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# Spatial variability of canopy volume in a commercial citrus grove

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***Abstract.*** *LiDAR (light detection and ranging) sensors have shown good potential to estimate canopy volume and guide variable rate applications in different fruit crops. Oranges are a major crop in Brazil; however the spatial variability of geometrical parameters remains still unknown in large commercial groves, as well as the potential benefit of sensor guided variable rate applications. Thus, the objective of this work was to characterize the spatial variability of the canopy volume in a commercial orange grove. A 25 ha orange grove located in São Paulo, Brazil was chosen for this study. A 2D LiDAR sensor and a GNSS (Global Navigation Satellite System) receiver were mounted on a vehicle to scan the sides of the tree rows as the vehicle moved along the alleys. At each scan, distance values were collected in 181 different directions in the vertical plane. Data were converted into a tridimensional georeferenced point cloud from which the canopy volume of individual trees was computed. A geostatistical analysis was performed to characterize the field's variability. The canopy volume varied from 1.29 to 26.5 m³ per tree showing a coefficient of variation of 20%. The geostatistical analyses showed a weak spatial dependence and a range of 127 m. The variability found in this field suggests that sensor-based variable rate applications is an appropriate approach to manage inputs according to tree canopy volume variability.*

***Keywords.*** *LiDAR; tree crops; variable rate application*

## Introduction

The sensor-based assessment of geometrical parameters in tree crops has become an important research topic in precision agriculture (PA). Tree canopy volume or height, for example, are indicators of crop development and are often related to crop yield (Zaman et al. 2006). The development of sensors that are able to collect large amounts of data over these parameters meets the needs of a PA system. These sensors can either provide information to assess the crop spatial variability through maps or enable variable rate applications accordingly to the canopy geometry based on real time sensor readings (Escolà et al. 2013; Gil et al. 2013).

Early research attempts on this topic are found in Florida, USA, where ultrasonic and laser sensors were investigated to estimate canopy volume in citrus groves (Tumbo et al. 2002). This initiative was encouraged due to the high canopy variability in Florida's groves, which is due mostly to punctual replacement of unproductive or disease infected trees. More recently, LiDAR sensors are found in many studies devoted to generate tridimensional models of different tree crops like vineyards (Arnó et al. 2012; Llorens et al. 2011), apple trees (Walklate et al. 2002), pear trees (Rosell et al. 2009), olive trees (Moorthy et al. 2011) and citrus (Lee and Ehsani 2009).

Orange groves cover approximately 480,000 ha of land in Brazil (Conab, 2013), supplying most of the orange juice for the world market. It represents an important agribusiness especially in the state of São Paulo, which concentrates the majority of the country's production. Some studies have characterized the spatial variability in commercial Brazilian groves. Soil properties, relief, and disease occurrences can vary significantly within a field (Leão et al. 2010; Molin et al. 2012; Oliveira et al. 2009; Siqueira et al. 2010). Naturally, yield spatial variability was also reported (Farias et al. 2003; Molin and Mascarin 2007). Though slowly deploying, a few PA practices like georeferenced soil sampling, yield mapping and variable rate fertilization are now taking place in the management of commercial groves.

The knowledge about the spatial variability of several relevant agronomical parameters has encouraged the development of new techniques and finally guided growers towards adoption of PA technologies. However, the spatial variability of geometrical parameters of the trees remains unknown for commercial Brazilian orange groves. Studies which employed LiDAR sensors to characterize fruit tree geometry are normally focused on developing methods to collect and process data. Usually, small experimental field plots are analyzed, so variability at large scale is not yet reported. Preliminary studies to characterize the variability of tree geometry are essential to estimate the potential benefits of canopy sensors in guiding variable rate applications. In commercial Brazilian groves it is expected to find significant variability in canopy size. This might be due to disease occurrences, leading to variability in short distances (at tree scale) as well as to soil type and relief variation, leading to variability at field scale.

The objective of this study is to characterize the spatial variability of tree canopy volume in a commercial Brazilian orange grove.

## Material and Methods

The data collection and data processing applied in this study was inspired by the method proposed by Rosell et al. (2009) on how to collect and manipulate 2D terrestrial LiDAR data and produce 3D point clouds of the crop.

### *The orange grove*

A 25 ha orange grove located in the state of São Paulo, Brazil, was used in this study. The variety of the trees was "Valencia" grafted to "Swingle" rootstock. Trees were planted in 2009 and were six years old at the time of this study. The spacing was 2.6 m between trees and 6.8 m between rows. Due to a 13 m gradient in elevation, this field was implemented with curve levels for soil conservation. The tree rows were planted as straight lines which occasionally crossed over the curve level lines.

*The equipment*

A 2D LiDAR LMS 200 sensor (Sick, Waldkirch, Germany), an RTK (*Real Time Kinematic*) GR3 GNSS receiver (Topcon, Tokyo, Japan) and a portable Toughbook CF-19 computer (Panasonic, Osaka, Japan) were used to collect tridimensional data of the grove. These were arranged on an ATV vehicle (Figure 1), so the sensor faced the side of the tree rows, with the GNSS receiver on the top and aligned with the center of the sensor.

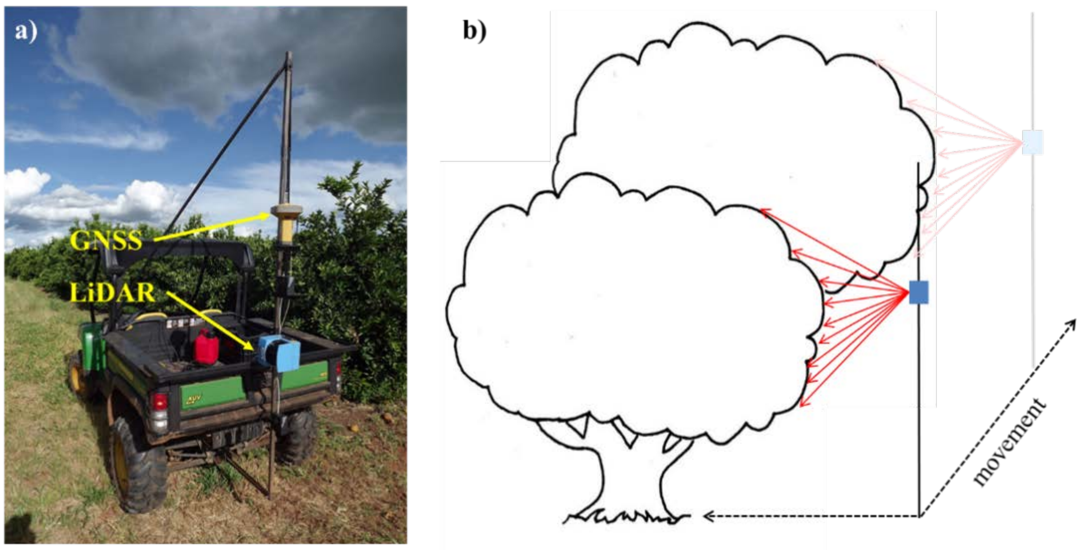



Figure 1: LiDAR sensor and GNSS receiver mounted on an ATV vehicle (a); LiDAR sensor facing the side of the tree row (b)

The sensor collected distance values in 181 directions (at one degree angular steps) in a vertical plane perpendicular to the moving direction every 13.3 ms (75 Hz). The range of the sensor was 8 m. At each scan the GNSS receiver provided the position of the sensor in the field with an accuracy of 10 mm (according to the manufacturer specifications). The vehicle moved along the alleys at 3.3 m $s^{-1}$, scanning each side of the tree row at a time. A data acquisition software was developed using the Processing 2 software (Reas and Fry, 2014), which triggered the data collection of both the LiDAR sensor and the GNSS receiver, synchronously. Data were saved in a file for every tree row, containing information about time, geographical coordinates, altitude and the 181 distances values for each scan.

*Data Processing*

The raw data of each tree row was processed using the R 3.2.2 software (R Core Team, 2014) in four steps: i) attributing GNSS coordinates to each laser beam impact to generate a georeferenced 3D point cloud; ii) filtering points of interest; iii) classifying points in groups (clusters), each representing one tree; iv) calculating the canopy volume of each tree.

The first step consisted in transforming the raw data, which are the polar coordinates (angles and distances) of LiDAR's impact points, into local rectangular coordinates ($x$, $y$, $z$), in which the position of the sensor was at the $x$ and $y$ origin (Figure 2a). This was achieved by applying a series of trigonometric equations to the polar coordinates. The final $x$ and $y$ coordinates of each point was then calculated by summing the local coordinates with the obtained $x$ and $y$ global UTM (Universal Transverse Mercator) coordinates of the sensor (Figure 2b).

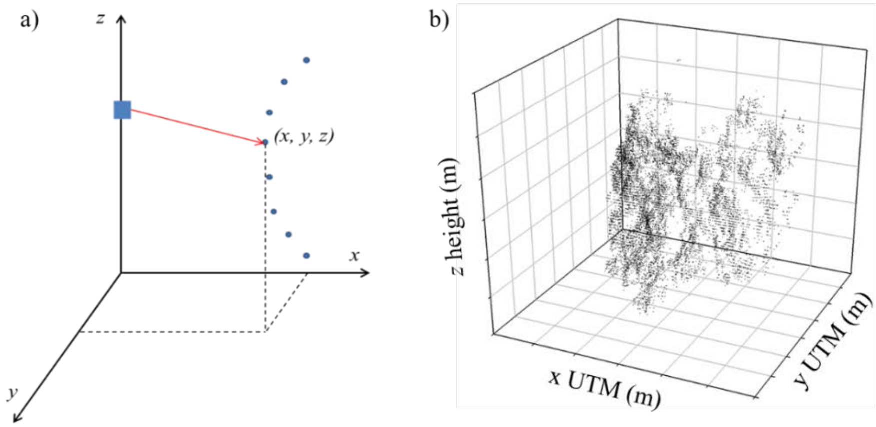



Figure 2: Local rectangular coordinates of points (a) and a georeferenced point cloud (b)

For filtering data, the points which represented the soil were excluded by establishing a minimum threshold of 0.40 m for the height (*z* coordinate) of each point. Discrepant data (points that were relatively far away from the target tree row) were also excluded by computing a linear regression with the *x* and *y* coordinates of the points of each row and then excluding those which represented a standard error above two standard deviations of the error distribution. After the filtering process the final point cloud represented only the crown of the trees for each row.

The next step of the data processing was to separate points into groups, each representing one tree individually. A *k*-means clustering algorithm was applied using the *x* and *y* coordinates of the points. The initial number of clusters was defined by dividing the length of the row by the spacing between the trees. Because trees were partially touching each other, some error in the cluster classification was expected. An accuracy of 90.2% of the applied cluster was assessed by visually recognizing 678 trees from the point cloud and comparing them with the outcome of the cluster classification.

Finally, a 3D object was modeled over the points of each tree using the *alpha shape* algorithm available in the *alpha shape 3d* library in R software (Lafarge and Pateiro-Lopez, 2014). This tool connects the outer points of the tree forming a 3D object. The level of concavity of the shape is given by an index which was set to 0.75 (Figure 3). The volume of the object was automatically retrieved by the algorithm. The final output of the processing steps is a GIS shapefile containing the polygons (cluster boundaries) and the canopy volume information for each tree in the row.

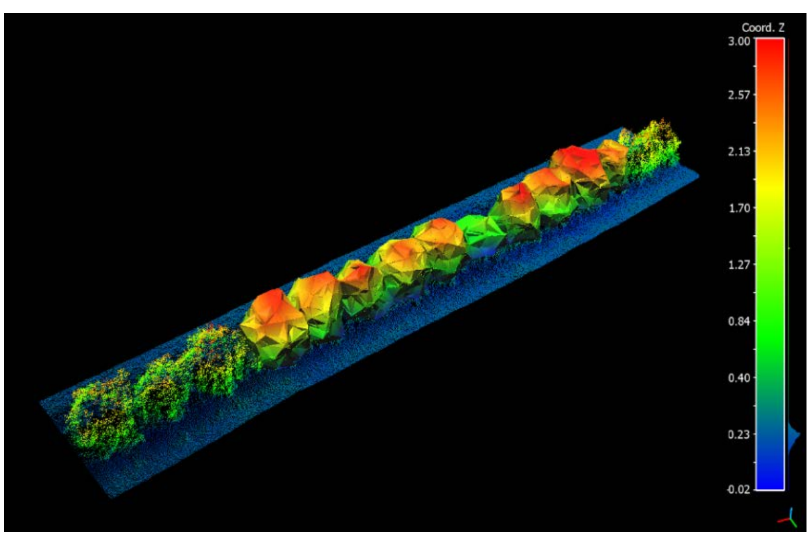



Figure 3: 3D representation of single tree geometry created over a point cloud

*Mapping the canopy volume*

To produce a map of canopy volume the mentioned shapefiles for each row in the field were imported into the QGIS 2.10 software (QGIS, GNU General Public License). Trees close up to 10 m to the field boundary were excluded since the cluster algorithm is more suited to errors in this region. Also, the trees within a 15 m buffer around the curve levels in the field were excluded. Due to the movement of the vehicle to cross over the curve levels, the canopy volume estimation loses accuracy in those regions. With the remaining trees, a map of points, each representing the canopy volume of one tree, was created by generating a centroid point within each cluster polygon. The final canopy volume map was generated by interpolating this data in a pixel grid of 5 m using ordinary kriging. The map was classified into five classes according to quantiles.

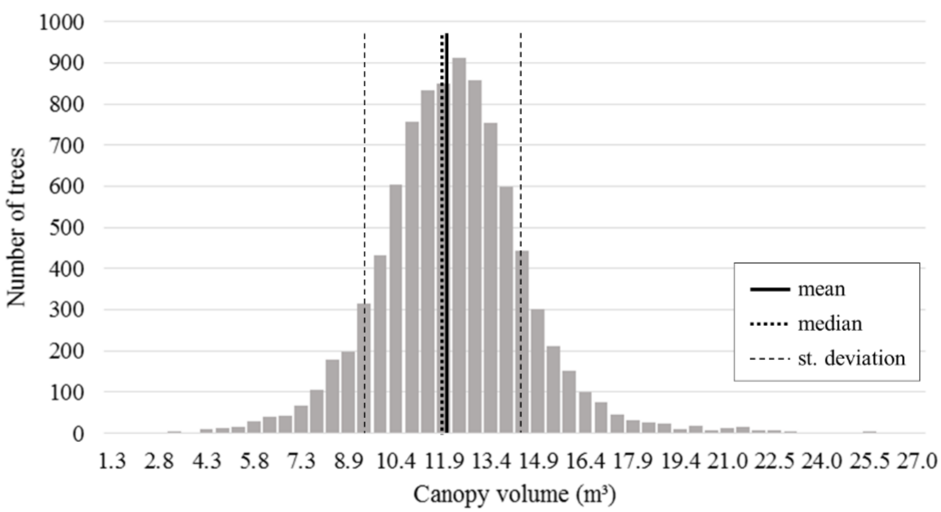
*Analyses of variability*

To characterize the spatial variability in the evaluated field descriptive statistics and geostatistical analyses were carried out over the tree canopy volume data. The Vesper 1.6 software (Minasny et al. 2002) was used to compute and fit the variogram.

## Results and discussion

The canopy volume of individual trees ranged from 1.29 $m^3$ (probably representing a young reset tree or a tree gap) up to 26.5 $m^3$. The histogram showed a normal distribution with coefficient of variation of 20% (Figure 4). If the demand of inputs by one plant was directly related to its size, 1197 out of 9119 trees in this field (about 13%) would receive a surplus of input of at least 20% by a uniform application adjusted to the mean tree volume. Likewise, 1119 trees (about 12%) in this field would receive at least 20% less input than the amount they really needed. A variable rate application system guided by canopy volume sensors would reduce losses and optimize the overall use of inputs in this field since the inputs would be adapted to the real needs of each plant.

Considering the normal distribution of canopy volume, the total amount of input used by a sensor-guided application would not differ significantly from the amount used by a conventional system, if the same average value is employed. Nevertheless, input savings are often reported in studies which compared variable rate application with the actual applied rate by the farmers. Zaman et al. (2006) got 40% saving in fertilizer in an orange grove and Gil et al. (2013) found 29% savings in agrochemicals in a vineyard by using ultrasonic canopy volume sensors.




| *Canopy Volume ($m^3$)* | |
|---|---|
| Mean | 11.94 |
| Median | 11.91 |
| Standard Deviation | 2.39 |
| Variance | 5.69 |
| Kurtosis | 2.62 |
| Skewness | 0.44 |
| Range | 25.20 |
| Minimum | 1.29 |
| Maximum | 26.50 |
| Coef. of variation | 20% |
| Observations | 9119 |

Figure 4: Histogram and descriptive statistics of tree canopy volume on the experimental grove

The final interpolated canopy volume map showed consistent regions of different canopy volume as well as abrupt variations in short distances (Figure 5 a). Variations in short distances are evidenced by the weak spatial dependence found in the variogram analysis (Figure 5 b). The nugget effect showed to be relatively high, occupying 80% of the spatial structure variance. This type of variation in canopy size might be due to local disease occurrences which lead to individual replacement and thus different development stages present in the tree rows. The high variability within short distances encourages the use of sensor-based variable rate applications since high frequency sensors are able to capture such a variability.

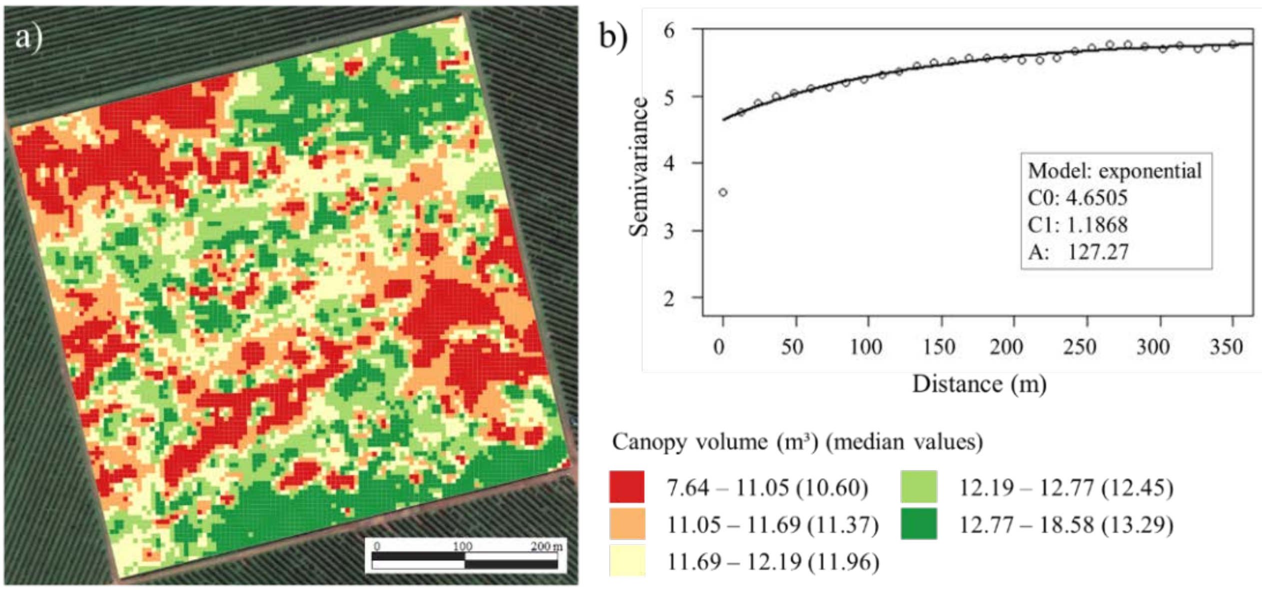



Figure 5: Map of tree canopy volume in a 25 ha orange grove (a); variogram and geostatistical parameters of canopy volume (b)

Variations in large regions in the field were also noticed, indicating that this field could be divided into zones for distinct management. The range in the variogram reached 127 m. The interpolated map is presented in five classes in which the median values varied from 10.6 up to 13.29 m³ per tree. This level of variation across the field might be imperceptible trough the human eye but it can certainly be mapped and managed using canopy sensor systems.

## Conclusions

The per tree canopy volume varied from 1.29 m³ to 26.5 m³ in the evaluated field, with a coefficient of variation of 20%. The spatial dependence of these parameter was weak, meaning that abrupt variations can be found within short distances. Also, large regions with difference in canopy volume were observed, suggesting that these could receive differential management considering their canopy size. Variable rate application of inputs guided by canopy sensors is a promising solution to treat canopy variability in commercial Brazilian groves.

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