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Prediction of Soluble Solid Content in Watermelon using Visible Shortwave Near Infrared Spectroscopy

M.L Siti Saripa Rabiah[1], M.N. Nazmi[1,2], B. Siti Khairunniza[1,2] and A. Najidah[1]

[1]Department of Biological and Agricultural Engineering,
Faculty of Engineering,
Universiti Putra Malaysia,
43400 Selangor, Malaysia.

[2]Smart Farming Technology Research Centre,
Faculty of Engineering,
Universiti Putra Malaysia,
43400 Selangor, Malaysia.

sariparabiahmatlazim@gmail.com

ABSTRACT

Watermelon is one of the popular tropical fruits in Malaysia. The production of watermelon is increasing over the year. Watermelon contains higher level of the vitamins and minerals. Quality of watermelon can be determined based on soluble solid content (SSC). This quality attribute is important factor by customers before them buying the fruits. However, the conventional method used in the farm was time-consuming, less efficient and non-consistent. So, there are need a robustness, rapid and consistent device, to evaluate the internal quality of watermelon to replace the conventional method. Therefore, the purpose of this study was to investigate the potential application of low cost spectroscopy method to predict sugar content of watermelon. A total of 21 of watermelon samples were studied. The spectral data were collected using spectroscopy in reflectance mode. Then the samples proceeded with SSC measurement. The spectral data were pre-processed for an optimal performance, before the calibration. Partial Least Square (PLS) was used to examine the relationship between spectral data and sugar content. The calibration model produced values of coefficient determination (R^2) and root mean square errors (RMSEP) of 0.93 and 0.6 respectively. The prediction models gave good R^2 and RMSEC values of 0.90 and 0.42 respectively. These results demonstrating the ability of UVNIR can be used to predict the soluble solid content of watermelon.

KEYWORDS

Non destructive, Soluble solid content, Watermelon, PLS, Spectroscopy.

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INTRODUCTION

Watermelon (Citrullus Lanatus) is the popular tropical fruits. China is the world's leading producer of watermelon with 66.7% of world production (72.943 billion Mt), followed by Iran with 3.61 % (3.947 Mt), Turkey with 3.55% (3.887 Mt) and Brazil with 1.97 percent (2.163 Mt), (FOA, 2013). Malaysia planted 11,986.8 hectares in 2016 with a production of 192910 metric tons valued at RM 244, 996. The information also shows that the yield average of melon in Malaysia is 17.4 Mt/ha (MOA, 2016).

Watermelon production in Malaysia is for fresh consumption, but it can also be processed for juice. This is because watermelon is not only made up of water and sugar, but it also contains higher level of the Vitamins A and C, sugar, minerals (potassium, iron, calcium, phosphorus, magnesium, zinc etc.) and organic acids (Tlilie et al., 2011). Over the years, consumers aware about the fruit quality before purchasing the crops. The consumer's attention to fruit quality is not limited to external attribute including color, size and shape but further extends to internal attributes such as SSC and nutritional content (Kumar et al., 2015). SSC is the most important internal quality index of watermelon and also relates to the fruit maturity and harvest time (Drogoudi and Pantelidis, 2011) and high sugar content is one of the major characteristics (Semmelmeyer, 2006).

Current practice to determine the quality attribute used in the farm is done by thumping the skin of the fruit in order to check its sound. The sound is used to detect the hallow heart defect in the fruit. Another popular technique was by searching for yellow spots on the skin surface. This conventional practice was performed by trained laborers. However, most aspects of the evaluation were always based on the visual appearances and defects of the fruit. This practice is quite time-consuming, laborious, tedious, less efficient, and non-consistent (Ali et. al, 2017). Thus, there are need a robustness, rapid and consistent device, to evaluate the internal quality of watermelon to replace the conventional method.

Lately, the application of spectroscopy in agricultural products is getting attention with increasing the number of publication for fast measurement of SSC and other quality attributes of mandarin (Kawano et al. 1993;) mango (Saranwong et al. 2004; Schmilovitch et al.,2000); kiwifruit (Clark et al., 2004; McGlone et la.,2002) apple (Moons et al., 1997; Lammertyn et al. 2000; Liu & Ying 2005; Fa et al., ,2009; Mendoza et al., 2012). pineapple (Chia & Rahim, 2012). Nawi, et al., (2013) also applied visible and shortwave near-infrared (Vis/SWNIR) spectroscopy to predict the sugar content of sugarcane based on skin scanning.

This spectroscopy technology was applied due to the robustness of the device, the lack of need for sample preparation and the ability to performed rapid measurements (Ignat et al.,2012) low cost, accurate and reliable method and can be used to analyze multiple attribute simultaneously (Alfatni et al.,2013). Thus, a new affordable technology which can provide accurate and consistent measurement is needed to replace the conventional method. Therefore, the purpose of this study was to investigate the potential application of low cost spectroscopy method to predict sugar content of watermelon. The specific objective was to determine the accuracy prediction model between spectral data and SSC.

MATERIALS AND METHODS

A total of 21 watermelon samples were harvested from local farm in Selangor All the samples were cleaned and stored under optimized condition at 8^0C and 85 % relative humidity before the measurement were taken and were equilibrated at room temperature.

Each watermelon samples were cut into halves from stem end to calyx before spectral data collection. The samples were scanning using spectroscopy. Spectra were collected for all samples in reflectance mode. UV NIR spectra were obtained using Ocean Optics HR4000 CG spectrometer (Ocean Optic HR4000, Ocean Optics Inc., Dunedin, Florida) with a spectral range from 200 to 1100 nm. A halogen light source (Model: HL 2000) which is a versatile white-light source was used to generate the light incident on the samples.

Kato, 1997 reported the distribution of sweetness varies, such as sweetness of the flesh in centre contracts to the flesh close to rind has a large difference. After the spectral data collection, each section watermelon was divided into three sub-portions. The watermelon juice was extracted and measured by a handheld digital refractometer (Pal-1, Atago Co., Tokyo, Japan).

In order to reduce low signal-to-noise ratio, the first 300 nm and the last 100 nm data points were removed from the original spectral data obtained from the spectrometer. The spectra data were pre-processed for an optimal performance, before the calibration. In this study, the raw spectral data was pre-processed using multiplicative scatter correction (MSC) method. MSC technique was chosen because it is the most effective normalisation technique offered by most chemometrics software packages (Næs et al., 2004). MSC was used to compensate for additive (baseline shift) and multiplicative (tilt) effects in the spectral data due to physical effects of the samples.

RESULTS

The reflectance spectral of watermelon in the wavelength range from 500 nm to 1000 nm was constructed as shown in Figure 1. There is an absorbance at 67 5nm which may be related to chlorophyll content of watermelon (Merzylak et al., 2003). There is no absorption peak around 960 nm that belong to water (Golic et al., 2003). The low absorption values in the region between 750 nm and 900 nm probably do not contain important information related to watermelon quality (Martinez et al., 2013).

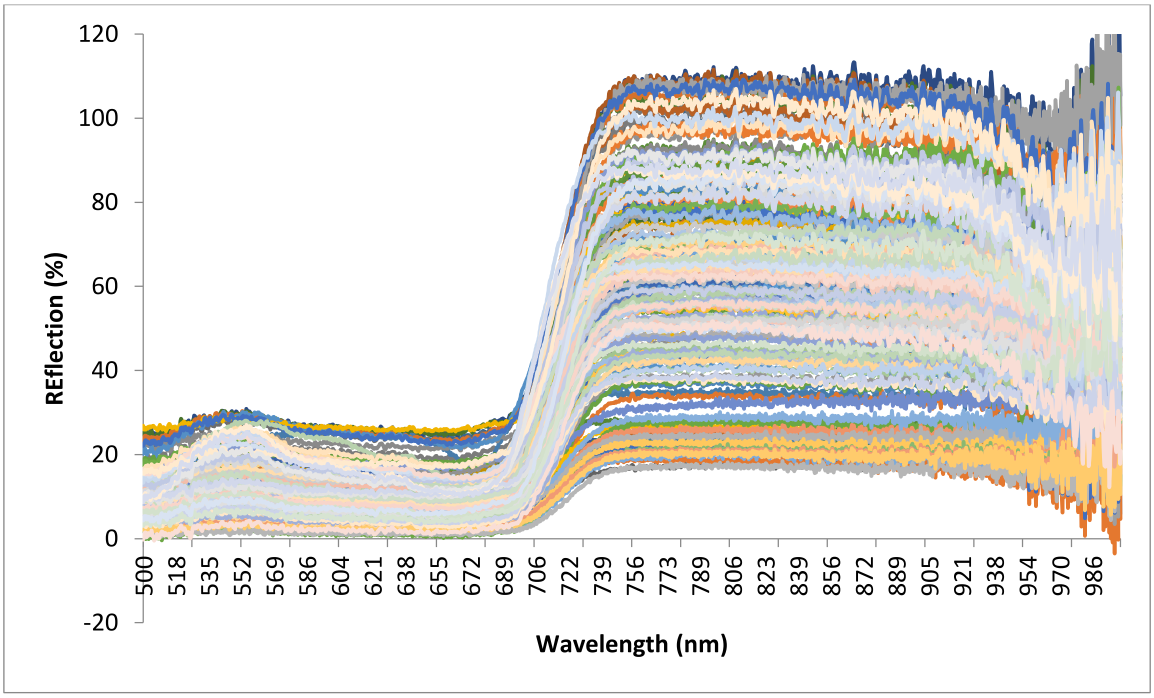

Figure 1: Typical reflectance spectra of all measured watermelon samples between 500 nm to 1000 nm.

Table 1: Performance of PLS models in prediction SSC of watermelon samples

Component	Calibration	Component	Prediction
R^2	0.9	R^2	0.93
RMSEC	0.42	RMSEP	0.6
N	32	N	10

The performance of PLS models in predicting watermelon based on SSC are presented in Table 1. The R2 and RMSEP of prediction model were used to measure the models' performances. The prediction accuracy for both calibration and prediction models for watermelons were generally good. For calibration models, R2 and RMSEP values being 0.90 and 0.42 respectively whereas value of R2 of prediction was 0.93 and RMSEP was 0.6. This model was considered appropriately accurate when value of R2 both in calibration and validation were high, while SEC and SEP value were low.

By knowing these properties, the quality watermelon can be modelled using regression of spectral and sugar content. PLS was used to examine the relationship between spectral and sugar content. A model was developed using the Unscrambler, version 9.2 (CAMO PROCESS AS, Oslo, Norway). When using the entire wavelength range, the average mean and Savitzky-Golay smoothing for pre-processing case yielded the best outcome. The calibration and prediction models represented by the value of R2 showed the highest accuracies were 0.09 and 0.93 respectively, demonstrating the ability of UV NIR can be used in evaluate the internal quality of watermelon.

CONCLUSIONS

This study showed the UVNIR spectrometer has the potential to measure SSC of watermelon. PLS was used for establishing mode of relation between reflectance transmittance and SSC parameter of watermelon. The calibration and prediction showed the highest accuracies of R2 were 0.90 and 0.93 respectively. The non-destructive UVNIR measurement provided good estimates of SSC index of watermelon, and the predicted values were high correlated with destructively measured value for SSC. The UV NIR reflectance technique will be valuable technique for detecting thick skin fruit. Based on finding in this study, it is possible to develop a non-destructive technique for measuring SSC of watermelon by U NIR Spectroscopy.

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