Prediction of Texture of Cooked White Rice by Near-Infrared Reflectance Analysis of Whole-Grain Milled Samples

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ABSTRACT

Although much work has been done using near-infrared (NIR) spectroscopy with rice, little is currently known about the effectiveness of NIR to predict functional attributes of rice such as cooked rice texture, especially as they are influenced by postharvest parameters. In this study, NIR spectroscopy was used for predicting cooked rice texture as affected by postharvest history. Cooked rice texture attributes were evaluated by a nine-member trained descriptive panel, and milled white rice was scanned using a near-infrared (NIR) spectrophotometer. Sensory attribute models were developed using partial least squares regression in combination with jack-knife, a model optimization method, using NIR reflectance spectra (400–2,500 nm) and 1st and 2nd derivatives. Cooked rice adhesion to lips ($R^2 = 0.88$), hardness ($R^2 = 0.79$), cohesiveness of mass (three chews) ($R^2 = 0.79$), and toothpack ($R^2 = 0.85$) were satisfactorily fitted (n = 201–202) using the 2nd derivative spectra. Other attributes evaluated, such as cohesiveness of mass (eight chews) ($R^2 = 0.69$), roughness of mass ($R^2 = 0.49$), and toothpull ($R^2 = 0.76$) were less successfully modeled. In addition, jack-knife significantly improved model statistics. Overall, NIR spectroscopy had potential application for predicting cooked rice texture. This finding is especially significant for applications such as breeding programs, where the amount of material available is limited.

The importance of whole rice has increased dramatically in the United States within the past few decades and is continuing to increase today. As the popularity of rice grows, so does the need to closely monitor quality attributes of rice, including cooked rice texture, as affected by postharvest conditions such as drying and storage conditions. Because of the time and cost involved in laboratory testing for functional properties, including rice texture, there is a need for rapid methods to quickly test for these attributes.

A number of instruments have been employed to measure the texture of cooked rice including the General Foods Texturometer (Szczesniak and Hall 1974; Suzuki 1979; Okabe 1979), the Instron food tester (Perez and Juliano 1979, 1981; Juliano et al 1981, 1984), the Tensipresser (Tsuji 1982), the Haake Consistometer (Manohar Kumar et al 1976), and the Texture Analyzer TAXT2 (Champagne et al 1998; Meullenet et al 1998). In addition to the use of various instruments, different cells such as flat plates or plungers (Champagne et al 1998; Sesmat and Meullenet 2000), puncture (Perez et al 1993), the Ottawa Texture Measuring System (Perez and Juliano 1979; Rousset et al 1995; Meullenet et al 2000; Sitakalin and Meullenet 2000), and the Kramer shear cell (Juliano et al 1981) are employed. These methods have been employed with some success and, in some cases, are closely related to sensory evaluation data. However, these methods are time-consuming and destructive.

Another method that could be used to assess functionality, including rice texture, is near-infrared spectroscopy (NIR), an analytical technique that has been used for the past 20 years to analyze various cereal grain constituents including moisture, protein, and oil (Williams 1975). With regard to rice, NIR has been used to accurately predict apparent amylose (Villareal et al 1994; Delwiche et al 1995, 1996), protein content (Delwiche et al 1996), and surface lipids (Chen et al 1997). Because rice functionality is a function of chemical constituents and their interaction, it seems logical that NIR could be used for directly assessing functional characteristics such as paste viscosity. However, there has been less success at predicting functional attributes such as alkali spreading value and viscosity (Delwiche et al 1996) or amylogram and cooking characteristics of short-grain Japanese rice (Kawamura et al 1998). Although NIR has been used to predict the quality of cooked rice texture (Windham et al 1997) with low to moderate success, little is currently known about the effectiveness of NIR to predict rice texture attributes especially as they are influenced by postharvest variables such as moisture content, storage temperature and duration. The successful development of NIR calibrations for predicting rice texture would find applications in rice processing operations as well as in breeding laboratories.

The objective of this study was to evaluate the use of NIR to predict the functional properties of milled white rice, including nine sensorial texture attributes, as affected by cultivar and rough rice storage history.

MATERIALS AND METHODS

Rice Samples

Rice was harvested at the University of Arkansas (UofA) Rice Research and Extension Center at Stuttgart, Arkansas (1996, 1997, and 1998) and at a private farm in Stuttgart, AK (1997) at a harvest moisture content of ≈18% wb. Cultivars harvested included one medium-grain (Bengal) and three long-grain (Cypress, Kaybonnet, and Drew) cultivars. The rice was either dried on-farm or transported to the UofA Rice Processing Laboratory and dried in laboratory drying facilities. After drying, the rice was slowly tempered (≈7 days) in an equilibrium chamber at 21°C to the target storage moisture content, 10, 12, or 14% wb. The rice was then divided into three lots using a Borner divider and placed into sealed plastic buckets, which were stored in temperature-controlled chambers at 4, 21, and 38°C. Subsamples were removed at specified intervals and subjected to various analyses. A total of 206 samples were analyzed from 1996 to 1998. Additional details about rough rice processing conditions can be found in Meullenet et al (1998, 1999, 2000) and Sitakalin and Meullenet (2000). In addition, the effects of postharvest processing conditions on sensory texture attributes of cooked rice will not be reported here because articles by Meullenet et al (1998, 2000) discuss these results.

Milling

After the samples were removed from storage, they were milled in duplicate before additional analysis. Stored samples were allowed to equilibrate to room temperature before hull and bran removal. A McGill sample sheller (husker) and a McGill No. 2 mill were used to remove hull and bran, respectively. Samples (150 g) were milled to a constant degree of milling (DOM 90). A Satake milling meter MM-1B was used for measuring the DOM. The white rice was sized on a shaker table to obtain head rice, defined as any kernels longer than 75% original length (USDA 1993).

NIR Analysis

For NIR analysis, ≈100 g of whole grain rice was scanned in a scanning monochrometer (NIRSystems 6500, Perstorp Analytical,

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Silver Springs, MD) equipped with the software WinISI II v. 1.04 (Foss NIRSystems/Tecator Infrasoft International, LLC.). The sample was poured into a rectangular transport cell and scanned in reflectance mode from 400 to 2500 nm at 2-nm increments. The average of 25 scans of each sample was stored for calibration.

Sample Preparation

Samples were cooked for 20 min in household steam rice cookers (National, model SR-W10FN) with a 1:2 (v/v) rice-to-water ratio, and immediately mixed and fluffed using a plastic fork. Samples were presented at 71°C ± 1 in preheated glass bowls insulated with Styrofoam cups and covered with watch glasses.

Methodology

Nine panelists trained in descriptive analysis techniques according to the Spectrum methodology (Sensory Spectrum, Chatham, NJ) with three years of experience in descriptive analysis developed a texture lexicon for cooked long and medium grain rice. Four 3-hr orientation sessions were necessary for the panel to develop the rice lexicon and test methodology necessary to describe texture characteristics of cooked rice. Nine texture attributes were identified as adequately describing the texture profile of cooked rice for the varieties studied (Fig. 1). The methodology developed for the evaluation of texture characteristics of cooked rice was organized in four consecutive stages. Adhesiveness to lips was evaluated first as a surface characteristic by compressing the sample between dry lips and evaluating the degree to which the samples adhered to the lips. During the first bite, hardness was assessed by compressing the sample between molars and evaluating the force required to bite through the sample. Cohesiveness of mass was measured after three and eight chews, and roughness of mass, toothpull and particle size were evaluated during the chewdown stage of the evaluation. Finally, toothpack and loose particles were evaluated after expectoration of the product or during the residual stage. Sensory scores were given by the panelists using paper ballots and numbers 0–15 (Meilgaard et al 1991). Intensities were assessed by comparison

TERM	DEFINITION	TECHNIQUE	REFERENCES	
SURFACE:				
Adhesiveness to lips	Degree to which the sample adheres to the lips.	Compress sample between lips, release, and evaluate.	Tomato Nougat Breadstick Pretzel Rod Rice Krispies	0.0 4.0 7.5 10.0 15.0
Particle size	Amount of space the particle fills in mouth.	Place sample in center of mouth and evaluate.	Rice grain (cooked) Tic Tac M & M (plain)	0.5 2.5 4.0
FIRST CHEW:				
Hardness	Force required to compress the sample.	Compress or bite through sample with molars or incisors.	Cream cheese Egg white American cheese Hotdog Olive Peanut Almond Carrot Life Savers	1.0 2.5 4.5 5.5 7.0 9.5 11.0 11.0 14.5
CHEWDOWN:				
Cohesiveness of mass	Degree to which chewed sample holds together.	Chew sample with molar teeth three and eight times and evaluate.	Licorice Carrot Mushrooms Hot dog American cheese Brownie Dough	0.0 2.0 4.0 7.5 9.0 13.0 15.0
Roughness of mass	Amount of roughness perceived in chewed sample.	Chew sample with molar teeth 8 times and evaluate.	Unchewed Jell-O Orange peel Cooked oatmeal	0.0 3.0 6.5
Toothpull	Force required to separate jaws during mastication.	Chew sample up to 3 times and evaluate.	Clam Caramel Jujubes	3.5 5.0 15.0
RESIDUAL:				
Toothpack	Amount of product packed into the crowns of teeth after mastication.	Chew samples up to 8 times, expectorate, feel surface of the crowns of teeth with tongue.	Captain Crunch Heath Bars	5.0 10.0
Loose particles	Particles remaining in and on the surface of mouth after swallowing.	Chew sample up to 8 times with molars, swallow and evaluate.	Carrot	10.0

Fig. 1. Lexicon for sensory texture attributes of cooked rice.

with carefully chosen references anchored on specific attribute scales. References are provided in Fig. 1.

Panelists were instructed to monitor temperature during the test using digital thermometers and to complete the evaluation before the temperature of the sample dropped to 60°C ± 2. The order of sample presentation was randomized across treatments but not across panelists because of limited sample availability and the importance of serving temperature. Nine to 12 samples were presented for texture evaluation at each of the testing sessions. In addition, the samples were evaluated twice by each of the panelists on two separate days. A reference rice sample was presented as a warm-up sample at the beginning of each session. Samples were presented monadically in individual booths featuring incandescent lighting and positive pressure. Panelists were allowed a 10-min break between each sample evaluation and instructed to clean their palates with water.

Data Analysis

Sensory means (nine panelists and two replicates) for each of the 206 samples evaluated were calculated using PROC MEANS (SAS Institute, Cary, NC). Correlations among sensory attributes were investigated using PROC CORR. Because particle size is a function of kernel size and not amechanical property and loose particles are an attribute for which very little differences were reported between samples, these two attributes were not modeled. Predictive models were evaluated using absorbance ($\log_{10}$(1/Reflectance)) and 1st and 2nd derivatives. The 1st and 2nd derivatives were computed according to the Savitzky Golay algorithm with 1 point on the left and right side and a second-order polynomial equation (Camo, Computer-Aided Modelling A/S, Trondheim, Norway.). The NIR data (1,050 wavelengths) were used to develop predictive models for each of the nine sensory texture attributes of cooked rice using partial least squares (PLS) regression with the PLS1 option in the multivariate regression software Unscrambler (v. 7.5, Camo, Norway). Predictive variables were standardized by weighting with the standard deviation so that all variables were given the same chance to influence the estimation of the texture attributes. Data was centered before PLS regression so that all results were interpretable in terms of variation around the mean, and the full cross-validation method was used. With the cross-validation, the same samples were used for both calibration and validation of the models. With full cross-validation, each sample is removed one at a time from the sample set, a new calibration (perturbed) performed and a predicted score calculated for the sample removed. This procedure is repeated until all samples have been removed from the sample set once. The root mean square error of prediction (RMSEP) is subsequently calculated. The predictive models were optimized using the jack-knifing method available as an option in the Unscrambler. Jack-knifing is a procedure that was designed to test the significance or lack of significance of the model parameters and is performed during cross-validation. During cross-validation, if a perturbed segment differs greatly from the common model (with all samples), it means that the sample or samples removed have seriously affected the common model. The approximate uncertainty variance of the regression coefficients can then be estimated and a *t*-test performed for each element relative to its estimated uncertainty variance, giving the significance level for each parameter. All parameters for which $P < 0.05$ were kept in the model. This allowed for removal of predictive variables either not influencing the prediction or creating noise in the model. This procedure reduced the uncertainty in the prediction models (Camo) and, in most cases, improved the validation statistics. Outliers were selected using the Unscrambler outlier selection tool (Camo). The selection of outliers was based on Hotelling T^2 statistics with $\alpha = 0.05$. If for a given sample, the observation was outside of the confidence region defined by the Hotelling T^2 statistic, the sample was considered as an outlier and removed from the sample set. After the model optimization by jack-knifing and outlier removal, the model was validated using a test set validation. The sample set was divided into two independent sets, a set of 65 randomly selected samples for validation, and the remainder of the samples for model calibration. This was performed to verify that the model statistics obtained with two independent sample sets were similar to that of the full cross-validation method. The root mean square error of prediction (RMSEP), calibration coefficient of determination (R^2), validation correlation of determination (r^2_{val}) and discrimination index (RPD = StDev/SEP) (Williams and Soebering 1993), which are all indicators of model predictive quality, were computed. To compare the effectiveness of the various models evaluated for a given attribute, a test described by Snedecor and Cochran (1967) designed to compare two correlated variances was performed so that RMSEP from the various models could be compared.

RESULTS

Sensory attributes were rather weakly correlated with each other (Table I). Adhesion to lips was most highly correlated to cohesiveness of mass evaluated after three chews ($r = 0.63$) and loose particles ($r = -0.61$). Hardness was correlated to the perception of roughness of mass ($r = 0.64$). Toothpull was correlated to toothpack ($r = 0.81$), both attributes being correlated to loose particles ($r = 0.59$, $r = 0.57$, respectively). Particle size was weakly correlated to all other sensory attributes.

Of the seven sensory texture attributes of cooked rice for which predictive models were evaluated, five were successfully predicted (r^2_{val} = 0.67–0.83) (Table II). Cohesiveness of mass after eight chews ($r^2_{val} = 0.61$) and roughness of mass ($r^2_{val} = 0.35$) were not satisfactorily predicted by NIR spectra or 1st and 2nd derivatives. The sensory texture attributes of cooked rice predicted well by NIR spectra results are summarized in Table II.

Adhesion to lips fitted well by either absorbance ($R^2 = 0.81$), 1st derivative ($R^2 = 0.85$) or 2nd derivative spectra ($R^2 = 0.88$) and all models were validated reasonably well (r^2_{val} = 0.77–0.83). However, the RMSEP (0.54) for the 2nd derivative spectra was significantly lower (according to the comparison of two correlated variances) (Snedecor and Cochran 1967) than that of the absorbance and 1st derivative spectra (RMSEP = 0.61 and 0.62, res-

TABLE I
Pearson's Correlations Among Sensory Attributes

	Adhesion to Lips	Particle Size	Hardness	Cohesiveness of Mass 3 Chews	Cohesiveness of Mass 8 Chews	Roughness of mass	Toothpull	Toothpack	Loose Particles
Adhesion to Lips	1.00								
Particle Size	–0.03	1.00							
Hardness	–0.32	0.21	1.00						
Cohesiveness of mass (3 chews)	**0.63**	0.07	0.02	1.00					
Cohesiveness of mass (8 chews)	0.34	–0.37	–0.40	0.07	1.00				
Roughness of mass	–0.22	0.42	**0.64**	0.22	–0.33	1.00			
Toothpull	0.03	0.09	0.46	0.21	0.29	0.44	1.00		
Toothpack	0.05	–0.11	0.31	0.04	0.38	0.14	**0.81**	1.00	
Loose Particles	**–0.61**	–0.06	0.44	–0.39	0.03	0.30	**0.59**	**0.57**	1.00

pectively). Accordingly, the largest discrimination index was achieved for the 2nd derivative spectra (RPD = 2.37). As a result, the 2nd derivative of the absorbance spectra was recommended for the prediction of adhesion to lips in cooked rice. For this model, the jack-knife optimization removed 71% of the predictive variables. Model optimization (jack-knife) resulted in a 29% improvement over the RMSEP of the nonoptimized model (after outlier removal).

Hardness was reasonably well fitted irrespective of spectral treatment (R^2 = 0.63–0.79). The RMSEP was lowest for the 2nd derivative spectra (RMSEP = 0.29) for both full cross and test set validations. However, the improvement reported in RMSEP for the 2nd derivative over that of the untransformed and 1st derivative spectra, even though statistically significant (Snedecor and Cochran 1967) was small. The use of jack-knifing removed 36, 37, and 81% of the predictive variables and decreased RMSEP by 6, 8.5, and 18%, for absorbance, 1st, and 2nd derivative spectra, respectively. Finally, the RMSEP evaluated by the test set method were similar to those calculated by full cross-validation (Table II), even though the 1st derivative model showed an increase in RMSEP (0.33 vs. 0.38). In summary, the prediction of cooked rice hardness could be achieved with any of the methods evaluated. However, a preference may be given to the untransformed and 2nd derivative spectra.

The fit of the NIR data to the perception of cohesiveness of mass evaluated after three chews was acceptable (R^2 = 0.79) using the 2nd derivative spectra. The RMSEP was significantly lower for this model than for the untransformed and 1st derivative spectra. Accordingly, the discrimination index (RPD = 1.90) was highest for the 2nd derivative spectra. The use of jack-knifing reduced the RMSEP drastically (32%). Approximately 84% of the regression coefficients were not significantly different from zero, and corresponding predictive variables were subsequently removed from the model.

The model statistics for cohesiveness of mass evaluated after eight chews were slightly poorer (R^2 = 0.67–0.69) than those for cohesiveness evaluated after three chews. The type of spectral data used did not seem to greatly influence the quality of results, even though the statistical comparison of RMSEP showed a significant difference between untransformed and 2nd derivative models. Jack-knifing once again improved RMSEP values by 14–30%, while 48–91% of the predictive variables were dropped from the models, depending on the type of spectral data used. Overall, the RMSEP values for these models were higher than desired (0.35–0.40), resulting in relatively low discrimination indexes (RPD = 1.58–1.66).

The fit of the NIR data to roughness of mass scores was poor, yielding the poorest model statistics (R^2 = 0.41–0.49) of any of the sensory attributes evaluated in this study. These poor results could have been caused by the small differences found between samples (SD = 0.34) by the trained panel. Discrimination indexes were low (1.18–1.23.

The fit of the NIR data to toothpull was acceptable for any of the three types of models evaluated (R^2 = 0.69–0.76). In addition, validation correlation coefficients were similar (r^2_{val} = 0.62–0.71) to those of the calibration. The model optimization through jack-knifing reduced 33, 35, and 66% of the variables while moderately improving RMSEP by 9, 4, and 20% for the untransformed, 1st

TABLE II
Model Statistics for Prediction of Cooked Rice Texture from NIR Spectroscopy

Attribute	Sensory Data Range	SD[a]	Method[b]	Samples[c]	PC[d]	% Variables Eliminated After Jack-Knife (%)	R^2	r^2_{val}[e]	RMSEP[f] Cross-Validation	*t*-Test Pair Comparisons of RMSEP[g]	RMSEP[h] Test Set	RPD[i]
Adhesion to lips	6.8–12.7	1.28	A	201	11	52	0.81	0.77	0.61	a[j]	0.62	2.10
			A(1st)	201	9	70	0.85	0.77	0.62	a	0.65	2.07
			A(2nd)	202	5	71	0.88	0.83	0.54	b	0.51	2.37
Hardness	2.5–5.7	0.50	A	201	11	37	0.64	0.59	0.32	ab	0.31	1.57
			A(1st)	200	10	37	0.62	0.58	0.33	a	0.38	1.52
			A(2nd)	201	5	81	0.79	0.67	0.29	b	0.29	1.73
Cohesiveness of mass (3 chews)	3.5–8.3	1.16	A	202	10	58	0.58	0.49	0.82	a	0.76	1.41
			A(1st)	201	8	49	0.56	0.46	0.85	a	0.83	1.36
			A(2nd)	201	4	84	0.79	0.72	0.61	b	0.64	1.90
Cohesiveness of mass (8 chews)	3.2–6.9	0.60	A	201	10	49	0.69	0.61	0.36	b	0.35	1.66
			A(1st)	201	10	59	0.67	0.59	0.38	ab	0.37	1.58
			A(2nd)	201	4	91	0.67	0.59	0.38	a	0.40	1.58
Roughness of mass	4.8–6.9	0.34	A	202	9	60	0.41	0.30	0.29	a	0.27	1.18
			A(1st)	200	13	84	0.49	0.35	0.28	a	0.28	1.23
			A(2nd)	201	3	96	0.41	0.25	0.28	a	0.27	1.23
Toothpull	1.3–3.6	0.53	A	202	8	35	0.71	0.64	0.31	a	0.32	1.70
			A(1st)	203	8	33	0.69	0.62	0.32	a	0.26	1.64
			A(2nd)	202	4	65	0.76	0.71	0.28	b	0.31	1.88
Toothpack	0.9–2.8	0.44	A	202	9	39	0.67	0.61	0.28	a	0.27	1.56
			A(1st)	201	8	38	0.69	0.64	0.27	a	0.29	1.62
			A(2nd)	202	4	82	0.85	0.77	0.18	b	0.18	2.19

[a] Standard deviation (sensory attribute).
[b] A = Absorbance (1/log(R)), A (1st) = 1st derivative, A(2nd) = 2nd derivative.
[c] Number of samples after outlier removal.
[d] Optimal number of principal components.
[e] Correlation for the validation (full cross-validation).
[f] Root Mean Square Error of Prediction determined by full cross- validation.
[g] Comparison of correlated variances *t*-test performed according to Snedecor and Cochran (1967).
[h] Root Mean Square Error of Prediction determined by test set validation (n = 65).
[i] Discrimination index RPD = SD/SEP.
[j] Values for sensory attribute with different letters are significantly different (P = 0.05).

and 2nd derivative spectra, respectively. The statistical comparison of RMSEP showed a significant improvement for the 2nd derivative model. However, the test set RMSEP values did not agree with this finding. Therefore, no recommendation is being made as to the type of spectral data to be used for best predicting toothpull.

Toothpack was also best predicted by the 2nd derivative of the absorbance spectra (R^2 = 0.85, r^2_{val} = 0.77). The improvement in 2nd derivative model RMSEP over those for the absorbance and 1st derivative spectra were significant according to the test of correlated variances (Snedecor and Cochran 1967). The low RMSEP (0.18) reported for this model yielded a discrimination index of 2.08. Jack-knifing eliminated 82% of the predictive variables from the model and improved RMSEP 31% over that of the full model after outlier removal. Furthermore, full cross and test set validations resulted in comparable RMSEP values (0.18).

DISCUSSION

The results presented here are interesting in the sense that they do not agree with conclusions reached by Windham et al (1997). They reported overall poor results for the prediction of cooked rice texture attributes from NIR reflectance data. Best modeling results were obtained for manual adhesiveness (relative ability of prediction = 0.57), visual adhesiveness (RAP = 0.54) and oral stickiness (RAP = 0.56). Although RAP were not discussed in the present study, they were calculated for comparison purposes with work published earlier by Windham et al (1997). RAP values for the present study were 0.39–0.88. Highest RAP values were reported for toothpull (0.88), adhesion to lips (0.86), and hardness (0.80). RAP values were lower for cohesiveness of mass evaluated after three and eight chews (0.71) and toothpack (0.70). The RAP value reported for roughness of mass (0.39) was marginal. In summary, the RAP values reported here for attributes related to rice stickiness (adhesion to lips, cohesiveness of mass, and toothpull) are significantly higher than those reported by Windham et al (1997). Additionally, other important attributes of cooked rice texture (hardness) were suitably predicted in the present study. There could have been several factors influencing the difference between the two studies. First, the samples used by Windham et al originated from different cultivars than those used in this study, except for Bengal. This could have been a factor as the samples used by Windham et al could have been exhibiting less variability in terms of texture properties. In addition, Windham et al investigated postharvest variables such as drying and storage moisture content while, in the present study, the variability in texture properties was created by various storage moisture contents, storage temperatures, and duration. From previous work reported by Meullenet et al (1998, 1999) on sensory properties of cooked rice as affected by postharvest handling, storage moisture content and temperature were major determinants of rice texture, while rice drying temperature had little effect. In addition, Windham et al (1997) did not report using jack-knifing for model optimization, while the benefits of this model optimization method on model statistics were evident in the present study. Finally, it is possible that the performance of the descriptive analysis panels was different, as rice is a difficult food to evaluate and panelists often have difficulties discriminating between samples.

It should also be noted that the results presented here for predicting sensory texture profiles of rice from NIR spectra do very well with predictive models previously reported by Meullenet et al (1998, 1999) and Sitakalin and Meullenet (2000) for predicting texture profiles of cooked rice from rheological measurements. For example, the RMSEC values reported by Sitakalin and Meullenet (2000) for adhesion to lips (0.41–0.68) are comparable to what is reported here (0.49). In fact, NIR predictive models were better for prediction of attributes such as hardness, cohesiveness of mass after eight chews, toothpack, and loose particles than models based on either extrusion or compression instrumental methods. Even though the sample size used in previous studies (Meullenet et al 1998, 1999, 2000; Sitakalin and Meullenet 2000) was smaller, the quality of the NIR models seems to equal that of rheological models.

CONCLUSIONS

NIR data adequately predicted five of the seven sensory texture attributes of cooked rice evaluated here. Although other research had previously evaluated the use of NIR for predicting functional attributes of rice, it the first time the method has been used successfully. The use of spectral derivatives (2nd) provided some model improvements for attributes such as adhesion to lips, hardness, cohesiveness of mass evaluated after three chews, and toothpack. The use of jack-knifing resulted in significant improvements of RMSEP. NIR methods for predicting cooked rice texture quality would likely find some applications in the rice industry as a tool to monitor rice quality online. Furthermore, NIR being a nondestructive method, could be implemented in rice breeding programs for screening of advanced breeding lines where some rice is milled for quality evaluation. However, to render this technique viable for a breeder, the calibrations should be performed on a sample set representative of the genetic material used in a particular program. Furthermore, beccause the kernel germ is destroyed during milling, calibrations for brown rice should be evaluated.

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