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Comparison of crop canopy reflectance sensors used to identify sugarcane biomass and nitrogen status

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Abstract Canopy reflectance sensors are useful tools for guiding nitrogen fertilization in crops. However, studies of sugarcane comparing the efficiency of different devices for determining crop parameters are scarce. The objective of this study was to compare the performance of canopy sensors in detecting sugarcane variability. Four nitrogen (N) rate experiments were conducted (plots), along with biomass sampling, chlorophyll meter readings and leaf N concentration determination in another four fields by canopy sensor readings guided samplings. The examined canopy sensors were GreenSeeker and two Crop Circle models (ACS-210 and ACS-430), which allowed the calculation of different normalized difference vegetation index (NDVI) configurations. Neither of the canopy sensors showed a correlation with the obtained chlorophyll meter readings (SPAD) or leaf N content within the fields, while high correlations with above-ground biomass were found, indicating that the plant population and vigor interfered with the canopy sensor readings. The devices showed similar suitability in terms of N rate differentiation and correlations with crop parameters. However, the NDVI calculated from the Crop Circle ACS-430 sensor using a red-edge waveband (NDRE) showed the best results, displaying the greatest range of measured values and the highest sensitivity as a biomass predictor. Regardless of the canopy sensor and wavebands used, all of the analyzed sensors proved to be good tools for identifying the variability of crop development in sugarcane fields.

Keywords Precision agriculture · Remote sensing · Proximal sensing · Vegetation indices · NDVI

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Introduction

Sugarcane (*Saccharum* spp.) is the most important crop for sugar and ethanol production in tropical and subtropical regions, accounting for approximately 80 % of global sugar production and approximately 35 % of global ethanol production (FAO 2011). However, nitrogen (N) fertilization of sugarcane remains a challenge, as there are no reliable methods for N soil availability analysis, mainly under tropical conditions, and there is a lack of reliable yield monitors and, consequently, yield maps that would allow for variable rate application. Therefore, the application of ground-based crop canopy reflectance sensors (canopy sensors) represents a noteworthy approach. The suitability of canopy sensors for guiding N application has been widely documented in crops such as maize and wheat (Lukina et al. 2001; Raun et al. 2005; Berntsen et al. 2006; Holland and Schepers 2010; Kitchen et al. 2010; Solie et al. 2012).

There are many available canopy sensors, but studies comparing the efficiency of these devices in determining crop parameters are scarce. Shaver et al. (2011) found that the results obtained using the GreenSeeker and Crop Circle ACS-210 canopy sensors were closely related to the yield and N rates in maize. Similar findings were reported by Hong et al. (2007) in terms of maize biomass accumulation and chlorophyll contents. Shaver et al. (2010) demonstrated that the Crop Circle ACS-210 sensor performed better than the GreenSeeker sensor in greenhouse maize, while GreenSeeker showed more variability in the readings obtained and was affected by the speed of movement. Tremblay et al. (2008) evaluated N-sensor and GreenSeeker in maize and wheat and affirmed that both sensors were capable of describing the N condition of the crops, but each sensor displayed unique sensitivity characteristics, and these authors concluded that the algorithms developed with one sensor for variable-rate N application cannot be transferred directly to another sensor.

In sugarcane, studies have demonstrated the efficiency of canopy sensors used to identify certain crop parameters. Molin et al. (2010) and Amaral and Molin (2014), working with the GreenSeeker and Crop Circle ACS-210 canopy sensors, respectively, detected a significant relationship between N rates and the measurements obtained using these devices. In another study, Portz et al. (2011) found that the N-Sensor ALS was able to identify biomass and N uptake variability in sugarcane fields. Furthermore, Amaral et al. (2012) and Lofton et al. (2012) verified the reasonable efficiency of this approach based on estimating sugarcane yields from canopy sensor readings (working with Crop Circle ACS-210 and GreenSeeker, respectively).

However, despite the availability of some published studies and others being developed regarding the use of canopy sensors in sugarcane, no study has yet compared the efficiency of different devices. Thus, the objective of the present study was to compare the performance of canopy sensors in detecting sugarcane variability, mainly in terms of biomass and N status, as well as to identify which crop parameters interfere with canopy sensor measurements. The results of this study will aid in determining which canopy sensors provide better results under the conditions of sugarcane cultivation.

Materials and methods

Crop canopy reflectance sensors

Three crop canopy reflectance sensors were tested: GreenSeeker (Trimble Navigation, Ltd., Sunny Vale, CA, USA) and two Crop Circle devices, models ACS-210 and ACS-430

(Holland Scientific Inc., Lincoln, NE, USA). These sensors are active and function based on two or three wavebands in the visible and near infrared (NIR) regions, providing variations of the normalized difference vegetation index (NDVI, Eq. 1) as outputs.

The GreenSeeker sensor works with wavebands in the red (660 nm) and NIR (770 nm) regions, thereby calculating the red NDVI. The ACS-210 also uses two wavebands, but centered on the amber (590 nm) and NIR (880 nm) regions, thus calculating the amber NDVI. In contrast, the ACS-430 functions with three wavebands in the red (670 nm), red-edge (730 nm) and NIR (780 nm) regions, enabling calculation of both the red NDVI and red-edge NDVI (NDRE). The NDVI calculations were performed as follows:

$$NDVI = \frac{NIR - VIS}{NIR + VIS} \tag{1}$$

where NIR is the reflectance in the near-infrared waveband and VIS is the reflectance in the visible or red-edge waveband, according to the applied sensor.

The canopy sensor readings were taken simultaneously when the sugarcane stalk height was $\sim$0.5 m (Amaral and Molin 2014). In all of the evaluations, the sensors were mounted on a high-clearance vehicle (Uniport 3000 NPK, Máquinas Agrícolas Jacto, Pompéia, SP, Brazil) and maintained at 0.8 m from the canopy (Fig. 1).

Plot experiments with N rates

To identify the efficiency of the canopy sensors in distinguishing different levels of N in the soil, four plot experiments were performed in the central-eastern part of the state of Sao Paulo, Brazil (21°21′ S – 48°04′ W) from 2011 to 2012: two in sugarcane-producing fields and two at research centers (Table 1). The plots consisted of six 15-m-long sugarcane rows spaced 1.5 m apart, and the treatments were comprised of different N rates (Table 1). Nitrogen fertilizer was manually applied as ammonium nitrate along the rows on top of straw immediately after harvest. A randomized block experimental design with four replications was applied, where the investigated areas were the four central rows. The vegetation index value for each plot was composed by the average of $\sim$400 canopy sensor readings.

Field measurement trials and sampling procedures

The canopy sensors were tested in terms of their efficiency in determining biomass, chlorophyll contents and leaf N concentrations. For this purpose, four sugarcane-producing fields ($\sim$5 ha each) were scanned with the canopy sensors (Table 1), with measurements being taken at 1 Hz in all of the rows (spaced 1.5 m apart) at a travel speed of $\sim$4.44 m s^{-1}.

The applied sample allocation and sampling procedure were performed according Portz et al. (2011). After scanning, the sensor data were analyzed to identify outliers, which were removed following the upper and lower quartile criteria. The cleaned data were interpolated using 10 m cells and the inverse distance method (SSToolbox, SST Development Group, Stillwater, OK, USA). Based on the interpolated surfaces, five classes were discriminated by natural breaks scale to express the field variability. Six sampling points were located in the middle of the representative areas of each class, summarizing 30 points per field.

Each sampling point consisted of four 5-m-long sugarcane rows. Inside this area, 30 chlorophyll meter readings (SPAD 502, Konica Minolta Sensing, Inc., Sakai, OS, Japan) were obtained on the most recent, fully expanded leaf (leaf top visible dewlap—TVD), midway between the leaf tip and the base and midway between the margin and the midrib. This same portion of the leaves was used to determine the leaf N concentration via the

Fig. 1 The (*a*) GreenSeeker, (*b*) Crop Circle ACS-210, and (*c*) Crop Circle ACS-430 canopy sensors mounted on the fertilizer application boom of a high-clearance vehicle

micro-Kjeldahl digestion and distillation method (Bremner and Mulvaney 1982). The above-ground biomass was also sampled by cutting 1.5 m subplots in three rows, summarizing the 4.5 m row length, and the fresh matter was weighed in the field.

Data analysis

To address the effects of the N rates among the fields in the plot experiments, the mean canopy sensor readings for each treatment were converted across replications into the sufficiency index (SI, Eq. 2) (Varvel et al. 1997) as follows:

$$\mathrm{SI} = \frac{CheckN}{HighN} \tag{2}$$

where *CheckN* is the NDVI value according to the treatment (N rate), and *HighN* is the NDVI value obtained in the treatment with the highest N rate.

Thus, the data from plot experiments were analyzed via ANOVA using a mixed model in which the N rates were considered fixed effects, and the blocks were considered random effects. Regression analyses, testing for both linear and quadratic components, were also applied to further the understanding of the sugarcane N response. Statistical analyses were performed using SISVAR statistical software (Federal University of Lavras, Lavras, MG, Brazil—Ferreira 2011).

The canopy sensor data from each sampling point in the field trials were obtained using a 5-m radius buffer, while all the readings value inside the buffer (one to four readings per point) were averaged. It was analyzed the relationships between crop parameters (biomass, chlorophyll content and leaf N concentration measured at each sampling points) and the canopy sensor readings. Correlation analyses were performed within and across the fields, and the significance of the correlations was verified using T tests ($p < 0.05$). To estimate the sensitivity of the canopy sensor readings in identifying the sugarcane biomass, relative values were obtained, in which the highest value within the fields was used as the denominator. The relationship between the relative values was estimated via linear regression (relative biomass on the x axis and relative sensor readings on the y axis;

Table 1 Characteristics of the experimental sites, cropping information and canopy sensors used in each of the trials

Field	Year	Variety	Soil classification		Ratoon[b]	Treatments		Sensors[d]
			USA	Brazil[a]		N rates (kg ha^{-1})	Cycles[c]	
Plot experiments, with N application rates								
Velha[e]	2011	RB867515	Hapludox	LVm	Fourth	0, 60, 120, 180, 240	First	GS, 210, 430
Piracicaba[f]	2011	IAC87-3396	Haplustalfs	PVe	Second	0, 50, 100, 150	Second	GS, 210, 430
Barra[f]	2012	SP81-3250	Quartzipsamment	NQ	Third	0, 50, 100, 150	Third	GS, 430
Izaura[e]	2012	CTC2	Haplustox	LVAd	Third	0, 60, 120, 180	First	GS, 430
Field measurement trials								
Alvorada[g]	2011	SP80-1816	Haplustalfs	PVd	Eighth	–	–	GS, 210, 430
Aparecida	2011	CTC2	Hapludox	LVm	Fourth	–	–	GS, 210, 430
ApArenoso	2012	CTC2	Hapludox	LVm	Fifth	–	–	GS, 430
ApArgiloso	2012	CTC2	Hapludox	LVd	Fifth	–	–	GS, 430

[a] Brazilian soil classification system (EMBRAPA 2006); LVm Latossolo vermelho mesotrófico, PVe Argissolo vermelho eutrófico, NQ Neossolo quartzarênico, LVAd Latossolo vermelho-amarelo distrófico, PVd Latossolo vermelho distrófico, LVd Latossolo vermelho distrófico

[b] Cumulative number of harvests performed in the field for the year of the study

[c] Number of crop cycles in which the treatments were applied

[d] Canopy sensors used: GS: GreenSeeker, 430: Crop Circle ACS-430, 210: Crop Circle ACS-210

[e] Experiment conducted in a sugarcane-producing field

[f] Experiment conducted in a research center

[g] In this field, leaf N analyses were not performed

Solari et al. 2008). The slope and root mean square error (RMSE) of each relationship were determined, and the sensitivity equivalent (SEq) was calculated (Eq. 3) as follows:

$$\mathrm{SEq} = \frac{\mathrm{slope}}{\mathrm{RMSE}} \tag{3}$$

According to Viña and Gitelson (2005), the SEq incorporates both the slope and RMSE and provides an effective assessment of differences in the ability of vegetation indices (canopy sensors readings) to assess canopy variation. The data were plotted using SigmaPlot software (SPSS Inc., Chicago, IL, USA).

Results and discussion

Relationships between sugarcane crop parameters for each field

The canopy reflectance in the visible and near infrared regions is influenced by the amount of green tissue present. Among the factors that can interfere with determining this parameter, the biomass content and chlorophyll content are highlighted when performing proximal sensing above crops. Thus, a good relationship between these parameters and canopy sensor readings has been reported in maize and wheat (Teal et al. 2006; Hong et al. 2007; Eitel et al. 2008; Solari et al. 2008).

However, because sugarcane is a semi-perennial crop, the variability of the crop population and skips within rows tend to be the main factors interfering with canopy sensor readings in sugarcane. Thus, a high correlation with biomass and no correlation with the SPAD readings was obtained (Table 2). This absence of correlation between canopy sensor readings and SPAD readings was showed by Amaral and Molin (2014) working with Crop Circle ACS-210 on sugarcane. Similarly, Sudduth et al. (2010) found that GreenSeeker and Crop Circle ACS-210 are more affected by variations in maize height than by SPAD readings and leaf N contents. Despite the observed efficiency in distinguishing between crop parameters, the correlations between the canopy sensor readings and the crop parameters were quite similar for all of the sensors.

Identification of sugarcane N status

Significant differences ($p < 0.05$) in the SI values were only detected by the sensors in half of the plot experiments according to the N application rates (Table 3). These differences were obtained in the plot experiments where the indicated N rates had been applied for two or three crop cycles (the Piracicaba and Barra fields, respectively), whereas in the plots undergoing their first year of treatment (the Velha and Izaura fields), no significant response was observed due to the high variability in the crop response. This result is likely due to conditions remaining from the previous crop cycle. Prado and Pancelli (2008) found that the crop response to N application in sugarcane occurs in the cycle following N application, which may explain the results presented here. Despite the variability in the plots and the difficulty of obtaining large responses to N application in the first year at certain N application rates, a linear trend was detected in the Velha plots and a quadratic trend in Izaura plots.

The lower the SI value (SI $<$ 1.0), the higher the response to N under those field conditions (Varvel et al. 1997). Thus, it was determined that the Crop Circle ACS-430

Table 2 Correlation coefficient between the canopy sensor readings and crop parameters (biomass, SPAD readings and leaf N concentrations) for the data collected in the four fields

Correlation coefficient (r)			
	Biomass	SPAD	Leaf N
Field: Alvorada[a]			
GreenSeeker	0.520**	0.334[ns]	–
ACS-210	0.812**	0.062[ns]	–
ACS-430$_{NDVI}$	0.812**	0.057[ns]	–
ACS-430$_{NDRE}$	0.810**	0.042[ns]	–
Biomass	–	0.067[ns]	–
Field: Aparecida			
GreenSeeker	0.425*	−0.092[ns]	0.250[ns]
ACS-210	0.708**	0.048[ns]	0.394*
ACS-430$_{NDVI}$	0.771**	−0.027[ns]	0.424*
ACS-430$_{NDRE}$	0.773**	−0.049[ns]	0.417*
Biomass	–	−0.076[ns]	0.464*
Field: ApArenoso			
GreenSeeker	0.826**	0.205[ns]	0.491[ns]
ACS-430$_{NDVI}$	0.848**	0.144[ns]	0.415*
ACS-430$_{NDRE}$	0.772**	0.384*	0.513**
Biomass	–	0.322[ns]	0.568**
Field: ApArgiloso			
GreenSeeker	0.812**	−0.167[ns]	−0.475*
ACS-430$_{NDVI}$	0.805**	−0.212[ns]	−0.574**
ACS-430$_{NDRE}$	0.791**	−0.186[ns]	−0.499*
Biomass	–	−0.189[ns]	−0.268[ns]

* and ** significant at the 0.05 and 0.01 levels, respectively

[ns] Non-significant at the 0.05 level

[a] In this field, leaf N analyses were not performed

sensor functioning in the NDRE (red-edge NDVI) showed the greatest sensitivity in differentiating the sugarcane canopy response in terms of N application. The same sensor generating the red NDVI presented a lower sensitivity in differentiating N rates when working with this index.

Shaver et al. (2011), working with the canopy sensors GreenSeeker and Crop Circle ACS-210 in maize, found that both sensors could efficiently identify the N rates applied to this crop but that GreenSeeker reached saturation earlier in the growing season, potentially limiting the use of this sensor at later growth stages when the plant biomass is higher, whereas Crop Circle ACS-210 showed a lower range of values according to N rates. Additionally, Erdle et al. (2012), working with GreenSeeker and the Crop Circle ACS-470 (a device similar to Crop Circle ACS-430), found that the indices obtained using red-edge wavebands function better than those generated using red wavebands in identifying the N status of wheat. Similarly, Shiratsuchi et al. (2010) obtained better results working with the NDRE than the NDVI in the identification of N levels in maize.

One reason for this result may be the signal saturation in the red waveband due to its high absorption by chlorophyll pigments, causing the NDVI based on red wavebands to be

Table 3 Sufficiency index obtained by averaging vegetation index values across replications within the N rates in the four plot experiments, analysis of variance and regression analysis

	Nitrogen rate (kg ha^{-1})					ANOVA	Regression analysis[a]
Plots: Velha							
	0	60	120	180	240	*P* value	
GreenSeeker	0.97	0.99	0.97	0.99	1.00	0.639	0.352 (LR[b])
ACS-210	0.95	0.98	0.97	0.99	1.00	0.175	0.038 (LR)
ACS-430$_{NDVI}$	0.91	0.95	0.91	0.95	1.00	0.459	0.161(LR)
ACS-430$_{NDRE}$	0.86	0.92	0.90	0.94	1.00	0.176	0.027 (LR)
Plots: Piracicaba							
	0	50	100	150		*P* value	
GreenSeeker	0.90a[a]	0.96b	0.99b	1.00b	–	0.041	0.008 (LR)
ACS-210	0.88a	0.95b	0.99c	1.00c	–	<0.001	<0.001 (LR)
ACS-430$_{NDVI}$	0.78a	0.94b	1.01b	1.00b	–	<0.001	<0.001 (LR)
ACS-430$_{NDRE}$	0.71a	0.91b	0.99c	1.00c	–	<0.001	<0.001 (LR)
Plots: Barra							
	0	50	100	150		*P* value	
GreenSeeker	0.83a	1.01b	0.95b	1.00b	–	0.007	0.023 (LR)
ACS-430$_{NDVI}$	0.76a	0.99b	0.94b	1.00b	–	0.048	0.062(LR)
ACS-430$_{NDRE}$	0.71a	0.98b	0.94b	1.00b	–	0.009	0.010(LR)
Plots: Izaura							
	0	60	120	180		*P* value	
GreenSeeker	0.92	0.92	1.05	1.00	–	0.169	0.611 (QR[c])
ACS-430$_{NDVI}$	0.96	0.99	1.07	1.00	–	0.324	0.243 (QR)
ACS-430$_{NDRE}$	0.93	0.95	1.04	1.00	–	0.100	0.349 (QR)

[a] Means followed by different letters within the same row are significantly different, as determined by the Scott-Knott test ($p < 0.05$)

[b] LR linear component fitted via linear regression

[c] QR quadratic component fitted via linear regression

saturated in the dense and multi-layered canopy and to show a nonlinear relationship with the biophysical parameters (Baret and Guyot 1991). For the same reason, the GreenSeeker and Crop Circle ACS-210 showed a decreased sensitivity in differentiating N rates, while still being efficient in determining N rates. These results corroborate those of studies that have found a similar ability of these canopy sensors to identify different levels of N applied to maize and wheat (Shiratsuchi et al. 2010; Shaver et al. 2011; Erdle et al. 2012).

Significant correlations with leaf N could also be found (Table 2). However, in most cases, these correlations were related to an increased leaf N concentration in plants in advanced stages of development (*data not shown*) due to their more extensive root system being exposed to larger areas of the soil, thereby taking in more N than the plants located in areas with any restriction to their development. Nevertheless, other factors can alter this relationship, such as high N levels due to soil organic matter mineralization and crop fertilization, thus impairing the relationship between leaf N and biomass and, consequently, the obtained canopy sensor readings. The N dilution effect can also impair this relationship, as observed in the ApArgiloso field and also found by Franco et al. (2010)

working with sugarcane fertilization. The effect of dilution is characterized by a reduction in leaf N concentration with an increase in the plant biomass (Jarrell and Beverly 1981). In this field, the crop development was greater than the N uptake (negative correlation between biomass and leaf N) probability due to high level of available water in the soil (heavy soil) which increases the crop development, causing the dilution effect. The soil compaction that tends to happen in heavy soils was not measured in the present study, but it can also limit root development, allowing for less soil exploration and, thus, less N uptake, what might cause the effect showed in the ApArgiloso field.

Despite the significant correlation between the canopy sensor readings and leaf N levels found in each field (Table 2), when the data from all of the fields were combined, the differences between the fields were observed to be greater than the variability within the fields, demonstrating that the leaf N concentration is a function of field conditions, resulting in relationship with the canopy sensor readings (Fig. 2). The Aparecida, ApArgiloso and ApArenoso fields were cultivated with the same sugarcane variety, but the mean leaf N concentration in the ApArenoso field (18.8 g N kg^{-1}) differed from that in the others (22.9 and 23.0 g N kg^{-1}, respectively, in the Aparecida and ApArgiloso fields). This differences can be explained by soil texture contrasts (ApArenoso, Aparecida and ApArgiloso soils containing 220, 490 and 512 g clay kg^{-1}, respectively, in fields). An explanation to differences in leaf N content is related to natural N available in the soil, where due to higher clay content, the soils tend to show higher organic matter levels, what in several cases is related to N availability. Therefore, the canopy sensor approach was not efficient in identifying the variability in sugarcane leaf N within the fields, regardless of the canopy sensor used, corroborating Amaral and Molin (2014).

Biomass estimation

In contrast to the leaf N concentration, a high correlation was found between the recorded biomass and canopy sensor readings when all of the data were combined (Fig. 3). To compare the data obtained from the different canopy sensors, the readings were normalized based on the highest value determined within all of the fields. This normalization demonstrated that Crop Circle ACS-430 showed the highest range of values, regardless the vegetation index used (NDRE or NDVI), emphasizing its superior ability in distinguishing sugarcane biomass. GreenSeeker displayed a lower range, and Crop Circle ACS-210 showed a lower sensitivity to biomass variability (low range), even though it was employed in only two of the four fields. A similarly low range of the NDVI generated using the ACS-210 sensor was also reported by Solari et al. (2008) and Shaver et al. (2011) and can be interpreted as indicating that this sensor shows a lower sensitivity in differentiating green tissues. Moreover, the higher NDVI data dispersion obtained from GreenSeeker and Crop Circle ACS-430_{NDVI} might be due to the fact that these sensors function using wavebands in the visible region of the spectrum, thereby increasing the reflectance “noise” due to soil background reflectance and the variety of colors (leaves and stalks). Taubinger et al. (2012), testing for factors interfering with canopy sensor readings in sugarcane, found that the vegetation indices based on visible wavebands were more susceptible to the influence of soil background than those based on red-edge wavebands.

It is interesting that a high correlation of the biomass with the absolute values of the sensors was observed, eliminating the need for data normalization and facilitating the adoption of canopy reflectance sensor by growers in general. Furthermore, regardless of the canopy sensor employed, the correlation with biomass was similar to that found in studies conducted on maize (Freeman et al. 2007; Hong et al. 2007) and wheat (Osborne 2007;

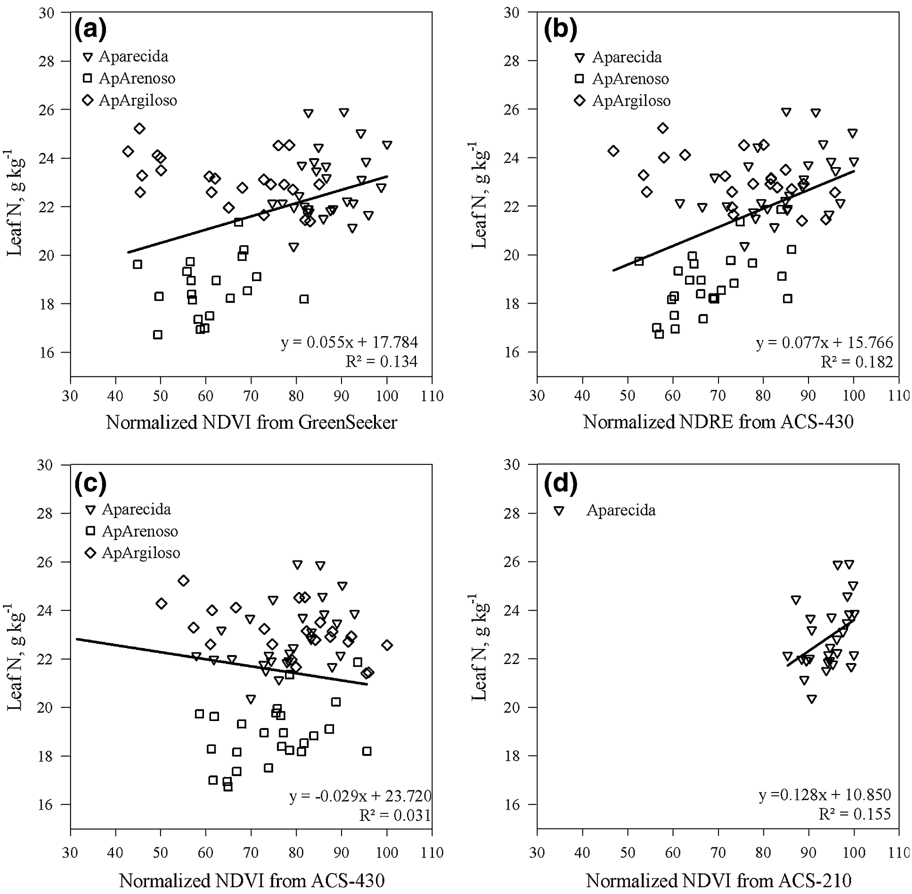

Fig. 2 Relationships between the variation in the leaf N concentration and the four normalized canopy sensor readings for the data collected in three fields and the respective linear regression equations and coefficients of determination (R^2). All three fields were scanned with the GreenSeeker (**a**), Crop Circle ACS-430$_{NDRE}$ (**b**) and ACS-430$_{NDVI}$ (**c**) canopy sensors, while only one field was scanned with Crop Circle ACS-210 (**d**)

Cao et al. 2012). Thus, sugarcane N uptake and yields may be efficiently estimated with these sensors, as carried out by Portz et al. (2011) and Lofton et al. (2012), respectively, allowing various approaches for variable N application rates based on canopy sensor readings to be employed (Lukina et al. 2001; Raun et al. 2005; Holland and Schepers 2010; Amaral et al. 2012; Solie et al. 2012). Any approach that might use this technology to guide variable N application must focus on applying N according biomass variability instead of crop N status.

Moreover, due to the efficiency of the canopy sensors in predicting biomass, any localized intervention taking crop development into consideration may be supported by canopy sensor readings. In this context, sampling allocation focusing on the identification of any factor that can impair crop development, such as pests and soil compaction, can be guided by maps generated from canopy sensor data. Additionally, the maps obtained from

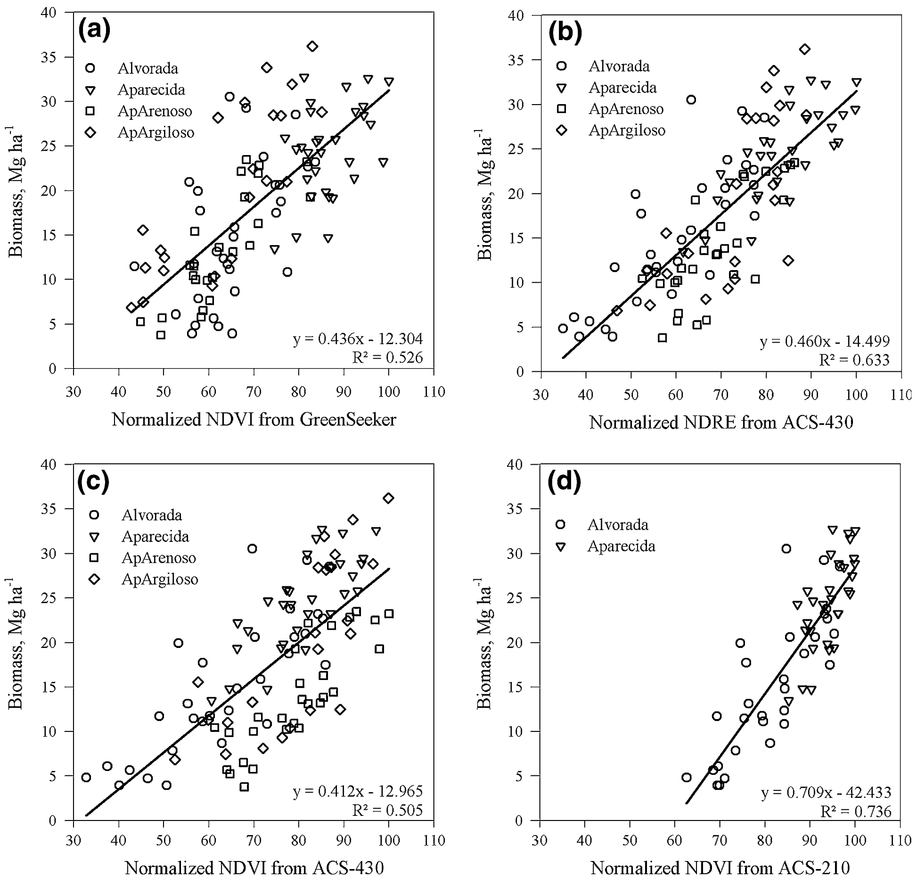

Fig. 3 Relationships between the variation in sugarcane biomass and the four normalized canopy sensor readings for the data collected in the four fields and their respective linear regression equations and coefficients of determination (R^2). All four fields were scanned with the GreenSeeker (**a**), Crop Circle ACS-430$_{NDRE}$ (**b**) and ACS-430$_{NDVI}$ (**c**) canopy sensors, while only two field was scanned with Crop Circle ACS-210 (**d**)

Table 4 Linear regression parameters between the relative sugarcane biomass determined from the measurements based on the readings of the four canopy sensors for the data collected in two fields (Alvorada and Aparecida fields) and in all four fields. The provided parameters are the slope, root mean square error (RMSE) and sensitivity equivalent (SEq = slope/RMSE)

	Slope		RMSE		SEq	
	2 fields	4 fields	2 fields	4 fields	2 fields	4 fields
GreenSeeker	0.420	0.437	0.096	0.097	4.394	4.504
ACS-210	0.376	NA[a]	0.051	NA	7.354	NA
ACS-430$_{NDVI}$	0.597	0.444	0.079	0.102	7.564	4.375
ACS-430$_{NDRE}$	0.656	0.498	0.085	0.088	7.729	5.679

[a] NA Data not available

canopy sensor readings may be useful in delineating management zones, as they can identify different crop development behaviors within fields.

To reliably test the sensitivity of the different vegetation indices obtained using the ACS-210 sensor in identifying chlorophyll contents in maize, Solari et al. (2008) proposed the SEq, a ratio between the slope and RMSE of the relationships between the chlorophyll content and vegetation index value, and found that the chlorophyll index (CI, obtained based on the amber waveband) is a better predictor than the NDVI (also based on the amber waveband). Based on this approach, the NDRE was more efficient in determining sugarcane biomass, as it showed the highest slope and a reasonable RMSE, resulting in the highest SEq (Table 4).

The two fields where the Crop Circle ACS-210 sensor was used showed the lowest data variation as well as the lowest slopes, thus compromising the efficiency of this sensor in identifying biomass. This sensor was only more sensible than GreenSeeker in these two fields. In contrast, considering all four study fields, GreenSeeker was the second most sensitive sensor in identifying biomass, being inferior only to Crop Circle ACS-430_{NDRE}.

Conclusion

The present study showed that canopy sensor readings are influenced differentially by different crop parameters, regardless of the canopy sensor used. While a significant correlation with chlorophyll contents has been found in maize and wheat, none of the analyzed canopy sensors showed a reasonable correlation with the obtained chlorophyll meter readings, due to the much higher interference of the investigated plant population with the reflectance readings. Additionally, a low correlation with the leaf N concentration was found across the fields, while no correlation was observed when all of the fields were analyzed together. These results show that the differences between the fields are more important than the variability within the fields in terms of leaf N concentrations; thus, the studied canopy sensors should not be employed in this approach.

Nevertheless, the canopy sensors efficiently differentiated the N rates applied to the sugarcane crop. However, skips within rows can impair these predictions when the response in terms of biomass accumulation is low. Additionally, all of the sensors were efficient predictors of biomass variability, though the NDRE obtained using the Crop Circle ACS-430 sensor showed the best results.

Regardless of the applied canopy sensor and vegetation index, all of the analyzed sensors proved to be good tools for identifying crop vigor variability in sugarcane fields. Thus, in addition to their traditional use in guiding N applications, these sensors can be efficiently employed in sugarcane to guide sampling allocation focusing on the identification of any factor that might impair crop development. Moreover, the generated data can be used to delineate management zones.

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