YIELD MAPPING FROM MANUALLY HARVESTED SUGAR CANE IN BRAZIL

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ABSTRACT

Up to date, the use of precision agriculture concepts on sugar cane is limited and one reason is due to difficulties in detecting the spatial yield variability and the effects of localized input applications. The main objective of this work was to explore the use of simple techniques to collect data in the field, during harvesting, to produce yield maps based on the harvesting systems used today, without interfering on it. The main hypothesis was that the weight load average on a small series of loads, represented by one truck or wagon is sufficiently representative for detecting yield variability based on the loads spacing in the row. Samples were taken in the fields from two loaders as treatments in 2002 and load coordinates from one field were collected in 2003 to calculate the area and yield of each load. Estimation of the total dispersion of load weights showed that it can be done by an interval of ± 2,5s from the weight average and treatments did not show the same trend on normality. Loaders averages differed, indicating that frequent calibrations would be necessary for using the average weight as an estimator of the load weights. It may be possible if using small population of loads. Data from 2003 allowed the estimation of yield points that were interpolated resulting in a surface map of sugar cane yield showing the variability within the field.

Keywords: precision agriculture, yield map, sugar cane

INTRODUCTION

With the advent of precision agriculture concepts, initially applied to grains, several solutions for yield mapping have been developed and tested. Commercial products have been available for grains since 1991 (BLACKMORE, 1994) and for cotton since 1997 (KHALILIAN et al., 1999). Works on other crops have been done, as coffee (SARTORI et al., 2002), peanuts (KVIEN, 1995), forage (AUERNHAMMER et al, 1995), hay (BASHFORD et al., 1995) and others. Initial attempts on generating sugar cane yield maps were conducted by Pierossi et al. (1997) using a instrumented truck for mechanically harvested chopped cane and Cox et al. (1998) with instrumentation on a harvester. BENJAMIN et al. (2001) designed and tested a sugar cane yield sensor based on a scale mounted on the floor of a sugar cane harvester elevator. Tests with different cane maturity, variety, flow rate and row lengths using a weigh wagon as comparison presented a prediction with slope of 0.9 and correlation of 0.966, Errors ranged from 0 to 33% and the average error of 118 tests was 11.05%. JHOTY et al. (2002) report an experiment of precision agriculture applied to sugar cane in Mauritius using a sugar cane yield monitoring system from Australia for generating yield maps. The sensor was based on a scale mounted on the floor of a sugar cane harvester elevator. Similarly, PAGNANO and MAGALHÃES (2001) presented a yield sensor using a weighing frame with transducers on the harvester elevator and reported average error of less than 3.2%, but very low individual row accuracy on field tests. Hernandez et al. (2003) presented a biomass flow sensor adapted to the harvester roller feeder using a displacement transmitter for measuring biomass input. Approaches of yield mapping on sugarcane using NDVI index from satellite images also have been proposed (Lamparelli et al., 2003).

A yield monitor added to a sugar cane harvester will produce sugar cane yield maps, but in several countries the harvesting mechanization is far from being dominant. Brazil is the largest producer in the World, with about 5 million hectares of cane and about 80% of the area is manually cut for harvesting. The use of techniques and management enhancements provided by precision agriculture has been widely expected by the sugar cane industry represented by approximately 260 sugar mills and their suppliers.

Sugar cane harvesting systems that depend on the use of manpower normally consist on burning the field prior to cutting to facilitate it. One cutter normally takes 5 rows and lay down the cane in one central row. A loader mounted on a tractor follows collecting and transferring it to a wagon or a truck (Figure 1). Initiatives have been tested on installing load sensors on the loader arm (Saraiva et al., 1999) but the speed as it happens does not allow for equalization of signal on the sensor, resulting in high uncertainty on the information.

Up to date, the use of precision agriculture concepts on sugar cane is limited and one reason is due to the difficulty in detecting the spatial yield variability and the effects of localized input applications. The main objective of this work was to explore the use of simple techniques to collect data in the field, during harvesting, to produce yield maps based on the harvesting systems used today, without interfering on it. The main hypothesis was that the weight load average on a small series of loads, represented by one truck or wagon is sufficiently representative for detecting yield variability based on distance between loads in a row.

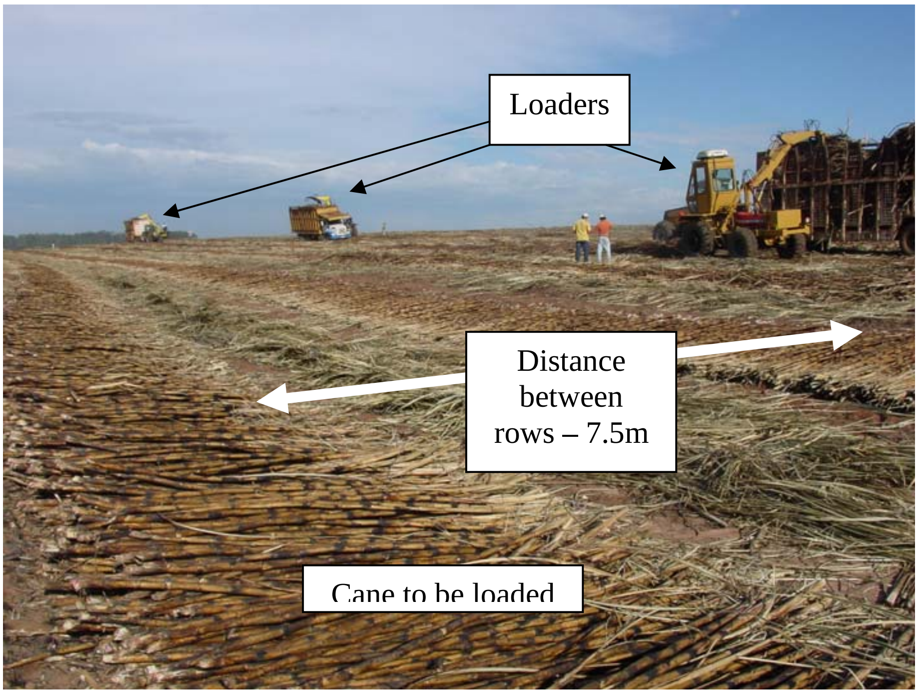


Figure 1. A representative condition of a sugar cane harvesting system based on hand cutting and mechanical loaders

MATERIAL AND METHODS

Initially field tests were conducted with the objective of collecting a series of data related to loads of representative loaders to analyze its weight characteristics and constancy. The field experiment was conducted during the 2002 (October, 2002) harvesting season for collecting data related to the loads of two loaders and their operators (treatments A and B) in one farm operated by a sugar mill, in Catanduva, São Paulo State, Brazil (49^0.17’ W, 21^0.07’ S). The experimental area was cultivated with the variety RB85 5536 on its first cut at row spacing of 1.5m. The two loaders used on the test were both Motocana model Super 2000 with specified load capacity of 11770N, maximum elevation height of 5.6m, with maximum grab opening of 1.6m and mounted on tractors MF 290 FWD with engine power of 60.3kW.

For each loader a series of 75 loads were randomly selected and set aside. On a third loader, similar to the other two, a load cell was used after collecting each load and packing it with a special chain for measuring the load of each one. A load cell Kyowa, model LU-2TE with maximum capacity of 19620N was used, connected to a digital register Microp with resolution of 0.98N and powered by a 12V battery. Initially the third loader took each load from the ground, the special chain was passed on it and it was laid down again for attaching the load cell between it and the loader grab for lifting it again and measuring its weight.

The data were analyzed using descriptive statistics and normality distribution by graphics and χ^2 test at 95% probability. An analysis of variance was applied for treatments A and B with F test and the average weight comparison was done using Tukey test, also at 95% probability.

A second phase of the work was conducted during the 2003 season (May 2003), in the same mill but at a different field, with the same variety (RB85 5536) and loaders as before. Three loaders were involved in the test and for each loader navigation GPS receivers were used for manually collecting the position of each load in a entire field. The exact time for collecting position was when the loader arm started lifting, signalizing the end of a load. Sugar cane was transferred to the trucks or wagons that after loaded were weighed in a scale at the mill entrance.

After a preliminary data processing a spreadsheet was generated containing for each load, the truck or wagon identification, its weight, the load average and its location. After transforming the coordinates from geographical to UTM format the distances between each load location were calculated and with the width of 7.5m of each line of five rows, it resulted in the area represented by each load. The location of each load was adjusted to the center of its area. Field boundary was used for defining the beginning of each row and the coordinates were pushed back to the center of each rectangle. Yield was calculated based on the load weight average and the area representative of each load. The data spreadsheet was then transferred to a GIS for spatial analysis and processing, and a statistical analysis was also performed on the yield data for identifying discrepancies using the quartile criteria from Tukey (1977) and removing points considered as discrepant.

RESULTS AND DISCUSSION

Descriptive statistics of the weight loads from the two treatments is presented on Table 1. The extremes, average, standard deviation and coefficient of variation were higher for the treatment A, indicating a better uniformity of loads weight on treatment B. Also, related to the format of the distributions (Figure 2), both treatments presented negative skiuness and kurtosis, indicating concentration of specific values of load weights. The confidence interval for the average weight was ± 275 N for treatment A and ± 248 N for treatment B and the coefficient of variation was between 14.1 and 13.3%.

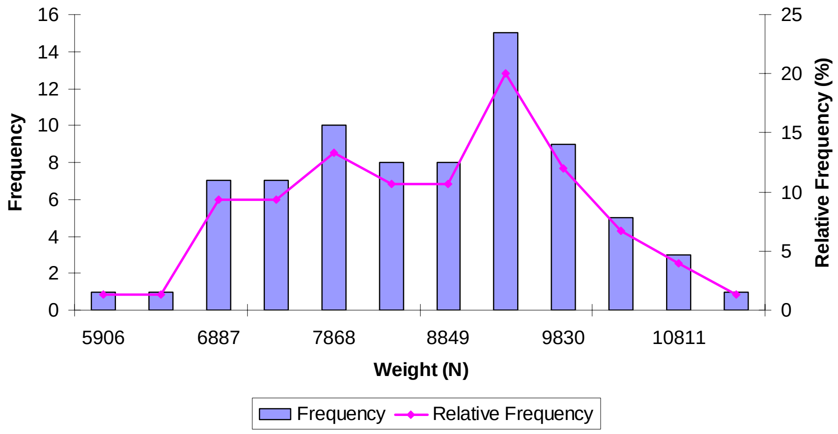
The histograms of load weight distribution show for treatment A concentration of loads (28%) between 9000 e 9600 N, not shown on treatment B. In terms of dispersion around average, 66,7% (50 loads) on treatment A resulted in load weights between ± 1,0 s, characterizing a normal distribution, and for treatment B, the interval of ± 1,0s involved only 60,0% of the total sample of load weights.

Table 2 presents the dispersion of average load weights for both treatments. At a confidence interval of ± 2,0s, 96% and 98% of the loads were involved, for treatment A and B, respectively. The total dispersion was includes in the interval of ± 2,5s.

Table 1. Descriptive statistics from data for the two treatments

Statistics	Treatment A	Treatment B
Average load weight (N)	8486	8075
Standard error (N)	138	124
Median (N)	8672	8198
Mode (N)	9113	9506
Average (N)	7769	7770
Standard deviation (N)	1194	1076
Variance (N^2)	$1.42.10^6$	$1.15.10^8$
Kurtosis	-0.68	-0.63
Skewness	-0.08	-0.3
Interval (N)	5375	4552
Minimum (N)	5905	5494
Maximum (N)	11281	10045
Confidence interval* (N)	275	248
Coefficient of variation (%)	14.07	13.33

* Confidence interval for the average of 95,0%.



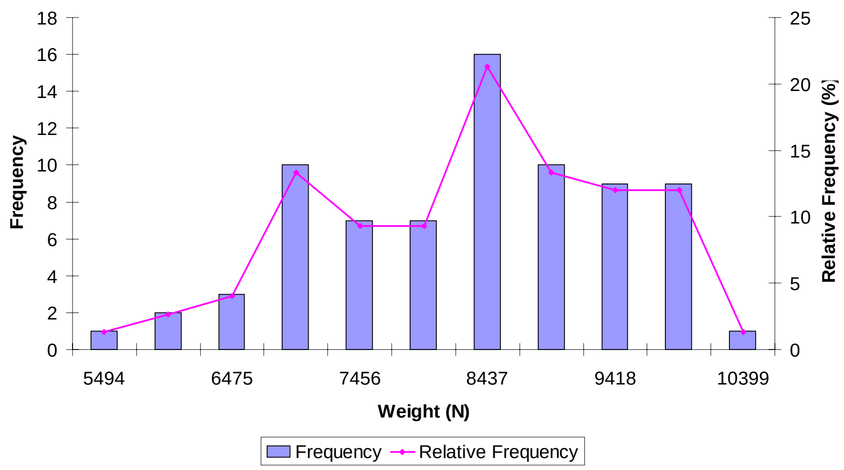


Figure 2. Histograms of frequency distribution of load weights for treatment A (top) and treatment B (bottom)

Graphics on Figure 3 show the normal probability distribution for a qualitative evaluation of normality. For both treatments loads were distributed quite normally, with a high correlation coefficient of 0.98. Treatment B presented better indication of normal distribution. The χ^2 test allows for a quantitative analysis of a normal distribution. The null hypothesis for the test was that load weights on both treatments were normally distributed. The critical value for χ^2 was 21,03. For treatment A χ^2 was 35.70 and for treatment B it was 12.80, indicating that the load weight distribution for treatment B follows the normality and treatment A does not.

Table 2. Load weights average dispersion for the two treatments

Treatment	1 SD			2 SD			2.5 SD		
	IL (N)	SL (N)	Loads (%)	IL (N)	SL (N)	Loads (%)	IL (N)	SL (N)	Loads (%)
A	7291	9681	67	6098	10874	96	5501	11471	100
B	6999	9151	60	5923	10227	98	5385	10765	100

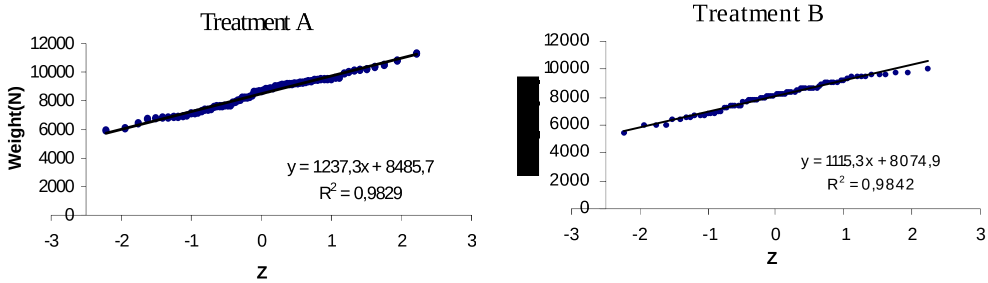
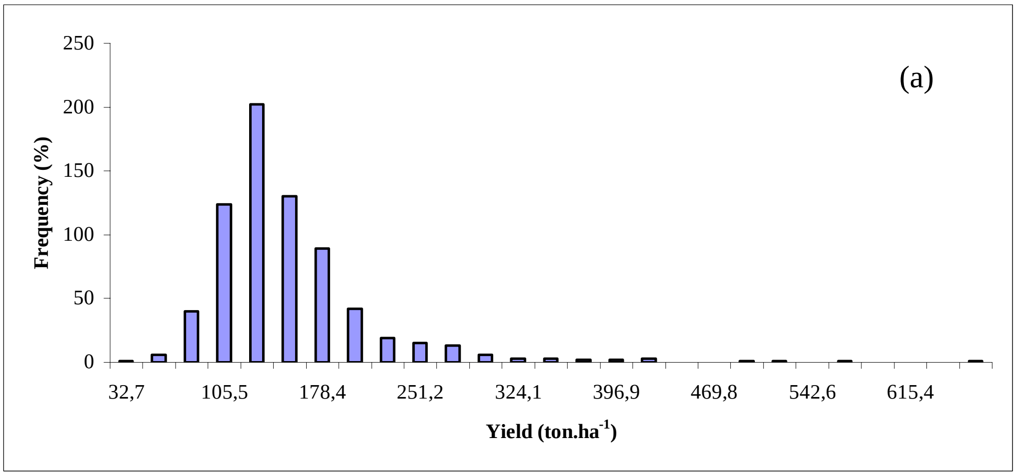


Figure 3. Normal probability distribution of load weights for treatment A (left) and treatment B (right)

From the average weight comparison the two treatments were significantly different. It indicates that frequent calibrations would be necessary and an average may be representative only for a small population of loads, like one truck or wagon that takes approximately 15 to 20 loads each.

An initial statistical analysis from data collected on the second part of the project corresponding to yield points calculated from distances and respective areas and truck or wagon weights distributed evenly for each load indicated that some of the collected points had to be considered as discrepant. From the criteria for removing discrepant data based on the quartiles, the lower limit was 27,3 $ton.ha^{-1}$ and the upper limit was 237,7 $ton.ha^{-1}$. Figure 4 shows the distribution of points before and after the filtering process and Table 3 presents the statistics of the two populations, before and after the filtering. Figure 5 presents the maps of the field data with the location of each collected point indicating those considered discrepant, the map of yield points and an interpolated view of the yield distribution in the field using inverse distance as interpolator.



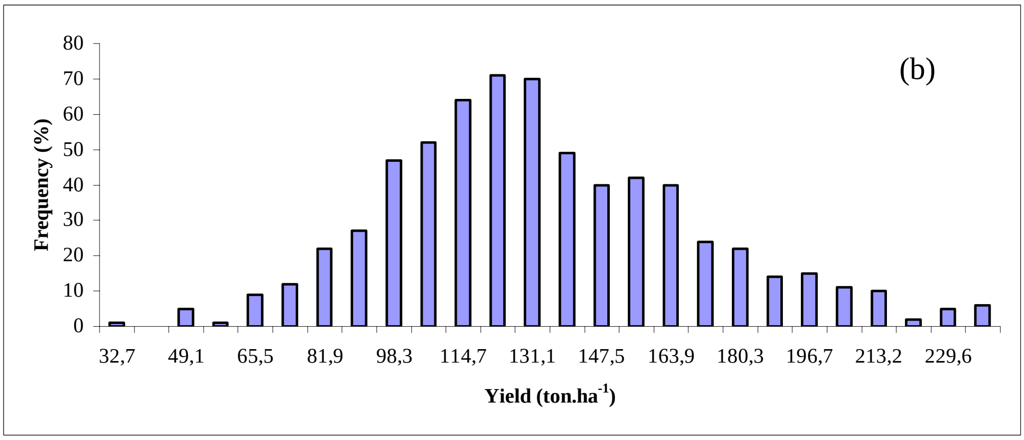


Figure 4. Histograms of frequency distribution of raw yield data (a) and yield data after removing discrepant points (b)

Table 3. Descriptive statistics of the yield points before and after the filtering

Parameter	Value	
	Raw data	Filtered data
Mean (ton.ha^{-1})	141.3	129.7
Median (ton.ha^{-1})	127.7	124.9
Minimum (ton.ha^{-1})	32.7	32.7
Maximum (ton.ha^{-1})	664.0	237.7
Lower quartile (ton.ha^{-1})	106.5	106.5
Upper quartile (ton.ha^{-1})	159.4	159.4
Variance	3.833.72	1.317.85
Standard deviation	61.92	36.30
Asymmetry	2.94	0.46
Kurtosis	14.93	0.11
Coefficient of variation (%)	43.82	29.04

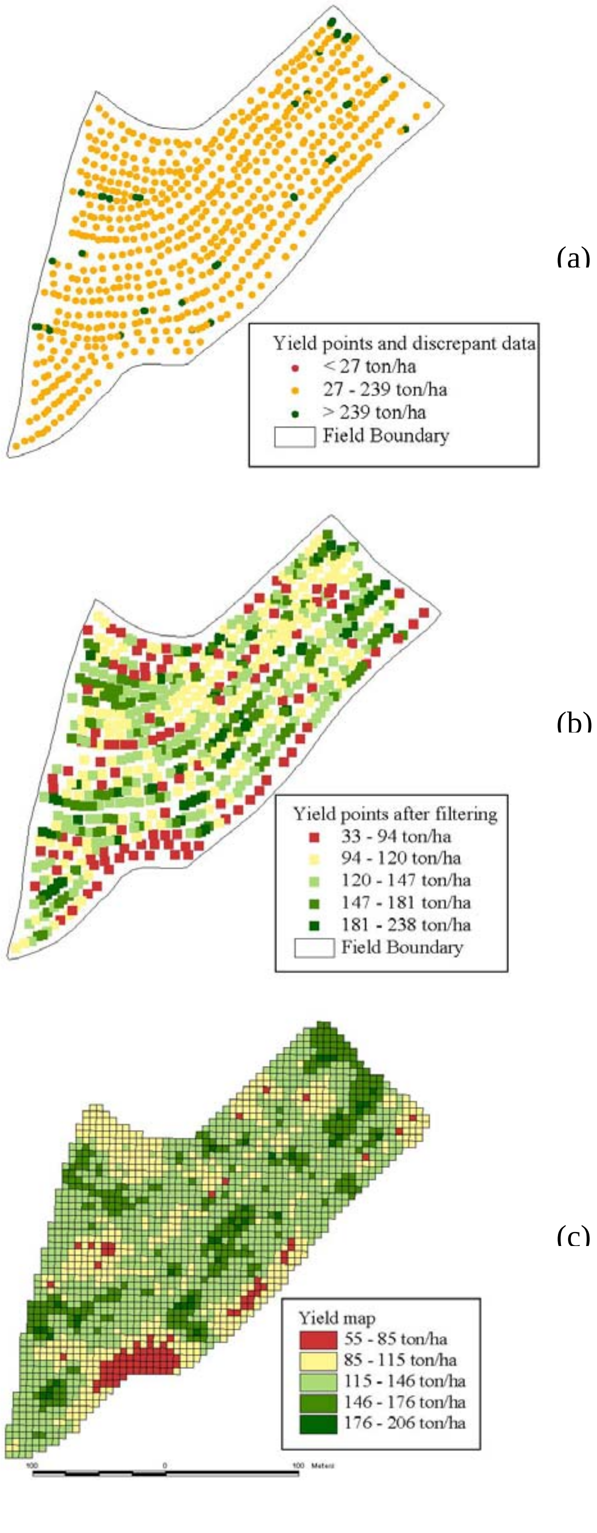


Figure 5. Map of yield points with discrepant data (a); yield points classified after removing the discrepant data (b); yield map after interpolation (c)

The discrepant data came only from points with high yields and probably related to distances shorter that what is possible between loads. One of the reasons for that may be related to the accuracy of the GPS receivers, not enough in this case. Loaders perform a straight operation with no reason for concentrating loads where there is no product. From Table 1 it is shown that the amount of product collected on each load can change in a range of about plus or minus 20 to 30% around the average load weight. It means that those points where not correctly collected, indicating some experimental error.

The system here proposed and tested is limited on its accuracy especially related to the uncertainty of the load weight on each point. The only source of information related to yield variability is the distance between loads and it has to be correctly collected. An automated system installed on the loaders can provide it but it still has to deal with a sequence of movements that the arm of the loader will perform each time it is really loading. Sometimes the operator will use the arm to make adjustments to the truckload and it cannot be taken as a load. A system composed by positioning sensors along the arm was already built to guaranty the accuracy of the automated data collection using this concept associated with a customized data logger and GPS receiver.

CONCLUSIONS

Estimation of the total dispersion of load weights from the first part of the work showed that it can be done by an interval of ± 2,5 SD from the weight average and treatments did not show the same trend on normality. Treatments differed, indicating that frequent calibrations would be necessary for using the average weight as an estimator of the load weights. It may be possible if using small population of loads like a truck or wagon.

The methodology showed to be effective in generating sugarcane yield maps, making it possible to visualize significant infield variability. It is espected that with an automatic data collection, directly in the loader, the procedure will improve and increase information quality.

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