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## Prediction of fruit texture with training population optimization for efficient genomic selection in apple

Morgane Roth, Mario Di Guardo, Walter Guerra, H el ene Muranty, Andrea Patocchi, Fabrizio Costa

► **To cite this version:**

Morgane Roth, Mario Di Guardo, Walter Guerra, H el ene Muranty, Andrea Patocchi, et al.. Prediction of fruit texture with training population optimization for efficient genomic selection in apple. *BioRxiv*, 2019, 10.1101/862193 . hal-02624727

**HAL Id: hal-02624727**

**<https://hal.inrae.fr/hal-02624727>**

Submitted on 26 May 2020

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1           **Prediction of fruit texture with training population optimization for efficient**  
2                           **genomic selection in apple**

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5 Morgane Roth<sup>1</sup>, Mario Di Guardo<sup>2,3</sup>, Walter Guerra<sup>4</sup>, H el ene Muranty<sup>5</sup>, Andrea Patocchi<sup>1</sup>,  
6 Fabrizio Costa<sup>2</sup>

7       1. Plant Breeding Research Division, Agroscope, Wadenswil, Switzerland

8       2. Department of Genomics and Biology of Fruit Crops, Research and Innovation Centre,  
9       Fondazione Edmund Mach (FEM), Via E. Mach 1, 38010 San Michele all'Adige, Italy

10      3. Dipartimento di Agricoltura, Alimentazione e Ambiente, University of Catania,  
11      Catania, Italy

12      4. Research Centre Laimburg, Laimburg 6, 39040 Auer, Italy

13      5. IRHS, INRAE, Agrocampus-Ouest, Universit e d'Angers, SFR 4207 QuaSaV,  
14      Beaucouz e, France

15  
16 **Corresponding author:** Morgane Roth, mroth@posteo.net, +33769852443

17 **Further e-mails:** Mario Di Guardo: mario.diguardo@unict.it ; Walter Guerra:

18 walter.guerra@laimburg.it ; H el ene Muranty: helene.muranty@inra.fr ; Andrea Patocchi:

19 andrea.patocchi@agroscope.admin.ch ; Fabrizio Costa: fabrizio.costa@fmach.it.

20  
21  
22  
23 Date of submission: 02.12.2019

24 Number of tables: 3

25 Number of figures: 5, all on color-online only

26 Word count: 6,606

27 Number of supplementary tables: 7

28 Number of supplementary figures: 7

29

30 **Title**

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32 Prediction of fruit texture with training population optimization for efficient genomic selection in apple

33

34 **Running title**

35 Genomic prediction for apple texture

36 **Keywords**

37 Apple, genomic prediction, rrBLUP, multi-trait, fruit texture, relatedness, training set

38 optimization

39 **Abbreviations**

<u>Full name</u>	<u>Abbreviation</u>
Acoustic Linear Distance	ALD
Acoustic Max Pressure	APMax
Acoustic Mean Pressure	APMean
Number of Acoustic Peaks	ANP
Bayesian Information Criterion	BIC
Best Linear Unbiased Predictor	BLUP
Collection	COLL
Discriminant Analysis of Principal Components	DAPC
Final Force	FF
Force Linear Distance	FLD
Initial Force	FI
Max Force	FMax
Mean Force	FMean
Single Nucleotide Polymorphism	SNP
Principal Component	PC
Principal Component Analysis	PCA
Number of Force Peaks	FNP
Test Set	TS
Training Set	TRS
Young Module	YM

40

41 **Highlight**

42 A genomic selection study, together with the optimization of the training set, demonstrated

43 the possibility to accurately predict texture sub-traits valuable for the amelioration of fruit

44 quality in apple.

45

46

47 **Abstract**

48 Texture plays a major role in the determination of fruit quality in apple. Due to its  
49 physiological and economic relevance, this trait has been largely investigated, leading to the  
50 fixation of the major gene PG1 controlling firmness in elite cultivars. To further improve fruit  
51 texture, the targeting of an undisclosed reservoir of loci with minor effects is compelling. In  
52 this work, we aimed to unlock this potential with a genomic selection approach by predicting  
53 fruit acoustic and mechanical features as obtained with a TA.XT*plus* texture analyzer in 537  
54 individuals genotyped with 8,294 SNP markers. The best prediction accuracies following  
55 cross-validations within the training set (TRS) of 259 individuals were obtained for the  
56 acoustic linear distance (0.64). Prediction accuracy was further improved through the  
57 optimization of TRS size and composition according to the test set. With this strategy, a  
58 maximal accuracy of 0.81 was obtained when predicting the synthetic trait PC1 in the family  
59 ‘Gala × Pink Lady’. We discuss the impact of genetic relatedness and clustering on trait  
60 variability and predictability. Moreover, we demonstrated the need for a comprehensive  
61 dissection of the complex texture phenotype and the potentiality of using genomic selection to  
62 improve fruit quality in apple.

63

64 **Introduction**

65 Fruits, during maturation and ripening, undergo a complex series of genetically  
66 programmed events contributing to their attractiveness and suitability for human  
67 consumption. Amongst the various physiological and physical changes, fruit texture is  
68 certainly the most important and investigated traits, especially in apple. A favorable texture is  
69 in fact highly appreciated by consumers, enabling, moreover, a long-term storage.

70 Texture can nowadays be dissected into two groups of sub-traits, mechanical and  
71 acoustic, contributing to distinguish between firm (based on mechanical sub-traits) and crispy  
72 (based on acoustic sub-traits) types of apples. These texture parameters have been already  
73 described and validated in apple (Costa *et al.*, 2011, 2012), and were implemented in QTL-  
74 mapping studies carried out with bi-parental populations (Longhi *et al.*, 2012) as well as more  
75 structured approaches, such as Pedigreed Based Analysis (PBA) and Genome-Wide  
76 Association Studies (GWAS, Kumar *et al.*, 2013; Migicovsky *et al.*, 2016; Amyotte *et al.*,  
77 2017; Di Guardo *et al.*, 2017; McClure *et al.*, 2019). These works elucidated the complex  
78 genetic control of the fruit texture in apple, identifying a large number of QTLs distributed  
79 over the apple genome, with the most relevant regions located on chromosome 3, 10 and 16.  
80 This genetic complexity is moreover reflected in the regulation of the cell-wall and middle

81 lamella disassembling, a physiological process orchestrated by a myriad of cell-wall  
82 modifying enzymes (Giovannoni, 2001; Costa *et al.*, 2010a). This highly polygenic control  
83 can hamper the selection assisted by molecular markers in breeding activities programmed to  
84 ameliorate fruit texture performance (Iwata *et al.* 2016). In the QTL mapping studies carried  
85 out to date, a major region was located on chromosome 10, close to the polygalacturonase  
86 locus (Costa *et al.*, 2010b; Longhi *et al.*, 2013). This QTL explains a high (about 40%) yet  
87 incomplete part of the texture variance, leaving room for better harnessing this trait. As  
88 introduced by Di Guardo *et al.* (2017), in modern breeding programs this locus has been fixed  
89 through successive rounds of *ad-hoc* crossing and selection. In turn, the phenotypic variance  
90 of modern families, obtained by crossing valuable parents for texture performance, might now  
91 be under the control of other loci with minor-effect. Selection based on QTLs associated to  
92 this trait can therefore be limited by the fact that QTL-based approaches ignore small effect  
93 QTLs possibly underlying the control of such traits (Desta & Ortiz, 2014). To face this  
94 limitation, an alternative approach for genome-assisted breeding known as genomic selection  
95 (GS) has been introduced by the seminal work of Meuwissen *et al.* (2001). In contrast to  
96 marker assisted selection, GS defines the estimation of the genetic merit of an individual  
97 taking into account all genome-wide distributed genetic markers, making it especially relevant  
98 for complex traits (Heffner *et al.*, 2009). GS considers two sets of individuals: the training set  
99 (TRS), genotyped and phenotyped to train a prediction model, and the test set (TS, also called  
100 validation set), represented by individuals only genotyped on which the genomic estimated  
101 breeding value (GEBVs) is estimated (Heffner *et al.*, 2009; Crossa *et al.*, 2017). In principle,  
102 the most favorable scenario for GS is to predict highly heritable traits in a TS highly related to  
103 the TRS. While trait heritability can be increased (to a certain extent) by more precise and  
104 more repeated phenotyping, relatedness between TS and TRS can be optimized with different  
105 strategies. Dedicated approaches and tools have been proposed to address this issue based on  
106 optimization parameters (Laloë, 1993; Rincent *et al.*, 2012; Isidro *et al.*, 2015) and algorithms  
107 (Akdemir *et al.*, 2015). In theory, it could thus be feasible to acquire phenotypic and  
108 genotypic data for a highly diverse TRS in the first place and, in the second place, to retain  
109 individuals of the optimal TRS for a given TS *in silico*.

110 GS has been largely applied in major crops for primary traits such as yield (Crossa *et*  
111 *al.*, 2017). In perennial species, GS would have a great potential in improving the breeding  
112 efficiency due to their long generation time (McClure *et al.*, 2014). It has been pioneered in  
113 forest trees (reviewed in Grattapaglia, 2017) and more recently in fruit trees such as crops  
114 from the *Malus*, *Citrus* and *Pyrus* genera (Muranty *et al.* 2015; Minamikawa *et al.*, 2017,

115 2018). GS has also been recently employed to investigate fruit quality in tomato (Duangjit *et*  
116 *al.*, 2016), while in apple standard fruit pomological traits were predicted using 8 to 20 full-  
117 sib families as training populations (Kumar *et al.*, 2012, 2015; Muranty *et al.*, 2015). In apple,  
118 low to high prediction accuracies were obtained depending on the cross-validation design and  
119 on trait heritability. Among these studies, fruit texture was only partially addressed via  
120 classical fruit firmness measurements (Kumar *et al.*, 2012, 2015; McClure *et al.*, 2018) and  
121 sensorial evaluation (Kumar *et al.*, 2015).

122 In this work, we attempted to predict fruit texture in 6 full-sib families with a diverse  
123 training set considering several acoustic and mechanical traits dissecting fruit texture. Further,  
124 we explored the methodological improvements that can be made to optimize the TRS  
125 according to the TS, which contributed to improve prediction accuracies. In this context, we  
126 discussed the feasibility of genomic selection for ameliorating fruit quality through molecular  
127 assisted breeding programs.

128

## 129 **Materials and methods**

130

### 131 *Plant Material*

132 The plant material and phenotyping strategies used in this work have been detailed in  
133 previous works (Costa *et al.*, 2011; Longhi *et al.*, 2012; Di Guardo *et al.*, 2017). Briefly, two  
134 types of plant materials have been used in this survey. The first was an apple collection  
135 represented by 259 accessions planted in three replicates at the experimental orchards of the  
136 Fondazione Edmund Mach (Trento) in the Northern part of Italy. The second type of plant  
137 material consisted of 6 full-sib biparental families, for a total of 278 offsprings. Two ('FjDe':  
138 'Fuji' x 'Delectable' and 'FjPL': 'Fuji' x 'Pink Lady') were located at the Fondazione Edmund  
139 Mach (same orchard as the collection), while the other four ('GaPL': 'Royal Gala' x 'Pink  
140 Lady', 'GaPi': 'Royal Gala' x 'Pinova', 'FjPi': 'Fuji' x 'Pinova' and 'GDFj': 'Golden  
141 Delicious' x 'Fuji') were planted at the experimental orchard of the Laimburg Research  
142 Center (Bolzano), located in the same area with near-identical climatic and pedological  
143 conditions. At the time of the analysis, all plants (from both collection and families, together  
144 named as 'population' here) were in a productive and adult phase. Fruit texture was  
145 phenotyped in 2012, 2013 and 2015 for the collection, and in 2012 and 2013 for 'FjDe' and  
146 'FjPL' and in 2012 and 2014 for the four remaining families (Table 1). Unlike the collection,  
147 each offspring belonging to the six families was represented by a single tree (no replicates).  
148 All plants, from both collection and bi-parental families, were grafted on 'M9' rootstock and

149 grown according to conventional horticultural management for plant training, pruning and  
150 pest-disease control.

151 Fruits were harvested from each plant at the time of the physiological ripening stage,  
152 established according to standard horticultural fruit quality parameters, such as the change in  
153 color of the skin, seeds and flesh, fruit firmness value and the iodine coloration index  
154 indicating the internal starch degradation. After harvest, fruits were stored for two months at  
155 2°C with 95% of relative humidity.

156

### 157 *Texture phenotyping*

158 The texture performance of the apple fruit was phenotypically dissected into  
159 mechanical and acoustic sub-traits with the use of a texture analyzer TA.XT*plus* (Stable  
160 MicroSystems Ltd., Godalming, UK) equipped with an acoustic envelop device AED (Stable  
161 MicroSystems Ltd., Godalming, UK), as described in Costa *et al.* (2011). For each genotype  
162 included in the population, a homogeneous set of five apples was collected. Four identical  
163 discs were isolated per fruit, avoiding seeds, seed cavity tissues or skin, for a total of 20  
164 measurements per genotype (5 biological replicates and 4 technological replicates). Each  
165 texture profile was then digitally elaborated identifying 12 texture measurements (*i. e.* ‘sub-  
166 traits’), four related to the acoustic performance and eight to the mechanical force-  
167 displacement. In brief, the mechanical sub-traits were coded as: initial, final, maximum and  
168 mean force (related to the different force values associated to the different parts of the force-  
169 displacement profile), area, force linear distance (derived length of the profile), Young’s  
170 module (also known as elasticity module) and number of force peaks. The acoustic sub-traits  
171 were maximum and mean acoustic pressure, acoustic linear distance and number of acoustic  
172 peaks. A more exhaustive and complete description of the texture sub-traits is reported in  
173 Costa *et al.* 2011.

174

### 175 *SNP genotyping*

176 The DNA employed for the genotyping of each individual considered in this survey  
177 was isolated from young leaves collected at the beginning of the vegetative phase with the  
178 Qiagen DNeasy Plant Kit and further quantified with a Nanodrop ND-8000  
179 (ThermoScientific, USA). SNP markers were genotyped through the HiScan (Illumina, USA)  
180 and the apple 20K SNP chip Infinium array (Illumina, USA) assembled within the framework  
181 of the European project FruitBreedomics (Bianco *et al.*, 2014). The SNP pattern was initially  
182 analyzed with the software GenomeStudio and further re-edited with ASSiST (Di Guardo *et*

183 *al.*, 2015). SNPs with minor allele frequencies lower than 0.05 and call rate below 0.2 were  
184 filtered out with the package ‘snpStats’ (Clayton, 2019). The final set of markers successfully  
185 recovered in the population consisted in 8,294 biallelic SNPs.

#### 186 *Analysis of the fruit texture sub-traits*

187 We used a mixed linear model to get the best linear unbiased predictors (BLUPs) of  
188 each individual's genotypic value. For each apple measured, we first calculated the mean over  
189 the four technical replicates to retain only the biological replication level in the model. Each  
190 of the twelve mechanical or acoustic sub-traits, considered as ‘Y’, was explained by the  
191 genotype as random effect, the trial (location by year) as fixed effect and the random effect of  
192 the error as:  $Y_{i,j,k} = \mu + genotype_i + trial_j + e_{i,j,k}$  (1), with each phenotypic datapoint  
193  $Y_{i,j,k}$  explained by the mean  $\mu$ , the genotype  $i$ , the trial  $j$  and the error for each combination of  
194 genotype, trial and replicate ( $k$ , *i.e.* a single apple). This model was fitted separately for all  
195 traits with the ‘lme4’ R-package (Bates *et al.*, 2015). Broad-sense heritability was calculated  
196 as  $h^2 = \frac{\sigma_g^2}{\sigma_g^2 + \sigma_e^2/n_{rep}}$  (2), where  $\sigma_g^2$  is the genotypic variance,  $\sigma_e^2$  is the error variance and  $n_{rep}$

197 the mean number of repetitions.

198 Principal component analysis (PCA) was performed on BLUPs with the ‘FactorMiner’  
199 R-package (Lê *et al.*, 2008). Only values from the collection were used to create the principal  
200 components, while the families were plotted as supplementary individuals with principal  
201 components (PC) coordinates calculated on the base of the PCs initially built with the  
202 collection. Coordinates of individuals on the first and the second PCs (‘PC1’ and ‘PC2’) were  
203 used for prediction and subsequently named ‘synthetic’ traits.

204

#### 205 *Kinship and clustering analyses*

206 The realized additive relationship was calculated with the ‘A.mat’ function of the  
207 ‘rrBLUP’ package (Endelman, 2011) and depicted in a heatmap plot obtained with the R-  
208 function ‘heatmap.2’ (package ‘gplots’, Warnes *et al.*, 2016). Genetic clustering was further  
209 assessed in the collection with a discriminant analysis of principal components (DAPC,  
210 Jombart *et al.*, 2010), carried out with the R-package ‘adegenet’ (Jombart, 2008) using the  
211 entire set of 8,294 markers. In the first step, six significant clusters were retained with the  
212 function ‘find.clusters’ using 300 principal components and selecting the number of clusters  
213 with the highest likelihood (based on the Bayesian information criterion value-BIC, Fig. S1).  
214 Out of these variables, 150 were retained and employed in the clustering computed with the



215 ‘dapc’ function, which created five principal components that maximized the inter-cluster  
216 distance while minimizing the inter-individual distance within each cluster. The assignment of  
217 offsprings to clusters was obtained with the function ‘predict\_dapc’. Pairwise Fst values  
218 between clusters were then computed with the entire SNP set with the function  
219 ‘pairwise.WCfst’ from R-package ‘hierfstat’ (Yang, 1998, Goudet 2005).

220

### 221 *Prediction models*

222 Genomic predictions were computed through two models implemented in the rrBLUP  
223 framework, as reported in Endelman *et al.* 2011 (and ‘rrBLUP R’-package):

224

$$225 \quad Y = \mu + Zu + e \quad (3), \text{ model A}$$

$$226 \quad Y = \mu + X\beta + Zu + e \quad (4), \text{ model B}$$

227

228 where  $Y$  is the vector of BLUPs of the genotypic values ( $n \times 1$ ),  $\mu$  is the mean of the  
229 phenotype,  $W$  is the  $n \times p$  incidence matrix linking the genotypes to observations of  $Y$ ,  $G$   
230 contains the allelic states of the marker loci (additive coding -1,0,1),  $u$  the  $p \times 1$  vector of  
231 random marker effects with  $u \sim N(0, I\sigma_u^2)$ , and  $e$  is a  $n \times 1$  vector of random errors. Model  
232 (B), contains also  $X$ , the  $n \times c$  incidence matrix for cluster assignment of each individual,  
233 where  $c$  is the number of clusters and  $\beta$  is the  $c \times 1$  vector of the cluster fixed effects.

234 A 5-fold cross-validation was applied within the collection with both model (A) and  
235 (B) respectively and repeated 100 times. For predicting each family (considered then as TS),  
236 three different TRS composition rules, named as “scenarios”, were tested using the two  
237 models *without a priori genetic information on individuals*. In scenario 1, each family was  
238 predicted using the collection only. In scenario 2, 30% of individuals of the predicted family  
239 were instead added to the collection in the TRS while the remaining 70% formed the TS. In  
240 scenario 3, a single half-sib family (*e.g.* ‘GaPL’ is half-sib with ‘FjPL’ and ‘GaPi’) was added  
241 to the collection to form the TRS, leading to two to four TRS possibilities (and accuracy  
242 values). To illustrate the scenarios taking ‘GaPi’ as an example, scenario 1 corresponded to  
243 [TRS = COLL // TS = ‘GaPi’] (one accuracy estimation only), scenario 2 corresponded to  
244 [TRS = 30% ‘GaPi’ offsprings + COLL // TS = 70 % remaining offsprings of ‘GaPi’]  
245 (sampling of the 30% repeated 100 times, giving 100 estimations of the accuracy), and  
246 scenario 3 corresponded to [TRS = ‘GaPL’ or ‘FjPi’ + COLL // TS = ‘GaPi’] (resulting here  
247 in the estimation of two accuracy values).

248 TRS optimization was then performed *with a priori genetic information on individuals*  
249 by varying TRS size with different optimization methods relying on the prediction model A.  
250 To this end, a relatedness-driven and a principal component-driven approaches were adopted.  
251 The relatedness-driven approach was tested in three different manners: (i) by starting with the  
252 10 most-related individuals and adding single individuals with decreasing mean relationship  
253 to the family, or (ii) with decreasing maximum relationship to the family (N=10 to N=259), or  
254 (iii) by starting with a TRS composed of the most related cluster and adding less and less  
255 related clusters successively (final TRS size N=259). In the principal component-driven  
256 approach, TRS individuals were selected with increasing TRS size using a protocol by  
257 Akdemir (R-package ‘STPGA’, 2019). The optimal TRS with increasing size from 10  
258 individuals to 259 with increments of 20 individuals was chosen based on the five principal  
259 components obtained with DAPC analysis and using the ‘CDmean’ design criteria and the  
260 function ‘GenAlgForSubsetSelection’. Here, individuals were chosen independently for each  
261 TRS size, meaning that we did not proceed to a gradual enrichment of the TRS.

262 All accuracy values were based on Pearson correlation calculated between observed  
263 values (*i.e.* BLUPs of genotypic values) and predicted values of the TS individuals. When  
264 standard deviations were not available, we calculated an approximate 95% confidence interval  
265 of the correlation coefficient with a Fisher’s Z-transformation (‘cor.test’ function in base R).  
266 Calculations were performed in R (R Core Team, 2014) and graphs were created with the R-  
267 package ‘ggplot2’ (Wickham, 2016).

## 268 **Results**

### 269 *Fruit texture phenotypic dissection* 270

271 The fruit texture phenotypic data used in this survey were represented by the analysis  
272 of multi-trait features accurately dissected into 4 acoustic and 8 mechanical sub-traits (Table  
273 2, Table S1). A mixed linear model was used to obtain BLUPs of genotypic values used in the  
274 further analyses. The texture sub-traits showed an overall high heritability, spanning from  
275 0.90-0.96 for the entire population (collection and families) to 0.88-0.94 for the apple  
276 accessions included in the collection (Table 2). In order to visualize the diversity and  
277 inheritance of fruit texture profiles, a principal component analysis (PCA) was performed  
278 using the twelve textural sub-traits measured in the collection, while individuals from families  
279 were considered as supplementary individuals (see also Di Guardo et al. 2017, Fig. 1). In this  
280 analysis, the first PC axis (PC1), explaining 80.5% of phenotypic variability, comprehensively  
281 summarizing the general variability of the twelve phenotypic variables. The second axis

282 (PC2), instead, mainly differentiated the acoustic from mechanical sub-traits, explaining a  
283 smaller, yet substantial, portion of the phenotypic variability (12.7%, Fig. 1A).

284 In the distinction between the two types of texture sub-traits (mechanical and acoustic)  
285 by PC2, it is worth noting that one mechanical variable (FNP) was oriented together with the  
286 acoustic group. FNP was in fact more correlated with acoustic sub-traits (mean correlation  
287 0.77) than with the rest of the mechanical ones (mean correlation 0.69, Fig. 1A). Individuals  
288 of the population were present in the four quadrants of the PCA 2D-plot, identifying different  
289 types of texture: mealy (negative PC1), predominantly firm (positive PC1 and negative PC2)  
290 and predominantly crispy (positive PC1 and positive PC2, Fig. 1B). With this regard, the  
291 distribution of texture profiles indicated that the collection is mainly composed of individuals  
292 with low to moderate crispiness and firmness at the exception of few outliers. It is also  
293 important to note that variation on the PC2 axis is much lower for accessions having a  
294 negative PC1 value, illustrating that mealy apples cannot be crispy (Fig. 1B).

295 The six parental cultivars, known to have different texture profiles after two months of  
296 storage, were, as expected, plotted over the different quadrants of the PCA 2D-plot (Fig. 1C).  
297 ‘Delectable’ and ‘Golden Delicious’ were plotted in the area corresponding to the mealy type of  
298 apple, while ‘Royal Gala’ was instead grouped with moderately firm apples. ‘Fuji’, ‘Pink  
299 Lady’ and ‘Pinova’ were instead positioned in the positive quadrant for both PC1 and PC2,  
300 corresponding to the crispy type of apple. The populations originated by the controlled cross  
301 of these varieties were also distributed over the PCA plot with specific orientations (Fig. 1B-  
302 C). In particular, ‘FjPL’ offsprings were mostly projected towards the ‘firm quadrant’, while  
303 ‘GDFj’ was more oriented in the ‘crispy quadrant’ (Fig. 1B). Moreover, the segregation of the  
304 families was very variable with regard to their corresponding parental profiles (Fig. 1C).  
305 While ‘GDFj’ was the only family showing a classic type of segregation (intermediate  
306 between the parents), the distributions of the other families were more similar to one of the  
307 two parents (‘FjDe’ and ‘GaPi’), with a varying number of offsprings being of transgressive  
308 type (‘FjDe’, ‘GaPL’, ‘FjPi’ and ‘FjPL’). In particular, while ‘Fuji’ and ‘Pink Lady’ showed a  
309 very similar texture profile on PC1 (2.99 and 3.14 respectively), major differences were  
310 observed on the PC2 (1.6 and 0.51 respectively, Fig. 1C, Table S1). Variation in the texture  
311 performance of ‘FjPL’ offsprings was also observed on the PC2 axis, although with a much  
312 broader variation with regards to ‘Fuji’ and ‘Pink Lady’. Accordingly, apples of this family  
313 were overall firm to very firm while having a very low to very high crispiness (Fig. 1C, Table  
314 S1, Fig. S2).

315

316 *Additive relationship and genetic clustering in the population*

317         The accuracy of genomic prediction is highly correlated to the level of relatedness  
318 between the training and the test sets (TRS and TS). To identify the overall patterns of  
319 relatedness between families and the collection, a clustering analysis of all the individuals  
320 based on their pairwise additive relationship was performed (Fig. 2). The parental cultivar  
321 ‘Royal Gala’ was found to be the most related to the rest of the collection (mean additive  
322 relatedness  $-6.32E-4$ ), while ‘Fuji’ was the most distantly related (mean additive relatedness -  
323 0.102, Table S2). Accordingly, ‘Royal Gala’-related families were more closely related to the  
324 collection respect to the four ‘Fuji’-related families, plotted together on the top-right panel of  
325 the heatmap (Fig. 2). Mean additive relationship values for each family reflected the patterns  
326 observed on the heatmap, namely higher values for ‘GaPi’ and ‘GaPL’ ( $-0.021$  to  $-0.020$ ) and  
327 lower for ‘Fuji’-related families ( $-0.056$  to  $-0.078$ , Table 1, Table S2).

328         To investigate the genetic structure of the collection and its impact on the prediction  
329 accuracy, a discriminant analysis of principal component with the entire SNP set (8,294  
330 SNPs) was performed. Through the BIC criteria, six clusters, described with five principal  
331 components, were defined as the most probable (see Methods, Fig. S1). All parental cultivars  
332 were assigned to cluster 5, except ‘Fuji’ that was grouped in cluster 2 (Fig. 3A, Table S3). Of  
333 these clusters, cluster 5 resulted to be the largest ( $N=66$ ), while the smallest was cluster 6  
334 ( $n=25$ , Table 1, Table S3). The cluster assignment in families was predicted using the  
335 principal components derived by the DAPC analysis carried out on the collection. Most of the  
336 individuals were assigned to the parental clusters 2 and 5, while 8 individuals of ‘FjDe’ and  
337 one of ‘FjPi’ were assigned to cluster 1 (Table 1, Fig. 3B-C). Overall, clusters 2 and 5  
338 contained the largest part of the whole population, while clusters 1, 3, 4 and 6 were the lowest  
339 represented (Fig. 3C, Table S3). However, while the DAPC analysis suggested this genetic  
340 clustering as the most realistic in the diversity panel represented by the collection, the  
341 pairwise  $F_{st}$ -values between clusters indicated a low genetic differentiation (values comprised  
342 between 0.002 and 0.018, Table S4). The  $F_{st}$  value between clusters 2 and 5, containing the  
343 parents and most of their offsprings, was for instance 0.013. As our design allowed the  
344 comparison of families obtained from crosses within cluster 5 (‘Royal Gala’-related) and  
345 between clusters 2 and 5 (‘Fuji’-related), the information on genetic clustering was further  
346 used to control the genetic background in the subsequent prediction models (‘model B’, see  
347 Methods). The phenotypic distributions across clusters reveal that clusters 2 and 5 have, for  
348 all traits except PC2, elevated values compared to other clusters, with values of cluster 2

349 individuals surpassing those of cluster 5 (Fig. S3), indicating a possible correlation existing  
350 between genetic clustering and texture.

351

### 352 *Cross-validations within collection*

353 A hundred 5-fold cross-validations within the collection were run with the additive  
354 rrBLUP model on BLUPs with and without considering the genetic clustering as a fixed effect  
355 (models A and B, respectively). In this context, PC1 and PC2 were also considered as traits,  
356 leading in the end to 14 predicted traits (Fig. S4). Instead of improving predictions, the  
357 inclusion of the clustering effect degraded accuracies for all traits, with a maximum accuracy  
358 decrease of 0.02 for the mean force (FMean). The highest mean prediction was obtained for  
359 the acoustic linear distance (ALD, *mean cor* = 0.64, Fig. S4) whereas the number of force  
360 peaks yielded the second highest accuracy (FNP, *mean cor* = 0.63, Fig. S4, Table S5).  
361 Moreover, while FNP yielded a relatively high accuracy as inferred from heritability (0.93,  
362 Table 2), the overall mean accuracies among traits did not follow the ranking of heritability  
363 obtained within the collection phenotypes (Wilcoxon signed-rank-test, p-value = 4.88E-4,  
364 model A).

365

### 366 *Genomic prediction of families without training population optimization*

367 In practice, families can be predicted with any available related genetic material that  
368 has been genotyped and phenotyped. For this reason, three different scenarios of training  
369 population design were tested, including or not individuals from the predicted family or from  
370 a half-sib family (see Methods, “Prediction models”). The predictions in each of these  
371 scenarios were calculated with the two prediction models (A and B, respectively depicted in  
372 Fig. 4, Fig. S5). Without clustering, overall three families (‘FjPi’, ‘GaPi’ and ‘GaPL’) could  
373 be predicted with moderate to high accuracies (accuracies ranging from 0.08 for PC2 in  
374 ‘GaPi’ to 0.73 for PC1 in ‘GaPL’, respectively), with PC1 being the best predicted trait  
375 among these families (mean for scenario 1, model A: 0.50, Fig. 4). The three remaining  
376 families yielded near-zero (‘FjPL’) or negative accuracies (‘FjDe’ and ‘GDFj’, mean  
377 accuracies between -0.29 and 0.30, Fig. 4). The correlations between predicted and observed  
378 values for each individual and for all traits and families obtained are depicted in Fig. S6  
379 (model A and scenario 1). Out of 252 combinations of trait, scenario and family predictions,  
380 only 74 gave better accuracies (considering an increase in accuracy larger than 0.01). When  
381 considering accuracies above 0.20, this number dropped to 40 out of 103 family-trait-scenario

382 combinations (maximum gain: 0.04, Table S6, Fig 4, Fig. S5). Thus, the implementation of  
383 clustering did not clearly improve the predictions of families.

384 It is also important to underline that the addition of related individuals to the collection  
385 did not systematically improve the predictions. For instance, in ‘GaPL’ the prediction was  
386 more accurate with scenario 1 with regards to scenario 2 and 3 (mean prediction accuracies of  
387 0.60, 0.56 and 0.53 respectively for scenario 1, 2, 3, respectively, model A). Scenario 2  
388 particularly improved the accuracies in ‘FjPi’ (mean accuracies of 0.32, model A) as it better  
389 predicted 12 out of 14 traits. Scenario 3 instead was the lowest performing, although it  
390 increased the prediction accuracy of 7 traits (8 with clustering) in ‘GaPi’ (mean accuracy of  
391 0.38, all values across trait in model A, Fig 4, Table S6).

392

### 393 *Genomic prediction of families with training population optimization*

394 To test the hypothesis that retaining only the most related individuals or clusters in the  
395 TRS might allow to maximize prediction accuracies, we compared the predictive abilities  
396 obtained for each family and trait using training sets with different sizes. This process started  
397 with a small TRS having the highest relatedness to which individuals were added in the order  
398 of decreasing relatedness to reach the size of the entire collection using three different  
399 enrichment procedures (see Methods). TRS optimization was also carried out with a more  
400 sophisticated approach based on the optimization algorithm presented by Akdemir *et al.*  
401 (Akdemir *et al.*, 2015; Akdemir & Isidro-Sánchez, 2019), using DAPC-defined principal  
402 components and the ‘CD-Mean’ value as decision criterion. The results obtained using these  
403 different methods are illustrated in Table 3, Fig. 5 and Fig. S7 for four traits selected for their  
404 practical relevance (ALD, FNP, PC1 and PC2) while results for the remaining traits are  
405 reported in Table S7. Regarding the four selected traits, the best accuracy for each of the  
406  $6 \times 4$  family-trait combinations was in most cases obtained with the addition of single  
407 individuals based on their relationship to the family (in 10 cases using the maximum  
408 relationship and in 10 cases using the mean relationship, Fig. 5A and B, Table 3, Table S7).  
409 The mean optimal population size was 92 individuals with a minimum size of 10 and a  
410 maximum size of 202 individuals (Table 3, Table S7), meaning that the entire collection was  
411 never considered as the optimal TRS for predicting texture. The maximal accuracies observed  
412 ranged from 0.01 to 0.81, which corresponded to a mean increase in accuracy of 0.17 when  
413 compared to predictions of families with the entire collection (minimum increase: 0.02;  
414 maximum increase: 0.40 – compared to scenario 1, model A). The highest accuracy was 0.81,

415 and was obtained for the “multi-trait” PC1 in ‘GaPL’ family with only 129 individuals, *i.e.*  
416 nearly half of the collection size. The distribution of accuracies with increasing TRS size in  
417 each family for the four focal traits was also investigated (Fig. 5). Overall, traits tended to  
418 follow the same trend within a family. In families ‘GaPL’ and ‘GaPi’, which had the highest  
419 relatedness to the collection among all families (Table 1), the accuracy was moderate to high  
420 from as few as 100 individuals for ALD, FNP and PC1, and remained relatively stable while  
421 increasing TRS size (Fig. 5A-D). ‘FjPi’ was the only family for which increasing TRS up to  
422 200 individuals resulted in a clear accuracy improvement, with any of the approaches  
423 implemented here (Fig. 5A-D). In families with overall low accuracies, such as ‘FjDe’, ‘FjPL’  
424 and ‘GDFj’, the highest accuracy was in most cases obtained with 10 to 70 individuals, and  
425 declined or remained stable with larger TRS size (Fig. 5A-D). In ‘GDFj’, for instance,  
426 accuracies above 0.2 were found only with a TRS of 10 to 66 individuals (Fig. 5A-C, Table  
427 S7). Moreover, while FNP was not predictable in ‘GDFj’ with the entire collection ( $cor =$   
428  $0.08$  for  $N = 259$ ), an improved accuracy of 0.32 was observed with as few as 15 individuals  
429 (based on maximum relationship, Fig. 5B).

## 430 Discussion

431 In this work we assessed the feasibility of genomic selection (GS) for apple texture by  
432 performing an in-depth analysis of this complex phenotype together with the genetic  
433 correlates influencing its genomic predictions. The results presented here on genomic  
434 prediction for apple texture evidenced a large potential for GS for this trait, providing  
435 important key elements and tools to set-up a prediction experiment given the available genetic  
436 information in any apple population.

437

### 438 *Family-dependent fruit texture profiles and fruit texture prediction*

439 The texture dissected “sub-traits” were highly heritable, although variability within  
440 families was very contrasted, showing, in specific cases, a transgressive segregation, such as  
441 ‘FjPL’. Although the traits were predictable with moderate to high accuracy within the  
442 collection (accuracies between 0.41 and 0.64), this was not easily achievable in all biparental  
443 families. Without TRS optimization, texture could be accurately predicted for ‘GaPL’ (mean  
444 accuracy of 0.57), while ‘GaPi’ and in ‘FjPi’ showed a moderate prediction accuracy (mean  
445 accuracy of 0.30). In contrast, near-zero or negative accuracies were instead obtained for  
446 ‘FjDe’, ‘FjPL’ and ‘GDFj’ across traits (mean accuracy of -0.05). Surprisingly, large negative  
447 accuracy values were repeatedly obtained in ‘FjDe’ and ‘GDFj’, which could be potentially  
448 explained by the strong epistatic effect possibly present in these families (Lehner, 2011) or by

449 a systematic bias due to the calculation of the Pearson correlation coefficient (Zhou *et al.*,  
450 2016), indicating that fruit texture cannot be predicted in these families using the entire  
451 collection as TRS. In contrast, previous works on firmness and crispiness yielded mostly low  
452 accuracies when predicting unobserved genotypes in a set of families or in a collection  
453 (between 0.15 and 0.35, Kumar *et al.* 2015, McClure *et al.* 2018). A much higher accuracy of  
454 0.83 was found for firmness by Kumar *et al.* (2012), which can be mainly explained by their  
455 crossing design and validation procedure. In the present study, the analysis of PCA allowed to  
456 better understand the relation between firmness and crispiness, both positively correlated and  
457 summarized by PC1 and PC2, with PC2 specifically dissecting the difference between these  
458 two texture sub-traits. When used as synthetic trait in the computation, PC1 was among the  
459 best predictable traits (accuracy of 0.59 in collection and highest accuracy among traits and  
460 family: 0.73 in GaPL), justified by the 80.5% of total phenotypic variation explained by PC1,  
461 while PC2 accounted only for 12.7%. Despite the lower variability of PC2, this trait could be  
462 predicted with a reasonable accuracy of 0.42 in the collection, while in most of the families  
463 the accuracy level was above 0.2 (with, and in some cases without TRS optimization). PC2  
464 was not predictable in ‘GDFj’ and ‘FjPL’, two families with moderate and high transgression  
465 on the PC2 axis. The results showed that using PC1 and PC2 as a first tentative to perform a  
466 multi-trait prediction was a relevant method to predict fruit texture profiles through an  
467 integrative approach.

468

#### 469 *Impact of genetic clustering and relatedness on prediction accuracy*

470 Having highly related individuals between the TRS and the TS is necessary but not  
471 always sufficient for an optimal TRS design; in fact enlarging the TRS with scarcely related  
472 individuals can diminish prediction accuracies (Lorenz & Smith, 2015). Moreover, trait  
473 variation can be coupled with genetic structure. Several studies have for instance showed the  
474 impact of genetic structure on genomic prediction, demonstrating that taking genetic structure  
475 into account can improve GS efficiency (Guo *et al.*, 2014; Isidro *et al.*, 2015; Rio *et al.*,  
476 2019). Although in apple the genetic structure is known to be weak, with substantial levels of  
477 admixture in apple cultivars (Urrestarazu *et al.*, 2016; Vanderzande *et al.*, 2017; Cornille *et al.*,  
478 2019), it could still have a relevant effect on predictions, depending on the population  
479 composition and the trait under investigation. Significant genetic structure has been identified,  
480 for instance, between dessert and cider apples, which could potentially be correlated with fruit  
481 quality traits (Lassois *et al.*, 2016). Through the implementation of the DAPC method, six  
482 significant although lowly differentiated genetic clusters were obtained, with families



483 belonging to one or two specific clusters, depending mostly to the assignment of their parental  
484 cultivars. While some degree of correlation was apparent between the genetic clustering of  
485 individuals and their phenotypic distribution (Fig. S3), the addition of the clustering effect  
486 into the prediction model almost systematically degraded the prediction accuracies. Moreover,  
487 the TRS optimization based on clustering was the lowest performing among the four methods  
488 tested. This could indicate that additive relationship alone already captured the genetic  
489 clustering present in our population. One important information given by the clustering  
490 patterns was that the ‘GaPL’ and ‘GaPi’ families, for which both parents were in the same  
491 genetic cluster or in the best represented cluster in the collection (Cluster 5), yielded the best  
492 predictions.

493 The genetic parameter having the largest impact on predictions was genetic  
494 relatedness, with the two families most related to the collection (‘GaPL’ and ‘GaPi’) yielding  
495 by far the highest accuracies compared to the remaining Fuji-related families. This  
496 observation finds consistency to the fact that genetic relationship is a fundamental parameter  
497 in genomic prediction (see *e.g.* Habier *et al.*, 2010; Clark *et al.*, 2012; Daetwyler *et al.*, 2014).  
498 The addition of closely-related individuals from the same family (scenario 2) or from a  
499 complete half-sib family (scenario 3) to the collection did not improve the prediction  
500 accuracy, except for ‘FjPi’, for which scenario 2 was the most accurate. This result might  
501 indicate that either the collection retains already ‘enough’ diversity to predict families, or that  
502 the excess of unrelated individuals in the collection cannot be corrected by adding related  
503 individuals. Thus, scenario 2 and 3 do not seem to effectively improve the TRS.

504 To this end, the gradual increase of the TRS size using *a priori* information of genetic  
505 parameters was used as an alternative optimization strategy. TRS optimization was tested in  
506 four different ways, based on *a priori* information on similarities between individuals. These  
507 were represented either by additive relationship or by genetically derived principal  
508 components coordinates (Fig. 5, Fig. S7, Table 3, Table S7). The results allowed in all cases  
509 to improve predictions tested beforehand with TRS scenarios 1 to 3 with a minimal increase  
510 of 0.2 and maximal increase of 0.4, reaching a maximum accuracy of 0.81 (‘GaPL’, PC1,  
511 Table 3). This means that the maximum accuracies were also never reached by employing the  
512 entire collection, especially for families with the lowest genetic relatedness to the TRS (*i.e.* to  
513 the collection here). The best prediction accuracy for fruit texture in apple was obtained with  
514 the implementation of 50 individuals in the TRS for families less related to the entire TRS and  
515 at least 100 accessions for families with a higher genetic relationship (or clustering within the  
516 major genetic cluster of the TRS, such as ‘GaPL’ and ‘GaPi’ here). These results are

517 consistent with previous findings in barley from Lorenz and Smith (2015), that showed the  
518 detrimental effects of adding unrelated individuals to the TS into the TRS, partially  
519 contradicting the idea that having at least one related individual in the TRS is sufficient to  
520 increase accuracies (Daetwyler *et al.*, 2014).

521 Our results thus provided useful information for the TRS composition, illustrating the  
522 complex roles of structure and relatedness in shaping texture variability in apple.

523

#### 524 *Towards a simplified assessment of fruit texture for genomic selection*

525 The improvement of fruit texture is still limited by the time-consuming and expensive  
526 assessment needed for its dissection and the low variation observed in modern elite apple  
527 accessions due to the fixation of PG1 (Atkinson *et al.*, 2012; Di Guardo *et al.*, 2017). Thus,  
528 even though we demonstrate the feasibility of GS for apple texture, its application will be  
529 considered only if predictions are precise enough to perform the costly phenotyping of the  
530 TRS. The characterization of texture is a challenging task, as this trait is composed of  
531 mechanical and acoustic sub-traits. The analysis of PC1 and PC2 relied on the texture  
532 dissection and the measurements of these 12 traits. In particular, FNP, which is the number of  
533 mechanical peaks observed in the mechanical profile generated by fruit compression on the  
534 texture analyzer, was highly correlated with the group of the acoustic traits related to  
535 crispiness. As mechanical traits are easier to measure than acoustic ones, FNP would be in  
536 practice the best measurement to choose for assessing crispiness. Since we also obtained high  
537 prediction accuracy for FNP (0.63 in collection and maximum of 0.78 in “optimized” family  
538 prediction), we propose this sub-trait as the most valuable descriptor for fruit texture,  
539 minimizing the effort needed to phenotype such as complex phenotype. Moreover, the  
540 predictions presented in this study have been performed with a set of 8,294 SNPs, which is  
541 still not dense enough considering the rapid decay of the linkage disequilibrium in apple  
542 (Laurens *et al.* 2018). Although we reached already satisfying accuracies with this amount of  
543 SNP, it would be useful to increase the number of markers with the available apple 480K  
544 (Bianco *et al.*, 2016) or by using genotyping-by-sequencing methods (Gardner *et al.*, 2014) to  
545 further improve predictions.

546 The use of principal component as synthetic traits resulted to be a valuable multi-trait  
547 approach to better predict and understand the texture variability. Here, we investigated in  
548 details that fruit crispiness (PC2) in particular is less variable than fruit firmness (PC1). While  
549 crispy apples are necessarily firm, the opposite relationship is in fact not validated. Our  
550 predictions indicated that fruit firmness in apple can be accurately selected (along PC1), but it

551 needs to be taken into account that an excessive value for this trait can lead to unpleasant  
552 quality perception for the consumer. On the other side, crispiness was better predicted with  
553 the PC2. Despite the lower variation for crispiness in our population, the selection for this trait  
554 resulted to be feasible, although with lower accuracy. To improve the predictions for  
555 crispiness we might need to increase the variability for this trait within the TRS. More  
556 generally, while the selection on fruit traits has shaped apple domestication, the current  
557 cultivated pool relies on a few founders, hence having a narrow genetic basis. Thus, a better  
558 targeting of apple texture might necessitate a pre-breeding step incorporating or generating  
559 genetic diversity for this trait with the use of mealy cultivars and of wild relatives of *Malus*  
560 *domestica* (Khan *et al.*, 2014; Peace *et al.*, 2019).

561

## 562 **Supplementary data**

563 **Table S1.** Texture genotypic values and coordinates for PC1 and PC2.

564 **Table S2.** Additive relationship matrix.

565 **Table S3.** Assignments of individuals to genetic clusters.

566 **Table S4.** Pairwise  $F_{st}$ -values between genetic clusters.

567 **Table S5.** Accuracies obtained in cross-validations within the collection using two models.

568 **Table S6.** Accuracies obtained in family predictions using two models and three TRS  
569 scenarios.

570 **Table S7.** Accuracies obtained in family predictions with TRS optimization with four  
571 methods.

572 **Fig. S1.** Bayesian information criterion values obtained in the discriminant analysis of  
573 principal components.

574 **Fig. S2.** Distribution of texture genotypic values according to the type of population.

575 **Fig. S3.** Distribution of texture genotypic values according to cluster assignments.

576 **Fig. S4.** Accuracies obtained from cross-validations within the collection.

577 **Fig. S5.** Accuracies obtained for each family in three prediction scenarios with model B.

578 **Fig. S6.** Observed vs. predicted values in predictions for each family on each trait with model  
579 A.

580 **Fig. S7.** Comparison of methods for the optimization of the training population.

581

## 582 **Acknowledgements**

583 This work was co-funded by the EU seventh Framework Programme by the FruitBreedomics  
584 Project No. 265582: Integrated Approach for increasing breeding efficiency in fruit tree crops

585 (www.FruitBreedomics.com). The views expressed in this work are the sole responsibility of  
586 the authors and do not necessarily reflect the views of the European Commission.

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## TABLES

**Table 1.** Description of the whole population and experimental design used for genomic prediction of texture. Maternal and paternal cultivars are given for full-sib biparental families. FEM, Foundation Edmund Mach; RCL, Research Center Laimburg. Cluster assignments as given by the discriminant analysis of principal components on 8,294 markers. Relationship to collection, mean additive relationship of progenies relative to collection.

Name	Mother	Father	Location	Evaluated years	# IDs	Cluster assignments (# IDs)						Relationship to collection
						1	2	3	4	5	6	
FjDe	Fuji	Delearly	FEM	2012-13	50	8	20	0	0	22	0	-0.056
FjPi	Fuji	Pinova	RCL	2012-14	70	1	30	0	0	39	0	-0.078
FjPL	Fuji	Pink Lady	FEM	2012-13	80	0	50	0	0	30	0	-0.071
GaPi	Royal Gala	Pinova	RCL	2012-14	36	0	0	0	0	36	0	-0.021
GaPL	Royal Gala	Pink Lady	RCL	2012-14	15	0	0	0	0	15	0	-0.020
GDFj	Golden Delicious	Fuji	RCL	2012-14	27	0	6	0	0	21	0	-0.057
Collection	-	-	FEM	2012-13-15	259	45	37	31	55	66	25	-



## TABLES

**Table 2.** Summary of texture traits assessed in the whole population.  $h^2$ , broad sense heritability. For comparison,  $h^2$  are also given considering measurements of the collection only.

Trait	Mean	SD	$h^2$	$h^2$ (COLL only)
ALD	5094	2049	0.938	0.928
ANP	50.4	39.1	0.924	0.909
APMax	65.2	4.38	0.921	0.880
APMean	49.6	3.12	0.951	0.915
Area	813	273	0.951	0.930
FF	10.1	3.98	0.946	0.929
FLD	101	5.78	0.955	0.937
Fmax	11.8	4.02	0.946	0.924
FMean	9.60	3.31	0.951	0.929
FNP	17.9	4.16	0.934	0.931
IF	9.94	3.29	0.933	0.906
YM	1.19	0.353	0.899	0.890

## TABLES

**Table 3.** Maximum accuracies obtained among four training set optimization methods in predictions made for each combination of trait and family.

Family	Trait	Accuracy	TRS size	Method
FjDe	ALD	0.23	77	Mean relationship
FjDe	FNP	0.18	21	Max relationship
FjDe	PC1	0.26	77	Mean relationship
FjDe	PC2	0.36	56	Max relationship
FjPi	ALD	0.36	189	Mean relationship
FjPi	FNP	0.59	174	Max relationship
FjPi	PC1	0.36	178	Max relationship
FjPi	PC2	0.26	202	Mean relationship
FjPL	ALD	0.10	130	CDmean-opt
FjPL	FNP	0.16	22	Max relationship
FjPL	PC1	0.20	120	Max relationship
FjPL	PC2	0.22	10	CDmean-opt
GaPi	ALD	0.46	156	Mean relationship
GaPi	FNP	0.40	13	Max relationship
GaPi	PC1	0.54	191	Clusters
GaPi	PC2	0.28	19	Mean relationship
GaPL	ALD	0.72	136	Clusters
GaPL	FNP	0.78	37	Max relationship
GaPL	PC1	0.81	129	Mean relationship
GaPL	PC2	0.40	140	Max relationship
GDFj	ALD	0.21	66	Mean relationship
GDFj	FNP	0.32	15	Max relationship
GDFj	PC1	0.19	31	Mean relationship
GDFj	PC2	0.01	10	Mean relationship

## FIGURE LEGENDS

**Figure 1.** Principal component analysis (PCA) of 12 texture sub-traits. A, PCA 2D-plot of variables, with acoustic traits in blue and mechanical traits in red with 1, ANP; 2, ALD; 3, APMAx; 4, APMean; 5, FNP; 6, FLD; 7, FF; 8, YM; 9, Area; 10, Fmean; 11, Fmax; 12, IF. B, PCA 2D-plot of individuals with collection individuals represented as dots and families as ellipses. C, PCA 2D-plot of individuals showing family offspring and their respective parents.

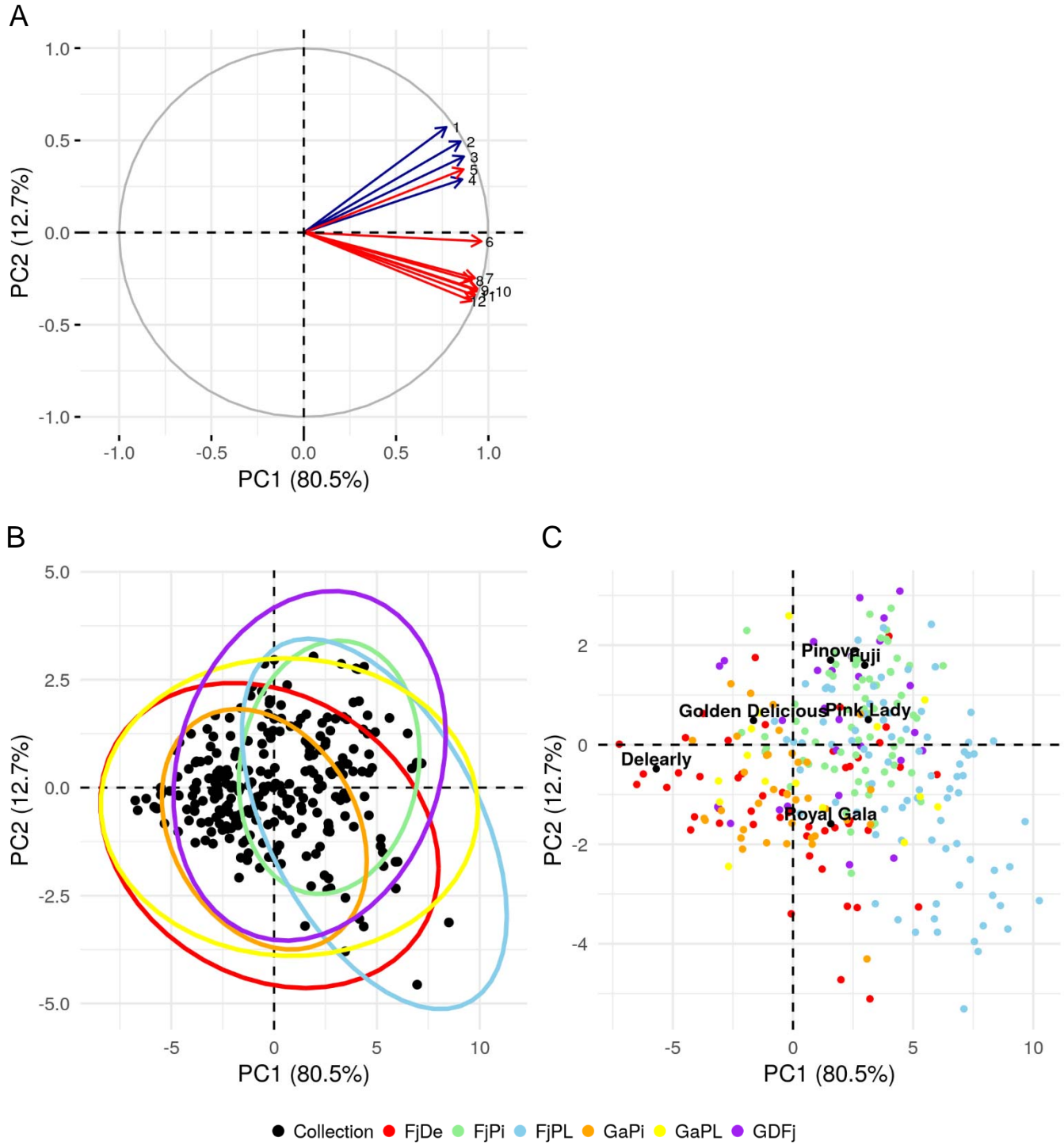
**Figure 2:** Realized additive relationship calculated with 8,294 SNPs. Families indicated in black with brackets and parents are indicated in red.

**Figure 3:** Discriminant analysis of principal components and cluster assignments of individuals based on 8,294 SNPs. A, projection on principal component (PC) 1 and 3 of the cluster assignments of individuals in the collection with parents of families indicated with their names. Black lines materialize the PCs defining clusters. B, Predicted cluster assignments of progenies of the six full-sib families projected on PC1 and PC3 axes and represented by dots, with collection individuals in the six genetic clusters represented as ellipses (same color legend as in part A). C, Distribution of individuals across the six genetic clusters in each population.

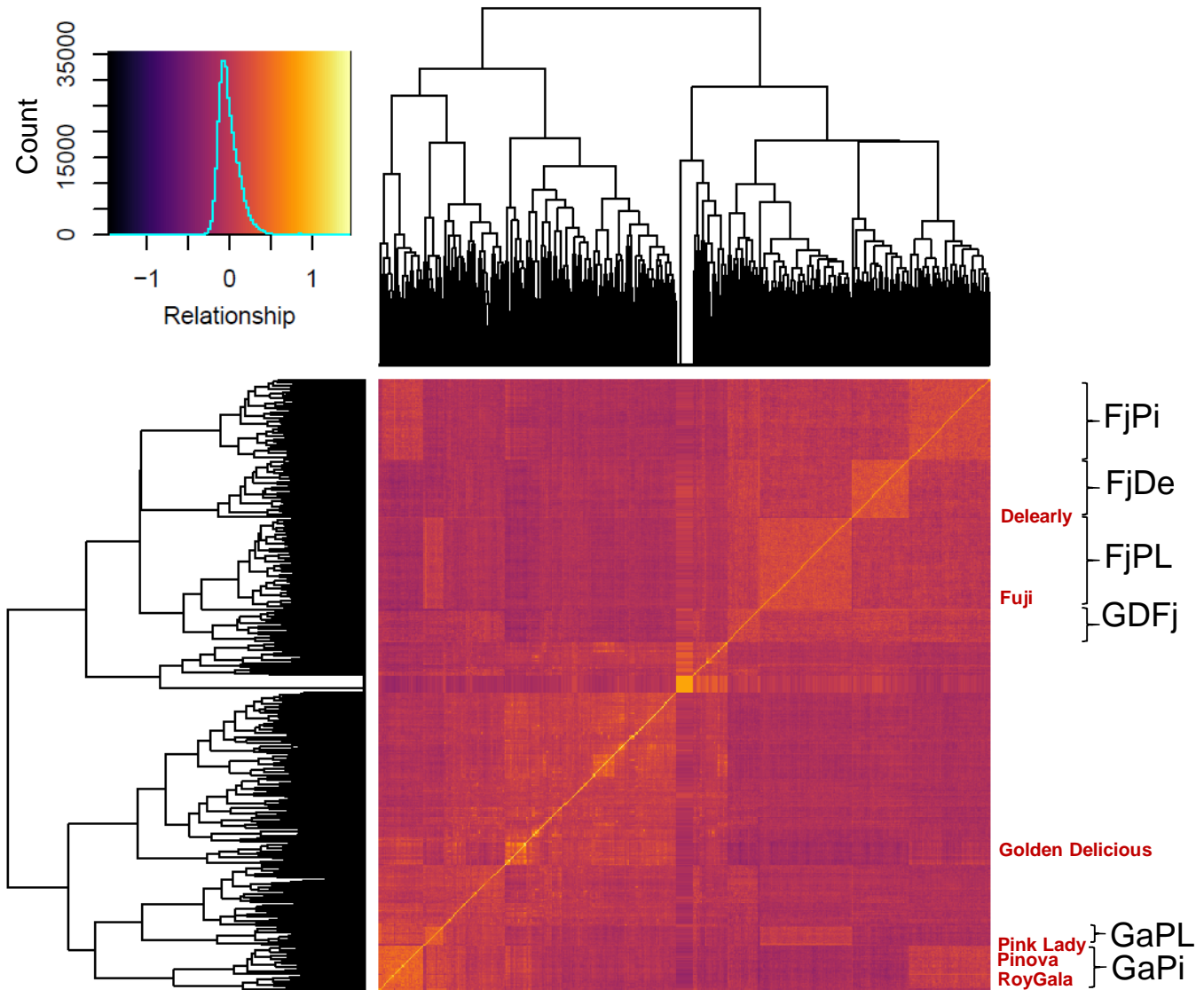
**Figure 4:** Mean and standard deviation of accuracies obtained in three prediction scenarios. In scenario 1, each family was predicted using the collection only. In scenario 2, 30% of individuals of the predicted family were added to the collection in the TRS and the remaining 70% formed the TS. In scenario 3, a single half-sib family was added to the collection to form the TRS. The predictions were made with model A, which does not take into account the genetic clustering of individuals.

**Figure 5:** Optimization of the training population for the prediction of each family using *a priori* information on individuals. A, addition of individuals in the TRS by decreasing mean relatedness to the predicted family; B, addition of individuals in the TRS by decreasing maximum relatedness to the predicted family; C, addition of clusters by decreasing mean relatedness to the predicted family; D, selection of individuals for TRS of different sizes based on the five principal components obtained with discriminant analysis of principal components and using the CDmean design criteria. The color legend applies for all parts of the figure.

FIGURE 1

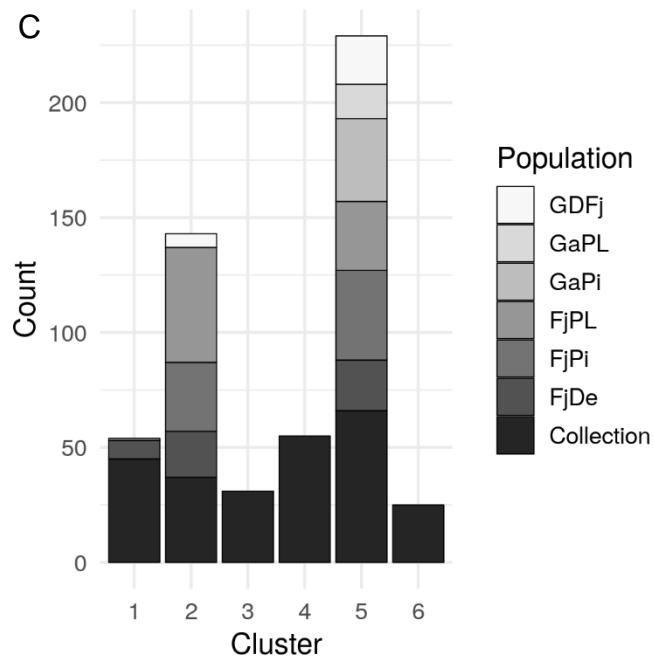
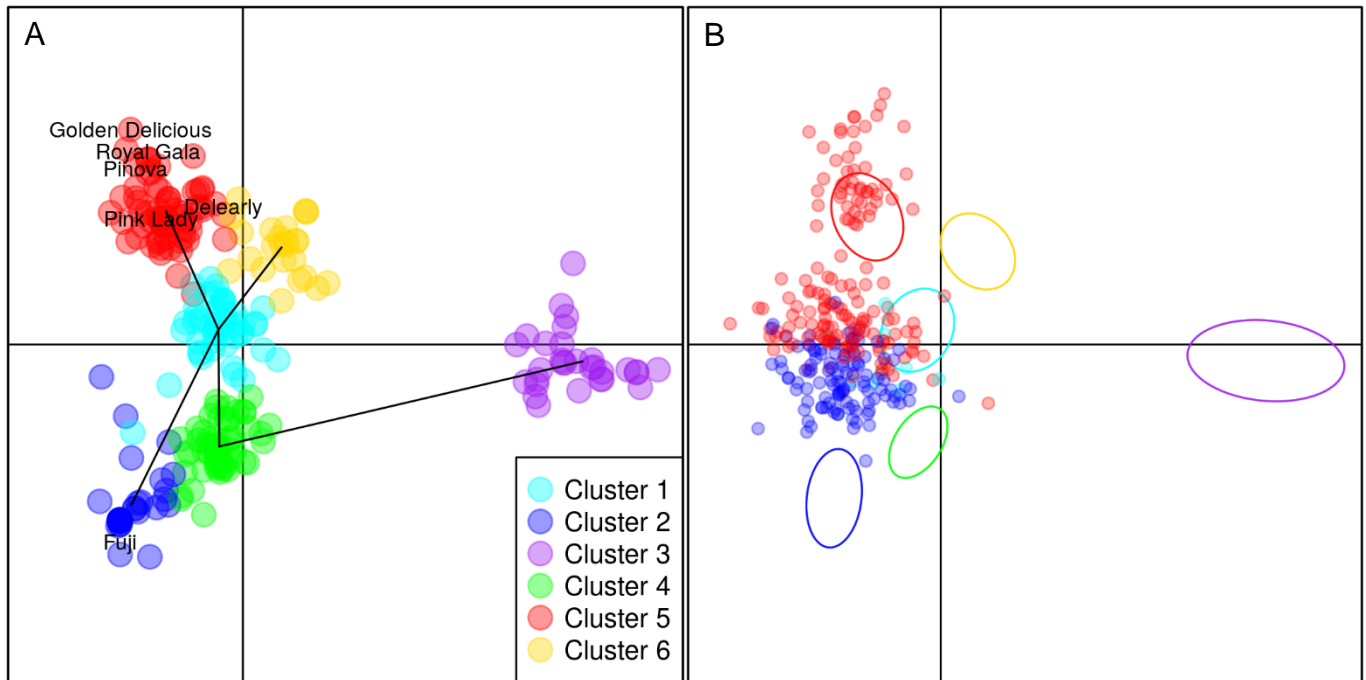


## FIGURE 2

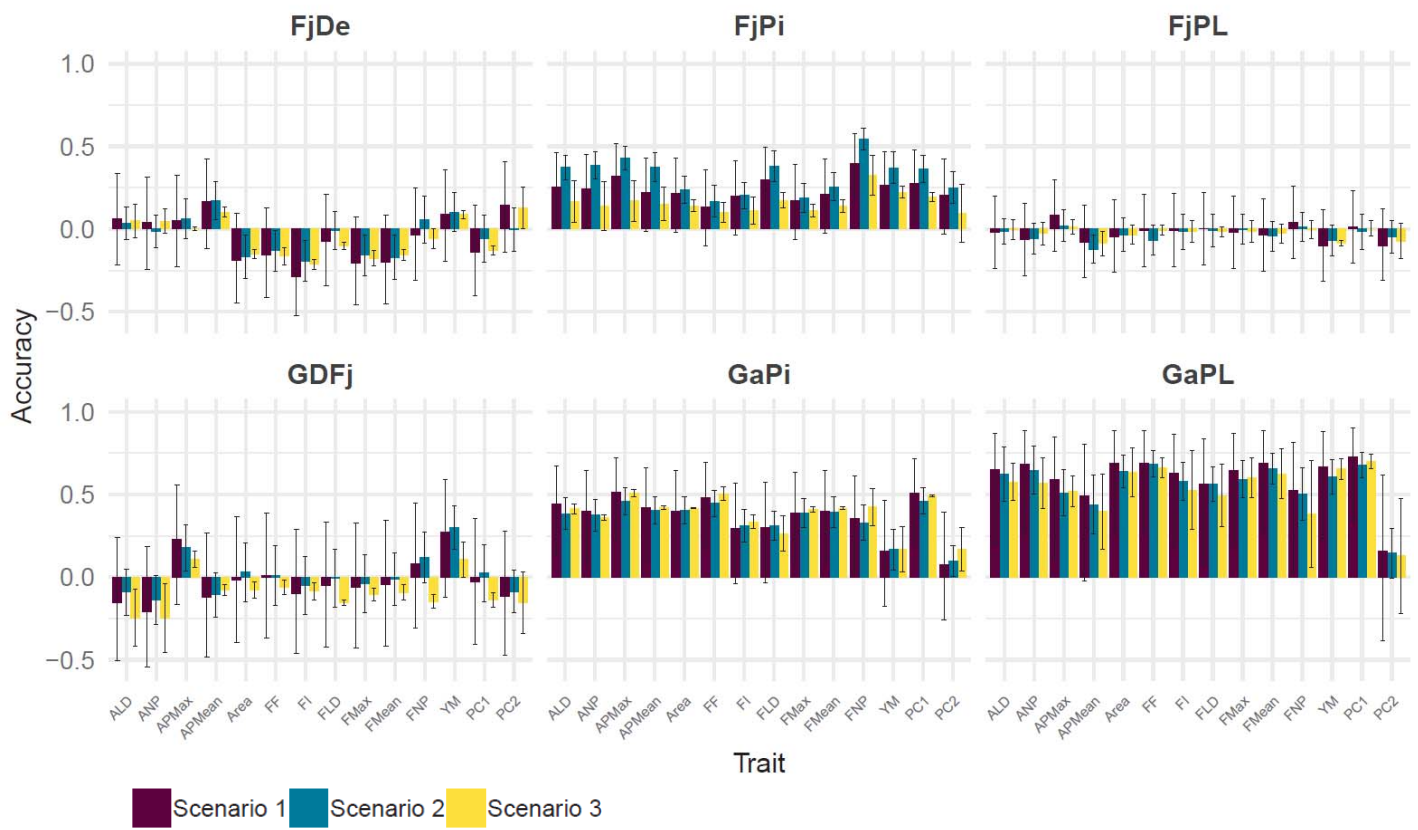


**Figure 2:** Realized additive relationship calculated with 8,294 SNPs. Families indicated in black with brackets and parents are indicated in red.

## FIGURE 3



## FIGURE 4



## FIGURE 5

