Prediction of soluble solid content, vitamin C, total acid and firmness in astringent persimmon (Diospyros kaki L.) cv. Rendeu using NIR spectroscopy

Nur Hasnah Ar¹, Yohanes Aris Purwanto*¹,², I Wayan Budiastra¹, Sobir²

¹ Department of Mechanical and Biosystem Engineering, Bogor Agricultural University
² Center of Tropical Horticulture Studies, Bogor Agricultural University

*E-mail: arispurwanto@apps.ipb.ac.id

Abstract. Internal content is one of the important quality criteria in fruit. Quantitative analysis is carried out by using a chemical method. This process is destructive, high cost and time consuming, thus not suitable for real-time measurement. The objective of this study was to evaluate the possibility of the use of near-infrared (NIR) spectroscopy as a rapid method of predicting the internal quantitative quality of persimmon fruit such as solid soluble content (SSC), vitamin C, total acid and firmness. The spectra pre-processing and Partial Least Square (PLS) method were utilized to develop a calibration model. The result showed that the best calibration model was SSC with (MSC) multiplicative scatter correction and 17 PLS factors; vitamin C with MSC and 16 PLS factors; total acid with MSC and 12 PLS factors; firmness with n01 (normalization between 0-1) and 12 PLS factors. This study demonstrated the possibility the use of NIR spectroscopy for rapid and non-destructive measurement of SSC and firmness contents in astringent persimmon. The low accuracy in predicting vitamin C and total acid was obtained due to a limitation of those the contents in persimmon.

1. Introduction

Persimmon (Diospyros kaki L.) is one of the horticultural products grown in the highlands [1]. Persimmon fruit is subtropical fruit originated in China and entered the territory of Indonesia at the beginning of the 20th century. The spread of persimmon in Indonesia includes Sumatra (Tanah Karo, Solok, Brastagi, and Toba) and Java (Cikajang, Indonesia, Bayongbong, Majalengka, Ciloto, Selo, Boyolali, Magetan, Malang-Tirtoyudo, Temanggung, and Junggo) [2]. Persimmon fruit can be consumed as a fresh fruit or made into processed products such as jelly, jam, ice cream and chips.

Persimmon can be classified into two general types, astringent and non-astringent types [2]. Persimmon describes with three rates of aging based on the days after bloom is 150 days, 170 days, and 190 days after bloom [2]. Persimmon shaped round like tomatoes, bright fruit and the fruit skin
was red-orange. With the appearance of the beautiful fruit color persimmon have prospects to be developed and become commodities export.

The degree of freshness, hardness, age, size and internal content are the quality criteria. One of the criteria that matter is the quality of the internal content (including soluble solid content (SSC), total acids, vitamin C). Traditionally, determining of SSC, vitamin C, total acid and firmness contents in persimmon fruits are conducted qualitatively based on subjective measurement by looking the fruit appearance. Standard methods for measuring the internal quality of persimmon are destructive and thus the same fruit cannot be continually monitored. This method is not efficient since it is time-consuming and destructive.

Near-infrared (NIR) spectroscopy is an electromagnetic wave which has the wavelength of 780-2500nm that serves to identify the chemical component in the quantitative and qualitative analysis. Most of the NIR spectra dominated by hydrogen bonding causes the hydrogen atom is the more potent. Hydrogen bonds can be either C-H, N-H, S-H, or O-H. Instruments used in NIR spectroscopy are light sources, detectors, optical detectors, sampling and data processing system.

Near Infrared (NIR) spectroscopy is a nondestructive approach [3], accurate, and fast which can replace chemical method [4]. NIR spectroscopy can be used for nondestructive measurements of fruit components, such as water content, acid, carbohydrate, protein and fat [5], starch and SSC [6], moisture content and peel hardness in mangosteen [7], lignin and moisture content in the wood [8].

Near infrared (720-1100nm) is used to determine ripeness for oil palm fresh fruit bunch [9]. The measurements are fast, highly precise, need no particular sample pretreatment, or chemical additives. Several studies have shown the ability of NIR spectroscopy to determine the bioactive component of agricultural products such as a) determining of SSC and acidity of loquats base on FT-NIR spectroscopy using Partial Least Square (PLS) method and first and second derivative, multiple scatter correction (MSC) and standard normal variate (SNV) pre-processing [10], b) determining of firmness and soluble tannin content of Mopashi persimmon using the second derivative based PLS method [11], c) determining of varieties persimmon fruit using PCA method [12].

The objectives of this study were to develop an NIR spectroscopy calibration model to predict SSC, vitamin C, total acid, and firmness in astringent persimmon cv. Rendeu using PLS method with different pre-processing spectral treatment.

2. Material and Method

2.1. Sample Preparation and Spectra Acquisition

The fresh astringent persimmon cv. Rendeu were harvested from a farmer persimmon in Garut, West Java, Indonesia. The 147 number of samples were divided randomly into two groups. A 98 sample of fruits were used as calibration set and the rest of the validation set. NIR spectrometer from Buchi NIRFlex N-500 Fiber optics solids which has a gun type probe and wavelength of 1000-2500nm with interval 0.4nm was used for spectra acquisition using NIRware 1.2 (Buchi Labortechnik AG, Flawil, Switzerland) was used to operate the instrument. Measurements of each sample were conducted at three different positions along a transect (near the top, middle, and near the bottom) of each fruit.

2.2. Chemical Analysis

Firmness was measured using hardness tester (FHR-1). SSC was estimated from a single refractometer (PAL-1 Atago, Japan) reading taken from the combined juice extracted from the three penetrometer holes used for firmness measurement (near the top, middle, and near the bottom) of each fruit. Vitamin C and total acid were measured on approximately 10g by fresh fruit weight, in term of the malic acid equivalent. The tissue was macerated and the juice, filtered from the homogenate, titrated using 0.01N Iodium for vitamin C and 0.1N NaOH for total acid. Subsequent analysis of the chemical analysis result used the average value of the three replicate measurements.

2.3. Data Analysis

The data used in this analysis was of the fresh astringent persimmon cv. Rendeu which was still in good (quality) condition, i.e., those acceptable to consumers. The total number of fruit was 147. The two-thirds of the data set was used for calibration, and the remaining one-third used for validation [7].
NIR spectra obtained from NIR instrument contain not only the information of the sample but also the background and noise. Therefore, the spectral pre-processing treatment method is required to get reliable, accurate and stable calibration model [13]. This method was utilized to minimize the contribution of information which was not relevant to spectrum to develop reliable model [14].

This study used both of original and several spectral pre-processing methods. Those were normalization between 0 and 1 (n01), smoothing (sa3), first derivative Savitzky-Golay 9 points (dg1), multiplicative scatter correction (MSC), the combination of n01 with dg1 (n01,dg1) and a combination of dg1 with multiplicative scatter correction (dg1,MSC) [15]. Normalization was used for creating scale sample all of the data were at approximately the same level based on area, mean, hose, maximum, peak, and vector units. Normalization of functioning spectral transforms spectrum into units of length so that the value of reflectance at a longer range. Normalization was used to eliminate multiplicative spectra effects [6]. Savizky-Golay smoothing (sa3) is the method often used for removing noise. Smoothing was also utilized in the optimization of the signal-to-noise rate. In general, this method combined with other data to perform the removal of noise. The algorithms for derivative are direct differentiation and Savitzky-Golay [13]. The first derivatives can be used to eliminate additive baseline effects while second derivatives were used to remove sloped additive baselines [6]. The first derivatives can be used to remove the background and enhance the resolution of spectral processing of derivatives to work separating the spectral that overlaps on the original ones. The resulting reflectances value will be reduced to smaller to clarify each of the peaks and valleys of the spectrum. MSC was used for the correction of scattering light by different particle sizes. These techniques were used to correct for additive and multiplicative effects in the spectral [16].

2.4. Calibration Method

NIR spectra usually contain unselective and widely overlapped bands. Therefore, quantification analysis requires chemometrics analysis such as PLS, principal component regression (PCR) or multiple linear regression (MLR) [17]. The PLS regression method is a very popular method for chemometric analysis [18]. In this study, selection the number of optimum PLS factors was done based on consistency value. Selected PLS factor has consistency value between 80-110%. The number of PLS factors was 1 to 20. The value of consistency was used to ensure that the number of selected PLS factors was optimal [19]. Statistical parameters used to evaluate the resulted model were standard error calibration set (SEC), standard error of prediction set (SEP), coefficient correlation (r), the ratio of prediction to deviation (RPD), and coefficient of variance (CV) [17].

3. Results and Discussion

3.1. Data of Destructive Persimmon

Table 1 shows the descriptive statistics summary for SSC, vitamin C, total acid and firmness in the calibration and validation set. Calibration and validation models, based on the correlation between NIR data and destructively determined SSC, vitamin c, total acid and firmness contents, were used to predict. The calibration and validation models were developed using the PLS method. The data employed in this analysis was of that fruit which was still in good (quality) condition, i.e., those acceptable to consumers. The total number of fruit was 147. Two-thirds of the data set was used for calibration, and the remaining one-third used for validation [7].
Table 1. Descriptive SSC, Vitamin C, total acid and firmness data for calibration and validation of NIR by PLS method

| Statistics description | SSC (°Brix) | Vitamin C (mg/100gr) | Total Acid (%) | Firmness Kgf |
|------------------------|------------|----------------------|----------------|-------------|
| No. Of data            | 429        | 369                  | 423            | 432         |
| Min(%)                 | 14.10      | 0.79                 | 0.04           | 0.08        |
| Max(%)                 | 31.33      | 3.64                 | 0.32           | 0.95        |
| Avr.(%)                | 22.85      | 1.9                  | 0.12           | 0.74        |
| Std.dev.(%)            | 3.95       | 0.5                  | 0.06           | 0.2         |
| CV                     | 11.26      | 34.05                | 48.34          | 12          |

3.2. Analysis of NIR Reflectance

The original reflectance spectra of persimmon samples (Figure 1) reveals some valley in region 1000-2500nm which indicates high noise. These valleys exist because molecule structures of persimmon contain many hydric groups (such as C-H and O-H). Spectrum data pretreatment by normalization into a 0-1 range was necessary to decrease the error value due to different in particle size and the range of reflectance value. After normalization, the reflectance data spectrum was transformed into absorbance log (1/reflectance). In the absorbance spectrum of persimmon, the peak was in the range of 1160-1200nm, 1140-1460nm, 1920-1940nm which reflect water content, 1160-1200nm, 1780nm, 1920-1940nm which reflect carbohydrate content such as fructose, sucrose, and galactose, 1440-1460nm, 1160-1200nm, 1440-1460nm, 2240-2280nm which reflects total acid content [13].

Figure 1. The original spectrum of persimmon (a) reflectance; (b) absorbance after normalization
C. Prediction of SSC, Vitamin C, Total Acid and Firmness in Persimmon

PLS is an effective method to reduce the dimension in NIR spectroscopy analysis. The spectra information of sample component is showed of PLS factors is essential to reduce noise and use the whole of spectral information [13]. The performance of parameters of the model using different pre-processing methods to predict SSC, vitamin C, total acid and firmness in persimmon is shown in Table 2.

Pre-processing of data is carried out before modeling will improve the calibration results. Application of NIR data processing and the number of the main components of optimal spectral NIR calibration model PLS applied to obtain the best in predicting the chemical content of material [17]. The data processing results of the spectrum are used in this research (Figure 3).

This pre-processing MSC produce the best calibration to predict SSC with higher accuracy and precision than other pre-processing (r = 0.86, SEP = 2.21%, RPD = 1.79 and CV = 9.84%). It indicated that pre-processing was important before developing a model as it would improve the accuracy and precision of calibration model [20, 21].

Figure 2. Scatter plot of measured the best calibration model to predict persimmon contents: SSC with MSC and 17 PLS factors, vitamin C with MSC and 16 PLS factors, total acid with MSC and 12 PLS factors, firmness with n01 and 12 PLS factors

| Parameter | Value | Description | Equation |
|-----------|-------|-------------|----------|
| r         | 0.86  | Correlation | r = 0.86 |
| SEP (%)   | 2.21% | Standard error of prediction | SEP = 2.21% |
| RPD       | 1.79  | residuals to predictive standard deviation | RPD = 1.79 |
| CV(%)     | 9.84% | Coefficient of variation | CV = 9.84% |

| Parameter | Value | Description | Equation |
|-----------|-------|-------------|----------|
| r         | 0.79  | Correlation | r = 0.79 |
| SEP (%)   | 0.51  | Standard error of prediction | SEP = 0.51% |
| RPD       | 0.99  | residuals to predictive standard deviation | RPD = 0.99 |
| CV(%)     | 30.50 | Coefficient of variation | CV = 30.50% |

| Parameter | Value | Description | Equation |
|-----------|-------|-------------|----------|
| r         | 0.65  | Correlation | r = 0.65 |
| SEP (%)   | 0.05  | Standard error of prediction | SEP = 0.05% |
| RPD       | 0.86  | residuals to predictive standard deviation | RPD = 0.86 |
| CV(%)     | 45.73 | Coefficient of variation | CV = 45.73% |

| Parameter | Value | Description | Equation |
|-----------|-------|-------------|----------|
| r         | 0.94  | Correlation | r = 0.94 |
| SEP (%)   | 0.07  | Standard error of prediction | SEP = 0.07% |
| RPD       | 2.90  | residuals to predictive standard deviation | RPD = 2.90 |
| CV(%)     | 9.72  | Coefficient of variation | CV = 9.72% |
Figure 3. Pre-processing data NIR persimmon with (a) normalization (n01), (b) first derivatif Savitzky-golay (dg1), (c) combination n01 and dg1, (d) Multiplicative Scatter Correction (MSC), (e) combination dg1 and Multiplicative Scatter Correction (MSC).

The vitamin C content calibration of persimmon resulted that spectral pre-processing of MSC produced the best calibration model compared to other spectral pre-processing ($r = 0.79$, SEP = 0.51%, RPD = 0.99, CV = 30.50%). Spectra pre-processing with MSC produced the best calibration model compared to other spectral pre-processing for total acid content calibration. This pre-processing reduced coefficient correlation between combination pre-processing (n01, dg1) model with MSC pre-processing from 0.71 to 0.65 but RPD increased from 0.82 to 0.86. In this study, NIR spectroscopy failed to predict vitamin C and total acid of Rendeu persimmon fruit (RPD < 1.5). The concentration of acids in most fruit and vegetables is smaller than sugar and possibly too small to affect the NIR spectrum significantly. Sugar the dominance of water absorption bands in fresh produce also makes minor contents difficult to measured [22].
Table 2. Parameter of NIR calibration and validation model for SSC, vitamin C, total acid contents and firmness in persimmon

| Content | Pre-processing | Consistency (%) | Factors | Calibration-set | Validation-set |
|---------|----------------|-----------------|---------|-----------------|----------------|
|         |                |                 |         | r   | SEC (%) | SEP (%) | RPD | CV (%) |
| SSC     | original       | 93.6            | 19      | 0.87 | 2.07    | 2.21    | 1.79 | 9.86 |
|         | n01            | 98.4            | 17      | 0.85 | 2.25    | 2.29    | 1.72 | 10.2 |
|         | dg1            | 84.4            | 9       | 0.84 | 2.28    | 2.7     | 1.46 | 12   |
|         | msc            | 97.3            | 17      | 0.86 | 2.15    | 2.21    | 1.79 | 9.84 |
|         | n01+dg1        | 86.3            | 9       | 0.85 | 2.23    | 2.58    | 1.53 | 11.5 |
|         | dg1+msc        | 88              | 9       | 0.85 | 2.22    | 2.52    | 1.56 | 11.3 |
| Vitamin C | original    | 89.3            | 17      | 0.79 | 0.5     | 0.56    | 0.89 | 33.8 |
|         | n01            | 80.3            | 19      | 0.83 | 0.46    | 0.57    | 0.88 | 34.4 |
|         | dg1            | 86.7            | 9       | 0.78 | 0.51    | 0.59    | 0.84 | 35.9 |
|         | msc            | 99.1            | 16      | 0.79 | 0.5     | 0.51    | 0.99 | 30.5 |
|         | n01+dg1        | 91.2            | 9       | 0.78 | 0.51    | 0.56    | 0.89 | 34.1 |
|         | dg1+msc        | 85.9            | 9       | 0.79 | 0.5     | 0.58    | 0.86 | 35   |
| Total acid | original  | 80.9            | 12      | 0.75 | 0.04    | 0.05    | 0.81 | 48.7 |
|          | n01            | 95.4            | 13      | 0.67 | 0.05    | 0.05    | 0.86 | 46   |
|          | dg1            | 77.9            | 7       | 0.75 | 0.04    | 0.05    | 0.78 | 50.5 |
|          | msc            | 98              | 12      | 0.65 | 0.05    | 0.05    | 0.86 | 45.7 |
|          | n01+dg1        | 84.8            | 7       | 0.72 | 0.04    | 0.05    | 0.82 | 48.3 |
|          | dg1+msc        | 83.3            | 7       | 0.72 | 0.04    | 0.05    | 0.8  | 49   |
| Firmness    | original    | 107             | 6       | 0.82 | 0.1     | 0.1     | 2.09 | 13.5 |
|           | n01           | 90              | 12      | 0.94 | 0.06    | 0.07    | 2.9  | 9.72 |
|           | dg1           | 83.6            | 6       | 0.89 | 0.08    | 0.1     | 2.09 | 13.5 |
|           | msc           | 84.9            | 12      | 0.94 | 0.06    | 0.07    | 2.74 | 10.3 |
|           | n01+dg1       | 84.1            | 6       | 0.92 | 0.07    | 0.09    | 2.35 | 12   |
|           | dg1+msc       | 74.2            | 6       | 0.9  | 0.08    | 0.1     | 1.94 | 14.5 |

The result of firmness content calibration of persimmon that spectral pre-processing of n01 increased correlation coefficient firmness content between no pre-processing with pre-processing from 0.82 to 0.94 while SEP value decreased from 0.10% to 0.07%. The model with an application of pre-processing n01 method showed higher accuracy and precision than the original model and other pre-processing.

D. Evaluation of Prediction

The best calibration model for predicting SSC, vitamin C and total acid contents presented by scatter plot in Fig. 2. The result showed that the best calibration models were SSC with (MSC) multiplicative scatter correction and 17 PLS factors; vitamin C with MSC and 16 PLS factors; total acid with MSC and 12 PLS factors; firmness with n01 (normalization between 0-1) and 12 PLS factors. The model provided a small value of SEC and SEP compared to other models. Since SEP value was not greater
than two times of SEC, overfitting can be prevented [17]. The slight different values of SEC and SEP indicated that the model has high precision.

The good model has the high correlation coefficient (r > 0.75). RPD values below 1.5 indicated that the calibration could not be used, between 1.5 and 2.0 is possible to distinguish high and low values [23]. Based on obtaining r, SEC, SEP, RPD and CV values, the resulted model to was possible to predict the persimmon SSC and firmness.

### 4. Conclusion

The calibration and validation model of NIR spectroscopy has been developed to predict SSC, vitamin C, total acid, and firmness in astringent persimmon cv. Reundeu using PLS method with different pre-processing spectra treatment. The best calibration model was obtained for: SSC with MSC and 17 PLS factors and firmness with n01 and 12 PLS factors were applied. It has a little SEC, SEP and CV, high r and RPD. In this study, the accuracy of the prediction of vitamin C and total acid using NIR spectroscopy was little due to a limitation of the content of those parameters in persimmon.

### Acknowledgment

The authors wish to express their appreciation for the financial support from Ministry of Research, Technology and Higher Education of the Republic of Indonesia through Competency Research Grant No. 451/IT3.11/PN/2016.

### References

[1] E.W.M. Verheij, and R.E. Coronel, “Edible fruits and nuts,” Plant Resources of South-East Asia (Prosea) No. 2: 298-301, 1991.

[2] Baswarsiati, Suhardi and D. Rahmawati, Potensi dan Wilayah Pengembangan Kesemek Junggo. Bulenin Plasma Nuftah, Vol. 12 No. 2, 2006.

[3] L.C. Lee, C.Y. Liong, and A.A. Jemain, “Applying Fourier-transform infrared spectroscopy and self organizing maps for forensic classification of white-copy papers,” International Journal on Advanced Science, Engineering and Information Technology Vol. 4 No. 6: 1033-1039, 2016.

[4] R.F. Gallego, J.M.H. Hierro, J.C.R Gonzalo, and M.T.E. Bailón, “Feasibility study on the use of near-infrared spectroscopy to determine flavonol in grape seeds,” Talanta 82: 1778-1783, 2010.

[5] C. Pasquini, “Near infrared spectroscopy: fundamentals, practical aspects and analytical applications,” J Braz Chem Soc, 14: 198-219, 2003.

[6] Y.A. Purwanto, I.W. Budiastra, E. Darmani, and N. Arifiya, “Measurement of starch and soluble solid content in papaya using near infrared spectroscopy,” Journal of Chemical and Pharmaceutical Research 7(6): 112-116, 2015.

[7] U. Ahmad, Sutrisno, Y.A. Purwanto, I.W. Budiastra, Y. Makino, S. Oshita, Y. Kawagoe, S. Kuroki, and D.D. Novita, “Prediction of hardness development in mango peel using NIR spectroscopy during low-temperature storage,” Engineering in Agriculture, Environment and Food 7: 86-90, 2014.

[8] L. Karlinasari, Y.A Purwanto, M. Sabed, I.N J, and Wistara, “Near-infrared (NIR) spectroscopy for estimating the chemical composition of (Acacia mangium wills.) wood,” J Indian acad Wood Sci 11(2): 162-167, 2014.

[9] D. Cherie, S. Herodian, U. Ahmad, T. Mandang, and M. Makky, “Optical characteristics of oil palm fresh bunch (FFB) under three spectrum regions influence for harvest decision,” International Journal on Advanced Science, Engineering and Information Technology Vol. 5 No. 3: 255-263, 2015.
[10] F.U Xia-ping, L.I Jian-ping, Ying, and Zhou, “Determination of soluble solid content and acidity of loquats base on FT-NIR spectroscopy,” Journal of Zhejiang University Science B. ISSN 167-1581: 120-125, 2009.

[11] Z. Peng, Y. Xue, J. Li, X. Feng, and B. Wang, “Research on nondestructive measurement of firmness and soluble tannin content of ‘mopanshi’ persimmon using vis/nir diffuse reflection spectroscopy,” Acta Horticulture 996, 2011.

[12] Z. Shunjuan, J. Dengfei, and Z. Haihong, “NIR spectroscopy identification of persimmon varieties based on PCA-SVM,” IFIP Advances in Information and Communication Technology, Vol. 345: 118-123, 2011.

[13] H. Cen, and Y. He, Y, “Theory and application of near infrared reflectance spectroscopy in determination of food quality,” Trends in Food Science & Technology 18: 72-83, 2007.

[14] M. Blanco, and I. Villarroya, “NIR Spectroscopy: a rapid-response analytical tool,” Trends in analytical chemistry 21: 240-250, 2002.

[15] Y.A. Purwanto, H.P. Sari, and I.W. Budiasta, “Effects of preprocessing techniques in developing a calibration model for soluble solid and acidity in ‘Gedong Gincu’ mango using NIR spectroscopy,” International Journal of Engineering Technology Vol. 7 No. 5: 1921-1927, 2015.

[16] Q.S. Chen, J.W. Zhao, S. Caitep, Z.M Guo, “Simultaneous analysis of main catechin content in green tea (Camellia sinensis (L.) by Fourier transform near infrared reflectance (FT-NIR) spectroscopy,” Food Chemistry 113: 1272-1277, 2009.

[17] [Andasuryani, Y.A. Purwanto, I.W. Budiasta, and K. Syamsu, “Determination of catechin content in gambir powder from dried gambir leaves quickly using FT NIR PLS model,” International Journal on Advanced Science, Engineering and Information Technology Vol. 4 No. 5: 2088-5334, 2014.

[18] H. Buddenbaum, and M. Steffens, “The effects of spectral pre-treatment on chemometric analysis of soil profiles using laboratory imaging spectroscopy,” Applied and Environmental Soil Science Vol. 2012: 1-12, 2012.

[19] E. Elfadl, C. Reinbrecht, and W. Clauepin, “Development of near infrared reflectance spectroscopy (NIRS) calibration model for estimation of oil content in a worldwide safflower germplasm collection,” International Journal of Plant Production 4: 259-270, 2010.

[20] Q. Ouyang, Q. Chen, J. Zhao, and H. Lin, “Determination of amino acid nitrogen in soy sauce using near-infrared spectroscopy combined with characteristic variable selection and extreme learning machine,” Food and Bioprocess Technology 6(9): 2486-2493, 2013.

[21] T. Udelhoven, C. Emmerling, and T. Jarmer, “Quantitative analysis of soil chemical properties with diffuse reflectance spectrometry and partial least-square regression: A feasibility study,” Plant and Soil 251: 319–329, 2003.

[22] B.M. Nicolai, K. Beullens, E. Bobelyn, A. Peirs, W. Saeyes, K.I. Theron, and J. Lamertyn, “Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy,” A Rev. Postharvest. Biol. Technol 46: 99-118, 2007.

[23] A.M. Mouazen, W. Saeyes, J. Xing, J.D Baerdemaeker, and H. Ramon, “Near infrared spectroscopy for agricultural materials: an instrument comparison,” J. Near Infrared Spectroscopy 13: 87-97, 2005.