Evaluation of digital elevation models (DEMs) from high and low pulse density in LiDAR data

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Abstract. In this paper we evaluated and compared digital elevation models (DEMs) and tree height estimation from high and low pulse density LiDAR data. To compare DTMs were calculated root mean squared error (RMSE), coefficient of variance of the root-mean-square error (CV-RMSE) and mean absolute error (MAE). To tree height estimation was inventoried four hexagonal plots, each approximately 1 ha in size. Within the plots were stem-mapped and measured individual tree height. Based on our results, we conclude that low pulse density LiDAR can be applying to terrain model create, however, recommended just to DTM created. Furthermore, when desire biometrics tree estimation from LiDAR, we recommended that use high pulse density, because this is more accuracy.

Palavras-chave: Remote Sensing, LiDAR, Digital Elevation Models.

1. Introduction

LIDAR (Light Detection and Ranging) is an optical remote sensing technology that has been an efficient tool to characterize digital elevation models (DEM). According Hudak et al. (2009), applications of LiDAR remote sensing are exploding, while moving from the research to the operational realm. Increasingly, natural resource managers are recognizing the tremendous utility of LiDAR-derived information to make improved decisions. The DEMs derived from the LiDAR data include the Digital Terrain Model (DTM) and the Digital Surface Model (DSM); subtracting the DTM from the DSM yields the Canopy Height Model (CHM) (Perko, 2010) (Figure 1).

There are many factors that affect the accuracy of DEMs, with the main factors including the accuracy, density and distribution of the source data, the interpolation algorithm, and the DEM resolution (Priestnall *et al.*, 2000). Some studies like Peuetz *at al.*, (2009) focused on the effects of LiDAR pulse density on DEM accuracy.

The aims of this study were (i) to compare the DEMs (DTM, DSM and CHM) derived from low versus high density LiDAR; (ii) to estimate tree height from high and low pulse LiDAR data; and, (iii) to evaluate the performance of low pulse density LiDAR on DEMs creation and tree height estimation. The hypothesis was that pulse density has strong influence on LiDAR products, and high pulse density performs better at the individual tree level.

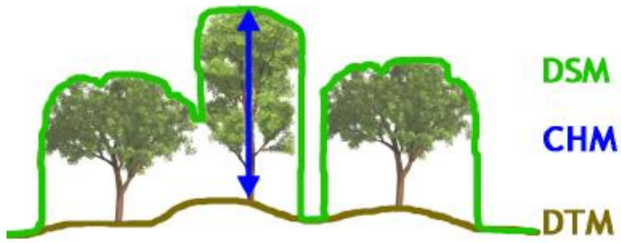

Figure 2: Explanation of relation between digital surface model (DSM), digital terrain model (DTM) and canopy height model (CHM). (Perko, 2010).

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.

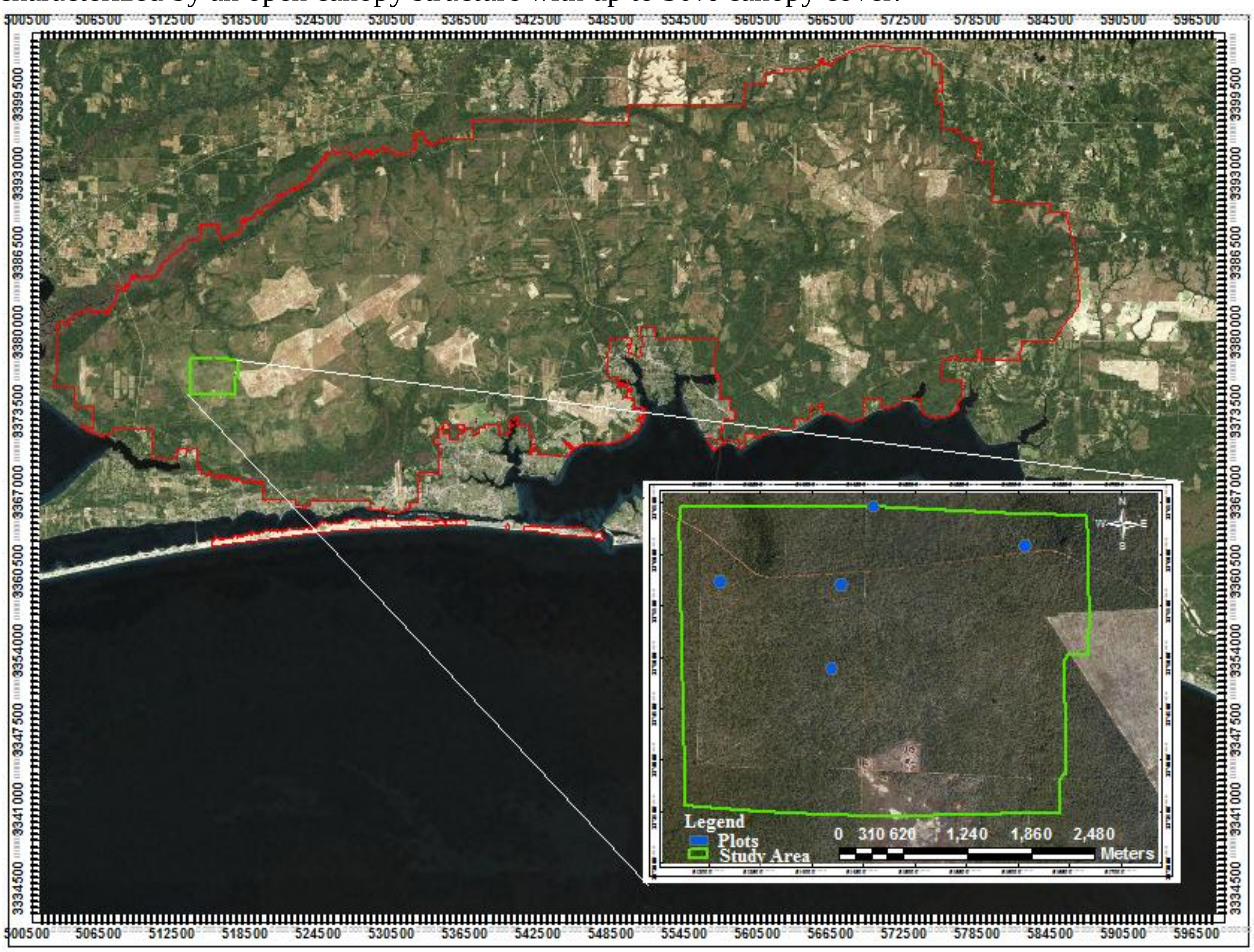

Figure 2. Study Area. Eglin AFB is the outer red outline, and the study area is the inset.

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). We measured individual tree height (ht), diameter at breast height (DBH) at 1.37 meters above ground, and density of trees per hectare (TPH) (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 2. 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).

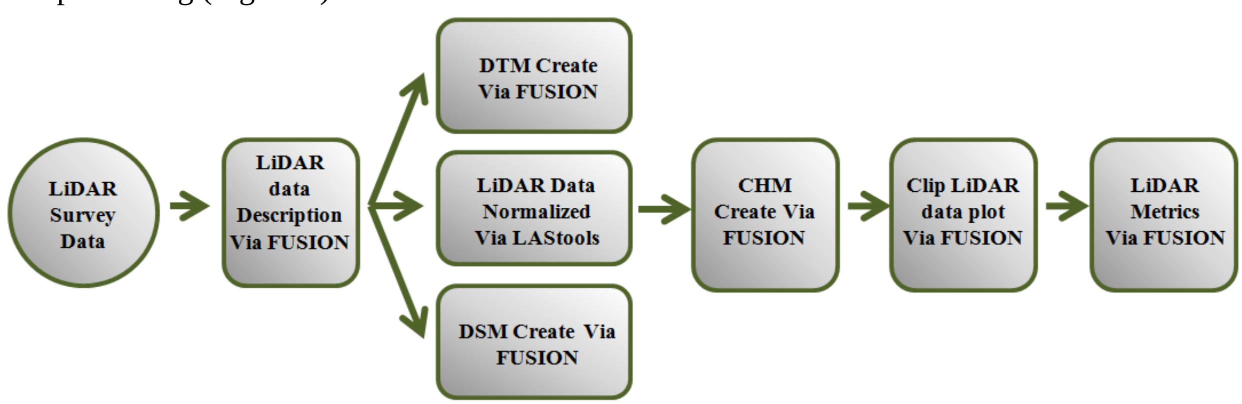

Figure 1. Steps to individual tree processing (DTM: Digital Terrain Model; DSM: Digital Surface Model; CHM: Canopy Height Model).

LiDAR processing was performed using the *CanopyMaxima* tools in FUSION software for individual tree detection. The LiDAR metrics measured were the mean, minimum and maximum tree heights.

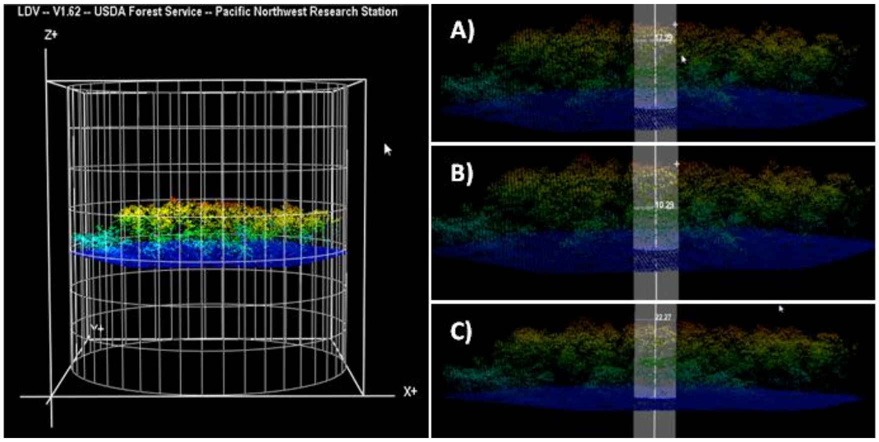

Figura 3. Illustration 3-D LIDAR point clouds in LiDAR Data view in Fusion. A) LiDAR points clouds of plot, B) Mean tree height, C) Minimum tree height and D) Maximum height

To compare DTM, DSM and CHM created from both LiDAR densities, we extracted 3000 randomized points using ArcGIS 10 software, and compared them using the Root Mean Squared Error (RMSE), Coefficient of Variance of the RMSE (CV-RMSE) and Mean Absolute Error (MAE):

$$\mathrm{RMSE}= \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2} \quad (1)$$

$$\mathrm{CV-RMSE}\ (\%) = \frac{\mathrm{RMSE}}{\bar{x}} * 10 \quad (2)$$

$$\mathrm{MAE}(\%) = \frac{(\bar{y}-\bar{x})}{\bar{x}} * 100 \quad (3)$$

Where y_i is predicted value (in this case is low pulse density LiDAR) and x_i is the actual value (high pulse density LiDAR). $\bar{x}$ is the average of the observed values and $\bar{y}$ is the average of the predicted values. This statistics were calculated using R Project for Statistical Computing software (R Development Core Team. 2007). Histograms and other graphics to illustrate the results were created with ggplot2.

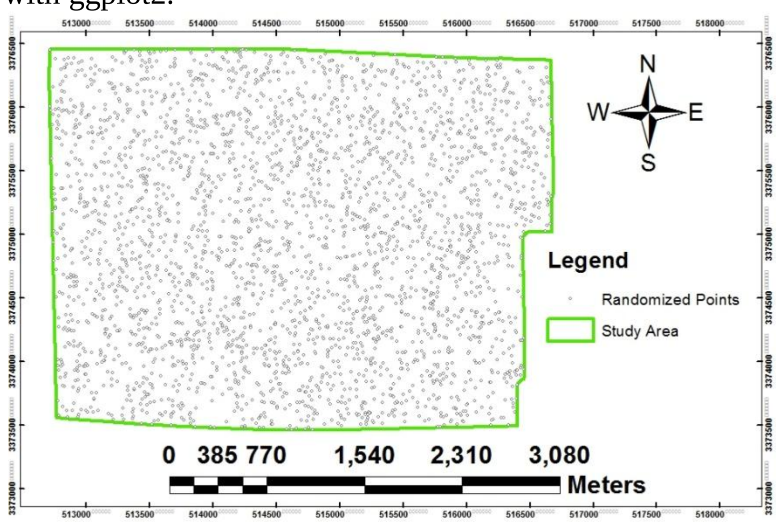

Figura 4. Randomized points in study area extracted to compare DTM, DSM and CHM.

3. Results and Discussion

3.1 Descriptive statistics of the elevation models.

Histograms in Figure 5 show skewed (non-symmetric) distributions in the elevation models. Distributional shapes were similar between the low and high density LiDAR derived DTMs but much less similar between the DSMs and CHMs.

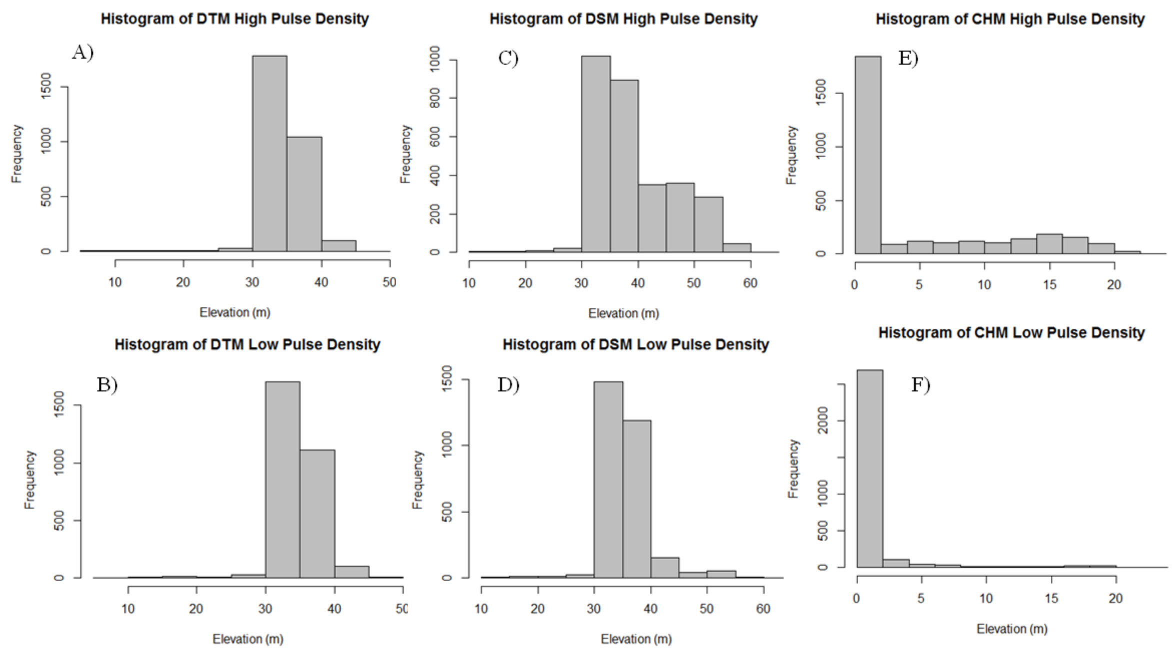

Figure 5. Histograms of randomized points extracted from elevation models. DTMs (A and B), DSMs (C and D) and CHMs (E and F) .

Scatter plots in Figure 6 show a close relationship exists between the low and high density LiDAR derived DTMs. However, correlations between DSMs and CHMs were inconsistent and biased.

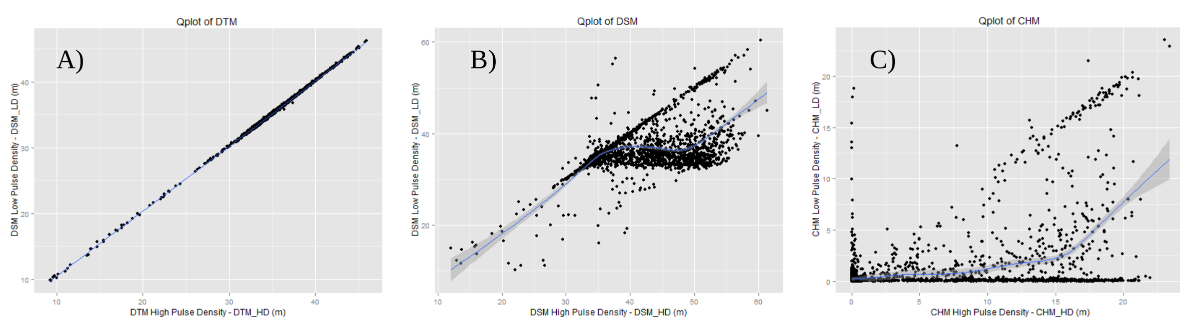

Figure 6. Randomized points extracted and compared between low and high density LiDAR derived elevation models. A) DTMs, B) DSMs and c) CHMs.

3.2 Comparation of the elevation models from low and high pulse density

Table 2 shows the statistcs used to evaluate the elevation models created from low and high pulse density LiDAR. The DTMs derived from low and high density LiDAR differed little, the CHMs the most, and the DSMs to an intermediate degree.. In general, the lower pulse density LiDAR slightly overestimated the DTM height, but greatly understimated the DSM and CHM heights relative to the elevations estimated from the higher density LiDAR.

Table 2. Statistical tests applied to evaluate elevation models.

Parameter	Statistic test		
	RMSE	CV-RMSE (%)	MAE (%)
DTM	0.1652	0.4761	0.3788
DSM	6.9454	17.6425	-9.2795
CHM	6.8743	147.7702	-78.0462

3.3 Tree heights obtained from low and high pulse density LiDAR at field validation plots

The results in figure 7 show that in general tree height estimation from both high and low density LiDAR was underestimated when compared with field data. When estimated tree heights were compared between the high and low densitiy LiDAR, the higher pulse density was more accurate. In all cases, estimated tree heights using the low pulse density LiDAR was below those estimated using the high pulse density, as well as more different from the field validation measurements. Also, figure 7 shows that the maximum tree height estimation from LIDAR was most accurate, followed by the minimum and average, using either LiDAR pulse density. A possible explanation for the low pulse density not performing as well for tree height estimation is that the point density applied was insufficient to detect all the trees, particularly the medium and small trees.

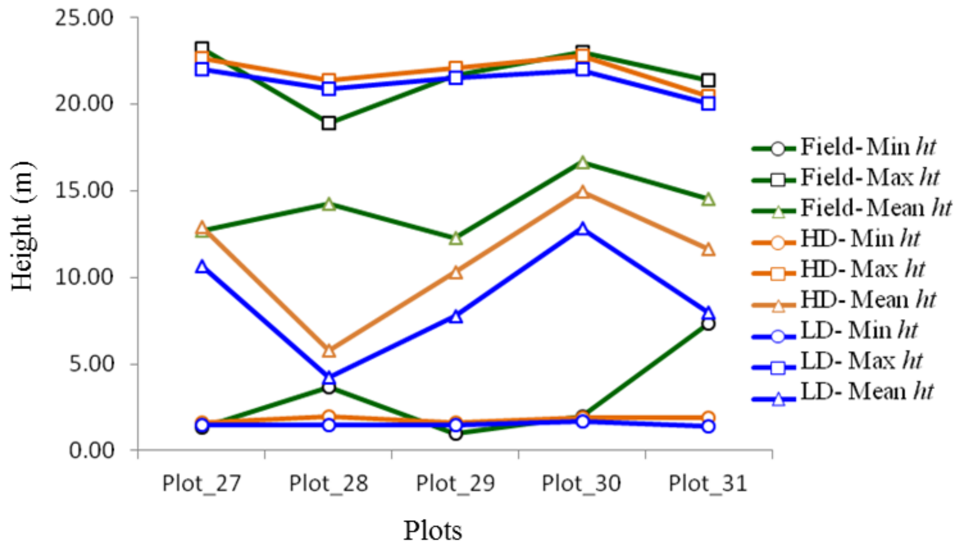

Figure 7. Tree heights from field plots used to validate low and high pulse density LiDAR. Ht: tree height, HD: High pulse density and LD: low pulse density.

3.4 Maps DTM, DSM and CHM created

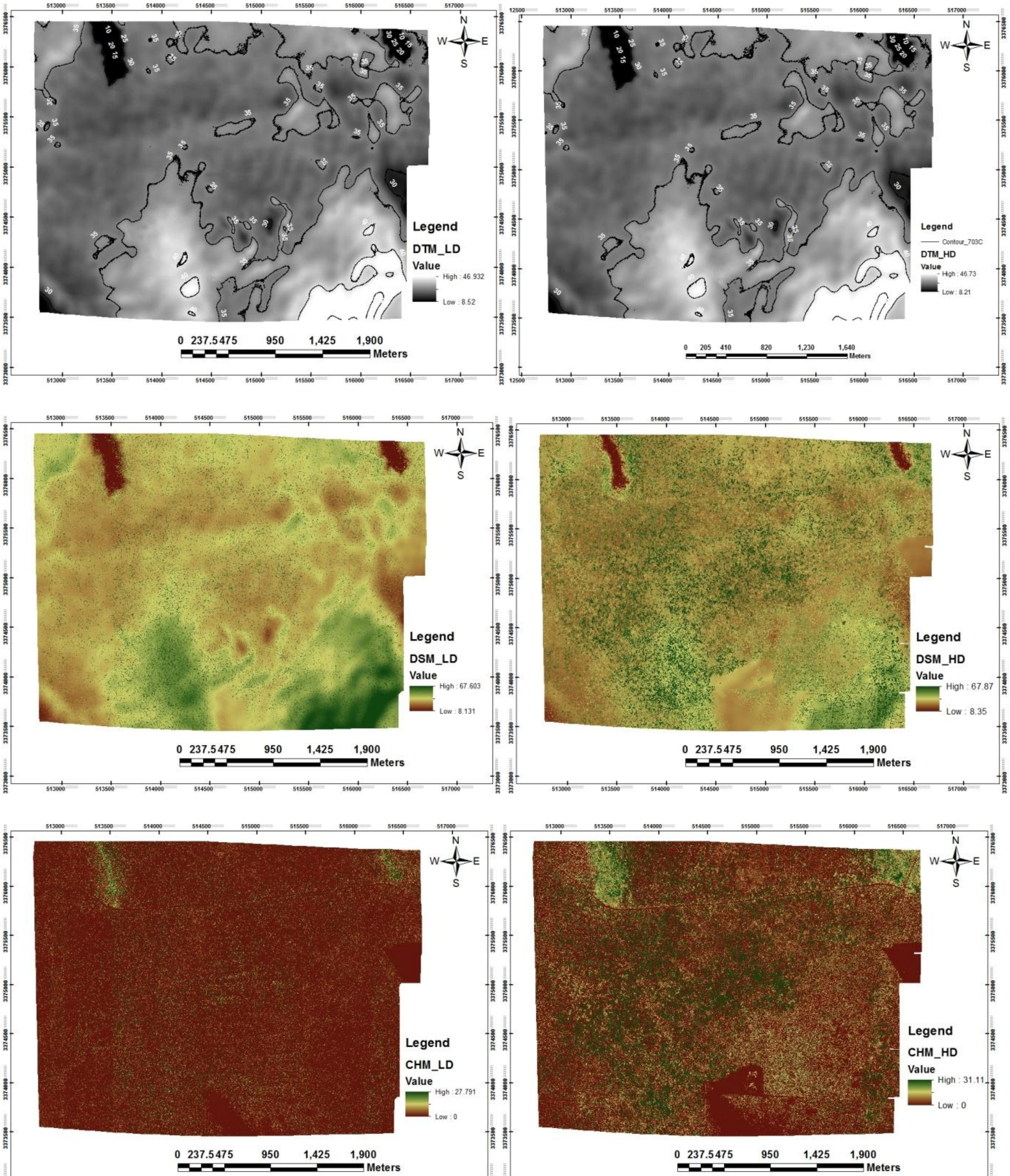

Figura 8. DTM (top), DSM (middle) and CHM (bottom) from low (left) and high (right) density LiDAR.

4 Conclusion

We conclude that low pulse density LiDAR can be used to create elevation models, however, we recommend just creating a DTM and not the DSM or CHM. Furthermore, when tree-level estimates from LiDAR are desired, we recommend the use of high pulse density for more accurate results.

Acknowledgements

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