

Prediction of Cooked Rice Texture Quality Using Near-Infrared Reflectance Analysis of Whole-Grain Milled Samples

WILLIAM R. WINDHAM,^{1,2} BRENDA G. LYON,¹ ELAINE T. CHAMPAGNE,³ FRANKLIN E. BARTON, II,¹
BILL D. WEBB,⁴ ANNA M. McCLUNG,⁴ KAREN A. MOLDENHAUER,⁵ STEVE LINScombe,⁶
and KENT S. McKENZIE⁷

ABSTRACT

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Rice quality is based on chemical and physical properties affecting its appearance, flavor, and texture characteristics. Sensory quality can be assessed by a combination of descriptive sensory and physicochemical property evaluations. The purpose of the present study was to assess the potential of near-infrared reflectance spectroscopy (NIRS) and NIRS in combination with other physicochemical measurements for the determination of sensory texture attributes in whole-grain milled rice samples. Six rice samples representing combinations of variety and growing locations received treatments of two degrees of milling and five drying conditions to achieve final moisture levels of 12 or 15% ($n = 120$). Quality measurements of the cooked rice included sensory and instrumental texture analyses. Quality measurements of the uncooked rice included amylose and protein (chemical reference), whiteness, transparency, and degree of milling (appearance units of milled rice), and NIRS analyses. Partial least squares (PLS) regression was used to reveal the relationships between the different types of measurements. The sensory texture attributes: manual adhesiveness (MADHES), visual adhesiveness (VADHES),

and stickiness to lips (STICKI) were related to deep-milled samples and positively correlated to amylose, whiteness, and milling degree. The attribute roughness (ROUGH) was related to light-milled samples and positively correlated to protein and negatively correlated to amylose. The main variation in sensory attributes was a result of amylose and protein contents of the rices. A noise-compensation value, relative ability of prediction (RAP), was used to express the degree of prediction ($1.0 =$ best possible prediction). NIRS gave the best prediction results for the texture attributes: MADHES, VADHES, and STICKI with an RAP of 0.57, 0.54, and 0.56, respectively. NIRS is best at predicting texture characteristics of cooked rice perceived in the visual, tactile, and initial oral phases of sensory evaluation. The calibration of NIRS plus physicochemical variables did not improve the predictability of sensory texture over NIRS alone. The prediction of sensory texture in rice by NIR needs to be further investigated on a large number of samples with different varieties, growing locations, cultivation methods, harvesting methods, and processing after harvesting.

The economic value of rice can be recognized by the increased interest in rice varieties and products found in supermarkets. Quality indexes are necessary to allow breeders to efficiently select the appropriate varieties that perform well for specific growing regions and that provide the necessary quality for consumers. Sensory quality is based on chemical and physical properties that initiate from the original stock, the growing and harvesting conditions, and postharvest processing and storage conditions. Control of final appearance, flavor, and texture characteristics of cooked rice begins long before the kernels are cooked. A multidisciplinary approach to definition and control of food quality must account for all these stages.

Assessment of quality of cooked rice can be determined by a combination of evaluations of physical, chemical, and sensory properties and by seeking an understanding of how they interrelate. Proximate composition (i.e., fat, moisture, protein), amylose content, whiteness, and hardness are determined on the raw kernels by various individual procedures. Sensory properties are studied by descriptive analytical sensory analysis or discrimina-

tive methods for relationships with consumer preference-acceptance tests. Traditional physicochemical methods are slow and generally lead to chemical waste production. Likewise, sensory analysis must be conducted under strict conditions of control. Overall quality assessment relies on the integration of all these properties.

Near-infrared reflectance spectroscopy (NIRS) is a rapid method for measuring some constituents of materials without requiring extensive sample preparation or producing chemical waste. NIRS has also been shown to produce accurate and reliable results to determine apparent amylose content (Villareal et al 1994), amino acids (Iwamoto et al 1986), lipids (Stermer et al 1977), moisture (Iwamoto 1987), and the degree of starch gelatinization (Onda et al 1994) in milled rice. Recently, Delwiche et al (1996) reported on the ability for NIRS reflectance analysis of whole-grain milled rice to predict apparent amylose, protein, whiteness, transparency, milling degree, and paste viscosity characteristics.

Few studies have addressed the potential of NIRS to determine sensory attributes. Prediction of sensory quality based on NIRS has been reported on peas (Martens and Martens 1986), green and black china teas (Yan et al 1990), and meat sausages (Ellekjaer et al 1993). The purpose of the present study was to assess the potential of NIRS, alone and in conjunction with other physicochemical properties, to analyze whole-grain milled rice to generate models to predict the sensory texture attributes of the cooked product.

MATERIALS AND METHODS

Rice Samples

Rices from 1994 of M401 and Koshihikari varieties grown in Arkansas and California, Bengal variety grown in Arkansas, and Calrose variety grown in California were harvested at 20% moisture and immediately dried to 12 and 15% moisture constants by five drying procedures. Drying procedures were: 1) air-drying at 18°C and 40% rh, 2) air-drying at ambient temperatures (26–

¹USDA/ARS, Richard B. Russell Research Center, Athens, GA. The mention of firm names or trade products does not imply that they are endorsed or recommended by the U.S. Department of Agriculture over other firms or similar products not mentioned.

²Corresponding author. E-mail: bobw@Athens.net

³USDA/ARS, Southern Regional Research Center, 1100 Robert E. Lee Blvd., New Orleans, LA 70124.

⁴USDA/ARS, Rice Quality Laboratory, Beaumont, TX.

⁵University of Arkansas Rice Research and Extension Center, Stuttgart, AR.

⁶Louisiana State University, Rice Research Station, Crowley, LA.

⁷California Cooperative Rice Research Foundation, Biggs, CA.

28°C), 3) continuous-flow drying with 60°C heated air (high-temperature commercial drying conditions), 4) continuous-flow drying with 50°C heated air (normal commercial drying conditions), and 5) continuous-flow drying with 32°C heated air (low-temperature commercial drying conditions). The continuous-flow drying was on a pilot-scale unit located at Riviana Foods, Inc. (Houston, TX) that simulates commercial dryers. After drying, the paddy (rough) rice ($n = 60$) was stored in sealed containers for approximately two to three months in a cool room maintained at 18°C. One week before sensory testing, the samples ($n = 60$) were shelled using a Satake rice machine, (model SB, Satake Engineering Co. Tokyo) and milled to provide two levels of milling (i.e., light and deep). Light (regular) milling was accomplished using a laboratory Satake one-pass mill (pearler, model SKD). The first pass was with a 50-g weight in the 5th position; the second pass was with a 50-g weight in the 3rd position. Deep milling was performed on 250-g portions of the regular-milled rice using a laboratory Satake grain testing mill (model TM05). Milling conditions were 1 min at 1,250 rpm using a fine mesh abrasive wheel. Brokeners were removed with appropriate laboratory sizing devices using standard indented plates and cylinders.

Physicochemical Analysis of Uncooked Whole-Grain Milled Rice

Protein ($N \times 5.95$) was determined in triplicate by the method of combustion (AOAC 1990). Apparent amylose content was determined in triplicate by the simplified assay method developed by Juliano (1971). Values for whiteness, transparency, and milling degree were measured on a Satake milling meter (model MM-1B) in accordance with manufacturer's instructions.

Spectroscopic Analyses of Uncooked Whole-Grain Milled Rice

A visible near-infrared scanning monochromator (model 6500, NIRSystems, Silver Spring, MD) was used to collect reflectance readings over a wavelength range of 400–2,498 nm. The instrument was operated by the software package NIR3 v.3.11 (Infra-soft International, Inc. Port Matilda, PA), which includes modules for acquisition and processing of spectra. In conjunction with sensory test sessions, uncooked whole-grain milled rice ($n = 120$) was scanned in duplicate in a transport cell in reflectance mode as described by Delwiche et al (1996). The duplicate scans of each sample were examined visually for consistency and averaged.

Sensory Evaluation: Experimental Design

The rices were designated by their variety-location, moisture, and milling treatment. There were 24 treatment groups (6 variety-location \times 2 moisture levels \times 2 milling degrees). There were 24 panel sessions, held two days a week for 12 weeks. Each treatment group was randomly assigned to a single panel session. Within each treatment group, there were samples of the five drying conditions. In addition, there was a sixth blind control sample, Calrose, which was also served as a warm-up consensus control sample before test presentations. The individual samples tested at each session were presented to the panelists in a random order at 20-min intervals. There were no replicates or repeated evaluations due to inadequate sample lots.

Sensory Evaluation: Panel Training

Ten panelists, previously trained in the principles and concepts of the texture profile analysis (Civille and Szczesniak 1973, Civille and Liska 1975, Munoz 1986, Skinner 1988) were chosen to participate in the study. They analyzed a wide range of rice varieties and conditions to develop a texture terminology list appropriate for evaluation of rice.

The term list included 16 sensory attributes that covered descriptions of the rice texture at difference phases, beginning

with some characteristics outside the mouth and ending with mouthfeel characteristics after the rice is swallowed. In Phase I, a teaspoon of rice was placed on a plate and manipulated with the back of the spoon, evaluating for manual adhesiveness (MADHES) and visual adhesiveness (VADHES). In Phase II, rice was compressed lightly between lips and evaluated for stickiness to lips (STICKI). In Phase III, the surface of rice placed behind front teeth was evaluated for initial starchy coating (ISTARCH), surface slickness (SLICK), and roughness (ROUGH). In Phase IV, one-half teaspoon of rice was evaluated at first bite for self adhesiveness (SADHES), springiness (SPRING), cohesiveness (COHES), hardness (HARDN). In Phase V, rice was evaluated during chew for cohesiveness of mass (COHES), chewiness (CHEWI), and uniformity of bite (UNIFORM). In Phase VI, after swallow characteristics of residual loose particles (RESID), toothpick (TOOTHPCK), and starchy mouthcoating (SMCOAT) were evaluated. These 16 sensory descriptors were placed on the ballot and used by the panel to evaluate the samples under study.

Product Testing: Cooking

Samples were cooked and tested individually at 20-min intervals. A 600-g portion of dry-milled rice was rinsed three times in enough cold water to cover the rice, strained to remove excess water, and then transferred to a preweighed rice cooker insert bowl. Water was added in an amount to equal a 1:1.3 ratio of rice to water by weight, accounting for the water retained on washing. Rice was presoaked for 30 min at room temperature and then cooked in a Panasonic rice cooker-steamer (model SR-W10GHP, JFC International, Inc., Norcross, GA) with a capacity of 1 L. When the cook cycle was complete, the cooker automatically shifted to a "warm" setting. Rice was held an additional 10–15 min.

The top 1-cm layer of cooked rice was skimmed off and discarded. Samples for analysis were taken from the middle of the container but not from within 1-cm of the edges and bottom. This portion was transferred to a prewarmed glass bowl and mixed gently to minimize damage of individual kernels. Portions (≈ 50 g/portion) were placed into individual glass cups covered with watchglasses. Each cup rested in a styrofoam caddy to keep the sample at a constant temperature for serving to panelists. Water was provided to panelists for mouth cleansing between samples. Samples were evaluated at individual test stations under low-pressure sodium vapor masking lights (CML-18, Trimble House, Norcross, GA). Panelists evaluated the samples for each of the 16 attributes, recording their responses on 15-point intensity line scales presented by the computerized sensory analysis system (CSA v 4.3, Compusense, Inc., Guelph, Ontario).

Before presentation of the test samples, the warm-up sample was presented to the panelists for evaluation. The blind-coded sixth samples were averaged over panelists and compared to the warm-up consensus sample at each session to determine any panelist performance drifts. For this report, attribute responses were tested by two-way analysis of variance for panelist and sample effects. Attributes that did not show significant sample differences were eliminated from inclusion in further multivariate analyses with other measurement variables. The average response over panelist was used in multivariate analyses.

Instrumental Texture Evaluations

At the same time that sensory panelists were evaluating the warm rice samples, the texture profile analysis (TPA) test was conducted on quadruplicate 1-g cooked rice aliquots, with a bench-top texture analyzer, TA.XT2 (Texture Analyzer TA.XT2, Texture Technologies Corp. Scarsdale, NY). The 1-g sample of cooked rice was arranged in a single grain layer on the base plate. A compression plate was set at 5 mm above the base. A two-cycle compression program (force vs. distance) was used to allow the plate to travel 4.9 mm, return, and repeat. Test speed was 1

mm/sec. Parameters derived from the two-cycle curves of the TPA test were: hardness, springiness, cohesiveness, chewiness, adhesiveness, and gumminess, as described by Bourne (1982). Definitions and calculation are given in Table I.

Multivariate Analyses

A commercial program for multivariate analysis (Unscrambler, v 5.5, CAMO, Trondheim, Norway) was used to process the data from all analyses and to develop chemometric models. The multivariate methods of partial least squares (PLS1 and PLS2) as described by Martens and Naes (1989) were used for predicting sensory attributes (dependent variables) from NIRS spectra, chemical and Satake milling meter values, and instrumental TPA texture data, alone and in different combinations. When only one dependent variable is modeled, the PLS algorithm is noniterative and is termed PLS1. When several variables are modeled simultaneously, it is iterative and is called PLS2. Sensory texture attributes comprised an 11-column matrix (i.e., sensory block Y). The instrumental block X was composed of one 664-column matrix with 653 NIRS variables plus two chemical variables (protein and amylose), three Satake milling meter variables (whiteness, transparency, and milling degree), six TPA variables (hardness, springiness, cohesiveness, gumminess, adhesiveness, and chewiness). Before PLS2 analysis, weighting was done by conventional standardization to equal variance (weight = $1/S_{tot}$, where S_{tot} = standard deviation of the variable in the calibration set). The con-

cepts and properties of PLS in relation to NIRS are discussed by Martens and Naes (1989).

The preprocessing data technique of multiplicative scatter correction (Isaksson and Naes 1988) was applied to the spectra to remove interferences arising from scatter and then transformed with a second derivative (gap = 20 nm) to enhance absorption peaks. The wavelength region was then truncated to 424–1,800 nm (653 spectral data points) because of low signal intensity and nonlinear response at longer wavelengths (Delwiche et al 1996).

The calibration models (PLS1 and PLS2) were validated using full cross-validation where each sample was used to test the model derived from all other samples. The accuracy of models was expressed by root mean square error of prediction (RMSEP) (Martens and Naes 1989). RMSEP is used for assessing the accuracy of dependent variables predicted from an instrument (e.g., NIRS) in absolute terms. However, to compare the predictive ability of different calibration models for different sensory attributes, the measure of the relative ability of prediction (RAP), as described by Martens and Martens (1986), was used. This is a background compensation number where a value of 1.0 represents the best possible prediction. RAP is defined for a sensory attribute as:

$$RAP = (S_{tot}^2 - RMSEP^2)/(S_{tot}^2 - S_{ref}^2)$$

where S_{tot} is the standard deviation of a sensory attribute, S_{ref} is the standard error of the reference method, which indicates the

TABLE I
Summary of Sensory Texture Attributes and Instrumental Texture Parameters in Cooked Rice

Variables	Abbreviation ^a	Minimum	Maximum	Mean	S_{tot} ^b	S_{ref} ^c
Sensory texture						
Manual adhesiveness	MADHES	5.04	7.66	6.56	0.39	0.06
Visual adhesiveness	VADHES	6.59	8.40	7.39	0.37	0.06
Stickiness to lips	STICKI	6.90	8.96	7.69	0.40	0.06
Initial starchy coating	ISTARCH	4.92	6.34	5.59	0.32	0.05
Surface slickness	SLICK	4.67	5.99	5.30	0.26	0.05
Roughness	ROUGH	3.91	4.81	4.41	0.19	0.05
Self adhesiveness	SADHES	5.41	7.09	6.16	0.36	0.05
Cohesiveness	COHES	5.84	6.52	6.20	0.16	0.04
Cohesiveness of mass	COHM	5.49	6.53	5.98	0.20	0.05
Uniformity of bite	UNIFORM	8.17	9.21	8.68	0.18	0.03
Starchy mouthcoating	SMCOAT	3.77	4.62	4.19	0.20	0.06
Instrumental texture ^d						
Hardness	hard	10.24	19.86	15.50	2.04	1.13
Springiness	springi	0.24	0.61	0.29	0.51	0.03
Cohesiveness	cohes	0.56	0.65	0.60	0.02	0.01
Chewiness	chew	1.65	4.24	2.75	0.58	0.28
Adhesiveness	adhes	-2.69	-1.11	-1.94	0.34	0.22
Gumminess	gum	5.94	12.62	9.35	1.34	0.80

^a As used in Figs. 1–3.

^b Total standard deviation.

^c Standard error of the reference method.

^d Instrumental parameters of the two-cycle curves. Hardness (hard), force value (kg) from the first major peak; Springiness (springi), sample recovery calculated as distance from start of peak to probe reversal for curve two divided by that of curve one; Cohesiveness (cohes), deformation represented by area second curve/area first curve; Chewiness (chew), hardness × springiness × cohesiveness; Adhesiveness (adhes), area of the negative peak on the first probe reversal; Gumminess (gum), hardness × cohesiveness.

TABLE II
Summary of Chemical and Satake Milling Meter Constituents in Whole-Grain Milled Rice

Variables	Abbreviation	Minimum	Maximum	Mean	S_{tot} ^a
Chemical reference					
Amylose	amy	16.40	23.50	19.42	1.51
Protein	pro	3.90	8.30	5.98	0.88
Satake milling meter					
Whiteness	Whi	32.30	52.00	43.93	5.59
Transparency	Tra	2.41	4.69	3.28	0.43
Milling degree	Mil	60.00	157.00	116.72	26.24

^a Total standard deviation.

uncertainty of the analysis due to panelist. Calrose, which served as the blind control was used to determine S_{ref} . S_{ref} is defined for a sensory attribute as:

$$S_{ref} = (MSE/[P \times R])^{0.5}$$

where MSE is the mean square error derived from two-way analysis of variance with samples and panelists as class-variables and P and R represent the number of sensory panelists and replicates, respectively.

RESULTS AND DISCUSSION

Analyses of variance of the sensory texture attributes indicated that springiness, hardness, chewiness, residual loose particles, and toothpack did not show differences in the samples due to the design variables. Because they did not discriminate differences among the samples, they were omitted from PLS1 and PLS2 analyses of the NIRS, and physicochemical measurements. In addition, there was no difference ($P > 0.05$) in sensory texture attributes due to drying procedure and moisture level. An overview of the sensory and instrumental TPA texture data, the chemical values, and Satake milling meter values are shown in Tables I and II, respectively. The standard deviation (S_{tot}) and standard deviation due to sampling and random measurement noise (S_{ref}) were used in the calculations of RAP.

Overall Relationships Between Sensory, Chemical, and Instrumental Data

To explore relationships between sensory texture scores, chemical measurements and the instrumental parameters, PLS2 was performed. Cross-validated PLS2 explained $\approx 48\%$ of the total variation in the sensory block that could be predicted by the instrumental block after four factors. Most of this variation (38%) was described by the first three factors. Martens and Martens (1986) reported that $\approx 55\%$ of the total variation in pea sensory variables could be predicted by eight chemical variables, tenderometer value, and 21 NIR variables by the first four factors.

The loadings for Factor 1 resulting from PLS2 of the instrumental block related to the sensory block are plotted in Fig. 1A. The loading values represent the contribution or correlation of the attributes and variables to the overall factor. Factor 1 had positive loading values for most of sensory attributes, instrumental TPA (i.e., cohesiveness and adhesiveness), all Satake milling meter variables, and amylose content. The NIR loading values for this factor were related to O-H absorbance due to moisture (958 nm), and C-H due to starch (878 and 979 nm) (Williams and Norris 1987), and therefore probably describe variations in starch content. Negative loadings values were primarily the instrumental TPA characteristics (hardness, springiness, gumminess, and chewiness), sensory roughness, and protein content. Factor 2 had positive loading values for amylose content, specific sensory, and TPA characteristics relating to stickiness. Protein content, sensory roughness, and instrumental TPA characteristics loaded negative for both Factors 1 and 2. The NIR wavelengths with negative loading values related to N-H absorbance due to protein (1,018 nm) and C-H due to oil (1,212 nm) in Factor 1 and protein (1,690 nm) and oil (930 and 1,387 nm) in Factor 2.

Sample scores that were calculated from these factors were then plotted as shown in Fig. 1B. In Factor 1, the light-milled (L) samples were separated from the deep-milled samples (D) in accordance with protein and amylose content. Light-milled samples were higher in protein and lower in amylose (6.7 and 18.0%, respectively) than deep-milled samples (6.2 and 18.9%). This is in agreement with Normand et al (1966), who reported that protein, fat, vitamins, and minerals in the peripheral layer below the bran coat and aleurone cells are removed with deep milling. Starch and amylose, by contrast, progressively increase toward the center of

the rice kernel. Scores for the first PLS2 factor had a correlation of -0.56 and 0.49 with protein and amylose, respectively. The texture analyzer variables of gumminess, hardness, chewiness, and springiness were also related to light-milled samples and were negatively correlated to Factor 1 scores and positively correlated to protein content. Deep-milled (D) samples, which had positive scores for Factor 1, conversely, had higher amylose, whiteness, milling degree, and were more transparent. Amylose, whiteness, milling degree, and transparency had positive correlations of 0.49 , 0.96 , 0.89 , and 0.39 , respectively, with Factor 1. Amylose content also correlated positively with whiteness, transparency, and milling degree ($r = 0.41$, 0.20 , and 0.40 , respectively). All sensory texture attributes, with the exception of ROUGH, had positive values for Factor 1, and for amylose, whiteness, and milling degree. The sensory variable ROUGH had negative loadings for

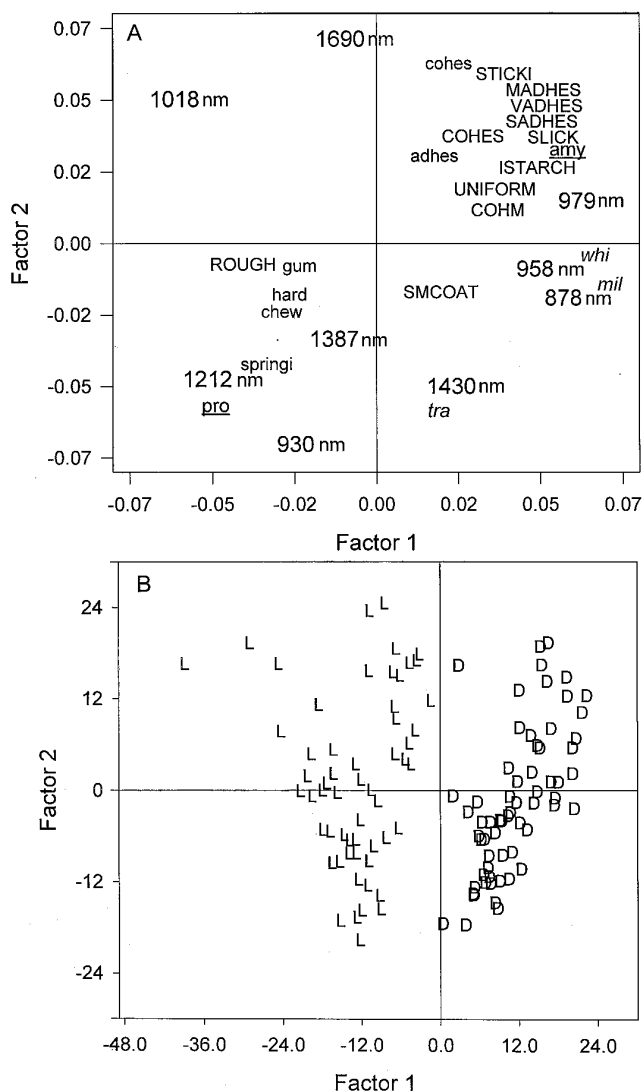


Fig. 1. Relationship of near-infrared reflectance spectroscopy (NIRS) results, seven physicochemical variables, and three Satake milling meter variables to 11 sensory descriptive attributes using partial least squares (PLS2). **A**, PLS2 loadings for Factors 1 and 2 plotted for 11 sensory attributes (uppercase abbreviations) vs. two chemical variables (underlined abbreviations), three Satake milling meter variables (italic abbreviations), six instrumental texture profile analysis (TPA) variables (lowercase abbreviations), and NIR wavelengths (nm). Abbreviations are listed in Tables I and II. **B**, PLS2 scores for Factors 1 and 2. L = light milled and D = deep milled.

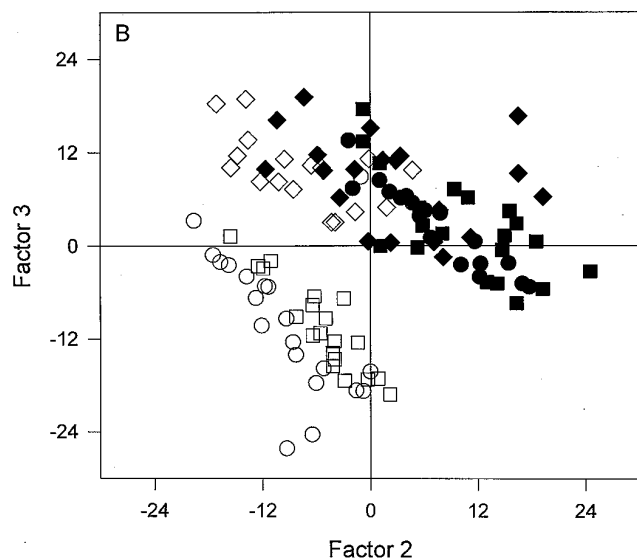
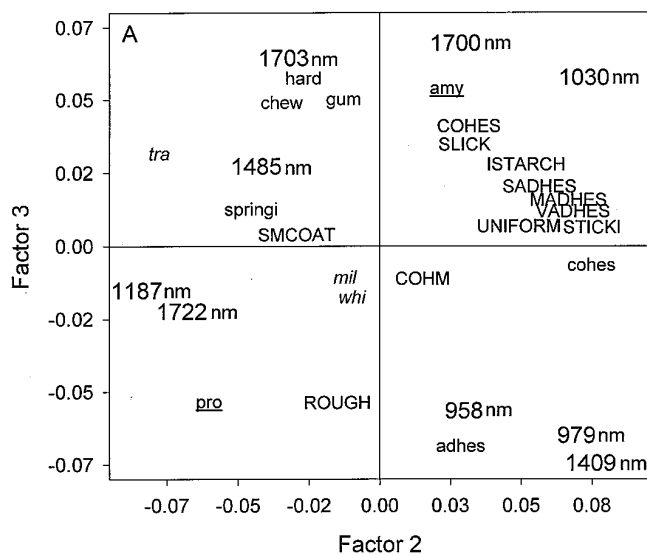


Fig. 2. Relationship of near-infrared reflectance spectroscopy (NIRS) results, seven physicochemical variables, and three Satake milling meter variables to 11 sensory descriptive attributes using partial least squares (PLS2). **A**, PLS2 loadings for Factors 2 and 3, plotted for 11 sensory attributes (uppercase abbreviations) vs. two chemical variables (underlined abbreviations), 3 Satake milling meter variables (italic abbreviations), six instrumental texture profile analysis (TPA) variables (lowercase abbreviations), and NIR wavelengths (nm). Abbreviations are listed in Tables I and II. **B**, PLS2 scores for Factors 2 and 3. \diamond = Koshihikari grown in Arkansas, \square = M401 grown in Arkansas, \circ = Bengal grown in Arkansas, \blacklozenge = Koshihikari grown in California, \blacksquare = M401 grown in California, and \bullet = Calrose grown in California.

Factor 1 and positively correlated to protein content ($r = 0.41$). Protein content had a negative correlation with amylose ($r = -0.62$) and all other sensory texture attributes.

In Figure 2A, Factor 3 had positive loading values for a combination sensory attributes, instrumental TPA characteristics, amylose content, and NIRS bands for protein (1,485 nm), oil (1,703 nm), and starch (1,700 and 1,030 nm). Loading negatively were adhesiveness, sensory ROUGH, protein content, and NIRS bands related to protein (1,187 nm), oil (1,722 nm), starch (979 nm), and water (958 and 1,409 nm). Scores from Factor 2 and 3 separated the samples by growing locations (Fig. 2B). Scores from Factor 2 describe a positive relation between amylose ($r = 0.27$) and the sensory attributes MADHES, VADHES, STICKI,

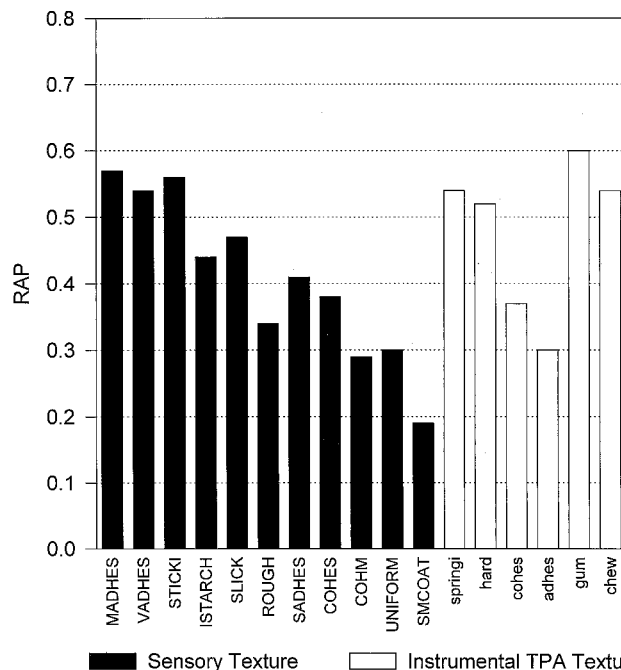


Fig. 3. Relative ability of prediction (RAP) of near-infrared reflectance (NIR) instruments for 11 sensory descriptive attributes and 6 instrumental texture profile analysis (TPA) variables. 1.0 = Best possible prediction, 0.0 = no predictive ability. Abbreviations are listed in Table I.

ISTARCH, SLICK, SADHES, and COHES (0.41, 0.34, 0.48, 0.27, 0.30, 0.34, and 0.28, respectively) and a negative relationship to protein ($r = -0.58$). The location of sample scores are in accordance with main chemical variation among the samples. Varieties grown in California were higher in amylose and lower in protein (18.9 and 5.7%, respectively) than those grown in Arkansas (17.7 and 7.1%). Varieties within growing location were to some extent explained by Factor 3 scores (Fig. 2B). Scores from Factor 3 mainly described the variations between varieties by amylose ($r = 0.47$), protein ($r = -0.37$) and the three instrumental TPA variables, hardness, gumminess, and chewiness.

From the overall analysis of the data, it was concluded that the sensory texture attribute roughness was related to protein content and to the instrumental TPA variables springiness, hardness, gumminess, and chewiness. The high positive or negative loadings at known absorbance for protein correlated with protein content of samples with low amylose. The C-H absorbance in the NIRS loading spectra might contain information about different oil contents of the samples since nonstarch nutrients are reduced by deep milling (Wadsworth 1993). All other sensory texture attributes were related to amylose, whiteness and milling degree. Factors related to these attributes and to physicochemical variables had high spectral loadings at wavelengths related to both starch and water.

NIRS as a Predictor for Sensory Texture

PLS1 was performed on the NIRS of whole-grain milled rice with regard to the sensory texture attributes. The NIRS analyses on the whole-grain milled rice explained ≈ 49 , 55, 35, 36, 28, 43, and 28% of total variation in the data for individual sensory attributes of MADHES, STICKI, ISTARCH, SLICKI, ROUGH, SADHES, and COHES, respectively, using three PLS1 factors. Two PLS1 factors explained ≈ 40 , 25, 24, and 16% of total variation in the sensory attributes VADHES, COHM, UNIFORM, and SMCOAT, respectively. The maximum values for relative predictive ability (RAP) of the 11 sensory attributes, when using NIRS for the prediction, are shown in Figure 3. NIRS gave the best prediction results for the texture attributes, MADHES, VADHES, and

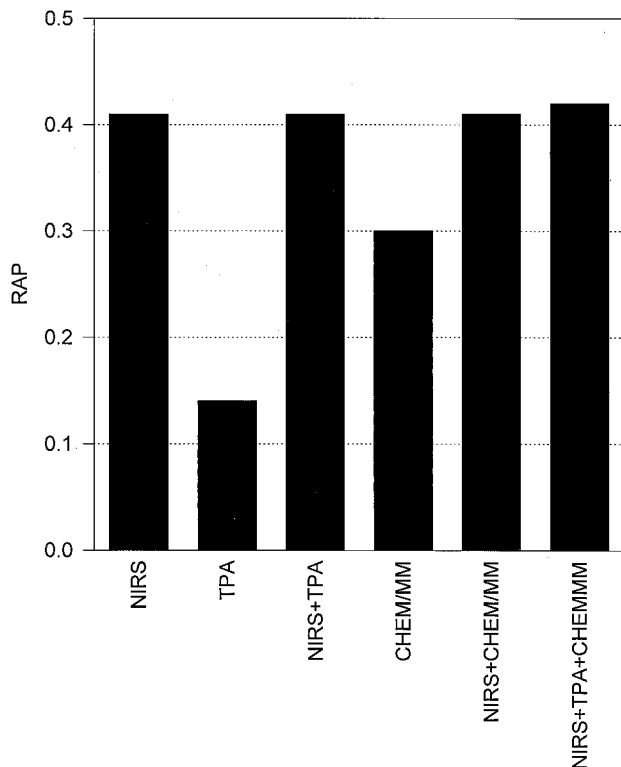


Fig. 4. Averages of relative ability of prediction (RAP) of the sensory descriptive attributes by near-infrared reflectance spectroscopy (NIRS), instrumental texture profile analysis (TPA), chemical (CHEM), and Satake milling meter analyses (MM), alone and in different combinations. 1.0 = Best possible prediction, 0.0 = no predictive ability.

STICKI, with a RAP of 0.57, 0.54, and 0.56, respectively. These three attributes were perceived in Phases I and II of evaluations. These performance statistics are lower than reported by Martens and Martens (1986) for NIR prediction of texture variation (e.g., hardness, juiciness, and mealiness with RAP = 0.82, 0.80, and 0.79, respectively) in peas. Predictability of ISTARCHE and SLICK was higher than ROUGH in Phase III. However, none of the Phase V and VI attributes were predicted well. Thus, NIRS of uncooked rice kernels is best at predicting texture characteristics of cooked rice that are evaluated sensorially in the early evaluation phases (i.e., Phases I, II, and III). The first phases represent visual and tactile evaluations and initial oral evaluations. The poor prediction potential of the latter phase models was possibly due to the relatively small variation in sensory data, compared to Phase I and II and that was reported by Martens and Martens (1986).

NIRS as a Predictor for Physicochemical Measurements

Optimal model conditions for protein, whiteness, transparency and milling degree occurred with 7, 5, 5, and 8 PLS1 factors with an RMSEP of 0.19, 0.59, and 0.12% and 2.25 respectively. These RMSEP values correspond to RAP values of 0.96, 0.98, 0.85, and 0.98, respectively. The PLS1 model factors account for 95, 97, 84, and 98% of the total variation in protein, whiteness, transparency, and milling degree, respectively. The NIRS wavelength region, derivative preprocessing, and performance statistics for these physicochemical measurements are in agreement with Delwiche et al (1996).

Results from a separate PLS1 analysis of the six instrumental TPA variables versus the NIRS variables are shown in Fig. 3 in terms of RAP values. The NIRS data explained 41, 35, 44, and 48% of the variation in data for springiness, adhesiveness, cohesiveness, and gumminess with a six-factor solution. Optimal model conditions for hardness and chewiness contained seven factors with an explained variance of 57 and 54%, respectively.

The predictability of the TPA variables was similar to the sensory texture attributes, but much lower than the RAP for the chemical and Satake milling meter data.

Combining Methods for Prediction of Sensory Texture

Separate PLS1 calibrations were developed for the sensory texture attributes with NIRS, TPA, and chemical and Satake milling meter data, alone and in different combinations (instrumental block). When using NIRS to predict sensory texture, we obtained an average RAP of 0.42 (Fig. 4). Correspondingly, TPA alone was found to be inferior to NIRS. NIRS together with TPA did not improve the prediction. When using chemical and Satake milling meter data, a RAP of only 0.30 was obtained, even though these attributes correlated to some sensory texture attributes. The calibration of NIRS, chemical, Satake milling meter, and TPA variables together did not improve the predictability of sensory texture over NIRS alone.

CONCLUSIONS

The main variation in sensory texture attributes was a result of amylose and protein contents of the rices. This variation arose as a result of the degree of milling treatments. The predictability of sensory texture attributes by NIRS was mainly related to changes in spectra caused by different protein, starch, and possibly lipid contents of the rice. Considering the narrow range of the sensory texture data, we feel NIRS has potential as a rapid tool to predict rice texture attributes in addition to predicting chemical composition and Satake milling meter values. Further study is needed on the prediction ability of sensory texture attributes by NIRS when the variation in sensory texture is caused by varietal differences as well as milling procedures which would provide a broader spectrum of rice texture characteristics.

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