

# Near-Infrared Reflectance Analysis for Prediction of Cooked Rice Texture

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## ABSTRACT

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The ability of near-infrared (NIR) spectroscopy to predict sensory texture attributes of diverse rice cultivars was examined. The sensory texture of 87 samples representing 77 different short-, medium-, and long-grain cultivars was evaluated by trained panelists using descriptive analysis. Correlations between sensory texture attributes and NIR reflectance data were examined using the multivariate method of partial least squares (PLS) regression. Texture attributes (hardness, initial starchy coating, cohe-

siveness of mass, slickness, and stickiness) measured by panelists in the early evaluation phases were successfully predicted ( $R^2_{\text{calibration}}$  0.71–0.96). Cohesiveness of mass, the maximum degree to which the sample holds together in a mass while chewing, was best modeled with  $R^2_{\text{calibration}} = 0.96$  and  $R^2_{\text{validation}} = 0.90$ . Key wavelengths contributing to the models describing the texture attributes were wavelengths also contributing to models for amylose, protein, and lipid contents.

The economic value of rice in domestic and international markets is strongly affected by the textural properties of the cooked rice. Conventionally, cooked rice texture is predicted by a battery of physicochemical tests (amylose and protein contents, alkali spreading value, amylographic gelatinization and paste viscosity characteristics, and water-uptake capacity). These analytical tools indicate generally whether cooked rice will be dry and flaky or soft and sticky. They do not capture the full complexity of cooked rice texture that is perceived by a person.

In the 1980's, taste analyzers were developed in Japan as a tool for relating sensory and physicochemical properties. These analyzers convert various physicochemical parameters of rice into taste scores based on correlations between near-infrared (NIR) measurements of key constituents (e.g., amylose, protein, moisture, fat acidity) and preference sensory scores. They provide rapid screening and are used by Japanese millers and wholesalers to grade rice, both domestic and imported. Worldwide adoption of such a taste analyzer would be desirable. However, the taste analyzers used in Japan are not universal or objective because they are based on preference sensory scores. An analyzer calibrated using preference scores can only assess whether the rice has quality characteristics deemed desirable by the target population represented by the sensory panel (in this case the Japanese).

Development of a universal taste analyzer is possible if descriptive analysis sensory scores are used for calibration instead of preference scores. Descriptive analysis is an objective tool (Civille and Szczesniak 1973; Civille and Liska 1975; Munoz 1986; Skinner 1988). Highly trained panelists evaluate the intensities of various textural attributes using standard reference scales for each attribute. Following calibration, panelists theoretically should give the same results for a given sample, regardless of nationality, age, or gender. Research results have shown that the descriptive analysis technique is sufficiently sensitive to find distinct, small differences in the texture of cooked rice (Lyon et al 1999).

A universal instrument such as an NIR spectroscope calibrated with descriptive sensory scores would provide an objective measure by correlating the intensity of textural descriptors with physicochemical measurements. The measurements provided by this universal

instrument could then be related to preference sensory scores to identify quality characteristics desired by various domestic and international markets. A universal instrument will help guide breeding efforts and rice selection and allow rice producers to direct cultivars to specific, high-value markets.

Few studies have addressed the potential of NIR spectroscopy to determine sensory attributes of foods (Martens and Martens 1986; Yan et al 1990; Ellekjaer et al 1993). Windham et al (1997) examined NIR spectroscopy as a predictor for cooked rice texture of three cultivars grown in four locations, dried by five processes to 12 and 15% moisture contents, and regular and deep milled. They demonstrated that NIR showed potential for predicting descriptive texture attributes perceived in the initial oral phases of sensory evaluation. Recently, Meullenet and Bellman-Horner (2000) used NIR for predicting descriptive texture attributes of four cultivars as affected by drying conditions and rough rice storage history. Cooked rice hardness ( $R^2 = 0.83$ ) and several other attributes were satisfactorily predicted.

In pursuit of a universal instrument, the ability of NIR spectroscopy to predict sensory texture attributes of diverse rice cultivars was examined in this study. Eighty-seven samples representing 77 different short-, medium-, and long-grain cultivars were used to generate models to predict sensory texture attributes of cooked rice as determined by a descriptive panel.

## MATERIALS AND METHODS

### Rice Samples

Samples of short-, medium-, and long-grain rice cultivars ( $n = 76$ ) grown in Louisiana, Arkansas, Texas, and California in 1996 were harvested at  $\approx 20\%$  moisture and dried to  $\approx 12\%$  moisture. Following drying, the rices were shipped to the USDA, ARS, Rice Research Unit (Beaumont, TX) where they were stored in closed containers for two to three months at  $18^\circ\text{C}$ . One week before initiating sensory and instrumental analyses, the samples were shelled using a Satake rice machine model SB and then immediately milled as described by Champagne et al (1999), using a laboratory one-pass mill (Satake pearler, model SKD). Milled samples were shipped overnight to the USDA, ARS, Southern Regional Research Center (New Orleans, LA). Milled rice samples also were obtained from 1996 crops produced in Taiwan ( $n = 2$ ), Korea ( $n = 3$ ), and Australia ( $n = 6$ ). When received, samples were immediately preweighed into portions for sensory, chemical, and instrumental analyses and stored in glass jars under a nitrogen headspace at  $4^\circ\text{C}$ .

### Chemical Analyses

Amylose was determined on the samples in duplicate by the simplified assay method developed by Juliano (1971). Protein contents ( $N \times 5.95$ ) were determined in duplicate by the combustion method on a nitrogen determinator (FP-428, LECO, St. Joseph, MI). Lipid content was determined in duplicate by extracting 5 g of rice with

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petroleum ether using a Soxhlet extraction apparatus. The alkali spreading value of whole grain milled rice was determined in accordance with the method of Little et al (1958) with minor modifications as described in Champagne et al (1999).

### Near-Infrared (NIR) Analyses

In conjunction with sensory test sessions, 100 g of uncooked, whole grain milled rice was scanned in a transport cell in reflectance mode on a visible near-infrared scanning monochromator (model 6500, NIRSystems, Silver Springs, MD). Reflectance readings were obtained over a wavelength range of 400–2,500 nm at 2-nm increments. Each sample was scanned in duplicate on two different occasions, corresponding to the schedule followed for the sample's evaluation by the sensory panel. Scans were averaged and means were used in the statistical analyses.

### Sample Preparation for Sensory Analyses

Portions of rice (600 g) were rinsed by covering the rice three times with cold water followed by straining to remove excess water. After rinsing, the samples were transferred to preweighed rice cooker insert bowls. Water was added in amounts to give rice-to-water weight ratios appropriate for three different cook types based on amylose content (0%, 1:1; 10–19%, 1:1.4; 20–25%, 1:1.7). Rice, known to cook similarly to a cook type that does not correspond to its amylose content, was cooked with an amount of water corresponding to the similar cook type (Champagne et al 1999). Following the protocol

described by Champagne et al (1999), rice was presoaked, cooked in rice cooker-steamers (Panasonic SR-W10G HP) to completion, held for 10 min at the warm settings, and sampled. Cooking was staggered so that samples were analyzed by the panel at 20-min intervals.

### Sensory Evaluation Protocol

Twelve panelists, previously trained in the principles and concepts of descriptive analysis were selected to participate in the study. The lexicon for rice texture used by the panel was based on that developed by Lyon et al (1999) and Goodwin et al (1996) and is described in Table I. The sensory texture profile included 13 sensory attributes that described rice texture at different phases of sensory evaluation, beginning with the feel of the rice when it is first placed in the mouth and ending with mouthfeel characteristics after the rice was swallowed. Each sample was presented to the panelists twice following a randomized design. The details of the procedure followed for presenting samples, standard (warm-up sample of Calrose), and blind control (Calrose) to panelists at each session are described by Champagne et al (1999).

### Statistical Analyses

For the sensory data, a scatterplot consisting of the scores assigned to each sample in a panel session was produced for each panelist and each attribute. For a given session, these scatterplots were visually examined to identify which panelists were not performing to consensus during a session, following the method described by Bett et al (1993). No outliers were identified for six attributes. For the other seven attributes, one, two, and three outlier scores were removed for three, three, and one attributes, respectively. Then panelist scores for each attribute in a session were averaged to obtain mean scores. The blind control samples were used to adjust out session effects. All sample means contained in panel sessions containing a blind control sample that fell outside 99% confidence limits of the blind control grand mean were adjusted inward to the 99 percentile. This

**TABLE I**  
Sensory Descriptive Texture Attributes and Definitions  
Used to Evaluate Cooked Rice Texture

Phases/Attributes	Definition
<b>PHASE I. Place six to seven grains of rice in mouth behind front teeth. Press tongue over surface and evaluate.</b>	
Initial starchy coating	Amount of pastelike thickness perceived on the product before mixing with saliva (three passes)
Slickness	Maximum ease of passing tongue over the rice surface when saliva starts to mix with sample
Roughness	Amount of irregularity in the surface of the product
Stickiness	Degree to which the kernels adhere to each other
<b>PHASE II. Place 1/2 teaspoon of rice in mouth. Evaluate before or at first bite.</b>	
Springiness	Degree to which grains return to original shape after partial compression
Cohesiveness	Degree to which the grains deform rather than crumble, crack, or break when bitten with molars
Hardness	Force required to bite through the sample with the molars
<b>PHASE III. Evaluate during chew.</b>	
Cohesiveness of mass	Maximum degree to which the sample holds together in a mass while being chewed
Chewiness	Amount of work to chew the sample
Uniformity of bite	Evenness of force throughout bites to chew
Moisture absorption	Amount of saliva absorbed by sample during chewing
<b>PHASE IV. Evaluate after swallow.</b>	
Residual loose particles	Amount of loose particles in mouth
Toothpack	Amount of product adhering in or on the teeth

**TABLE II**  
Physicochemical Properties and Sensory Attributes Evaluated  
for 87 Rice Samples

	Mean	Maximum	Minimum	SD <sup>a</sup>
Amylose, %	18.6	24.9	10.3	4.4
Protein, %	8.3	11.0	5.2	1.0
Lipid, %	0.5	1.1	0.2	0.1
Alkali spreading	4.6	7.0	2.0	1.8
Initial starchy coating	2.3	3.2	0.9	0.4
Slickness	4.7	6.3	3.6	0.6
Roughness	6.2	7.5	5.2	0.4
Stickiness	5.0	6.2	2.9	0.6
Springiness	4.0	4.6	3.3	0.3
Cohesiveness	5.0	5.8	3.9	0.4
Hardness	4.5	6.4	3.1	0.6
Cohesiveness of mass	5.7	6.7	3.9	0.5
Chewiness	5.5	6.0	4.9	0.2
Uniformity of bite	8.0	9.9	6.8	0.5
Moisture absorption	5.0	5.7	4.2	0.3
Residual loose particles	4.1	4.7	3.6	0.2
Toothpack	4.3	5.1	3.6	0.3

<sup>a</sup> Standard deviation.

**TABLE III**  
Models for Predicting Textural Attributes from Near-Infrared (NIR) Spectroscopy<sup>a</sup>

Textural Attribute	PC	R <sup>2</sup>		RMSEC		RMSEP		DI
		Calibration	Validation	Calibration	Validation	RMSEC/RMSEP		
Initial starchy coating	4	0.88	0.76	0.13	0.20	0.65	2.0	
Slickness	4	0.81	0.53	0.25	0.38	0.66	1.6	
Stickiness	3	0.71	0.58	0.28	0.33	0.85	1.8	
Hardness	4	0.85	0.67	0.22	0.32	0.69	1.9	
Cohesiveness of mass	6	0.96	0.83	0.12	0.22	0.55	2.3	

<sup>a</sup> PC = optimal number of partial least squares components, R<sup>2</sup> = coefficient of determination for calibration and validation models, RMSEC = root mean square error of correlation, RMSEP = root mean square error of prediction, DI = discrimination index (standard deviation of texture attribute/RMSEP).

adjustment was required in either no sessions or one or two sessions only for each descriptor.

Correlations between sensory texture attributes, compositional, and NIR reflectance data were examined using the multivariate method of partial least squares (PLS1) regression as described by Martens and Naes (1989). A commercial program for multivariate analysis was used to process the data (Unscrambler, v7.5, CAMO, Trondheim, Norway). The preprocessing data technique of multiplicative scatter correction (Isaksson and Naes 1988) was applied to the NIR spectra to remove interferences arising from scatter. The spectra were then transformed to enhance absorption peaks with a second derivative (gap = 20 nm) using Savitzky-Golay differentiation algorithm computed by the Unscrambler program. The wavelength region was truncated to 700–1,078 and 1,118–2,018 nm to consider only the infrared region and to avoid low signal intensity and nonlinear response at longer wavelengths (Delwiche et al 1996). The wavelength region 1,078–1,118 nm was not included because detectors are switched at 1,100 nm resulting in the baseline shifting in this region. Full-cross validation was used to determine estimates of validation error in fitting the model and the optimal number of PLS-components to keep before overfitting. Full cross-validation consists of leaving out one sample from the calibrating data set and calibrating the models on the remaining data points, then predicting the value for the left-out sample and computing the prediction residuals. The process is repeated until every sample has been left out once; then all prediction residuals are combined to compute the validation residual variance and root mean square error of prediction (RMSEP) (Unscrambler). Full cross-validation was selected for validation because of the relatively limited number of samples in this study and the uncertainty in picking out representative samples from this diverse group for test set validation. Full cross-validation also allowed use of jack-knifing to refine the model through elimination of  $x$  variables not significantly contributing to prediction. In jack-knifing, using the estimates of the variances for the  $B_i$  coefficients,  $t$ -tests were performed for each element in  $B_i$  relative to the square root of its estimated variance  $S^2B_i$ . Coefficients were considered significant at the 95% confidence level ( $P < 0.05$ ).

TABLE IV  
Correlation Coefficients ( $r$ )<sup>a</sup> Between Amylose, Protein, and Lipid Contents and Sensory Texture Attributes

Attribute <sup>b</sup>	Amylose	Protein	Lipid
<b>Initial starchy coating</b>	-0.60	-0.38	0.21
<b>Slickness</b>	-0.29	-0.51	0.22
Roughness	0.01	0.36	-0.23
<b>Stickiness</b>	-0.64	-0.38	0.05
Springiness	0.27	0.19	-0.04
Cohesiveness	-0.35	-0.15	0.08
<b>Hardness</b>	0.46	0.30	-0.12
<b>Cohesiveness of mass</b>	-0.77	-0.29	0.14
Chewiness	-0.10	0.01	-0.14
Uniformity of bite	-0.32	-0.10	0.06
Moisture absorption	-0.34	-0.26	0.21
Residual loose particles	-0.11	0.23	-0.17
Toothpacking	-0.43	-0.05	0.08

<sup>a</sup> Correlation coefficient ( $r$ ) values at  $P < 0.05$ .

<sup>b</sup> Attributes successfully predicted by near-infrared spectroscopy are in bold.

## Physicochemical Properties

Rice cultivars were selected so that the set of samples would have a uniform distribution of amylose and protein contents and alkali-spreading values. The mean, maximum, minimum, and standard deviation are shown in Table II. Amylose and protein contents of the nonwaxy cultivars were 10.3–24.9% and 5.2–11.0%, respectively. Alkali-spreading values were 2.0–7.0, indicative of high to low gelatinization temperature types. The physicochemical property data for the 87 rice samples analyzed in this study were reported earlier (Champagne et al 1999).

This set of rice samples contained both conventional and nonconventional short-, medium-, and long-grain cultivars (Champagne et al 1999). Conventional U.S. long-grain cultivars cook dry and fluffy and are characterized by relatively high amylose content and intermediate- to high-gelatinization temperatures (Webb 1985). In contrast, conventional short- and medium-grain cultivars in the United States cook moist and clingy and have comparatively low amylose content and relatively low gelatinization temperatures. Nonconventional cultivars in the set were “exceptions to the rule.”

## Models

The relationships between each of the sensory texture attributes and the NIR spectral data were examined by PLS1. Initially models for each of the constituents were generated using all spectral data (at 2-nm intervals) in the 700–1,078 and 1,118–2,018 nm range. Spectral data that were significant in explaining the initial models were determined through the jack-knifing and  $t$ -test procedures and were used in developing the final models. Jack-knifing reduced the number (up to 661) of coefficients used in each initial model to  $\approx 60$  in the final model.

Five of the 13 attributes were successfully predicted by NIR ( $R^2$  calibration model 0.71–0.96). Table III lists the optimal number of PLS components in the models for these five attributes, coefficient of determination ( $R^2$ ) for calibration and validation models, root mean square error of calibration (RMSEC), and root mean square error of prediction (RMSEP) for the models, RMSEC-RMSEP ratio, and the discrimination index (DI = standard deviation of attribute/RMSEP). Four of the five attributes (initial starchy coating, slickness, stickiness, and hardness) are associated with the feel of the rice when it is first put into the mouth (Phase I and II). The other Phase I (roughness) and Phase II (springiness and cohesiveness) attributes were poorly modeled. The strongest model was developed for cohesiveness of mass, a Phase III attribute.

In agreement with the results presented here Windham et al (1997) found NIR to best predict texture characteristics measured by sensory panelists in the early evaluation phases. However, in their study, where the variation in sensory properties of three cultivars was primarily due to environmental and postharvest handling (drying, degree-of-milling), cohesiveness of mass was poorly predicted with relative ability of prediction (RAP) = 0.29. Meullenet and Bellman-Horner (2000) reported a strong correlation of NIR with cohesiveness of mass ( $R^2_{\text{calibration}} = 0.74$ ) using four cultivars subjected to different drying and rough rice storage conditions. Meullenet and Bellman-Horner (2000) were also successful in modeling residual loose particles ( $R^2_{\text{calibration}} = 0.88$ ) and toothpack ( $R^2_{\text{calibration}} = 0.85$ ),

TABLE V  
Models for Predicting Amylose, Protein, and Lipid Content from Near-Infrared (NIR) Spectroscopy<sup>a</sup>

Component	PC	$R^2$ Calibration	$R^2$ Validation	RMSEC Calibration	RMSEP Validation	RMSEC/RMSEP	DI
Amylose	4	0.92	0.81	1.26	1.91	0.66	2.3
Protein	3	0.92	0.85	0.26	0.38	0.68	2.6
Lipid	3	0.94	0.90	0.04	0.04	1.00	2.5

<sup>a</sup> PC = optimal number of partial least squares components,  $R^2$  = coefficient of determination for calibration and validation models, RMSEC = root mean square error of correlation, RMSEP = root mean square error of prediction, DI = discrimination index (standard deviation of texture attribute/RMSEP).

two Phase IV attributes. These attributes were poorly modeled in our study where a wider range of genetic variation was evaluated.

### Relationships Between Texture Attributes and Amylose, Protein, and Lipid Contents

Amylose content and, to a lesser extent protein content, influence cooked rice texture (Juliano et al 1965; Sowbhagya et al 1987; del Mundo et al 1989). Lipids may complex with higher molecular weight amylose and the longer amylopectin chains during cooking and also influence cooked rice texture (harder, less sticky) (Priestley 1976; Biliaderis et al 1993; Ong and Blanshard 1995). In this study, the ability of NIR to predict a sensory texture attribute was related to the strength of the relationships between the attribute and amylose, protein, and lipid contents. Cohesiveness of mass, initial starchy coating, and stickiness had fairly strong negative correlations and hardness a positive correlation with amylose, as shown in Table IV. Likewise, slickness had a fairly strong negative correlation with protein content. Correlations between these texture attributes and lipid were weaker. The attributes (roughness, springiness, cohesiveness, chewiness, uniformity of bite, moisture absorption, residual loose particles, and toothpacking), which were not successfully predicted by NIR, generally showed weak correlations with amylose, protein, and lipid contents.

### Key NIR Wavelengths Contributing to Models

Comparing the NIR wavelengths contributing to models for sensory texture with those that contribute to the models for amylose, protein, and lipid provided further insight into the influence of these compositional factors on rice texture.

The models for amylose, protein, and lipid are described in Table V. The predictive abilities of these models are typical of models reported for amylose (Villareal et al 1994; Delwiche et al 1995, 1996), protein content (Delwiche et al 1996), and lipid (Chen et al 1997).

The predictability of sensory texture attributes using NIR spectroscopy was mainly related to differences in spectra resulting from differences in amylose, protein, and lipid contents. The significant coefficients of the model for each attribute were compared with the significant coefficients of the models for the compositional factors to determine which wavelengths mutually contributed to the models (Tables VI–VIII). Several wavelengths contributing to the models

**TABLE VI**  
NIR Wavelengths (2nd derivative spectra) Mutually Contributing to Models for Amylose and Sensory Texture Attributes

Amylose Model Wavelength	Attribute				
	Hardness	Initial Starchy Coating	Cohesiveness of Mass	Slickness	Stickiness
706			x		
708					x
734		x			
766			x		
868	x	x	x		x
932	x		x		
1040	x		x		x
1196		x		x	x
1308	x		x	x	
1422			x		
1472					
1518		x	x		x
1526	x (1522) <sup>a</sup>				
1572	x	x			x
1796		x			
1882			x		
1888			x		
1904			x		x
1954				x	

<sup>a</sup> Actual wavelength contributing to model for attribute.

for initial starchy coating and cohesiveness of mass also contributed to the models describing amylose and lipid contents. Only a few wavelengths contributing to the model for protein content contributed to these attributes. Several wavelengths contributing to the model for stickiness contributed to the model for amylose content; whereas, several wavelengths contributing to the model for slickness contributed to the model for protein content. Several wavelengths contributing to the models for amylose, protein, and lipid contents contributed to the model for hardness. Based on the weak correlations of lipid with the texture attributes (Table IV), it was unexpected to observe NIR wavelengths related to lipid contributing to the NIR models for the attributes.

Two wavelength regions (1,654–1,666 nm and 1,966–1,996 nm) contributing to the models for initial starchy coating, cohesiveness of mass, and stickiness were not included in the models for the compositional factors.

## CONCLUSIONS

NIR spectroscopy has the potential to serve as a rapid tool for predicting sensory texture attributes of cooked rice representing diverse cultivars grown in various locations. Texture attributes (hard-

**TABLE VII**  
NIR Wavelengths (2nd derivative spectra) Mutually Contributing to Models for Protein and Sensory Texture Attributes

Protein Model Wavelength	Attribute				
	Hardness	Initial Starchy Coating	Cohesiveness of Mass	Slickness	Stickiness
768					
870				x	
904				x (902) <sup>a</sup>	
1022				x	
1128			x		
1136				x	
1142				x	
1184	x	x			
1188	x		x	x	
1260					x
1274			x		
1360	x				
1586					
1686	x	x			x
1704					
1906	x				

<sup>a</sup> Actual wavelength contributing to model for attribute.

**TABLE VIII**  
NIR Wavelengths (2nd derivative spectra) Mutually Contributing to Models for Lipid and Sensory Texture Attributes

Lipid Model Wavelength	Attribute				
	Hardness	Initial Starchy Coating	Cohesiveness of Mass	Slickness	Stickiness
704		x	x (706) <sup>a</sup>		
710					x (708)
886	x (888)				
894		x (892)	x (892)		
924	x	x	x		
1044				x	x
1144				x (1142)	
1422			x		
1426					
1518		x	x		x
1690		x (1692)	x (1692)		
1704					
1808			x		
1876	x (1878)				
1880			x (1882)		

<sup>a</sup> Actual wavelengths (in parentheses) contributing to model for attribute.

ness, initial starchy coating, cohesiveness of mass, slickness, and stickiness) measured by sensory panelists in the early evaluation phases were successfully predicted. Key wavelengths contributing to the models describing these texture attributes were wavelengths also contributing to the models for amylose, protein, and lipid contents. Further investigations are needed to evaluate the robustness of and fine-tune the models using various samples with differing genetic and environmental backgrounds, and determine their applicability in developing a universal taste analyzer.

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