LiDAR remote sensing to individual tree processing: A comparison between high and low pulse density in Florida, United States of America

Carlos Alberto Silva [1]
Andrew Hudak [2]
Robert Liebermann [2]
Kevin Satterberg [3]
Luiz Carlos Estraviz Rodriguez [1]

[1] University of Sao Paulo - USP/ESALQ
Post office box 96 - 13416-000 - Piracicaba - SP, Brazil
Carlos_engflorestal@yahoo.com.br
lcer@usp.br
[2]Rocky Mountain Research Station, US Forest Service1221 S. Main St. Moscow, Idaho 83843- Idaho, USA
ahudak@fs.fed.us
rjl@mail.ru
[3]University of Idaho –Idaho/USA
Post office box- 83843 - Moscow - Idaho, USA
kevinlsatterberg@gmail.com

Abstract. In this study we evaluated the performance of individual tree detection in high and low pulse density lidar datasets, applying variable windows size (VWS) and fixed windows size (FWS) for local maxima filtering implemented in FUSION software's CanopyMaxima tool. We verified that pulse density LIDAR in this case didn't show a strong influence individual tree detection, however, the type and size of windows on local maxima filtering have strong influence. The fixed windows size for 1m x 1m (FWS_1) had a better performance to individual tree detection in both pulse densities. We also verified that when increase the window size in FWS, the accuracy was decreasing. The performance in VWS both in high and low density in general was less than FWS_1 size.

Palavras-chave: Remote Sensing, LiDAR, Individual Tree.

1. Introduction

LIDAR (Light Detection and Ranging, also LADAR) is an optical remote sensing technology which has been increasingly applied to forest management. This technology is characterized by accurate forest mensuration (Hudak *et al*., 2012, Maltamo *et al*., 2004, Nasset, E. 2004b). Individual tree level identification has always been of high interest, and several approaches of LIDAR-based individual tree extraction in forest have been achieved during the past few years. Some of main works applying LiDAR data to individual tree detection and can be seen in Hyyppä et al., (2001), Persson et al., (2002), Brandtberg et al., (2003), Popescu et al., (2003) and Popescu and Wynne, (2004).

The local maxima filtering method has been the method applied to individual tree detection using LiDAR data. This algorithm is reported in Popescu et al. (2002) and Popescu and Wynn (2004), and implemented in the TreeVAW software (Kini and Popescu, 2004). Recently, McGaughey (2012) also implemented this algorithm with the CanopyMaxima tool of FUSION. CanopyMaxima uses a canopy height model to identify local maxima using a variable or fixed window size (FWS). The variable window size (VWS) is based on canopy height. According to McGaughey (2012), for some forest types this tool can identify individual trees. However, it does not work in all forest types, and it can only identify dominant and co-dominant trees in the upper canopy.

In this study, we applied local maxima filtering implemented in the CanopyMaxima tool for individual tree detection from high pulse density (≥ 3 pulse/m^2) and low pulse density (≤ 1 pulse/ m^2) LiDAR in a longleaf pine forest in Florida (USA). The aims of this study were (i) to investigate the identification of individual trees from LiDAR with different pulse densities; and (ii) to compare the results from variable window size (VWS) local maxima filtering to those obtained from fixed windows size (FWS) local maxima filtering using both pulse densities. Our hypothesis is that pulse density and type and size of windows have strong influence on individual tree detection.

2. Methodology

2.1 Study Area

The study area is located in the west-central area of Eglin Air Force Base (AFB) in the Florida panhandle at approximately 30° 30' 46", -86° 50' 30". The predominantly longleaf pine forest is characterized by an open canopy structure with up to 50% canopy cover.

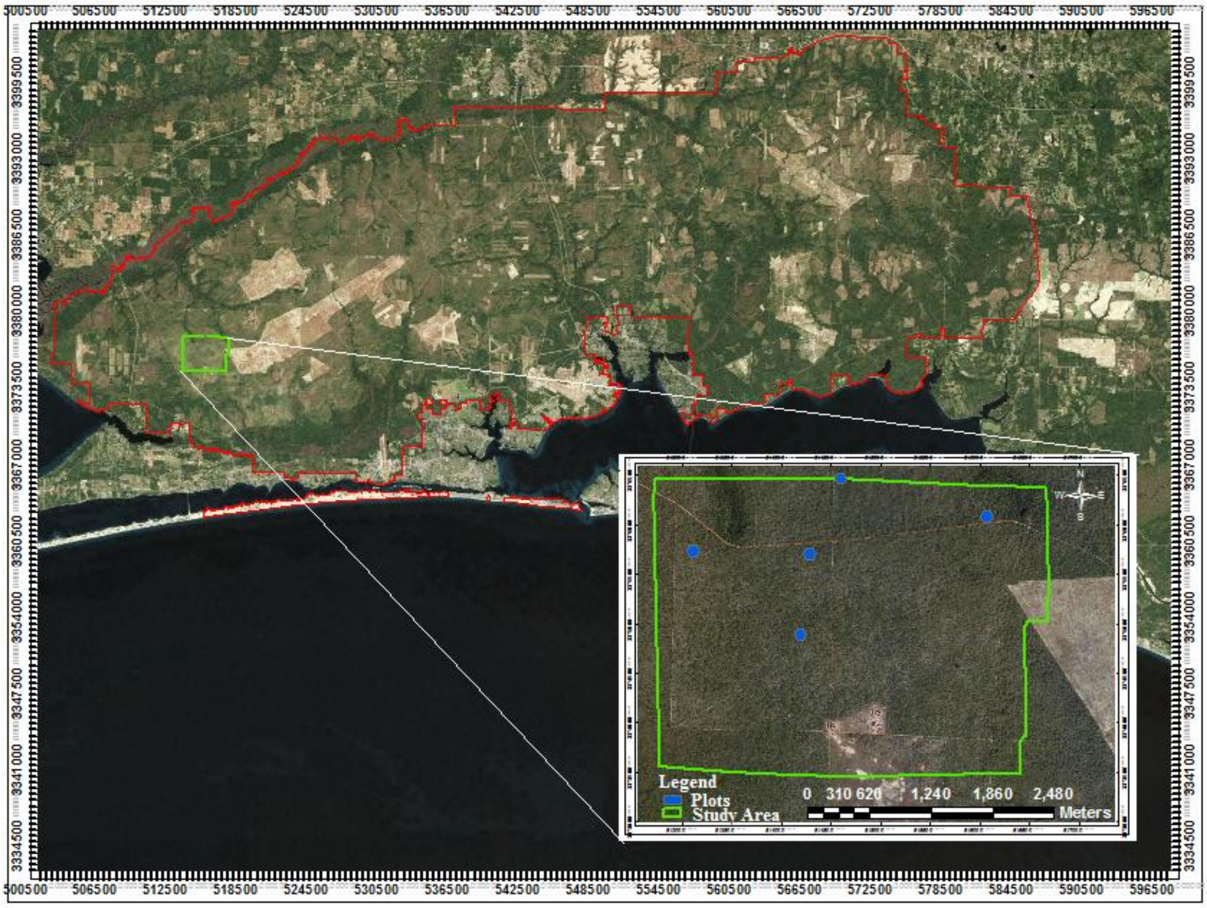


Figure 1. Study Area. Eglin AFB is the outer red outline, and the study area is the inset.

2.2 Field data Collection

The study area boundary was defined by the spatial extent of high density airborne LiDAR dataset used in this analysis (described below). Four hexagonal plots, each approximately 1 ha in size, were wholly contained within this area, plus the southern half of a fifth hexagonal plot on the northern edge (Fig. 1). Individual trees within the plots were stem-mapped but only to an accuracy of 2-3 m; also measured were individual tree height (ht), diameter at breast height (DBH) at 1.37 meters above ground, and density of trees per hectare (TPH) were measured (Table 1).

Table 1. Descriptive statistics of forest inventory plots.

Character	Tree height (m)	Density of tree (Nº/ha)
Mean	14.06	489
Standard deviation	1.73	204
Minimum	12.26	145
Maximum	16.64	643

2.3 LiDAR surveys and data processing

The Lidar data include two discrete datasets. The first dataset with relatively high pulse density was collected 5-6 February 2011 by Kucera International using a Leica ALS60 sensor operating in MPiA mode. The second dataset was collected with low pulse density using a Leica ALS-50 on 28 February 2006. The LiDAR data were classified as Unclassified, Bare Earth, and Low/Noise Points using standard classification number tagging.

Table 1. Flight parameters and scanning system settings.

Parameters	High pulse density	Low pulse density
Laser pulse density (nominal)	4.5 pulses/m^2	1.0 pulse/m^2
Laser pulse rate	176,100 Hz	44,000 Hz
Maximum returns per pulse	4	4

We used FUSION (McGaughey, 2012) and LAStools (LAStools, 2012) software for LiDAR data processing (Figure 2).

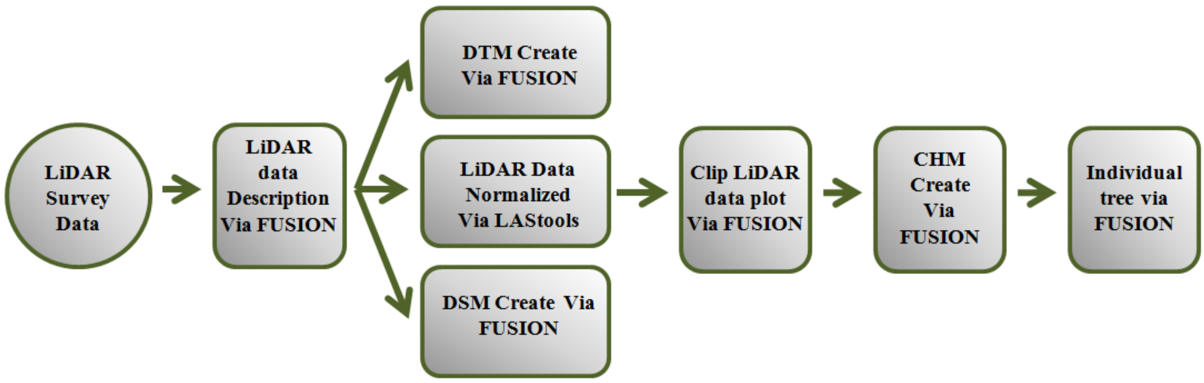


Figure 2. Steps to individual tree processing. (DTM: Digital Terrain model; DSM: Digital Surface Model; CHM: Canopy Height Model, of resolution 1m x 1m)

The CanopyMaxima tool window size is determined by the height of the surface at the center of the window using the following equation:

$$\boldsymbol{width = A + B * ht + C * ht^2 + D * ht^3} \quad (1)$$

Where: width is windows size; A,B,C and D are polynomial coefficients and ht is CHM height.

We ran *CanopyMaxima* using:

a) The variable windows size (VWS_1) applying equation coefficients from Kini and Popescu (2004) for mixed pines and deciduous trees:

$$\boldsymbol{width(m) = 2.51503 + 0.00901 ht^2} \quad (2)$$

b) The variable windows size (VWS_2) applying equation coefficients estimated from the field data. The model created was:

$$\boldsymbol{width=5.4005-0.628*ht+0.0588*ht^2+-0.0012*ht^3} \qquad (3)$$

c) Fixed windows size (FWS) applying the constants of 1, 2, 5, and 10 for the intercept of the equation and zero for the height (ht). We obtained a fixed windows size of:

FWS_1: dimension of 1m x 1m => $\boldsymbol{width=1 - 0*ht+0*ht^2+-0*ht^3}$ (4)
FWS_2: dimension of 1m x 1m => $\boldsymbol{width=2 - 0*ht+0*ht^2+-0*ht^3}$ (5)
FWS_5: dimension of 5m x 5m => $\boldsymbol{width=5 - 0*ht+0*ht^2+-0*ht^3}$ (6)
FWS_10: dimension of 10m x 10 m => $\boldsymbol{width=10 - 0*ht+0*ht^2+-0*ht^3}$ (7)

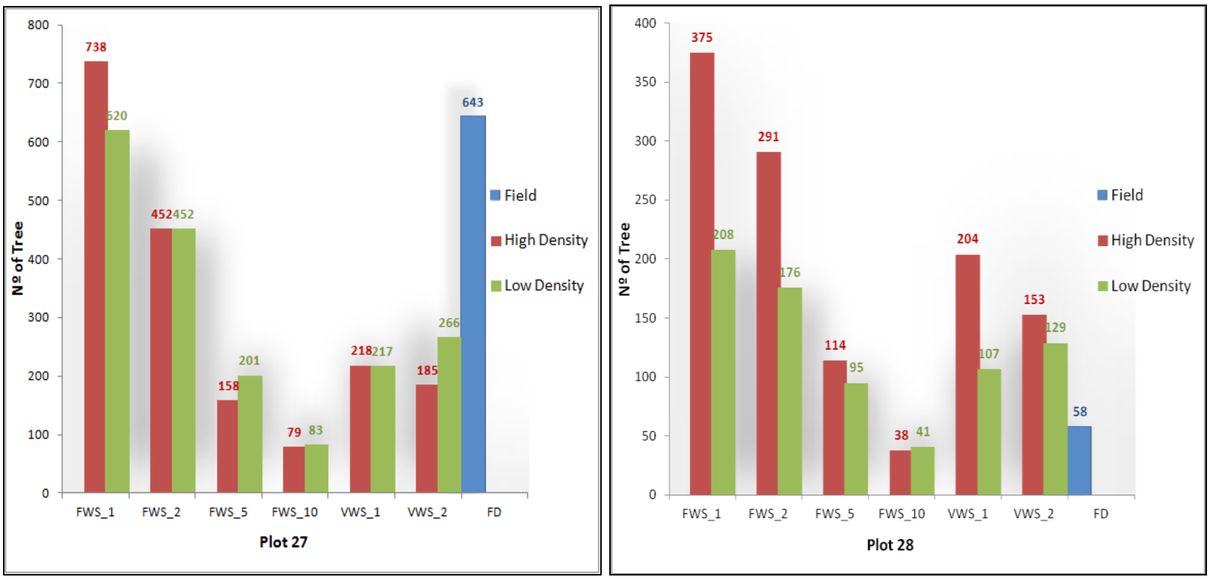
To available the performance of individual tree detection, we used:

Absolute Error (Nº tree) = Nº tree detected – Nº tree observed (8)
Relative Error (%) = ((Nº tree detected – Nº tree observed)/ Nº tree observed)*100 (9)

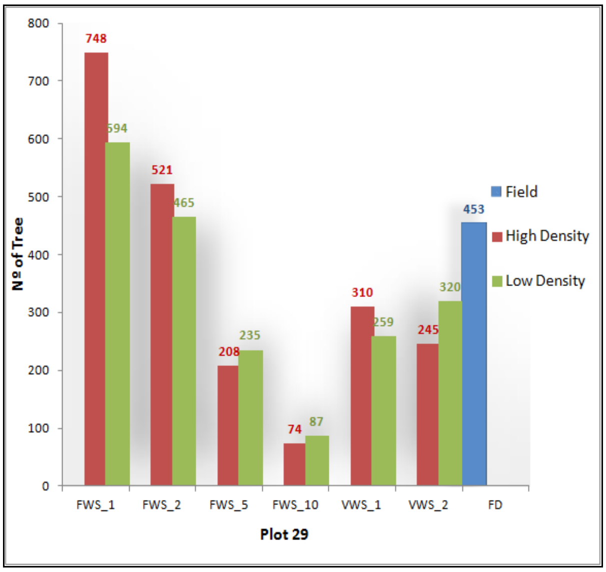
3. Results and Discussion

3.1 Individual tree detection

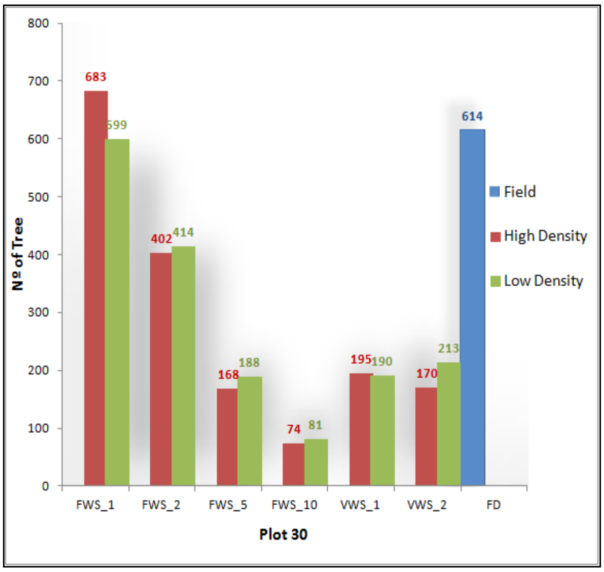
In this study we confirmed type and size of windows have a strong influence on individual tree detection. However, pulse did not show a significant difference on individual tree detection. Furthermore, FWS_1 had a better performance in both pulse densities, although FWS_2 had showed accuracy in high pulse density on plot_29. The VWS_1 as well as VWS_2 in general also didn't have good performance. The results of individual trees detection can be seen in figure 3.



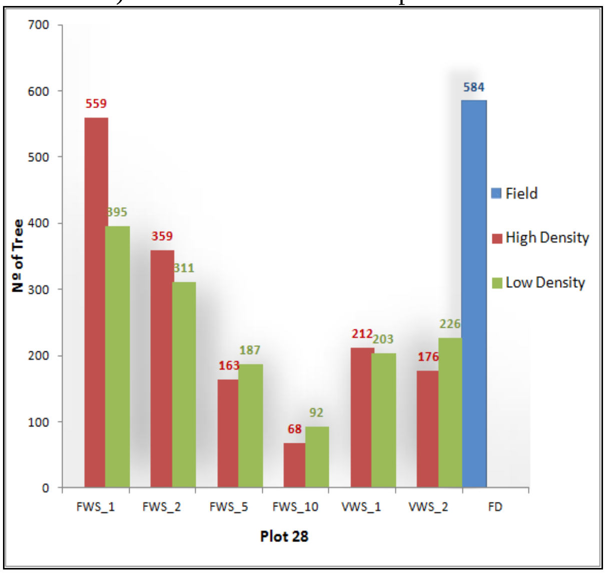
a) Individual tree detection plot 27 b) Individual tree detection plot 28



c) Individual tree detection plot 29



d) Individual tree detection plot 30



e) Individual tree detection plot 31

Figure 3. Individual tree detection for 4.5 plots using WVS and FWS in low and high pulse density.

3.2 Statistics of individual tree detection

Although pulse density did not show significant difference on individual tree detection between them, we verified that the relative error of number individual tree detection to FWS_1 ranged between -4 and 547% in high pulse density and -2 and 259 % in low pulse density. Also, we verified that when increase the window size, the accuracy decreases. In VWS the relative error of number individual tree detection ranged between -34 and -88 % to VWS_1 and -61 and -252 % to VWS_2 in high pulse density. In low pulse density the results were less accurate, but, theses had the same behavior than high pulse density. The table 2 is review about statistics of individual tree detection.

Plots	Parameters	Windows size					
		FWS_1	FWS_2	FWS_5	FWS_10	VWS_1	VWS_2
High Density							
Plot_27	Nº Tree	738	452	158	79	218	185
	Absolute Error(Nº Tree)	95	-191	-485	-564	-425	-458
	Relative Error(%)	15	-30	-75	-88	-66	-71
Plot_28	Nº Tree	375	291	114	38	204	153
	Absolute Error(Nº Tree)	317	233	56	-20	146	95
	Relative Error(%)	547	402	97	-34	252	164
Plot_29	Nº Tree	738	452	158	79	218	185
	Absolute Error(Nº Tree)	285	-1	-295	-374	-235	-268
	Relative Error(%)	63	0	-65	-83	-52	-59
Plot_30	Nº Tree	683	402	168	74	195	170
	Absolute Error(Nº Tree)	69	-212	-446	-540	-419	-444
	Relative Error(%)	11	-35	-73	-88	-68	-72
Plot_31	Nº Tree	559	359	163	68	212	176
	Absolute Error(Nº Tree)	-25	-225	-421	-516	-372	-408
	Relative Error(%)	-4	-37	-69	-84	-61	-66
Low Density							
Plot_27	Nº Tree	620	83	452	201	217	266
	Absolute Error(Nº Tree)	-23	-560	-191	-442	-426	-377
	Relative Error(%)	-4	-87	-30	-69	-66	-59
Plot_28	Nº Tree	208	41	176	95	107	129
	Absolute Error(Nº Tree)	150	-17	118	37	49	71
	Relative Error(%)	259	-29	203	64	84	122
Plot_29	Nº Tree	594	87	465	235	259	320
	Absolute Error(Nº Tree)	141	-366	12	-218	-194	-133
	Relative Error(%)	31	-81	3	-48	-43	-29
Plot_30	Nº Tree	599	81	414	188	190	213
	Absolute Error(Nº Tree)	-15	-533	-200	-426	-424	-401
	Relative Error(%)	-2	-87	-33	-69	-69	-65
Plot_31	Nº Tree	395	92	311	187	203	226
	Absolute Error(Nº Tree)	-189	-492	-273	-397	-381	-358
	Relative Error(%)	-32	-84	-47	-68	-65	-61

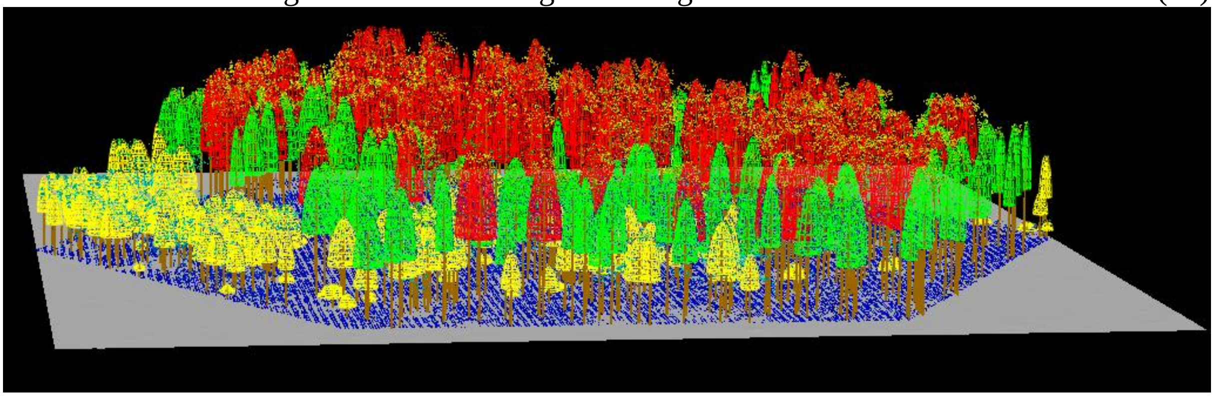
Table 2. Statistics of individual tree detection

Figure 4 shows this performance of individual tree detection in three dimensions (3D) in FUSION software. Is easy to identify the difference between high and low pulse density. To better visualize the tree, heights were created 3 classes: Red (ht>16.84), Green (11.63<ht>16.84) and Yellow (ht<11.63). These values were calculated from field data plots using average and standard deviation, as shown in the equations 6, 7 and 8 below:

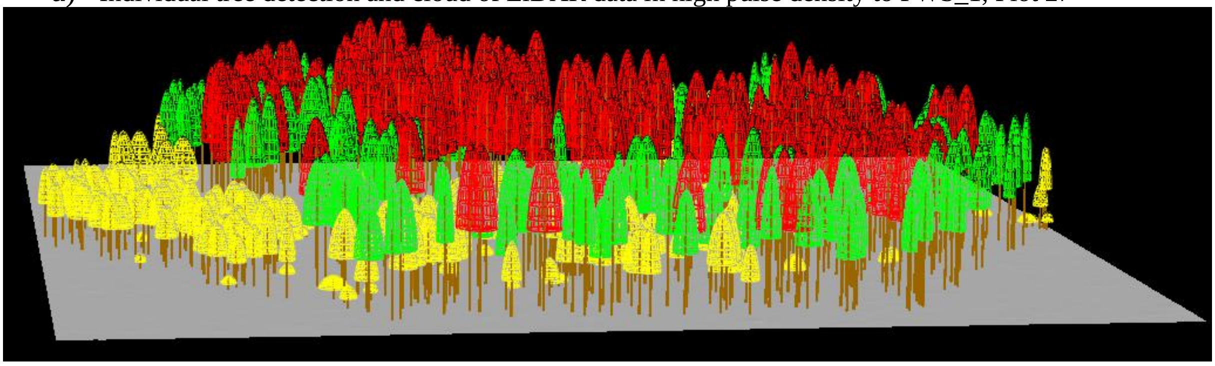
Red: average + standard deviation/2 = 14.24+5.21/2 = 16.84 m (9)

Yellow: average - standard deviation/2 = 14.24 - 5.12/2 = 11.63 m (10)

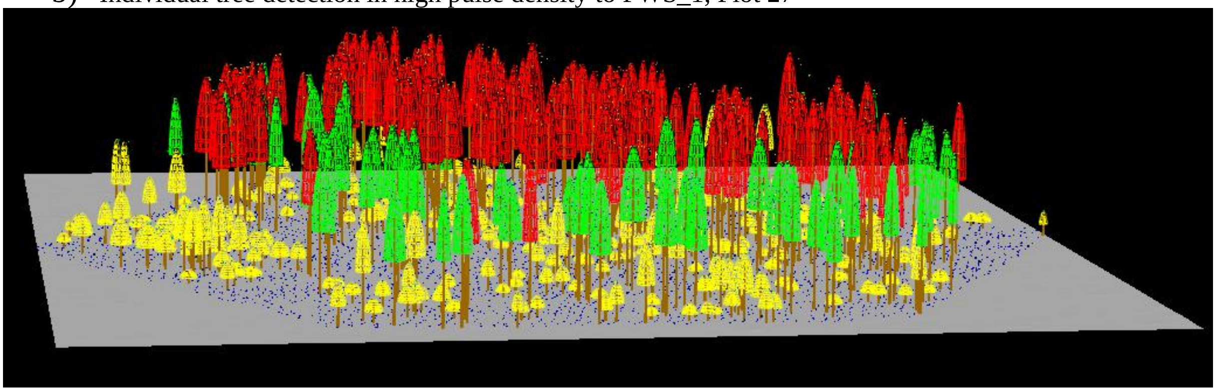
Green: range between red and green= range between 16.84 and 11.63 m (11)



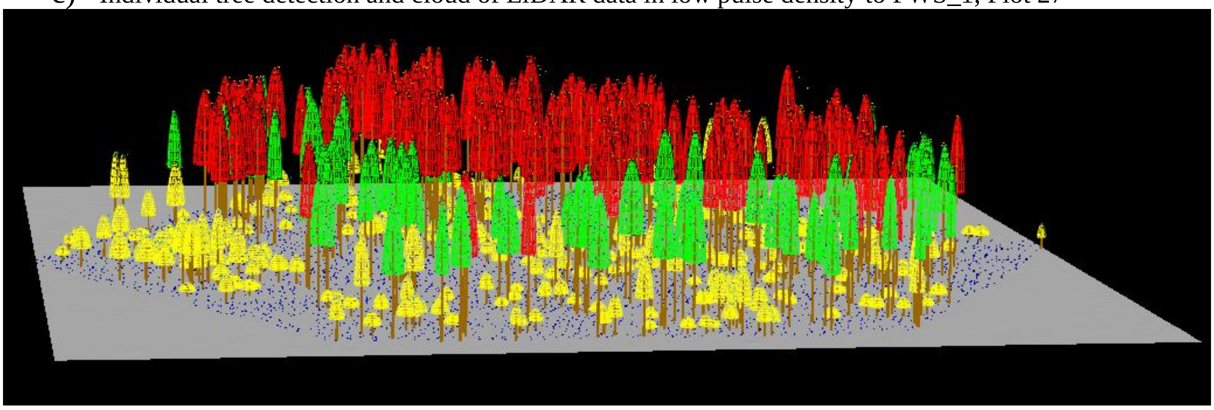
a) Individual tree detection and cloud of LiDAR data in high pulse density to FWS_1, Plot 27



b) Individual tree detection in high pulse density to FWS_1, Plot 27



c) Individual tree detection and cloud of LiDAR data in low pulse density to FWS_1, Plot 27



d) Individual tree detection in low pulse density to FWS_1, Plot 27

Figure 4. Performance of individual tree detection in three dimensions (3D) in FUSION software

4. Conclusion

This work confirmed that LiDAR remote sensing has potential to individual tree detection. The pulse density LiDAR and type and size of widows are important parameters that need to be considered in individual tree processing. Although some authors report that FWS can be inconsistent with the complex canopy structure, we recommend testing FWS together with VWS, because in this case some FWS size has shown better performance than VWS.

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