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Prediction of Sugarcane Quality Parameters Using Visible-shortwave Near Infrared Spectroradiometer

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Abstract

This study was undertaken to explore the potential of spectroscopic method to predict sugarcane quality parameters by directly scanning the internode samples. Spectral data was collected from 125 internode using a visible-shortwave near infrared spectroradiometer (VNIRS). The spectral data was calibrated using Partial Least Square (PLS) method against the reference values of Brix, fibre content (FC) and moisture content (MC). The prediction results for Brix, FC and MC as represented by coefficient of determination (R^2) were 0.88, 0.93 and 0.90, respectively. These results suggested that the spectroscopic method could be used to predict sugarcane quality parameters with good accuracy.

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Keywords: Sugarcane; sugar content; quality; Brix; spectroscopic; internode

1. Introduction

Sugarcane (*Saccahrum* spp.) is an important crop in Australia with the production value ranging from AUD$1.5 to 2.5 billion per year (Anonymous, 2011). In this industry, sugar content is one of the key parameters which are used to determine the payment to growers. Sugar content of sugarcane is measured as commercial cane sugar (CCS). CCS is derived from the Pol, Brix and fibre content. Ability to measure sugar content in the field is very important especially for assessing the crops growth and development, harvesting management, adoption of precision agriculture technique and payment purposes to growers.

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However, current measurement of quality in a field is conducted by manual harvesting method where the quality parameters were later measured at laboratories. This practice is difficult, costly and time consuming procedure. Thus, a method for in-field quality determination without the necessity for exhaustive manual measurements would be beneficial to the industry.

Recent study by Staunton et al. (2011) has developed a simple method to estimate the levels of Brix, Pol, moisture, fibre and CCS present in sugarcane based on sugarcane biomass ternary relationships. The method assumes that the composition of all healthy sugarcane is constrained to follow the same ternary growth curve and that the determination of a sample's position on the growth curve can be used to estimate the levels of all ternary parameters (Brix, fibre and moisture) and non-ternary parameters (Pol in juice and CCS). This study has opened up a new dimension for in-field quality monitoring systems. To apply this finding effectively, further study is needed to identify which one of the ternary parameters would be the easiest to be measured in a field. For calibration purposes, the relative ease of reference value determination would also need to be considered. Once the optimum quality parameter has been identified, the next research step is to develop the instrument to measure the targeted quality parameter.

Many studies have reported the application of spectroscopic methods in sugar industry to predict quality level (Berding et al., 1991; Mehrotra and Siesler, 2003; Nawi et al., 2012, 2013a, 2013b, 2013c, Taira et al., 2010). The ability of spectroscopic methods, coupled with a PLS regression analysis to simultaneously determine several quality components by a single scanning has given this equipment capability to measure sugarcane ternary quality parameters. Therefore, the aim of this paper was to explore the potential of using a portable visible and shortwave near infrared spectroradiometer (VNIRS) to non-destructively predict all ternary quality components from a single scanning of sugarcane internodes. This study used internode samples for the measurement in order to simulate the billet scanning in a real harvesting environment. The specific objectives of this paper were: 1) to investigate the ability of VNIRS to predict ternary parameters from internode samples; 2) to identify the best ternary quality parameter which could be predicted by VNIRS.

2. Materials and methods

2.1 Sample preparation and reference method

A total of 125 internodes were extracted from eleven sugarcane stalk samples. The stalk samples were collected from a propagation block at the research station of Bureau of Sugar Experimental Station (BSES), Bundaberg, Queensland in May 2012. They were a plant crop that was planted in September 2011 and harvested at 8 months old. The crop was grown under commercial conditions with the fertilization based on soil test and the six easy steps nutrition guidelines (Schroeder et al., 2009). The stalks were taken from commercial variety trials represented three different maturity stages, namely early-maturing (Q155), mid-maturing (Q208) and late-maturing (Q190) crops. The selection of these three varieties was designed to ensure the models developed in this study cover the range of Brix (7.6 to 22.2) which is commonly experienced during commercial harvesting.

Whole stalk samples were first topped to remove all leaf materials and then cut into individual internode using a scissor. Each internode sample was first weighed to obtain the weight of the wet internode, W_I. Then, it was perpendicularly cut into four portions approximately at the same length (Fig. 1). After cutting, each cut portion was immediately scanned on skin and cross-sectional surface using spectroradiometer.

Fig. 1. Photo of cut internodes and the schematic of the four sections scanned (Nawi et al., 2013c).

2.2 Spectral acquisitions

The spectral data of the samples were measured using a handheld VNIRS (FieldSpec® Pro HandHeld spectroradiometer, 325 to 1075 nm, Analytical Spectral Devices (ASD), Inc., Boulder, USA). The scanning was undertaken using the 25° field-of-view (FOV) of the spectroradiometer. The reflectance spectra from 325 to 1075 nm were measured at 1.5 nm intervals. Following the method described by Nawi et al. (2013a), the spectral scanning were conducted inside a black box where two halogen lamps (Lowell Pro-Lam 14.5 V tungsten bulb, Ushio Lighting, Inc., Japan) were used to provide illumination to the sensor. The lamps were placed at a distance of 800 mm above the sample at the angle of 45°. The distance between sample and sensor was set at 70 mm, resulting in a measured spot of 0.031 m diameter as calculated based on formula given by ASD (2005). Distance between sensor and samples were maintained by fixing the sensor to a tripod and samples were held by a fixed sample holder.

The equipment was set to record the average reading of 25 scans for each spectrum. Relative reflectance spectra were calculated by dividing stalk radiance with reference radiance from a spectralon white reference panel for each wavelength. Later, the reflectance data were transformed into absorbance data. All spectral data were stored in a computer and processed using the RS3 software for Windows (Analytical Spectral Devices, Boulder, USA) designed with a Graphical User Interface. In order to avoid a low signal-to-noise ratio, the first and last 75 nm data points were removed from the original spectral data. Therefore, only the wavelength regions between 400 and 1000 nm were used for the calculations. Then the spectra of each portion (C1 to C4) from the same internode were averaged into one internode spectrum and later used in calibration and prediction model development.

2.3 Spectral data preprocessing

Before the calibration, the spectral data was preprocessed for optimal performance. Preprocessing of spectral data is a key part of spectral analysis to improve the accuracy. In this study, multiplicative scatter correction (MSC) was applied. MSC technique is the most popular normalization technique offered by most chemometrics software packages MSC is used to correct for light scattering variations in reflectance spectroscopy (Næs et al., 2004). The pretreatments were implemented by “The Unscrambler V 9.6” (Camo Process AS, Oslo, Norway).

2.4 Brix measurement

After the spectra acquisition, all of the cut sections from the same individual internode were squeezed using a clamp to extract a representative juice sample for Brix measurement. The extracted juice of each cut section from the same internode was collected and mixed in a container, shaken and poured onto refractometer to measure the Brix. The Brix measurement was made using handheld Brix refractometer (Model: RHB-32ATC, China, the Brix range is 0-32% with automatic temperature compensation).

2.5 Moisture content measurement

A standard industry method for moisture content (MC) determination of prepared sugarcane is achieved by using Spencer type drying ovens with air at 100-105 °C for an approximately one hour until constant weight was obtained (BSES, 2001). However, since this standard method was designed to process high volume of samples per time (e.g. 1000 g samples for SRI type oven), it is not practical to be applied for processing an individual internode sample. Instead, the MC of each internode sample was obtained by drying the samples at 60 °C for 24 hr (Purcell et al., 2009). The weight of wet internode sample and metal container, W_I was measured before it was squeezed for the Brix measurement. After the sample was squeezed, it was put into a metal container and placed into a drying oven to determine the weight of dried internode, D_I (Fig. 2). The drying oven used was Qualtex, Solidstat, model OM18SZ2, manufactured in Australia by Watson Victor Ltd, which operated in the temperature range of 0 to 270°C. The MC of each internode was determined based on a wet basis method (MC %, w.b.) using the following formula:

$$MC, \% \, (w.b.) = \frac{W_I - D_I}{W_I} \quad (1)$$

where W_I is weight of the wet internode with metal container and D_I is weight of the dried internode with metal container.

Fig. 2. Cut section of internode samples which have been oven dried.

2.6 Fibre content measurement

Fibre content (FC) can be determined using Method 4 (BSES 2001) by washing the fibrated samples (in a cotton cambric bag) for three cycles in an automatic washing machine, and drying at 100-105°C for approximately one hour until constant weight was achieved. However, due to a small volume of individual internode sample, this standard method is not practical to be adopted. In this study, the FC for each internode sample was determined using the mathematical method proposed by Watson et al. (1999) as detailed below:

$$°Brix \; in \; sugarcane = Brix \; in \; juice \; x \; \frac{\left(100 - (fibre \,\% + 3)\right)}{100} \quad (2)$$

$$Fibre \,\% = 100 - moisture \,\% - °Brix \; in \; sugarcane \quad (3)$$

Combining the above equations yields:

$$Fibre\ \% = \frac{(100^2 - 100\ \times moisture\ \% - 97\ \times °Brix\ of\ juice)}{(100 + °Brix\ of\ juice)} \tag{4}$$

2.7 Development of calibration and validation models

Before the calibration, the internode samples were divided into two sets. One set (75%) was used to develop a prediction equation (calibration set) and another part (25%) was used to validate the predictive equation (validation set). Samples for validation were selected by taking one of every four samples from the whole sample set, ensuring that the validation process was performed using a set comprising 30 samples which has not been included in the calibration development. Prior to the development of calibration model, the spectra data was analyzed using principal component analysis (PCA) method in order to extract useful information, decrease the noise and reduce the number of latent variables (Wu et al., 2008). PCA was also used to detect some spectral outliers which could affect model performance in each data set. One identified outlier was found in the data set and removed before the development of the PLS models.

Partial least square (PLS) is a multivariate-regression method which is widely applied for spectral data analysis. PLS models do not include latent variables that are less important to describe the variance of the quality parameter (Jong, 1993). Thus, PLS method was used in this study to interpret the spectra and develop calibration and prediction models for all ternary parameters. In the development of PLS model, full cross validation (leave-one-out) was used to evaluate the quality and prevent over-fitting of the calibration model (Arana et al., 2005). In this paper, the PLS models were developed using The Unscrambler V 9.6 software with maximum ten principle components (PCs). The performance of the final PLS calibration models was evaluated by the coefficient of determination for prediction (R^2) and root mean square error of prediction (RMSEP). A proper model should have a low RMSEP but high R^2 values for both calibration and prediction models.

3. Results and discussion

3.1 Spectra overview for skin and cross sectional scanning

The summary of statistical characteristics for calibration and prediction data sets of internode samples is shown in Table 1. Generally, all ternary parameters in both data sets showed similar statistical characteristics. A relatively wide range of Brix values (11 to 22.2) was found due to the inclusion of three different varieties with different maturity stages. The range of moisture (66 to 84.2%) was in the comparable range (62.3 to 89.4%) as reported by Staunton et al. (2011). The mean of fibre found in this study of 5.4% was lower than the fibre content of 10.6% as reported by Staunton et al. (2011). The difference was due to the fact that this study used individual internode samples while Staunton et al. (2011) used the fibre content measured from prepared sugarcane samples.

Table 1. Summary of statistical characteristics of internode samples.

Model	Sample no	Component	Max	Mean	Min	SD
Calibration	95	°Brix	22.2	18.4	12.2	2.39
		Fibre (%)	11.5	5.4	0.4	2.51
		Moisture (%)	84.2	75.8	66.0	3.65
Prediction	30	°Brix	21.9	18.2	11	2.60
		Fibre (%)	8.3	5.4	0.2	2.47
		Moisture (%)	83.3	76.0	68.8	3.93

SD = Standard deviation

Typical absorbance curves of CSSM and SSM are shown in Fig. 3. The spectral curves of both CSSM and SSM in the range of 400 to 1000 nm look similar with obvious absorption peaks around 680 and 958 nm. The peak of 680 nm was probably due to chlorophyll pigment (Abbott et al., 1997). The absorption peak around 958 nm could be related to water in the stalks (Williams and Norris, 1987). From 700 nm onwards, it can be seen that the curve represents CSSM was higher than the SSM curve. The difference was due to a sugarcane flesh having higher absorption than sugarcane skin surface. This finding was consistent with a study conducted by Lu et al. (2000) on peeled and unpeeled apples. This pattern also suggested that the cross-sectional surfaces reflected more incidents light back to sensor than the skin. Since the skin scanning was applied on fresh sample with cylindrical shape, only the incident light that fell on the direct surface with light source would be reflected back to sensor while most of the incident light was reflected somewhere else.

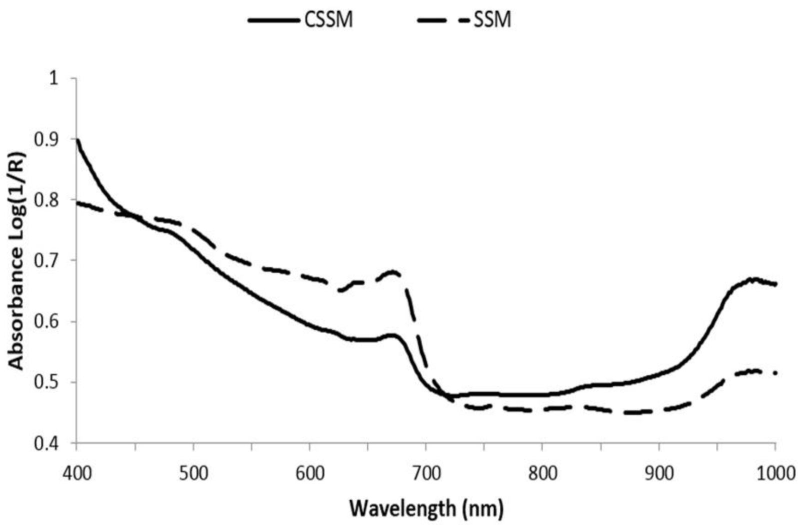

Fig. 3. Typical of absorbance curve of CSSM and SSM.

3.2 Selection of the best parameter for spectroscopic prediction

The performance of PLS models in predicting ternary parameters based on both SSM and CSSM methods are presented in Table 2. The R^2 and RMSEP of prediction model were used to measure the models performance. Generally, SSM performed better than CSSM in predicting ternary parameters. For example, R^2 and RMSEP of FC prediction by SSM were 0.93 and 0.86, whereas for CSSM were 0.83 and 1.63 respectively. This difference was probably due to the nature of the skin surface which was homogenous in terms of surface roughness and color. However, the relatively low R^2 result for SSM was due to the fact that the surface of the stalk was coated with a thin protective layer of waxy material which varied in amount with the type of cane, and was moisture resistant (Barnes, 1953). On the hand, the prediction ability for CSSM depended on fibre characteristic and moisture level.

Among these three ternary parameters, MC was found to be the best parameter to be predicted by VNIRS using both scanning methods. For Brix and FC, the accuracy varies for different methods. For SSM, the prediction of FC yielded the highest accuracy (R^2 = 0.93) while for CSSM, the prediction of Brix and MC yielded the same accuracy values (R^2 = 0.89). Overall, the prediction performance for all quality parameters was reasonably good with all R^2 values are above 0.80. The accuracy obtained in this study is acceptable for real field application considering the heterogeneous nature of the internode samples and the difference Brix values of stalks from bottom to the top. The results indicated that VNIRS and PLS can provide a satisfactory method for predicting sugarcane quality parameters from solid samples.

Table 2. Performance of PLS models in prediction TGM parameters.

Component	SSM					CSSM				
	LVs	Calibration		Prediction		LVs	Calibration		Prediction	
		R^2	RMSEC	R^2	RMSEP		R^2	RMSEC	R^2	RMSEP
°Brix	10	0.90	1.04	0.88	1.19	10	0.87	1.15	0.89	1.14
Fibre	10	0.91	0.99	0.93	0.86	10	0.93	0.92	0.83	1.63
Moisture	10	0.89	1.56	0.90	1.70	10	0.94	1.26	0.89	1.87

n = sample number; LVs = latent variables

4. Conclusions

This study has demonstrated the ability of spectroscopic method as a portable, rapid, less expensive and nondestructive measurement technique to predict sugarcane quality parameters by directly scanning the stalk samples. Based on SSM, the prediction results for Brix, FC and MC as represented by R^2 were 0.88, 0.93 and 0.90, respectively. For CSSM, the R^2 for Brix, FC and MC were 0.89, 0.83 and 0.89, respectively. Overall, it is found that SSM performed better than CSSM in predicting ternary parameters. The results showed that the prediction of sugarcane ternary parameters using spectroscopic is feasible. These results suggested that the spectroscopic method can be used to predict sugarcane quality in the field based on stalk samples. However, further research is needed before this method can be installed on a chopper harvester to produce quality map across the paddock.

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