Nondestructive Prediction of Quality for 'Bartlett' Pears

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ABSTRACT

Nondestructive measurement of pear quality was assessed using the F-750 Produce Quality Meter and the DA meter to determine their ability to measure internal soluble solids and dry matter content and predict fruit capacity to ripen, response to SmartFresh and post-storage quality. Robust, accurate and consistent calibration results were obtained at 729-975 nm for soluble solids and dry matter content, which are key quality parameters for fruit. The F-750 spectra had good correlation with fruit ripening capacity and response to SmartFresh indicating high potential to nondestructively segregate fruit into groups by their need for conditioning treatment. Calibration models from the 2015 season were used to predict fruit quality and ripening behavior in 2016. Each model could predict the quality in the 2016 season, but with high bias component due to inherent fruit variability. A combined calibration model developed by including the fruit spectra from 2015 and some from 2016 season can predict the quality of independent populations from the same orchard and region. The effect of temperature on model development and robustness of the calibration model for better prediction of the quality parameters from the combined model was observed, and the benefits of a combined temperature model was demonstrated.

OBJECTIVES

1. To determine the potential of the F-750 and DA-Meter to build accurate models developed from harvest-time and cold storage spectra to predict pear ripening capacity, with and without conditioning treatment, and fruit response to SmartFresh, as well as post-storage quality.

- 2. To evaluate the accuracy of the models for determining fruit's capacity to ripen and response to SmartFresh with 'Bartlett' pears from different harvest seasons and orchards.
- 3. To evaluate the influence of environmental factors, such as temperature, in the development and performance of the models.
- 4. To validate the models for determining soluble solids content, dry matter content, firmness and ripening capacity in pears from different harvest seasons and orchards.

MATERIALS AND METHODS

1. Fruit samples and preparation

Mature green 'Bartlett' pear fruit, sizes 6 to 11, were harvested from two orchards in Courtland, CA (Sacramento County) and two orchards near Kelseyville, CA (Lakeport county) for 2015 and 2016 seasons, from trees flagged two weeks before harvest (Fig. 1). Fruit were harvested first near the start of commercial harvest and then at nearly weekly intervals during the season to capture three (early, mid, late) stages (15-20)of maturity lbs. firmness); thereby creating variation in the fruit sample.

Figure 1: Flagging the trees in pear orchard in Sacramento, 2015 season

In 2015, fruit from the first orchard in Courtland, CA were picked on July 6, 13, and 23, and from the second orchard on July 8, 15 and 22. For the 2016 season, picking was made on July 8, 15 and 23 from the first orchard while it was picked on July 6, 14 and 21 from the second orchard. For Lakeport orchards, in 2015 fruit from the first orchard were picked on July 27, August 3 and 10, and from the second orchard on July 29, August 5 and 12 while in 2016 the first orchard was picked on August 3, 8 and 13 and August 1, 10 and 15 for second orchard.

Fruit were picked from bottom, middle and top, and inside and outside of the canopy from flagged trees so as to increase variation in the sample. Manually picked fruit were immediately packed into cardboard boxes and transported by car with air conditioning (at 68°F) to the postharvest lab at the University of California, Davis within 1-5 hours on the day of harvest. Upon arrival in the laboratory, fruit were sorted for uniform appearance and sorted for any external visible defects, such as sunburn, bruises or cuts. Fruits without visible external defects were used for the experiment. Each fruit in the given model was marked at two spots on opposite sides of the equator.

2. Models and population description

Four different models were proposed to assess the quality of pear fruit.

Model 1 measures the quality of pear fruit <u>at-harvest</u>. All non-destructive measurements (F-750, DA index, size, weight, color) and destructive measurements (firmness, starch content, dry matter (DM) and soluble solids content (SSC)) were measured on the harvest date on green mature fruit.

Model 2 is for assessing the ability of fruit to ripen <u>without conditioning</u> treatment. The fruits were kept at room temperature (68 °F) until ripe. Fruit were assessed for all non-destructive measurements at the green mature stage (harvest) and full ripe stage, and all destructive assessments at the full ripe stage. The correct ripening stage was assessed by measuring the firmness of extra fruit receiving the same treatment at various ripening stages using a penetrometer. Fruit were considered to be fully ripe at firmness of around 3 lbs.

Model 3 measures the response of pear fruit to <u>SmartFresh™</u> to <u>delay ripening</u>. Fruits for this model were cooled for 6 hrs at 32°F on the harvest day before SmartFresh treatment. Fruits were then treated with 300 ppb SmartFresh at 32°F for 24h, and transferred and kept at 68°F until fully ripened. The correct ripening stage was assessed by measuring the firmness of extra fruit receiving the same treatment at various ripening stages using a penetrometer. Fruit were considered to be fully ripe at firmness of around 3 lbs.

Model 4 is for measuring the quality of pear following **cold storage** (4 mo. @ 32°F).

For all of these models, fruit from the 2015 season were used as the calibration set for calibration model development while 2016 season fruit were used to test the prediction of the calibration models. Eighty fruit were used for calibration model development for each harvest (three harvests) and both orchards in two locations (Sacramento and Lake County), while 36 fruits were used for prediction purposes. For each model, a total of 480 fruit were used for calibration model development while a total of 216 fruit were used for prediction purpose for one district, including all three harvests from both orchards. A total of 960 fruit were used for each model combining both locations for the calibration set while 432 fruit were used for each model for prediction sets.

Nondestructive and destructive quality assessment details

Fruit from each model were assessed for its general features using different destructive and nondestructive tools. Nondestructive assessments for each fruit sample included size, weight, color, F-750 spectra acquisition, DA Index, and photo, while destructive measurements included firmness, starch content, soluble solids content (SSC) and dry matter content (DMC). Fruits samples stored for 4 months of cold storage will be taken out from cold storage in December and January and kept at 68°F to allow for ripening and assessed for quality parameters. The details of measurement are provided in Table 1.

Table 1: Non-destructive and destructive assessment tools and techniques for pear quality assessment

S	Measuremen	Measurement	Instrument	Image of instrumentation
N	t Types	details	used	
1	Nondestructive	e measurements		
1.	Size	Each fruit was passed through hole best fitted and size of hole indicates size of fruit.	Ring Sizer	866666
1. 2	Color	Minolta color reading is taken from marked spots, single measurement per market spot.	Minolta colorimeter (Model CR-400, Ramsey, New York	
1. 4	Spectra	Spectra were acquired in interactance optical geometry by putting the marked spot of fruit at the head	F 750 Produce Meter (CID Bioscience, Oregon, USA); a handheld instrument using an	177.2 Moon Apple Sal and Tas Card Salver & Solat 4.5 Last Sample 19 NSTRUMENTS APPLED FOOD SCINICE APPLED FOOD SCINICE

		of F750 Produce Meter.	interactance optical geometry with a Xenon Tungsten Lamp and a MMS-1 photodiode array spectrometer (310-1100 nm).	
1. 5	DA Index	DA is an index of chlorophyll content in fruit and was measured at each marked spot on the fruit.	DA Meter, (T.R. Turoni srl, Italy)	
2	Destructive me	1	Гл.:4 Та. 4	_
2.	Firmness	Firmness was measured on opposite sides of the equatorial region of each fruit after removing a thin slice of skin. The force required for an 8-mm diameter probe to penetrate the flesh to a depth of 5 mm was determined.	Fruit Texture Analyzer (GS-14, Güss, Strand, Western Cape, South Africa).	
2. 2	Starch content	Fruits were cut in core and the surf immersed in the After one minute removed from the the treated surface	ace was iodine solution. fruits were solution and	

		with distilled water of iodine with the cut surface of the dark bluish black used as an indication content. Starch is were scored immediate from 0 to 5; 0: 10 0% starch)	starch on the fruit gives color and is ation of starch odine patterns dediately (scale	
2. 3	Soluble solids content (SSC)	Flesh beneath the skin at marked spot, was cored using 16 mm core to 10 mm depth and cut into two halves, first half was used for SSC measurement using temperature compensated digital refractometer.	Digital refractometer (Reichert AR6 Series; Reichert Inc., Depew, NY)	PLEASE LEAVE POWER ON AT ALL TIMES REICHERT AND SERIES Membrane Reinsteller 10:56 a 10:56 a
2. 4	Dry matter content (DMC)	Flesh beneath the skin at market spot, was cored using 16 mm core to 10 mm depth and cut into two halves and second half is weighed on a pre-weighed foil tray. Samples were oven dried at 150 °F until constant weight (~48 h).	Gravity convection oven , VWR International, PA, USA)	

4. Mutlivariate data analysis and chemometrics

For 2015 season, the training data set was converted to second derivative using the Model Builder 1.0.0.1 (Felix Instruments, Camas, WA, USA) and converted to an MS Excel file for further analysis. Multivariate data analysis and all chemometric analysis was undertaken using The Unscrambler software (version 10.4, Camo, Oslo, Norway). The 2016 season data was collected in Absorbance units and converted to second derivative using Dataviewer software (Felix Instruments, Camas, WA, USA). Spectral data used for the analysis was restricted to 729-975 nm to include information on relevant carbohydrates, sugar and water absorption bands. Calibration models developed using partial least squares regression (PLSR) were assessed using the criteria of correlation coefficient of determination (R² cv), root mean square error of cross validation (RMSECV) and number of principal components (PCs), while predictive performance was assessed based on coefficient of determination of prediction (R² p), root mean square error of prediction (RMSEP) and bias.

Models 1, 2, 3 and 4 from Sacramento and Lakeport were built using Unscrambler at 729-975 nm for DM and SSC and Model 2 was built for the DA Meter. However, for other reference parameters including firmness and color, inconsistent results were achieved for calibration and prediction and they are not presented in this report. Fruit from model 4 for the 2016 season are currently in storage, and results will be available at a later date. Hence, this report includes reports from all models for 2015 season and prediction results for 2016 for each model, except model 4 (after storage).

RESULTS

1. Spectral features

The typical visible near infrared (vis-NIRS) spectra of pear depicts instrumental noise in the region of 300-400 nm and chlorophyll and water peaks at 670-680 nm. Similarly, a water absorbance peak can be observed at 960 nm. Fig. 2A presents typical visible-NIR absorbance spectra from Bartlett pears (36 fruits) acquired in interactance optical geometry using the F-750 Produce Meter showing light absorbance at a given wavelength region and Fig 2B shows the rate of change in absorbance with wavelength derivatizing the absorbance values.

Figure 2: Harvest time (Green, mature) absorbance (Abs) (A) and interpolated second derivatives (d2A) spectra (B) from 36 fruits of orchard 1, harvest 1, Sacramento, Model 1.

2.

Ripening time

The time required for Bartlett pears to ripen at 68°F at harvest varies with harvest maturity as shown in Table 2. In addition, the amount of ripening inhibition that occurs after fruit are treated with SmartFresh varies with harvest maturity (Table 2).

Table 2: Ripening time (days) for fruits ripened at harvest without treatment or treated with SmartFresh at harvest. Fruit were from three harvests from two orchards (1 and 2) in each district (Sacramento and Lakeport) and season (2015 and 2016).

Season	/Location	Model 2	No (Conditioning	Model	3, Sr	nartFresh
		H1	H2	H3	H1	H2	H3
Location	n: Sacramento						
2015	ORCHARD 1	15	11	8	31	28	24
2015	ORCHARD 2	12	9	8	23	19	14
2016	ORCHARD 1	17	23	15	27	31	30
2016	ORCHARD 2	16	13	13	32	26	30
Location	n: Lakeport						
2015	ORCHARD 1	9	8	8	19	19	18
2015	ORCHARD 2	9	9	8	19	19	16
2016	ORCHARD 1	16	14	13	30	28	27
2016	ORCHARD 2	18	14	11	29	28	26

H1= Harvest 1, H2= Harvest 2, H3= Harvest 3

Fruit from three different harvests from the same orchard had different spectral properties, and first harvest fruit were distinctly different from the remaining two harvests while there was less distinction between fruit spectral features for mid and late harvests (Fig 3). Score plots based on the spectral absorbance values at 729-975 nm grouped the fruits from first harvest separately from two consecutive harvests. This could mean that fruit can be segregated nondestructively into groups that can ripen without added ethylene or cold storage and those that cannot ripen without conditioning.



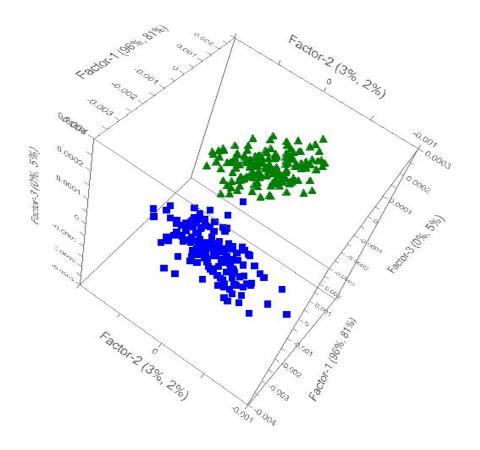


Figure 3: Score plots based on the spectra of fruits from three different harvests showing their differences and similarities based on spectral features.

Partial least squares regression results for three harvests showed that the prediction of ripening days for each harvest was possible using the spectral information. This was highly correlated (R² as high as 0.92) with an error of 1.19 days using the second derivative spectra from fruit at 729-975 nm (Fig 4). The second and third harvest fruit spectra looked similar and grouped closer together in the score plot (Fig 3).

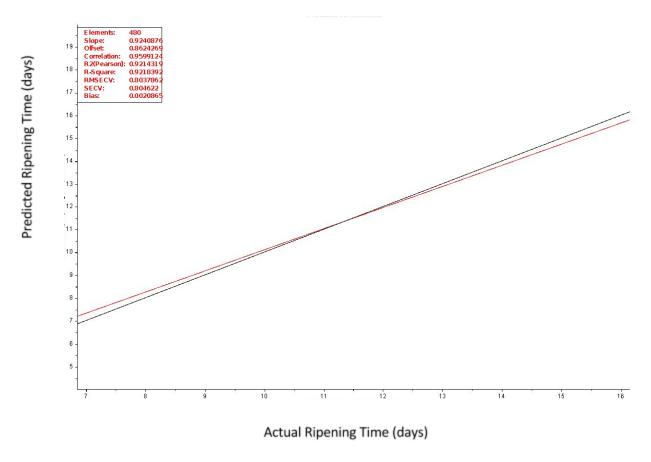


Figure 4: Prediction ($R^2 = 0.9294$) of ripening time based on the second derivative spectra at 729-975 nm for Model 2, Orchard 1 fruits in Sacramento, 2015 season.

The prediction for other orchards in Sacramento for 2015 and 2016 season was also comparable, with relatively higher error in prediction (RMSECV) as observed in Table 3. The RMSECV (days) for the SmartFresh treated fruit was higher, but these fruit generally took about twice as many days to ripen as the non-conditioned fruit.

Table 3. Relationship between actual and predicted ripening time (days) for fruit samples ripened with No Conditioning or following treatment with SmartFresh from a single orchard or both orchards from Sacramento in 2015 and 2016 seasons.

	(1)	Model 2 No conditioning)	Model 3 SmartFresh Treatment		
Season : 2015	R ²	RMSECV (days)	R ²	RMSECV (days)	
Orchard 1	0.92	0.8	0.77	1.37	
Orchard 2	0.92	1.15	0.77	2.1	
Both orchards Combined	0.65	1.47	0.62	3.4	
Season : 2016					
Orchard 1	0.45	2.49	0.67	1.03	
Orchard 2	0.62	0.86	0.63	1.5	
Both orchards Combined	0.27	2.73	0.13	2.00	

3. Using DA meter for quality evaluation

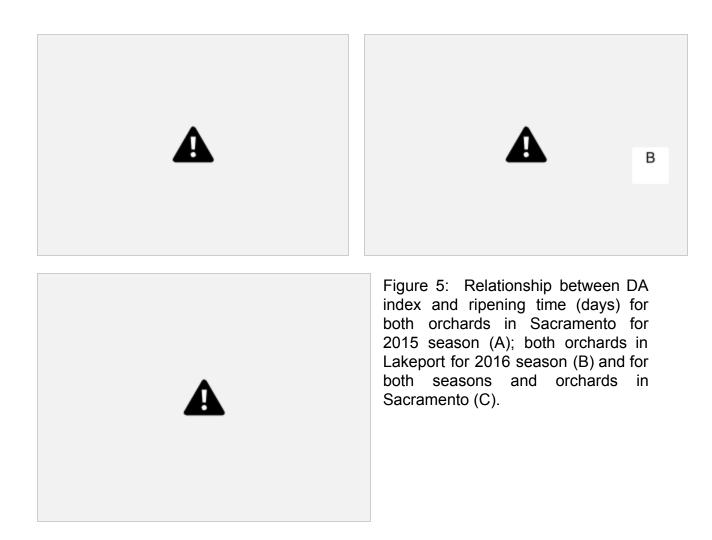
3.1 Relationship between DA Index and ripening time (days)

The DA index at harvest and time for ripening of fruits are presented in Table 4.

Table 4: Average DA Index and ripening days for all three harvests of pear from both orchards in Sacramento and Lakeport for 2015 and 2016 seasons. (Note: Number of fruits for 2015 and 2016 season are respectively 80 and 36).

			Sacramei	nto Orchards	Lakeport O	rchards
Season	Orchard	Harvests	Ripenin	DA Index	Ripening	DA
			g time		time	Index
			(Days)		(Days)	
		Early harvest	15	2.19	9	2.00
	Orchard 1	Mid harvest	11	2.03	8	1.92
		Late harvest	8	1.88	8	1.79
		Early harvest	12	2.11	9	1.94
2015	Orchard 2	Mid harvest	9	2.00	9	1.83
		Late harvest	8	1.88	8	1.73
		Early harvest	17	2.04	16	1.91
	Orchard 1	Mid harvest	23	1.92	14	1.74
		Late harvest	15	1.81	13	1.61
2016		Early harvest	16	2.04	18	1.84
	Orchard 2	Mid harvest	13	1.94	14	1.74
		Late harvest	13	1.83	11	1.61

A good correlation exists between the DA index at harvest and ripening time (days) within the same orchard for one season (with R² value as high as 0.99; data not shown) while combining data across two orchards gives mixed results with some improvement in relationship (Fig 5A) or reduced correlated (Fig 5B); but combining across orchards and seasons yielded very poor results for both regions (Fig 5C).



3.2 Relationship between ability of fruit to ripen at harvest and nondestructive assessment

In an exercise involving 100 fruits to assess whether the DA index or F750 spectra at harvest was different for fruits that fail to initiate ripening showed a higher (2.03±0.14) DA index for fruits unable to ripen and lower DA index (1.96±0.15) for fruit able to ripen, averaging 53 and 47 fruits, respectively, however the differences were very smaller. The spectral features of the fruit at harvest also varied, with consistently higher absorbance for fruits unable to ripening without any external conditioning treatment compared to those capable of ripening, with prominent differences in the visible region of the electromagnetic spectrum (Figure 6).



Figure 6: Spectral differences at harvest between fruits cable of ripening and Not Capable of Ripening at harvest with corresponding differences in DA index readings at harvest (in inset).

3.3 Relationship between F-750 and DA Index and post-storage quality

In 2015 we assessed whether the DA meter or the F750 could predict the quality of fruit after extended cold storage with a focus on defect related parameters, namely scald and internal breakdown.

The DA index at harvest had no relationship with scald or internal breakdown after 4 months of storage at 68F, across three harvests for both orchards in both locations (data not shown).

The F-750 spectra at harvest could not predict whether fruit will develop scald or internal or internal breakdown after storage based on the harvest time spectral information (data not shown).

4. Study on effect of temperature on model development and prediction

A study on the effect of fruit temperature on model performance was assessed in the 2016 season for all harvests in one orchard in both locations. Fifty fruit were kept at 32, 50 or 68F for 24 hrs before their spectra was collected to assess DM and SSC. Spectra from fruit measured at different temperatures were used to predict fruit DM and SSC at the same or different temperatures, and other calibrations were made using measurements at multiple temperatures. The model and bias for prediction using spectra from different temperatures for calibration and prediction model was assessed (Table 5).

Temperature had a high influence on the prediction of SSC and DM. The calibration model developed using the spectra acquired at 68F can predict fruit quality stored at the same temperature with little bias, whereas the bias increased for prediction of SSC of fruits stored at lower temperatures. The bias and root mean square of prediction for predicting quality of fruit at 50F using fruit spectra acquired at 68F was almost 3 whereas it increased 6 times when predicting fruit held at 32F. A temperature compensated model developed using the spectra taken from fruit after 24 hrs storage at 32, 50 and 68F, despite fairly low calibration statistics, can predict all the fruit population stored at 32, 50 and 68F without any bias (Table 5). This enables a model to be developed that can predict SSC and DM in fruit at a range of temperatures with good accuracy.

Table 5: Calibration and prediction results for soluble solids content for green mature fruits stored at 32, 50 and 68F for 24 hrs using second derivative spectra at 729-975 nm for 2016 season.

	Calibr	ation results			Predi	ction resul	<u>ts</u>
Cal set	R ² cv	RMSECV	PC s	Predicted set	R ² p	RMSE P	Bias
				Pop 1 after 24 hrs storage at 0 C	0.61	4.03	4.00
Pop1 at 20C	0.5	0.63	5	Pop 2 after 24 hrs storage at 10 C	0.58	2.27	2.14
				Pop 3 after 24 hrs storage at 20 C	0.53	0.76	-0.17
				Pop 1 after 24 hrs storage at 0 C	0.43	8.92	8.89
Pop 2 at 20C	0.58	0.71	4	Pop 2 after 24 hrs storage at 10 C	0.52	5.00	4.94
				Pop 3 after 24 hrs storage at 20 C	0.62	0.67	0.26
				Pop 1 after 24 hrs storage at 0 C	0.53	7.25	7.21
Pop 3 at 20C	0.71	0.54	6	Pop 2 after 24 hrs storage at 10 C	0.71	3.97	3.92
				Pop 3 after 24 hrs storage at 20 C	0.79	0.46	0.01
				Pop 1 after 24 hrs storage at 0 C	0.66	0.61	0.06
Temperature compensated	0.57	0.7	8	Pop 2 after 24 hrs storage at 10 C	0.69	0.62	-0.09
model (0C + 10C + 20C)				Pop 3 after 24 hrs storage at 20 C	0.73	0.51	-0.01

5. Prediction of dry matter and soluble solids content using spectral information

Soluble solids content (SSC), and firmness are the major quality parameters of commercial importance and are integral components of commercial produce specifications. The results from firmness were not consistent across the population (data not shown) while those for DM and SSC are encouraging and consistent across population and harvests and are discussed in the following subsections. The region of high chemical information for carbohydrates was assessed based on regression coefficients following partial least square regression for absorbance values across full wavelength (350-1150 nm) against reference parameters. For DM, a region of high regression coefficients (b-coefficients) (729-975 nm) was chosen for further analysis (Fig. 7)).

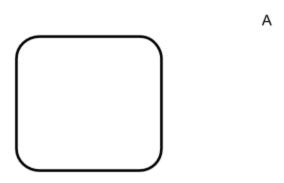


Figure 7: Selection of wavelength region for dry matter content based on regression coefficients following partial least square regression at given wavelength. A. Regression coefficients for full wavelength 350-1150 nm; B. regression coefficients for 729-975 nm.

The calibration model with high correlation coefficient of determination (R^2cv) and lowest root mean square of cross validation (RMSECV) and number of principle components (PCs) was suggested by the analysis software (Unscrambler). Less than 5% of outlier samples were removed, as shown in regression analysis. A typical PLS calibration (A) and prediction (B) models are presented in Fig. 8 for SSC from Model 2, of Lakeport Orchards.

The calibration model includes fruit spectra from harvest time (green mature) and full ripe stages whereas prediction set is independent population and includes fruit spectra from harvest time and full ripe stage. The error of measurement of soluble solids for the calibration model was 0.5% while the prediction error in predicting the soluble solids for the independent set was 0.55 %. These are very accurate predictions.

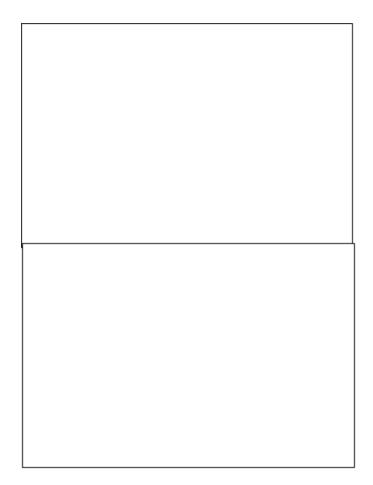


Figure 8: Calibration (A) and prediction statistics (B) for a SSC model from Model 2 for Lakeport orchard, 2015 season, using a second derivative absorbance spectra at 729-975 nm.

6. Changes in DA Index and Fruit Spectra during Ripening

DA index, a measure of chlorophyll content, decreases during ripening from an average value of 2.03 at the green mature stage to 0.45 at the full ripe stage. The chlorophyll content for the first harvest is generally higher than consecutive harvests (Table 6). Firmness changed from an average of 17.11 lbs to 2.62 lbs at the green mature stage to full ripe stage.

Table 6: Changes in DA Index and firmness in 'Bartlett' pears at green and full ripe stage for Model 2 fruits in three harvests from Orchard 1 (O1), Sacramento for 2015 season.

		Har	vest 1	Harv	est 2	Harv	est 3
Parameters		Mean	SD	Mean	SD	Mean	SD
DA Index (no unit)	HARVEST	2.19	0.09	2.03	0.25	1.88	0.11
	RIPE	0.32	0.16	0.3	0.15	0.67	0.22
	HARVEST	19.10	1.709	16.51	1.24	15.72	0.98
Firmness (lbs)	RIPE	2.29	0.41	2.44	0.36	3.13	0.64

The spectral features from the F-750 showed little change in absorbance between harvests with a generally higher absorbance for the first harvest compared to later harvests (data not shown).

During ripening, the skin pigmentation changes mainly with the decrease in chlorophyll content as shown in Fig. 9. A generally higher absorbance was observed for green mature fruit compared to fully ripe fruit between 500-1000 nm.





Figure 9: Raw absorbance spectra (A) of a pear fruit at mature green stage and full ripe stage, acquired by F750 Produce Meter using interactance optical geometry between 300-1100 nm; green mature fruit set (B) and full ripe fruit set (C).

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Furthermore, the spectral features taken from the same fruit continued to change with ripening, with a general decrease in light absorbance in vis-NIR spectral region as ripening progresses, and with the highest decrease in absorbance at the chlorophyll peak as indicated by loss of chlorophyll during ripening.

In addition, there were some differences in the rate of biochemical and physiological changes during ripening for fruits treated with SmartFresh and those receiving no treatment as observed by their respective spectral signatures (Fig. 10). The fruit treated with SmartFresh had ripening delayed by two weeks compared to non-treated fruit. Also, the green color of the fruits was retained for three weeks in SmartFresh treated fruit while non treated fruit lost their chlorophyll in approximately one week and ripened in 12 days (Fig. 10AB). The soluble solids content in the fruit changed during ripening as predicted by the calibration model developed using second derivative spectra at 729-975 nm. The rate of change was slower for SmartFresh treated fruits compared to non-treated fruits.

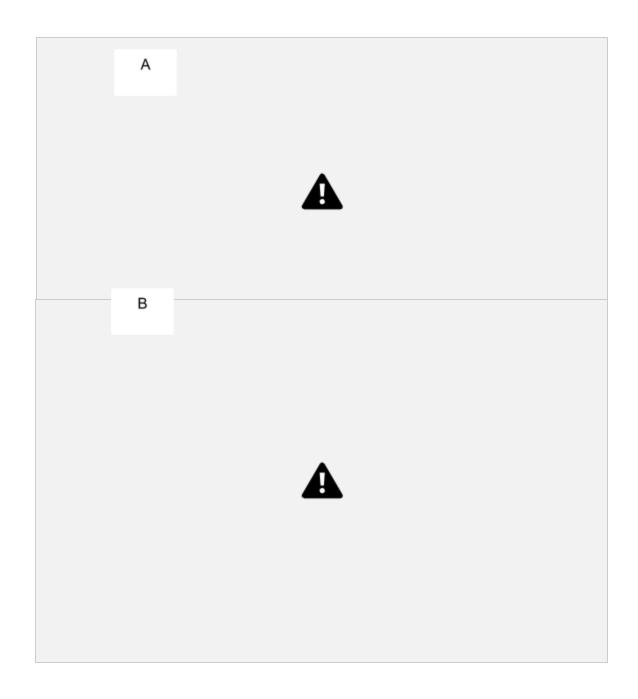


Figure 10. Spectral changes and prediction of SSC in single fruit on different days during ripening for fruits receiving no treatment (A) and SmartFresh treatment (B), from Orchard 2 Sacramento fruits in 2016 season.

The spectral feature changes during ripening with high absorbance at the chlorophyll peak (670nm) and water peak (960nm) for green mature fruit while chlorophyll content decreases as ripening progresses with consequent change in spectral features. The change in SSC of the same fruit can be predicted by spectra during ripening. In the

above example, predicted SSC on the harvest day for the same fruit is 11.34 and it increased up to 13.92 during the final week of ripening. The predicted final SSC in ripe fruit was is only 0.63% less than the actual SSC measured by refractometry. There was no difference in prediction performance of the fruit SSC using the F750 Produce Meter. The change in SSC from harvest to the full ripe stage was observed in fruit from all harvests as shown in Table 6 which shows the average of 80 fruits for each harvest; however, the increase was slightly smaller in later harvested fruit. The rate of change in SSC in non-conditioned fruit was higher than in SmartFresh treated fruit (Table 7).

Table 7: Soluble solids content in fruits at harvest and full ripe treated with SmartFresh (Model 3) and no conditioning (Model 2) for 2015 season, Orchard 1, Sacramento. Each model contains 80 fruits.

	Soluble Solids Content (SSC)						
	Harvest 1 Harvest 2 Harvest 3 Mean ± S						
Model 1 (Harvest Time SSC)	12.69	13.16	13.25	13.03 ± 0.3			
Model 2 (Full Ripe SSC)	13.97	14.31	14.23	14.17 ± 0.17			
Model 3 (Full Ripe SSC)	13.90	13.88	13.49	13.75 ± 0.23			

4.2 Quality prediction between seasons

All calibration models developed during for the 2015 season performed very well as depicted by high correlation coefficients for cross validation (0.79 and 0.77 for DM and SSC with respective error of 0.6% and 0.5%), while the prediction performance in 2016 was poor with high bias terms which are attributed to inherent differences between fruit properties between the seasons (Table 8). However, this prediction error was minimized by developing a calibration model using the fruit spectra from both seasons and predicting quality parameters of the remaining fruit from 2016 not included in the calibration models (Table 9). A model developed using the fruit spectra from both seasons in Orchard 1 in Sacramento County can predict the quality attributes for Orchard 2 in the same district, and also for the fruit from both orchards in another district with slightly better prediction for SSC than DM across the results (Table 9).

Table 8: Prediction of dry matter and soluble solids content of 'Bartlett' pears from 2016 season (prediction season) using the calibration model developed using spectra from 2015 season

Season / Model	Quality						
(Calibration set)	paramete		RMSEC		Prediction set		
	r	R ² cv	V	PCs		R^2p	RMSEP
A. Sacramento							
2015 Madal 1	DM	0.70	0.0	0	0040 Madal 4	0.47	4.07
2015 Model 1	DM	0.79	0.6	8	2016 Model 1	0.47	1.27
	SSC	0.62	0.79	7		0.61	0.92
2015 Model 2	DM	0.71	0.71	6	2016 Model 2	0.27	1.58
	SSC	0.62	0.79	7		0.36	0.98
2015 Model 3	DM	0.71	0.72	6	2016 Model 3	0.17	1.52
	SSC	0.71	0.6	7		0.35	1.52
B. Lakeport							
2015 Model 1	DM	0.75	0.6	9	2016 Model 1	0.27	2.59
	SSC	0.72	0.48	9		0.49	1.20
2015 Model 2	DM	0.75	0.55	11	2016 Model 2	0.22	1.64
	SSC	0.77	0.50	9		0.38	0.90
2015 Model 3	DM	0.7	0.62	6	2016 Model 3	0.34	1.74
	SSC	0.75	0.51	6		0.51	1.11

Table 9: Prediction of dry matter and soluble solids content between two orchards in Sacramento and Lake county for **Model 1** using second derivative spectra at 729-975 nm, for 2015 and 2016 seasons.

Season /Orchard details	Quality parameters				Calibration statistics
A. Sacramento					
		R ² cv	RMSECV	PCs	Prediction set 1
2015 Orchard 1	DM	0.72	0.54	8	2015 Orchard 2
	SSC	0.69	0.51	8	2015 Orchard 2
2015 Orchard 2	DM	0.56	0.54	7	2015 Orchard 1
	SSC	0.6	0.45	7	2015 Orchard 1
Orchard 1, 2015 and 2016 (combined)	DM	0.59	0.74	8	Orchard 2, 2015 and 2016
	SSC	0.73	0.48	11	Orchard 2, 2015 and 2016
Orchard 2, 2015 and 2016 (combined)	DM	0.56	0.74	9	Orchard 1 2015 and 2016
	SSC	0.7	0.49	9	Orchard 1 2015 and 2016
B. Lakeport					
2015 Orchard 1	DM	0.79	0.58	8	2015 Orchard 2
	SSC	0.75	0.48	8	2015 Orchard 2
2015 Orchard 2	DM	0.7	0.55	6	2015 Orchard 1
	SSC	0.68	0.43	5	2015 Orchard 1
Orchard 1, 2015 and 2016 (combined)	DM	0.7	1.02	7	Orchard 2, 2015 and 2016
	SSC	0.73	0.69	7	Orchard 2, 2015 and 2016
Orchard 2, 2015 and 2016 (combined)	DM	0.52	1.33	7	Orchard 1 2015 and 2016
	SSC	8.0	0.59	9	Orchard 1 2015 and 2016
Orchard 1 and 2, Sacramento 2015	DM	0.74	0.61	9	Orchard 1 and 2 Lakeport 2015
	SSC	0.72	0.48	10	

^{*} values in parentheses are bias corrected RMSEP values

DISCUSSION

The F-750 shows promise as a mechanism to determine which fruit require conditioning treatment prior to marketing to assure reasonably quick and uniform ripening. The first harvest which ripened most slowly and needed ethylene or cold exposure to ripen efficiently showed significantly different spectra from the second and third harvests. It may also be possible to separate the second harvest from the third harvest. Further work is needed to confirm and refine this relationship, but the results look promising.

The F-750 handheld Produce Meter is useful for noninvasive quality assessment in 'Bartlett' pears. Dry matter and soluble solids content were consistently well predicted across all three harvests and both orchards in two locations. The ability of the F-750 to predict soluble solids content and dry matter nondestructively continues to appear promising. Assessment of these quality characteristics in individual pieces of fruit is possible using online sorting devices using NIR techniques which can be used to sort fruit by sensory quality and potentially by storage potential. Handheld devices can assist in making better harvest decisions by letting growers know whether desired quality criteria have been met or not, before actual harvest, by nondestructive prediction of dry matter and/or soluble solids content.

A good calibration model was achieved for DM and SSC, which are very important and commercially applicable for noninvasive prediction of pear quality. However, the prediction results for DM is still inconsistent across orchards and season.

Temperature of the pears during spectra acquisition is very important as visible-near infrared spectra are highly influenced by temperature and a temperature compensated model is desirable for accurate and consistent prediction of the fruit at different temperatures. We demonstrated that if the model is built using the spectra acquired from fruits at a range of temperatures, this greatly improves its ability to predict fruit SSC and DM in fruit of various temperatures within the range.

Due to inherent climate difference between seasons, the calibration model developed for one season have been unable to predict the SSC and DM for the next season without including spectra from fruit from the prediction season in the calibration models. This would require PCAs to measure some fruit at the start of the harvest season to update the models each season.

The DA-Meter and F-750 have not yielded any encouraging predictive performance for assessing the potential of fruit to develop internal breakdown or scald after cold storage. Further evaluation of the pears from cold storage in 2016 will continue after the writing of this report and may improve the predictive capability. Additional work on all of our models will be conducted over the next few months to fully assess the potential of these two devices.