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Determination of moisture content of peanut (*Arachis hypogea* Linn.) kernel using near-infrared hyper-spectral imaging technique

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Key words: Near infrared hyperspectral imaging, Optimal wavelengths, Partial least square regression, Peanut kernel, Peanut moisture content

Abstract

Moisture content is a very essential indicator for quality and storage stability of peanuts but its measurement is tedious and time-consuming. This study ventured in a rapid and non-destructive way of determining and predicting the moisture content of peanut kernels utilizing latest technology. This study generally aims to investigate the potential of hyperspectral imaging technique in the near- infrared region (900nm – 1700nm) for determining and predicting moisture content of peanut kernels. Using partial least square regression (PLSR), spectral data from the peanut kernel hyperspectral images were extracted to predict MC. The MC PLSR model displayed good performance with determination coefficient of calibration (R2c), cross- validation (R2cv) and prediction (R2p) of 0.9309, 0.9094 and 0.9316, respectively. In addition, root mean square error of calibration (RMSEC), cross-validation (RMSECV) and prediction (RMSEP) of 1.6978, 1.9571 and 1.8715, respectively. Optimization was done by selecting wavelengths with the highest absolute weighted regression coefficients resulting to 20 wavelengths identified. These wavelengths were used to build the optimized regression model which resulted to better model with R2c of 0.9357, R2cv of 0.9142 and R2p of 0.9445 as well as RMSEC, RMSECV and RMSEP of 1.6822, 1.8316 and 1.9519, respectively. The optimized model was applied to the peanut kernel hyperspectral images in a pixel-wise manner obtaining peanut kernel moisture content distribution map. Results show promising potential of hyperspectral imaging system in the near- infrared region combined with partial least square regression (PLSR) for rapid and non- destructive prediction of moisture content of peanut kernels.

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Introduction

Moisture content (MC) is a basic and equally significant indicator for quality and storage stability in peanuts (Jin, Li, & Cheng, 2015). It is an important parameter that should be measured, monitored and controlled during harvesting, drying, processing, marketing and storage (Kandala & Sundaram, 2014; Jin, Li, & Cheng, 2015; Govindarajan, Kandala, & Subbiah, 2009). The Philippine National Standard recommends to dry peanuts at MC generally lower than 10% (moisture content is expressed in wet basis throughout this article) to avoid growth of molds during storage (Bureau of Agriculture and Fisheries Standards, 2015) and to increase their shelf life (Sundaram, Kandala, & Butts, Sorption isotherm modeling of different peanut types, 2010). For longer shelf life, it is recommended to store peanut kernels at the following conditions: <7% MC at 1 to 5°C for at least 1 year or <6% MC at -18°C for 2 to 10 years. Peanut moisture content will be maintained at 7 to 7.5% if stored at RH between 55% and 70% at 1 to 5°C (Maness, 2016).

Different methods in peanut moisture content determination namely oven drying method (ASABE Standards, 2010; AOAC International, 2000; Butts, Lamb, Sorensen, & Chen, 2014), use of microwave resonator (Kraszewski & Nelson, 1993), NIR reflectance spectroscopy (Sundaram, Kandala, Govindarajan, & Subbiah, 2012; Govindarajan, Kandala, & Subbiah, 2009), electronic moisture analyzer specifically the CI meter (Kandala, Butts, & Lamb, 2008) and capacitance sensor (Kandala & Sundaram, 2010) are all reliable but time consuming, destructive, tedious and cannot be implemented for online detection (Jin, Li, & Cheng, 2015). A rapid and non-destructive determination of moisture content in peanuts as an indicator of quality is indeed very significant.

With the increasing awareness to food quality and safety that consumers demand, application of non-destructive technologies, known to be fast, reliable, accurate, simple and able to do real – time detection is being encouraged. Hyperspectral imaging is one of the most promising techniques used for quality evaluation (Barbin, Elmasry, Sun, & Allen, 2010; Abdullah, Elmasry, Sun, & Allen, 2010; Elmasry, Kamruzzaman, Sun, & Allen, 2012; Huang, Liu, & Ngadi, 2014) and still currently explored for other possible applications most especially in the food industry.

Hyperspectral imaging combines both spectroscopic and imaging techniques in one system obtaining spectral and spatial data simultaneously of the object being studied (Elmasry, Kamruzzaman, Sun, & Allen, 2012). Thus, gaining its fame as a non- destructive, rapid and real-time detection tool for food quality and safety assessment (Huang, Liu, & Ngadi, 2014). It has been widely used in the grain industry (Wang, et al., 2014; Kong, Zhang, Liu, Nie, & He, 2013; Williams, Geladi, Britz, & Manley, 2012; Berman, et al., 2007; Manley, Wiliams, Nilsson, & Geladi, 2009) which includes peanut (Jin, Li, & Cheng, 2015).

Jin *et al* in 2015 applied hyperspectral imaging technology for determination of moisture content in peanut kernels. The developed optimized model showed good performance at both spectral ranges: 400nm to 1000nm and 1000nm to 2500nm. It was found out that at the NIR region, O-H group overtone and combination bands are pronounced thus NIR hyperspectral imaging will be very well suited for MC determination in peanuts (Kandala & Sundaram, 2012).

This study generally aims to investigate the potential of hyperspectral imaging technology in the near-infrared (NIR) region from 900nm to 1700nm combined with PLSR analysis for determining and predicting moisture content of peanut kernels. Specifically, it aims to: develop a prediction model for moisture content using hyperspectral imaging in the NIR region; validate the model; identify and select optimal wavelengths that relates to moisture content of the peanut kernels and lastly to generate the moisture content distribution map of the kernels.

Materials and methods

The experiment is generally divided into several steps as shown in fig. 1. It consists of different sub-processes as follows:

Sample preparation and moisture content determination

Peanuts (BPI-Pn9 variety) were obtained from Enrile, Cagayan. Two hundred (200) peanut kernels with varied moisture content consisted the test samples in which 150 samples was used as the calibration set and the remaining 50 kernels as the prediction set. Moisture content of the kernels were obtained using the standard air oven method (ASABE Standards, 2010) at 130°C for 6 hours.

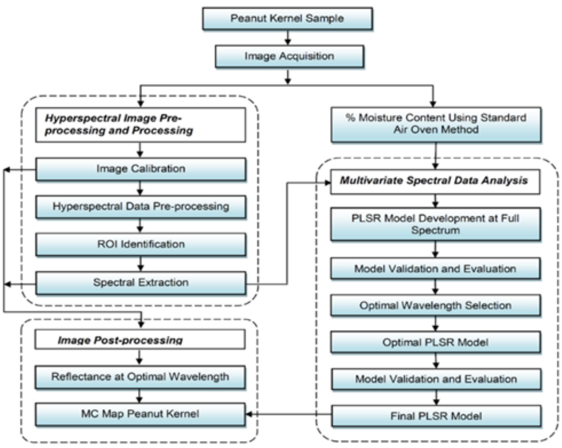

Fig. 1. General steps involved in the experiment.

Hyperspectral data acquisition

A typical push-broom hyperspectral imaging system (Fig. 1) of Specim Spectral Imaging Ltd. (Oulu, Finland) consisting primarily of a VLNIR- CL- 100 hyperspectral imaging camera with spectral range of 900nm to 1700nm, a Lab Scanner, halogen lamp, magma box and the data acquisition component. It consisted of a semi- ruggedized laptop (Dell Latitude 5405 Model) and data acquisition software Spectral DAQ VLNIR with ENVI 5.2 + IDL for pre and post processing of acquired hyperspectral data.

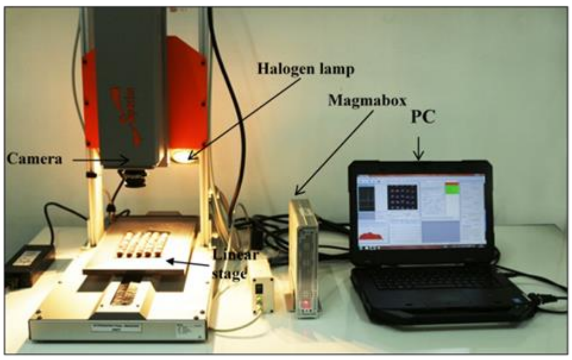

Fig. 2. The hyperspectral imaging system.

Image was acquired at the actual range of 898.71nm to 1750.96nm with an interval of 3.3nm having a total of 256 spectral bands. Image of fifty kernels (50) were taken simultaneously using the Spectral DAQ VLNIR software at an exposure time of 12.5ms and 40 Hz frame rate.

Hyperspectral image-pre-processing and processing

Image calibration was done to correct both the spatial and spectral characteristic of the raw image obtained as shown in fig. 3. This was done using the ENVI Classic software with the reference images consisting of the white and dark images. To improve robustness of the calibration model, pre-processing of spectral as well as spatial data was done using ENVI 5.2 software. Masking was done to address the problem in the saturated image caused by the lighting system innate in the current hyperspectral imaging set up. A rectangular region of interest (ROI) with a dimension of 20 (x –axis) by 10 (y –axis) shown in fig. 3 was chosen in each peanut kernel for hyperspectral data extraction. Spectral data in the form of reflectance as well as the spatial coordinates of each pixel was extracted from each chosen ROI (band 1 to band 256) in the form of a matrix file. The mean reflectance of individual kernel ROI was used to build the spectral signature of each kernel.

Multivariate spectral data analysis

Unscrambler X 10.5 free trial version by CAMO Software was used to undertake multivariate analysis. Multivariate regression specifically partial least square based on linear algorithm was utilized because it is known as the most robust and reliable tool in developing multivariate calibration models (Elmasry, Kamruzzaman, Sun, & Allen, 2012). It was used to predict the moisture content of each peanut kernel based from the reflectance. The calibration set consisted of 150 peanut kernels with mean spectra from band 1 to 256. These were used to build the calibration model which was validated using full cross- validation. The models were evaluated by comparing actual values obtained with the predicted values. Evaluation was dependent on the values obtained for the determination coefficients of calibration (R2c), cross- validation (R2cv), and prediction (R2P) and root mean square error of calibration (RMSEC), cross validation (RMSECV), and prediction (RMSEP).

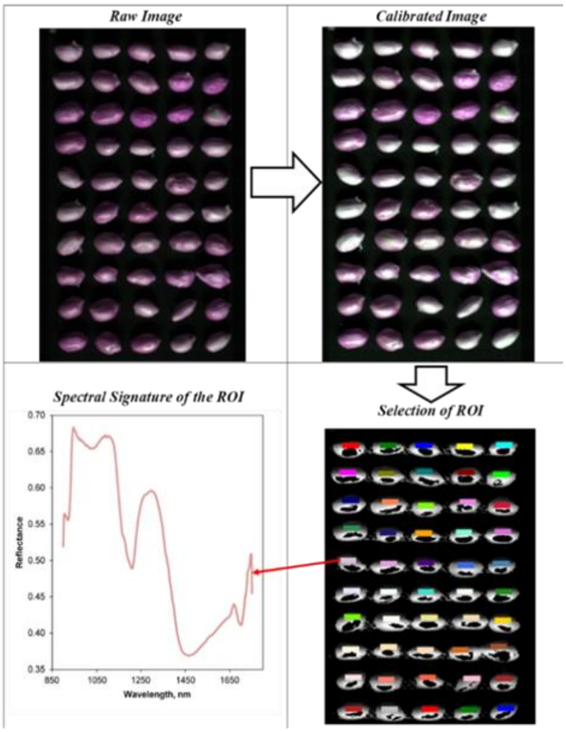

Fig. 3. Spectral data extraction from peanut kernel.

Selection of optimal wavelengths

The huge amount of data inherent in each hyperspectral image causes longer processing time, thus a means of decreasing the input data is necessary for a more efficient system. Owing to the fact that not all the wavelengths are related to the moisture content of the peanut kernel, significant wavelengths were identified. These are wavelengths with the highest absolute regression coefficients (Jin, Li, & Cheng, 2015; Wang, et al., 2014; Liu, Qu, Sun, Pu, & Zeng, 2013) displayed as peaks in the regression coefficient plot for the whole spectrum. This process aimed at obtaining a simplified model (decreased spectral bands as predictors) with the same or even better quality.

Moisture content mapping

Using MatlabR2013a software, moisture content distribution map of each kernel was produced by applying the optimized MC PLSR model to all the hyperspectral images in pixel- wise level. These images were created to visualize the moisture content distribution in each peanut kernel.

Results and discussion

Spectral signature of peanut kernel

The moisture content of the peanut samples in wet basis ranged from 7.6% to 33.22% having a wide range of variability which is good in generating stable calibration models with wide range of applicability (Liu, Qu, Sun, Pu, & Zeng, 2013). Spectral signature of each peanut kernel was obtained by plotting the mean reflectance at full spectrum of the ROI for each kernel. The spectral signature of some sample peanut kernels at different moisture content is shown in fig. 4.

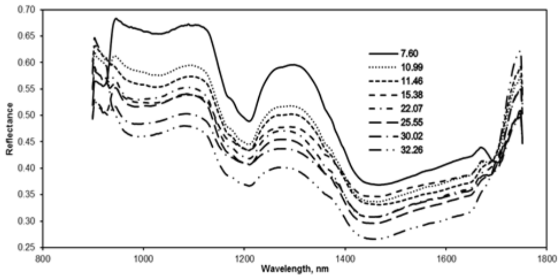

Fig. 4. Spectral signature of the sample peanut kernels at different levels of moisture content.

It can be noted that peanut kernels at different levels of moisture content exhibit the same shape of spectral signatures only with different amplitudes. Reflectance of the kernels at wavelengths of approximately 950nm to 1680nm are inversely proportional to the moisture content. As the moisture content of the kernels increases, the reflectance decreases as shown by the behavior of the spectral signatures displayed in the plot with 7.6% MC in wet basis having the highest curve among the rest of the curves. This implies that kernels having lower moisture content have higher reflectance, which is mainly attributed to the effect of water in the peanut kernel. Water shows strong absorption at the NIR region implying lower reflection (Achata, Esquerre, O'Donnell, & Gowen, 2015).

This behavior of the spectral signature for peanut kernels was also observed by Govindarajan *et al* (2009) as shown in their findings that kernels with lower MC have lower absorbance implying higher reflectance and vice versa. This is not only true for peanut kernels but also for other products like meat (Elmasry, Iqbal, Sun, Allen, & Ward, 2011). This only shows that the water present in each product is the major contributor to the specific behavior of the spectral signature of the products.

The spectral signature of the kernels have common notable peaks that can be attributed to their reflectance and absorption bands which vary in great extent to their composition. In the infrared region, it is known that liquid water exhibits three major vibrational absorbance peaks due to asymmetric stretching, symmetric stretching and bending vibrations (Achata, Esquerre, O'Donnell, & Gowen, 2015). Light absorption in the NIR region is mainly caused by the vibration of functional groups of organic ingredients of the kernel. These bands are strong overtone and combination absorptions of hydrogen containing bands O - H present in water, C - H present in fats and oil as peanut is known to have high oil content, and N - H present in protein which is also rich in peanuts.

Achata *et al.* (2015) developed a table adopting the approach of Weyer and Workman as cited showing estimated position of overtones and combinations of fundamental asymmetric, symmetric and bending vibrations of the water molecule. The first notable reflectance peak was at 902nm which is possibly attributed to water combination vibrations of the 3Vs (third overtone of symmetric stretching) and Vas + 2Vs (first overtone of asymmetric stretching and second overtone of symmetric stretching). First absorption peak was estimated at 918.68nm to 931. 99nm. This is probably related to the second overtone O – H and N – H stretches and third overtone C – H stretches noting their proximity to the 925nm absorption peak of peanut as cited (Jin, Li, & Cheng, 2015). Using the table of Achata, this are probably related to the water combination vibrations of the following: 3Vas, 3Vs , Vas + 2Vs and 2Vas + Vs (Achata, Esquerre, O'Donnell, & Gowen, 2015).

Another strong reflectance was noted at 1088.5601nm to 1095.23nm which is near the 1100nm where weak absorbance (also equal to strong reflectance) was also observed by Govindarajan *et al* (2009). This wavelength is possibly associated with water combination vibrations of the first overtone of bending vibration and second overtone of symmetric stretching (Vds + 2Vs). Another absorption peak at 1205.3199nm was attributed to the combination of O - H stretching which is common with the existing models for peanut kernels (Jin, Li, & Cheng, 2015; Govindarajan, Kandala, & Subbiah, 2009). This is presumably associated with the second overtone of symmetric stretching and first overtone of bending vibration of water.

Fourth wide reflectance peak at approximately 1300nm is also observed which is the same again with the two existing models for peanut kernels. With its proximity to 1349nm, this could possibly attributed to the vibrational combination of the first overtone of asymmetric stretching and symmetric stretching of water (Achata, Esquerre, O'Donnell, & Gowen, 2015). At around 1450nm is another notable peak absorbance of the spectral signature. This was probably related to the overtone O- H which again can be observed to be common for all the models. For the range 1000nm to 1700nm, the spectral signature of the model of Govindarajan *et al.* (2009) and Jin *et al.* (2015) is exactly the same with the model built in this study implying the unique spectral signature of peanut kernels regardless of its variety or country of origin.

Moisture content prediction models using full spectrum

Mean reflectance of each kernel ROI and the measured moisture content using analytical method were used in the multivariate analysis to build calibration and prediction models which both showed good performance. The plot in fig. 5 shows the goodness of fit of the data points with the regression line. The model showed good capability in predicting moisture content of peanut kernels as shown by the determination coefficients as follows: R2c = 0.9309, R2cv = 0.9094 and R2p = 0.9317 with RMSEC of 1.6978, RMSECV of 1.9571 and RMSEP1 of .8715.

Optimized moisture content PLSR model

The vast amount of data contained in a hyperspectral image creates the problem of high dimensionality due to the colinearity among the contiguous wavelengths (Elmasry, Kamruzzaman, Sun, & Allen, 2012). This also causes slow processing of data. Not all the wavelengths relate to the water content of the peanut kernels implying the need to optimize to come up with the key wavelengths that will build a prediction model maintaining or even exceeding the original determination or correlation coefficients.

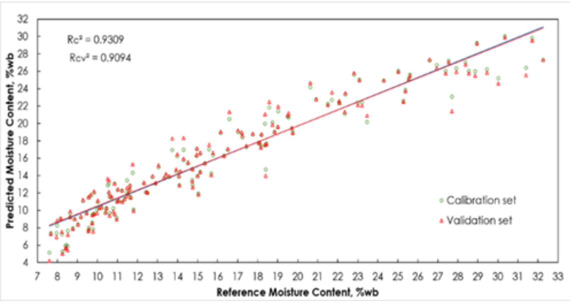

Fig. 5. Measured and predicted moisture content of peanut kernel calibration and validation sets using PLSR methods at full spectrum.

According to Liu *et al.* (2013), there is no standard method in selecting significant wavelengths from the whole spectrum. But there are number of approaches that have been proposed and used. One of which is the use of correlation coefficients or also known as weighted regression coefficients or beta coefficients as cited by Elmasry *et al.* (2012).

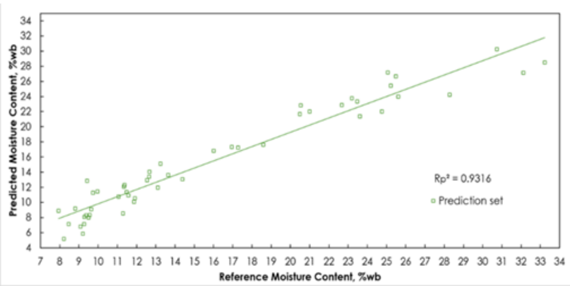

Fig. 6. Measured and predicted moisture content of peanut kernel prediction set using a full spectrum.

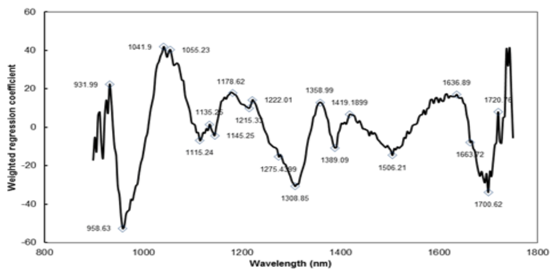

Fig. 7. Weighted regraession coefficients full NIR spectrum of the moisture content PLSR.

There were numerous studies recorded that used this method. Govindarajan *et al.* (2009) in their study were able to identify five (5) discrete wavelengths that corresponded to the largest peaks and valleys in the beta coefficient plot. Liu *et al.* (2013) on the other hand, in their study for the prediction of salt contents and water activity of porcine meat slices also used the same method. They noted the wavelengths with weighted regression coefficients having the highest absolute value. These key wavelengths were used to build the final PLSR model. Also, Jin *et al.* (2015) established different PLSR models using different important wavelength combinations as a result of their optimization process. Wavelength combinations that yielded the highest determination coefficient was used to build the final PLSR model for the determination of moisture content of peanut kernels.

Optimization lead to the final moisture content PLSR model given by equation:

$$MC = 15.7401 + 19.61791\,\lambda 931.99 - 525.0982\,\lambda 958.63 + 382.3892\,\lambda 1041.9 + 373.7798\,\lambda 1055.23 - 73.57477\,\lambda 1115.24 - 9.262369\,\lambda 1135.25 - 62.65506\,\lambda 1145.25 + 148.773\,\lambda 1178.62 + 23.12367\,\lambda 1215.33 + 61.78926\,\lambda 1222.01 - 150.0962\,\lambda 1275.4399 - 293.0202\,\lambda 1308.85 + 166.5295\,\lambda 1358.99 - 91.37688\,\lambda 1389.09 + 20.22804\,\lambda 1419.1899 - 127.3643\,\lambda 1506.21 + 246.805\lambda 1636.89 + 4.554485\,\lambda 1663.72 - 234.7841\,\lambda 1700.62 + 124.9209\,\lambda 1720.76 + e$$

where:

MC = predicted moisture content in% wet basis

β_0 = regression constant equal to 15.7401

β_n = regression coefficient at waveband

λ_n = reflectance at wavelength n

e = moisture content residual

Initial model built for the moisture content of the peanut kernels consist of 256 uniformly spaced wavelengths from the full spectrum. The weighted regression coefficients corresponding to each wavelength were plotted for easier visualization of the peaks in the plot as shown in fig. 7.

From the 256 wavelengths, 20 key wavelengths were identified represented by dots with their corresponding wavelengths. These wavelengths include the following: 931.99nm, 958.63nm, 1041.9nm, 1055.23nm, 1115.24nm, 1135.25nm, 1145.25nm, 1178.62nm, 1215.33nm, 1222.01nm, 1275.4399nm, 1308.85nm, 1358.99nm, 1389.09nm, 1419.1899nm, 1506.21nm, 1636.89nm, 1663.72nm, 1700.62nm, and 1720.76nm. Images of the peanut kernels at these key wavelengths is shown in the appendix. These wavelengths served as the new predictors for the optimized moisture content model. Applying PLSR again with these key wavelengths yielded a better result for both the calibration and prediction models as shown in fig. s 7 and 8. A comparison of the MC PLSR model at full spectrum and the optimized model is shown in table 1.

Table 1. Summary of the determination coefficients for the peanut kernel moisture content PLSR model at full spectrun and optimized wavelengths.

Classification of Model	No. of Wavelengths	Calibration		Cross- validation		Prediction	
		R^2_c	RMSEC	R^2_{cv}	RMSECV	R^2_p	RMSEP
Full Wavelength	256	0.9309	1.6978	0.9094	1.9571	0.9361	1.8715
Optimized	20	0.9357	1.6373	0.9142	1.9043	0.9385	1.7756

It can be noted that the optimized model having only 20 key wavelengths as predictors gave a better performance eliminating the bulk of input data and decreasing the processing time.

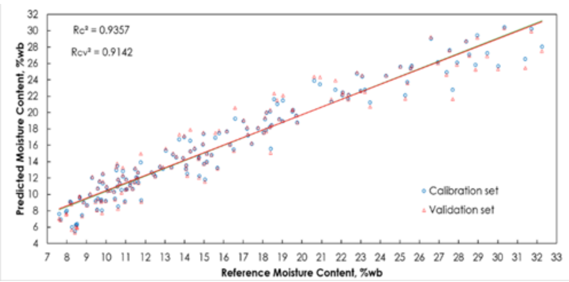

Fig. 8. Measured and predicted moisture content of the peanut kernel for the prediction set using optimized PLSR.

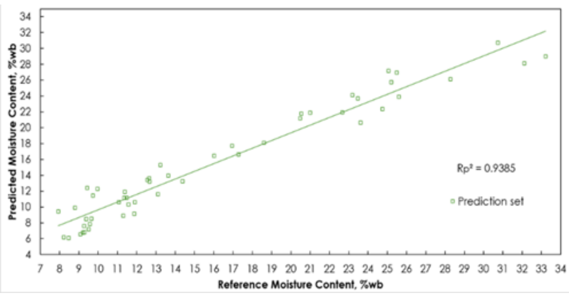

Fig. 9. Measured and predicted moisture content of the peanut kernel for the calibration and validation sets using the optimized PLSR model.

Moisture content distribution map

Applying the final moisture content PLSR model in a pixel- wise manner for the kernels, a concentration map was developed using Matlab software. A visualization of the moisture content distribution map is shown in fig. 10. Each level of moisture content in wet basis corresponds to a specific color as represented by the color bar. It can be noted that in a peanut kernel, the moisture content is not uniform. Also, the saturation effect of the lighting system can be visibly seen at the upper portion of the kernel with red and yellow colors.

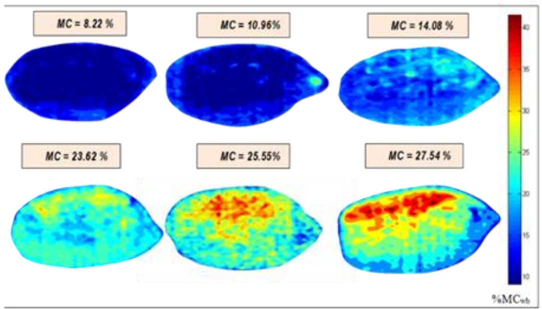

Fig. 10. Concentration map of the peanut kernel moisture content.

Summary and conclusion

Hyperspectral imaging technique at the near infrared region (900nm to 1700nm) combined with PLSR analysis has a great potential for peanut kernel moisture content determination and prediction. The PLSR model at full spectrum showed good predictability performance with R2p of 0.93. Optimized model with twenty (20) key wavelengths showed better performance with R2p of 0.9385.

Applying the optimized model in a pixel-wise manner to the peanut kernel hyperspectral images provided its moisture content distribution map showing non-uniform moisture distribution in a peanut kernel. Results of this study can be very useful in the development of multispectral imaging system for quality and safety evaluation of peanut kernels associated with moisture content.

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