained. In most cases, the value for each terrain is 0.5. The value in this case depends on the resolution. That's why we assigned a value of 3.8 for the only classification. After the use of CSF, we obtained two models: the Digital Terrain Model (DTM) and the normalized Digital Surface Model (nDSM). The DTM is a three-dimensional representation of the ground surface. It is important to classify it to avoid errors when estimating the height of trees.

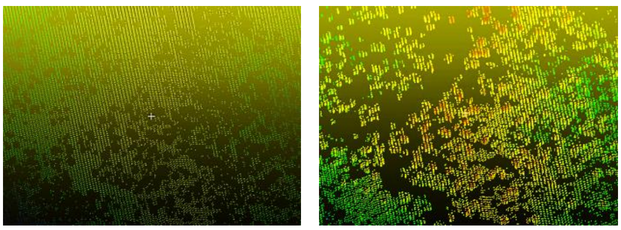

Figure 3. (a) Ground points, (b) non-ground points

3.4 Interpolation

Interpolation is so important in the analysis of LiDAR point cloud processing and extraction [8]. The interpolation option in Cloud Compare consists of a linear interpolation with the nearest non-empty neighbouring cells. This gives very suitable results in the presence of small holes. However, it can be less accurate on large holes. It doesn't work outside the convex hull of the non-empty cells. However, satisfactory results were obtained by creating a raster image of points depending on the values entered in the parameters. The interpolation of a digital terrain model or a digital surface model from a point cloud provides topographic information. After this operation, the point clouds of the DTM and DSM were transformed into raster images. Then the export of these images was recorded in a Geotiff format according to the height to calculate the height model of each tree. (Cloud Compare, 2022)

3.5 Creation of the Height of the Canopy

The Canopy Height Model represents the height of each tree in a given area. For the creation of the canopy height model, the difference between the digital surface model and the digital terrain model was calculated (CHM = DSM – DTM). In this section, we will determine the height of the crowns of individual trees to perform morphological operations and to extract and model properties of individual trees. To confirm the calculation of the CHM generation, a histogram was created with the canopy heights and the forest tree density. Figure 5 depicts the DTM (black line), DOM (blue line), and tree height (the searched height in red line). The result delivered a height model of all tree objects with a histogram ranging from 0 to 35 m in height. Figure 6 (a), (b), (c) depict the DTM, DSM and CHM representation.

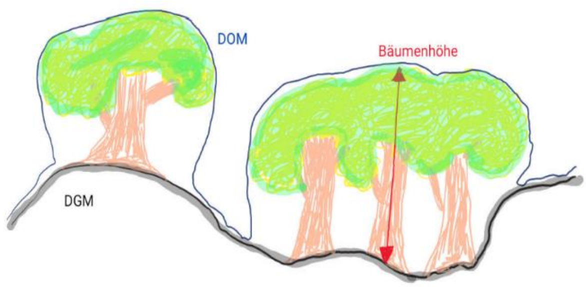

Figure 4. Representation of DOM, DTM and height of trees.

3.6 Segmentation

Segmentation is used in the analysis and processing of image objects (Fischer 2011). It is an optimal and appropriate method for data interpretation for any approach to extract structural image information. Their goal is to simplify and reduce the content of objects without affecting the distinctive properties of a given region. The use of segmentation is to interpret the quantity of the object segments in an image. The canopy height model generated above creates an identical elevation segmentation for each individual tree. The imreconstruct function (MATLAB, 2019) could enable the realization of this segmentation. The input of the imreconstruct function is two entities, namely Mask and Marker. The function allows the morphological reconstruction of the marker and the mask of the image to be obtained. In image reconstruction, a difference between the lower level of a region (marker) and the upper level (mask) is considered. The low level provides less information. Therefore, the reference is more on the high level necessary for extracting data from single trees. This high-level process works by assigning a fixed value (15 m) to the objects defined in the image at a specific height. Due to the maximum grouping of objects in different regions, the detected information was extracted according to the conditional result. The value assigned to the height must not be too large to avoid removing the tree objects from the image. The smaller the selected value, the more information is used. In this case, the value is 15 m. After this procedure, A morphological filter was assigned on the image to remove noise.

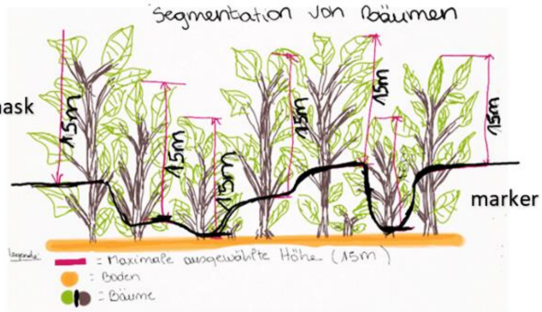

Figure 5. Delimitation of the mask and marker.

3.7 Postprocessing

After performing the segmentation, a post-processing will be assigned to the result of the segmentation. According to the result of image segmentation, there are some holes, which are the imperfections of the segmentation result. In this study, the Imfill function was used (MATLAB, 2019). The filling filter is a function that identifies holes and allows filling them in certain areas of the image after segmentation. The filling process avoids empty areas in each region. The morphological filters, such as erosion followed by dilation, were also applied hierarchically with an appropriate structural element to eliminate noise contained for each segment in the image. The size of the structural element depends on the size or density of the object to be represented. It is therefore a question of choosing the smallest form to bring in all the selected elements. It should still be larger than all the noise regions. With the opening filter, the result is more satisfactory as it eliminates noise faster.

3.8 Binary Image Generation

The small storage space occupied by a binary image and the simplicity of the morphological operators involved are the advantages of a binary image. An image created by segmentation and processed with various operators is easier to convert to a binary image. Each pixel obtained after transforming the image has a certain number of pixels of neighbouring objects, the logical value of which ranges from 0 to 1. A value of 1, called a pixel, represents the foreground, while a value of 0, also called a pixel, represents the background in an image. All of these individual tree objects are made up of a series of pixels that are connected to each other. From this, the properties of a binary image can be derived according to the shape, size, and location of the objects.

3.9 Border Extraction

This procedure was applied to represent the borders of each individual tree. The BWboundaries function defines a label for each pixel contained in the binary image (MATLAB, 2019). Using this feature gives the possibility to create a label on the final image by marking the borders of each region according to the assigned character. Most often these parameters depend on properties of the image.

3.10 Extraction Statistical Information

This chapter is about getting an overview of the determination of all statistical information from individual trees. An essential function is used to calculate the properties of the tree segments. One of them is application-oriented methods. In this study, the Regionprops function was used to obtain all the properties of individual trees in the image (MATLAB, 2019). This function measures all pixels associated with each tree in a given area of the image. Through its parameters, it assigns analysis properties to each pixel to define the precise functions of the attributes depending on the object's position. After the analysis, for each pixel, the area, the diameter, the perimeter, the eccentricity, the length of the major axis, the length of the minor axis, the orientation, which here represents the angle of the major axis of a region, the coordinates of the centroid (x, y), the coordinates of the circumscribed frame of a region, and many others are calculated. All these elements are identifiable by a computation label for each pixel region. As already mentioned above, the Regionprops function performs statistical calculations and is very useful as it allows one to extract various information about regions in an image. The table below shows only 4 tree objects out of 815 with some properties. (See Table 1)

Properties Object. NR	Major Axis Length	Minor Axis Length	Eccentricity	Angle [°]
1	23.99	23.99	0.84	74.41
2	30.42	30.42	0.77	-78.24
3	22.38	22.38	0.81	79.82
4	36.29	36.29	0.84	-83.58

Table 1. Some properties of each tree object.

3.11 Single Tree Modelling

In forestry, modeling is an indispensable process for the biological study of trees (Nasiri, Darvishsefat et al. 2022). In the context of image processing, certain geometric shapes were dealt with. To represent the center and circles of each object defined on an image, parameters such as the radius and coordinates (X, Y) of the center (centroid) were applied. The center of a segment is an imaginary reference point located at the mean position of the segment's mass. In this case, the center can be shown either inside or outside each segment. The simulation of the circles became necessary to precisely define the region of each tree object.

4. EXPERIMENTAL PROTOCOL

All the qualitative results for each step are presented in Figure.6, and the quantitative statistical attributes for the first 7 individual tree segments on both the DSM image and the CHM image are displayed in Table 2 and Table 3. The Ground Truth segmentation image is generated from the Image Segmenter toolbox (MATLAB, 2019). Finally, the subset of the ground truth segmented image and the proposed method segmented image are the two inputs to calculate the precision, recall, and F1 score for evaluation, which are presented in Table 4.

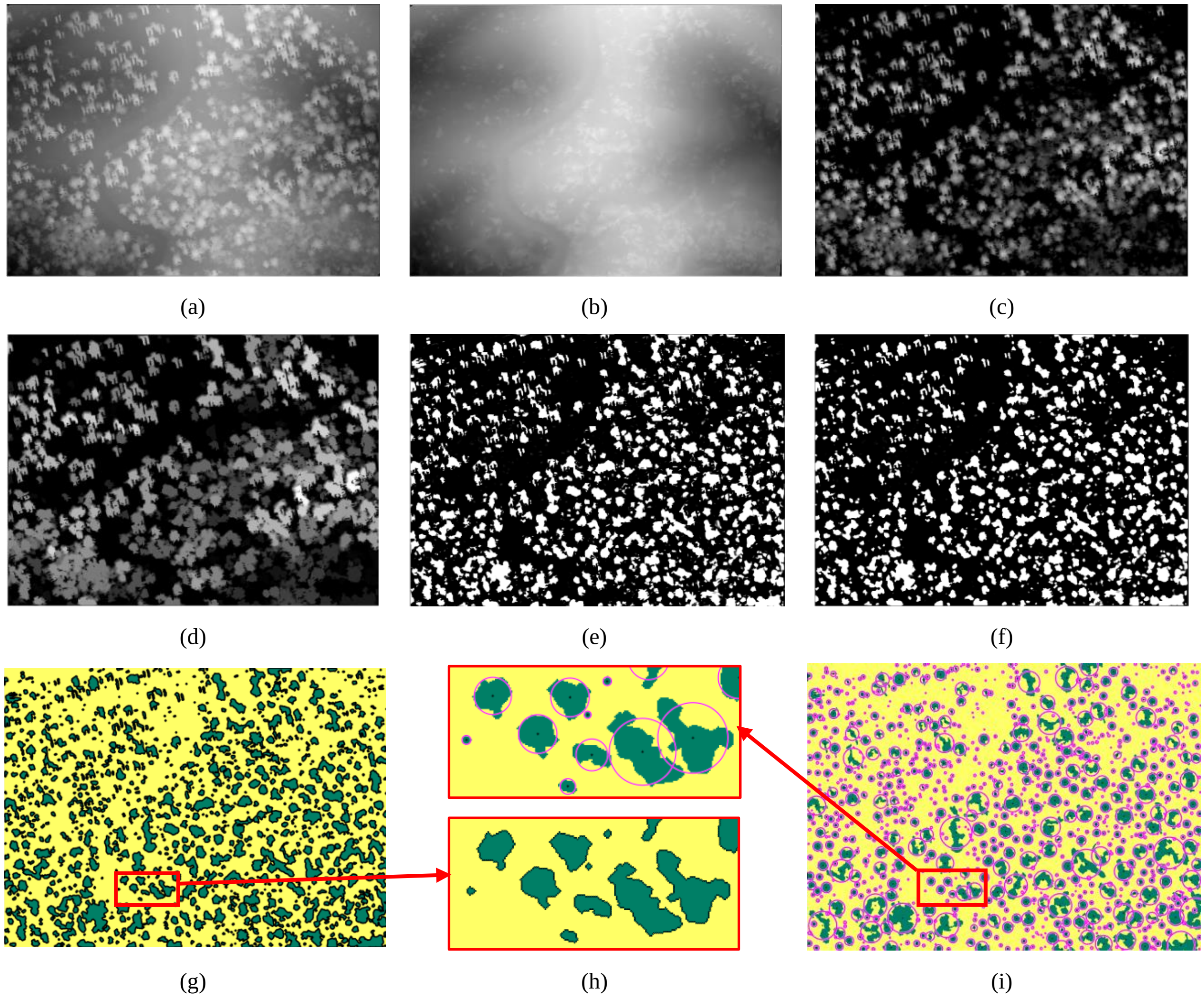

Figure 6. The qualitative results of the proposed method are: (a) DSM, (b) DTM, (c) CHM, (d) the result of reconstruction, (e) the segmentation result, (f) the postprocessing result, (g)the representation of the segment borders, (i) Representation of circles and centers of individual trees.

DSM	Average Height (m)	Standard Deviation (m)	Minimum Height (m)	Maximum Height (m)
Segment 1	331.9227	4.0345	323.8565	339.6600
Segment 2	317.4815	4.9152	305.0780	326.0100
Segment 3	299.3423	1.0977	296.0418	300.9366
Segment 4	301.7189	4.2736	292.8840	307.9400
Segment 5	311.2239	4.1404	303.5400	317.8190
Segment 6	295.7501	1.9608	293.2575	300.8580
Segment 7	307.9217	3.5178	300.8209	316.2090

Table 2. The four attributes for the first 7 individual tree segments on DSM image

CHM	Average Height (m)	Standard Deviation (m)	Minimum Height (m)	Maximum Height (m)
Segment 1	26.3694	3.9776	19.1959	34.0375
Segment 2	20.9005	4.7806	8.2093	28.8791
Segment 3	0.8915	0.9736	0.0148	3.9382
Segment 4	10.6182	4.3445	3.1634	18.0486
Segment 5	21.0663	4.2119	13.2854	27.7005
Segment 6	1.5096	1.8115	0.0150	6.9139
Segment 7	11.0764	3.8814	5.5225	20.4919

Table 3. The four attributes for the first 7 individual tree segments on CHM image

In the study of detecting each object in the image, accurate evaluation measures are applied when comparing reference and segmented data. To determine the global and local consistency of the error, the confusion matrix is used. This analysis was made according to the information sought. In image processing, accuracy is defined as the number of relevant and correct elements or objects compared to the total number proposed for a data analysis (Adam, Chatzilari et al. 2018). The precision measurement is calculated from the equation (1).

$$precision = \frac{|TP|}{|TP| + |FP|} \tag{1}$$

where TP = True Positives
FP = False Positives

In the same context as precision, recall is defined as a measurement of the number of relevant elements in a returned image compared to the elements that are not considered relevant, although they are relevant. In mathematics, recall is defined as the sum of correctly detected relevant and positive elements compared to the sum of correctly positive and false negative elements (Adam, Chatzilari et al. 2018). The recall measurement is calculated from the equation (2).

$$recall = \frac{|TP|}{|TP| + |FN|} \tag{2}$$

where FN = False Negatives

F1 is a metric for calculating the combination of Precision and Recall. It gives a harmonic mean between Precision and Recall. The results correspond well to the real system (Adam, Chatzilari et al. 2018). The F1 measurement is calculated from the equation (3).

$$F_1 = \frac{2 \cdot precision \cdot recall}{precision + recall} \tag{3}$$

The difference between the ground truth segmented image generated from the reference image (CHM) and the segmented image generated from the proposed method is used to measure the above metrics. Thanks to the (MATLAB, 2019) classification toolbox, the number of true positives (TP), the number of false positives (FP), and the number of false negatives (FN) could be calculated from the confusion matrix. After this process, precision, recall, and F1-score were calculated according to the respective formulas defined above to determine if too much information loss had occurred during image processing. The TP denotes the individual trees that were classified correctly, and the FN represents those individual trees that were not classified in the results of the proposed method. FP is the background which is assigned to the individual tree class. When precision takes the value of 1, it corresponds to the total absence of false positives. Moreover, if the recall is equal to 0, this indicates a result that does not contain any relevant objects in the image (Adam, Chatzilari et al. 2018). The results are summarized in Table 4.

Table 4. Quantitative evaluation results.

TP	FP	FN
86	31	7
Precision	Recall	F1score
0.73	0.92	0.81

5. CONCLUSIONS

The analysis of point clouds from LiDAR remote sensing led to the generation of 3 main models, namely DSM, DTM, and CHM. The canopy height model could provide the ability to identify the heights and other statistical attributes of each tree. The extraction of the statistical data obtained by the segmentation procedure allowed the modeling of each tree segment located on the image. For evaluation, precision, recall, and F1-score were used. The precision result is 73%. This simply means that, despite some errors in detecting the structure of individual trees, the Li-DAR was able to record relatively correct data with precision. The recall rate is 92%. Overall, it can be concluded that this comparison principle is very effective in improving the ability to detect objects in the two images. With the obtained value of F1(81%), the comparison of delineation and classification met the user's expectations. From the evaluation, it can be concluded that all criteria are fulfilled and that the result of the segmented image can be taken into account.

REFFERENCES

Adam, A., et al. (2018). "H-RANSAC: A hybrid point cloud segmentation combining 2D and 3D data." ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci **4**(2): 1-8.

Douss, R. and I. R. Farah (2022). "Extraction of individual trees based on Canopy Height Model to monitor the state of the forest." Trees, Forests and People **8**: 100257.

Fischer, F. (2011). Extrahierung der 3D-Struktur von Einzelbäumen aus LiDAR-Daten.

Kankare, V., et al. (2015). "Diameter distribution estimation with laser scanning based multisource single tree inventory." ISPRS Journal of Photogrammetry and Remote Sensing **108**: 161-171.

Lehmann, T., et al. (1997). Klassifikation und Mustererkennung. Bildverarbeitung für die Medizin, Springer**:** 395-429.

Maas, H. G., et al. (2008). "Automatic forest inventory parameter determination from terrestrial laser scanner data." International journal of remote sensing **29**(5): 1579-1593.

Nasiri, V., et al. (2022). "Modeling forest canopy cover: A synergistic use of Sentinel-2, aerial photogrammetry data, and machine learning." Remote Sensing **14**(6): 1453.

Popescu, S. C., et al. (2003). "Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass." Canadian journal of remote sensing **29**(5): 564-577.

Ralph, J. B. D. (2005). "Idaho Panhandle National Forests."

Rohs, M. S. K. (2005.). CG2-S12-08-Segmentation. MHCI Lab, LMU München, München. Online verfügbar unter

Silva, C. A., et al. (2016). "Imputation of individual longleaf pine (Pinus palustris Mill.) tree attributes from field and LiDAR data." Canadian journal of remote sensing **42**(5): 554-573.