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Determination of Moisture Content in Rice Using Non-Destructive Short-Wave Near Infrared Spectroscopy

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Abstract. Determination of indices of the indigenous west Sumatran rice varieties was done to rapidly evaluate its moisture contents (MC) by means of non-destructive evaluation. The objective of this study was to identify the MC of two indigenous rice from west Sumatra, Indonesia, namely Junjuangan and Mundam, cultivars. The evaluation was rapidly performed by means of non-destructive evaluation using 1000-2500 nm short wave infrared (SWIR) spectral assessment. The paddy grains samples with identical MC were put into 10 cm petri dish and measured using SWIR spectrophotometer. The grains' actual MC was then measured by primary method, based on weight measurement. In this study, the spectral data of the grains was then processed by means of Principal Component Analysis (PCA) before correlated with its MCs by Partial Least Square (PLS) method. The model calibration obtained for SWIR spectrophotometer showed correlation of 0.826 and 0.955, with root mean squared error calibration (RMSEC) of 2.97 and 1.4 for Junjuangan and Mundam rice respectively. Moreover, model validation produced correlation of 0.788 and 0.968, RMSEP of 3.8 and 1.29, and bias of 0.193 and 0.171 for Junjuangan and Mundam rice, respectively. The results indicated that the MC of paddy grains could be precisely identified by means of non-destructive evaluation using spectral analysis.

INTRODUCTION

As the main staple food, rice is consumed by most Indonesian. It is the largest agricultural commodities traded in the country, a total of 56.54 million ton annually [1]. Rice is the foundation of food security in Indonesia. Immediately after harvest process, rice is dried before being processed. Several post-harvest-processing stages should be undertaken before it become edible. On traditional harvest, rice will be reaped in-situ before being stacked and thrashed manually. Mechanical thrasher has been introduced in Indonesia since 1970 to speed up the process and reduce grain loss. The machine directly cleans and hauls the rice until it become ready to be dried [2]. Ideally, rice is dried to 12-14 % before being milled [2]. If the grain intended for storage, then its moisture content (MC) is further reduced to as low as 9 % [3].

The rice has a hard-protecting layer namely hulls or husk, consists mainly of silica and lignin, covering the grain to protect the seed during the growing season [4]. Under the hulls, a second protecting layer, i.e. bran consists of the combined aleurone and pericarp and become the integral part of whole grains [5]. Before marketed as brown rice, the grain is milled to remove the husk [3]. In Indonesia, consumers favored white rice as compared to brown rice. White rice is milled rice that has its husk, bran, and germ removed. This rice produces better organoleptic properties (i.e. flavor, texture and appearance) and has longer shelf life to prevent spoilage [2]. Subsequent polishing procedure will result in bright, white and shiny rice, that improves its selling price. MC plays the crucial role during the post-harvest processing of rice [6]. Cracked or even broken kernel will occur if the MC is too high upon processing [7]. As a result, the rice quality and its selling price will reduce, while product losses will amount [8]. Therefore, the MC should be

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determined correctly prior to these processes. MC can be sampled by oven-method or rice moisture meter [9]. However, sampling only consider small part of the product, while measuring all rice together is simply unrealistic. Moreover, with destructive process in nature, it will lead to overall product losses.

Recent progress in quality inspection for food and agricultural products suggest that, nondestructive approach offers lower cost and higher accuracy, while delivering results more rapidly. Instead of the expensive and time demanding chemical analysis, the physicochemical properties can be predicted correctly using nondestructive evaluation (NDE) methods [10-14]. NDE can also be used to identify plants properties and morphologies [15-16]. Moreover, by utilizing ultraviolet, visible, and infrared absorbance spectroscopy, rice quality attributes can be identified with acceptable result [17-18]. Other study has successfully determined the mono-saccharides in rice using the similar approach [19]. However, sample preparation for these studies limited the practicability for measuring bulk samples.

Sample preparation in FT-NIR spectroscopy is simpler. FT-NIR spectroscopy could be used for rapid detection of moisture content without destruction of samples. The technique had successfully determined the MC of meat [20], green tea granules [21], tea powder [22], freeze-dried materials [23], bael-pulp [24], epoxy resins and fiber-reinforced composites [25], and rice pasta [26]. However, study on MC in rice kernel using NDE-based FT-NIR spectroscopy is limited, for rice cultivar originated from west Sumatra, Indonesia. In this study, two local rice cultivars (Junjuangan and Mundam) were measured using FT-NIR spectrometer for the determination of its MC. The study was carried out with the objective of developing a rapid method for rice kernel MC determination in a commercial scale. The method could be used to measure bulk samples rapidly with lower cost as compared to traditional oven method. Models were developed by regressing the spectral data with sample actual MC using principal component analysis (PCA) and partial least square (PLS) regression method. Models were validated using different set of samples and its performance evaluated using root mean square error (RMSE) analysis.

MATERIALS AND METHOD

The samples were two local rice cultivars, namely Junjuangan and Mundam. The samples were harvested manually by hand to minimize damage. The rice then air cleaned and stored in -80°C cold storage to limit any chemical changes. For spectral measurement, the samples were densely-placed in 10 cm Petri dish (BÜCHI Labortechnik AG, Switzerland), then immediately shaken to minimize empty spaces between grains. Although the grains samples come in different sizes, the weight variation between samples, upon measurements, is not significantly differ. The petri dish was then placed into the spectrometer (NIRFlex N-500, BÜCHI Labortechnik AG, Switzerland). A full scan (1000-2500 nm) in slow speed configuration was set to the apparatus, for measuring the samples' diffused reflectance. Ambient conditions were less than 80 % of relative humidity, and room temperature of 25 °C. the spectrometer resolution was set to 8 cm^{-1} with boxcar apodisation. The selected type of interferometer polarisation was interferometer with TeO_2 wedges. The device wavenumber accuracy was ± 0.2 cm^{-1} as measured with HF gas cell. Spectrometer signal to noise ratio was 10000 as measured with standard liquids (Blackman apodisation). The recorded signal was collected and processed using spectroscopy software (UnscrambleX®, Camo Analytics, Norway). The measurements were replicated 10 times to limit data variations. The data then averaged and smoothed using 3 spectral points Savitzky–Golay [27].

The MC of the samples determined using the oven method. The samples were dried immediately after its spectral respond recorded. The drying temperature was set at 105 °C. The samples were weighed every hour and drying process stopped when the samples reached a constant weight. The wet based MC of the samples were determined by calculating the weight differences between wet and dried samples and ratio of the difference with its original weight.

Principal component analysis (PCA) was used to correlate the spectral data with samples cultivars and MC. Samples' cultivars classification by PCA performed by transforming the recorded spectral data onto an orthogonal space. The possible correlation between spectral variables and cultivars initially determined into a number of principal components (PC) which explained more than 99 % of the input variables (absorbance data). By transforming the data, the PCs produced the largest possible variance sequent.

Modeling the rice MC according to its spectral response was performed by the partial least square (PLS) regression method. While it had similar statistical method to the PCA, PLS performed better in finding linear regression model by projecting the predicted MC and the observable MC to a new space [28]. The PLS was known as bilinear factor models [29]. Modeling the MC with PLS aimed to find the fundamental relations and latent variables to model the covariance structures of samples cultivar and MC. Working in the multidimensional direction, PLS explained the maximum multidimensional variance direction to identify the MC and Cultivar accurately. Furthermore, PLS regression was more suited since the number of the samples is less than the spectral data variables [29].

For modeling the cultivars and MC, 2/3 of samples were selected according to the Randomized Complete Block Design (RCBD). The selected samples diffused spectral data then were correlated to its cultivars and MC using the PLS regression to train the models. The rest 1/3 of samples then used to validate the models. The model performance, in calibration and validation, then measured by the Root Mean Square Error (RMSE) analysis. The RMSE calculated the prediction errors, which determine how far the prediction data located from the regression line data points. This deviation known as model residuals, indicated the accuracy of the models as explained by its concentrated data around the line of best fit. RMSE was commonly used in regression analysis to verify experimental results. RMSE above 5 (> 5 %) was considered as poor, since the MC datum ranged between 0 – 100 %.

RESULTS AND DISCUSSION

The MC was presented in **Table 1** according to its cultivar. From the measurements, the rice samples from Junjuangan had more MC range (10.5-27 %, wet basis) as compared to the samples from Mundam cultivar (14-27 %). Cultivar and MC influenced the spectral properties of the samples (Figure 1). The diffused reflectance of the electromagnetic radiation from Junjuangan rice produced higher spectral data when the MC was lower. In contrast, the Mundam cultivar produced higher spectral data when the sample had higher MC. However, the trend was not uniformly applied to all MC. For example, Junjuangan rice with MC of 10.5 % had lower spectral data than the one with the MC of 19.7 %. Similarly, the Mundam rice with MC of 14 % had higher spectral data than the sample with 16 % MC from the same cultivar. The measurement results suggested that, the diffused reflectance attributes for each cultivar increased and peaked at certain MC, before it started to reduce.

TABLE 1. MC as measured by oven according to its cultivar

Sample No	Cultivars	MC (%)	Replication
1	Junjuangan	27	5
2	Junjuangan	25.7	5
3	Junjuangan	24.8	5
4	Junjuangan	22.5	5
5	Junjuangan	19.7	5
6	Junjuangan	15.7	5
7	Junjuangan	10.5	5
8	Mundam	27	5
9	Mundam	26.3	5
10	Mundam	24.8	5
11	Mundam	22.9	5
12	Mundam	20.7	5
13	Mundam	16	5
14	Mundam	14	5

Classification of the MC samples according to its cultivar was done using the PCA. Using KMO and Bartlett's test of sphericity, the principal components (PC) were extracted by determining the Eigenvalues greater than 1, through limited number of iterations until all spectral data reached convergence, 99 % explained. To better distinguish each principal component, a rotation technique was applied based on Varimax method [17-18], in which each principal component will be less dependent towards each other.

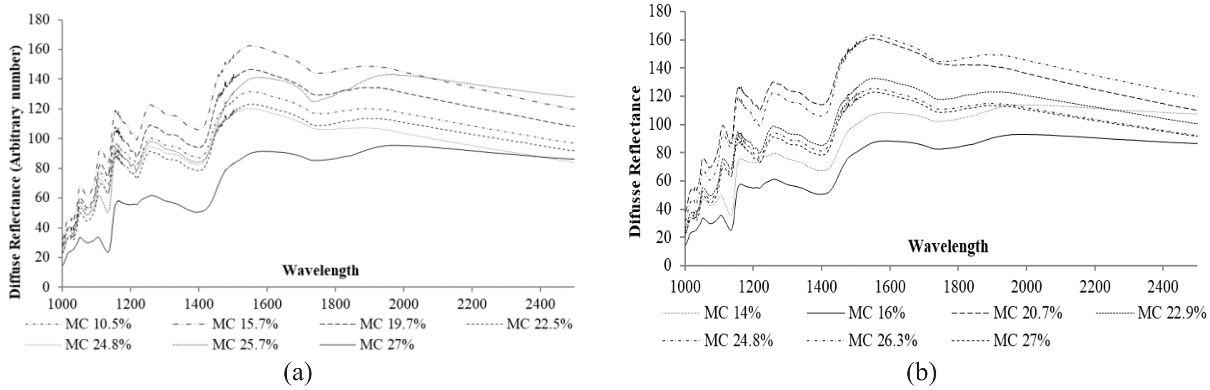


FIGURE 1. Spectral properties of rice with different MC from (a) Junjuangan cultivar and (b) Mundam cultivar

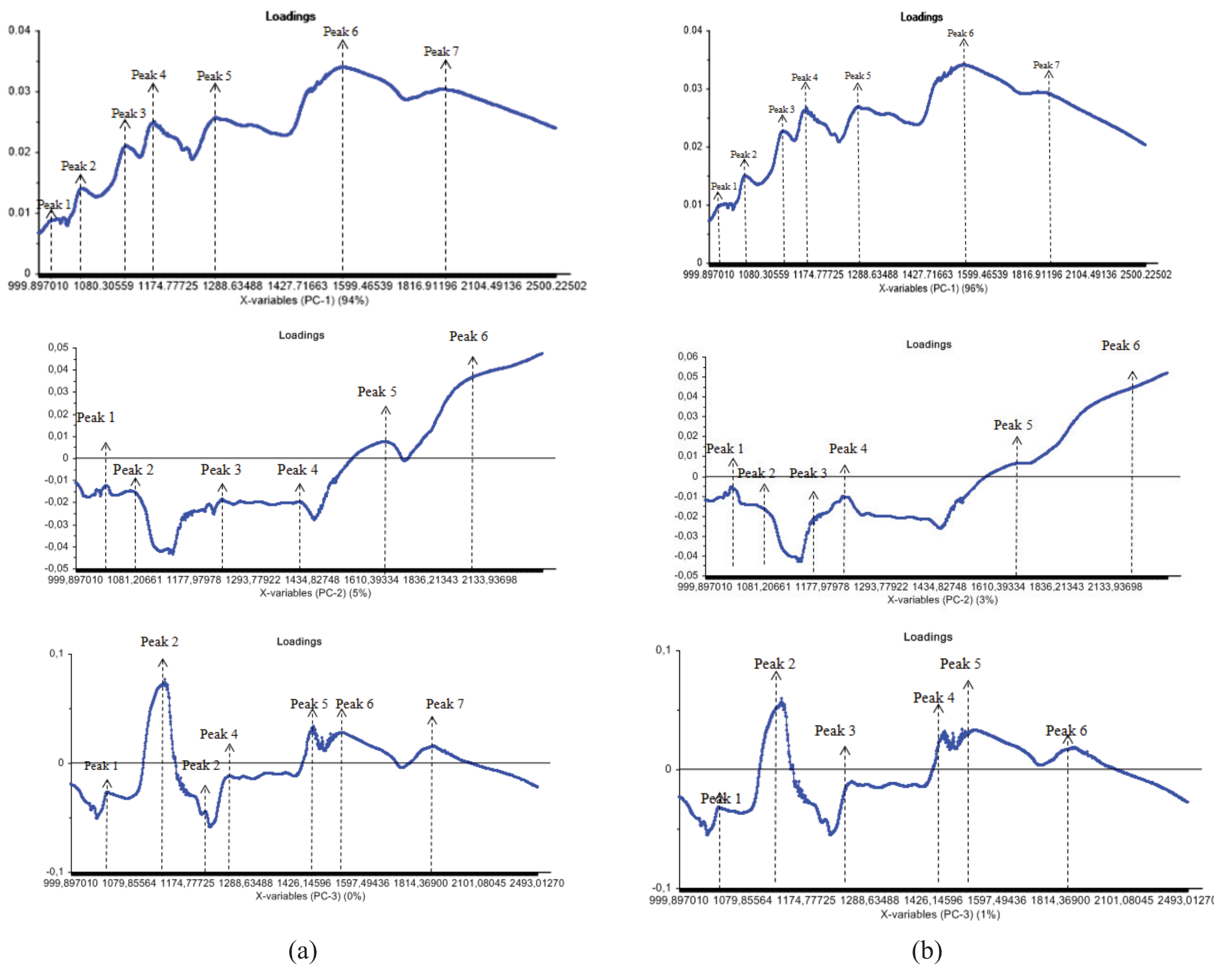


FIGURE 2. The loading plot of the first (PC1), second (PC2) and third (PC3) principal components obtained from PCA of MC from (a) Junjuangan and (b) Mundam cultivars

3 PCs were introduced to explain variance of data from all samples with the confidence level of 99.9 % (Figure 2). The first PC (PC1) of the Junjuangan rice peaked at 1016, 1051, 1113, 1150, 1257, 1532, and 1924 nm. The second PC (PC2) peaked 1043, 1077, 1232, 1409, 1666, and 2139 nm. The third PC (PC3) peaked at 1048, 1135, 1210, 1252,

1454, 1537, dan 1876 nm (Figure 2a). On the other hand, the first PC (PC1) of the Mundam rice peaked at 1014, 1050, 1112, 1152, 1254, 1538, and 1885 nm. the second PC (PC2) peaked at 1036, 1086, 1170, 1221, 1661, and 2200 nm. The third PC (PC3) peaked at 1047, 1139, 1256, 1453, 1533, and 1878 nm (Figure 2b).

Several peaks in PCs of both cultivars PCs had similar wavelength, suggesting that some overtones and combination bands vibrated the sample molecules within the close range, regardless of its cultivars. These peaks also indicated that overtones occurred at about 2 and 3 times the frequency of the fundamental vibration. Reflectance intensity increased with increasing overtones, and the wavelength band overlap increased with increasing overtones.

Beside overtone of fundamentals, there were vibrations in the Near-IR band which was called as combination bands. These bands were the sum of several fundamentals from different vibrations, characteristically by the emission of vibration from a single photon of light. The combination bands were typically found at lower energies than overtones. From three PCs obtained from Varimax extraction method using Eigen values greater than 1, the PCA scores explaining the classification results of rice MC group membership according to cultivar is presented in Figure 3.

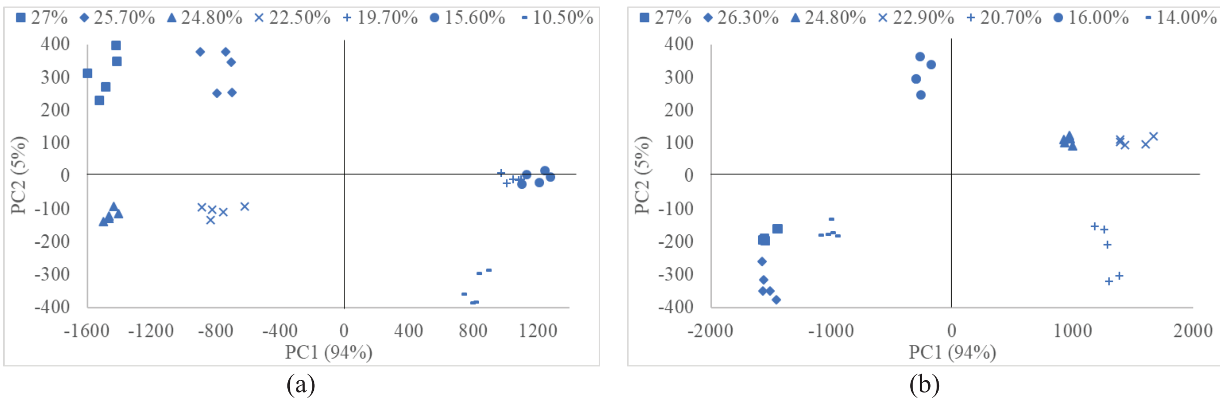


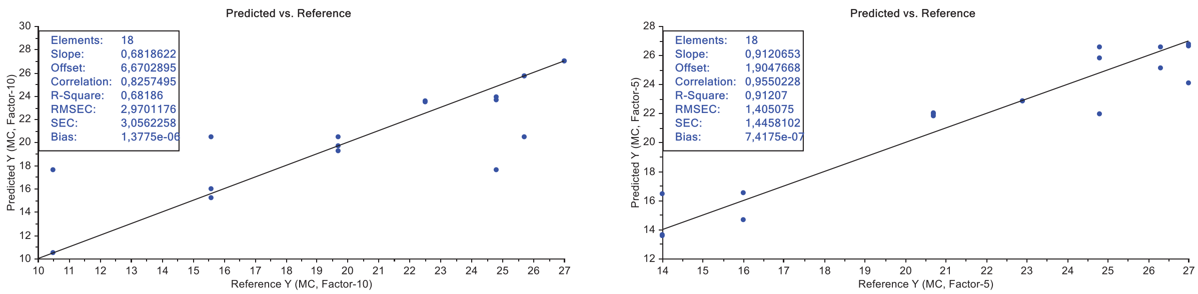
FIGURE 3. PCA classification of rice MC for (a) Junjuangan and (b) Mundam cultivars.

The PCA successfully grouped samples according to its MC, for both cultivars. However, overlapping was observed between group of rice with MC of 19.7 % and 15.6 % in Junjuangan cultivar (Figure 3a). The case was not observed in Mundam cultivar (**Figure 3b**). The plotted data from the samples, as seen in Figure 3, located away from the center of the axis. For the Junjuangan cultivar, the rice with high MC (22.5 %, 24.8 %, 25.7 %, and 27 %) located in the left region of the axis, in 2nd and 3rd quadrant. Samples with lower MC, in majority, located in the 4th quadrant. On the other hand, samples from Mundam cultivar obtained different results. Rice with highest and lowest MC from this cultivar located at the same quadrant as seen in Figure 3b. Results suggested that rice from Mundam cultivar had more complexed molecular structure where the level of MC produced composite diffused reflectance results when samples measured by the FT-NIR spectrometer.

While PCA successfully grouped the samples according to its MC, the PCA could not produce a model to predict the MC according to its spectral data. The PCs could not explain which spectral wavelength correspond to most of the MC. Although the PCs produced peaks that indicate certain wavelengths could be consider for grouping the MC, the peaks alone could not directly correlate to the samples MC. Further regression analyses using PLS were performed to model the samples MC, by correlating the MC to the spectral data.

To successfully establish the MC model of the samples, Randomized Complete Block Design (RCBD) was used to select 2/3 of samples data for training the model. The data calibrated the regression between MC and its spectral data using a statistical engineering software. Model established by assigning the spectral diffused-reflectance data of the samples as covariate, and rescaled the data using multiple scatter correction (MSC). The MSC is a mathematical treatment to correct the scatter in the sample's spectra [30]. The scatter was produced by differences in physical properties of the samples. The samples MC was assigned as dependent variable for training the model. The initial calibrated model results presented in **Figure 4**.

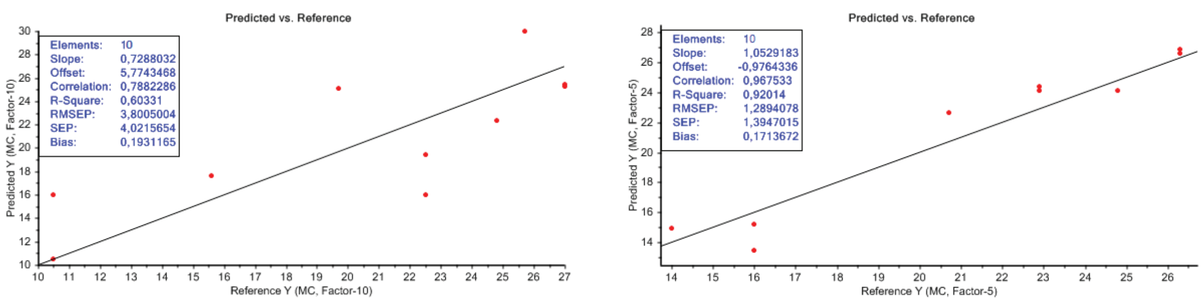
The calibrated model for determination of the MC from Junjuangan produced a correlation of 0.826, R^2 of 0.681 and RMSEC of 2.97. On the other hand, the model for determination of MC from Mundam cultivar produced higher correlation (0.955), R^2 (0.912) with lower RMSEC (1.4). The results indicate that PLS regression could model the rice MC according to its diffused reflectance spectral data. In addition, rice from Mundam cultivar obtained higher correlation between its spectral data and MC, thus PLS regression could produce better calibration model for this object. This might correlate to the variance of physical properties of the grains, in which PLS could not exactly regress the correlation strongly. Total protein content, and composition of sugars or carbohydrates in the rice could influence this analysis. Therefore, the PLS regression model would be influenced by the sample's physio-chemical properties.



(a) (b)

FIGURE 4. Calibration result with R^2 of 0.681 for (a) Junjuangan (a) and (b) 0.912 for Mundam cultivars

The results show that the bias of the MC model for both cultivars was still within acceptable range. The deviation of prediction upon training and testing of the model produced offset of 6.67 for Junjuangan and 1.9 for Mundam. The results produced better model prediction as compared to previous findings [17-18]. For validating the model, rest 1/3 of the sample data was used. The results showed in Figure 5.



(a) (b)

FIGURE 5. Model validation of the MC using PLS for (a) Junjuangan and (b) Mundam cultivars

The MC of the samples had correlation of coefficient of 0.6 for Junjuangan and 0.92 for Mundam. The model suggested that PLS regression was applicable to predict the MC of Junjuangan and Mundam rice by measuring its electromagnetic radiation reflectance within the range of 1000-2500 nm. The coefficient of correlation value of the model when predicting the sample MC from Mundam cultivar was high. However, the same method only produced model with medium correlation for predicting the value of the MC from Junjuangan. The difference between prediction and actual MC calculated as RMSEP. The MC model for Junjuangan produced RMSEP of 3.8 upon validation. The model for Mundam performed better upon validation with RMSEP of 1.29.

The results suggested that the developed model had better accuracy when predicting MC of rice from Mundam cultivar. This phenomenon might be related to the amount and phase of moisture in the samples, and the properties of the electromagnetic radiation itself. The reflectance of electromagnetic radiation by water could occurr in the wide range of regions, and heavily influenced by the state of the water itself, especially in the liquid phase [17-18]. In the infrared band, the reflection of electromagnetic radiation by water was strong, when the water present in liquid phase and no scattering effect produced during measurements by spectrophotometer [17]. In contrast, in the NIR band, water strongly reflected the electromagnetic radiation in organic material [18].

In the process of developing the MC prediction model using PLS regression for the rice from Junjuangan and Mundam cultivars, most influenced electromagnetic radiation wavelengths for model development were identified. These wavelengths were considered as the proper covariate for predicting the MC in the samples. From the results, the developed model was fit to predict MC of rice from Junjuangan and Mundam cultivars. The model was established by correlating their spectral reflectance properties. The model produced good accuracy with high sensitivity. Nonetheless, when predicted MC from Junjuangan, model produced higher residual, although still within acceptable boundary. The quality of edible rice produced through harvesting-ripping-milling-polishing heavily depends on its MC when the process started. The product appearance and quality would determine its price. Grain losses during the milling and polishing process could be caused by improper MC upon drying, in combination with the poor technical performance of milling machinery as well as the operator ineptitude. Single pass milling machine tend to have less grain yield when processing the rice. Although this kind of machine had been outlawed in Sumatra, nonetheless, reports suggested that, some traders still imported this milling type as coffee grinders, for milling rice [31]. Grain could be further lost in storage. Pest infestation was a real threat when milled rice was stored over a month. There were measures to control infestation, such as the fumigation. However, added cost of the lethal gas tablets might not economically be acceptable [32]. In addition, problems arose when fumigation performed with rice stored in bags in an open warehouse. In this case, the effectiveness of this methods would greatly reduce. Other measurement done by local private millers, re-milled the infested rice, passed them through the whitening section, where 10 % of product weight was lost.

In Indonesia, rice purchased after milled, instead of paddy. It had greater quality control, however being more susceptible to infestation by insect-pests than paddy. However, one of the greater concerns was the frequent use of chemical pesticides. It caused harmful effects due to possible contamination. The problem would significantly worrisome when rice stored in larger volume and longer period.

Milling and storing rice with appropriate MC would limit these losses. Milling and polishing rice with MC of 12-14 % would reduce cracking extend its self-life [33]. Improper drying would cause the MC higher than expected. When this rice was milled, the results would be a lower ratio of head rice and broken kernel. While the broken kernel itself had similar content to the head rice, the consumer preference as well as quality standard only considered head rice for consumption. Thus, the broken kernel, while it still edible, considered as waste or product loss.

Accurately determined MC was the most important key for the post-harvest processing. Managing the products and marketing them would be much easier if its quality meets the certain standard. The interrelated features which determine the quality of rice, among other, were MC, purity degree, varietal purity, cracked grains, immature grains, discolored or fermented grains, and damaged grains [33]. These characteristics were determined by the environmental conditions and post-harvest practices.

Certain rice processing required ideal MC [17]. Reducing the rice MC too low would require considerable economic resources, man-power and time [18]. Improper MC measurements might result in extra drying cost and harvesting loss [2]. High MC would lead to spoilage when the grain was stored, due to fungus and micro-bacterial activity. Setting up the MC too high upon milling would produce lower head rice, thus more rice kernel broken or damaged during the process [3]. Furthermore, since the value of rice and paddy grains were set based on its weight, lower MC would correlate to the reduction of mass, and lead to the loss of profit when the product sold.

CONCLUSIONS

In this study, nondestructive evaluation method was developed to model the MC of rice from Junjuangan and Mundam cultivars. The models correlated the reflectance SWIR of the rice samples to its physicochemical property. Both models produced good accuracy and sensitivity, although some offset were observed when predicting the MC samples from Junjuangan cultivar. The study results offered a more accurate, reliable and practical solution for nondestructive evaluation of grains internal property.

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