THE INTERNATIONAL SOCIETY OF PRECISION AGRICULTURE PRESENTS THE
13th INTERNATIONAL CONFERENCE ON
PRECISION AGRICULTURE
July 31-August 4, 2016 • St. Louis, Missouri USA

NIR spectroscopy to map quality parameters of sugarcane

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A paper from the Proceedings of the
13th International Conference on Precision Agriculture
July 31 – August 4, 2016
St. Louis, Missouri, USA

Abstract. *Precision Agriculture aims to explore the potential of each crop considering the differences within the field. One information that is considered the most important is the yield or the obtained income in the field. However, in the case of sugarcane, quality will also directly influence farmer's income. Several studies suggest harvester automation aiming to monitor yield, but few consider the quality analysis in the process. Among the existing methods for measuring sugar content the one that is best suited to this need is the spectroscopy. Therefore, it is necessary to assess the feasibility of its use and to investigate the spatial variability of sugarcane quality attributes in a field. Georeferenced samples were obtained from a 16.5 ha field for quality analysis (total solid content, sucrose content, fiber content, purity and total recoverable sugar) and the results were correlated with spectra from NIR (near-infra-red) region obtained using two different field spectrophotometers: Veris Vis-NIR Spectrophotometer (Veris Technologies, Inc., Salina, KS, EUA), and the AgriNir (Dinamica Generale, Pogio Rusco, Italy). The spectra were obtained in both juice and fibrate sample forms. For the correlations, multivariate analyzes using Partial Least Square Regression and leave-one-out cross validation were used. Maps were made using laboratory results and predictions made by the spectral measurements. It was found spatial dependence among samples; the variograms suggest that two samples per ha would be enough to map these parameters in the field. A coefficient of variation of 5% was obtained in the field, which could justify local management actions. Spectra from fibrate samples were better correlated with sugar content than those from juice samples. The R^2 obtained for total recoverable sugar were 0.22 for juice samples, 0.42 for fibrate samples using Veris spectrophotometer and 0.65 for fibrate samples using AgriNir. Overall, spectrometry showed good potential to predict quality and was effective in mapping regions with different levels of quality attributes over the field. The correlations between the normalized maps of the predictions and the laboratory results for total recoverable sugar was 0.64 for juice samples,0.68 for fibrate samples using Veris spectrophotometer and 0.83 for fibrate samples using AgriNir.*

Keywords. *Precision agriculture; Sugarcane quality; Geostatistic; Multivariate analysis*

Introduction

Yield mapping is an important tool for decision-making in the precision management of sugarcane production systems. It enables the use of precision farming tools and analysis that allows spatially based farming management and associated variable rate applications (Davis et al. 2009).

There are some efforts to obtain yield maps of sugarcane, but little has been done to assess the quality of the product. This can be a major limitation for the full adoption of precision agriculture by the sugarcane industry (Bramley, 2009). Also, there is no relationship between the quality and sugarcane yield (Sukhchain et al. 1997). Therefore, quality maps should be made as additional information in order to improve the establishment of management zones, seeking out local management actions (Johnson; Richard, 2005).

Varella et al. (2012) proposed a methodology for mapping Brix in sugarcane and observed that with 2.04 samples per hectare they were able to validate kriging interpolation. With 202 georeferenced samples in a field of 6.8 ha Bramley et al (2012) observed a low coefficient of variation in the sugar content (3.8%) but the variation was shown spatially structured along the plot; Brix and Pol also followed the same pattern of variation over the field.

In Brazil, sugarcane producers have their income payment related with the quality of sugarcane, which is expressed by the total concentration of sugars (sucrose, glucose and fructose) recovered in the industrial process (Total Recoverable Sugars – TRS) (Burniquist, 1999). This payment system justifies that, in addition to yield mapping, quality characteristics should be mapped. With the adoption of local management actions in areas where the quality parameters are outside of the standards, it is possible to obtain a better quality product in part of area and thus increase the economy return (Bredehoeft et al., 2000; Medema and Van Berjeijk, 2000). Bramley et al. (2012) indicate that the producers of sugarcane may have resistance in the adoption of variable rate technology aiming fertilizer saving and yield increase due to the possibility of quality loss because of the fewer amount of inputs applied.

Also, the possibility of access real time quality information during the harvest could help the industry to change their process according to the quality of the product that is coming from the field. Sugarcane industries have the advantage of using GNSS tracking and telemetry technologies to monitor harvest operations in real time (Dines et al. 2012). This can be an useful additional information to help the management of industry procedures.

Several methods are commonly used for measuring the quality of sugarcane in industrial level, as refractometry, polarimetry, chromatography and spectrometry (Mehrotra and Seisler, 2003). However, some issues should be considered before the deployment for field use, like the sampling acquisition time, the need for sample preparation, the sample quantity needed and the cost and practicality of the equipment. Spectrometry can be considered the most promising technology because of the speed of the measurements and sample form, although other methods can be considered.

Nawi et al. (2014) listed several quality measurement technologies existed for the cane sugar industry evaluating their potential for field use. The authors considered that the spectrometry would be the best method among the existing techniques. They observed that spectrometers are capable of measuring the quality of sugar cane in different sample forms, including solid ones. Thus the authors considered several possible locations for the sensor in the harvester considering each sample form. Considering the possibility of use a field sensor for sugarcane quality coupled in a harvester, accuracy of NIR technology must be investigated to predict those parameters and the spatial dependence in the field, to justify the map formulation and investigate the number of samples required.

The objective of this study is to investigate the use of NIR spectroscopy to map quality parameters of sugarcane; it was investigated if NIR measurements were able to predict sugar content correlating the measurements with laboratory analysis and if it was possible to map those parameters in a field. The spatial dependence of the data was also investigated.

Material and Methods

Georeferenced samples were obtained from a 16.5 ha field during harvesting by collecting four stalks in each sampling point. The whole stalks were manually cut and the tops of the stalks were removed by cutting each stalk near the growing point and removing all leaf materials. A total of 91 samples were collected (approx. 5.4 samples per ha), according to Figure 1.

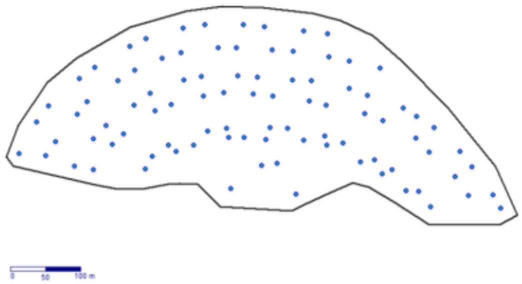


Figure 1: Sample locations in the field

The four stalks were than disintegrated and homogenized to compose a single sample. Part of the disintegrated sample was separated for NIR measurements, and other part was compressed to extract the raw juice sample. Part of the juice sample was separated for NIR measurements and other part was sent to laboratory analysis. Total solid content (Brix), sucrose content (Pol), fiber content (F), purity (Q), reduced sugar (RS) and total recoverable sugar (TRS) was measured using laboratory analysis according to CONSECANA- SP (2006).

Two commercial spectrometers were used, Veris Vis-NIR Spectrophotometer (Veris Technologies, Inc., Salina, KS, EUA), which is mostly used for soil analysis (LUND, 2011 ; KWEON et al., 2008) was used for both fibrate and juice samples and the AgriNir (Dinamica Generale, Pogio Rusco, Italy), which is mostly used for forage analysis (Lundström, 2013; Paul, 2010), was used just in fibrate samples.

Both spectrometers use active light and auto-calibration systems. The samples were placed in recipients provided by the equipment's manufactures. Figure 2 shows the equipment's with the samples ready to be scanned.

a) b)

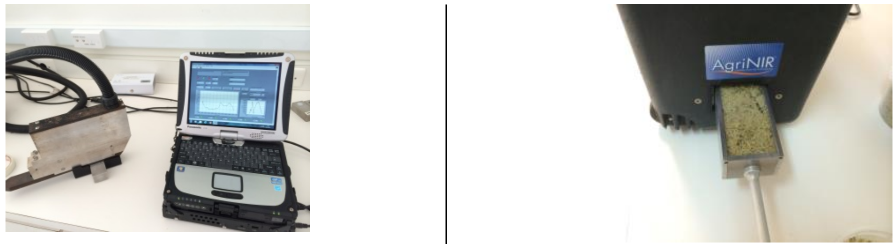


Figure 2: Equipment's with samples: a) Veris Spectrometer, showing the equipment below and the fiber samples and juice sample above; b) AgriNir Spectrometer, showing the equipment below and the fiber sample above.

On both equipment the spectra from the NIR region was used. Veris Spectrometer has a wavelength range from 1070 to 2220 nm and the AgriNir has a wavelength range from 1100 to 1800 nm. To correlate the spectral measurements with the laboratory analysis Partial Least Square Regression (PLSR) and leave-one-out cross validation were used.

As the AgriNir system provides three spectral results for each sample, the prediction and the leave-one-out cross validation were made for each spectra from the sample and after, averaging the results from the same sample to get the validation curve.

On Veris equipment the single spectra provided by the equipment was correlated with the laboratory analysis using leave one-out-cross validation and PLSR. With this equipment, both juice and fibrate sample forms were used.

The spatial dependence between samples were analyzed by making variograms and kriging method was used for the interpolations with Vesper software (Whelan et al., 2002). Maps were made for the laboratory results as well as for the predictions using the different methodologies.

Data were normalized to evaluate the ability of spectrometry to identify regions with different quality attributes in the field [Normalized data point = (mean data / data point)* 100] and correlation between the normalized maps were made.

Results and discussion

In order to evaluate the quality variation in a commercial field, Table 1 presents the mean, median, standard deviation, kurtosis, asymmetry and the quality data measured by the industry after the harvest.

Table 1- Descriptive statistic values from the attributes measured in laboratory

	TRS	Brix	Pol	Fibers (F)	ARC	Q (purity)
Mean	134.59	17.49	13.49	10.71	0.51	89.07
Stand. Dev.	7.14	0.70	0.81	0.56	0.08	2.80
C.V. (%)	5.31	4.00	6.00	5.27	16.56	3.14
Kurtosis	-0.35	0.04	-0.30	-0.89	5.22	5.45
Asymmetry	-0.18	-0.35	-0.14	0.11	-0.98	1.00
Number of Samples	91	91	91	91	91	91
Industry Data	108.39	15.68	10.5624	12.81	0.73	80.68

It is shown that the variation and the distribution varies according to the measured attribute. The data measured by the industry showed lower quality parameters than the measures in the samples; this difference is mainly due to the higher amount of straw residue present in the material that goes to the industry. Such factor must be taken into account mainly due to the tendency of the industry to take materials with a greater amount of straw, either for energy production or for second-generation ethanol (SANTOS et al., 2012; JUNIOR et al., 2010). Therefore, it is important to test samples obtained directly from the harvester in future studies.

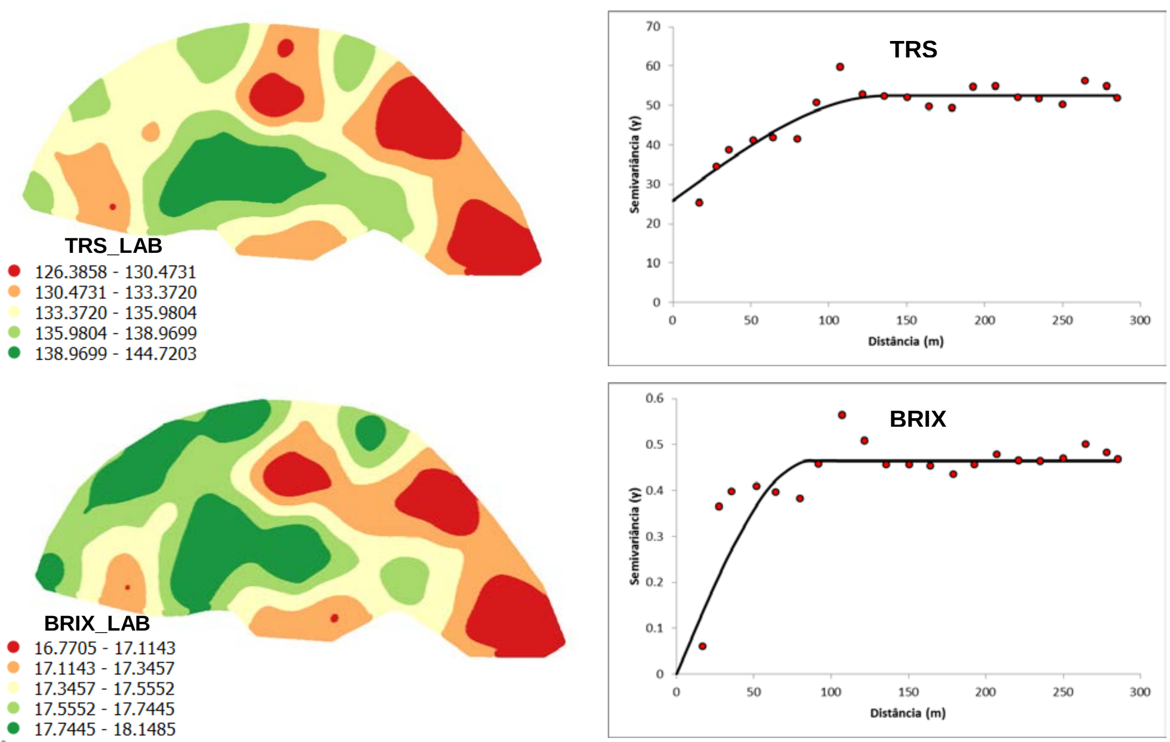
The coefficient of variation was higher than the observed by Bramley et al. (2012) (3.8%), possibly because the field analyzed by the authors was smaller (6.8 ha) but it can also be related to environmental characteristics of the fields.

Table 2 presents the correlations between the quality attributes analyzed. It is shown that fiber content has low influence in sugar content and Pol and Brix have high correlation. However, Pol is a better attribute to predict TRS than Brix, because of the influence of reducing sugars.

Table 2 – Correlation between the quality attributes analyzed

	Brix	Q (purity)	Fiber (F)	Pol	RS	TRS
Brix	1.00					
Q (purity)	0.56	1.00				
Fiber (F)	0.41	0.25	1.00			
Pol	0.89	0.85	0.24	1.00		
RS	-0.58	-1.00	-0.30	-0.86	1.00	
TRS	0.91	0.83	0.23	1.00	-0.83	1.00

In order to analyze the spatial distribution of quality attributes Figure 2 shows the quality maps, interpolated to a 5m² grid, using Vesper program with kriging method. The respective variogram used for interpolation is also presented.



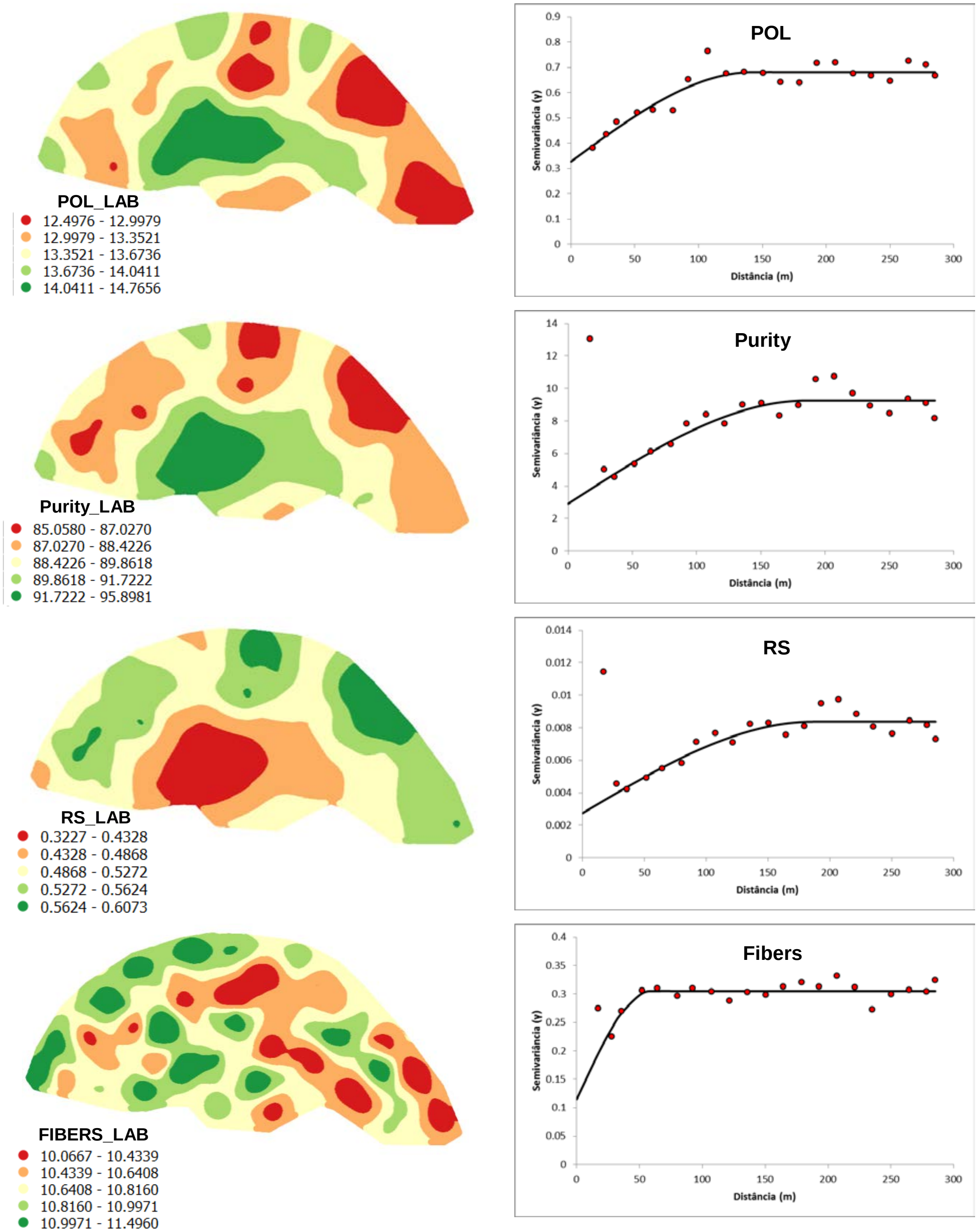


Figure 2 - maps of the quality parameters analyzed – TRS, Brix, Pol, Purity, RS and Fiber (left); variograms used for interpolation (right).

Table 3 shows the values of range, sill, nugget and the Spatial Dependence Index. The attribute that showed the lower range was the Fiber content, however all attributes presented a spatial dependence at least moderated, following the classification proposed by Cambardella et al. (1994). As the range of the attributes were in general higher than 100, it means that two samples per hectare would be enough to map these parameters in a field (MULLA; McBRATNEY, 2000).

Table 3 – Spatial dependence parameters from the variogram used in interpolation

	RS	TRS	Brix	FIBERS	Pol	PURITY
Range	186,5	136,6	86,5	59,1	142,1	185,5
Sill	0,008	52,550	0,464	0,305	0,681	9,260
Nugget	0,003	25,840	0,000	0,115	0,327	2,913
SDI	67,25	50,83	100,00	62,25	51,95	68,54
Model	Spherical	Spherical	Spherical	Spherical	Spherical	Spherical

Figure 2 shows the correlations between the predictions using the AgriNir equipment and the laboratory results, using PLSR and leave-one-out cross validation. The parameters that were better correlated with the spectra measurements were the TRS (R^2=0.654), closely followed by Brix (R^2=0.651) and Pol (R^2 = 0.638). RS, Fibers and Purity did not have good correlations with the spectral measurements, with an R^2 of 0.352, 0.326 and 0.349 respectively.

AgriNir equipment had a better performance in predicting the quality parameters than Veris, as shown in Figure 3. The parameters that were better predicted were almost the same. Brix had the better correlation (R^2=0.505), followed by Pol (R^2=0.431), TRS (R^2=0.417), Fibers (R^2=0.317), RS (R^2=0.316) and the parameter that was worse correlated with spectral measurement was the Purity (R^2=0.259), this parameter also showed bad correlation when using the AgriNir equipment.

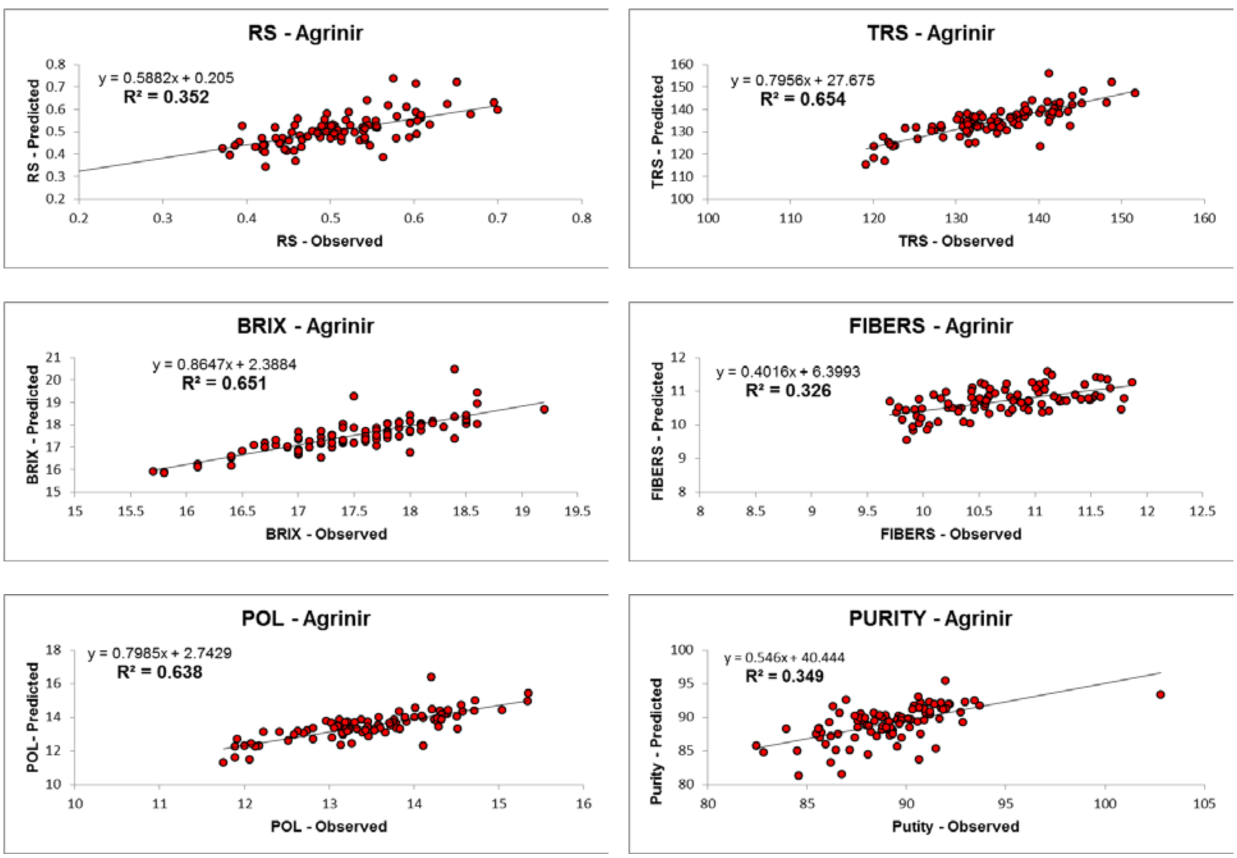


Figure 3: Correlations between the spectral measurements and the laboratory data using the AgriNir equipment.

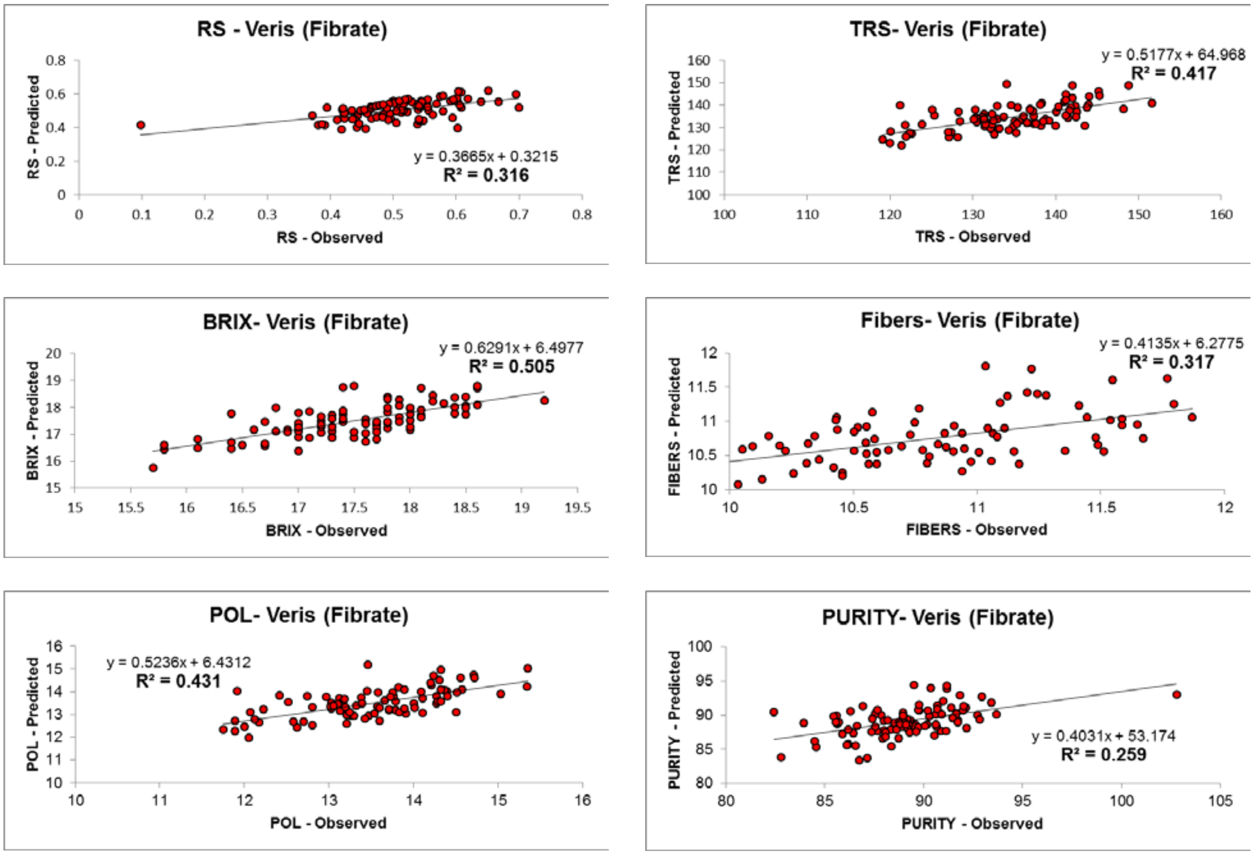


Figure 4: Correlations between the spectral measurements and the laboratory data, using the Veris equipment with fibrate samples.

The spectra obtained from juice samples were less effective in predicting quality parameters than using solid samples. Figure 5 shows the correlation between the spectra obtained from juice samples using Veris equipment and the laboratory results. All regression coefficients were lower than 0.3. In this case the fiber content was the parameter with the lowest correlation (R^2=0.129), followed by BRIX (R^2=0.200), Purity (R^2=0.259), TRS (R^2=0.265), RS (R^2=0.275) and POL was the attribute that was better predicted using juice samples (R^2=0.285).

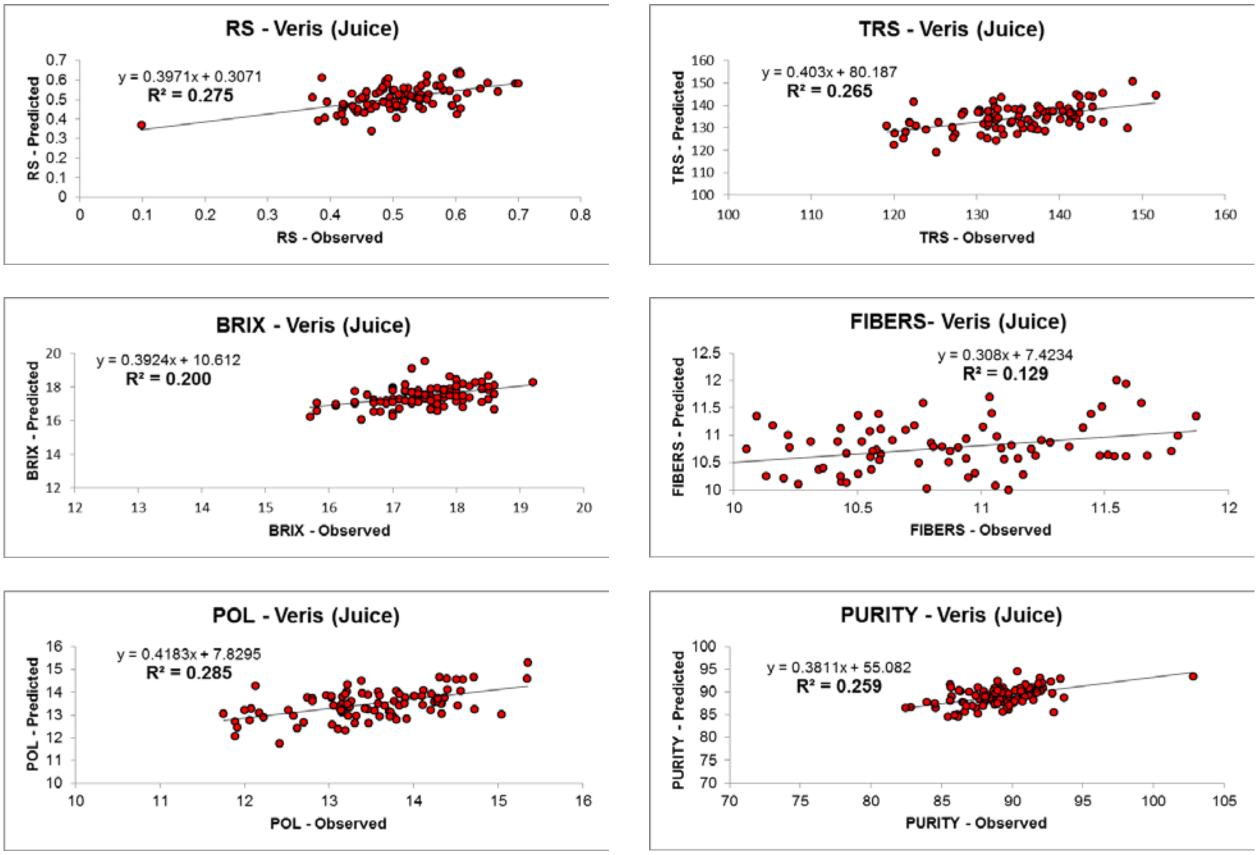


Figure 5: Correlations between the spectral measurements and the laboratory data, using Veris equipment with juice samples.

To illustrate the ability of the method to identify spots with different quality attributes within a field, Figure 6 shows the TRS map normalized by mean, estimated using the predictions above. The variogram used for the interpolation is also shown to demonstrate the spatial variability of the predicted data.

Table 4 presents the correlation matrix between the laboratory data maps and the predicted maps. The correlation between the normalized maps were better than the ones between the samples, showing that the methods were more effective in defining “zones” with different attributes in the field than to measure the exact value of the attribute, which should be improved with more calibrations.

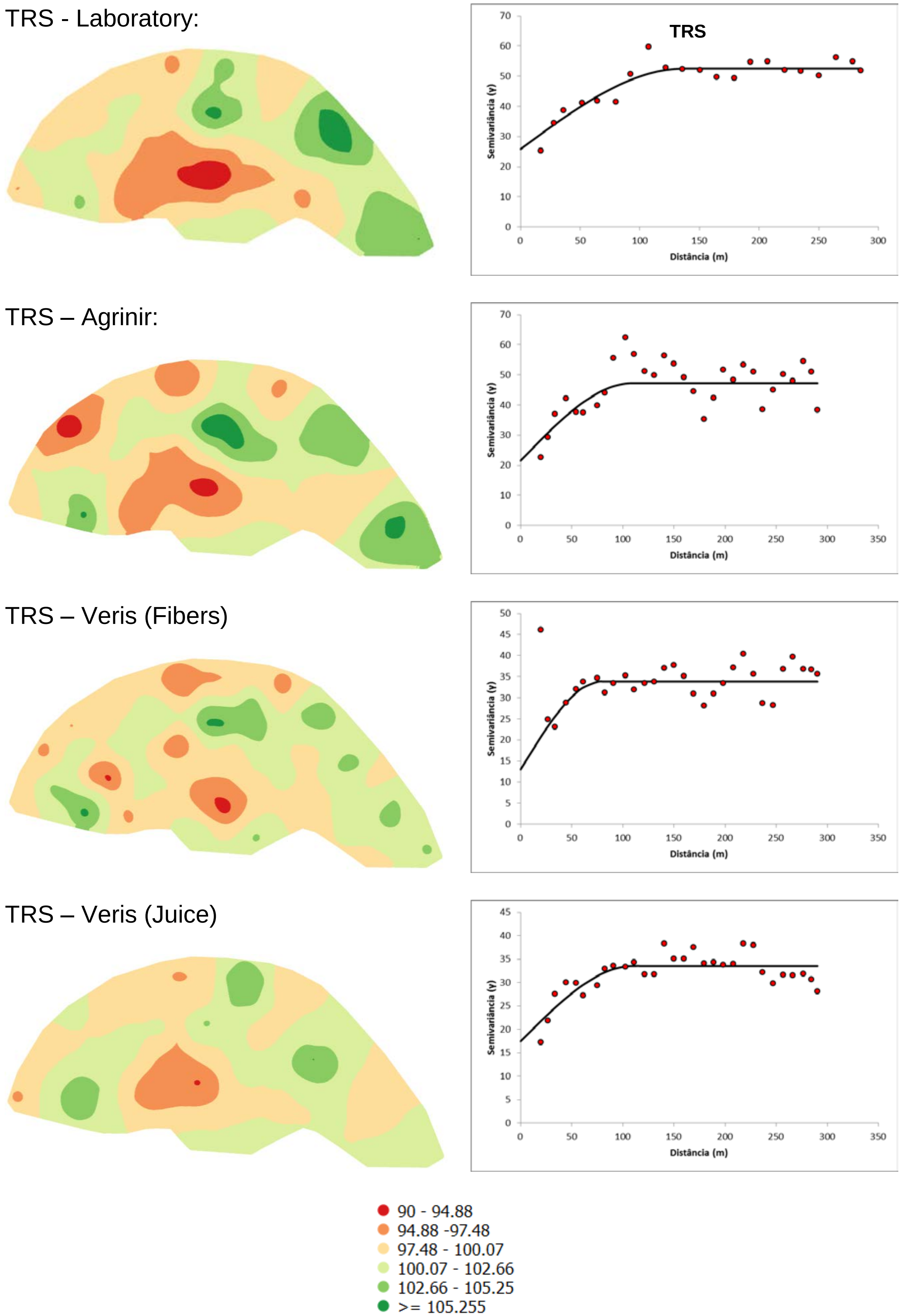


Figure 6: Normalized TRS maps using spectral predictions

Table 4 - Correlation between normalized laboratory data maps and normalized predicted maps with the different methods.

	TRS	RS	BRIX	Fibers	POL	Purity
AgriNir	0.83	0.41	0.89	0.60	0.83	0.36
Veris (Fibers)	0.68	0.53	0.79	0.61	0.69	0.45
Veris (Juice)	0.64	0.59	0.68	0.35	0.63	0.58

In general, TRS, Pol and BRIX were the parameters that were better predicted using spectrometry. Brix was the parameter that was better predicted using spectroscopy, as Brix, Pol and TRS has a high correlation between each other, it must be investigated if spectroscopy is effective in predict TRS in low quality samples of sugarcane (when Brix and Pol are different). The parameters related to differentiate the type of the sugar content, as Purity and RS were difficult to predict, these parameters were better predicted using juice samples.

Conclusions

Quality parameters of sugarcane were able to be mapped in a commercial field. Spatial dependence among samples was found and the variograms suggest that two samples per ha would be enough to map these attributes in the field. The parameter with less spatial dependence was fiber content. A coefficient of variation of 5% in TRS was obtained in the field, which could justify local management actions. Spectra from fibrate samples were better correlated with sugar content than those from juice samples. Predictions using the AgriNir showed better results than the ones from Veris Spectrophotometer.

Overall, spectrometry showed good potential to predict quality and was effective in mapping regions with different quality levels over the field. The correlations between normalized maps of the predictions and laboratory results for total recoverable sugar were better than the correlations between samples. Purity and RS content were the parameters that less correlate with the spectral measurements.

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