NIR assessment of soluble solids and dry matter content in a range of fruits and vegetables

K.B. Walsh,[a] M. Golic,[a] C.V. Greensill[b]

[a]*Plant Sciences Group, Central Queensland University, Rockhampton, 4702, Australia*

[b]*Faculty of Engineering and Physical Systems, Central Queensland University, Rockhampton, 4702, Australia*

Introduction

Fruit quality is described primarily by sugar content (as indexed by soluble solids content, SSC), by dry matter content (DM, as a measure of starch content) and acidity[1]. Near infrared (NIR) spectroscopy has been used for the non-invasive assessment of fruit SSC and DM over the last several decades. Literature reports, however, have involved the use of a wide array of instrumentation, varying in optical geometry, wavelength resolution, detector type and electronic stability. These reports also vary widely in the type of chemometric treatment (MLR, PLS, use of derivatives) and in population structure for calibration and validation sets. Given these differences, comparisons of the performance of the technique across different fruit types have been limited.

In this study a single NIR instrumentation platform and chemometric approach was used to develop calibration models across a range of fruits.

Materials and methods

Spectra were acquired using a Carl Zeiss MMS1/NIR-enhanced spectrometer (300–1100 nm), with a teflon plate as a white reference. The spectrometer was used in the "non-contact" configuration reported by Greensill and Walsh (2000), in which a single 100W lamp and a colliminating lens at the front of the detector assembly (15 mm diameter) was employed.[2] Spectra were acquired at integration times varied between fruit types in order to achieve a similar signal level, i.e. 10 ms for tomatoes, 15 ms for apple and nectarines, 20 ms for peaches and rockmelons, 30 ms for mandarins and 50 ms for pineapples. Fruit were positioned approximately three centimeters from the front of the detector assembly.

Juice was extracted from a 20 mm diameter core, following removal of the non-edible 'skin'. Juice was assessed for Brix using a digital refractometer (RFM320; Bellingham & Stanley Ltd). Dry matter content was assessed following oven drying at 70°C for 24 h.

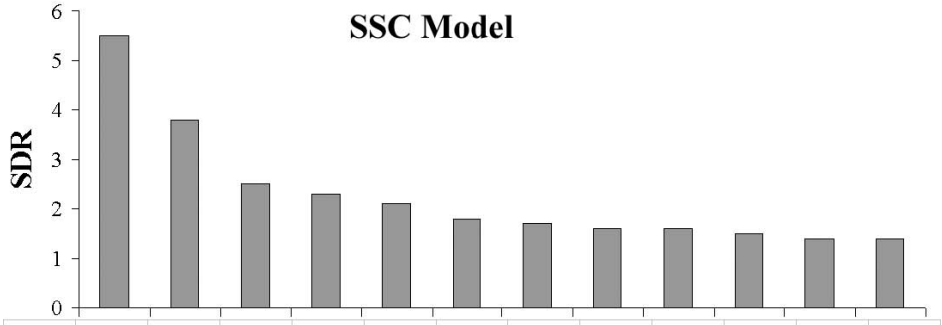
The Unscrambler v7.5 chemometric software was used for PLS regressions on spectral (Savitzky–Golay second derivative of absorbance over half window of four pixels using a second order polynomial) and constituent data. Calibration performance for determination of soluble solids content (SSC) of a range of fruit was compared in terms of root mean standard error of cross-validation (*RMSECV*), regression coefficient (*R*), and the standard deviation ratio (*SDR* = *SD*/*RMSECV*).

Results and discussion

SSC calibration performance varied between fruit types, with a *RMSECV* of 0.3 or less recorded for apple, tomato, peach and nectarine, a *RMSECV* of less than 0.5 recorded for plums and

Near Infrared Spectroscopy: Proceedings of the 11th International Conference.

mandarins, and a *RMSECV* of 0.9 or less recorded for papaya, onion, rockmelon, banana and honeydew (Figure 1).



Fruit	Apple	Peach	Nectarine	Banana	Mandarin	Plum	Onion	Papaya	Rockmelon	Honeydew	Pineapple	Tomato
n (outliers)	100 (1)	100 (3)	87 (3)	56 (2)	100 (2)	50 (2)	100 (1)	100 (0)	100 (5)	100 (1)	100 (5)	110 (4)
Mean	13.7	9.1	9	21.3	14.1	13.6	6.7	11.1	7.9	8.4	14.7	4.65
SD	1.21	1.13	0.76	1.76	1.05	0.86	1.26	1.16	1.21	1.38	1.81	0.3
RMSECV	0.22	0.3	0.3	0.89	0.49	0.47	0.73	0.71	0.73	0.9	1.19	0.22
R	0.98	0.96	0.9	0.86	0.88	0.84	0.81	0.79	0.79	0.75	0.69	0.7
Terms	11	7	6	3	5	8	4	5	6	5	7	4

Figure 1. PLS1 calibration model statistics for soluble solids content across a range of fruit, based on 734 to 931 nm interactance spectra.

Calibration performance, in terms of *RMSECV*, was related to skin (non-edible portion) thickness. Good results were obtained with thin skinned fruit (exocarp, *ca* 1 mm depth), such as apple and tomato. In these fruit, the tissue sampled optically was the same as that assessed by destructive procedures. In apple, the sampled (mesocarp) tissue was also structurally homogenous flesh, with little variation in the attribute of interest within the sampled region. Thus better results were recorded for peaches and nectarines, with thin skin and reasonable mesocarp homogeneity, compared to mandarins, which have a thicker skin (exocarp and mesocarp, *ca* 5 mm depth) and relatively inhomogenous flesh (endocarp, being comprised of numerous juice sacks which create a variety of scattering centres). Rockmelons were relatively poor in terms of model *RMSECV*, as expected for a fruit with a thick rind (exocarp and non-edible mesocarp, *ca* 10 mm).

A calibration offset was also caused by the presence of significant levels of organic acids (data not shown). Such acids contribute to refractometer readings, inflating apparent SSC.

The current optical sampling geometry was not appropriate to fruit such as pineapple (*RMSECV* > 1).

However, while instrumentation and chemometric treatment were constant, population constituent range varied between commodity groups. Thus calibration performance was also influenced by the range (SD) of the attribute of interest. SDR is a measure of the utility of a prediction with respect to population variation.

Model results for the apple population were excellent (SDR = 5.5), consistent with the thin skin and a reasonable population variation (SD > 1 SSC). Peaches and nectarines are closely related in botanical terms, and have similar skin thickness and mesocarp homogeneity. However, the SD of the peach population employed was higher than that of the nectarine population (1.13 and 0.76, respectively), and this is reflected in model performance in terms of SDR. This principle was most clearly illustrated with tomato, for which calibration performance was excellent in terms of

RMSECV and poor in terms of SDR, a function of the low standard deviation value of the sample set.

The technology was also well suited to sorting of dry matter content in kiwifruit (*RMSECV* 0.38, SDR > 3, R 0.94), and useful, in decreasing order of accuracy, for sorting of banana, mango, avocado, potato and tomato (tomato: *RMSECV* 0.23, SDR 1.3, R 0.75) (Table 1). As for the SSC models, the level of model performance is attributed to skin thickness, tissue homogeneity and population variation.

Table 1. PLS1 calibration model statistics for dry matter content across a range of fruit, based on 734 to 931 nm interactance spectra.

Fruit	*n* (outliers)	Mean	*SD*	*RMSECV*	*R*	Terms	*SDR*
Kiwifruit	144 (0)	15.3	1.2	0.38	0.94	5	3.3
Banana	87 (1)	29.2	3.6	1.36	0.93	4	2.7
Mango	112 (0)	15.3	1.1	0.46	0.89	4	2.4
Avocado	100 (0)	20.5	2.5	1.15	0.86	3	2.1
Potato	49 (1)	13.4	1.7	1.09	0.76	5	1.6
Tomato	104 (6)	5.6	0.3	0.23	0.75	7	1.3

Fruit could also be classified into broad type using PCA and SIMCA (Table 2). Only peaches gave extraordinary classifications with four misclassified as nectarines (not an unusual expectation) and one as rockmelon (an highly unusual classification, although representing only 1% of the total population). It was not possible to differentiate between the apple varieties Hi Early and Granny Smith (using the wavelength range 734 to 931 nm).

Table 2. SIMCA classification of fruit type based on 734 to 931 nm interactance spectra.

	Not Identified	Apple Hi Early	Apple Granny Smith	Peach	Nectarine	Mandarin	Rock-melon	Pine-apple	Tomato	Total
Apple- Hi Early	4	43	53							100
Apple- Granny Smith	4	40	56							100
Peach	2			94	4		1			100
Nectarine	2				85					87
Mandarin	1					103				104
Rockmelon	4						90			94
Pineapple	—							100		100
Tomato	6								104	110

Conclusions

We have assessed the performance of a single instrumentation platform and chemometric procedure for predicting SSC and DM content in fruits and vegetables. The optical arrangement employed is well suited to prediction of SSC of apples, stonefruit and mandarins and of DM in

kiwifruit, mango and avocado. The technique could also be useful in sorting other fruit where a larger variation (SD) of the SSC and DM exists in the population of interest.

Acknowledgements

We thank Horticulture Australia Ltd. for funding support.

References

1. For example see: S. Kawano *NIR news*, **5(6),** 10 (1994).
2. C.V. Greensill and K.B. Walsh, *Meas. Sci. Technol*. **11,** 1176 (2000).