

1 **Assessment of macadamia nut quality defects by means of near infrared**  
2 **spectroscopy (NIRS) and nuclear magnetic resonance (NMR)**

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23 **Abstract**

24 Macadamia kernels are visually sorted based on the presence of quality defects  
25 by specialized labors. However, this process is not as accurate as non-destructive  
26 methods such as near infrared spectroscopy (NIRS) and nuclear magnetic resonance  
27 (NMR). Thus, NIRS and NMR in combination with chemometrics have become  
28 established non-destructive method for rapid assessment of quality parameters in the  
29 food and agricultural sectors. Therefore, the quality of macadamia nuts was assessed by  
30 NIRS and NMR using chemometric tools such as PCA-LDA and GA-LDA to evaluate  
31 kernel defects. Macadamia kernels were classified as: 1=good, marketable kernels  
32 without defects; 2=kernels with discoloration; 3=immature kernels; 4=kernels affected  
33 by mold; and 5=kernels with insect damage. Using NIRS, the GA-LDA resulted in an  
34 accuracy and specificity of 97.8 % and 100 %, respectively, to classify good kernels. On  
35 the other hand, PCA-LDA technique resulting in an accuracy higher than 68 % and  
36 specificity of 97.2 % to classify immature kernels. For NMR, PCA-LDA resulted in an  
37 accuracy higher than 83% and GA-LDA resulted in an accuracy of 100%, both to  
38 classify kernels with insect damage. NIRS and NMR spectroscopy can be successfully  
39 used to classify unshelled macadamia nuts based on the defects. However, NIRS out-  
40 performed NMR based on the higher accuracy results.

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42 **Keywords:** *Macadamia integrifolia* Maiden & Betche, TD-NMR, PCA-LDA, GA-  
43 LDA, chemometrics.

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## 46 **1. Introduction**

47 Macadamia (*Macadamia integrifolia* Maiden & Betche) nut growers are keen  
48 to continuously improve nut quality as this is the main characteristic required by the  
49 final consumers. Nogueira (2008) mentioned that the quality of macadamia fruit is  
50 associated with favorable climatic conditions, planning and orchard management,  
51 varieties, pest control, plant nutrition, harvest and post-harvest practices. All these  
52 factors are decisive for macadamia development and nut quality.

53 According to O'Hare et al. (2004), the main defects that can be observed in  
54 macadamia nuts are immaturity; small nuts; cracks in the shell that allow the occurrence  
55 of biological and chemical contamination; lipids oxidation, which result in unpleasant  
56 odor and taste; bruises, and high moisture. Guthrie et al. (2004) reported other defects  
57 that may be considered, as such: fungal growth, decomposition, germination, and  
58 discoloration of macadamia nuts. Therefore, sound and/or good macadamia nuts must  
59 have light cream color, no signs of mold, decay, insect scars, blemishes, hollow centers,  
60 dark centers, shriveling, off-odors, adhering shells, and loose of extraneous material  
61 (Wall, 2013).

62 Macadamia industry has developed various parameters of quality standards.  
63 The Southern African Macadamia Growers' Association (SAMAC) classifies  
64 macadamia nuts into three classes: first grade, commercial grade, and local market.  
65 These classes are established based on kernel color, flavor and odor, kernel dust, insect  
66 infestation, foreign material. A limit of 1.5 % is used reject the nuts based on the  
67 presence of insect damage, discoloration, and immaturity (SAMAC, 2018). On the other  
68 hand, the United Nations Economic Commission for Europe (UNECE) has a higher  
69 tolerance (5 %) for the presence of these defects (UNECE, 2010).

70           The sorting process of macadamia kernels in the industry can be carried out  
71 manually (Piza, 2005) or electronically (France, 2007), but both present flaws, since  
72 manual sorting of defective kernels can decrease dramatically with the use of inadequate  
73 lighting and untrained personnel, and the electronic selection uses color to sort kernels,  
74 which may lead to improper selection, since immature kernels can only be identified  
75 based on the deformed, wrinkled, and shrunken kernel (SAMAC, 2018).

76           The increasing requirements of consumers, regulatory agencies, and  
77 competitors have been an impulse for the development of more accurate quality  
78 assessment techniques in the food industry. In this regard, near infrared spectroscopy  
79 (NIRS) in combination with chemometric modelling have become an established  
80 method for rapid assessment and non-destructive quality parameters in the food and  
81 agricultural sectors (Abbott, 1999; Jensen et al., 2001), since it is fast, safe, relatively  
82 inexpensive technique and provides automation of quality control processes in products  
83 of agroindustry (Pasquini, 2003).

84           NIRS has been used to evaluate macadamia nut quality. Guthrie et al. (2004)  
85 developed modified partial least squares regression (MPLS) models for oil content  
86 determination in intact macadamia kernels with a root mean square error of calibration  
87 (RMSEC) of 2.4 % and discriminated intact kernels with brown centers or rancidity  
88 from each other and from sound kernels using PCA. Canneddu et al. (2016) developed  
89 models for predicting peroxide value (PV) and acidity index (AI) using PLSR and  
90 classification models to discriminate defects present on shelled macadamia nuts using  
91 FT-NIR. The best model for PV prediction resulted in a coefficient of determination  
92 ( $R_p^2$ ) of 0.72, and for AI prediction a SEP of 0.14 % and a  $R_p^2$  of 0.80. Adequate  
93 classification models (93.2 %) for defects was possible using principal component  
94 analysis linear discriminant analysis (PCA-LDA). Carvalho et al. (2017) classified

95 intact macadamia nuts according to cultivars using PCA-LDA and genetic algorithm  
96 with linear discriminant analysis (GA-LDA), reporting an accuracy higher than 94.4 %  
97 and a value of 82.7 % for sensitivity using GA-LDA, respectively. The better  
98 performance of GA-LDA can be due to that GA algorithm selects several wavenumbers  
99 in a single band, due to collinearity problems. Carvalho et al. (2019) evaluated the  
100 oxidative stability in intact macadamia nuts during drying process and reported a SEP  
101 of 0.55 meq.kg<sup>-1</sup> and R<sup>2</sup>c of 0.57 for PV prediction, and SEP of 0.14 % and R<sup>2</sup>c of 0.29  
102 for AI prediction. These results demonstrate that NIRS can be used to assess the  
103 oxidative stability of intact macadamia nuts.

104 Nuclear magnetic resonance (NMR) has also been stated as an alternative  
105 method among non-destructive techniques to evaluate fruit quality (Abbott, 1999). TD-  
106 NMR has wide applications for qualitative and quantitative in food analysis (Conalgo,  
107 1996). In this regard, Pedersen et al. (2000) combined low-field nuclear magnetic  
108 resonance (LF-NMR) and PCA to classify rape and mustard seeds according on the  
109 type of seed, obtaining two distinct groups and 100 % of explained variance. This  
110 technique was also applied to evaluate the efficacy of hydrophobic coatings as a barrier  
111 to the oxidation of macadamia nuts (Colzato et al., 2009).

112 Although some results can be found regarding the use of NIRS to assess  
113 macadamia quality defects (Canneddu et al., 2016), this study was performed evaluating  
114 the macadamia in nut not the kernel (unshelled), and no reports were found on using  
115 NMR to evaluate macadamia kernel defects. Therefore, the objective of this study was  
116 to develop NIRS and NMR calibration models to evaluate macadamia kernels based on  
117 the most common defects aiming to improve the quality control process in the  
118 macadamia industry.

119

## 120 **2. Material and Methods**

### 121 **2.1. Plant material**

122 Macadamia (*Macadamia integrifolia* Maiden & Betche) kernels were obtained  
123 in a commercial orchard located in Dois Córregos, São Paulo, Brazil (22° 37' S, latitude,  
124 48° 38' W, longitude, 753 m altitude) in 2017 harvest season. Nuts were harvested three  
125 times during the season (April, June, and August) and kernels were visually sorted by  
126 the industry personnel based on their quality attributes, as such: 1=good, marketable  
127 kernels without defects; 2=kernels with discoloration; 3=immature kernels; 4=kernels  
128 affected by mold; and 5=kernels with insect damage. (Figure 1). These quality attributes  
129 represented the five studied classes (model). It is important to state that the nuts were  
130 dried by the processing industry and used in the analyses without any previous  
131 treatment.

### 132 **2.2. NIR spectra acquisition**

133 On the surface of each macadamia kernel two Fourier Transformed (FT) NIR  
134 reflectance spectra (11,544 – 3,952  $\text{cm}^{-1}$ , nm, resolution of 16  $\text{cm}^{-1}$ , and 64 scans) were  
135 collected using a Bruker NIR spectrometer (Tango, Ettlingen, Germany) after  
136 temperature stabilization at  $\sim 25^\circ\text{C}$ . The two replica spectra measured per nut were  
137 averaged, so the model is made on a sample basis. Samples were collected in three  
138 different harvests, where 20 nuts were sorted and used for spectra acquisition for each  
139 defect class. This resulted in a total of 300 measured samples (20 nuts x 5 classes x 3  
140 harvests).

### 141 **2.3. Time domain (TD) NMR measurements**

142 TD-NMR measurements of macadamia kernels (n=100) were carried out at 22  
143  $^\circ\text{C}$  in a 0.27 T (11.3 MHz for  $^1\text{H}$ ) benchtop SLK200 Spinlock instrument (Spinlock  
144 Magnetic Resonance Solutions, Cordoba, Argentina). The measurements were

145 performed using the standard CPMG sequence to obtain the exponential decay signal  
146 that is governed by the transverse relaxation time ( $T_2$ ). The sequence used  $\pi/2$  and  $\pi$  of  
147 11.6 and 19.6  $\mu\text{s}$ , respectively, an echo time of 600  $\mu\text{s}$ , 4 scans and 1500 echoes.  
148 Samples harvested in June 2017 were used and for each defect class 20 nuts were sorted  
149 and used for spectra acquisition, totaling 100 spectra. The mass of the samples ranged  
150 from 14 to 24 g depending on the sample density. The samples were the same used to  
151 collect the NIRS spectra, but the spectra were collected on different days.

## 152 **2.4. Chemometrics**

153 Data analysis of NIR and TD-NMR were performed within MATLAB R2014b  
154 environment (MathWorks Inc., USA) using PLS Toolbox version 7.9.3 (Eigenvector  
155 Research Inc., USA) and lab-made routines. Three different pre-processing methods  
156 were applied to test the averaged sample spectrum (average of 10 spectra per sample):  
157 (1) only mean-centering; (2) standard normal variate (SNV) followed by mean-  
158 centering; (3) Savitzky-Golay second derivative (window of 5 points, 2<sup>nd</sup> order  
159 polynomial function) followed by mean-centering. The data was split into training (70  
160 %, 210 samples), validation (15 %, 45 samples) and test (15 %, 45 samples) sets using  
161 the Kennard-Stone sample selection algorithm (Kennard and Stone, 2012). The training  
162 and validation sets were used for model construction and internal optimization,  
163 respectively; while the test set was used to evaluate the final predictive performance of  
164 the classification models built towards external samples.

165 Multivariate classification was performed by means of principal component  
166 analysis linear discriminant analysis (PCA-LDA) and genetic algorithm linear  
167 discriminant analysis (GA-LDA). PCA-LDA performs a feature extraction using  
168 principal component analysis (PCA) followed by a linear discriminant classifier (LDA)  
169 (Morais and Lima, 2018) For this, PCA is applied to the pre-processed data reducing

170 the original number of variables (i.e., wavelengths) to a few number of principal  
 171 components (PCs) accounting for the majority of the original data variance. Each PC is  
 172 composed by scores and loadings, where the first represents the variance between the  
 173 samples and the latter the variance on wavelength direction (Bro and Smilde, 2014).  
 174 LDA is applied to the PCA scores in a non-Bayesian form as follows (Dixon and  
 175 Brereton, 2009; Wu et al, 1996).

$$176 \quad L(\mathbf{x}_i) = (\mathbf{x}_i - \bar{\mathbf{x}}_k)^T \mathbf{C}_{\text{pooled}}^{-1} (\mathbf{x}_i - \bar{\mathbf{x}}_k) \quad (1)$$

177 where  $L(\mathbf{x}_i)$  represents the LDA classification scores for sample  $i$ ;  $\mathbf{x}_i$  is the input vector  
 178 (i.e., the PCA scores) for sample  $i$ ;  $\bar{\mathbf{x}}_k$  is the average vector of class  $k$ ;  $\mathbf{C}_{\text{pooled}}$  is pooled  
 179 covariance matrix; and T represents the matrix transpose operation.

180 GA-LDA is feature selection technique followed by an LDA classifier. Initially,  
 181 a genetic algorithm (GA) is applied to reduce to the spectral data into a few number of  
 182 variables based on an evolutionary process (Bro and Smilde, 2014); then LDA is  
 183 applied to these variables according to Eq. 1. These variables are in the same scale of  
 184 the original spectral data and are selected according to the lowest risk of miss  
 185 classification  $G$ .  $G$  is calculated in the validation set as (Carvalho et al. 2017).

$$186 \quad G = \frac{1}{N_v} \sum_{n=1}^{N_v} g_n \quad (2)$$

187 where  $N_v$  is the number of validation samples and  $g_n$  is defined as:

$$188 \quad g_n = \frac{r^2(x_n, m_{I(n)})}{\min_{I(m) \neq I(n)} r^2(x_n, m_{I(m)})} \quad (3)$$



189 in which the numerator is the squared Mahalanobis distance between sample  $x_n$  (of  
 190 class index  $I(n)$ ) and the mean  $m_{I(n)}$  of its true class; and the denominator represents  
 191 the squared Mahalanobis distance between sample  $x_n$  and the mean  $m_{I(m)}$  of the  
 192 closest wrong class. GA was performed through 100 generations, having 200  
 193 chromosomes each. Cross-over and mutation probabilities were set at 60% and 1%,  
 194 respectively. The algorithm was repeated three times and the best result was chosen.

195

## 196 **2.5. Figures of merit**

197 The classification performance of each algorithm was evaluated according to  
 198 the quality parameters of accuracy (total number of samples correctly classified  
 199 considering true and false negatives), sensitivity (proportion of positives correctly  
 200 identified) and specificity (proportion of negatives correctly identified). These  
 201 parameters are calculated as follows (Morais and Lima, 2017):

$$202 \quad \text{Accuracy (\%)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \times 100 \quad (4)$$

$$203 \quad \text{Sensitivity (\%)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \quad (5)$$

$$204 \quad \text{Specificity (\%)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100 \quad (6)$$

205 where TP stands for true positives; TN for true negatives; FP for false positives; and FN  
 206 for false negatives.

207

## 208 **3. Results and Discussion**

### 209 3.1. NIR spectra

210 The raw FT-NIR spectra obtained from all macadamia kernels and the average  
211 spectra from each quality attribute class can be seen in Figure 2. It was not possible to  
212 observe spectral differences between the quality attributes when all macadamia kernels  
213 were assessed (Figure 2A). On the other hand, the mean spectra were quite different for  
214 each defect category (Figure 2B), especially at the wavelength 1,900 nm to 2,500 nm.

215 The FT-NIR spectra presented absorption bands at 1,200 nm, which are related  
216 to CH stretch second overtone (Cozzolino et al., 2005), while those at 1,700 – 1,800 nm  
217 are associated to the first overtones of CH stretching vibrations of  $-\text{CH}_3$ ,  $-\text{CH}_2-$  and  $-\text{HC}=\text{CH}$  (Armenta and La Guardia, 2007). Absorption bands at 1,350 – 1,600 nm and  
218 1,950 nm and 2,100 nm are related to the presence of glucose, sucrose, and fructose  
219 (Lanza and Li, 1984) and immature kernels have higher sucrose and reducing sugar  
220 contents than fully mature kernels (Wall, 2013). In Figure 2B can be seen that at 1,350  
221 – 1,600 nm the immature kernels exhibit a higher absorption intensity, since maturity is  
222 inversely related to sugar content (Ripperton et al., 1938).

224 The wavelength region situated at 2,200 – 2,500 nm is mainly related to the  
225 oxidation and hydrolytic degradation of lipids (Cozzolino et al. 2005). It is possible to  
226 observe that the immature kernels, classified as kernel which is misshapen, abnormally  
227 small or partially aborted, including shriveled and shrunken kernels (SAMAC, 2016)  
228 present a lower absorption band (2,200 nm - 2,500 nm) (Figure 2B). This result might  
229 be due to the fact that maturity is correlated with oil content (Cavaletto, 1985),  
230 consequently with less lipid degradation.

#### 231 3.1.1. Model development

232 To correlate the FT-NIR spectra to the quality categories, discriminant  
233 classifications based on PLS-DA and GA-LDA were used and compared and evaluated  
234 in terms of sensitivity, specificity, accuracy, separately for each category.

235 Regarding pre-processing, SNV lead to best results using PCA-LDA, resulting  
236 in an accuracy of 68 % and a specificity of 97 % for immature kernels (Table 1). The  
237 accuracy shows the proportion of samples correctly grouped, while specificity  
238 represents the probability of a sample without the desired characteristic to be given a  
239 negative test result (Amodio et al., 2017). However, the sensitivity presented low  
240 values (67 %), and this parameter describes the model ability to correctly recognize  
241 samples belonging to a class (Ballabio and Consonni, 2013). For example, if none of  
242 the marketable kernels were classified as other class (FN is equal to zero), the  
243 sensitivity for the marketable kernels class would have been equal to 100 %.

244 Cannedu et al. (2016) classified marketable macadamia kernels in relation to  
245 non-marketable kernels using PLS-DA and reported percentages of 88 % for calibration  
246 and 87 % for prediction. These results were inferior than what we obtained, probably  
247 because we used more samples ( $n = 300$ ) than Cannedu et al. (2016) ( $n = 100$ ).  
248 Therefore, the inclusion of more data into the dataset improved the robustness and  
249 increase the classification accuracy.

250 Marketable kernels and kernels with defects (immature, insect damage, mold,  
251 and discoloration) could be discriminated from each other using GA-LDA (Figure 3).  
252 The accuracy and specificity of GA-LDA for marketable kernels achieved a value of  
253 97.8 % and 100 %, respectively (Table 2).

254 To perform the GA-LDA, some of the wavelengths were selected (Table 3).  
255 This selection was based on compounds of particular interest, e.g., 1,020 nm and 1,173  
256 nm, representing the C–H groups from lipids; 1,485 nm and 1,789 nm, related to the

257 first overtone of stretching and anti-symmetric O–H bond and second overtone of  
258 stretching O–H bend, respectively. Absorption bands at the wavelength near 1,450 and  
259 1,940 nm are related to the presence of water in foods (Moscetti et al., 2014) and this  
260 explains why the wavelengths 1,485 nm, 1,975 nm and 1,987 nm were selected by GA.

261 It is possible to observe that the kernels with discoloration had a higher  
262 moisture content than the others (Figure 2B), and these moisture contents correspond to  
263 water activities ( $a_w$ ) greater than 0.8 at which browning reaction rates are high (Wall,  
264 2013), and maintaining nuts-in-shell at high moisture content can cause discoloration  
265 (Walton et al., 2013).

### 266 **3.2. TD-NMR**

267 The typical curves of the CPMG decays for the different defects found in  
268 macadamia kernels can be seen in Figure 4. It can be observed that kernels with insect  
269 damage presented a faster settling time compared to the others, whereas the kernels with  
270 presence of fungi (moldy) showed the slower signal decay (Figure 4).

271 The intensity of the TD-NMR signals from relaxation (our case) and diffusion  
272 measurements is related to the water content related to water status, water  
273 compartmentalization and molecular mobility in the food sample (Kirtil et al., 2017). In  
274 order to evaluate the influence of the water content on the nutrient content of the food, it  
275 is important to note that there are variations in the moisture content of the kernels, since  
276 these moisture contents correspond to water activities at which microbial growth rates  
277 are high (Wall, 2013). This explains the fact that moldy kernels have a higher moisture  
278 content.

279 In Figure 5 it is possible to observe that there was not a clear separation  
280 between the defect classes. However, in Figure 5A there was a tendency of separation  
281 between the good and immature kernels. Probably because there are differences in the

282 decay time between these classes (Figure 4), with showed that the most rapid decay is  
283 due to solid components, mainly composed of proteins and carbohydrates (Prestes et al.,  
284 2007) and immature kernels present a higher carbohydrate concentration, represented by  
285 sucrose and fructose higher than mature kernels (Wall, 2013).

### 286 *3.2.1. Model development*

287 The best TD-NMR classification models were obtained using the PCA-LDA and  
288 GA-LDA without pre-processing the signals (Table 4). Using PCA-LDA, it was  
289 possible to achieve 86 % accuracy for the training set and 83.3 % for the validation set  
290 to classify kernels with insect damage. On the other hand, the GA-LDA analysis  
291 obtained 64 % for the calibration set and 100 % for the validation set, allowing the use  
292 of this model to classify kernels with insect damages.

293 TD-NMR has been used to classify other oleaginous produces including nuts.  
294 Di Caro et al. (2017) studying not damaged and moldy hazelnuts kernels highlighted  
295 that NMR might be used to discriminate oils extracted from both kernel classes. Di Caro  
296 (2018) also reported that using NMR was possible to obtain values of 97 % for  
297 sensitivity and 81 % for specificity to classify in-shell damaged hazelnuts. Therefore,  
298 NMR might be a useful analytical tool for quality control in nut industry.

### 299 **3.3. NIRS versus TD-NMR**

300 The results obtained from both techniques for the development of the  
301 classification models for macadamia kernels quality defects can be seen in Table 1, 2,  
302 and 4. Overall, the NIRS showed better classification capability as higher values of  
303 accuracy were obtained using GA-LDA models. The lower performance of the  
304 classification models developed using the TD-NMR signals might be related to the  
305 number of samples, as just the kernels harvested in June 2017 were used.

306 NIRS and TD-NMR present many similarities as they are fast non-destructive  
307 analytical methods, do not need sophisticated sample preparation, and the results can be  
308 collected, processed, and stored directly in a microcomputer (Colnago, 1996; Pasquini,  
309 2003). However, when it comes to NMR spectroscopy, high cost is normally considered  
310 as one of the most serious drawbacks and this technique requires special skills to  
311 interpret the spectra acquisition (Xu et al., 2015). Another limitation of NMR  
312 spectroscopy is the insensitivity to minor fat component detection (Kucha et al., 2018).  
313 These suggest that, due the fact that NIRS is useful for detecting components with up to  
314 0.1 % concentration (Xu et al., 2015) and NMR presents lower sensitivity, NIRS models  
315 presented more satisfactory results.

316

#### 317 **4. Conclusions**

318 NIRS and TD-NMR combined with chemometric methods proved to be  
319 powerful tools to classify macadamia kernels based on their quality defects. However,  
320 NIRS out-performed TD-NMR based on the higher accuracy results.

321 NIRS and TD-NMR spectroscopy can be successfully used to evaluate the  
322 quality of unshelled macadamia nuts and have potential to improve the existing  
323 postharvest techniques used in the macadamia industry.

324

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434 **Tables**

435 **Table 1.** Values of accuracy, sensitivity and specificity to classify macadamia kernels  
 436 based on quality defects using PCA-LDA and NIRS.

<b>Classes</b>		<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>
<b>Pre-Processing</b>						
<b>Raw</b>	AC(%)	88.9	84.4	75.6	82.2	75.6
	SENS(%)	88.9	66.7	44.4	44.4	22.2
	SPEC(%)	88.9	88.9	83.3	91.7	88.9
<b>SNV</b>	AC(%)	80.0	68.9	88.9	75.6	75.6
	SENS(%)	66.7	55.6	55.6	11.1	33.3
	SPEC(%)	83.3	72.2	97.2	91.7	86.1
<b>2<sup>nd</sup> Derivative</b>	AC(%)	82.2	73.3	86.7	88.9	75.6
	SENS(%)	66.7	44.4	77.8	66.7	11.1
	SPEC(%)	86.1	80.6	88.9	94.4	91.7

437 SNV= standard normal variate; AC= accuracy; SENS= sensitivity; SPEC= specificity.

438 1=good, marketable kernels without defects; 2=kernels with discoloration; 3=immature

439 kernels; 4=kernels affected by mold; and 5=kernels with insect damage.

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443 **Table 2.** Values of accuracy, sensitivity and specificity to classify macadamia kernels

444 based on quality defects using GA-LDA and NIRS.

<b>Classes</b>		<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>
<b>Pre-Processing</b>						
<b>Raw</b>	AC(%)	86.7	82.2	86.7	86.7	82.2
	SENS(%)	66.7	66.7	55.6	66.7	55.6
	SPEC(%)	91.7	86.1	94.4	91.7	88.9
<b>SNV</b>	AC(%)	97.8	84.4	88.9	91.1	84.4
	SENS(%)	88.9	88.9	55.6	77.8	55.6
	SPEC(%)	100	83.3	97.2	94.4	91.7
<b>2<sup>nd</sup> Derivative</b>	AC(%)	91.1	75.6	84.4	86.7	68.9
	SENS(%)	66.7	44.4	44.4	55.6	55.6
	SPEC(%)	97.2	83.3	94.4	94.4	72.2

445 SNV= standard normal variate; AC= accuracy; SENS= sensitivity; SPEC= specificity.

446 1=good, marketable kernels without defects; 2=kernels with discoloration; 3=immature

447 kernels; 4=kernels affected by mold; and 5=kernels with insect damage.

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451 **Table 3.** Selected variables for GA-LDA to classify macadamia kernels using different  
 452 pre-processing.

<b>Pre-processing</b>	<b>Selected variables (nm)</b>
<b>Raw</b>	882; 886; 946; 990; 1171; 1395; 1429; 1511; 1622; 1664; 1942; 1979; 2075; 2187; 2260; 2328
<b>SNV</b>	866; 1020; 1173; 1280; 1485; 1578; 1789; 1975; 1987; 2083; 2170; 2277; 2300; 2388; 2451
<b>2<sup>nd</sup> Derivative</b>	894; 898; 1078; 1251; 1335; 1436; 1488; 1952; 1964; 2126; 2328; 2356

453 SNV=standard normal variate

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456 **Table 4.** Values of accuracy to classify macadamia kernels based on quality parameters

457 using PCA-LDA, GA-LDA and TD-NMR spectroscopy.

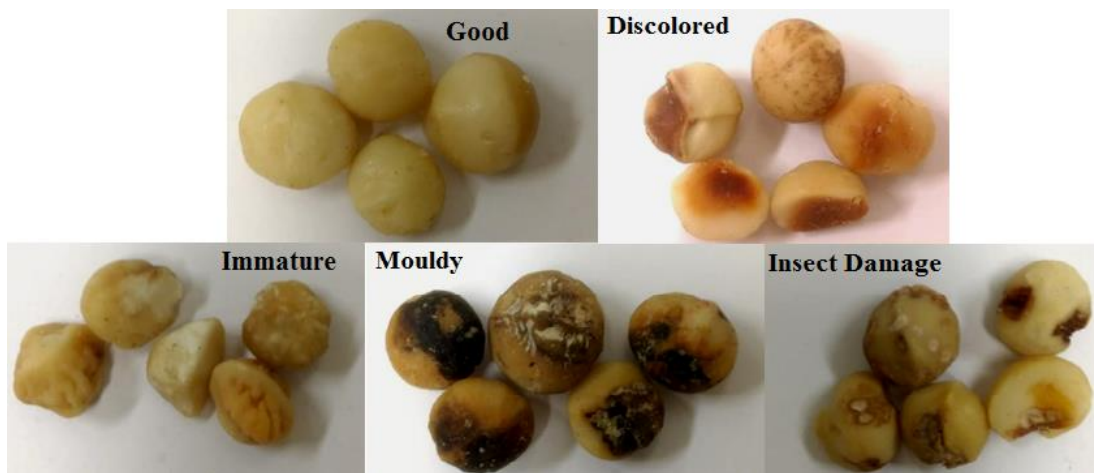
<b>Classes</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	
<b>Pre-Processing</b>						
<b>Nil</b>	PCA-LDA					
	Training (%)	64.3	35.7	42.9	85.7	64.3
	Validation (%)	16.7	33.3	16.7	66.7	83.3
	GA-LDA					
	Training (%)	64.3	50.0	35.7	64.3	50.0
	Validation (%)	66.7	16.7	66.7	66.7	100

458 1=good, marketable kernels without defects; 2=kernels with discoloration; 3=immature

459 kernels; 4=kernels affected by mold; and 5=kernels with insect damage.

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462 **Figures**

463

464 **Figure 1.** Macadamia kernels quality defects: 1=good, marketable kernels without

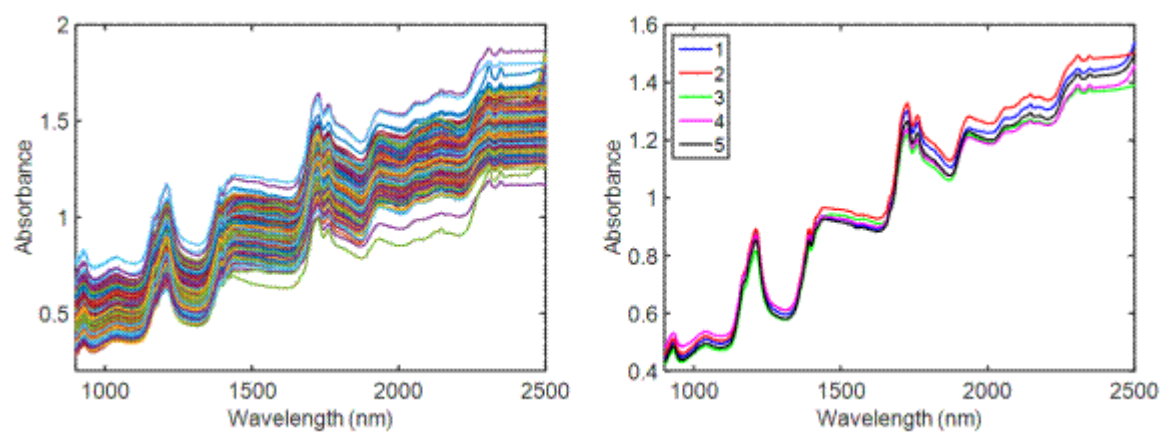
465 defects; 2=kernels with discoloration; 3=immature kernels; 4=kernels affected by mold;

466 and 5=kernels with insect damage.

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471 **Figure 2.** Raw NIR spectra (a) and average NIR spectra (b) of macadamia kernels.

472 1=good, marketable kernels without defects; 2=kernels with discoloration; 3=immature

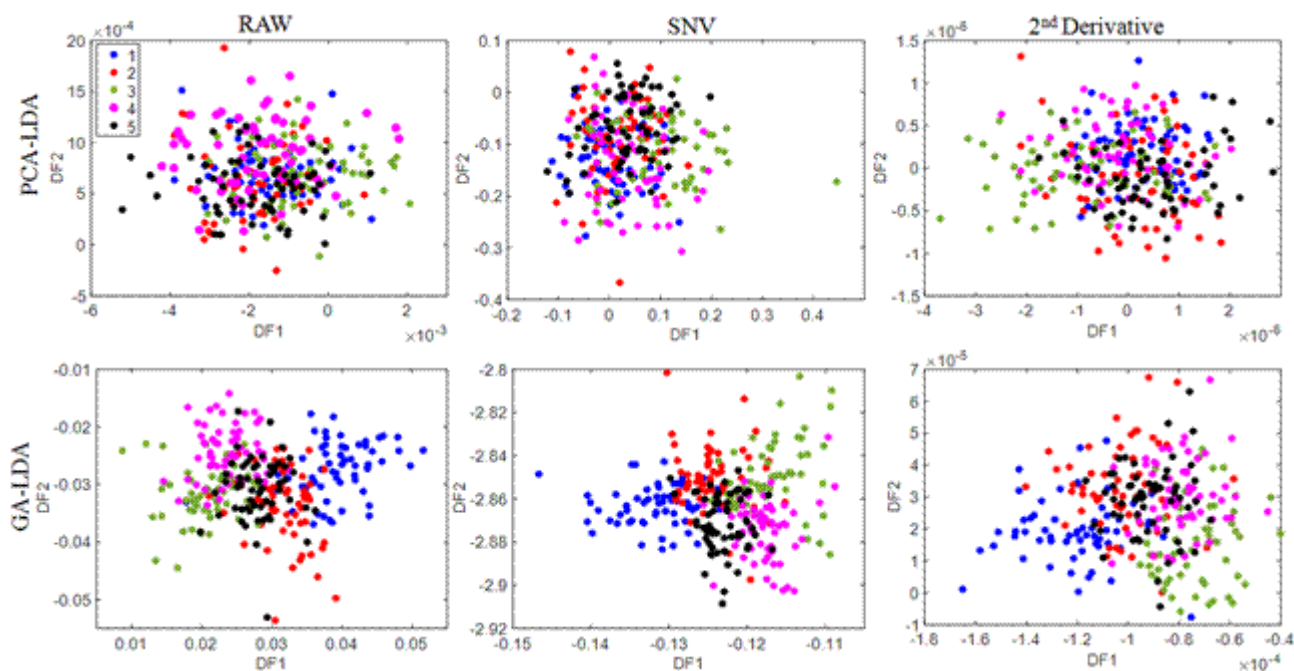
473 kernels; 4=kernels affected by mold; and 5=kernels with insect damage.

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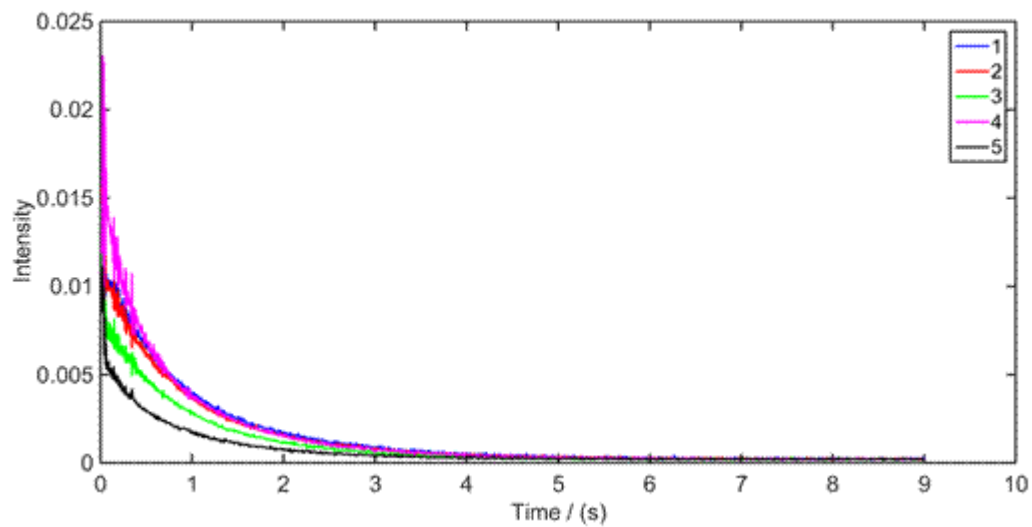


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478 **Figure 3.** Discriminant function (DF) plot of PCA-LDA and GA-LDA with raw NIR  
 479 spectra of macadamia kernels, SNV and 2<sup>nd</sup> derivative Savitzky-Golay. 1=good,  
 480 marketable kernels without defects; 2=kernels with discoloration; 3=immature kernels;  
 481 4=kernels affected by mold; and 5=kernels with insect damage.

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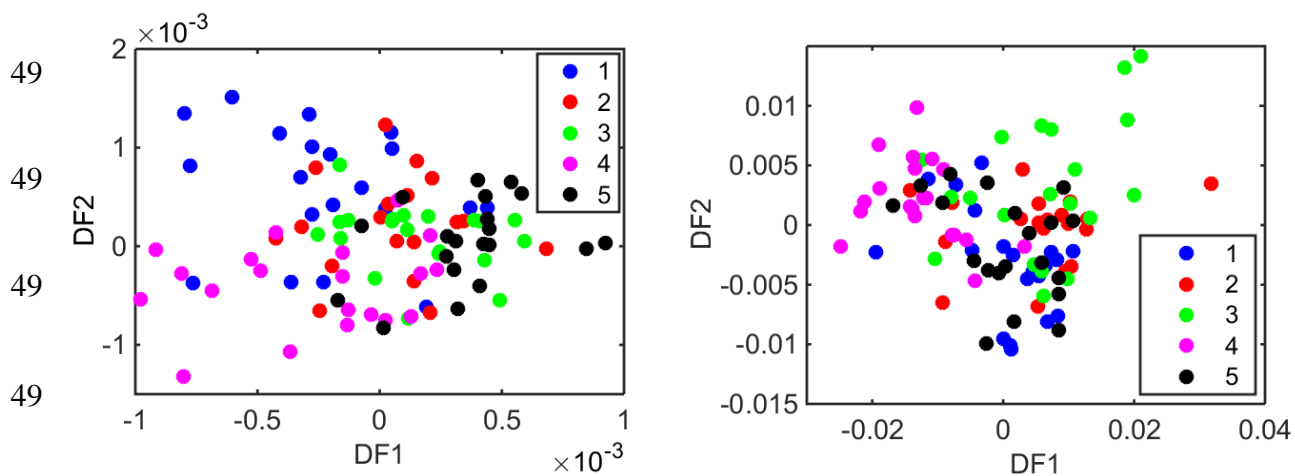
484

485 **Figure 4.** Typical CPMG decay curves of macadamia kernels with different quality  
486 defects. 1=good, marketable kernels without defects; 2=kernels with discoloration;  
487 3=immature kernels; 4=kernels affected by mold; and 5=kernels with insect damage.

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495 **Figure 5.** Discriminant function (DF) of PCA-LDA (A) and GA-LDA (B) with raw  
 496 TD-NMR spectra of macadamia kernels. 1=good, marketable kernels without defects;  
 497 2=kernels with discoloration; 3=immature kernels; 4=kernels affected by mold; and  
 498 5=kernels with insect damage.

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