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Prediction of moisture content uniformity using hyperspectral imaging technology during the drying of maize kernel**

Min Huang[1,2], *Weiyan Zhao*[1], *Qingguo Wang*[1], *Min Zhang*[2]*, *and Qibing Zhu*[1]

[1]Key Laboratory of Advanced Process Control for Light Industry (Ministry of Education),
[2]State Key Laboratory of Food Science and Technology; Jiangnan University, Wuxi, Jiangsu, China, 214122

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A b s t r a c t. Moisture content uniformity is one of critical parameters to evaluate the quality of dried products and the drying technique. The potential of the hyperspectral imaging technique for evaluating the moisture content uniformity of maize kernels during the drying process was investigated. Predicting models were established using the partial least squares regression method. Two methods, using the prediction value of moisture content to calculate the uniformity (indirect) and predicting the moisture content uniformity directly, were investigated. Better prediction results were achieved using the direct method (with correlation coefficients R_p = 0.848 and root-mean-square error of prediction RMSEP = 2.73) than the indirect method (R_p = 0.521 and RMSEP = 10.96). The hyperspectral imaging technique showed significant potential in evaluating moisture content uniformity of maize kernels during the drying process.

K e y w o r d s: maize kernels, hyperspectral imaging, moisture content uniformity, drying

INTRODUCTION

Drying is a mass transfer process consisting of removal of water or another solvent by evaporation from the material. This process is important and often used as a final production step before selling or packaging products. In the past decades, many drying techniques have been widely reported and used in food manufacturing. For a drying process, drying uniformity is one of important parameters to evaluate the quality of dried products and drying technology. Drying uniformity is defined as the relative standard deviation (RSD, ratio of standard deviation to mean measurement value) of temperature, moisture content (MC), colour, and shrinkage (Wang *et al*., 2013a; 2013b). Among them, moisture content uniformity (MCU) was gradually concerned by scholars. MC non-uniformity can cause many disadvantages, such as relatively short safe storage life, reduce storage stability, and can even cause mildew deterioration and reduce product use value at serious non-uniformity (Hashemi and Murray Douglas, 2003). Generally, MCU is calculated by the definition (ratio of MC standard deviation to MC mean measurement value). The number of selected samples determines the accuracy of uniformity measurement. The more selected samples, the higher uniformity. Since the traditional laboratory methods for MC measurements of agricultural foods, the gravimetric oven method and Karl Fisher titration (Aguilera, 2003), are destructive measurements, the same samples cannot be used for further analysis, which limits the number of selected samples for calculating uniformity.

Rapid non-destructive technologies for measuring the drying qualities of agricultural products have been studied extensively (Faustino *et al*., 2007; Fernández *et al*., 2005; Nowak and Lewicki, 2005; Mendoza *et al*., 2006; Toyoda *et al*., 2001). Among these approaches, machine vision and near-infrared spectroscopy are the two main methods (Lucas *et al* 2008; Makky *et al*., 2014; Mireei *et al*., 2010; Romano *et al*., 2012; Wu *et al*., 2010). However, the machine vision method can only acquire average image information within the visible range and near-infrared spectroscopy can only acquire spectral information and cannot obtain the spatial information of the samples. As a relatively novel non-destructive technology, hyperspectral imaging integrates the advantages of machine vision and near-infrared spectroscopy, while overcoming the

*Corresponding author e-mail: min@jiangnan.edu.cn
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drawbacks of both techniques when used alone. Hyperspectral imaging provides more detailed or complete information, including internal structure characteristics, morphological information, and chemical composition (Huang *et al*., 2013). This technology has been applied to non-destructive measurement of agricultural products for evaluating internal quality (Ariana and Lu, 2008; Huang and Lu, 2010; Li *et al*., 2012; Liu *et al*., 2006) and pesticide residues (Del Fiore *et al*., 2010; Peng *et al*., 2011; Shahin and Symons, 2011). Thus, this technology may have the potential to be used as an alternative method for predicting the MCU of materials during drying.

In this study, we used maize kernels as raw materials to process dried products and evaluate the MCU during drying based on hyperspectral reflectance imaging technology. The specific objectives are as follows:

- to extract image traits from preprocessed hyperspectral reflectance images of dried maize kernels using the mean method; and
- to evaluate the capability of partial least squares regression (PLSR) models for predicting the MCU of maize kernels during drying.

MATERIALS AND METHODS

Fresh maize (*Zea mays* L.) kernels used in this study, harvested at the commercial state, were purchased from a local market. To achieve a broader distribution of MC and reduce non-uniformity of initial MC, the maize kernels were soaked in water for 12 h. Then they were drained and kept at 4 °C and 95% relative humidity in a refrigerator and were used within 3 days. Fresh samples were kept at room temperature (~24 °C) for one hour before the experiment was started.

Maize kernels were dried using a high-precision laboratory dryer developed at the State Key Laboratory of Food Science and Technology, Jiangnan University, China (Wang *et al*., 2013b). This microwave-assisted pulse-spouted bed vacuum- drying (PSMVD) experimental system essentially included a cylindrical multimode microwave cavity, a circular duct vacuum drying chamber, a pulse-spouted system, a heat supply system, a vacuum system, and a water load system. A detailed description of the dryer system is given by Wang *et al.* (2013b).

In this study, the experimental parameters were set as follows:

- the pressure was set at 7-10 kPa,
- the power was set to 516 W, and
- the samples were spouted in the preselected time interval of 5 s and held for 3 s by allowing nitrogen gas to flow periodically into the drying chamber.

Fresh maize kernels with a mass of 200 g were used for each batch. To achieve broad sample distribution of MC, six batches at different drying times (from 10 to 60, in steps of 10 min) were tested. The experiments were replicated thrice for each drying time. For each batch, two hundred dried maize kernels were selected randomly for hyperspectral imaging and then tested using reference methods for MC. In total, 3600 kernels were used for further analysis.

An in-house developed line-scan hyperspectral reflectance imaging system was used to acquire hyperspectral reflectance images from the maize kernels. The system includes a back-illuminated 1392 × 1024-pixel CCD (charge-coupled device) camera (Pixelfly QE IC 285AL, Cooke, USA), a spectrograph (1003A-10140 Hyperspc™ VNIR C-Series, Headwall Photonics Inc., Fitchburg, USA) with a 25 µm slit covering an effective range of 400 nm to 1 000 nm, a zoom lens (10004A-21226 Lens, F/1.4 FL23 mm, Standard Barrel, C-Mount., USA), a single optic line-light powered by a 150-W DC light source (halogen lamp, EKE, 3250K, Techniquip, USA), and a horizontal motorized stage. Ten maize kernels were placed onto a 20×20 cm black background board in two rows and perpendicular to the scanning line of the hyperspectral imaging unit. Coupled with the distance between the zoom lens and the sample (25 cm), a 35 mm scan length of longitudinal and a 80 µm horizontal step size parameters were preset to acquire the whole undistorted image of one group samples.

For each group of samples, 438 scans covering a 35 mm distance were acquired at an exposure time of 110 ms for each hyperspectral reflectance image. The hyperspectral imaging system had 0.15 mm/pixel spatial resolution and a 0.644 nm spectral interval using a 1 392 pixel camera. After 10 spectral binning operations, the resultant hyperspectral reflectance images had a 6.44 nm spectral interval and 94 wavelengths. Thus, a spatial block of a 1,392 438× 94 image was created, which was represented by a 2-D image with x-axis and y-axis coordinate information. Another axis was represented by spectral information. Darkness and reflectance images of white Teflon were also acquired for all the five groups of samples and used as reference to obtain relative reflectance images. All the acquired images were completed by Hyperspectral Scanning and Image Rendering Software, Rev a.2.1.3 (Headwall Photonics, Inc., USA).

The MC, expressed in on a percent wet basis (% w.b.), was measured by the gravimetric method using a convection oven. The samples dried at different times using the PSMVD experimental system were placed into the oven (Binder FED, Berlin, Germany) at 105°C until they reached a constant weight (Ning, 1997). The weight was measured using an analytical balance (Hengping FA1104, Shanghai, China; ±0.0001 g). The MC was measured and MCU was calculated.

The light source variation effect was corrected by obtaining relative reflectance images using the following equation:

$$T_R = \frac{T_S - T_D}{T_F - T_D} \, , \tag{1}$$

where T_R is the relative reflectance, T_S and T_F are the absolute reflectance of the sample and of the reference (*ie* Teflon), respectively; and T_D is the dark signal for the CCD detector. Thus, all further analyses were conducted on the relative reflectance images.

Segmentation of the maize kernels from the hyperspectral image background is a key step in extracting the image features used to develop the prediction models. Among the image segmentation methods, the global threshold approach is a traditional technique with the advantages of easy calculation and high efficiency.

After the automatic segmentation of the image background at each wavelength, a large amount of spatial and spectral information was obtained from the true image of each maize kernel. Image analysis mainly aims at effective extraction of useful information. Considering the apparent changes in the surface of the maize kernels and the MC of the maize kernels during the drying process, mean reflectance was applied to extract and predict the MCU of the dried grains during the drying process. Similar to the near-infrared spectrum, the mean value of relative reflectance images (mean of the i pixel intensity in the image at each wavelength) provides physical and chemical information on the samples. The mean reflectance is expressed in Eq. (2):

$$\overline{R} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{i=1}^{N} T_R(i,j) \ , \qquad (2)$$

where $\overline{R}$ is mean reflectance, $T_R(i, j)$ is the relative reflectance intensity of the pixel (i, j), (i =1,2 ...M, j = 1,2 ...N); and M, N are the number of total horizontal and vertical pixels for a maize kernel, respectively.

PLSR was used to predict the MCU using the mean reflectance feature parameter. In this study, two methods were investigated including indirect prediction and direct prediction uniformity. In the indirect method, MC was adopted as a reference variable to develop the calibration model and the prediction value of MC was used to calculate the MCU, which was investigated if one of the models could be used to predict the MC and MCU simultaneously. Two hundred maize kernels for each drying time (10, 20, 30, 40, 50, and 60 min) were randomly divided into two sets: 3/4 of the samples were used for calibration and the remaining 1/4 was used for prediction (independent validation). The calibration sets from each drying time made up the whole calibration set and the prediction sets from each drying time made up the whole prediction set for predicting the MC of the maize kernels, respectively. For evaluating the performance of the indirect model, the MC prediction values of 10, 30, and 50 grains in the prediction set for each drying time were selected in one subset to calculate the MCU, respectively.

Unlike in the indirect method, MCU was adopted as a reference variable in the direct method. In order to compare it with the indirect model, the same amount of samples (10, 30, and 50 grains) was selected in one subset to calculate the MCU as a reference, then the calibration model was developed using the mean reflectance spectra and the MCU reference directly.

For both methods, the PLSR models (*ie* selection of the appropriate number of latent variables) were determined by a full cross-validation of the calibration samples using leave-one-out cross validation until the root-mean-square error of cross validation (RMSECV) reached the minimum. After the calibration model was developed, this model was used to predict the independent set of samples that had not been used in the calibration. The calibration and prediction procedure described above was repeated 10 times by selecting a random set of samples. The average values of the correlation coefficient (*ie* R_C, R_{CV}, and R_P) and root-mean-square error for calibration and prediction (*ie* RMSEC, RMSECV, and RMSEP) were calculated to evaluate the performance of the models. The PLSR was run in Matlab (2009b) with PLS-Toolbox 5.0 (Eigenvector Research, Inc., Wenatchee, WA, USA).

RESULTS AND DISCUSSION

Table 1 shows the statistics for the gravimetric method measurement of MC for fresh and dried maize kernels at different drying times (from 10 to 60 min).

Figure 1 shows the contour segmentation result of representative dried maize kernels (10, 30, and 50 min) at a 718.2 nm wavelength.

Figure 2 shows the representative colour images of fresh and dried maize kernels with apparent differences in MC. The samples with higher MC appear smooth and rounded with a homogenous glossy surface. As the drying time increases, the MC decreases, thus causing the samples to have textured surfaces. Shrinkage also occurs as the maize samples lose MC.

Figure 3 shows the representative relative reflectance spectra for fresh and processed maize kernels at different drying times (10, 20, 30, 40, 50, and 60 min). A typical downward peak was observed at 960 nm, corresponding to MC absorption. Along the increase in the drying time, the absorption peak gradually disappeared because of the MC loss. Over the full wavelength region, the relative reflectance for the fresh maize kernels was generally greater than that for the dried sample. For the wavelength range from 400 to 920 nm, an evident decrease in relative intensity was observed at the initial drying periods between 10 and 30 min. Thereafter, the intensity of reflected light tended to increase as observed between 40 and 60 min of drying.

At the initial periods of drying, microstructural changes occurred on the surface of the maize kernels because of the evaporation of moisture in the immediate surroundings of the grain surface. During this initial period, vapour diffusion is the predominant mechanism, and the rate of evaporation remains constant, thus resulting in textural

T a b l e 1. Statistics of the MC measurements for fresh and dried maize kernels

Drying time (min)	Max (%)	Min (%)	Mean (%)	Standard deviation (%)	RSD (%)
0 (Fresh)	79.51	74.46	77.36	0.98	1.27
10	71.69	61.69	66.63	1.91	2.87
20	62.03	48.74	55.66	2.59	4.65
30	44.35	27.41	34.94	3.49	9.99
40	21.49	11.19	15.67	2.53	16.14
50	12.86	7.13	9.89	1.17	11.83
60	10.15	5.95	8.32	0.65	7.81

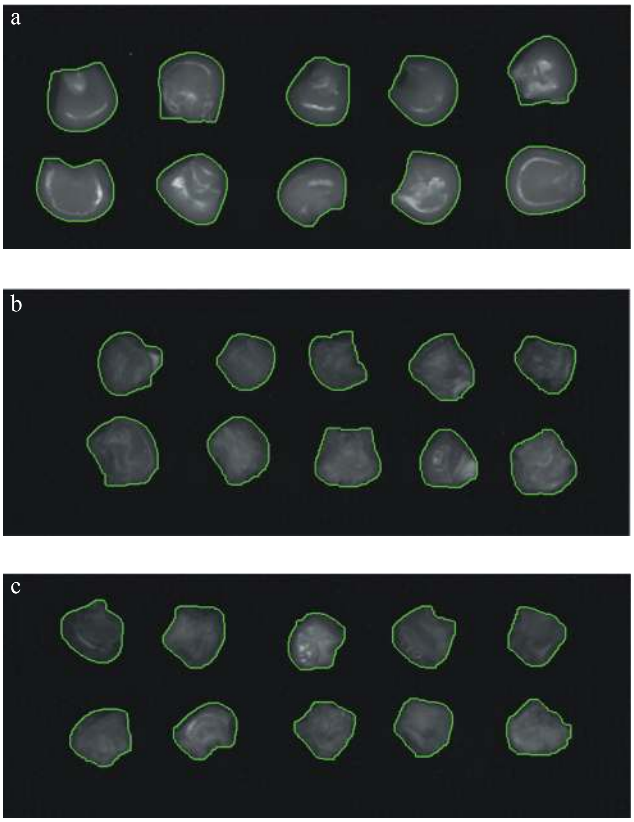

Fig. 1. Contour segmentation results for dried maize kernels: a – 10, b – 30, c – 50 min at a wavelength of 718.2 nm.

changes on the grain surface going from slight to moderate, as observed between 10 and 30 min of drying (Fig. 2b to 2d). However, as soon as the outer layers of the grain cells on the surface become 'unsaturated' with moisture, the drying rate falls sharply because the diameters of pores and capillaries decrease. This condition results in shrinkage and compactness of the surface microstructure. This compact and brittle structure of the maize kernel probably explains the increase in relative intensity values observed at 40 and 60 min of drying (Fig. 3).

The indirect method, which used the prediction value of MC to calculate the uniformity, was analysed in this study. Mean reflectance spectra were used to develop the MC prediction model coupled with the PLSR algorithm. The MC prediction results are shown in Table 2. The average of 10 calibration and prediction models for MC yielded good results, with R_p = 0.992, RMSEP = 2.89 %. The ratio of prediction deviation (RPD), that is, the ratio of the standard error of performance to the standard deviation of the reference data (Huang and Lu, 2010), is an essential parameter in evaluating the performance of prediction models. An RPD between 1.5 and 2 indicates that the model can discriminate low from high values of the response variable. A value between 2 and 2.5 indicates that coarse quantitative predictions are possible, whereas a value between 2.5 and 3 or above corresponds to good and excellent prediction accuracy, respectively (Nicolaï *et al*., 2007). In this study, the RPD value for MC model was larger than 7.0, so these models can be used to predict the MC and calculate its uniformity further.

For this method, a different number was selected in one subset for computation including 10, 30, 50 maize kernels. Table 3 shows the calculation results of MCU used the prediction values of MC. Although the average correlation coefficient, R_p, of 10 runs increased with the increase in the kernel number in one subset, it was less than 0.6, and the RPD was only 0.5. Figure 4 shows the prediction results for MCU versus the actual measurements for one of the 10 runs for 50 maize kernels in one subset.

Since the indirect method yielded poor prediction results for the MCU of dried maize kernels, the direct method was researched, that is, calibration models were developed for describing the relationship between the mean reflectance spectra and MCU directly. The MCU prediction results for the three different numbers of samples in one subset are shown in Table 4. Compared with the indirect method, the direct method yielded better results for the calibration and prediction models. The average correlation, R_p, of 10 runs was higher by 33.6-62.8%, whereas the average

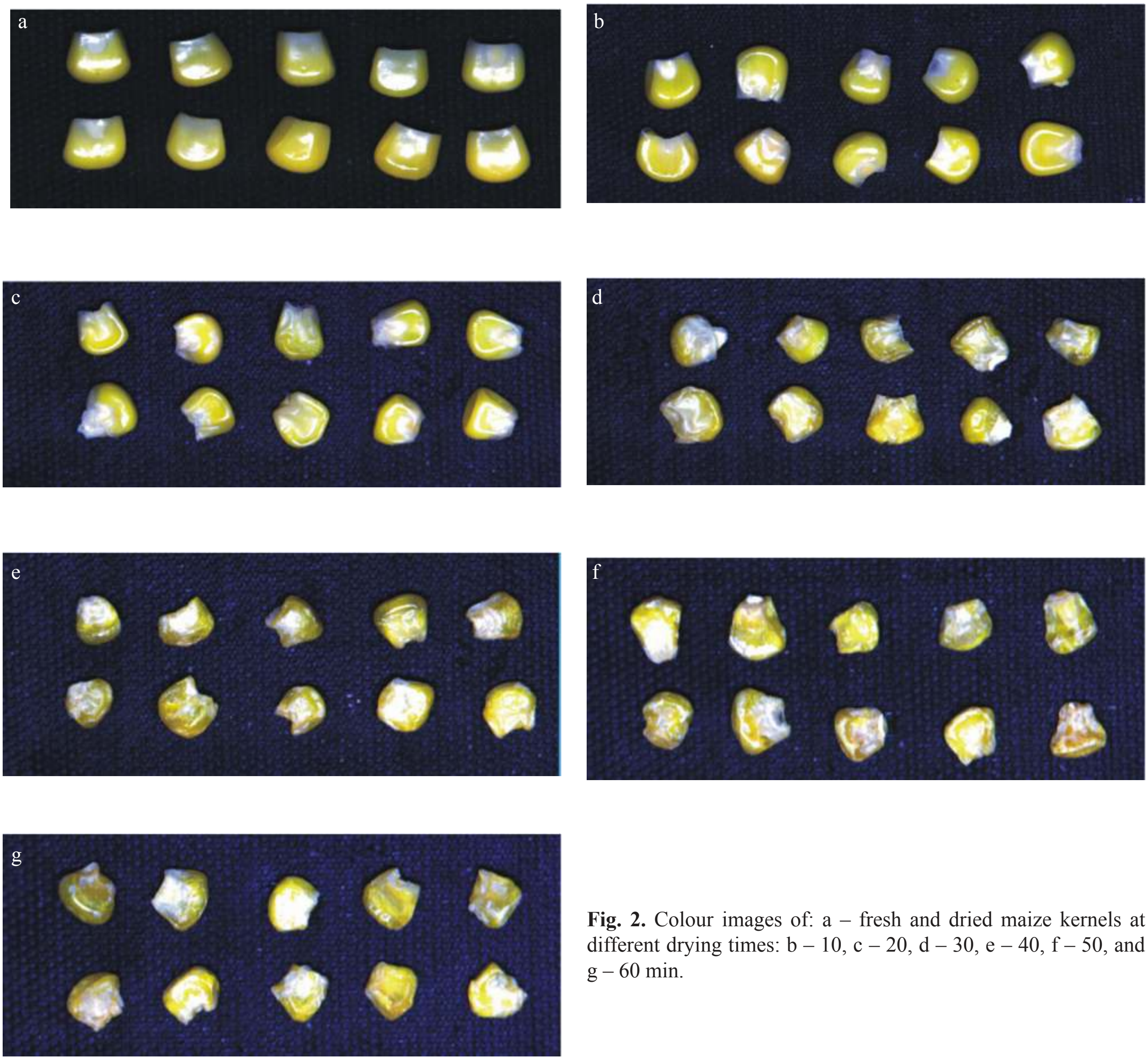

Fig. 2. Colour images of: a – fresh and dried maize kernels at different drying times: b – 10, c – 20, d – 30, e – 40, f – 50, and g – 60 min.

RMSEP values were reduced by 54.9-75.1%. The RPD was improved from 0.5 to 1.1, 0.5 to 1.5, and 0.5 to 1.9 respectively for the different numbers of samples. Figure 5a,b show the prediction results for MCU versus the actual measurements for one of the 10 runs for 30 and 50 maize kernels in one subset, respectively.

In this study, a non-destructive detection technique was the first attempt applied to predict the moisture content uniformity of materials in the drying process. Scholars have done valuable work in this field in recent years using the traditional measuring method, such as Wang *et al.* (2013b), who used the traditional method to calculate the moisture content uniformity. This method can calculate the drying uniformity, but it wastes time and energy. Wang *et al.* (2014) researched the drying uniformity in radio frequency drying of macadamia nuts; the results show that uniformity needs very strict conditions. The sample would be damaged and cannot be used again. Compared with the traditional measuring method (Wang *et al.,* 2013b; Wang *et al.,* 2014), hyperspectral imaging technology has rapid, energy-saving, and non-destructive advantages.

This research has demonstrated that the hyperspectral reflectance imaging technique yields good results in predicting the MCU of maize kernels during drying. Compared with the indirect method, direct prediction models yielded superior results for MCU predictions of dried maize kernels. Although good prediction results for MC were obtained by PLSR models, poor results were obtained for calculating uniformity by the indirect method. The MC was an intermediate variable to calculate the uniformity, and each prediction value had an error corresponding to the actual value. When more prediction values were used to calculate

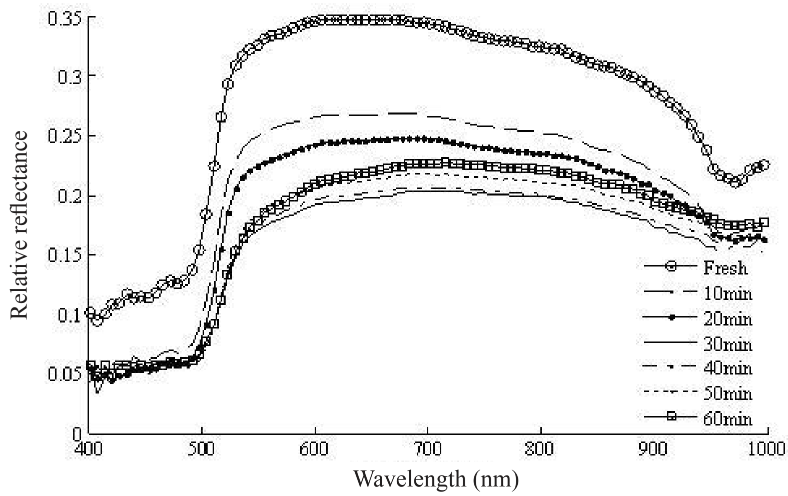

Fig. 3. Relative reflectance for fresh maize kernels at different drying times (10, 20, 30, 40, 50, and 60 min).

T a b l e 2. Average of 10 calibration and prediction results for MC by mean reflectance coupled with PLSR models for dried maize kernels

LVs	R_C	RMSEC (%)	RCV	RMSECV (%)	R_P	RMSEP (%)	RPD
15	0.993	2.71	0.992	3.00	0.992	2.88	7.9

LVs – number of leaves, R_C, R_{CV}, and R_P – correlation coefficient of calibration, cross validation, and prediction, respectively, RMSEC, RMSECV, and RMSEP – root-mean-square error of calibration, cross validation, and prediction, respectively, RPD – ratio of the standard error of performance to the standard deviation of the reference data.

T a b l e 3. Average of 10 calibration and prediction results for MCU calculating by MC prediction values

Number of maize kernel	R_P	RMSEP	RPD
10	0.324	15.17	0.5
30	0.493	11.63	0.5
50	0.521	10.96	0.5

Explanations as in Table 2.

the uniformity, the cumulative error resulted in poor uniformity accuracy. Therefore, one model could not predict the MC and MCU of dried maize kernels simultaneously.

Although the models by the direct method yielded better results for MCU, more work has to be done to improve prediction accuracy. Future studies will address wavelength-selection approaches to identify the optimal wavelengths among the 94 wavelengths in order to remove redundant information. Moreover, future works will focus on the evaluation of moisture uniformity within a kernel using hypersectral imaging.

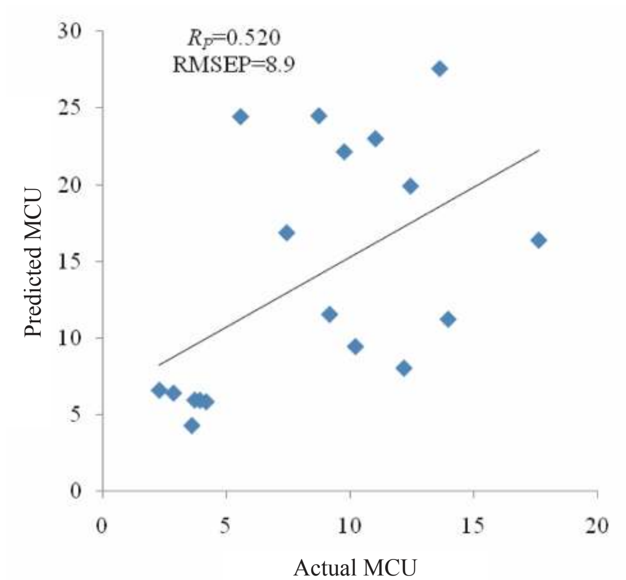

Fig. 4. Prediction of the uniformity of maize kernels using PLSR models by MC prediction values for 50 maize kernels in one subset.

T a b l e 4. Average of 10 calibration and prediction results for MCU by mean reflectance coupled with PLSR models for dried maize kernels

Number of maize kernel	LVs	R_C	RMSEC	R_{CV}	RMSECV	R_P	RMSEP	RPD
10	7	0.583	5.76	0.473	6.32	0.433	6.84	1.1
30	6	0.831	2.87	0.744	3.54	0.745	3.57	1.5
50	5	0.889	2.26	0.832	2.75	0.848	2.73	1.9

Explanations as in Table 2.

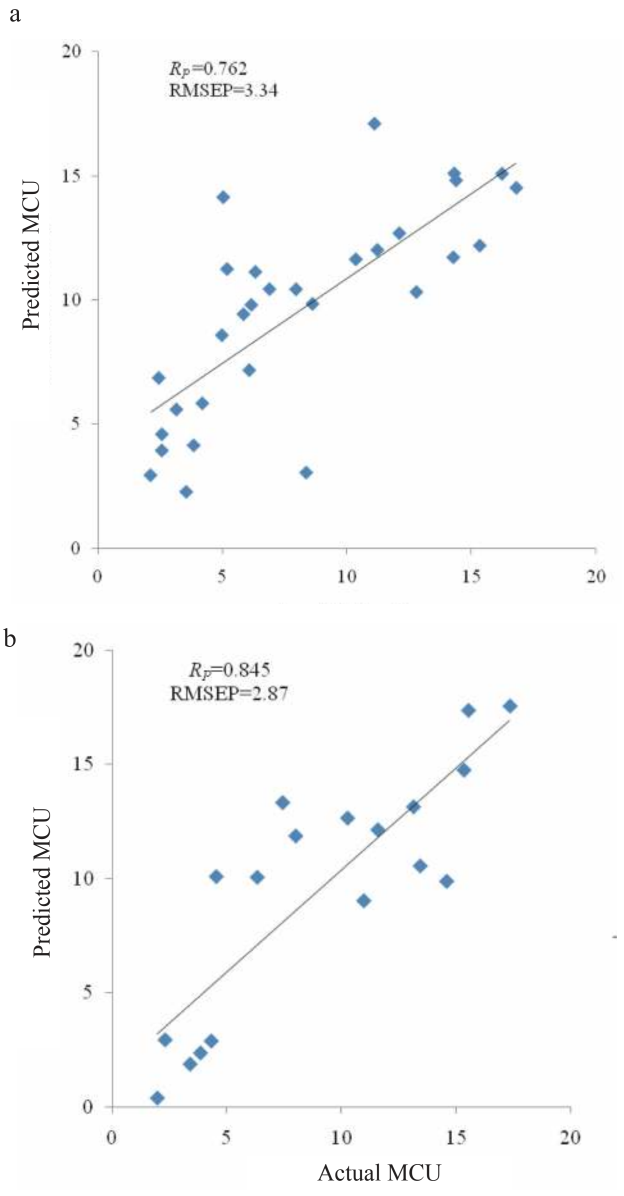

Fig. 5. Prediction of the MCU of maize kernels using PLSR models for: a – 30 maize kernels and b – 50 maize kernels in one subset.

CONCLUSIONS

1. The method using the prediction value of moisture content to calculate the uniformity (indirect) was investigated by hyperspectral imaging technology in the wavelength range of 400 nm to 1 000 nm coupled with partial least squares regression models, which presents really poor results.

2. Compared with the indirect predictions of moisture content uniformity, direct partial least squares regression with mean reflectance yielded better results (R_P = 0.848 and root-mean-square error of prediction = 2.73).

3. The research results indicate that hyperspectral reflectance images over the wavelength range of 400 to 1 000 nm could be used to evaluate the moisture content uniformity of maize kernels during the drying process.

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