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Measuring height of sugarcane plants through LiDAR technology

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Abstract. *Sugarcane (Saccharum* spp.*) has an important economic role in Brazilian agriculture, especially in São Paulo State. Variation in the volume of plants can be an indicative of biomass which, for sugarcane, strongly relates to the yield. Laser sensors, like LiDAR (Light Detection and Ranging), has been employed to estimate yield for corn, wheat and monitoring forests. The main advantage of using this type of sensor is the capability of real-time data acquisition in a non-destructive way, previously to harvesting. Currently, there are few studies dealing with sugarcane canopy sensors for biomass estimation. The objective of this study is the use of LiDAR technology to measure height of sugarcane plants in the pre-harvest period. Measures were carried out with the sensor fixed on a mechanical arm over experimental plots of sugarcane 10 days before harvest. The experiment consisted of 8 plots of 12 x 30 m each consisting of four nitrogen treatments. The laser sensor used was a SICK LMS200 which collects distance and angle values in different directions in a 2D plane with a wavelength of 905 nm, angular resolution of 1º, scan angle of 180º, frequency of 75 Hz and 8 m of range. A GNSS receiver with RTK differential correction was used in conjunction with the sensor for georeferencing data. The sensor was approximately 4 m above the ground, focusing vertically to the plants. The distance values were transformed, through R and QGIS software, into a point cloud which each point has a real geographical coordinate. The average yield of plots estimated was 107.24 t ha^{-1}. There was no correlation between height of plants measured by the sensor and estimated yield (r= -0.52) as did not exist significant variability on both. Despite that some adjustments can be done in the data acquisition, like the sensor stabilization and its position due to terrain inclination. Laser sensors can provide complementary information for helping on sugarcane yield estimation as yield monitors are not yet popular as on grain crops. More studies are needed to validate its application for biomass and yield estimation in production scale of sugarcane.*

Keywords. *laser sensor, spatial variability, yield monitoring.*

INTRODUCTION

Precision agriculture and sugarcane scenario

Competitiveness of the agricultural sector clearly shows the need to achieve higher levels of production through agricultural practices associated with the control of applied inputs. The use of Precision Agriculture (PA) technologies results in a higher demand for equipment to obtain data, especially related to the variability of crops in the field, which contributes to monitoring the production cycle of crops in order to make better use of inputs and resources available in the field.

The Brazilian production for sugarcane crop achieved, approximately, 617 million tons, which represents an increase of 8.0% in relation to the cycle of 2014/15. The current yield of the harvested crop reached 83 t ha^{-1} (CONAB, 2016).

Precision agriculture has contributed to the maintenance of the production of sugarcane system focusing on reducing costs, minimizing environmental impacts and improving the quality of the product (MAGALHÃES and CERRI, 2007). Silva et al. (2011) reported that automatic steering system is the mainly PA tool used in the sugarcane production allowing reduction in soil compaction, traffic control and longevity of the sugarcane field.

Yield maps, for sugarcane crop, began in the studies conducted by Pierossi and Hassuani (1997) for the harvest of chopped sugarcane in Brazil and by Cox et al. (1997) with the development of instrumentation for harvesters in Australia. According Bramley (2009) yield maps allows identification of heterogeneity present in the crop and, consequently, its management differently. Figure 1 shows a yield map of a sugarcane field (6.7 ha) in Australia, where yield changes can be verified even in nearby regions.
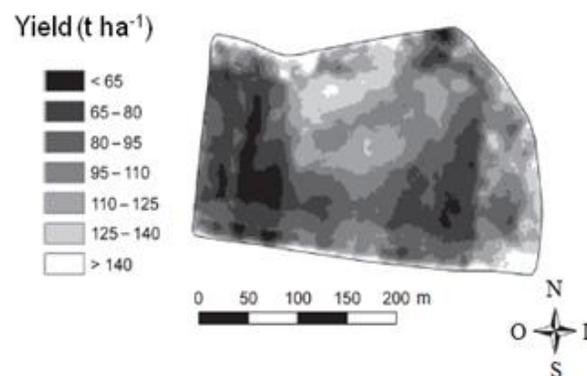

Fig 1. Yield map of 6.7 ha for sugarcane in Australia. Bramley and Quabba (2001)

Due to the scarce availability of alternatives for measuring yield in sugarcane crop, a methodology

that allows data acquisition, non-invasively, close to harvesting, is essential for yield monitoring.

LiDAR technology and applications

LiDAR (*Light Detection and Ranging*) technology, originated in the 1960s, is a type of remote sensing capable of measuring distances using pulses emitted by a instantaneous laser and non-destructive way. The main components of this technology are the laser operating between 600 nm and 1000 nm, scanner, optical sensors, photodetectors and electronic receivers for transmission and reception of each pulse (ROSELL and SANZ, 2012).

The laser sensors operation is based on calculating distance between sensor and obstacle. The most commonly used type of laser sensor is based on the concept of time-of-light (TOF), which measures the interval time between laser pulse emission and its reception. This principle can be applied for studies that aim to estimate geometric parameters (height, volume, etc.) of objects (ZHENG et al., 2013). Most of forestry research employs airborne LiDAR technique to estimate parameters, as height and biomass, in forest areas (LI et al. 2014; LUO et al. 2015; POPESCU et al. 2011).

Furthermore, laser sensors can be used to detect obstacles in agricultural machines using autonomous direction (DOERR et al., 2013), estimates of biomass in pastures density (GARCÍA et al., 2010) and automated irrigation systems in vineyards (KANG et al., 2011). For terrestrial laser scanning this technique can be used to develop crop models (TILLY et al. 2014) and measuring corn plant location and spacing (SHI et al. 2015). Selbeck et al. (2010) evaluated a laser sensor in the experimental fields of maize, using a commercial equipment allocated 3.70 m above the ground, to calculate the biomass of plants. The results showed high correlation ($R^2 = 0.94$) with the real biomass data. Schirrmann et al. (2016) have been used laser sensors in crops, as wheat, to estimate biomass from plants height data obtained before harvest.

The use of this kind of approach may represent an opportunity for the development of yield prediction models. So, the objective of this study is to use LiDAR technology to measure height of sugarcane plants in the pre-harvest period and relate it to biomass production.

MATERIAL AND METHODS

A laser sensor LMS200 (SICK AG, Waldkirch, Germany) and a GR3 GNSS receiver (Topcon, California, USA) were employed. The laser sensor, based on the TOF concept, comprises a light beam of 905 nm and it is inserted into the security class 3 (EN 50178, 1997), therefore, does not damage to the user's view. Some technical specifications about the sensor are presented in the Table 1.

Table 1 – Technical specifications of the sensor LMS200 (SICK AG, Waldkirch, Alemanha)

Specifications	Values
Wavelength	905 nm
Operating voltage	24 V
Operating range	8 - 80 m
Angular resolution	0,25º; 0,5º; 1º
Frequency	25; 35; 50; 75 Hz
Response time	53; 26; 13ms
Resolution	± 10 mm
Accuracy	± 35 mm
Temperature range	0 - 50ºC
Data transmission rate	9,6; 19,2; 38,4; 500 kBauds
Weight	4,5 kg
Dimensions	156 mm x 155 mm x 210 mm

The scan angle of the sensor is 180° for measurements up to 10 m with 10% reflectivity for outdoor ambient. For data acquisition was used the RS-422 communication protocol and frequency of 75 Hz. The angular resolution of the sensor was set to 1º and 8 m of range. According to the manufacturer, for this configuration, the response time is 13 ms and the statistical error estimated at ± 5 mm.

The coordinates of each point were obtained by means of geographic coordinates recorded by the GNSS (Global Navigation Satellite System) receiver using a set of L1/L2 + GLONASS receivers with differential correction RTK (Real Time Kinematic). This level of accuracy was necessary because of the point clouds georeferenced and the employment of RTK signal in most of agricultural operations. The GNSS receiver was connected to the computer via serial RS-232.

A portable computer, Toughbook CF-18 (Panasonic, USA), was used with a programming routine described in the Processing software (Processing Foundation, 2014) for receiving data from the laser sensor and GNSS receiver. Figure 2 shows a scheme with main components used for acquisition data of the laser sensor.
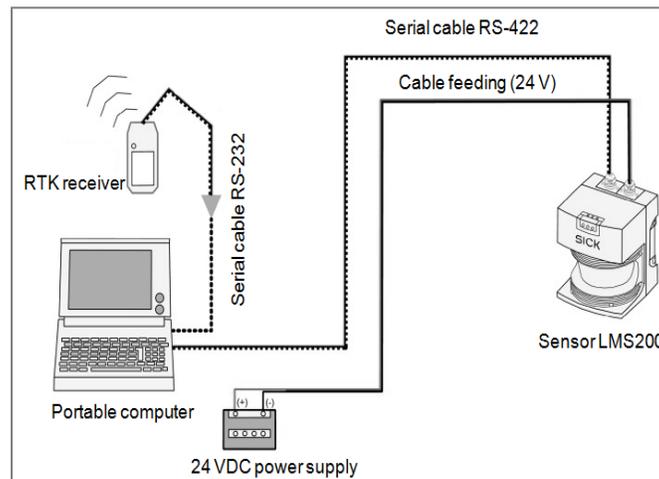
Fig. 2 - Scheme with the main components for acquisition data using a laser sensor. Adapted from Rosell et al. (2009)

We collected the data in an experimental area that consists of 0.65 ha with a sugarcane variety (IAC 95-5094) of 12 months age. Plants were arranged in 16 plots, as shows Figure 3, with eight plots of 15 m x 30 m each and other eight plots of 12 m x 30 m each. The plants were spaced at 1.50 m between rows and subjected to different treatment of nitrogen levels (0, 60, 120 and 180 kg ha^{-1}).
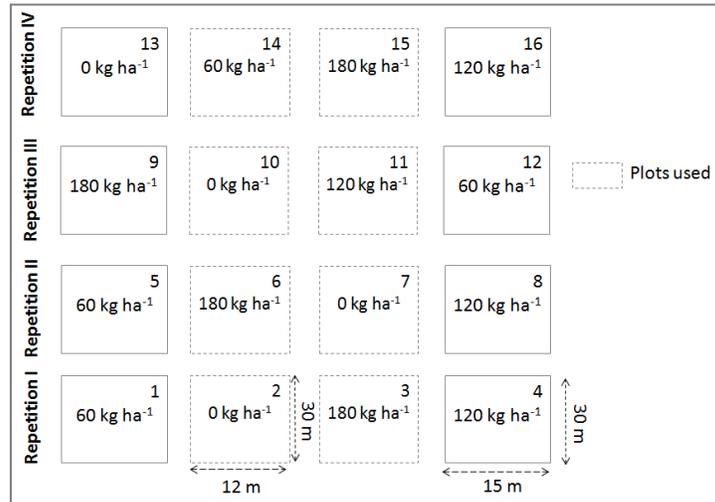
Fig. 3 – Experimental area of sugarcane

Due to the slope land and the presence of leaves "lying ground" on the borders of plots, the sensor showed some errors in the data acquisition, therefore, was considered eight central portions of the experimental area, totaling 0.29 ha. Data acquisition occurred 10 days before sugarcane harvest. Plants height data were collected manually through a topographical rule, individually in five plants of each plot, obtaining the average height of sugarcane plants. Manual measurements were obtained 15 days before harvest. Sugarcane yield for each plot was estimated by the method proposed by Martins and Landell (1995).

The three-dimensional plotting requires that each point cloud presents geographic coordinates (UTM - Universal Transverse Mercator) represented by x, y and z axis, where the x-axis represents the direction of tractor movement and the y-axis the direction of scan angle by the laser sensor. The coordinate z is calculated from the scan angle sensor and the distance between sensor and sugarcane plants. Figure 4 illustrates the sensor position for acquisition data in the sugarcane field.
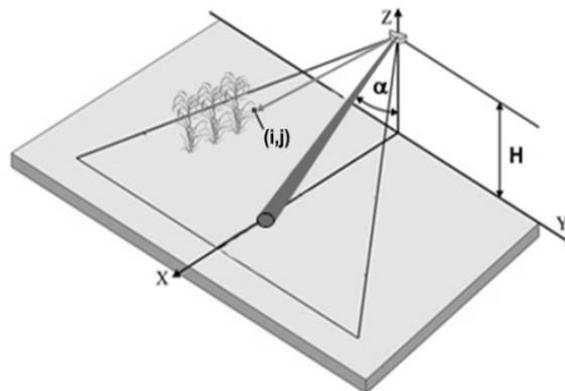

Fig. 4 – Positioning laser sensor for acquisition data in sugarcane field

The equipments were allocated 4 m above the ground (Figure 5) with the sensor focusing vertically to the plants. The agricultural vehicle crossed plots with a constant speed of 1.0 m s^{-1} in carriers of 3

m wide. A structure (cantilever beam) coupled rigidly to the side of the tractor was developed to provide stability to the sensor.
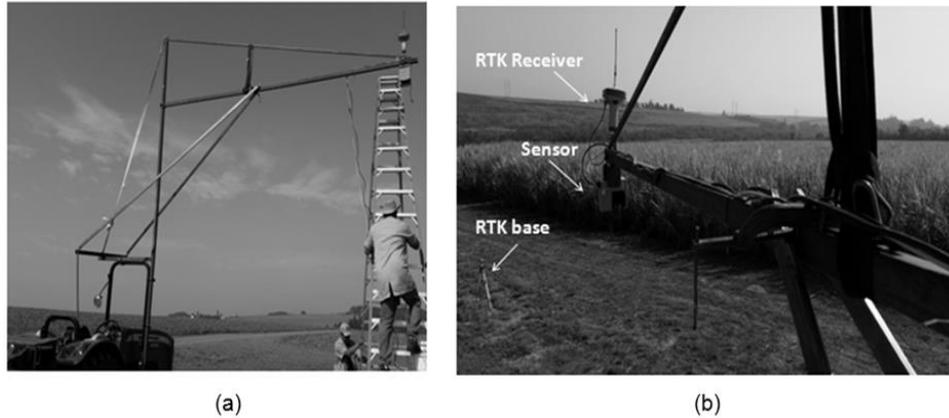

Fig. 5 - Structure beam type in balance coupled rigidly to the side of the tractor (a); equipments in the structure (b)

The distance values provided by the sensor were in the form of polar coordinates, which subsequently were converted into Cartesian coordinates from equations 1 and 2.

$$x_{ij} = d_{ij} \text{ sen } (\alpha_{ij}) \tag{1}$$

$$z_{ij} = H - d_{ij} \cos (\alpha_{ij}) \tag{2}$$

where, x_{ij}: cartesian coordinate *x*-axis in the point *ij* (m), d_{ij}: distance between sensor and target in the point *ij* (m), α_{ij}: measuring angle (^{0}), z_{ij}: cartesian coordinate *z*-axis in the point *ij* (m), H: sensor height above the ground (m).

This procedure was developed in RStudio (R Development Core Team, 2014), where is necessary to indicate the sensor height above the ground (H). The point cloud was assessed using CloudCompare® software to identify the height of sugarcane plants in experimental area. Its corresponding histogram was obtained by the same software using the Gaussian distribution. An individual file was generated for each plot through QGIS software (OSGeo, 2014) due to the computational performance.

A data cleaning was done, which involves the elimination of outliers and the overlap of 4 m due to the reading range achieved by the sensor on the path crossed. The average height of sugarcane plants ($\overline{H}$) was calculated from equation 3 in a spreadsheet from the files generated in the previous step.

$$\overline{H} = \sum_{i=1}^{n} \frac{zi}{n} \tag{3}$$

where, $\overline{H}$: average height of sugarcane plants (m), z_i: cartesian coordinate *z*-axis in the point *ij* (m), n: number of points.

The spatial variability of the plants height indicated by the laser sensor was verified calculating the coefficient of variation (CV), according to the equation 4.

$$CV = \frac{100 \times \sigma}{\overline{H}} \qquad (4)$$

where, CV: coefficient of variation (%), σ: standard deviation (m), H̄: average height of sugarcane plants (m).

RESULTS AND DISCUSSION

As the volume of data generated by the sensor after processing is about 27 million points, the information of each plot was extracted individually to improve computational performance and obtaining total values for each plot.

Figure 6 shows the result from data cleaning, where homogeneity in the experimental area can be verified with respect to the plants height. The corresponding histogram obtained by the Gaussian distribution, allows checking the plants height distribution of the data set.
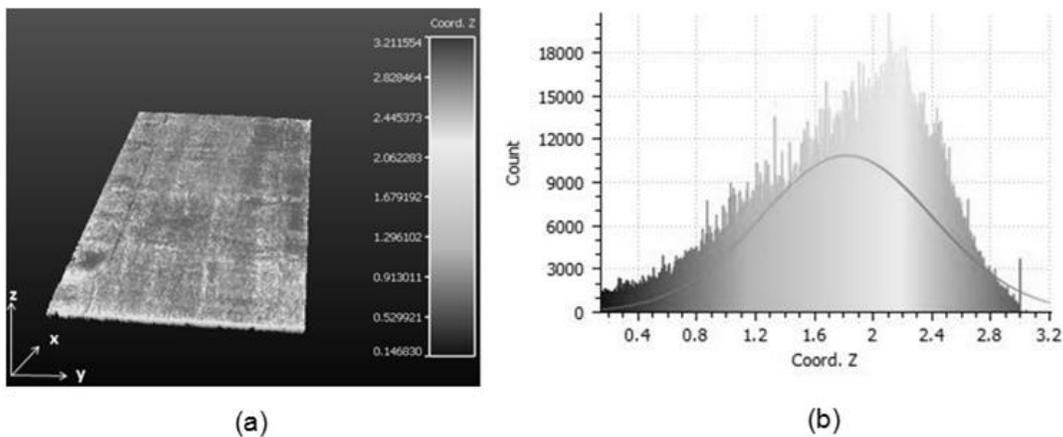

Fig. 6 - Plants height, obtained by the laser sensor, of the experimental area (a); histogram (b)

The data processing result from the laser sensor, considering the eight plots is shown in Figure 7. The point clouds generated can identify the three-dimensional shape of the experimental area and its georeferencing.
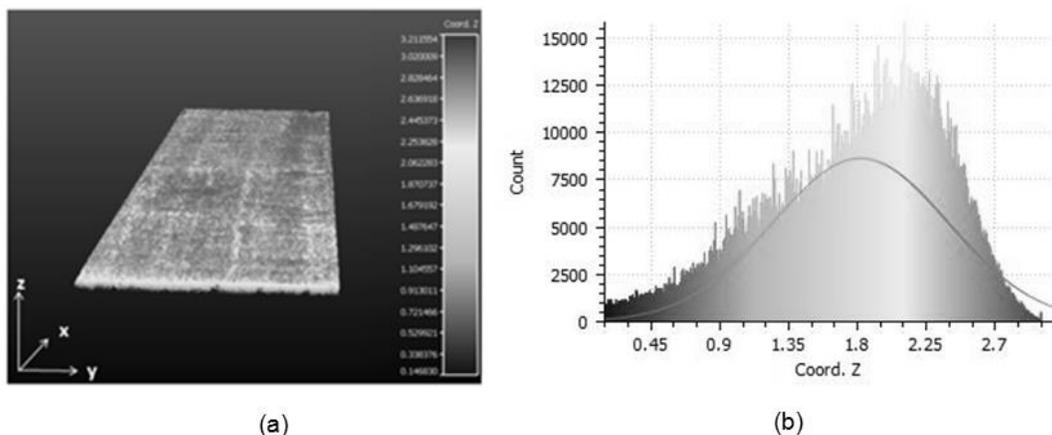

Fig. 7 - Plants height, obtained by the laser sensor, of the eight plots (a); histogram (b)

The individualized plot, as plot number 7 showed in Figure 8, allows obtaining the average height of sugarcane plants and verifying possible differences between each evaluated plot.
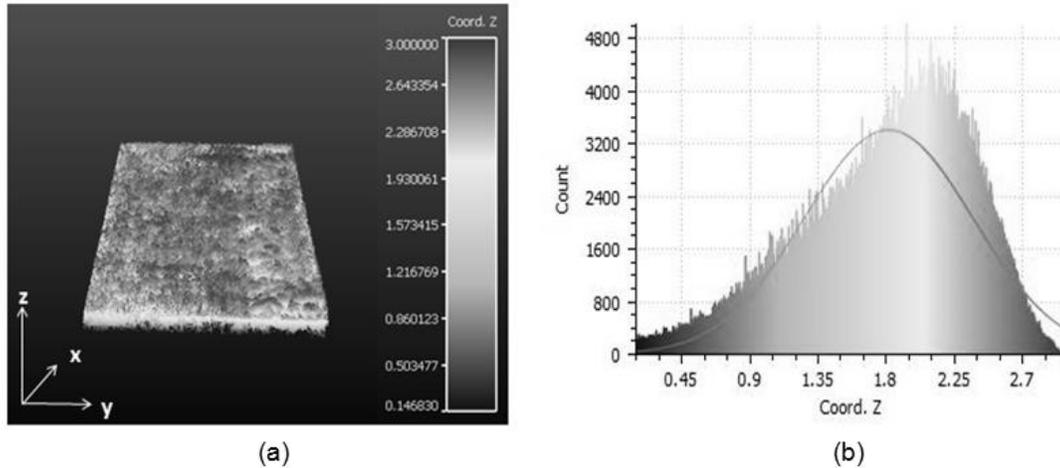

Fig. 8 - Plants height, obtained by the laser sensor, of plot number 7 (a); histogram (b)

There is high vegetation density during this stage of sugarcane maturation and it is impossible to individualize plants in the point clouds, which means that the resolution of the laser sensor employed allows only get the features on a small scale.

The descriptive statistics of the raw data obtained by the laser sensor in the experimental area is shown in Table 2. Besides of the data cleaning result considering 16 plots, only data from eight experimental plots were processed.

Table 2 - Descriptive statistics of the raw data and the data resulting from the processing of the eight plots

	Plants height (m)				
	Number of points	Minimum	Maximum	Average	Standard deviation (m)
Raw data	27,457,455	0.14	3.21	1.82	0.58
Data cleaning	27,066,379	0.14	3.21	1.82	0.58
Processed data	17,914,232	0.14	3.08	1.82	0.58

Even with the adopted procedures, data cleaning and its processing, no changes were observed in the average plant height and the standard deviation. The minimum value (0.14 m) refers to the distance between GNSS receiver and laser sensor. Despite the data cleaning, computational performance still had some limitations, so an individualization of the plots was done, as shown in Table 3.

Table 3 – Descriptive statistics of the data processed individually

		Plants height (m)				
Plots	Number of points	Minimum	Maximum	Average	Standard deviation (m)	Coefficient of variation (%)
02	1,941,625	0.14	2.96	1.93	0.58	30.05
03	2,390,518	0.14	2.94	1.82	0.56	30.77
06	2,175,248	0.14	3.00	1.99	0.57	28.64
07	2,798,935	0.14	3.00	1.94	0.55	28.35
10	1,921,656	0.14	2.96	1.96	0.55	28.06
11	2,576,604	0.14	2.99	2.02	0.56	27.72
14	1,734,159	0.14	3.08	2.00	0.56	28.00
15	2,553,001	0.14	3.01	2.15	0.57	26.51

The number of points processed individually is significantly lower when compared to the total processing experimental area, resulting in a feasible processing time. The result shows a variation of up to 30.77% in plants height, so there was no statistically significant difference in relation to average height of sugarcane plants between plots considered in this study. Table 4 presents manual measurements in the experimental area, such as the height of sugarcane plants and the estimated yield of each plot.

Table 4 – Height and estimated yield of sugarcane measured manually for each plot

Plots	Plants height (m)	Yield (t ha^{-1})
02	3.63	102.30
03	3.49	107.80
06	3.59	111.20
07	3.64	110.10
10	3.74	112.00
11	3.75	111.90
14	3.67	113.00
15	3.69	89.60

Variation of the yield and plants height parameters measured manually were, respectively, 7.0% and 2.0% indicating that no significant variability was verified among evaluated plots. Figure 9 shows the average plants height obtained by processing of the laser sensor data versus that obtained manually referring to the eight assessed plots, in addition to the power trend line used in the regression.
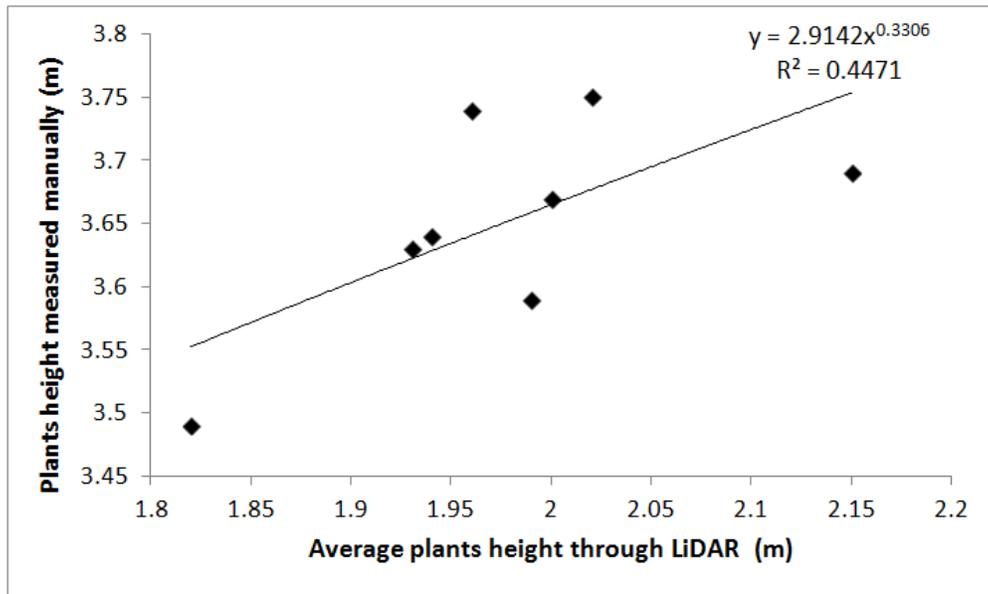
$$y = 2.9142x^{0.3306}$$
$$R^2 = 0.4471$$

Fig. 9 - Average plants height obtained by the laser sensor and obtained manually

More points would be needed for comparative purposes and validation of the method. A moderate correlation ($r = 0.65$) between the height indicated by the laser sensor and that manually measured is because of the presence of leaves that are detected as an obstacle by the sensor, unlike what happens in the biometry by hand.

There is no correlation between the height data from the sensor and yield ($r = -0.52$), as well, no variability using these parameters was verified. The correlation between the height measured manually and yield is 0.01.

The low level of correlation among the evaluated parameters can be explained by the few points of manuals measurements and plots assessed, which has small ranges of variation to be compared with the data from the laser sensor. Certainly, the ideal condition would be to compare these data with yield measured in the field by a yield monitor.

An alternative to manual measurements and almost uniform plots would be the use of yield monitor data in broader yield variability, under field conditions, to better explore the relationship with the crop height measured by the laser sensor.

FINAL CONSIDERATIONS

The measurement system should be improved to the conditions of commercial areas of sugarcane, where there is no possibility of entering with an agricultural vehicle. Furthermore, the presence of leaf "lying ground" in the pre-harvest period is a challenge that has to be faced as it represents a noise to the laser sensor measurements. Regarding the quality of the laser sensor measurements in the field it was found that terrain inclination and the incident light in the equipment affects its data acquisition. Therefore, such conditions should be considered on the next steps of investigation and field uses.

The perspective is that LiDAR technology will be available in agriculture as a form of real-time monitoring of the crop, probably by aircraft. The information about production parameters, such as sugarcane biomass estimation may be an important input for logistics planning in the pre-harvest period.

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