Potential Solution to Contribute for Sugar Cane Spatial Variability Management

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•ABSTRACT:

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In Brazil, the application of site-specific management in sugar cane has been delayed for many reasons, including lack of relevant technology which could really help producers increase their competitiveness. Sugar mills usually have large cultivated areas under their control, with an average size of over 40 thousand hectares. With such huge areas, it is difficult for them to find a technology that could help in the adoption of precision agriculture (PA), which enables the producer to understand and manage more precisely the inherent spatial variability found in the field, in order to obtain higher productivity and economic returns, and reduce negative environmental impacts. Vegetation Index (VI) used as an indicator of biomass can be easily obtained either by ground sensors or by orbital and non-orbital imagery obtained using an Unmanned Aerial Vehicle (UAV). The objective of the study was to evaluate the sugarcane biomass prediction using VI data obtained by means of a field sensor and an UAV on a field scale, and correlate the results with terrain and soil data. The experiment was conducted in a 40 ha sugar cane field planted in the north part of São Paulo state, Brazil on its first ratoon. Soil attributes were measured after harvesting, and biomass data was measured 90 and 180 days after crop emergence (DACE). The results showed that VI obtained by ground and non-orbital sensors have correlation with biomass production, but not with soil chemical attributes, which means that field spatial variability is more dependent of other factors than soil chemical attributes. These results could help justify the use of crop sensors and UAV by mills which could independently obtain high resolution imagery at low cost, and evaluate field conditions at the time when intervention is still possible.

Keywords: Precision agriculture, Vegetation indices, Field sensor, UAV, Brazil.

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1INTRODUCTION

Sugarcane (*Saccharum* spp.) has significant importance in the tropical and subtropical regions of the world, especially for sugar and ethanol production. Recently, the sugarcane crop has been drawing global interest as a raw material for the production of energy, since it presents highly positive energetic and greenhouse gases emission (GHG) balance (Macedo, et al. 2008; Renouf, et al. 2008; Smeets et al. 2009). Brazil is the largest sugarcane producer worldwide, and its production is increasing to meet global bioethanol and sucrose demands. Although nearly 90 Mha are available for agricultural expansion in Brazil (Cerqueira Leite *et al*., 2009), sugarcane production is increasing not only in new sugarcane areas, but more so through yield improvements in existing fields. Increases in sugarcane production are obviously related to increases in sugarcane biomass and ethanol production per unit of area. Sugarcane production is estimated to have a potential of doubling its yield per unit of area (Waclawovsky *et al.*, 2010). Adoption of precision agriculture (PA) to manage soil according to its spatial needs is a likely prerequisite to higher yields (Bramley, 2009). By combining a yield map, topographic information, maps of physical and chemical soil attributes, and imagery, it is possible to define management strategies to improve the performance of the crop, and to reduce negative environmental impacts of sugarcane production.

In PA, data collection and evaluation methods have high operation and analysis costs, preventing its practice in certain situations, from the logistic and economical point of view. To overcome this barrier, many studies have been engaged in the development of sensors on-the-go, which may present different principles of operation, but with responses that can be indirectly related to soil mechanical, physical and chemical characteristics and plant behavior. Thus, the data acquisition can be faster, with large numbers of data at a lower cost (Peets et al. 2012).

Vegetation Indices (VI) have been developed to track the vigor of plants and can be easily obtained either by ground sensors or by orbital (satellite) and non-orbital imagery, obtained using an Unmanned Aerial Vehicle (UAV). VI has been used with success in predicting in-season N requirements for crops, using aerial color infrared photography (Sripada et al. 2006), which were taken by means of a sophisticated methodology. UAV can be an inexpensive and practical tool to obtain high resolution remotely sensed data. Although there have not been many case studies of UAV in PA, examples of its applications in environmental studies are becoming increasingly more apparent in the literature. On the same way, studies with ground sensor have demonstrated its suitability to identify sugar cane variability (Portz, et al. 2012; Molin et al. 2010). Such studies may provide insight as to how applicable these instruments may be for various PA endeavors (Zhang and Kovacs 2012).

The objective of the study was to evaluate the sugar cane biomass prediction using VI data obtained using a field sensor and low cost UAV on a field scale, and correlate the results with terrain and soil data.

1STUDY AREA AND METHODS

Experiments were conducted on 40-hectare fields in Serra Azul – SP, Brazil (21.2731 S e 47.5397 W) during the first ratoon season of a sugarcane crop (CTC09). Soils on the study sites are generally uniform, Typic Quartzipsamment, by Embrapa (1999) and US Soil Taxonomy (USA, 1975). The total precipitation after harvesting, from September 2012 to May 2013, was 725 mm, and average temperatures of 25 ºC.

To obtain the vegetation indices data (VI), the area was scanned in December 2013, when the cane presented three months of development and average height of 0.6 m, using as an Crop Circle active canopy reflectance sensor (ACS-210, Holland Scientific Inc. Lincoln, NE, USA) mounted on a high clearance vehicle, with a sensor measurement being taken at each 3 rows. This sensor recorded canopy reflectance in the red-edge (730 nm) and near infrared (NIR, 780 nm) wavebands at 1 Hz, connected with a GPS at the same rate. Aerial imagery was obtained by means of a UAV (swinglet CAM, SenseFly, Ecublens) using a 16MP camera (ELPH 300 NDVI, Canon, USA) with 0,012 m resolution, and interference filters with blue and green channel, and provide image in the red and NIR region of the spectrum (670 and 770 nm) obtained in 9 of May 2013.

The data generated by Crop Circle and SenseFly are in different wavelength and therefore produced different VI. For Crop Circle, the red-edge normalized differential Vegetation Index (NDRE) was calculated, and for SenseFly, green normalized differential Vegetation Index and Green Soil Adjust Vegetation Index (GNDVI and GSAVI) were calculated. Those VI cannot be directly compared, but they provide similar information about the biomass production, which can be used to evaluate field status. GNDVI is calculated using reflectance ratios in the NIR and green portion of the spectrum (Mulla 2012), the green NDVI is more sensitive to changes in chlorophyll concentration and potential crop yield than the traditional NDVI using the red waveband (Gitelson, et al. 1994). GSAVI is a transformation technique to minimize soil brightness influences from spectral vegetation indices (Huete 1988; Sripada et al. 2006).

$$NDRE = (NIR-RE)/(NIR-RE) \quad (1)$$

$$GNDVI = (NIR-G)/(NIR+G) \quad (2)$$

GSAVI = 1.5*(NIR-G)/(NIR+G+0.5) (3)

Based on the yield map obtained from the previous year, 22 points in the area were selected for biometric analysis. On each point, ten cane stalks were removed for characterization, determining the mean diameter of stalks, height, and weight of stalk, trash and tops. The data for biometric analysis was done just few days before VI data collecting (December 2012 and May 2013). The results were then compared with crop reflectance. To establish a correlation between VI and crop biometrics information, a buffer area with 3 m radius around the sampling point was created. In this buffer area, the imagery maximum value of reflectance for each band was selected to calculate the VI, and a linear correlation between this VI and crop results was evaluated.

In order to have non-yield-limiting amount of nutrients in the area, a soil survey was conducted just after harvesting in September 2012, in a 50x50 m grid (164 points). Based on the results of macronutrients, a fertilizer recommendation was done phosphorus (P) and potassium (K), for nitrogen (N) the recommendation was based on yield expectation taking into account previous year yield map. All fertilizers were applied using variable rate technology (VRT) (Uniport, Jacto, Pompéia) according to usual recommendations for sugarcane crop planting (Raij et al. 1997) 60 days after harvesting (DAH).

The geostatistic analysis were performed for all data in the study, interpolating a grid pattern of 3 m by means of Kriging site for neighboring blocks, using ArcGIS software (Environmental Systems Research Institute, Redlands, CA). Since ground collected data was less dense than UAV data, a grid based on existing point data of NDRE was used to extract data from UAV imagery to calculate GNDVI and GSAVI.

1RESULTS AND DISCUSSION

Initial maps of soil chemical attributes, elevation, apparent electrical conductivity (ECa) and previous year yield provided a visual representation of the variability across the field, Figure 1. Maps were also produced from ground sensor (NDRE), and aerial sensor (GNDV and GSAVI), Figure 2.

At the early stage of the crop development (60 DAH), the results of canopy reflectance obtained with crop circle are highly influenced by soil brightness reflectance, since the crop height was low and there are many open spaces. Nevertheless, it was possible to observe that at certain parts of the field, the biomass was more developed than others, as it can be confirmed by biometric data obtained at this stage, Table 1. GNDVI measured 180 DAH, represents better canopy reflectance since the crop was closer. At this stage there is very low soil influence, as it is seen when the data is compared with GSAVI, and very low difference is detected between these two sets of imagery. The differences among of the NDRE and GNDVIVI maps can be attributed to the different amounts of biomass at the sensing time (60 versus 180 DAH). The imagery shows that in the southern part of the field the biomass reflectance is higher, which could be an indicative that yield will also be higher in that area. It is also possible to see that in the north part of the field there are some spots with lower GNDVI, which represent lower biomass, those differences are reflected at biometric evaluation which presents a high coefficient of variation, .

Figure 1 – Maps of some soil attributes, apparent electrical conductivity at 0.9 m, elevation and previous year crop yield.

Linear correlation between GNDVI and crop performance at this stage, measured through the biometric parameters, was established (Table 2). The best GNDVI correlation obtained was with the tops reflectance (r = 0.3), which has a strong correlation to yield (r =0.81).

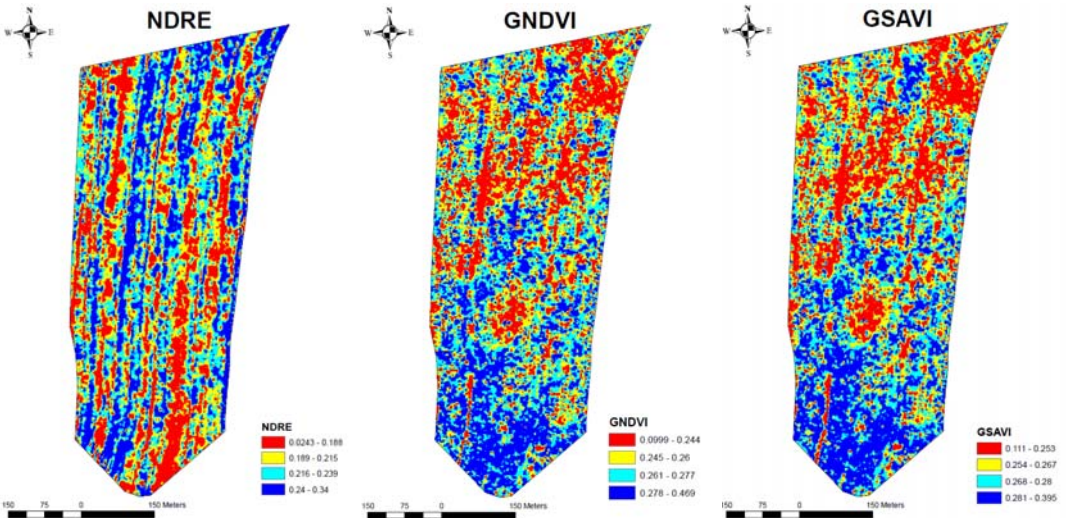

Figure 3 – Vegetation indices from ground and aerial sensor.

Table 1 – Results Biometric evaluation in December 2012 and May 2013

ecember 2012 May

December 2012 ay

May

2013Tillers/Tillers/Population/Population/Mg/ha Mg/ha Tillers/Tillers/Population/Population/Mg/ha Mg/ha Mean Mean 29.6 2

illers/m Population/ha Mg/ha Tillers/m Population/ha Mg/ha Mean 29.6 19

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Population/ha Pg/ha Tillers/m Population/ha Mg/ha Mean 29.6 197600 2.5 13

Mg/ha Millers/m Population/ha Mg/ha Mean 29.6 197600 2.5 13.0 16721 1

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97600 9.5 13.0 16721 16.7 Standard deviation d.9 26439.0 0.9 2.2 6010.2 6.0 Coef. of variation v3.4 13.4 35.9 16.9 35.9 35.9

Table 2 – Linear correlation between sugar cane biometric parameters and GNDVI.

NDVI N°

GNDVI G°

N°

tillers/m Nops

Tops

C0199, Magalhães, P.S.G., Sanches, G.M., Molin, J.P., Portz, G., Amaral, L., Kolln, O.T., Duft, G.D. "Potential Solution to Contribute for Sugar Cane Spatial Variability Management". EFITA-WCCA-CIGR Conference "Sustainable Agriculture through ICT Innovation", Turin, Italy, 24-27 June 2013

(Mg/ha) (talk weight/tiller
(kg) (talk
(Mg/ha) (otal Biomass
(Mg/ha) (GNDVI 1.00 N° Tillers/m -0.13 1.00 Tops
(Mg/ha) (.30 0.30 1.00 Stalk weight/tiller (kg) 0.28 -
0.53 0.46 1.00 Stalk (Mg/ha) 0.25 0.09 0.76 0.77 1.00 Total Biomass
(Mg/ha) (.21 0.12 0.81 0.74 0.96 1.00

Although ground and aerial data were collected at different stages of the crop development, it is possible to observe that the VI has no correlation with soil attributes or field elevation. Even though soil ECa at 0.9 m also does not explain VI obtained, its correlation with GNDVI was more significant, which could be an indicative of a need for further investigation in the causes for field variance of the VI.

1CONCLUSIONS

Low cost UAV could be convenient to collect field data for VI determination. Although VI has only a moderate correlation with biomass production, and no correlation with soil attributes, it may be a useful tool to detect some yield tendencies in the area and places for deeper investigation of crop spatial variance causes.

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