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ORIGINAL ARTICLE

Differences in physicochemical properties of commercial rice from urban markets in West Africa

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Abstract Rice consumers in West Africa (WA) have an acquired preference for imported rice. Enhancing consumption of local rice requires matching the grain quality attributes of the imported benchmarks in addition to increasing productivity of local rice cultivars. Thus, there is a need to develop screening tools that will aid breeding programs select for high-yielding and stress-tolerant cultivars whose grain quality are at par with imported rice. Hence, this study evaluated various grain quality characteristics of 316 commercial milled rice samples from urban markets in three WA countries (Benin, Cameroon, and Ghana) and developed linear discriminant models (LDAs) to classify rice according to their origins and to predict the imported rice classification of local germplasm based on their grain quality attributes. More than half of the commercial rice samples that were collected originated from Thailand (60%); in contrast, only a small fraction was locally grown (2%). The commercial rice from different origins were distinguishable based on the quality attributes evaluated, contributing to the relatively high classification rates achieved by the fitted LDAs. These results indicate that multivariate models could be useful during varietal improvement as tools for screening for cultivars that can match the quality of imported rice.

Keywords Grain quality · Varietal improvement · Consumer preference · Multivariate analysis

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Introduction

In sub-Saharan Africa, rice (*Oryza* spp.) is the most rapidly growing food commodity (AfricaRice 2018). Rice consumption is increasing steadily as urban populations continue to grow. Consequently, the demand for rice is surpassing local production capabilities (Seck et al. 2010; AfricaRice 2018). Rice self-sufficiency ratio—the amount of domestically-produced (i.e. local) rice that is consumed relative to the total amount of rice that is consumed—was estimated at 54% (USDA 2017) within the sub-region between 2010 and 2015. Thus, countries in this sub-region rely on imports to meet consumer demands. A reported 7.6 million tons of rice, at a cost of US $4 billion, was imported into WA in 2015 (USDA 2017).

This reliance on imports for rice requirements is extremely risky, as was shown by the 2007–2008 food crisis (Seck et al. 2010). Hence, it is necessary for governments to aim for rice self-sufficiency. Strategies to achieve this goal include expansion of production areas; promotion of mechanization; improvement of postharvest management practices to reduce losses; and introduction of policies to protect the market share of locally-produced rice (AfricaRice 2011; AfricaRice 2018; Fiamohe et al. 2018). A prominent component of the strategies is the development of breeding programs focused on rice yield enhancement and rice adaptation to Africa's harsh production environments (Manful 2010; Saito et al. 2012). However, consumer attitudes towards the quality of domestically grown rice is typically not integral to this process.

Market studies conducted within the region reported that urban rice consumers consider domestically produced rice to be of poor quality and inferior to imported rice (Tomlins et al. 2005; Coulibaly et al. 2015; Demont et al. 2017). Most local varieties have low milling recoveries, high levels of chalkiness, and poor cooking characteristics (Futakuchi et al. 2013) in addition to containing impurities and being sold in poorly-labeled and unattractive packages (Fiamohe et al. 2018). In order to reduce import dependency, consumer concerns about domestically produced rice (the demand side of the value chain) must be addressed alongside improvements in supply (Fiamohe et al. 2018). As consumers' incomes increase and markets become more liberalized, consumers' preferences for rice have been shown to shift from lower to higher quality (Cuevas and Fitzgerald 2012); thus, demand for high-quality rice is predicted to increase in WA in light of the surge in urban populations and the increase in medium-income households (Mubila and Yepes 2017).

Improving the quality of domestically produced rice in WA will have to include breeding programs and post-harvest processes aimed at developing finished products that match or exceed rice quality benchmarks, which are mostly imported products. Fortunately, rice cultivars in WA have been shown to have diverse grain quality attributes (Graham-Acquaah et al. 2018). The missing link is a means to effectively exploit the diversity of domestic rice and find cultivars that match WA consumer quality requirements. To facilitate this process, the quality of imported rice needs to be profiled using the current suite of methods for evaluating grain quality that is available to most breeding programs within WA.

Routinely evaluated grain-quality attributes include appearance (e.g., cleanness, color, chalkiness, grain dimensions), milling (e.g., milled rice and head rice yields), and cooking and eating-related characteristics (e.g., amylose content, pasting properties, cooki2015ng time, swelling ratio, texture, and taste). Despite the numerous variables being collected, the traditional data analysis approach tends to be univariate (Yeater et al. 2015). This strategy is limited because rice grain quality is a composite of several attributes. A more complex but pragmatic approach to assess grain quality is to use multivariate (MV) analyses that considers multiple attributes at a time.

Multivariate analysis refers to a broad category of methods that are employed when multiple variables are used to describe, explain variability in data and to develop a model that predicts the classification or the response of an unknown sample (Yeater et al. 2015). MV approaches applied in rice grain quality studies include, among others, principal components analyses (PCA), cluster analyses, multivariate analysis of variance (MANOVA), and discriminant analyses (DA) (Yeater et al. 2015; Vemireddy et al. 2015; Wangcharoen et al. 2016; Maione and Barbosa 2018).

The current study employed MV analyses to (a) compare physicochemical properties of commercial rice samples sold in selected WA urban markets; (b) to distinguish and classify commercial samples from different originating countries based on their quality traits; and (c) to demonstrate the prospects of using such a multivariate-modelling approach to identify breeding lines whose composite quality matches that of imported rice.

Materials and methods

Sample procurement

Sample collection was conducted in selected central and regional markets in 42[1] urban areas in three WA countries (Benin, Cameroon[2], and Ghana) through the AfricaRice Africa-wide processing and value-addition taskforce (Supplementary material 1). In Benin, sample collection covered 30 urban areas located throughout the country. In Ghana and Cameroon, sample collection was restricted to eight and four urban areas, respectively.

Central markets are usually located in urban centers and are generally remote from production areas. These markets open daily and sometimes have peak periods, often referred to as "market days", that are recognized by traders and consumers. Central markets are characterized by the presence of intermediaries (middlemen), warehouses, and financial services; they are also characterized by the complex relationship between both wholesale marketing and retail marketing (Gounsé 2004). Regional markets, on the other hand, are located in large urban centers that are close to farming areas. These markets supply processed products for rural areas and agricultural products for urban populations. The social norms of localities where these markets are situated determine the "market days". Compared with central markets, regional markets have a much greater proportion of intermediaries, but producers are also

[1] Includes both urban and peri-urban areas.

[2] Cameroon is geographically and historically a WA country but politically considered a part of Central Africa.

present. These intermediaries sell local and imported commodities and conduct currency exchange and other marketing functions (Gounsé 2004).

From each selected market, a preliminary reconnaissance of all rice types and rice brands sold on that market was conducted. Based on this, the top 10 most recurring white (non-parboiled) rice brands were selected and half a kilogram of each brand was purchased. When the number of brands was less than or equal to 10, all brands available were purchased. The origin country of each rice brand was noted. Local (i.e., produced in a WA country) non-parboiled rice was only available for purchase in Benin markets. Purchased samples were sealed in plastic bags and stored at − 4 °C in a laboratory refrigerator (REVCO REL2304D22, ThermoFisher Scientific, Waltham, MA, USA) until evaluated.

Grain quality evaluation

Impurities

From each sample, a 50 g sub-sample of rice was weighed and manually sorted for any material other than rice kernels. These foreign materials were weighed and the percentage of impurities determined as:

$$Impurities\,(\%) = \frac{mass\ of\ foreign\ materials\,(\mathrm{g})}{50\,\mathrm{g}} \times 100$$

Head rice ratio (%)

One hundred grams (100 g) each of purchased rice was separated into intact and broken grains using a rice grader (TRG, Satake, Japan). Intact kernels (head rice) were considered as milled-rice kernels that remained at least three-fourths of the original kernel length. Head rice ratio (HRR) was calculated as:

$$HRR\,(\%) = \frac{mass\ of\ head\ rice}{mass\ of\ milled\ rice} \times 100$$

Color measurement

A color meter (CR-400, Minolta Co., Ltd., Tokyo, Japan) was used to measure the color of head rice utilizing the *L, a, b* uniform color space procedure as described by Graham-Acquaah et al. (2015). The value of *L* expresses the lightness value, *a* and *b* are the red/green and yellow/blue coordinates of the *L, a, b* color space system, respectively.

Chalkiness and grain dimensions

Chalkiness and grain dimensions were determined using an imaging system (S21 Rice Statistic Analyzer, LKL Technologia, Brazil) as described by Graham-Acquaah et al. (2015) with slight modifications. Chalkiness was determined by processing the captured images and applying the "basic filter—chalky distribution". The percentage of the total chalky area of 50 g head rice samples were recorded and reported as the percentage chalkiness (% Chalky area) of the samples. Kernel dimensions were determined by applying the "advanced filter-length distribution". The kernel length and width were used to calculate the length/width ratio (LWR) of samples. This metric indicates kernel shape: bold (< 2), medium (2.1–3), and slender (> 3) (Calingacion et al. 2014).

Cooking duration

Cooking duration was determined using the method described by Fofana et al. (2011). A test sample of head rice (5 g) was heated in vigorously boiling distilled water (135 mL) in a 400-mL beaker and covered with a watch glass (10 min). A subsample (10 grains) was then retrieved every minute with a perforated ladle. The grains were pressed between two Petri dishes and were considered cooked when at least nine out of the 10 grains no longer had opaque centers. The duration it took for this to happen was then recorded as the cooking duration for the sample. The cooking duration measurement was conducted in duplicate.

Swelling (volume expansion) ratio

Swelling ratio of cooked rice was determined using the method described by Fofana et al. (2011). Milled rice (8 g) was placed into a wire mesh cooking basket. The height (H1) of the raw rice in the cooking basket was measured using a caliper (SPI 6'' dial caliper 15-100-500, Swiss Precision Instrument Inc., CA). The samples were then cooked for their respective pre-determined cooking durations in a vigorously boiling water bath. The cooking basket was subsequently removed and kept upright for the water to drain (2 min). The height (H2) of the cooked rice in the cooking basket was measured using the caliper. The measurements were carried out in duplicate. Swelling ratio was calculated as:

$$\text{Swelling ratio} = \frac{H2}{H1}$$

Apparent amylose content

Apparent amylose content (AAC) was determined in duplicate using the iodine colorimetric method (ISO 2011). Head rice (5 g) was ground into flour using a cyclone mill with a 0.5-mm sieve (UDY, Fort Collins, CO). Ethanol (1 mL, 95%) and sodium hydroxide (1 M, 9 mL) was added to rice flour (100 mg) and the suspension was heated in a boiling water bath until gelatinization of the starch occurred. After cooling, acetic acid (1 M, 1 mL) and iodine solution (2 mL) were added and the volume made up to 100 mL with distilled water filtered (0.45 µm) using a Millipore system. The iodine solution was prepared by dissolving iodine (0.2 g) and potassium iodide (2.0 g) in Millipore-filtered distilled water (100 mL). Absorbances of digested rice flour solutions were measured (AutoAnalyzer 3, Seal Analytical, Germany) at 600 nm, and AAC was calculated from a standard curve generated from the absorbance values of four well-known standard rice cultivars (IR65, IR24, IR64, and IR8).

Pasting properties

The pasting properties of rice flour samples were measured using a Rapid Visco-Analyzer (RVA super4, Newport Scientific, Australia) equipped with Thermocline for Windows (TCW3) software. The general pasting method 162 (ICC 2004) for flour samples was used. Measurements were conducted in duplicates.

Data analyses and model development

Data analyses were conducted using JMP Pro 14 (SAS Institute, Cary, NC). Multivariate analyses of variance (MANOVA) using the Identity response matrix were conducted to ascertain the overall (composite) difference in the physicochemical properties of rice samples from different origins (Local, India, Pakistan, Thailand, USA, and Vietnam). Wilk's Lambda was chosen as the test statistic. This was followed by univariate analysis of variance (ANOVA) and post hoc test (Tukey's HSD) to determine differences in specific grain quality traits among samples from different origins. Pearson's correlation analyses was conducted to determine the relationships among the measured grain quality attributes.

Linear discriminant analyses (LDA) were conducted to derive models for classifying the rice samples based on their origin. LDA looks for patterns within the dataset based on the grouping variable—in this case, the originating country—and subsequently uses the underlying patterns (algorithm-generated) of group membership to assign groups to new samples (Yeater et al. 2015). For LDA, data were split into training (75%) and validation (25%) sets. For both sets, the number of data points for the six countries were selected to be reflective of their proportions within the entire dataset. Samples were given proportionate probabilities to be grouped into the six countries (Local, India, Pakistan, Thailand, USA and Vietnam). Two linear discriminant functions were fitted to differentiate the groups of samples and to classify them based on their grain quality characteristics. Discriminant function 1 (LDA 1) used 15 variables while LDA 2 used 13 variables. HRR and impurities, both affected by postharvest handling/processing practices (Africa Rice Center 2011; Futakuchi et al. 2013), were removed from LDA 2 to test the effects of intrinsic rice quality attributes in prediction. The LDA models were compared based on the number of predictors (quality traits) used and their prediction accuracy. The prediction accuracy of each model was determined by the misclassification rates in the training and validation datasets and the area under the receiver operator characteristic (ROC) curve (Mandrekar 2010). The area under the ROC curve (AUC) indicated the capability of a model to discriminate among groups; the higher the AUC, the better the discrimination power (Mandrekar 2010; van Borries et al. 2018).

The fitted LDA models were used to classify 40 advanced breeding lines/cultivars. These included 25 advanced breeding rice lines undergoing multi-environment trials (MET); nine near-isogenic lines (NILs) that are being improved for resistance to rice yellow mottle virus (RYMV); five new cultivars that have been earmarked for release (Orylux 1, 3, 4, 5 and 6); and one popular cultivar often used as a check in Africa Rice trials (WITA 4). These samples were obtained from AfricaRice breeders and evaluated in the grain quality laboratory of AfricaRice using same procedures as outlined for the market samples.

Results and discussion

Survey background

As shown in Table 1, Benin had the highest number of samples, followed by Ghana, and then by Cameroon. Most rice samples from these urban markets were imported from Thailand (60%), agreeing with previous report stating that Thailand is a predominant source of imported rice in the region (Fiamohe et al. 2018). The other sources of imported rice were India (14%), Vietnam (13%), Pakistan (7%) and the USA (4%). Markets in Cameroon where samples were collected did not sell rice from the USA or from Vietnam. On the other hand, local rice was only collected in Benin (Table 1); one factor that led to the availability of local rice in Benin is the heavy investment in its rice sector (Assogba 2016), which has enabled the

Table 1 Price distribution and sources (originating countries) of commercial rice samples collected from 35 urban areas in three West African countries

Originating country	Study country															
	Benin				Cameroon				Ghana				All three countries			
	Rice price per kg (USD)			Number of samples	Rice price per kg (USD)			Number of samples	Rice price per kg (USD)			Number of samples	Rice price per kg (USD)			Number of samples
	Mean	Min	Max		Mean	Min	Max		Mean	Min	Max		Mean	Min	Max	
Local[a]	0.73	0.60	0.94	7	–	–	–	0	–	–	–	0	0.73	0.60	0.94	7 (2%)
India	0.93	0.70	1.40	26	0.70	0.70	0.70	3	1.18	0.99	1.48	15	1.00	0.70	1.48	44 (14%)
Pakistan	1.22	0.70	2.40	14	–	–	–	0	1.28	1.16	1.48	9	1.24	0.70	2.40	23 (7%)
Thailand	1.10	0.80	2.40	95	0.90	0.70	2.00	49	1.91	0.99	4.26	45	1.24	0.70	4.26	189 (60%)
USA	1.00	1.00	1.00	2	–	–	–	0	2.02	1.67	2.64	12	1.94	1.00	2.64	14 (4%)
Vietnam	0.90	0.90	0.90	1	–	–	–	0	1.85	0.99	3.15	39	1.82	0.90	3.15	40 (13%)
All	1.06	0.60	2.40	145	0.89	0.70	2.00	52	1.76	0.99	4.26	120	1.30	0.60	4.26	316

[a]Rice produced in Benin

country to produce, process and market local rice (white non-parboiled) at a comparatively larger scale than the other countries in this study.

Though available in Benin markets, local rice is not popular in WA as indicated by the low market share. Production limitations aside, the persistent low market share of locally-produced white rice in urban markets in WA can be associated with urban consumers' acquired taste and preference for imported rice, their neophobia for locally-produced rice, and their perception that local rice are of inferior quality (Demont et al. 2017). In Benin, the average price of the local rice collected was lower than that of any group of imported rice (Table 1).

Univariate comparisons

The apparent price differential between local and imported rice has been associated with undesirable grain quality attributes (Fiamohe et al. 2018, Africa Rice Center 2011). Head rice recovery and physical appearance of milled rice are important components of consumer purchase criteria while cooking and eating-related properties are important for the reputation and marketability of rice (Lyman et al. 2013; Calingacion et al. 2014). Table 2 shows that imported rice samples in WA had significantly higher HRR than local rice. On the other hand, local rice samples had significantly more impurities than imported rice (Table 2). Cleanness (absence of impurities) has been suggested as a major detriment to the marketability of locally produced rice (Fiamohe et al. 2018), which signifies a need for improvement in local postharvest processing practices in order to produce rice that is at par with those imported. Thai rice had the longest grains while Indian and locally produced rice had the shortest grains (Table 2). The average grain lengths of the samples indicate that the WA markets trade medium- to long-grain rice. Additionally, local rice kernels, on average, were of medium shape while imported rice kernels were slender.

Samples imported from the USA had the highest chalkiness values while those originating from Thailand had the lowest (Table 2). Except for the USA-sourced samples, the other imported rice samples and the local rice samples all had average chalkiness values between 20% and 30%. Chalkiness in local rice was comparable to chalkiness in imported rice. Rice from the USA recorded the greatest L-value (Table 2), implying that their kernels were the whitest among the samples. Chalkiness of these samples could explain the distinctive color since chalkiness appears as white patches on the surface of rice kernels; this is supported by the direct correlation between chalkiness and L-values (Supplementary material 2). Locally produced rice samples did not have significantly different L-values to the USA-sourced samples (Table 2).

Table 2 Comparisons of head rice ratio, appearance (dimensions, chalkiness and color) characteristics, apparent amylose content, paste viscosities and cooking properties of commercial milled rice samples collected from 35 urban areas in three West African countries

Grain quality attribute	Originating country					
	Local[#]	India	Pakistan	Thailand	USA	Vietnam
Head rice ratio (%)	$61.7^{d} \pm 26.2$	$79.3^{c} \pm 11.4$	$86.0^{bc} \pm 13.2$	$90.3^{ab} \pm 9.4$	$92.5^{ab} \pm 3.7$	$94.7^{a} \pm 2.8$
Impurities (%)	$4.2^{a} \pm 6.2$	$1.8^{b} \pm 2.5$	$1.5^{b} \pm 1.4$	$1.6^{b} \pm 1.9$	$2.1^{b} \pm 1.7$	$0.8^{b} \pm 0.6$
Grain dimensions						
Length (mm)	$6.4^{cd} \pm 0.4$	$6.3^{d} \pm 0.4$	$6.5^{c} \pm 0.3$	$6.8^{a} \pm 0.2$	$6.5^{bc} \pm 0.1$	$6.7^{b} \pm 0.2$
Width (mm)	$2.2^{a} \pm 0.3$	$2.1^{cd} \pm 0.1$	$2.0^{d} \pm 0.2$	$2.1^{c} \pm 0.1$	$2.1^{bc} \pm 0.1$	$2.1^{ab} \pm 0.1$
LWR	$2.9^{b} \pm 0.5$	$3.1^{b} \pm 0.3$	$3.3^{a} \pm 0.4$	$3.3^{a} \pm 0.2$	$3.1^{ab} \pm 0.1$	$3.1^{b} \pm 0.1$
Chalkiness (%)	$30.0^{abc} \pm 5.2$	$29.6^{b} \pm 11.8$	$23.5^{bc} \pm 9.0$	$22.5^{c} \pm 6.3$	$39.9^{a} \pm 8.4$	$27.8^{b} \pm 11.3$
Color						
L	$67.3^{ab} \pm 2.8$	$67.4^{ab} \pm 4.9$	$65.3^{b} \pm 4.1$	$66.0^{b} \pm 2.6$	$69.2^{a} \pm 2.7$	$65.9^{b} \pm 3.6$
a	$-0.5^{ab} \pm 0.6$	$-0.7^{a} \pm 0.4$	$-0.6^{a} \pm 0.4$	$-0.9^{bc} \pm 0.4$	$-1.1^{c} \pm 0.4$	$-0.9^{c} \pm 0.2$
b	$11.0^{ab} \pm 2.2$	$10.89^{ab} \pm 1.9$	$10.3^{b} \pm 1.5$	$11.4^{a} \pm 1.6$	$10.7^{ab} \pm 1.9$	$9.0^{c} \pm 1.0$
Apparent amylose content (%)	$21.1^{bc} \pm 6.2$	$25.7^{ab} \pm 2.4$	$27.0^{a} \pm 1.6$	$26.7^{a} \pm 5.0$	$23.0^{abc} \pm 0.5$	$21.7^{c} \pm 5.6$
Paste viscosities (cP)						
Peak	$2797^{a} \pm 862$	$1733^{b} \pm 636$	$2164^{a} \pm 573$	$1333^{c} \pm 545$	$2200^{ab} \pm 184$	$2397^{a} \pm 350$
Breakdown	$953^{a} \pm 407$	$241^{c} \pm 211$	$234^{cd} \pm 160$	$126^{d} \pm 201$	$581^{b} \pm 162$	$441^{b} \pm 204$
Setback	$822^{c} \pm 484$	$1523^{ab} \pm 502$	$1730^{a} \pm 443$	$1054^{c} \pm 361$	$1308^{bc} \pm 276$	$1595^{ab} \pm 258$
Cooking properties						
Cooking time (mins)	$18.6^{ab} \pm 0.9$	$17.6^{b} \pm 1.4$	$17.0^{b} \pm 1.7$	$18.4^{a} \pm 1.5$	$18.0^{ab} \pm 1.0$	$17.9^{ab} \pm 1.5$
Swelling ratio	$3.1^{ab} \pm 0.1$	$2.7^{b} \pm 0.5$	$2.9^{ab} \pm 0.5$	$3.0^{a} \pm 0.4$	$3.2^{a} \pm 0.2$	$3.1^{a} \pm 0.2$

[#]Rice produced in Benin. Mean values with different alphabets across rows are significantly different at $p < 0.05$; *LWR* length to width ratio

Rice cooking and eating characteristics are largely determined by the properties of the starch, which constitutes about 90% of a milled rice kernel. Apparent amylose content is considered as the single most important indicator of cooked rice quality (Calingacion et al. 2014). Rice with high amylose content (> 25%) tend to cook dry and to be firm upon cooling; those with low amylose content (< 20%) cook moist and are relatively stickier and softer upon cooking (Fofana et al. 2011). Samples imported from the USA and Vietnam, and locally produced rice were classified as intermediate AAC while the samples from Thailand, Pakistan, and India were high AAC (Table 2).

Differences in textural properties among rice cultivars with similar AAC have been reported (Allahgholipour et al. 2006), indicating the need to look at indicators of textural properties, such as paste properties measured by RVA. Aside from texture, RVA parameters are also able to indicate the functionality of rice for various food-processing applications (Champagne et al. 1999; Marengo et al. 2017). Peak viscosity provides a measure of the extent to which starch granules swell in the presence of water, heat, and shear (Fitzgerald et al. 2003). Thai rice samples had significantly lower average peak viscosity than the other samples. Local rice had highest average peak viscosities although this did not differ significantly from samples from Vietnam, USA and Pakistan (Table 2). These indicate that the starch granules in local samples were capable of swelling the most while those in the Thai rice samples had the least capacity to swell. Breakdown viscosity measures the resistance of starch to fragmentation during cooking (Ma et al. 2017). The local samples had the highest breakdown values (Table 2), which suggests that their starch granules swelled the most and had the highest tendency to burst. Breakdown was determined to be negatively correlated with AAC for this set of samples (Supplementary material 2). Setback viscosity, on the other hand, measures the ability of heated starch to recover its viscosity upon cooling and provides an indication of the texture of cooked rice. Local and Thai rice had the lowest average setback, indicating that these samples were the softest among those collected (Table 2; Allahgholipour et al. 2006). Meanwhile, the average cooking times of samples grouped by importing country were below 20 min but local rice had the longest cooking time (Table 2). Rice imported from India swelled the least.

The standard deviations for the various grain attributes (Tables 2) suggest that Thailand and India, the two biggest rice-exporting countries in the world, export rice that are

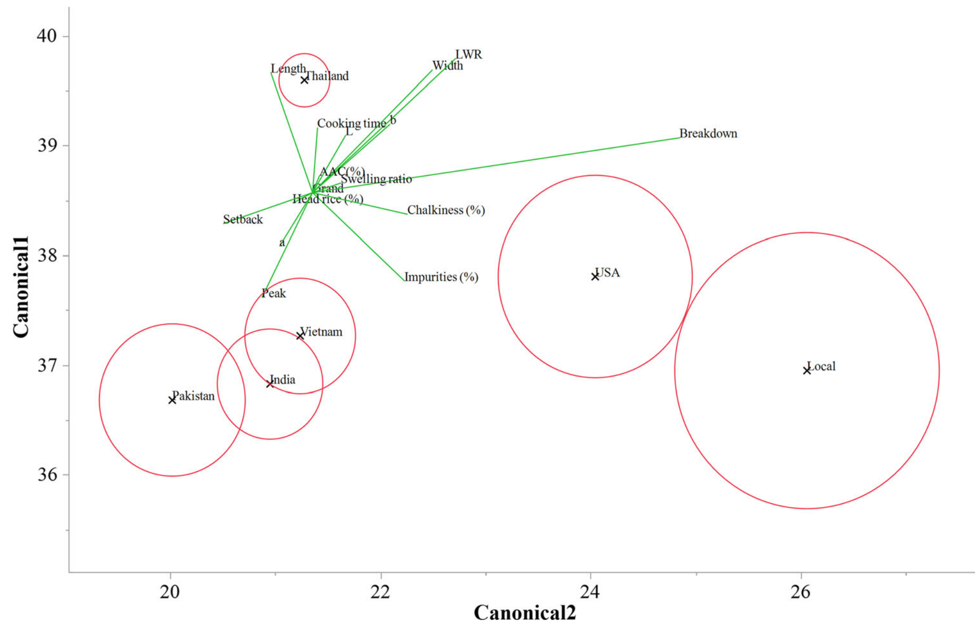

Fig. 1 Canonical centroid plot of grain quality attributes of rice from different origins depicting differences in the composite quality of rice from different countries

most diverse in quality. Rice from USA was the least diverse in terms of quality attributes.

Multivariate analyses methods for differentiating among rice samples from different originating countries

Rice grain quality is a composite of multiple variables (e.g., appearance, milling, cooking, and eating characteristics). In a study of grain quality attributes in different countries, over 18 rice quality trait combinations are reportedly preferred by different groups of consumers (Calingacion et al. 2014), indicating the complexity of matching consumer preference with grain quality traits.

When more than one response variable (e.g., quality trait) is being compared, conducting multivariate analyses of variance (MANOVA) is more useful than series of univariate analyses of variance (ANOVA) which increases the probability of type 1 error (Morrison 2005). Hence, MANOVA was conducted to determine if there were significant differences on a combination of quality attributes among the rice samples grouped according to origin (one local and five imported). The canonical centroid plot derived by MANOVA (Fig. 1) suggests that rice from India, Pakistan, and Vietnam had similar composite qualities (characterized by peak viscosity and setback), which were distinct from samples originating from Thailand, the USA, and from locally produced rice. Breakdown, impurities, chalkiness, and swelling ratio distinguished samples of local rice and USA-imported rice from the others. Kernel length appeared to be the major distinguishing feature of rice from Thailand. On the other hand, composite quality values (canonical variable derived from a linear combination of the other variables) of rice samples from different origins were significantly different from each other. These results suggest that overall (composite) quality of cultivars from a particular country could be distinguished from cultivars from another country.

Both LDA models generated AUCs greater than 0.9 for all rice origins (Fig. 2), signifying that both models performed well in discriminating rice according to origin. These models performed better in predicting group membership of local rice (0.998), USA rice samples (0.996), and rice samples from Vietnam (0.987) than the other groups of rice samples, indicating that these rice groups had more homogenous rice than others.

The overall percentage misclassification rates (Table 3) of LDA 1 was lower for both the training (12.6%) and validation (18.2%) sets than those of LDA 2 (13.4% and 22.1% for the training and validation datasets, respectively). This indicates that postharvest quality metrics improved model predictions because local rice had significantly greater amount of impurities and lesser HRR than the other samples (Table 2). However, it must be noted that both models misclassified some local samples as imported rice, confirming that there are local rice samples that could potentially match imported rice. This suggests that LDA 1 and 2 can be used to identify advanced breeding lines that are similar to imported varieties. It is assumed that these advanced lines would be more readily accepted by consumers that prefer imported rice.

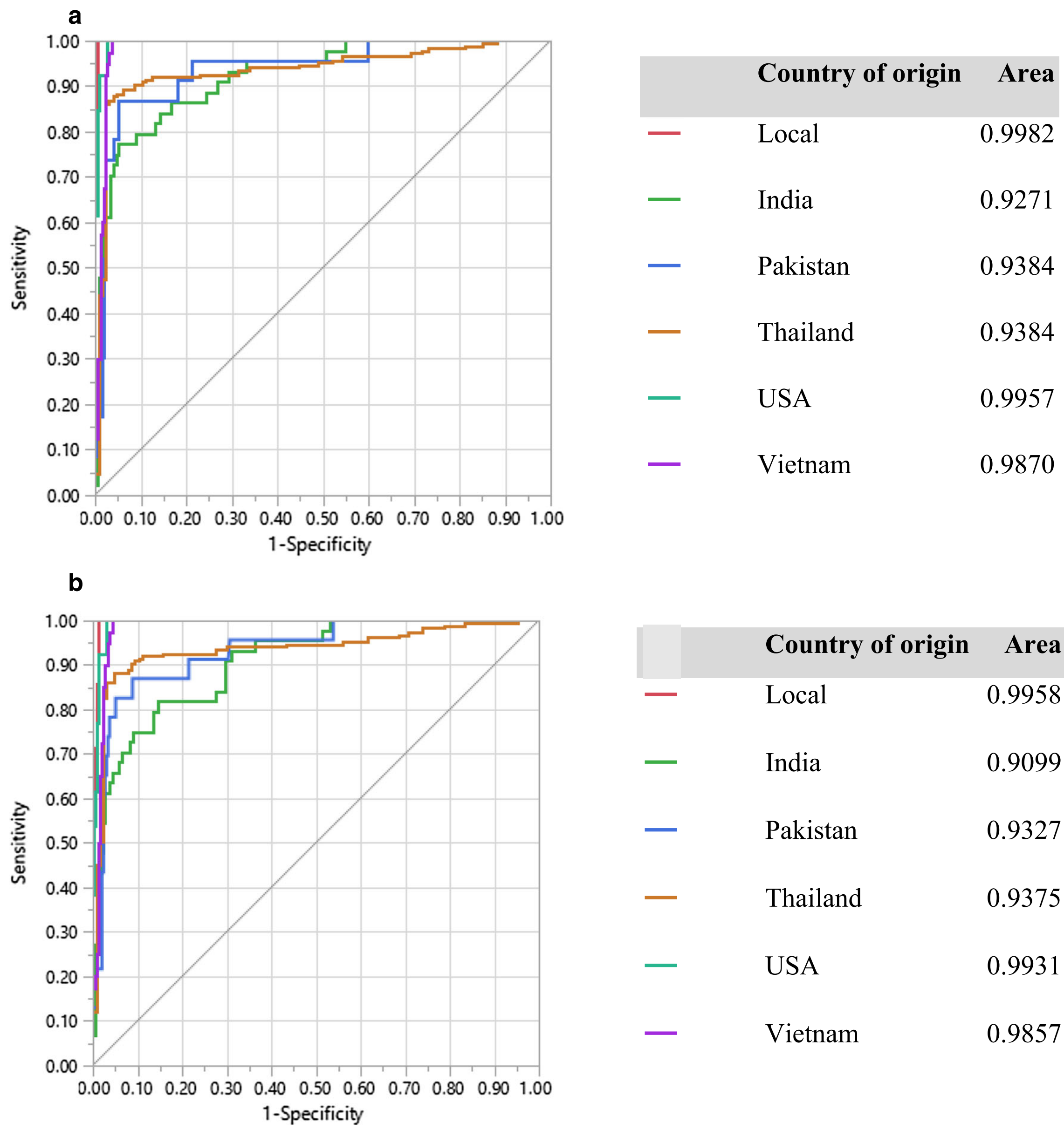

Fig. 2 Receiver operating characteristic (ROC) curve of **a** LDA model 1 **b** LDA model 2. LDA model 1 contains 15 grain quality attributes as predictors namely: Impurities, head rice ratio, grain dimensions (i.e., length, width, and length-to-width ratio), chalky area, color (i.e., L, a, b values), apparent amylose content, paste viscosities (i.e., peak, breakdown and setback); cooking properties (i.e., cooking time and swelling ratio). LDA model 2 contains 13 grain quality attributes as predictors. Impurities and head rice ratio are excluded as these are more likely to be affected by processing factors (color figure online)

Demonstrating utility of models in varietal improvement programs

Table 4 shows the grain quality characteristics and the predicted classifications of 40 breeding lines. LDA 1 indicated that 17 lines shared traits with rice from India (9), Thailand (3), Pakistan (3), and USA (2). LDA 2, on the other hand, predicted that 23 of the breeding lines belonged to rice imported from USA (11), India (7), Pakistan (2), Vietnam (2), and Thailand (1). Ten breeding lines were consistently misclassified as imported rice by both models: NIL3 and NIL7 (USA), WITA4 (Thailand); Orylux1 and Orylux3 (Pakistan); Orylux 6, MET7, MET10, MET13, and MET17 (India). These lines could be advanced to the next stage of breeding for rice that share similarities with imported varieties.

Table 3 Comparison of misclassification rates of fitted LDA models

Model Description			Number of samples	Number misclassified	Percent misclassified	Originating country	Misclassification within groups					
Model	Number of predictors	Context					Local	India	Pakistan	Thailand	USA	Vietnam
LDA 1	15: Impurities, head rice ratio, length, width, LWR, chalkiness, color (i.e. L, a, b values), apparent amylose content, peak viscosity, breakdown setback; cooking time, swelling ratio	Training	239	30	12.55	Local[a]	6	0	0	0	0	0
						India	0	25	5	4	1	1
						Pakistan	0	2	12	0	1	0
						Thailand	2	4	1	126	1	6
						USA	0	0	0	1	9	0
						Vietnam	0	0	0	1	0	31
		Validation	77	14	18.18	Local[a]	1	0	0	0	0	0
						India	0	6	0	0	2	0
						Pakistan	0	2	5	1	0	0
						Thailand	0	3	2	40	1	3
						USA	0	0	0	0	3	0
						Vietnam	0	0	0	0	0	8
LDA 2	13: Length, width, LWR, chalkiness, color (i.e. L, a, b values), apparent amylose content, peak viscosity, breakdown, setback; cooking time, swelling ratio.	Training	239.00	32.00	13.39	Local[a]	5	0	0	1	0	0
						India	0	24	5	4	2	1
						Pakistan	0	2	11	0	1	1
						Thailand	3	5	1	128	0	3
						USA	0	1	0	0	9	0
						Vietnam	0	0	1	1	0	30
		Validation	77.00	17.00	22.08	Local[a]	1	0	0	0	0	0
						India	0	5	0	0	3	0
						Pakistan	0	2	4	1	0	1
						Thailand	0	4	2	39	1	3
						USA	0	0	0	0	3	0
						Vietnam	0	0	0	0	0	8

[a]Rice produced in the three study countries (Benin, Cameroon, and Ghana)

Table 4 Grain quality characteristics and predicted grouping of selected breeding lines/cultivars

Line/ cultivar	Impurities (%)	Head rice ratio (%)	Grain dimensions			Chalkiness (%)	Color			RVA paste properties			AAC (%)	Cooking properties		Predicted group	
			Length(mm)	Width (mm)	LWR		L	a	b	Peak (cP)	Break-down (cP)	Setback (cP)		Cooking time (min)	Swelling ratio	Model 1	Model 2
NIL 1	0.1	24.2	6.7	2.4	2.8	42.4	72.3	− 1.1	8.2	2914	532	3654	28.9	17	3.5	India	USA
NIL 2	0.1	40.0	6.7	2.4	2.8	38.4	72.9	− 1.5	9.1	2903	492	3497	29.1	17	3.0	India	USA
NIL 3	0.1	40.2	6.6	2.3	2.9	24.6	62.7	− 0.4	9.2	1538	253	2217	28.7	17	5.2	USA	USA
NIL 4	0.1	55.9	6.6	2.0	3.2	18.4	61.2	− 0.1	11.1	2200	864	628	20.8	20	3.6	Local	Local
NIL 5	0.1	82.7	6.5	2.1	3.0	24.3	66.6	− 0.1	13.6	2381	765	531	19.6	20	3.6	Thailand	Local
NIL 6	0.1	68.8	6.7	2.1	3.2	19.6	65.3	− 0.5	10.4	2339	1077	273	20.6	20	3.6	Local	Local
NIL 7	0.1	57.9	6.5	2.1	3.1	35.8	64.4	− 1.5	11.7	2604	1169	− 172	16.6	20	3.6	USA	USA
NIL 8	0.1	40.7	6.4	2.1	3.1	30.2	61.0	0.1	11.0	2307	1119	95	21.4	20	3.6	Local	Local
NIL 9	0.1	38.0	6.5	2.0	3.2	30.6	66.5	− 1.5	12.5	2635	1134	− 52	17.6	19	3.6	Local	USA
WITA 4	0.1	80.0	6.4	2.2	3.0	19.5	63.4	− 0.1	12.9	1818	474	1008	22.3	16	3.6	Thailand	Thailand
Orylux 1	0.1	55.3	5.9	1.9	3.1	17.5	64.2	− 0.9	9.8	2675	75	1914	24	19.7	2.9	Pakistan	Pakistan
Orylux 3	0.1	19.3	5.9	1.9	3.1	28.7	65.1	− 0.8	9.8	2889	341	1734	22	19.7	3.1	Pakistan	Pakistan
Orylux 4	0.1	24.4	6.2	1.9	3.2	44.2	66.6	− 0.8	10.8	1974	377	1164	22	20	3.3	Thailand	USA
Orylux 5	0.1	20.6	5.9	1.8	3.3	14.6	61.0	− 0.7	9.3	1807	680	565	22	17	2.9	Local	India
Orylux 6	0.1	32.3	5.8	1.7	3.4	18.3	61.4	− 0.4	10.9	1500	77	1652	15	17	3.2	India	India
MET 1	0.1	53.5	6.4	2.2	2.9	20.6	64.5	− 0.6	8.3	3118	1502	− 196	17.7	19	3.2	Local	Local
MET 2	0.1	10.3	6.5	2.3	2.9	54.2	68.9	1.0	11.2	3294	1050	992	29.7	19.3	2.9	Local	Local
MET 3	0.1	27.5	6.4	2.2	2.9	42.7	70.5	− 0.3	9.5	3011	623	1572	29.3	19.3	3.2	Local	Vietnam
MET 4	0.1	21.0	6.3	2.2	2.9	50.4	72.5	− 0.8	8.2	3185	926	1306	30.3	18.3	3.0	Local	Local
MET 5	0.1	84.3	5.9	2.1	2.8	28.0	65.4	− 0.7	8.6	2379	776	1009	25.1	19.3	3.1	India	India
MET 6	0.1	28.6	6.5	2.2	3.0	39.7	68.0	− 0.1	9.7	3155	889	1336	30	18.1	3.3	Local	Local
MET 7	0.1	72.4	5.8	2.1	2.7	33.9	68.2	− 0.7	8.5	2246	657	967	25.1	16.9	3.1	India	India
MET 8	0.1	13.7	6.3	2.3	2.7	67.0	77.8	− 0.8	8.6	2407	913	1016	30.5	19.1	3.0	Local	USA
MET 9	0.1	9.8	6.6	2.1	3.1	46.7	68.3	− 0.2	9.5	3282	918	1341	27.8	18.9	2.9	Local	Local
MET 10	0.1	70.4	6.0	2.2	2.8	36.6	69.1	− 0.7	8.1	2291	704	987	26.1	19.3	2.9	India	India
MET 11	0.1	53.6	6.2	2.3	2.7	31.3	67.2	2.0	10.0	3306	908	1259	31.7	18.4	2.2	Local	Local
MET 12	0.1	43.2	6.5	2.3	2.9	47.5	73.8	− 0.6	8.0	3350	962	1069	31.2	17.3	3.1	Local	Local
MET 13	0.1	77.2	6.0	2.2	2.8	38.0	71.4	− 0.6	8.6	2380	721	1056	26.7	19.1	3.1	India	India
MET 14	0.1	39.7	6.2	2.2	2.8	35.0	71.1	− 0.4	9.0	3063	1222	740	25.7	19	3.0	Local	Local
MET 15	0.1	22.0	6.3	2.2	2.8	57.1	72.9	− 0.5	7.9	3453	1131	1019	31.3	19.3	3.2	Local	Local
MET 16	0.1	41.2	6.1	2.2	2.8	36.4	71.7	− 0.7	7.9	2794	1280	931	29.4	18.3	2.9	Local	Local
MET 17	0.1	55.3	5.8	2.1	2.7	35.3	69.6	− 0.5	8.6	2442	719	1511	26.8	18.2	3.1	India	India
MET 18	0.1	31.1	6.7	2.3	2.9	46.0	72.6	− 0.6	9.1	3061	958	1759	30.3	19.2	3.0	Local	USA

Table 4 continued

Line/cultivar	Impurities (%)	Head rice ratio (%)	Grain dimensions			Chalkiness (%)	Color			RVA paste properties			AAC (%)	Cooking properties		Predicted group	
			Length(mm)	Width (mm)	LWR		L	a	b	Peak (cP)	Break-down (cP)	Setback (cP)		Cooking time (min)	Swelling ratio	Model 1	Model 2
MET 19	0.1	32.7	6.2	2.2	2.9	53.9	72.9	− 0.8	7.8	3594	1157	1091	31.9	18.6	3.1	Local	Local
MET 20	0.1	78.2	5.7	2.2	2.6	22.1	65.9	− 0.6	9.6	2392	997	635	21.1	17.2	2.9	India	Local
MET 21	0.1	35.7	6.0	2.1	2.9	38.2	68.6	− 0.6	8.8	2091	677	982	29	19.1	3.3	Local	USA
MET 22	0.1	36.2	6.2	2.5	2.5	47.0	71.3	− 0.7	8.7	3314	482	1914	28.6	18.3	3.3	Pakistan	Vietnam
MET 23	0.1	62.9	6.3	2.2	2.9	30.5	67.7	− 0.6	8.1	3224	1191	865	26.9	19.3	3.1	Local	Local
MET 24	0.1	21.8	6.3	2.2	2.9	57.4	72.8	− 0.5	7.9	2685	960	1026	28.9	18.1	3.1	Local	USA
MET 25	0.1	23.9	6.1	2.1	2.9	46.0	68.7	− 0.5	8.2	2011	712	827	28.6	16.9	2.9	Local	USA

LWR length to width ratio, *AAC* apparent amylose content

Conclusion

This study demonstrated that multivariate data analysis could be used in identifying materials for targeted and market-oriented breeding objectives. Grain quality is a complex breeding objective because it is defined by multiple variables. MANOVA and discriminant analyses demonstrated that local rice and rice imported from various countries have distinctive composite grain qualities. These differences could be used to predict the quality (e.g., similarities with imported varieties) of breeding lines. The models' predictive power can be improved by: (1) using specific premium imported rice types; (2) including more samples from more WA countries (3) adding sensory evaluation variables in the model. Multivariate data analysis would enhance participatory varietal selection (PVS) schemes because it can identify market-ready breeding lines.

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