LWT - Food Science and Technology 42 (2009) 1125–1131

Contents lists available at ScienceDirect

LWT - Food Science and Technology

journal homepage: www.elsevier.com/locate/lwt

Non-destructive assessment of apricot fruit quality by portable visible-near infrared spectroscopy

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ARTICLE INFO

Article history:
Received 5 May 2008
Received in revised form
21 January 2009
Accepted 29 January 2009

Keywords:
NIR
Apricot
Quality
Non-destructive
PLS-regression
FDA

ABSTRACT

The ability of portable Near Infrared Spectroscopy to determine apricot fruit quality has been studied. Calibration models allowing the determination of soluble solids content (SSC), total acidity (TA) and firmness (Fi) of apricots were carried out with variable precisions. Models were built for each variety and global models combining different varieties were attempted. SSC was determined with a root mean square error of cross-validation (RMSECV) comprised between 0.67 and 1.1 °Brix and *R*-values between 0.88 and 0.96. Concerning Fi, the accuracy of the prediction was variety dependant. These predictions were correct for the varieties Kioto and Harostar with RMSECV-values between 6.2% and 13% (*R*-values between 0.85 and 0.92) and unsatisfactory for Bergarouge (RMSECV = 24%). TA was predicted with RMSECV-values between 0.79 and 2.61 g 100 ml^{-1} and *R*-values between 0.73 and 0.97. In a second application, near infrared spectra were used to classify apricot fruits according to their variety and colour intensity with correct efficiency. The results obtained in the present study showed that NIRS technology could be applicable to apricot quality and that such portable devices could help to obtain a complete follow-up of the fruits in orchards and during post-harvest.

1. Introduction

During the last decades, the development of rapid and non-destructive methods allowing the measurement of food quality has increased (Chen & Sun, 1991). Concerning fresh apricot production, the determination of fruit quality overcomes an important problem of sampling. Apricot quality is particularly variable depending on the variety, geographical origin, environmental factors and fruit location on the tree. The influence of these numerous acting factors in the orchard consequently creates significant variability at harvest time, making the organization of fruits in homogeneous batches difficult (Grotte, Gouble, Reling, Bogé, & Audergon, 2006). The development of a non-destructive method could allow the analysis of a larger number of fruit and so reduce the problems of sampling. Also, to be efficient, such measurement must be rapid due to the large number of fruits to be analyzed by the growers and industry.

The official standard of apricot quality only relies on the fruit calibre. However, physico-chemical requirements are regularly established for every new variety (Lurol, Hilaire, Lichou, & Jay, 2007). The two most important features measured on apricot are the soluble solids content (SSC) expressed in °Brix and the firmness, measured with a durofel device fitted with a 0.1 cm^2 diameter probe, expressed in DI_{10} (Durofel Indice). Such methods are expensive, time consuming and require the analysis of a subset of fruits that must be representative of a large batch.

Among the non-destructive methods applied to agriculture, Near Infrared Spectroscopy (NIR) is probably the most studied and accomplished one. Most studies focused on apple, mango and kiwi fruit. On apple fruit, absorbance in the NIR range has been correlated to consumer preferences or sensory panels to determine the organoleptic properties (Mehinagic et al., 2003) and the physico-chemical features such as SSC, acidity and firmness (Camps, Guillermin, Mauget, & Bertrand, 2007b; McGlone, Robert, Martinsen, & Martinsen, 2002; Moons & Sinnaeve, 2000; Ventura, De Jager, De Putter, & Roelofs, 1998; Zude, Herold, Roger, Bellon-Maurel, & Landahl, 2006). Also, NIR has been used to determine the optimal picking date of apple (Peirs, Lammertyn, Ooms, & Nicolaï, 2000), to detect some internal fruit disorders (Clark, McGlone, & Jordan, 2003) and to classify the apple fruit during storage and a shelf-life period (Camps, Guillermin, Mauget, & Bertrand, 2007a). Schmilovitch, Mizrach, Hoffman, Egozi, and Fuchs (2000) established several correlations between NIR data and various physiological parameters of mango fruit. Other studies allowed to determine the internal quality of kiwi fruit (McGlone, Jordan, Seelye, & Martinsen, 2002; McGlone & Kawano, 1998; Schaare & Fraser, 2000).

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doi:10.1016/j.lwt.2009.01.015

Until now, few studies about the NIR application to apricot fruit quality have been performed. In order to have a better follow-up of fruit quality and maturity in pre-harvest and during storage, a portable technology would be suitable. Only a few studies have been carried out with such technology on apricot or on others fruits. Carlini, Massantini, and Mencarelli (2000) who worked with a laboratory NIR spectrometer reported correct levels of correlations between SSC and NIR absorbance of apricot. Such results show the potential for developing an NIR technology as a non-destructive tool for measuring apricot quality.

Thus, the aim of the present study was to determine the quality of three apricot varieties by non-destructive NIR spectroscopy, using a portable device. Two approaches were tested:

- First, in order to determine the SSC, TA and Firmness values of apricot, spectra and data obtained from destructive tests were subjected to PLS regressions (Partial Least Square Regression).
- In a second approach, the NIR data as classification tool were analyzed. Spectra were subjected to a FDA (factorial discriminant analysis) to classify the fruit according to the variety and according to the coloured or non-coloured side.

2. Materials and methods

2.1. Apricot fruit

Three apricot varieties were analyzed in our study, Bergarouge, Harostar and Kioto. Fruits were harvested in the experimental orchards of the AGROSCOPE Changins-Wädenswil ACW Research Station (Switzerland) in 2007. Fruits were packed in cartons directly after harvest and brought to the laboratory and analyzed the same day. Bergarouge ($n = 66$) and Harostar ($n = 66$) were picked on a single day while two dates of harvest were necessary for the picking of Kioto. The two dates defined two levels of fruit maturity at the harvest moment. Therefore, Kioto fruits were separated into two batches, Kioto (1) ($n = 66$) and Kioto (2) ($n = 66$), Kioto (2) being harvested one week after Kioto (1). A total of 264 apricot fruits were used for the experiment.

2.2. NIR spectroscopy

Spectra were directly acquired, in reflectance mode, on the whole fruit using a Visible-NIR spectrometer (Costa, Fiori, & Noferini, 2006). The portable NIR device consisted of a commercial single-beam spectrometer (Ocean optics S-2000, USA) with a standard diffraction grating (650–1200 nm, near infrared). A 10-watt tungsten halogen lamp generated the light. The reflected light was directed to the spectrometer via a bundle of 7200-μm optical fibre linked to the probe end (Costa, Noferini, Fiori, Miserocchi, & Bregoli, 2001).

Fruits were equilibrated at room temperature approximately half a day before spectral acquisitions. A blank scan was carried out before each set of analyzed sample. For each fruit, visible-NIR measurements were carried out on opposite sides (coloured and reverse (non-coloured) side) along the equator of the fruit. Two spectral measurements per fruit were done, resulting in a total of 528 spectra.

2.3. Pre-treatment of spectral data

Two pre-treatments were applied to the spectra to cope with the effects of uncontrolled baseline and intensity variations. These pre-treatments were the following:

(1) The standard normal variate correction (SNV) method (Barnes, Dhanoa, & Lister, 1989).
(2) A second derivative applied on spectra after SNV in order to minimise the overlapping effect of absorption bands and variations due to radiation scattering (Moons & Sinnaeve, 2000).

2.4. Destructive analyses

Firmness (Fi) of apricots was measured using a durofel device fitted with a 0.10 cm^2 probe (Durofel, COPA-Technologie S.A./CTIFL). Two measurements were performed per fruit, first on the coloured side and then on the reverse side. The results were expressed in DI_{10} (Durofel Indice, where the durofel device was fitted with a 0.10 cm^2 probe).

Immediately after Fi measurements, each fruit was mixed using a juice centrifuge and the obtained juice was filtered using a filter paper (S & S faltenfilter, LS 14.5, Schleicher & Schüll AG, CH-8714 Feldbach). The filtered juice was used to measure the soluble solids content and total acidity. One measure of soluble solids content and total acidity was performed per fruit.

Soluble Solids Content (SSC) of filtered juice was determined using a refractometer (ATAGO, C.O., LTD, Model PR-1) and expressed in °Brix.

Total Acidity (TA) has been measured by using a titrimeter (Metrohm, 719S, Titrino). 5 ml of filtered juice was titrated with NaOH (0.1 mol/L) and the results were expressed in meq 100 ml^{-1}.

2.5. Factorial discriminant analysis (FDA)

FDA was carried out on the spectral data. A given spectrum curve forms a vector x_i of p wavelengths. The n spectra were gathered into a matrix X dimensioned $n \times p$. In FDA, the qualitative groups to be discriminated were the varieties (Bergarouge, Harostar, Kioto (1) and Kioto (2)) and the fruit side (coloured side: C and uncoloured side: N).

A criterion of the FDA efficiency is the proportion of correctly classified observations in validation sets. These validation tests were carried out by dividing the data matrix, X, into a training and a validation set. The FDA model was computed on the calibration set. The observations of the validation set were then classified using the established model. The correctly classified observations were then counted and expressed in percentages. Such validation tests were independently carried out ten times, placing two thirds ($2n/3$) of the observations in the calibration set and the remaining ones ($n/3$) in the validation set. FDA computes a set of discriminant scores, which are linear combinations of the original variables.

The discriminant scores are new "synthetic variables" calculated so they can discriminate the observations. It is interesting to examine the correlation between the discriminant scores and the predictive variables. For this purpose, the correlation coefficients between the discriminant scores and the original variables (600 steps of wavelength absorbencies) were computed. As it is impossible to show 600 values of correlation coefficients, the correlation values were graphically represented as curves giving the correlation coefficient of the absorbance at each wavelength with a given discriminant score. All the statistical procedures were carried out using the Matlab 6.0 environment (The MathWorks, Inc., Natick, MA USA).

2.6. PLS regression

Partial least square regressions (PLS) were carried out to perform linear models of prediction between spectral data and the values obtained from the destructive tests. In order to get efficient

and reliable models, a minimum number of latent variables were used in the models (Peirs, Scheerlinck, & Nicolaï, 2003). Cross-validation procedures were used by placing [2/3] of spectra as the calibration set and the remaining [1/3] as the validation set. The accuracy of the predictions was discussed according to the correlation coefficient value (R, Eq. (1)), the root mean square error of calibration (RMSEC, Eq. (2)) and the root mean square error of cross-validation (RMSECV, Eq. (3)).

$$R = 1 - \sqrt{\frac{\sum(y_{cal} - y_{act})^2}{\sum(y_{cal} - y_{mean})^2}} \quad [1]$$

$$\text{RMSEC} = \sqrt{\frac{\sum(y_{cal} - y_{act})^2}{n}} \quad [2]$$

$$\text{RMSECV} = \sqrt{\frac{\sum\left(y_{pred} - y_{act}\right)^2}{n}} \quad [3]$$

n is the number of spectra, y_{act} the actual value, y_{mean} the mean value, y_{cal} the calculated value and y_{pred} the predicted value of the physical parameter.

The interpretation of predictive models is known to be difficult in terms of wavelengths importance. Because of the co-linearity of the wavelengths, it is impossible to isolate a single one but the interpretation of absorption bands remains possible (McGlone & Kawano, 1998). Different interpretations of PLS models exist, either according to the PLS factors or regression beta-coefficients. In our study, the interpretation of the beta-coefficients is used to determine the relevant wavelengths regions of the models. An important value of the beta-coefficient is interpreted as a relevant absorption region for the considered predictive model. All PLS modes were carried out using the Matlab 6.0 environment (The MathWorks, Inc., Natick, MA USA)

3. Results and discussion

3.1. Apricot quality

Table 1 shows the values of quality features measured on each apricot variety. SSC and Fi were significantly different for the three varieties. No difference was measured between the fruits of the two harvest dates for Kioto. Harostar presented the highest SSC and Fi values and Bergarouge the lowest. Concerning TA, significant differences were measured among all varieties but also between Kioto (1) and Kioto (2), Kioto presenting the highest TA-value and Bergarouge the lowest.

Fi of coloured and uncoloured sides was also compared. No significant difference was measured but it was noted that coloured sides were slightly firmer than non-coloured ones for all varieties. Significant differences measured among the three apricot varieties allowed a large range of quality values to be determined. This large range of values will be used in the following part of the study that aims at building predictive models of apricot quality.

Table 1
Values of firmness (Fi), soluble solids content (SSC) and total acidity (TA) measured on apricot fruit. N: non-coloured fruit side, C: coloured fruit side and n: the number of fruits.

Variety	Analyzed fruit side	Parameters of quality			
		Firmness	Firmness	SSC	TA
Bergarouge ($n = 60$)	N ($n = 30$)	48.43[a]	51.16[a]	11.52[a]	14.52[a]
	C ($n = 30$)	53.88[a]			
Harostar ($n = 60$)	N ($n = 30$)	76.42[c]	77.11[c]	13.32[c]	25.47[b]
	C ($n = 30$)	77.78[c]			
Kioto (1) ($n = 60$)	N ($n = 30$)	65.74[b]	67.73[b]	11.86[b]	29.46[d]
	C ($n = 30$)	69.78[b]			
Kioto (2) ($n = 60$)	N ($n = 30$)	66.63[b]	66.89[b]	11.93[b]	27.59[c]
	C ($n = 30$)	67.15[b]			
Degree of freedom		7	3	3	3
F-value		70.23	154.18	79.88	1084.12
p-value		<0.05	<0.05	<0.05	<0.05

Numbers with different superscript letters within columns by variety or fruit side differ significantly ($p < 0.05$) by analysis of variance and Tukey test.

3.2. PLS prediction of SSC, TA and firmness

In order to determine the quality features of the three apricot varieties (Bergarouge, Harostar and Kioto), PLS regression models were built using a collection of 528 spectra. For the development of predictive models, Kioto (1) and Kioto (2) were pooled in a single batch (Kioto). First, calibrations were attempted paying particular attention to choosing a relative small number of latent variables (LV) to be introduced to the models. Limiting this number is necessary in order to perform a reliable model. This choice was carried out by performing artificial models in which a large number of LV has been introduced. The optimal number of LV corresponds to a compromise allowing a model presenting both the relative lowest RMSECV-value and highest R-value. Fig. 1 shows an example of an artificial model aiming at predicting SSC-values for Bergarouge. In this case, the optimal number of LV lies between 5 and 7, corresponding to the inflexion curves of both R- and RMSECV-values as a function of LV number. In our study, the smallest number of LV was always privileged, here corresponding to 5. A similar procedure was performed to determine the number of LV of all PLS models (Table 2).

SSC was reliably predicted regardless of the apricot variety. SSC was particularly well predicted for Kioto with a coefficient correlation value of 0.90 and an RMSECV-value of 0.67 °Brix, which represent a precision of 5.7% (Table 2). Predictions were similar for Harostar and slightly less efficient for Bergarouge which rose to 1.0 °Brix (9.2%).

Prediction of Fi was attempted and succeeded for two varieties, Harostar and Kioto. Harostar PLS-values were particularly reliable with RMSEC and RMSECV-values of 3.4% (2.7 DI_{10}) and 6.2% (4.87

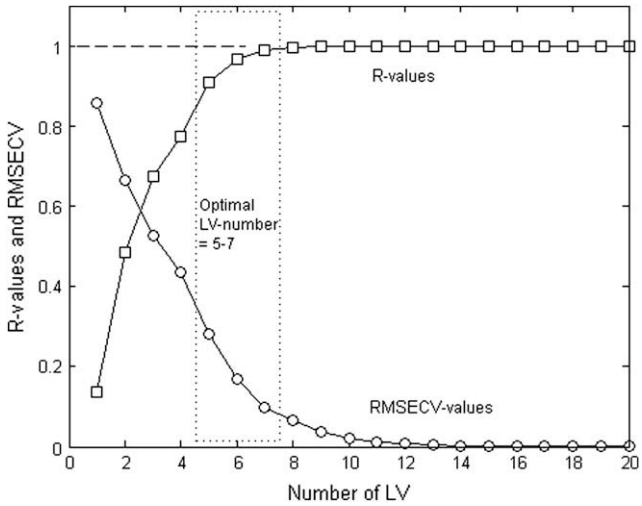

Fig. 1. Number of latent variables. Determination of the optimal number of latent variables for the prediction of soluble solids content of the variety Bergarouge. R-values (square symbols) and RMSECV-values (circle symbols) as a function of the number of latent variables (LV) introduced in the PLS model. R-values: correlation coefficient, RMSECV: root mean squares error of cross-validation.

Table 2
PLS-values for soluble solids content (SSC), total acidity (TA) and firmness (Fi) models, B: Bergarouge, H: Harostar and K: Kioto and for the global models (all varieties gathered in a single data set): B + H + K. LVs: number of latent variables, *R*: correlation coefficient, RMSEC: root mean square error of calibration (relative RMSEC), RMSECV: root mean square error of cross-validation (relative RMSECV), Min: minimal value, Max: maximal value and mean: mean value.

Parameters	Variety	LVs	*R*	RMSEC	RMSECV	Min	Max	Mean
SSC	B + H + K	8	0.90	0.6 (4.7%)	1.1 (9.32%)	8.7	16.3	12.2
	B	5	0.96	0.25 (2.2%)	1.0 (9.2%)	9.40	13.10	11.35
	H	3	0.88	0.38 (2.9%)	0.97 (7.2%)	10.5	16.3	13.32
	K	4	0.90	0.29 (2.4%)	0.67 (5.7%)	10.1	13.2	11.93
TA	B + H + H	7	0.91	2.47 (9.6%)	4.39 (17.5%)	11.36	40.88	25.06
	B	7	0.97	0.3 (2.0%)	1.8 (12.9%)	11.36	17.58	14.43
	H	3	0.90	0.95 (3.8%)	0.79 (7.1%)	20.38	30.06	25.47
	K	5	0.73	1.61 (5.9%)	2.61 (9.4%)	23.42	34.46	27.58
Fi	B + H + K	7	0.88	5.4 (7.9%)	10.9 (15.0%)	24	88	68.49
	B	4	0.90	5.3 (9.8%)	13.0 (24.1%)	24	73	54.07
	H	3	0.85	2.7 (3.4%)	4.87 (6.2%)	66	88	77.79
	K	4	0.92	3.9 (5.9%)	8.9 (13.3%)	35	81	66.29

DI_{10}), respectively (Table 2). Firmness of Kioto prediction remained reliable with a RMSEC-value lower than 6% and about 13% for the RMSECV-value. Fi prediction of Bergarouge was not satisfactory with RMSECV exceeding 24% meaning about 13 DI_{10}.

Global models of SSC, TA and Fi were attempted. SSC (Fig. 2a) prediction remained correct with RMSEC and RMSECV-values of 0.6 and 1.1 °Brix, respectively (Table 2). Nevertheless, as it has been already demonstrated in previous studies, models of SSC prediction were more accurate and reliable when a single variety is considered than global model pooling several ones (Golic & Walsh, 2006; Peirs et al., 2000). The most relevant wavelengths to predict the SSC were located in the vicinity of 1040–1100 nm (Fig. 3a). In this region, absorbance is mainly related to the 2nd overtone of NH and the combination of the OH chemical bond. In practice, previous studies showed that absorbance in the vicinity of 1000 nm was correlated to SSC in apple (Kawano, 1994; Renfu & Peng, 2005; Walsh, Golic, & Greensill, 2004).

In the present study, the possibility to efficiently predict SSC of three apricot varieties using a single PLS model was shown. Global models of Fi prediction remained correct but the unsatisfactory results of Bergarouge limited the accuracy of the model. Fi was predicted with a precision of 15% (Table 2; Fig. 2b). This prediction partly relied on the absorbance in the visible range, *i.e.* 695 nm and 710 nm, meaning that skin colour changed with the decrease of Fi (Fig. 3c). McGlone, Robert, et al. (2002) and Zude et al. (2006) have already shown that a relationship existed between a decrease in chlorophyll content and apple firmness during storage or a shelf-life period. Zude et al. (2006) suggested that such relationship could be due to parallel metabolic processes of chloroplast degradation and pectin conversion occurring during the fruit maturation. Also, wavelengths in the vicinity of 990, 1050 and 1240 nm were relevant. TA prediction was less accurate with RMSEC and RMSECV-values of 9.6% and 17.5%, respectively (Table 2). Such predictions relied on absorbance at 695 nm and absorbance in the large spectral region comprised between 940 nm and 1140 nm (Fig. 3b).

Few studies have reported the ability of a portable NIR technology to determine apricot quality. Carlini et al. (2000) reported promising results showing accurate relationships between visible-near infrared absorbance and SSC of apricot. They showed that SSC could be predicted with a 0.75 °Brix precision, a result comparable to our model for Kioto and better than our other models. However, these results were obtained by collecting visible-near infrared spectra by using a NIRSystems 6500 (Silver Spring, MD, USA) spectrometer that is a laboratory device and not a portable one.

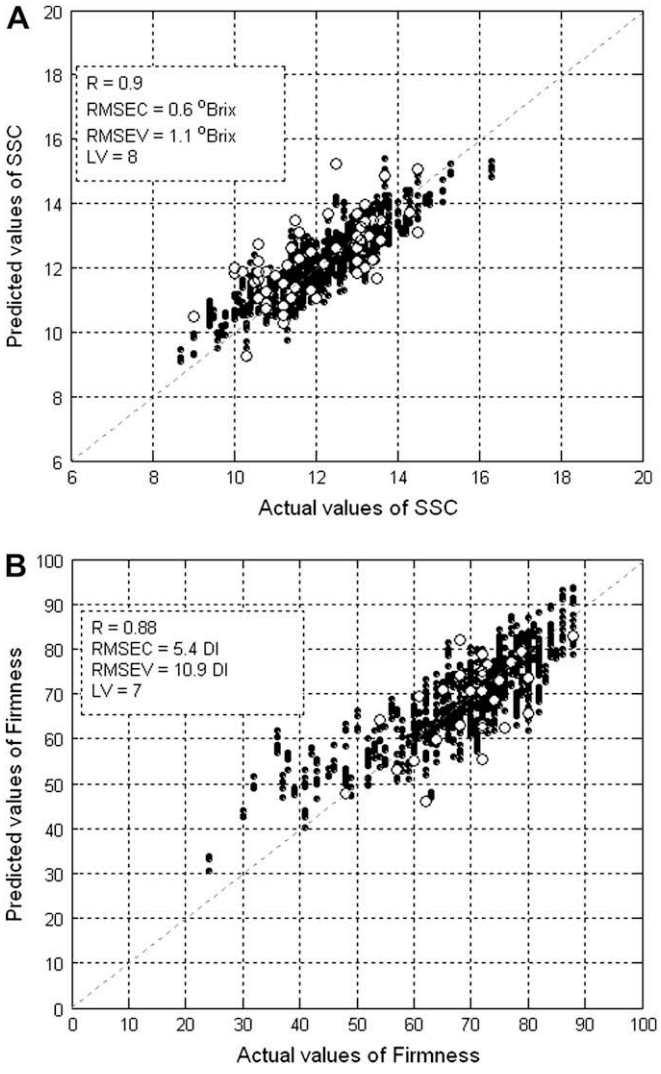

Fig. 2. PLS prediction of soluble solids content and firmness. Plots present the actual *vs.* predicted values of soluble solids content (A) and firmness (B) of global PLS models (all apricots varieties were gathered in a same data set). Full circles: calibration, white circles: cross-validation.

Furthermore, such a device measures the absorbance in a range between 400 nm and 2500 nm, a range of wavelengths which is, with difficulty, transferable to a portable device.

Costa, Noferini, and Fiori, (2004) performed a preliminary analysis aiming at predicting the SSC and firmness of two apricot varieties: Bergarouge® (Arvine) and Goldrich, by using a portable NIR device. In this study, the PLS models were built with a 30 spectra collection per variety. The authors presented a correct level of prediction of SSC with a standard error of prediction (SEP) value of 1.5 °Brix for both varieties. Firmness predictions were less accurate with SEP values between 0.34 and 0.58 kg cm^{-2} in range values of 0.2–2.2 kg cm^{-2} and 0.1–3.8 kg cm^{-2} for Bergarouge and Goldrich varieties, respectively. In the same way, Bureau, Reich, Marfisi, Audergon, and Albagnac (2005) built accurate predictions of SSC of 13 apricot varieties but they met difficulties in predicting firmness values (R^2-value = 0.48).

Firmness prediction was variety dependent and a global model could be considered if a preliminary selection of the variety to be introduced is made. In agreement with Costa et al. (2004), the results allowed us to confirm that firmness prediction of Bergarouge variety is particularly difficult.

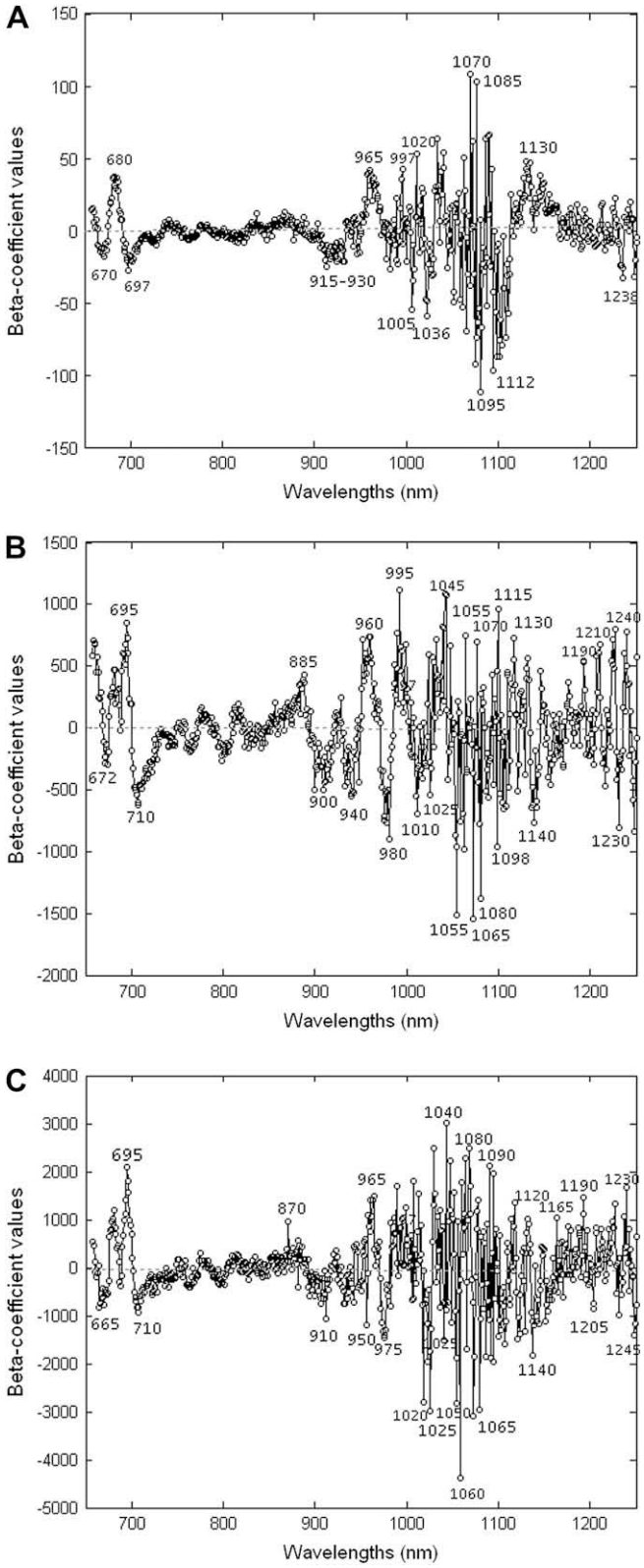

Fig. 3. Relevant wavelengths of PLS models. Beta-coefficient values of PLS prediction of soluble solids content (A), total acidity (B) and firmness (C) of the global models (all apricots varieties were gathered in a same data set).

Models of TA prediction have been established for the strawberry (Shao & He, 2008), the tomato (Pedro & Ferreira, 2007), the mandarin (Gomez, Yong, & Garcia Perreira, 2006) and the apple (Lammertyn, Nicolai, Ooms, De Smedt, & De Baerdemaeker, 1998) with correct precisions. Concerning tomato, SEP was about 9.6% what corresponds to the range of RMSECV-values obtained in our study. However, the results obtained on apricot must be carefully considered. Indeed, contrary to the variability of SSC and Fi, the values of TA did not allow covering a continued range. Consequently, studies have to be performed to reach a reliable and accurate prediction of TA.

3.3. Classification of fruit according to the variety and the analyzed side

In the first part of the study, the ability of visible-near infrared absorbance has been used as potential non-destructive measurement of SSC, Fi and TA of apricot. However, spectral data can also be used to classify the fruits according to a given variability (*i.e.* varieties, storage conditions, geographic origin, etc.).

In this second part, the ability of the visible-near infrared spectra to classify the apricot fruit according to their variety and to discriminate the two sides of the fruit was tested. The two sides of a given fruit corresponded to the coloured (C) and the non-coloured (N) side. In a first analysis, the fruit were classified according to the varieties, each variety counting 60 fruits (Bergarouge, Harostar, Kioto (1) and Kioto (2)). In a second analysis, the same fruits were classified according to fruit side of each variety. In this last analysis eight groups were classified (4 varieties × 2 fruit sides), each group counting 30 fruits (Table 3).

Table 3 shows the matrix of confusion of the FDA performed on spectra. The four groups corresponding to the varieties were correctly classified with more than 86% accuracy. Harostar and Kioto (1) were particularly well discriminated with 97% and 96%, respectively. Bergarouge and Kioto (2) were correctly classified with 86% and 92%, respectively, but some confusion appeared between this two last groups. 12% of Bergarouge fruits were assimilated to Kioto (2) and inversely, 8% of Kioto (2) fruits were classified as Bergarouge ones. However, the level of classification remained good and the confusion quite low. FDA maps allowed discriminating Kioto (1) and Harostar from Kioto (2) and Bergarouge according to the first factorial score (Fig. 4a). The second factorial score allowed differentiating Kioto from the two other varieties. The correlation between the factorial scores and the absorbance spectra at each wavelength step allowed the relevant wavelengths to be determined. Therefore, Kioto (1) and Kioto (2) were clearly classified according to absorbance in the vicinity of

Table 3
Matrix of confusion: Classification of apricot varieties by FDA performed on Spectral data. C: coloured side, N: non-coloured side, V: correct classification of varieties, V × S: correct classification of varieties according to their side.

Classification											
Group		Bergarouge		Harostar		Kioto (1)		Kioto (2)		Correct classification	
		C	N	C	N	C	N	C	N	V × S	V
Bergarouge	C	58	–	–	–	–	–	8	–	88%	86%
	N	5	51	–	–	–	–	2	8	77%	
Harostar	C	–	–	62	4	–	–	–	–	94%	97%
	N	–	1	18	44	–	1		2	67%	
Kioto (1)	C	–	–	–	1	61	2	2	–	92%	96%
	N	–	–	–	2	5	59	–	–	89%	
Kioto (2)	C	7	–	–	–	–	–	59	–	89%	92%
	N	–	4	–	–	–	–	10	52	79%	

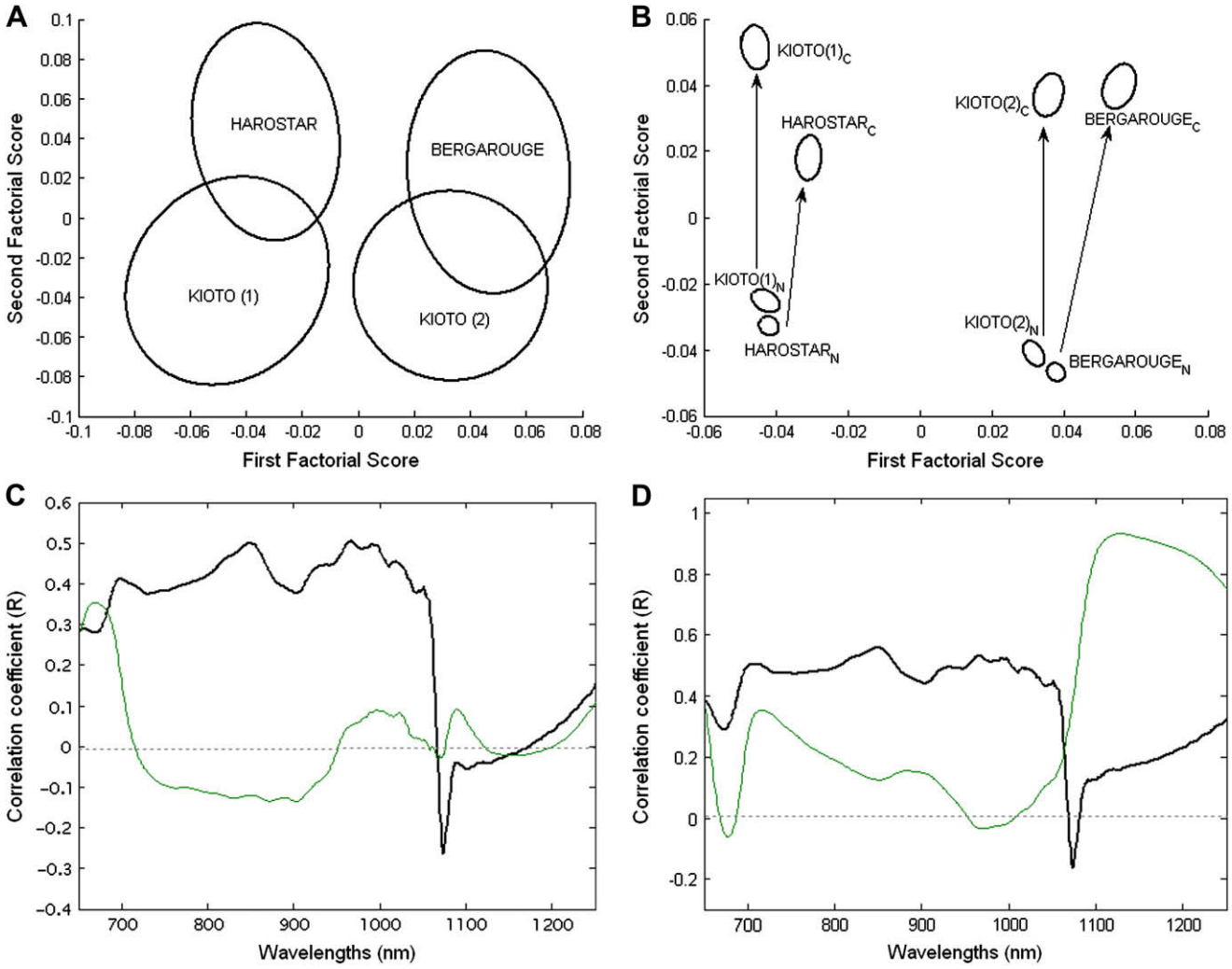

Fig. 4. FDA maps and relevant wavelengths. Discrimination of varieties (A), discrimination of fruit *side* (B); the groups to be discriminated are represented by the ellipses of confidences of the centroïds (threshold $p \leq 0.05$). Correlation between the factorial scores of the FDA and the absorbance spectra at each wavelength: discrimination of varieties (C), discrimination of fruit *side* (D). The black line: correlation of the first factorial score, the grey line: correlation of the second factorial score.

580 nm, which could correspond to a difference in colouration of fruit skin, Kioto (2) presenting a blusher skin colour than Kioto (1) (Fig. 4c). The difference between Kioto and the two other varieties relied on absorbance between 700 and 1050 nm. Such absorbance could be due to chlorophyll content but also to water and carbohydrate content that classically absorbs in the vicinity of 950–1000 nm. Such absorbencies correspond to the second overtone of O-H and N-H, third overtone of C-H and combination of O-H chemical bonds (Zude et al., 2006).

The classification of fruits according to the fruit side was also correct. Coloured sides were generally more easily classified than non-coloured ones. Confusion appeared for a part of non-coloured fruit sides that were classified as coloured ones, about 14% and 8% to Harostar and Kioto (2), respectively. The second factorial score of the FDA map allowed discriminating the coloured fruit sides from non-coloured ones while the first factorial score classified the varieties (Fig. 4b).

The second factorial score was clearly correlated to absorbance between 1080 and 1200 nm that correspond to the combination of the O-H chemical bond, the fundamental bands being located in the mid-infrared range (between 3000 cm^{-1} and 1700 cm^{-1}) (Fig. 4d). Such information could be due to a difference in biochemical properties of the two fruit sides, the coloured ones being firmer and with higher SSC than non-coloured ones. To confirm such hypothesis, further analyses have to be performed.

4. Conclusion

A portable and non-destructive technique using the NIR infrared absorbance was evaluated to determine the quality of apricot fruit.

Correct predictions of SSC and Fi of apricot were reasonably possible. Furthermore, promising levels of predictions for SSC were obtained when several apricot varieties were pooled in a single batch. However, such a model remains less robust and models based on a single variety have to be recommended. Fi predictions were correct but appeared unsuitable for the development of global models. TA models need complementary studies to be considered as correct.

NIR signature has been used as a non-destructive tool able to classify the fruits according to their variety and differences were detected between the two sides of the fruits. In this way, such NIR portable device seems to be an interesting way to a rapid classification of fruits according to a given variability (*i.e.* genetic, maturity, etc.). Such classification was better with using coloured side to perform spectral measurement. Nevertheless, further studies including external validations and analyses of a bigger number of fruits and varieties have to be performed before this technique is

sufficiently efficient and robust enough. Finally, because the quality is partially conditioned by the events occurring during the pre-harvest period, developing a portable and non-destructive technology is an important step for current and future research in agriculture. Thus, new calibrations performed in the orchard during the fruit growing period are now necessary.

Acknowledgment

The presented work was realized with the financial support of the Action Cost 924 (*Enhancement and Preservation of Quality and Health Promoting Components in Fresh Fruits and Vegetables*) and the State Secretariat for Education and Research SER (Switzerland).

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