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## Evaluation of a robust regression method (RoBoost-PLSR) to predict biochemical variables for agronomic applications: Case study of grape berry maturity monitoring

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1 Evaluation of a robust regression method  
2 (RoBoost-PLSR) to predict biochemical variables for  
3 agronomic applications: case study of grape berry  
4 maturity monitoring

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11 **Abstract**

12 Visible and near infrared spectroscopy (VIS-NIR) is increasingly being  
13 transferred from laboratory to industry for in-line and portable applications  
14 in various domains. By intensively using VIS-NIR spectroscopy, some ab-  
15 normal observations may certainly arise. It is then important to properly  
16 handle outliers to elaborate effective prediction models. The objective of  
17 this study is to investigate the potential of using a robust method called  
18 Roboost-PLSR to improve prediction model performances for a viticulture  
19 application. This work focuses on a case study to predict sugar content in  
20 grape berries of three different grape varieties of *Vitis Vinifera* in a maturity  
21 monitoring context. Hyperspectral images were acquired of grape berries of  
22 Syrah, Fer-Servadou and Mauzac varieties. Reference measurements of sugar  
23 levels were made in the laboratory by densimetric baths. Performances of  
24 RoBoost-PLSR models were compared to performances of reference models

25 using Partial Least Square Regression (PLSR). Reference prediction criteria  
26 using PLSR were obtained for all varieties with these following values: Syrah  
27 ( $R_p^2 = 0.971$ ;  $RMSE_p = 5.36$  g/L), Fer-servadou ( $R_p^2 = 0.788$ ;  $RMSE_p = 11.69$   
28 g/L) and Mauzac ( $R_p^2 = 0.690$ ;  $RMSE_p = 15.61$  g/L). Prediction qualities  
29 are improved with RoBoost-PLSR: Syrah ( $R_p^2 = 0.990$ ;  $RMSE_p = 3.14$  g/L),  
30 Fer-Servadou ( $R_p^2 = 0.848$ ;  $RMSE_p = 10.20$  g/L) and Mauzac ( $R_p^2 = 0.927$ ;  
31  $RMSE_p = 7.58$  g/L). Results confirm that Roboost-PLSR method allows a  
32 better consideration of outliers within the calibration set.

33 *Keywords:* Robust regression, Chemometrics, Spectroscopy, Grapes,  
34 maturity

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## 35 1. Introduction

36 It is increasingly common that visible and near-infrared (VIS-NIR) spec-  
37 troscopy transfers from laboratory to industry for in-lign and portable ap-  
38 plications in various domains. By intensively using VIS-NIR spectroscopy,  
39 some abnormal observations may certainly arise. Among these, observations  
40 are called leverage points when they have a strong impact on the construc-  
41 tion of a prediction model. When they are detrimental to the prediction  
42 model, they are called outliers. It is then important to properly handle these  
43 outliers to elaborate effective prediction models. In chemometrics, Partial  
44 Least Square Regression (PLSR) (Wold et al., 2001) is a widely-used tool.  
45 Particularly, PLSR is effective when dealing with high-dimensional data such  
46 as spectral data, where the sample number is lower than variable number.  
47 Besides, the PLSR method performs admirably when the relationship be-  
48 tween explanatory variables and response variable to be predicted is linear.

49 However, estimating this linear relationship may be disturbed in presence of  
50 outliers ([Serneels et al., 2005a](#)).

51 These outlier data are generally due to variations of measurement condi-  
52 tions (view angle, reference, sensor temperature), physico-chemical variations  
53 in measured samples or experimental errors (annotation, operator). All these  
54 variations require efforts to identify and remove outliers from the calibration  
55 set. In addition, inspecting each observation manually is complicated and  
56 time-consuming in the case of large databases.

57 These problems are also found in agronomy, where the use of VIS-NIR  
58 spectroscopy is tending to be more frequently used ([Ryckewaert et al., 2021](#)).  
59 Indeed, rich spectral information is an added value to predict biochemical  
60 variables to assess agronomic parameters for various agronomic applications.  
61 This technological trend operates at different scales depending on the objec-  
62 tives: prediction models can be used at fruit scale for quality control, at the  
63 leaf/canopy scale for plant health monitoring or at the plot scale for produc-  
64 tion monitoring. Multiple use cases of spectral data encourage a particular  
65 development on the management of outliers.

66 Robust methods have been developed to address this issue ([Serneels et al.,](#)  
67 [2005b](#); [Hubert and Branden, 2003](#); [Filzmoser et al., 2008, 2020](#); [Griep et al.,](#)  
68 [1995](#); [Metz et al., 2021](#)). Indeed, this type of method aims at reducing the  
69 outlier impact automatically on PLSR model calibration. Recently, a method  
70 called Roboost-PLSR has been developed ([Metz et al., 2021](#)) and has shown  
71 its effectiveness to manage PLSR model calibration in the presence of outlier  
72 data.

73 This article highlights the interest of RoBoost-PLSR method to improve

74 prediction models for agronomic applications and more particularly in the  
75 case of monitoring grape berry maturity of *Vitis Vinifera*. For this purpose,  
76 Roboost-PLSR method was compared to the reference method PLSR to pre-  
77 dict sugar content in grape berries of three different grape varieties.

## 78 **2. Materials and methods**

### 79 *2.1. Biological material and reference measurements*

80 Grape berries were collected during a campaign carried out in Gaillac  
81 (France), in summer 2020. The sampling started one or two weeks after ve-  
82 raison and preharvest, on three plots corresponding to three different grape  
83 varieties of the experimental vineyard Domaine Expérimental Viticole Tar-  
84 nais: with two red grape varieties (Syrah and Fer Servadou) and one white  
85 grape variety (Mauzac). Thirty bunches were randomly sampled in each plot  
86 about once a week.



Figure 1: Picture of densimetric baths used for maturity degree sorting of grape berries.

87 In the laboratory, grape berries were cut from bunches at the pedicel level  
88 to preserve entire fruits. Grape berries were then sorted in batches with same

89 maturity degree using sodium chloride (NaCl) baths to achieve a densimetric  
90 sorting (see fig. 1). Indeed, the increase in berry density during ripening is  
91 mainly due to sugar accumulation in berries (Lanier and Morris, 1978a,b).  
92 To this end, twelve NaCl baths with increasing concentrations from 70 to  
93 190 g/L were used to classify berry density corresponding to sugar concen-  
94 trations from 110 to 279 g/L (Bigard, 2018). First, berries were immersed  
95 in the highest NaCl concentration solution. Then, floating fruits were re-  
96 moved and immersed in a solution of lower concentration, whereas sinking  
97 fruits were removed and sorted into the density level corresponding to the  
98 NaCl solution. The procedure was repeated for all baths in order to obtain  
99 twelve classes of homogeneous maturity. Sugar content measurements were  
100 performed on berry musts (one must corresponds to one hundred berries)  
101 with a refractometer (HI-96816, Hanna Instruments).

## 102 *2.2. Spectral acquisition*

103 Before preparing a hundred berry must, these berries were placed on  
104 a tray for spectral acquisition. Reflectance spectra were acquired with a  
105 hyperspectral camera (Specim IQ, Specim, Finland) having a spectral range  
106 from 400 nm to 1000 nm and a spectral resolution equal to 7 nm (see Fig 2).

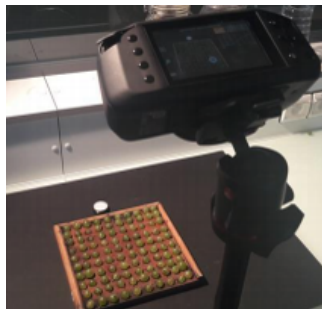


Figure 2: Hyperspectral acquisition of grape berries.

107 For each sample, reflected light intensity ( $I_s(\lambda)$ ) was measured at each  
108 wavelength  $\lambda$ . The camera was positioned 1.5 m from the scene. Dark current  
109 image ( $I_b(\lambda)$ ) was also recorded for each measure. A certified reflectance  
110 standard (Labsphere, SRS-40-010) was used as a reference reflected intensity  
111 ( $I_o(\lambda)$ ) to standardise images from non-uniformities of instrumentation (light  
112 source, lens, detector). Illumination was provided using a halogen lamp  
113 (Arrilite 750 Plus ARRI, Munich, Germany). Constant angles of  $-50^\circ$  and  
114  $50^\circ$  were maintained between the halogen lamp axes and the hyperspectral  
115 camera axis. From these measurements, a reflectance image ( $R_s(\lambda)$ ) was  
116 obtained for each sample where each pixel of this image is a reflectance  
117 spectrum:

$$R_s(\lambda) = \frac{I_s(\lambda) - I_b(\lambda)}{I_o(\lambda) - I_b(\lambda)} \quad (1)$$

### 118 *2.3. Image preprocessing*

119 A segmentation process was implemented to retrieve berry reflectance  
120 spectra from images. First, three reference spectra were defined, correspond-  
121 ing to each grape variety, by calculating an averaged spectrum from a manual  
122 selection of an area of a berry. Then, the segmentation was performed by  
123 comparing each image pixel with these previously defined spectra (see fig.  
124 [3](#)).

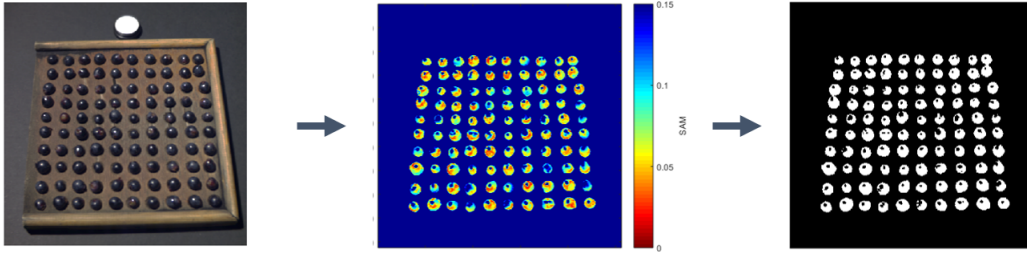


Figure 3: Segmentation by using spectral similarity threshold.

125 To this end, Spectral Angle Mapper (SAM) (Kruse et al., 1993; Yuhas  
 126 et al., 1992) was selected to evaluate spectral similarity between the refer-  
 127 ence spectrum defined for a given grape variety and spectra contained in  
 128 hyperspectral images. Indeed, this criterion corresponds to an angle between  
 129 two spectra (assimilated to vectors) and is favourably independent to inten-  
 130 sity levels. The angle  $\alpha$  defined between the corresponding variety reference  
 131 spectrum  $\mathbf{y}$  and the spectrum of a given pixel  $\mathbf{x}$ , was calculated as follows:

$$\alpha = \cos^{-1} \frac{\sum_{\lambda} \mathbf{x}\mathbf{y}}{\sqrt{\sum(\mathbf{x})^2 \sum(\mathbf{y})^2}} \quad (2)$$

132 By defining a spectral similarity threshold, berry spectra were retrieved  
 133 from the images (see fig. 3). Finally, for each image a berry average spectrum  
 134 was computed, to consider a unique sugar content.

## 135 2.4. Data analysis

### 136 2.4.1. Regression methods used

137 RoBoost-PLSR (Metz et al., 2021) was used as a robust regression method  
 138 to predict sugar content  $\mathbf{Y}$  from spectral data  $\mathbf{X}$ . The purpose of this method  
 139 is to define the outlyingness for each individual. This measure is expressed as



140 a weight which is integrated in the calibration of the RoBoost-PLSR model.  
141 This methods reduces outlier effect on model calibration by weighting them.  
142 A particularity of this method is that outliers are defined latent variable  
143 by latent variable. For each model with one latent variable, observation  
144 weights are calculated according to three criteria:  $\mathbf{X}$  residuals,  $\mathbf{Y}$  residuals  
145 and leverage points with the hyperparameters  $\alpha$ ,  $\beta$  and  $\gamma$  respectively. In this  
146 study, sixty-four combinations of values for  $\alpha$ ,  $\beta$  and  $\gamma$  were tested to optimise  
147 the model with these following possible values: 2, 4, 6, and infinite. RoBoost-  
148 PLSR was compared to the reference regression method PLSR (Wold et al.,  
149 2001).

150 Calculations were performed with the R software (version 3.6.1 (Core Team,  
151 2013)), `rnirs` package for PLSR (<https://github.com/mlesnoff/rnirs>) and  
152 `roboost` package for RoBoost-PLSR (<https://github.com/maxmetz/RoBoost-PLSR>).

#### 153 *2.4.2. Calibration and test set definition*

154 To compare PLSR method with RoBoost-PLSR method, models were  
155 established from three data sets corresponding to the three different grape  
156 varieties. For each grape variety, data were split into two sets, one calibra-  
157 tion set and one test set. The calibration set was formed with 75% of the  
158 whole data set whereas the test set was formed with the remaining 25%.  
159 This partitioning was chosen in order to have a sufficient amount of data to  
160 evaluate the criteria on the test set. As showed in table 1, the total number  
161 of observations was different depending on the grape variety.

Table 1: Number of observations constituting the whole data set, the calibration set and the test set, for the three grape varieties, Syrah, Fer and Mauzac.

Number of observations	Syrah	Fer	Mauzac
Whole dataset	126	63	85
Calibration set	95	48	67
Test set	31	15	18

162 Besides, test sets were created avoiding abnormal observations according  
 163 to (Metz et al., 2021).

164 *2.4.3. Assessment criteria*

165 PLSR models were calibrated by performing a cross-validation procedure  
 166 (Browne, 2000). For each grape variety, a k-fold cross-validation with five  
 167 blocks was defined on the corresponding calibration data set.

168 Model evaluation was performed using several criteria: root-mean-square  
 169 error (RMSE), median absolute deviation (MAD) and determination coeffi-  
 170 cient  $R^2$ . Besides, the number of latent variables was optimised thanks to  
 171 the RMSE parameter and was chosen to be lower than twenty. These criteria  
 172 were calculated thanks to the following equations:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (\hat{y}_i - y_i)^2}{N}} \quad (3)$$

$$\text{MAD} = \text{median}(|y_i - \tilde{y}|) \quad (4)$$

$$R^2 = 1 - \frac{\frac{\sum_{i=1}^N (\hat{y}_i - y_i)^2}{N}}{\frac{\sum_{i=1}^N (y_i - y_m)^2}{N}} \quad (5)$$

173 with  $\hat{y}_i$  the predicted value,  $y_i$  the observed value,  $y_m$  the average of all re-  
 174 sponse values and  $N$  the total number of observations.  $\text{RMSE}_{cv}$ ,  $\text{MAD}_{cv}$  and  
 175  $R_{cv}^2$  denoted criteria obtained in the cross-validation step whereas  $\text{RMSE}_p$ ,  
 176  $\text{MAD}_p$  and  $R_p^2$  denoted those obtained with the independent test set.

177 Likewise PLSR, RoBoost-PLSR models were calibrated by performing a  
 178 k-fold cross-validation procedure with five blocks. However, so-called robust  
 179 evaluation criteria were calculated by using a procedure of trimming (Filz-  
 180 moser and Nordhausen, 2021) Trimming consisted in sorting out observations  
 181 according to their weights before removing a percentage of observations hav-  
 182 ing the weaker weights. Moreover, this percentage was adapted to each of  
 183 the three grape varieties: 5% for Syrah, 15% for Fer and 20% for Mauzac.  
 184 Among these new criteria, r- $\text{RMSE}_{cv}$  and r- $R_{cv}^2$  were defined, corresponding  
 185 respectively to the trimmed RMSE and the trimmed coefficient of determina-  
 186 tion. The MAD calculated previously (eq. 4) was retained as it is considered  
 187 a criterion for evaluating robustness.

188 So-called robust evaluation criteria were chosen according to Filzmoser  
 189 and al work (Filzmoser and Nordhausen, 2021). MAD, considered as a ro-  
 190 bustness evaluation criterion, was computed. r- $\text{RMSE}_{cv}$  and r- $R_{cv}^2$  were com-  
 191 puted as follows:

$$\text{r-RMSE}_{cv} = \sqrt{\frac{\sum_{i=1}^{N_t} (\hat{y}_i - y_i)^2}{N_t}} \quad (6)$$

$$\text{r-R}_{cv}^2 = 1 - \frac{\frac{\sum_{i=1}^{N_t} (\hat{y}_i - y_i)^2}{N_t}}{\frac{\sum_{i=1}^{N_t} (y_i - y_m)^2}{N_t}} \quad (7)$$

192 With  $\hat{y}_i$  the predicted  $y$ ,  $y_i$  the observed  $y$ ,  $y_m$  the average  $y$  and  $N_t$  the  
 193 number of retained observations. The r-RMSE was chosen as the criterion  
 194 to minimise during cross-validation.

### 195 **3. Results and discussion**

#### 196 *3.1. Data visualization*

197 Sugar content distributions measured on grape berries of the three vari-  
 198 eties (Fer Servadou, Mauzac and Syrah) can be seen in Figure 4.

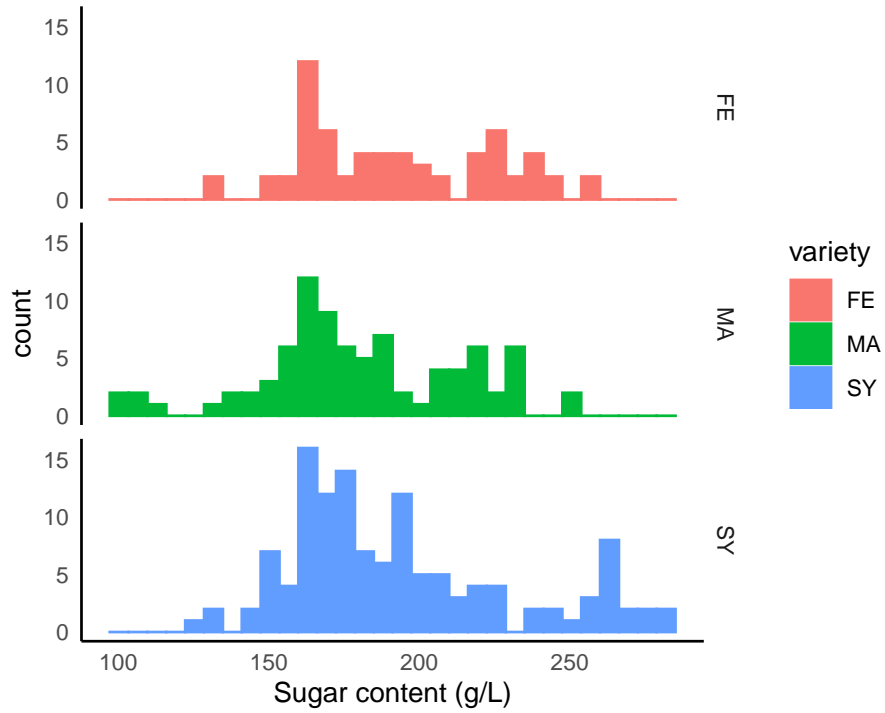


Figure 4: Sugar content (g/L) histograms for the three grape varieties: Fer Servadou (FE), Mauzac (MA) and Syrah (SY)

199 For the three varieties, sugar content values are similar and comprised  
 200 between 100 and 300 g/L. Most values lie between 150 and 200 g/L which  
 201 correspond to expected sugar contents for grape berries at different maturity  
 202 stages. As sugar content values cover the same range for the three varieties,  
 203 comparing results obtained for each grape variety is relevant.

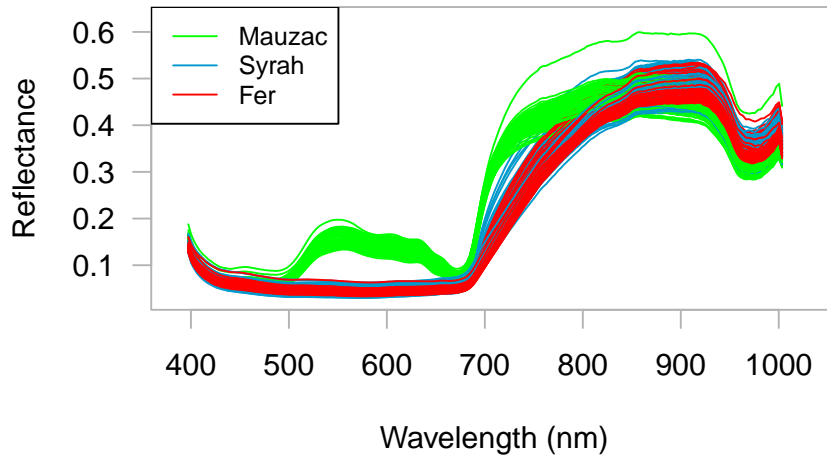


Figure 5: Reflectance spectra of the whole data set

204 Reflectance spectra comprised between 400 nm and 1000 nm of the whole  
 205 data set are shown in figure 5. The two varieties Syrah and Fer Servadou are  
 206 similar over the whole spectral range. However, Mauzac spectra differ from  
 207 the two other varieties. Mainly, reflectance values are higher in the spectral  
 208 range comprised between 500 nm and 680 nm. Moreover, the spectrum slope  
 209 is steeper around 700 nm.

210 Syrah and Fer Servadou are red grape varieties and are known to possess  
 211 high anthocyanin contents. Besides, visible light is largely absorbed by an-  
 212 thocyanins which causes low reflectance values between 500 nm and 700 nm,  
 213 as can be seen on spectra for these two varieties. Spectra visualisation con-  
 214 firms the establishment of prediction models by variety.

215 *3.2. Prediction models*

216 *3.2.1. PLSR models*

217 Table 2 presents the values of the four criteria, latent variable number  
 218 (nLV), prediction error ( $\text{RMSE}_{cv}$ ), median ( $\text{MAD}_{cv}$ ) and determination co-  
 219 efficient ( $\text{R}_{cv}^2$ ), based on the cross-validation of the three grape variety PLSR  
 220 models.

Table 2: Selected criteria obtained for cross-validation of PLSR prediction models on calibration data set: latent variable number (nLV), prediction error ( $\text{RMSE}_{cv}$ ), median ( $\text{MAD}_{cv}$ ) and determination coefficient ( $\text{R}_{cv}^2$ )

Model	Variety	nLV	$\text{RMSE}_{cv}$ (g/L)	$\text{MAD}_{cv}$ (g/L)	$\text{R}_{cv}^2$
PLSR	Syrah	6	9.31	8.09	0.937
	Fer Servadou	7	19.45	15.84	0.623
	Mauzac	5	28.78	18.40	0.298

221 Results show large disparities between grape varieties. Indeed, Syrah has  
 222 the best results with a higher  $\text{R}_{cv}^2$  of 0.937 and lower  $\text{RMSE}_{cv}$  and  $\text{MAD}_{cv}$ , of  
 223 respectively 9.31 g/L and 8.09 g/L. For Fer Servadou variety,  $\text{RMSE}_{cv}$  and  
 224  $\text{MAD}_{cv}$  have values equal to 19.45 g/L and 15.84 g/L, which are nearly twice  
 225 as large as the Syrah values. For Mauzac variety,  $\text{RMSE}_{cv}$  value is equal to  
 226 28.78 g/L and  $\text{MAD}_{cv}$  value is 18.40 g/L. These values are two to three times  
 227 higher than the ones obtained for Syrah.

228 Likewise, determination coefficient values differ between the three grape  
 229 varieties.  $\text{R}_{cv}^2$  obtained for Fer Servadou and Mauzac varieties are equal to  
 230 0.623 and 0.298 respectively, much lower than Syrah result, especially for  
 231 Mauzac. High discrepancies can be seen among the three grape varieties.

232 3.2.2. *RoBoost-PLSR models*

Table 3: Selected criteria obtained for cross-validation of RoBoost-PLSR prediction models on calibration data set: trimming, hyperparameters, latent variable number (nLV), prediction error (r-RMSE<sub>cv</sub>), median (MAD<sub>cv</sub>) and determination coefficient (r-R<sub>cv</sub><sup>2</sup>)

Model	Variety	Trimming	Hyperparameters ( $\alpha$ ; $\beta$ ; $\gamma$ )	nLV	r-RMSE <sub>cv</sub> (g/L)	MAD <sub>cv</sub> (g/L)	r-R <sub>cv</sub> <sup>2</sup>
RoBoost-PLSR	Syrah	5%	Inf; 4; 6	6	8.57	6.86	0.951
	Fer	15%	Inf; 4; Inf	7	12.5	14.3	0.844
	Mauzac	20%	Inf; 4; 6	6	12.1	15.50	0.794

233 The table 3 shows parameters from cross validation of RoBoost-PLSR  
 234 method. These parameters are trimming percentage, hyperparameters ( $\alpha$ ,  $\beta$ ,  
 235  $\gamma$ ), latent variable number, r-RMSE<sub>cv</sub>, MAD<sub>cv</sub> and r-R<sub>cv</sub><sup>2</sup>. Hyperparameter  
 236 values  $\alpha$ ,  $\beta$  and  $\gamma$  are respectively equal to infinite, 4, 6 for Syrah; infinite,  
 237 4, infinite for Fer Servadou; and infinite, 4, 6 for Mauzac. Hyperparameters  
 238  $\alpha$ ,  $\beta$  and  $\gamma$  are selective criteria for outlier detection respectively on  $\mathbf{X}$ ,  $\mathbf{Y}$   
 239 and leverage points. The lower the hyperparameter, the higher the outlier  
 240 number identified by the model. Conversely, an infinite value means no  
 241 outlier identified. This implies that there is no outlier detected by cross-  
 242 validation on  $\mathbf{X}$  for the three grape varieties ( $\alpha = \text{Inf}$ ). However, this is not  
 243 the case for  $\mathbf{Y}$  (i.e. measures of sugar content), where  $\beta = 4$  for the three  
 244 grape varieties and means that several outliers are detected. Indeed, outliers  
 245 could be introduced during sugar content measurements by densimetric bath.  
 246 Finally, based on hyperparameter  $\gamma$  values, no leverage point is identified for  
 247 Fer Servadou variety whereas some are detected for Mauzac and Syrah.

248 Among the three grape varieties, Syrah obtains the best results with a  
 249 r-RMSE<sub>cv</sub> equals to 8.57 g/L which corresponds to the lowest value. Further-



250 more, this value is slightly lower than the one obtained with the PLSR model  
251 (see table 2). Regarding Fer Servadou and Mauzac varieties,  $r\text{-RMSE}_{cv}$  values  
252 are close to each other with values equal to 12.5 g/L and 12.1 g/L respec-  
253 tively. These results are improved compared to the values previously obtained  
254 with PLSR cross-validation (see table 2) and closer to Syrah value. Indeed,  
255 during the cross-validation procedure, RoBoost-PLSR deals with outliers by  
256 attributing weights to observations.

257 Besides, the same analysis can be done for  $r\text{-R}_{cv}^2$  values. Syrah obtains  
258 the best value with 0.951 whereas Fer Servadou and Mauzac obtain 0.844  
259 and 0.764. Again, these values are lower and closer to each other than the  
260 ones previously obtained with PLSR cross-validation (see table 2).

261 Finally, the comparison of both cross-validation results, PLSR (table 2)  
262 and RoBoost-PLSR (table 3), indicates that RoBoost-PLSR decreases the  
263 prediction quality discrepancies between grape varieties. This result confirms  
264 the presence of outlier points among Fer Servadou and Mauzac data sets.

### 265 3.2.3. *Observed vs. predicted values of calibration models*

266 The visualisation of observed values by predicted values shown in fig-  
267 ure 6 helps to better understand criteria values obtained in cross-validation  
268 (tab 2 and 3). It provides a means to assess model quality, observation by  
269 observation.

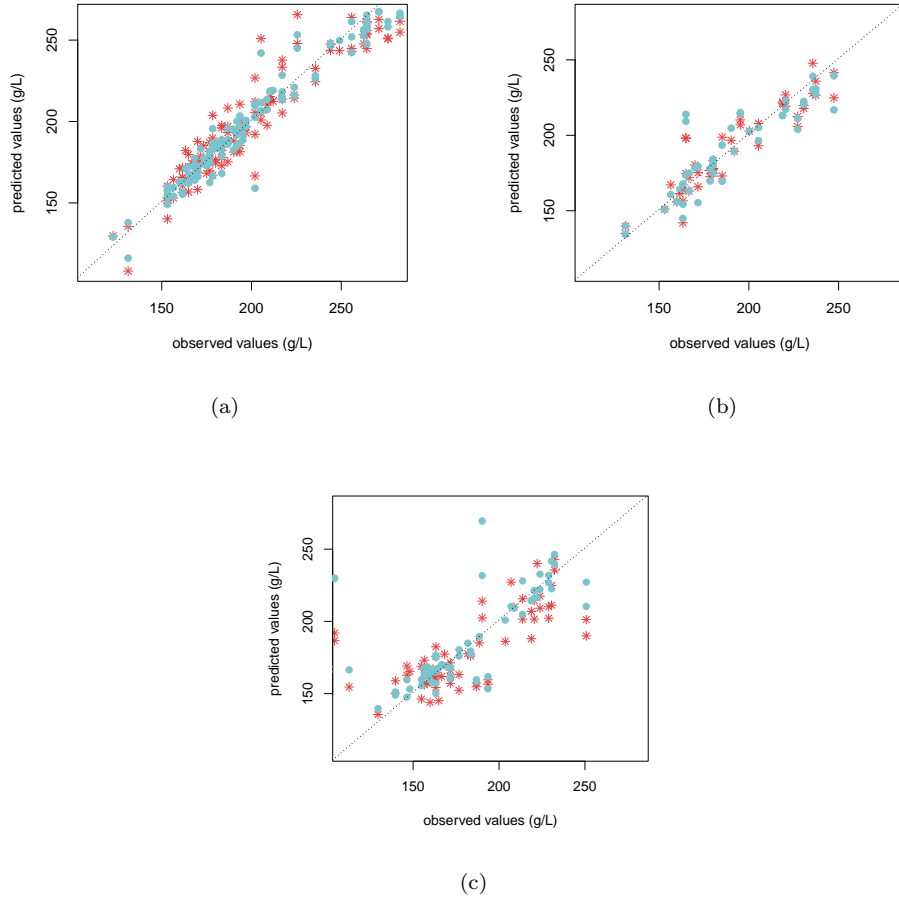


Figure 6: Sugar content observed values versus predicted values based on (\*, red) PLSR and (•, blue) RoBoost-PLSR for the three grape varieties: (a) Syrah, (b) Fer, (c) Mauzac

270 Figures 6a, 6b and 6c compare predicted values of the calibration data  
 271 set obtained with RoBoost-PLSR and PLSR for Syrah, Fer and Mauzac  
 272 respectively.

273 Regarding Syrah variety (fig. 6a), relationship between predicted  $\mathbf{Y}$  and  
 274 observed  $\mathbf{Y}$  is linear and point dispersion is the lowest obtained for the three

275 varieties and this with RoBoost and PLSR. The same holds true for Fer  
276 Servadou variety (fig. 6b), where a linear tendency between predicted  $\mathbf{Y}$  and  
277 observed  $\mathbf{Y}$  can be noticed. However, several points obtained with PLSR  
278 deviate from this tendency. These same points are further deviated from the  
279 linear trend with RoBoost-PLSR. The identified points deviating from the  
280 linear tendency are possibly outliers (also called vertical outliers) or leverage  
281 points.

282 As far as Mauzac is concerned (fig. 6c), the relationship between pre-  
283 dicted  $\mathbf{Y}$  and observed  $\mathbf{Y}$  deviates from a linear tendency with several points  
284 strongly dispersed. Some points deviate more strongly from this trend than  
285 previously. These same points are even further apart with RoBoost-PLSR,  
286 while an improvement appears on the majority of the other points. These  
287 points are clearly identified by the RoBoost-PLSR method as vertical outliers  
288 or leverage points. These points are weighted when building the prediction  
289 model with RoBoost-PLSR. RoBoost-PLSR thus improves the linearity be-  
290 tween predicted and observed values.

291 By comparing these three figures (6a, 6b and 6c), calibration data set  
292 which have the best predictions are Syrah first, then Fer Servadou and finally  
293 Mauzac. This confirms the results obtained in cross-validation (table 3).

### 294 *3.3. Model prediction on independent test sets*

295 For each grape variety, PLSR and RoBoost-MLSR models previously pa-  
296 rameterized during cross-validation steps and calibrated with calibration data  
297 sets are now tested on the test data sets.

Table 4: Performance evaluation of PLSR and RoBoost-PLSR prediction models on test data sets: latent variable number (nLV), prediction error ( $\text{RMSE}_p$ ), median ( $\text{MAD}_p$ ) and determination coefficient ( $R_p^2$ )

Model	Variety	nLV	$\text{RMSE}_p$ (g/L)	$\text{MAD}_p$ (g/L)	$R_p^2$
PLSR	Syrah	6	5.36	4.99	0.971
	Fer Servadou	7	11.69	12.04	0.788
	Mauzac	5	15.61	10.97	0.690
RoBoost PLSR	Syrah	6	3.14	3.38	0.990
	Fer Servadou	7	10.20	10.50	0.848
	Mauzac	6	7.58	9.36	0.927

298 Table 4 outlines the prediction quality of both PLSR and RoBoost-PLSR  
 299 models, applied to the test data sets of each grape variety. To this end,  
 300 the following criteria are presented: latent variable number (nLV),  $\text{RMSE}_p$ ,  
 301  $\text{MAD}_p$  and  $R_p^2$ .

302 First of all, a higher heterogeneity among results can be noticed for PLSR  
 303 models than for RoBoost-PLSR ones. Regarding PLSR models, Syrah has  
 304 the best performances, with the lowest  $\text{RMSE}_p$  and  $\text{MAD}_p$  values, equal to  
 305 5.36 g/L and 4.99 g/L respectively, and the highest  $R_p^2$  value, equals to 0.971.  
 306 Fer Servadou and Mauzac have  $\text{RMSE}_p$  and  $\text{MAD}_p$  values, two to three times  
 307 higher than Syrah ones.  $\text{RMSE}_p$  are equal to 11.69 g/L and 15.61 g/L for Fer  
 308 and Mauzac respectively, whereas  $\text{MAD}_p$  values are 12.04 g/L and 10.97 g/L  
 309 respectively. Moreover,  $R_p^2$  are lower than for Syrah, with respective values of  
 310 0.788 and 0.690. As said before during cross-validation step (section 3.2.1),  
 311 discrepancies among varieties arise with PLSR models.

312 As far as RoBoost-PLSR models are concerned, all three varieties pre-  
313 dictions are improved compared to PLSR models. This is all the more true  
314 in the case of Mauzac and Syrah. Indeed, Syrah obtains  $R_p^2$ ,  $RMSE_p$  and  
315  $MAD_p$  values equal to 0.990, 3.14 g/L and 3.38 g/L respectively. Besides,  
316 Fer Servadou obtains  $R_p^2$ ,  $RMSE_p$  and  $MAD_p$  values equal to 0.848, 10.20  
317 g/L and 10.50 g/L. Lastly, Mauzac obtains  $R_p^2$ ,  $RMSE_p$  and  $MAD_p$  values  
318 equal to 0.927, 7.58 g/L and 9.36 g/L. These last results outperform PLSR  
319 models and lead to performances close to Syrah ones.

320 It is worth noticing that PLSR model allows to predict sugar content for  
321 Syrah in an effective way. This implies that there is a limited number of  
322 outlier points in the data set. The same does not hold true for Fer Servadou  
323 and Mauzac, as noticed in figure 6. In all cases, RoBoost-PLSR method  
324 allows to build predictive models with higher performances than PLSR when  
325 dealing with outliers points among calibration data sets.

#### 326 4. Conclusion

327 The potential of RoBoost-PLSR method to calibrate prediction models  
328 in the presence of outliers in an agronomic context was studied. The method  
329 was evaluated on a case of Vitis Vinifera grapes berry maturity context and  
330 especially to predict berry sugar content. RoBoost-PLSR method was com-  
331 pared to the reference method (PLSR) on spectral data from berries of three  
332 grape varieties (Syrah, Mauzac, Fer Servadou). For these three varieties,  
333 results obtained from RoBoost-PLSR method outperformed those from the  
334 PLSR method. The improvements in the prediction of sugar content for Fer  
335 Servadou and Mauzac are the most significant due to a potentially higher

336 outliers number in the calibration set.

337 This study validates the use of the RoBoost-PLSR method for monitoring  
338 grapes berries maturity in the laboratory. The advantage of this method is  
339 to provide good prediction models despite outliers presence. Despite optimal  
340 measurement conditions, outliers were identified as detrimental to the model  
341 calibration. This method could be challenged on data collecting directly in  
342 the field where measurement conditions most often lead to outliers. This  
343 would open up multiple possibilities for the use of VIS-NIR spectroscopy  
344 for agronomic applications. Other robust methods could be compared to  
345 RoBoost-PLSR in such an application context. This method also contributes  
346 to perspectives in other disciplines where multivariate data is involved such  
347 as analytical chemistry.

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