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Additional Information

1 **Breeding tomato flavor: modeling consumer preferences of tomato**
2 **landraces.**

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14

15 **Abstract**

16 Tomato landraces are highly appreciated by consumers, who are willing to pay a price
17 premium for them. But little is known regarding sensory perception and its relationship with fruit
18 composition. The Spanish variety “Moruno” was selected as a model for this purpose. A
19 collection of 30 populations was grown in different environments and evaluated by a consumer
20 panel. Partial least square (PLS) models were then developed relating determinant flavor
21 descriptors (sweetness, sourness, taste and aroma intensity, aftertaste persistence and agreeability,
22 and overall flavor acceptability) with compositional variables such as soluble solids, pH, titratable
23 acidity, individual sugars, organic acids, volatiles, and derived variables. PLS models identified
24 relationships that had not been uncovered with correlation and simple regression analysis and
25 offered low cross-validation errors (<15% of the range of variation). Although plant yield
26 negatively affected sensory perception, it was possible to identify populations with a good
27 combination of both traits.

28

29 **Highlights**

30 Volatiles and soluble solids interact in all the sensory descriptors

31 PLS models uncover the role of compounds not highlighted in correlation analysis

32 Model error (RMSECV) represented less than 15% of the range of variation

33 **Chemical compounds studied in this article**

34 Fructose (PubChem CID: 5984); Glucose (PubChem CID: 5793); Citric acid (PubChem CID:
35 311); Malic acid (PubChem CID: 525); Glutamic acid (PubChem CID: 611); 6-Methyl-5-hepten-
36 2-one (PubChem CID:9862).

37 **Keywords:** *Solanum lycopersicum* L., sugar, acid, volatiles, PLS models, consumer panel.

38

39 **1. Introduction**

40 Consumer complains on tomato flavor became commonplace during the 90s (Bruhn et
41 al., 1991). At the same time, the interest in tomato landraces increased exponentially. Quality
42 markets specialized in high quality produces exploited this interest and their price in the market
43 quadrupled (Cebolla-Cornejo et al., 2007).

44 Several causes explain the loss of flavor in modern commercial varieties. First, the
45 maximization of the limits on productivity did not contribute to maintaining a high level of sugars
46 in fruit, as photoassimilates have to be partitioned into more sinks, and thus, the accumulation of
47 hexoses per fruit decreases (Bertin et al., 2000). Apart from raising productivity, the need to
48 reduce yield losses led to the introgression of genes, most of them from wild relatives. It has been
49 proven the existence of a considerable level of linkage drag in tomato that can lead to important
50 metabolomic changes (Zhu et al., 2018). During these selection programs, breeders focused on
51 production traits and external appearance and little attention was paid to flavor. Consequently,
52 several favorable alleles regarding the production of aroma volatiles were lost over consecutive
53 breeding cycles (Tieman et al., 2017), and thus, flavor was deeply deteriorated. Additionally, the
54 introgression of new specific traits resulted in negative side effects. It would be the case of delayed
55 fruit ripening, controlled by genes such as *rin*, which decreases consumer acceptance (Causse et

56 al., 2003), probably due to lower carotenoid accumulation and a negative impact on apocarotenoid
57 production, which affect taste perception. The use of genes such as uniform ripening to improve
58 external appearance also had a negative impact on sugar accumulation, as it reduced the
59 accumulation of photoassimilates directly synthesized in fruit (Powell et al., 2012).

60 In order to establish breeding objectives, tomato flavor started to be modelled from the
61 seventies. Stevens et al. (1977) determined that tomato flavor was deeply influenced by the
62 accumulation of sugars, acids and the relation between them. In this sense, Malundo et al. (1995)
63 established that for a certain sugar content there is an optimal acid accumulation level and
64 increased acid accumulation had a negative effect on preference. Years later, Baldwin et al. (1998)
65 reported that the perception of sweetness is better explained by sucrose equivalent levels which
66 weighs each sugar content by its sweetening power. The contribution to sourness of each organic
67 acid is more complicated. Malic acid may be perceived as sourer (De Bruyn et al., 1971), but the
68 accumulation levels of citric acid are higher. It seems that glutamic acid does not play an
69 important role in sourness, but some studies reported that a high ratio between sucrose equivalents
70 and glutamic acid may be convenient to improve tomato taste (Bucheli et al., 1999; Fulton et al.,
71 2002). Nonetheless, Casals et al. (2018) concluded the opposite, reporting that consumers value
72 glutamic acid contents positively, at least in cherry tomatoes.

73 The volatile profile of tomato is rather complex and it has an impact on flavor in two
74 ways. The first is the direct impact on aroma. Among the 400 volatiles described in tomato fruit,
75 the initial studies in tomato confirmed that at least 30 had an impact on tomato aroma (Buttery &
76 Ling, 1993). Unlike other species such as banana, in tomato there is not a volatile with a major
77 impact on sensory perception. Additionally, several compounds influence how sweetness and
78 sourness are perceived (Baldwin et al., 1998). They are classified attending to their chemical
79 characteristics (alcohols, aldehydes, apocarotenoids...) or their metabolic origin. Branched chain
80 aminoacid derived volatiles (3- and 2-methylbutanal...) and fatty acid derived volatiles (hexanal,
81 E-2-hexenal, Z-3-hexenal...) tend to offer green notes to tomato aroma and are usually found at
82 high concentrations. Apocarotenoids, which are found at low concentrations, are usually
83 perceived as floral or fruity. On the other hand, phenylalanine derived volatiles, including

84 compounds such as phenylacetaldehyde, 2-phenylethanol, guaiacol or eugenol, have a sensory
85 effect difficult to predict as they have been reported to have both positive and negative effect,
86 probably depending on their different concentrations (Martina et al., 2021). Tandon et al. (2000)
87 suggested that tomato flavor would improve by increasing the levels of compounds contributing
88 to floral (6-methyl-5-hepten-2-one and β -ionone), fruity (cis-3-hexenal and geranylacetone) and
89 fresh (3-methylbutanol and 1-penten-3-one) notes, or by decreasing the levels in compounds
90 which contribute to stale (hexanal, trans-2-hexenal and 3-methylbutanal), pungent (2-
91 isobutylthiazole) and alcohol (2-phenylethanol) notes.

92 Several classic studies have tried to model flavor perception and chemical composition
93 using linear regression models (i.e. Baldwin et al., 1998; Tandon et al., 2003; Abegaz et al., 2004).
94 In a first approach, some of them have been performed either using a broad spectrum of variance
95 represented in few materials. In contrast, recent approaches have analyzed the variation in large
96 collections of different materials including landraces, commercial cultivars, or even wild
97 representatives. For example, Tieman et al. (2017) did not offer a prediction model, but
98 highlighted the importance of 33 chemicals that correlated with consumer liking and 37 that
99 significantly correlated with flavor intensity, with 28 of them being associated with both overall
100 liking and flavor intensity.

101 Few studies have been focused on the analysis of specific landraces and few have
102 predicted models using similar materials with subtle differences. But the truth is that consumers
103 highly appreciated tomato landraces and are willing to pay a price premium for them (Cebolla-
104 Cornejo et al., 2007). This is the case of the Spanish Moruno variety of tomato which is highly
105 appreciated by its organoleptic characteristics (Moreno et al., 2019). Tomato landraces are
106 exposed to several factors such as seed-mixing, cross-pollination, and farmer selection (Cortes-
107 Olmos et al., 2015) that increase their variability even in the accumulation of taste-related
108 compounds (Cebolla-Cornejo et al., 2013). Therefore, the analysis of a collection of Moruno
109 populations offers an incredible opportunity to increase our knowledge regarding consumer
110 preference in tomato as conditioned by the accumulation of taste and aroma related compounds.

111 **2. Materials and methods**

112

113 *2.1. Plant materials and field trials*

114 A collection of 30 populations (accessions) belonging to the Spanish “Moruno” tomato
115 landrace (Table 1) highly appreciated by consumers due to its high quality, was analyzed in a 4
116 year-field study. These populations have an indeterminate growth habit and are characterized by
117 medium to large sized fruits, a dark red or brown colour, strong to medium-ribbing intensity, dark
118 shoulders and a predominantly flattened shape. All of them were obtained from local farmers or
119 from the Spanish seedbanks. The study was developed on 10 different populations per year during
120 the Years 1 to 3; in the Year 4, seven of the populations studied in the previous seasons were
121 considered. These populations were selected considering their best results in the previous trials
122 regarding specific parameters including sensory evaluation. Additionally, the commercial control
123 “Royesta” F1 hybrid (Reimer Seeds), with high acceptance by consumers in Mediterranean areas,
124 was included as a reference.

125 Cultivation was performed during the spring-summer growing cycle (May to Sept) at the
126 experimental farm of the Research Centre “El Chaparrillo”, Regional Institute for Agro-Food and
127 Forestry Research and Development (39°0’N, 3°56’W, altitude 640 m), in Ciudad Real (Central
128 Spain). The climate of this region is continental Mediterranean, with a mean, maximum and
129 minimum air temperatures during the four cropping periods at a range of 20.4 to 22.3°C, 28.3 to
130 31.0°C and 11.4 to 13.0°C, respectively.

131 The field trials were conducted in a randomized complete block design with four
132 replicates. Each experimental plot consisted of eight plants (32 plants per population) staked with
133 a separation of 2.0 m between rows and 1.0 m between plants. For the different controls, the
134 central six plants of each plot were considered. Plants were cultivated using organic farming
135 practices (EC n.834/2007), and no chemical fertilizers nor pesticides were applied. Common
136 fertilization and trickle irrigation practices for tomato organic farming production cultivation in
137 the area were followed.

138

Table 1. Populations evaluated of the “Moruno” tomato landrace and year of cultivation.

Year	Accession	Local name	Origin		
			Town	Province	Coordinates
1	SL-2	“Plano de El Avellanar”	San Pablo de los Montes	Toledo	39°32'N 4°19'W
1	SL-6	“Moruno de San Pablo”	San Pablo de los Montes	Toledo	39°32'N 4°19'W
1	SL-11	“Moruno de El Avellanar”	San Pablo de los Montes	Toledo	39°32'N 4°19'W
1, 4	SL-25	“Moruno”	La Malaguilla	Guadalajara	40°49'N 3°15'W
1	SL-27	“Morado”	Anchuras	Ciudad Real	39°28'N 4°50'W
1, 4	SL-33	“Negrillo”	Almoguera	Guadalajara	40°18'N 2°59'W
1	SL-41	“Negro rosa”	Elche de la Sierra	Albacete	38°27'N 2°3'W
1, 4	SL-62	“Moruno”	Socuéllamos	Ciudad Real	39°17'N 2°47'W
1, 4	SL-72	“Bonito”	Ciudad Real	Ciudad Real	38°59'N 3°55'W
1	SL-74	“Moruno”	Ciudad Real	Ciudad Real	39°0'N, 3°56'W
2, 4	SL-112	“Moruno de Aguas Nuevas”	Aguas Nuevas	Albacete	38°55'N 1°55'W
2	SL-113	“Moruno”	Aguas Nuevas	Albacete	38°55'N 1°55'W
2	SL-114	“Moruno”	Aguas Nuevas	Albacete	38°55'N 1°55'W
2	SL-116	“Moruno”	Aguas Nuevas	Albacete	38°55'N 1°55'W
2	SL-122	“Morao”	Aguas Nuevas	Albacete	38°55'N 1°55'W
2	SL-136	“Morao”	La Poblachuela	Ciudad Real	38°59'N 3°55'W
2	SL-154	“Moruno”	Elche de la Sierra	Albacete	38°27'N 2°3'W
2	SL-160	“Moruno”	Albacete	Albacete	38°59'N 1°51'W
2	SL-163	“Morao”	Arroba de los Montes	Ciudad Real	39°09'N 4°32'W
2	SL-165	“Morado”	Navas de Estena	Ciudad Real	39°29'N 4°31'W
3	SL-20	“Gordo”	Priego	Cuenca	40°27'N 2°19'W
3	SL-140	“Morao”	Arenales de San Gregorio	Ciudad Real	39°18'N 3°01'W
3	SL-143	“Moruno”	Socuéllamos	Ciudad Real	39°17'N 2°47'W
3	SL-149	“Negro”	Riópar	Albacete	38°30'N 2°25'W
3	SL-150	“Negro”	Riópar	Albacete	38°30'N 2°25'W
3, 4	SL-204	“Morao dulce”	Priego	Cuenca	40°27'N 2°19'W
3	SL-207	“Negro plano”	Brihuega	Guadalajara	40°45'N 2°52'W
3	SL-208	“Morao”	Priego	Cuenca	40°27'N 2°19'W
3	SL-209	“Moruno”	Elche de la Sierra	Albacete	38°27'N 2°3'W
3, 4	SL-252	“Moruno”	El Alcornocal	Ciudad Real	40°44'N 3°52'W

140

141

142 *2.2. Sampling and basic determinations*

143 The total yield was recorded throughout the whole harvest period (kg plant⁻¹). For further
144 characterization and sensory analysis, fruits in the optimum ripe stage, when the fruit surface was
145 homogeneously red colored, were hand-picked in the middle of the harvesting period (first half of
146 September). Three healthy fruits representing the predominant external appearance of each
147 population were taken from each plant (18 fruits per experimental plot, 72 fruits per population)
148 for the different studies. Mean fruit weight (g), number of locules, and fruit dry matter (obtained
149 in an oven set at 70°C until constant weight and expressed as grams per 100 g fresh weight) were
150 considered. Basic quality parameters were determined including total soluble solids content
151 (SSC), pH, and total titratable acidity. SSC were measured using a digital refractometer ATAGO
152 PR-32 (Atago Co. LTD, Tokyo, Japan) with automatic temperature compensation, which
153 provides values as °Brix. pH was determined using a pH meter, and titratable acidity was
154 quantified by titrating 5 g of tomato paste with 0.1 mol L⁻¹ NaOH to pH 8.1 with an automatic
155 sample titrator (TitroMatic 1S- 2B, Crison, Barcelona, Spain). Acidity was expressed as grams of
156 citric acid equivalent per 100 g fresh weight (% citric acid). Each sample was analyzed three
157 times.

158

159 *2.3. Quantification of sugars, acids, and volatiles*

160 The levels of compounds related to taste and aroma perception were determined in six
161 additional fruits per experimental plot (one fruit per plant, 24 fruits per population). These
162 analyses included the quantification of reducing sugars (fructose and glucose), acids (citric, malic,
163 glutamic), and volatiles related to aroma. For that purpose, fruits were washed with distilled water,
164 homogenized and stored at -80°C until analysis.

165 Reducing sugars and acids were determined by capillary zone electrophoresis using a
166 P/ACE System MDQ (Beckman Instruments, Fullerton, CA, USA), following the method
167 described by Roselló et al. (2002). Fused silica capillaries (Polymicro technologies, Phoenix, AZ,
168 USA) were used, with a 50 µm internal diameter, 363 µm external diameter, 67 cm total length,
169 and 60 cm effective length. Capillaries were initially conditioned with NaOH, then separation

170 buffer (20 mM 2,6-pyridin dicarboxylic acid and 0.1% w:v hexadimethrine bromide, pH = 12.1)
171 was run for 20 minutes at 20°C. Samples were thawed and centrifuged (510 g) for 5 minutes. The
172 upper phase was then diluted (1:10) in deionized water and filtered using 0.2 µm membranes.
173 Samples were injected hydrodynamically for 20 seconds at 0.5 psi. Then separation took place at
174 -25 kV fixed voltage and 20°C. Capillary was rinsed with SDS (60 mM) for 3 minutes at 20 psi
175 between samples, followed by the separation buffer at 20 psi for 3 minutes. Reagents and
176 standards were purchased from Sigma-Aldrich. Each sample was analysed twice and
177 quantification was performed with calibration curves of 5 points and $R^2 > 0.98$. Results were
178 expressed as g kg^{-1} fresh weight. This method enables the quantification of glutamic acid, as it
179 can be seen in its optimization reported by Cebolla-Cornejo et al. (2012).

180 The extraction and analysis of volatiles related to aroma were performed as described by
181 Beltran et al. (2006). A tomato sample of 30 g with 5% (w/w) CaCl_2 and with the addition of 50
182 µL of $15 \mu\text{g mL}^{-1}$ methyl salicylate- D_4 (surrogate/internal standard) were extracted by dynamic
183 head space (purge-and-trap) using SPE Tenax cartridges (Supelco, Sigma-Aldrich Química S.A.,
184 Madrid, Spain) and solvent elution. Chromatographic determination was carried out using a
185 Varian CP-3800 gas chromatograph coupled with a mass spectrometry detector (Saturn 4000,
186 Varian). Separation of the analytes was carried out on a 30 m x 0.25 mm DB-5MS (0.25 µm film
187 thickness) Varian capillary column, using helium at 1 mL min^{-1} as carrier gas. The temperature
188 program was as follows: 45°C for 5 min, then raised to 96°C at a rate of 3°C min^{-1} , then raised to
189 150°C at a rate of 6°C/min , and finally raised to 240°C at a rate of 30°C/min , with a final
190 isothermal stage of 1.5 min (total chromatographic analysis time of 36 min). Injection of 1 µL
191 (splitless mode, temperature 200°C) was carried out using a Varian 8400 autosampler. The gas-
192 chromatograph was directly interfaced with the ion trap Varian 4000 mass-spectrometer in the
193 external ionization configuration with an electron ionization energy of 70 eV in the positive ion
194 mode. Transfer line temperature was established at 250°C and ion source and trap temperatures
195 were adjusted to 200°C. Quantitation of analytes in the sample extracts was performed using
196 calibration curves using relative areas to internal standard.

197 Reference aroma compounds were obtained from Sigma-Aldrich Química S.A. (Madrid,
198 Spain; including Supelco and Fluka products) as pure compounds. Stock solutions of the aroma
199 standards at 500 $\mu\text{g L}^{-1}$ were prepared in acetone and stored at -18°C . Working solutions were
200 prepared by volume dilution in diethyl ether-hexane (1:1). The internal standard methyl salicylate-
201 D_4 was of 99.5% purity and was purchased from SigmaAldrich Sigma-Aldrich Química S.A.
202 (Madrid, Spain). Calcium chloride 97% (Riedel de Haen) was purchased from Supelco (Sigma-
203 Aldrich Química S.A., Madrid, Spain). Organic solvents (hexane, ethyl acetate, diethyl ether) of
204 trace residue analysis quality were purchased from Scharlab (Barcelona, Spain). Results were
205 expressed as ng g^{-1} fresh weight.

206

207 *2.4. Sensory analysis*

208 The remaining fruits were used for the sensory analysis by a consumer panel. This panel
209 consisted of 15 to 20 panellists, depending on the year, including males and females in similar
210 rates, aged 22-52. The panellists were all familiar with taste panel procedures and the terminology
211 used, and consumed tomatoes. The sensory analysis was performed within the day after harvest,
212 and until then the fruits were stored at $\sim 15^{\circ}\text{C}$. Fruits were washed, cut radially into wedges (about
213 eight wedges per fruit), and coded with random numbers. The panellists ranked the fruit samples
214 from the different populations according to the following sensory attributes: sweetness, sourness,
215 taste intensity, aroma intensity, aftertaste persistence, aftertaste agreeability, flesh firmness, skin
216 firmness, grainy texture, floury texture, juicy texture, and overall flavor acceptability. For rating
217 the different fruit textures (grainy, floury, or juicy texture), the percentage of panelists who
218 appreciated each texture is expressed. For the other sensory attributes, a hedonic scale from 1 to 9
219 (1 = low satisfaction or intensity; 9 = high satisfaction or intensity) was used (Baldwin et al.,
220 2015). The panellists were given water and unsalted crackers between samples, and the tests were
221 conducted in partitioned booths in a climate controlled tasting room.

222

223 *2.5. Statistical analysis*

224 A Partial Least Square (PLS) regression model for overall flavor acceptability (Y vector)
225 from the other sensory descriptors (X variables) was developed (Supplementary Table 1). PLS
226 regression models with the whole set of samples were also obtained for each sensory descriptor
227 variable (Y vector) from compositional variables (X matrix). SSC, Titratable acidity, pH, malic
228 acid, citric acid, glutamic acid, fructose, glucose, sucrose, sucrose equivalents, Citric acid
229 equivalents and 39 volatile compounds were used as direct compositional variables. Several ratios
230 between sugars and/or acid compounds and inverse or quadratic forms of compositional variables
231 were also included in the in the PLS models (Supplementary Table 2) using a total of 198 X
232 variables in the initial models. Sucrose equivalents were calculated as the weighted sum of sugar
233 concentration using the relative sweetening power of each sugar: 1 for sucrose, 1.73 for fructose
234 and 0.74 for glucose (Baldwin et al., 1998). Citric acid equivalents were calculated as the weight
235 sum of citric and malic acid considering their relative sourness: 1 for citric acid and 1.14 for malic
236 acid (Stevens et al., 1977).

237 Prior to modelling, data were pretreated using autoscale (mean center and scale each
238 variable to unit standard deviation) to correct different variable scaling and units. Venetian blinds
239 was chosen as cross-validation method to allow an estimation of the model performance. Outlier
240 identification was performed using a graphical evaluation of Q residuals and leverage. Any outlier
241 point that showed a large Q residual or unusual distribution was removed and the model was
242 recalculated. Normalized residuals and leverage parameters were also considered for outlier
243 identification (values < -3 or > 3) and elimination in response variables.

244 Variable selections were performed to improve the initial PLS models using a multistage
245 criterion. First, an interval PLS (iPLS) forward variable selection procedure (Nørgaard et al.,
246 2000) starting from the variables reported as determinants in tomato flavour (Baldwin et al., 1998;
247 Tandon et al., 2003; Abegaz et al., 2004; Tieman et al. 2017) were executed to find the first set
248 of explaining variables. Second an iPLS reverse variable selection (Nørgaard et al., 2000) from
249 the previous set of selected variables was executed to refine the initial selection, discarding
250 irrelevant variables. A final refinement in the variable selection of the model was performed

251 discarding variables using the selectivity ratio (Sratio) criterion (0.1 fraction removed per
252 iteration, Rajalahti et al., 2009) to obtain the final models (Supplementary Tables 1 and 2).

253 Resulting prediction model performance was evaluated in terms of outlier diagnostics,
254 the number of latent variables (LV), coefficient of determination of cross-validation (R^2_{CV}), cross-
255 validation bias (CV bias) and root mean square error of cross-validation (RMSECV). The ratios
256 RMSECV/Range of variation were also calculated as a percentage for each descriptor in order to
257 contextualize the results.

258 All PLS models were performed using Matlab v 9.8 (Mathworks Inc, Natick, MA, USA)
259 and the PLS Toolbox 9.0 for Matlab (Eigenvector Research Inc, Wenatchee, WA, USA). Pairwise
260 correlations were graphically represented as heatmaps using the software heatmapper
261 (<http://www.heatmapper.ca>). Principal component analysis (PCA) biplots were obtained to
262 describe the variation in volatiles and sensory variables. This analysis was performed with S-plus
263 v.8.01 (Insightful Corp., Seattle, WA, United States).

264

265 **3. Results and discussion**

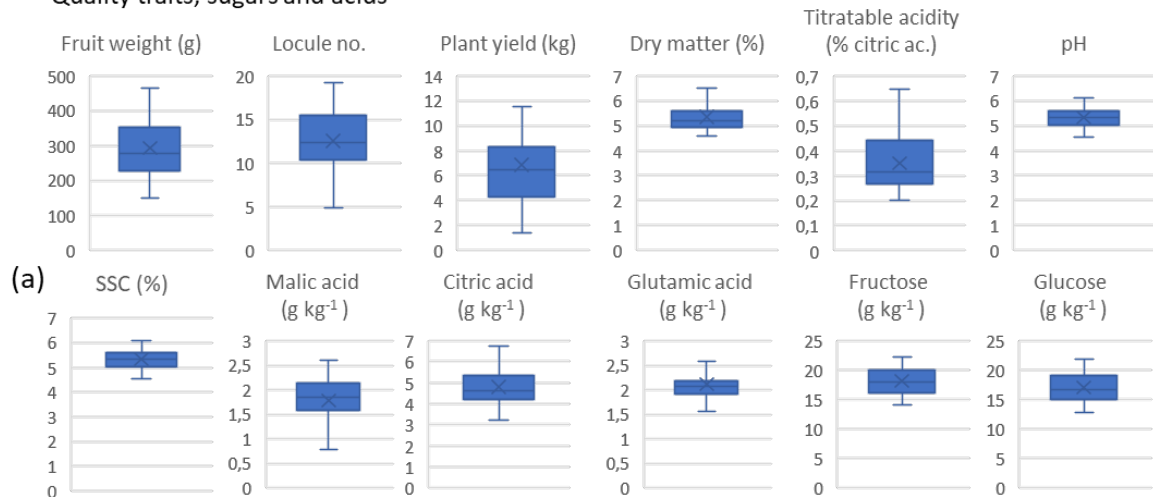
266 *3.1. “Moruno” landrace: Levels of variation in composition and sensory perception*

267 Spain, as the introduction point of tomato from America into Europe, has a high level of
268 diversity of this species. Centuries of cultivation resulted in a high number of landraces which are
269 highly appreciated by consumers. Accordingly, they are willing to pay up to 4.7 times the price
270 of conventional modern varieties in order to recover the true flavor of tomato (Cebolla-Cornejo
271 et al., 2007). Among these landraces, “Moruno” outstands by the high appreciation of its savory
272 fruits in the area (Moreno et al., 2019). Consequently, it was considered a good case study to
273 model consumer perception of tomato landraces.

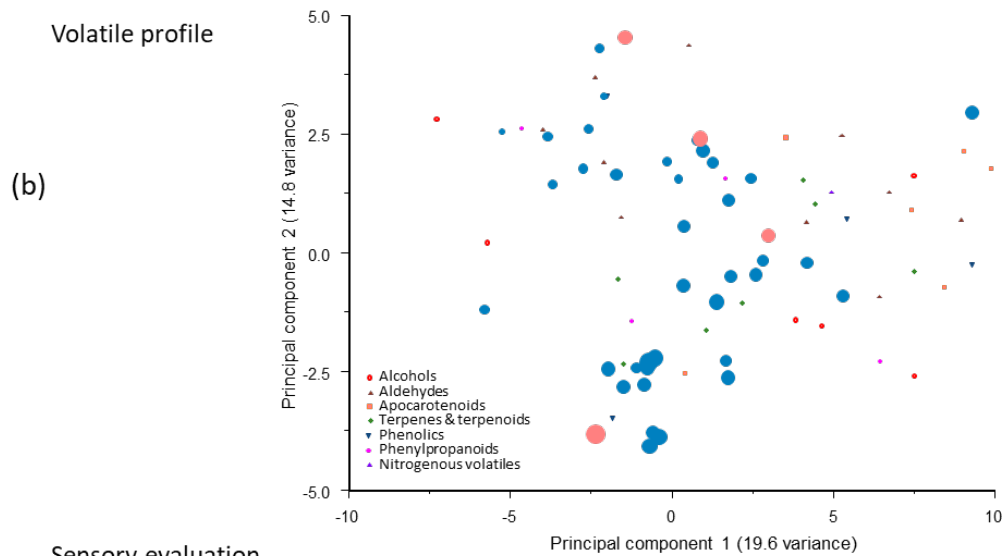
274 “Moruno” tomatoes can be recognized by a common external appearance with big ribbed
275 fruits and dark color, but important differences between populations (accessions) can be found.
276 Indeed, in the present study, the different “Moruno” populations showed a high level of variation
277 in morpho-agronomical traits (Fig. 1a). In general, fruits showed medium to big size, with a high
278 number of locules and dark color, while plant yield remained generally under 10 kg plant⁻¹, but

279 the coefficient of variation (%CV) for fruit weight reached 28%, being even higher for plant yield
280 (44%). Previous studies with a lower number of populations of this landrace had already showed
281 important differences in fruit size and plant yield, as some populations doubled the values reached
282 by others (Moreno et al., 2019). This seems to be a common trend at least in Spanish tomato
283 landraces. In this sense, Cebolla-Cornejo et al. (2013) found high levels of variation not only
284 between populations but within populations of different Spanish landraces.
285

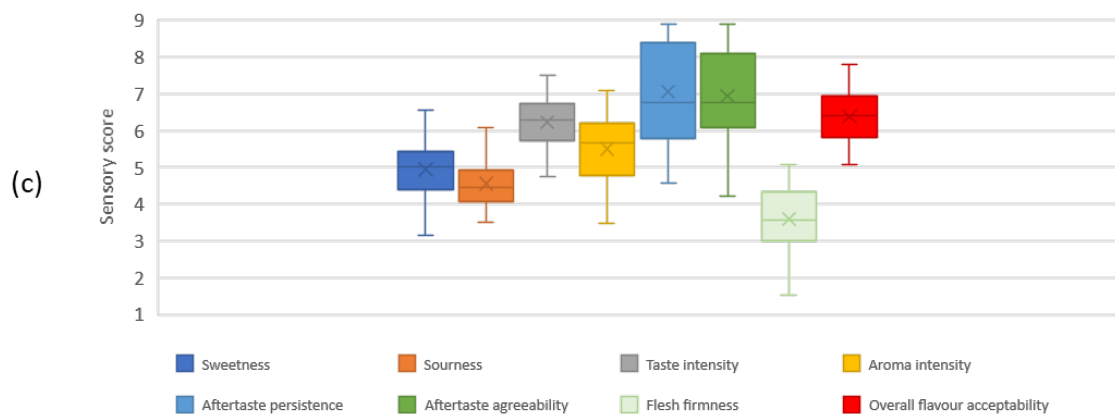
Quality traits, sugars and acids



Volatile profile



Sensory evaluation



286

287 **Fig. 1.** Profile of variation in the collection of samples assayed regarding to (a) agronomical traits,
 288 fruit quality parameters and compounds related to taste; (b) principal component analysis biplot
 289 of fruit volatiles representing the variability the volatile profile related to aroma (red dots:
 290 commercial control; blue dots: “Moruno” populations; dot size is proportional to yield); (c)
 291 sensory scores (1: low satisfaction or intensity; 9: high satisfaction or intensity) of the descriptors
 292 evaluated by the consumer panel. Error bars represent standard deviations.

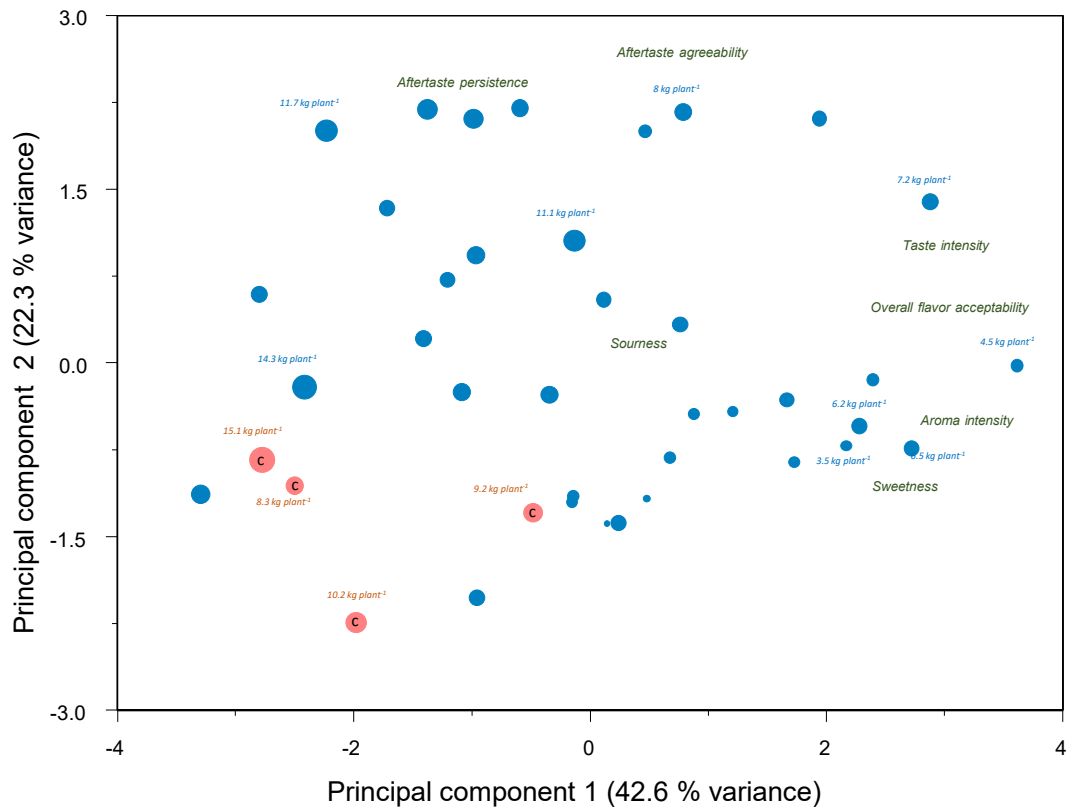
293

294 Differences in basic quality parameters including dry matter, titratable acidity, pH, or
295 SSC were more limited (Fig. 1a). pH was the most stable trait with %CV of 2%, followed by SSC
296 (8%) and dry matter (11%), while the variation in titratable acidity was considerably high (30%).
297 When individual sugars and acids were analyzed, a higher level of variation was detected. It was
298 higher in acids than in sugars and especially high in malic acids content (%CV=26%), as expected
299 considering the high variation detected in titratable acidity.

300 The variation in the volatile profile was schematized using a principal component analysis
301 (PCA) (Fig. 1b), which confirmed a high dispersion of the “Moruno“ populations in all the
302 evaluated volatiles classes: alcohols, aldehydes, apocarotenoids, terpenes and terpenoids,
303 phenolics, phenylpropanoids, and nitrogenous volatiles. This variability was also found in the F1
304 hybrid commercial control, highlighting the considerable effect of the environment on the volatile
305 profile. In this case, it should be considered that the expected variability of commercial F1 hybrids
306 in genotype is negligible, thus, the differences have to be due to environmental effects.
307 Interestingly most of the populations with lower and higher yields plotted in a profile
308 characterized by lower accumulation of most volatiles, specially apocarotenoids. Indeed, these
309 populations present negative scores for principal component 1 and this component presents
310 positive loadings with most volatiles, and especially carotenoids.

311 The high level of variation in individual compounds associated with taste and aroma
312 perception (Fig. 1a and 1b) was reflected in the values obtained in sensory descriptors evaluated
313 by the consumer panel (Fig. 1c). This variation was higher in traits related to aroma perception
314 and sweetness and lower for sourness (Fig. 1c). A PCA confirmed the sensory variability present
315 in the populations evaluated by the consumer panel (Fig. 2). Environmental effects can be, again,
316 clearly visualized through the dispersion of the F1 hybrid commercial control. Compared to the
317 dispersion observed in the volatile profile (Fig. 1b), the effect of the environment on sensory
318 descriptors is highly reduced (Fig. 2). Consequently, the higher variability observed for sensory
319 perceptions in populations of “Moruno” landrace must be related to genetic differences. In fact,
320 it has been suggested that tomato landraces are affected by seed mixing and spontaneous cross-

321 pollination events (Cortés-Olmos et al., 2015). Then, farmers would apply strong selections to
 322 recover fruit morphology traits typical of the landrace. But variation would be maintained in
 323 internal traits related to functional or organoleptic quality.
 324



325
 326 **Fig. 2.** Biplot representation (scores and loadings) of principal component analysis of sensory
 327 descriptors of “Moruno” landrace populations (blue dots), and commercial control (C, red dots).
 328 Dot size is proportional to plant yield.

329
 330 Interestingly, this biplot (Fig. 2) confirmed the difficulty of combining overall flavor
 331 acceptability and yield (dot size is proportional to plant yield). In this sense, those accessions with
 332 higher yields (close to the best performance of the commercial control) are far from the ideal
 333 consumer perception summarized by the overall flavor acceptability. Thus, accessions with a
 334 lower yield, generally performed better in sensory terms. Nonetheless, it was still possible to
 335 identify accessions with acceptable yields and good sensory performance. Altogether, the high
 336 diversity in soluble solids, volatiles, and sensory perception obtained, enabled the development
 337 of reliable models of consumer flavor perception.

338

339 *3.2. Overall flavor perception as affected by other sensory descriptors*

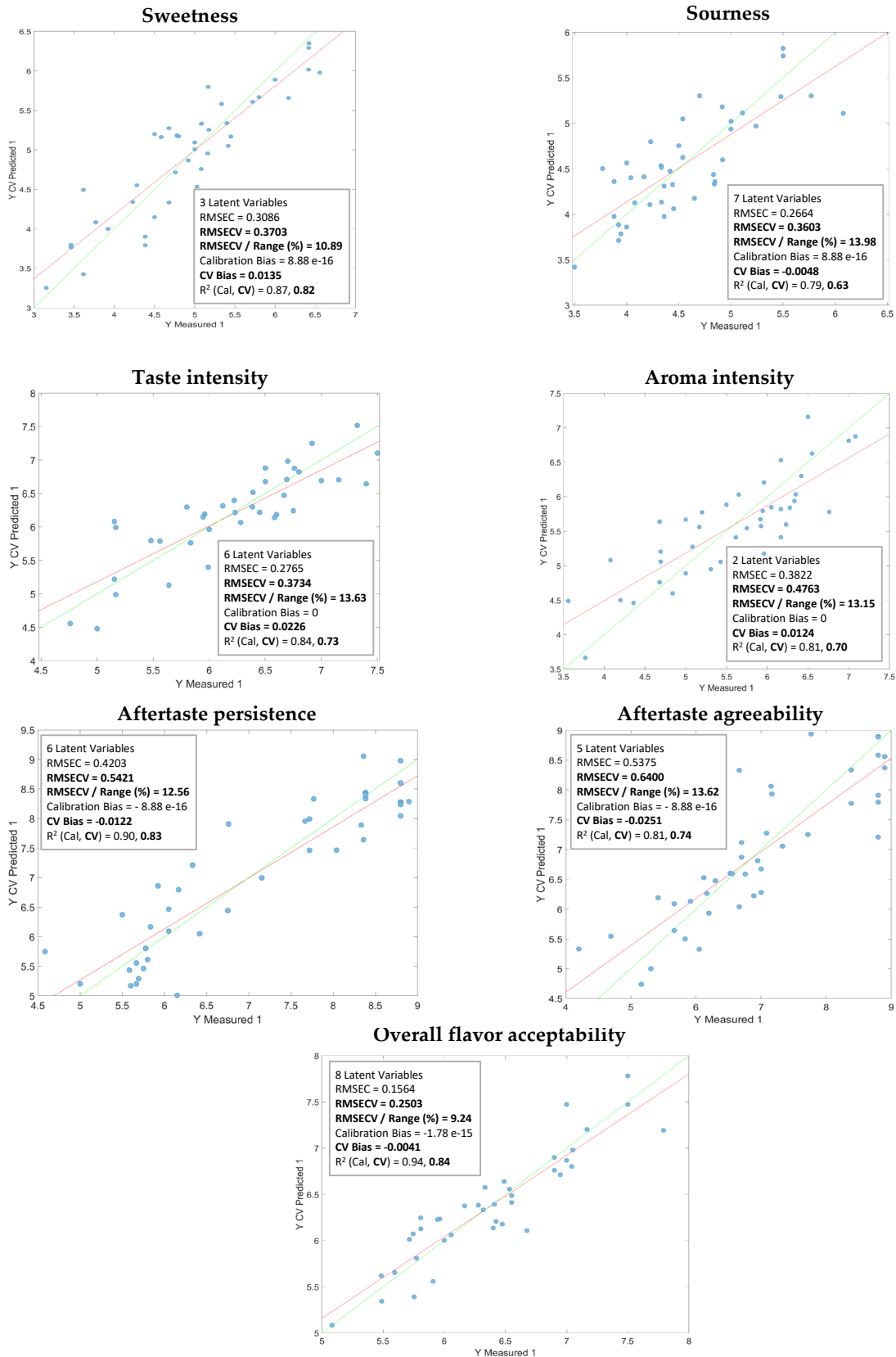
340 In order to analyze which descriptors had a higher influence on consumer acceptability
341 of this high quality landrace, a multi-stage selection variable procedure (iPLS and Sratio methods)
342 was performed. The analysis suggested two latent variables that included sweetness, sourness,
343 taste, aroma, aftertaste persistence, aftertaste agreeability, and flesh firmness as main
344 determinants of overall flavor acceptability (Supplementary Table 1). Other textural perceptions
345 were excluded as they were not significant. The model offered a moderate cross-validation
346 coefficient of determination ($R^2_{cv}=0.61$), but with a restricted error, with a root mean square error
347 of cross-validation (RMSECV) value of 0.41, representing a 15% of the range of variation of the
348 overall flavor acceptability. PLS overall flavor perception model was exported to a linear model.
349 According to this model, overall flavor acceptability can be inferred from the regression
350 coefficients as all descriptors used the same scale. It depended positively on sweetness, taste and
351 aroma intensities, and negatively of sourness, with similar contributions in absolute values. On
352 the other hand, aftertaste agreeability, aftertaste persistence, and flesh firmness only introduced
353 slight tinges. In recent models using neuronal networks, Cortina et al. (2018) described, in Andean
354 landraces and other materials, a higher preference for tomatoes rated high in sweetness and
355 intermediate in sourness, a preference already reported by Baldwin et al. (1998) in a collection of
356 24 cultivars, though in that work they later found correlations of overall acceptability with
357 sweetness, but not with sourness. This perception seems to agree with our results.

358

359 *3.3. Modelling sensory descriptors with compositional variables*

360 Specific compositional PLS models were developed for each sensory descriptor
361 (Supplementary Table 2, Fig. 3). After identifying and removing outliers, iPLS forward models
362 were initially ran considering each sensory descriptor and the concentrations of taste and aroma
363 related compounds, as well as inverse and quadratic derivatives, other derived variables such as
364 ratios between sugars and acids, sucrose equivalents or citric acid equivalents, which had been
365 previously linked to tomato flavor as they weight with the sweetening or acidulant power of each

366 compound (Galiana-Balaguer et al., 2018). In some cases, such as in sweetness, the initially
367 obtained model excluded compounds or variables that had been previously described as important
368 in similar regressions or that showed high linear correlation. Accordingly, the models were
369 repeated forcing the initial inclusion of these variables in the iPLS forward analysis.



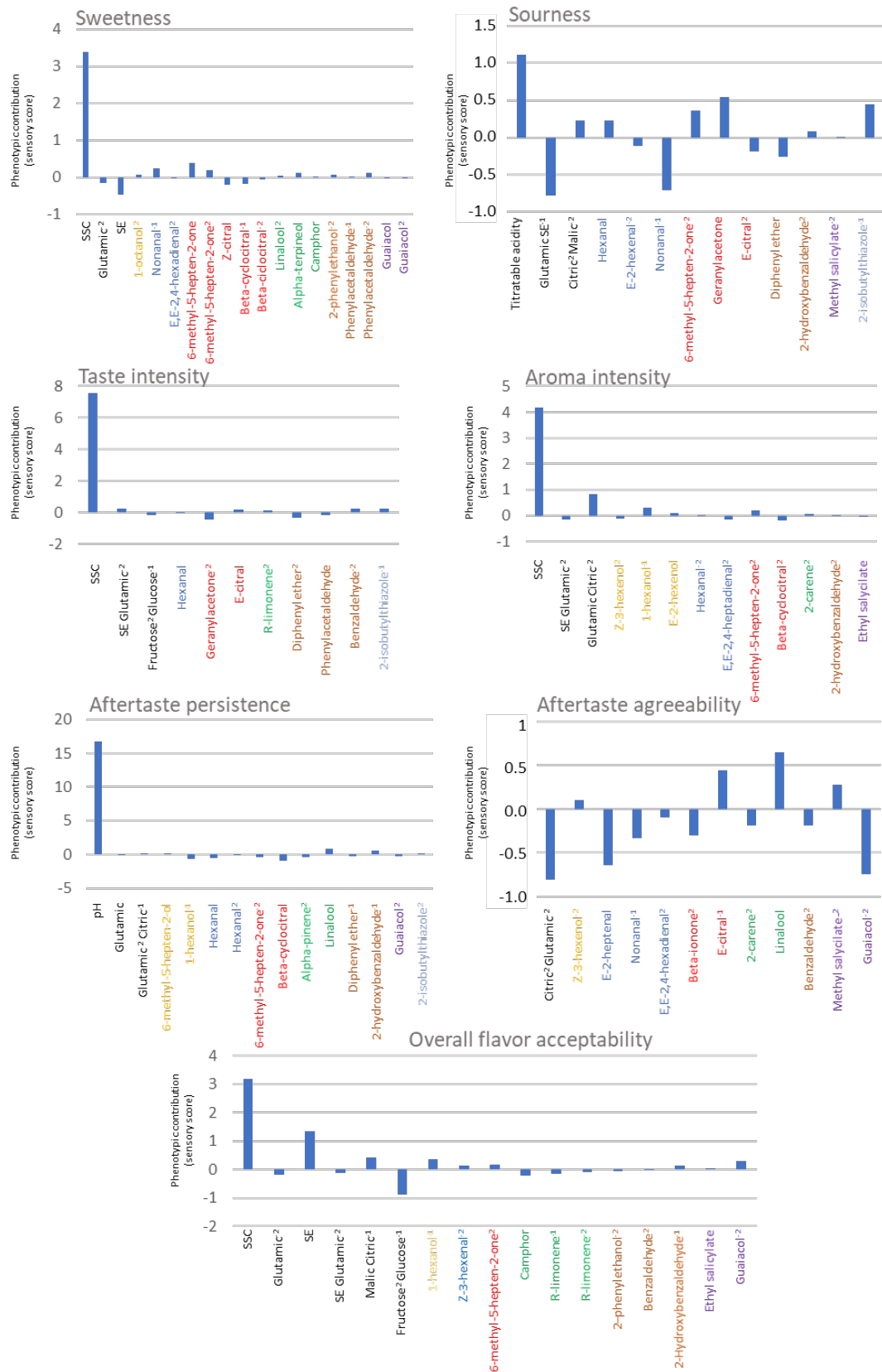
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Fig. 3. Performance of PLS models relating sensory descriptors and chemical composition. RMSE: Root Mean Square Error; C: calibration; CV: cross-validation; RMSECV/Range (%): ratio RMSECV to range of variation of the descriptor. Red line: Linear regression model between predicted and measured values. Green line: 1:1 relationship between predicted and measured values.

376 Although the model performance improved in some cases, it was necessary to check if all
377 the forced variables were really required. For that purpose, a subsequent iPLS reverse analysis
378 was performed to discard spurious variables and the performance increased after deleting some
379 of the initially required variables. Alternative variable selection methods such as VIP (variable
380 importance in projection) or Sratio (selectivity ratio), that focus on variables with higher linear
381 correlation, were also evaluated, but the resulting PLS models showed a worse performance, with
382 higher RMSECV values and lower R^2_{cv} . Accordingly, the models for the different sensory
383 descriptors did not always include variables with high linear correlation. For example, sweetness
384 presented relevant ($>|0.4|$) positive correlations with SSC, titratable acidity, hexanal, 6-methyl-5-
385 hepten-2-one, and beta-cyclocitral and negative with fructose to glucose ratio, 2-phenylethanol,
386 alpha-pinene, and 3-carene (Supplementary Fig. 1). But the final model did not include most of
387 these compounds. Even when they were initially forced to participate in the model, its
388 performance worsened considerably. In a final stage, the Sratio variable selection method was
389 applied to the selected set of variables to identify variables that could be excluded considering
390 their low contribution to the phenotype. Some of the variables with low mean contribution to the
391 final predicted value were discarded. The final PLS models obtained applying the described multi-
392 stage variable selection procedure for each descriptor were exported to linear models and the
393 mean contribution of each variable to the predicted descriptor value was calculated (Fig. 4). In
394 some cases, variables with low contribution to the descriptor values were included in the model,
395 but their removal decreased both RMSECV and R^2_{cv} values, so they were maintained.

396 Sweetness perception was finally modelled using three latent variables that included 19
397 initial variables. The model offered a R^2_{cv} value of 0.82 and a RMSECV of 0.37 was obtained,
398 which represented a 10.89% of the range of variation of the descriptor, %RMSECV
399 (Supplementary Table 2, Fig. 3). SSC, sucrose equivalents and glutamic² were included in the
400 model, with a large mean contribution to the descriptor of the former (Fig. 4).

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Fig. 4. Mean phenotypic contribution of each compound to the mean predicted value of each descriptor calculated with PLS models. Groups of compounds: sugars and acids, alcohols, aldehydes, phenylpropanoids, apocarotenoids, terpenes & terpenoids, phenolics, nitrogenous volatiles.

407 The model also included 16 variables related to volatile contents, with minor
408 contributions to the descriptor. Among them, stands out the positive contribution of 6-methyl-5-
409 hepten-2-one. The inverse negative relationship of beta-cyclocitral indicated a positive role, while
410 negative roles were identified in nonanal and z-citral (neral).

411 The perception of sweetness depends on the amount of sugars present in the fruit. These
412 contents are represented in the model by SSC and sucrose equivalents (SE). The last variable
413 represents the sum of individual sugars weighed by their sweetening power. SE already showed
414 a high correlation with sweetness perception in the models developed by Baldwin et al (1998).
415 Tandon et al. (2003) also found a higher relationship between SE and sweetness than with the use
416 of total sugars. In the model obtained in the present work, SE nuances the contribution of SSC.
417 The participation of acids in the model was expected, but no variable related with acidity was
418 selected in the model. Traditionally, titratable acidity has been linked with the perception of not
419 only sourness but also sweetness (Kader et al., 1977; Tandon et al., 2003). In our case,
420 glutamic⁻² made slight contributions to the descriptor value, indicating a preference for higher
421 glutamic values. Few studies have analyzed in depth the role of glutamic acid in tomato flavor
422 perception. Bucheli et al. (1999) revealed a major role of the SE glutamic⁻¹ ratio, thus suggesting
423 a negative role. But in a more recent study, Casals et al. (2018) confirmed the importance not only
424 of acidity in the perception of sweetness, but also glutamic acid levels in cherry and standard fresh
425 market tomatoes, as in our model.

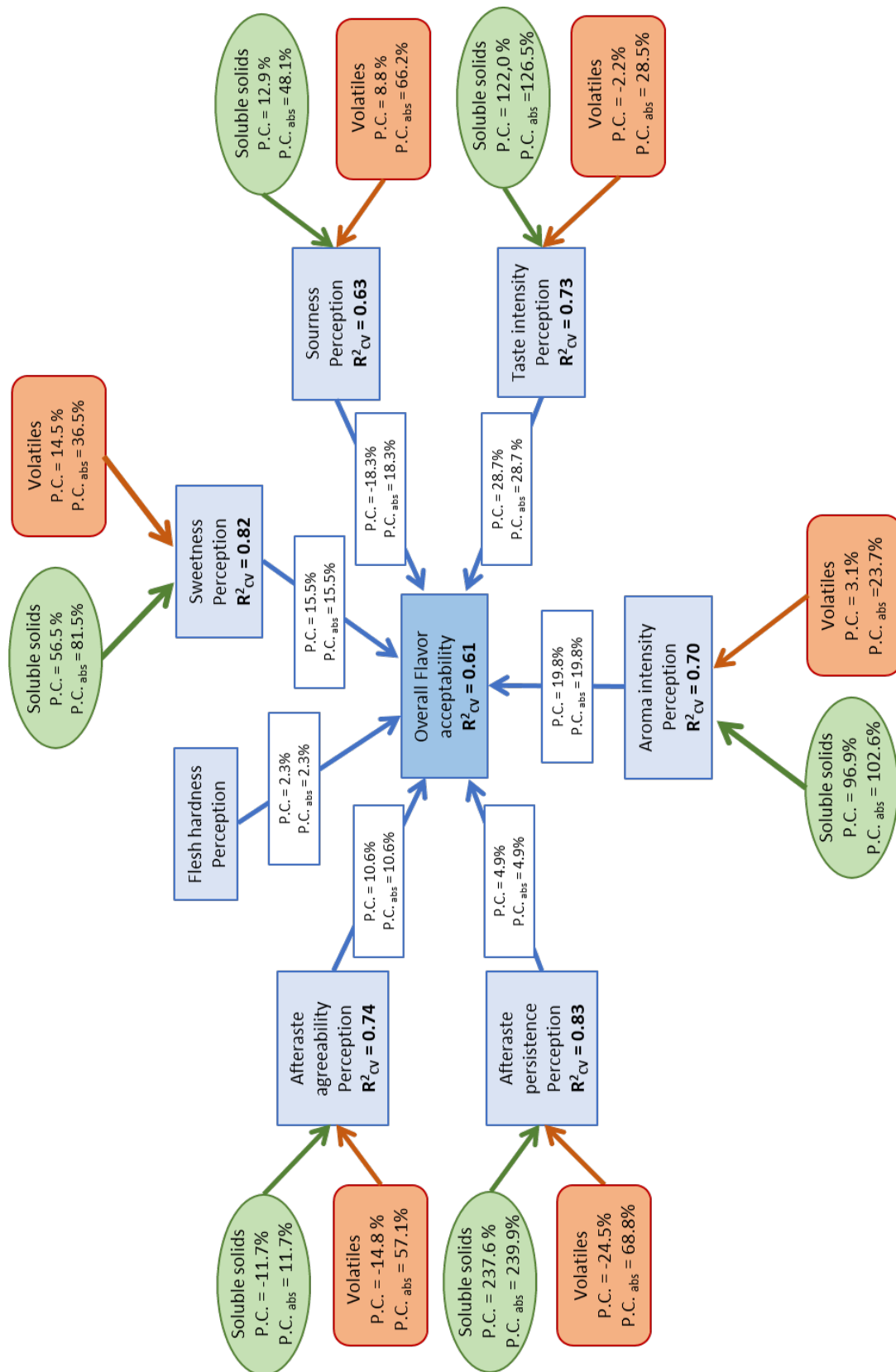
426 Several works have remarked the influence of volatiles in the perception of sweetness. In
427 1998, Baldwin et al. already described the importance of apocarotenoids, offering fruity or floral
428 notes, which were related to this sensory perception, as well as some alcohols, while Krumbein
429 and Auerswald in the same year highlighted the role of 1-penten-3one and 2-methyl-4-pentenal.
430 Later, Tandon et al. (2003) found high correlation levels between sweetness and isobutylthiazole
431 and acetone, and more recently, Baldwin et al. (2015) confirmed the relevance of volatiles such
432 as acetaldehyde, hexanal, trans-2-hexenal, 1-penten-2-one, 6-methyl-5-hepten-2-one,
433 geranylacetone, b-ionone, 2 + 3-methylbutanol, cis-3-hexenol and methylsalicylate in the
434 perception of sweetness. Tieman et al. (2012), in a large studio including commercial varieties

435 and landraces, reported that sweetness was related to fructose, geranial, 2-methylbutanal, 3-
436 methyl-1-butanol and other compounds associated with flavor intensity, including 2-butylacetate,
437 cis-3-hexen-1-ol, citric acid, 3-methyl-1-butanol, 2-methylbutanal, 1-octen-3-one, and E,E-2,4-
438 decadienal. Following a similar approach years later, Tieman et al. (2017) highlighted the role of
439 apocarotenoids in the perception of sweetness, though the analysis of correlations was focused on
440 overall liking and flavor intensity. In addition, not all the studies have included as many volatiles
441 in the perception of sweetness. For example, in a recent study, Cheng et al. (2020) only stood out
442 the role of E,E-2,4-decadienal. In our model, a high number of variables (16) related to 12
443 volatiles were selected, including one alcohol, two aldehydes, three apocarotenoids, three
444 terpenoids, one phenylpropanoid and two phenolics (Fig. 4). However, the contribution of several
445 of them to the descriptor value was very low, and only phenylacetaldehyde, 6-methyl-5-hepten-
446 2-one, nonanal, z-citral, beta-cyclocitral and alpha-terpineol outstood.

447 Although apocarotenoids appear consistently related to the perception of sweetness, it
448 seems clear that other volatiles also play an important role. It also can be concluded that
449 considering the disparity in the volatiles selected in different works, specific models for flavor
450 perception would be required for specific materials, considering the divergence between general
451 models generated with a high number of different genotypes and specific models. It seems clear
452 though that 6-methyl-5-hepten-2-one plays a major role. Although each volatile makes a low
453 mean contribution to the descriptor value, altogether represent (in absolute values) a 36.5% of the
454 mean predicted value of sweetness (Fig. 5).

455 The model for sourness perception included titratable acidity and the ratios glutamic SE⁻
456 ¹ and citric² malic⁻² among soluble compounds, as well as 10 variables related to three aldehydes,
457 three apocarotenoids, one phenylpropanoid, two phenolics and one nitrogenous volatile (Fig. 4).
458 Seven latent variables were selected in the PLS model, which offered a moderate performance,
459 with R²_{cv} = 0.63 and RMSECV of 0.36, representing a 14% of the range of variation of the
460 descriptor (Supplementary Table 2, Fig. 3).

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Fig. 5. PLS model relating overall flavor acceptability with other sensory constructs and PLS models relating sensory descriptors and variables related to soluble solids or volatiles contents. P.C.: phenotypic contribution of each group of variables (sum) to the mean predicted value of the descriptor. P.C._{abs}: P.C. calculated with contributions in absolute values. R²_{cv}: coefficient of determination of the model for cross-validation.

468 Volatiles played a major role in the phenotypic contribution of the sourness perception,
469 even higher than soluble solids in absolute values (Fig. 5). Several works have also related not
470 only sugars and acids but also volatiles in the perception of sourness. Baldwin et al. (1998)
471 highlighted the correlations with SSC, pH, acetaldehyde, acetone, 2-isobutylthiazole,
472 geranylacetone, beta-ionone, ethanol, hexanal and cis-3-hexenal. Tandon et al. (2003) obtained a
473 more limited model including titratable acidity and pH and considered acetone and beta-ionone
474 as positively correlated with sourness. In both models, beta-ionone was selected as an important
475 compound conditioning sourness. However, in our model this compound was not included, but
476 other apocarotenoids did, including geranylacetone with a positive role, and E-citral (geranial)
477 and 6-methyl-5-hepten-2-one with a negative role (the latter due to an inverse relationship).
478 Hexanal was included in the model as in the work by Baldwin et al. (1998). Traditionally, it
479 became clear that not only acids affect the perception of sourness, as their relationship with acids
480 is also crucial, being the tomatoes perceived as more acidic with lower values of hexoses.
481 Interestingly, volatiles also affect sourness perception. In some models, the same compound has
482 been related both with sweetness and sourness. This effect has also been found with nonanal⁻¹ in
483 both models. In the case of 6-methyl-5-hepten-2-one, though, higher values contributed positively
484 to sweetness but negatively to sourness.

485 It is difficult to compare the rest of the descriptors with previous works, as they are not
486 usually included. In our case, the model for taste intensity showed a good performance
487 (Supplementary Table 2, Fig. 3). Six latent variables were selected, offering $R^2_{cv} = 0.73$ and
488 $RMSECV = 0.37$ (13.6% of the range of variation). Sugars seemed to play an important role,
489 represented with the selection of the variables SSC, SE glutamic⁻², and fructose² glucose⁻¹ ratios
490 (Fig. 4), with a major contribution of the former. But also one aldehyde, two apocarotenoids, one
491 terpenoid, three phenolic and one nitrogenous volatiles were included (Fig. 4). Nonetheless, in
492 this case, the phenotypic value of the descriptor was mainly determined by soluble solids (Fig. 5).

493 In the aroma intensity model (Supplementary Table 2, Fig. 3), two latent variables were
494 selected, offering a moderate performance, with $R^2_{cv} = 0.70$ and $RMSECV = 0.48$ (13.2% of the
495 range of variation). As expected, a higher number of volatiles (10) was included in the model,

496 with three alcohols, two aldehydes, two apocarotenoids, one terpenoid, one phenylpropanoid and
497 one phenolic (Fig. 4). But interestingly, soluble solids had a major contribution *via* SSC, SE
498 glutamic⁻² and glutamic citric⁻². In fact, the mean phenotypic contribution in real or absolute
499 values of soluble solids was higher than that of the volatiles (Fig. 5).

500 Aftertaste descriptors offered higher RMSECV values (Supplementary Table 2, Fig. 3),
501 though they represented less than 13.6% of the range of variation. Specifically, aftertaste
502 persistence was modelled with six latent variables (RMSECV = 0.54 and $R^2_{cv} = 0.83$) and included
503 the variables pH, glutamic, the ratio glutamic² citric⁻¹, and 12 variables related to 11 volatiles: two
504 alcohols, one aldehyde two apocarotenoids, two terpenoids, and three phenylpropanoids (Fig. 4).
505 Interestingly, pH made with difference the highest mean contribution to the descriptor value, with
506 fruits with higher pH offering a higher aftertaste persistence. On the other hand, the model for
507 aftertaste agreeability (Supplementary Table 2, Fig. 3) required five latent variables ($R^2_{cv} = 0.74$,
508 RMSECV = 0.64, %RMSECV = 13.6%). The model selected the ratio citric² glutamic⁻² and 11
509 volatiles: one alcohol, three aldehydes, two apocarotenoids, two terpenoids, two
510 phenylpropanoids and one phenolic volatile (Fig. 4). Interestingly, aftertaste persistence was
511 mainly conditioned by contributions of soluble solids variables while aftertaste agreeability
512 depended more on volatile variables (Fig. 5).

513 In the study by Baldwin et al. (1998), aftertaste intensity was found to correlate with
514 acetaldehyde, beta-ionone and ethanol, though more compounds were related to aftertaste sour
515 (acetaldehyde, hexanal, and 2-isobutylthiazole) and aftertaste bitter (soluble solids, acetaldehyde,
516 l-penten-3-one, beta-ionone, ethanol, methanol, and 2+ 3-methylbutanol). Among them, only 2-
517 isobutylthiazole was selected in our case for aftertaste persistence with a positive role and beta-
518 ionone for aftertaste agreeability but with a negative role. It seems necessary then to obtain
519 specific models for specific materials.

520 Finally, overall flavor acceptability was modelled with eight latent variables and offered
521 an excellent fit with $R^2_{cv} = 0.84$ and RMSECV = 0.25, representing less than 10% of the range of
522 variation (Supplementary Table 2, Fig. 3). Soluble solids represented the main mean contributions
523 to the descriptor value, with high positive contributions of SSC and SE and negative of the ratio

524 fructose² glucose⁻¹. Glutamic⁻² and the ratios SE glutamic⁻² and malic citric⁻¹ were also included
525 in the model, but their contributions to the phenotypic value were lower (Fig. 4).

526 Baldwin et al. (1998) concluded that among soluble solids components, overall
527 acceptability was related to the ratio total sugars to titratable acidity, SE to titratable acidity and
528 titratable acidity. Previously Malundo et al. (1995) found that increasing sugars and acids
529 improved tomato acceptability but only up to a point, at which higher acid levels reduced liking,
530 justifying the importance of sugar to acids ratio. In our case, with a specific type of tomato, the
531 role of sugar is clear with the contributions of SSC and SE to acceptability, while the role of acids
532 is represented by the malic citric⁻¹ ratio. Interestingly, our model highlights the role of glutamic
533 acid and the ratio SE glutamic⁻², suggesting a beneficial effect of increasing concentrations of
534 glutamic acid considering the negative relationship of these variables with acceptability. Bucheli
535 et al. (1999) found that the best markers for tomato fruitiness in tomato varieties included reducing
536 sugars, malic and glutamic acid, with a negative role of the latter. Similarly, in *S. pimpinellifolium*
537 breeding lines they observed a positive role of reducing sugars to glutamic acid ratio, reducing
538 sugars, glucose, and a negative one of glutamic acid. This was one of the first mentions of a
539 relative role of glutamic acid, which the authors justified considering that the most effective
540 activity as flavor potentiator of this compound was exerted at a pH (5.5-8.0) higher than tomato
541 pH (4.0-4.6). Our results revisit the role of glutamic acid, highlighting the fact that, in certain
542 contexts, glutamic acid can play a positive role in flavor acceptability. Eleven variables related to
543 10 volatiles were also selected in our model. In absolute values, the contributions of volatiles to
544 the overall flavor acceptability values (1.58) represented a 26% of the contribution of variables
545 related to soluble solids (6.1). Considering inverse relationships, according to the model,
546 acceptability mainly increased with increasing contents of 6-methyl-5-hepten-2-one and R-
547 limonene and decreasing levels of 1-hexanol, camphor, 2-hydroxybenzaldehyde and guaiacol,
548 some of them due to an inverse relationship. According to *The good scent company* database
549 (www.thegoodscentcompany.com), positive volatiles represent fruity and citric notes, while
550 negative volatiles represent pungent green (1-hexanol), medicinal (camphor and 2-
551 hydroxybenzaldehyde) and spicy woody phenolic notes (guaiacol). Additionally, Z-3-hexanal⁻²,

552 2-phenylethanol², benzaldehyde² and ethyl salicylate were also included in the model but with
553 lower contributions.

554 Baldwin et al. (1998) found that E-6,10-dimethyl-5,9-undecadien-2-one and 6-methyl-5-
555 hepten-2-one had preferable odors in tomato fruits. Years later, Piambino et al. (2012) found in a
556 collection of different tomato types that Z-3-hexen-1-ol and 2-isobutylthiazole played a major
557 positive role, while 2-butanol, benzylalcohol, 6-methyl-5-hepten-2-ol and Z-2-nonenal had a
558 negative influence. In a latter review, Klee and Tiemann (2018) highlighted the positive role on
559 consumer preferences of fructose and glucose, 1-nitro-2-phenylethane, 1-nitro-3-methylbutane,
560 1-penten-3-one, 2,5-dimethyl-4-hydroxy-3(2H)-furanone, 2-isobutylthiazole, 2-phenylethanol,
561 3-pentanone, 6-methyl-5-hepten-2-ol, 6-methyl-5-hepten-2-one, benzaldehyde, benzyl cyanide,
562 Z-4-decenal, heptaldehyde, isovaleric acid, isovaleronitrile, nonyl aldehyde, phenylacetaldehyde,
563 E-2-heptenal, E-2-pentenal, E-3-hexen-1-ol, and a negative role of butyl acetate, eugenol, hexyl
564 acetate, isobutyl acetate, prenyl acetate and salicylaldehyde. One of the last studies on this topic
565 developed by Cheng et al. (2020) in a collection of different tomato types, reported that the
566 volatiles that contributed more to tomato flavor were E,E-2,4-decadienal, E-2-hexenal, 1-(2,6,6-
567 trimethyl-1-cyclohexen-1-yl)-2-buten-1-one, 6-methyl-5-hepten-2-one, hexanal, 2-
568 isobutylthiazole, 2,6,6-trimethyl-1-cyclohexene-1-carboxaldehyde, E-6,10-dimethyl-5,9-
569 undecadien-2-one, 4-allyl-2-methoxyphenol, E-2-heptenal, E-2-octenal, Z-3-hexen-1-ol, and
570 methyl salicylate. They also found that malic acid, 2-E-3-(3-pentyl-2-oxiranyl)acrylaldehyde, 2-
571 hydroxy-ethyl benzoate, methyl salicylate and 2-methoxyphenol were disliked by the evaluation
572 panels. All being considered, it seems evident that floral and fruity notes of apocarotenoids are
573 generally preferred, while pungent and medicinal notes might be negative. But the role of each
574 specific compound changes depending on the different studies. This seems to point out again that
575 specific models are required for specific materials and that models generated with a wide diversity
576 of tomato types may not be as generalizable as it would have been considered. This problem has
577 also been detected in other contexts related to tomato quality. For example, NIR models
578 developed with a high number of different varieties representing a wide spectrum of variation are
579 not as reliable as specific models developed for specific contexts (Ibáñez et al., 2019)

580

581 **4. Conclusions**

582 Models relating sensory evaluation and fruit composition in tomato, despite offering a
583 general view, are rather variable, probably due to the differences in the materials tested. Even
584 global models, developed with a high number of varieties grown in different years, seem to do
585 not apply to specific contexts. Indeed, the soluble solids and volatiles identified as determinants
586 for flavor perception in the present study showed only a minimum overlap with global scale
587 studies. Our results confirm the role of volatiles in the definition of descriptors related to taste, as
588 well as the contribution of soluble solids to aroma perception. In terms of overall acceptability,
589 though, soluble solids play a major role that is then tinged by different volatiles. Among them our
590 work shows that 6-methyl-5-hepten-2-one is a key volatile that should be specially considered in
591 the development of breeding programs. In this context, the specific accumulation of individual
592 sugars, should also be addressed, as they tinge sensory descriptors. Nonetheless, it seems clear
593 that general models do not apply in the case of tomato and it would be required to develop specific
594 models for specific materials. In this context, this study offers valuable information from the
595 methodological point of view. PLS methods have proved to be a reliable tool to model tomato
596 sensory perception, offering low %REMSECV values and highlighting the role of certain
597 compounds that do not stand out for high linear correlations. The models obtained already
598 represent ideal targets to be considered in the development of breeding programs, considering the
599 high acceptability of the tomato landrace “Moruno”. On the other hand, the evaluation of the
600 sensory profile of different populations of the same landrace again highlights the huge variation
601 present in these genetic resources. It has become commonplace the generalization that landraces
602 stand out by their organoleptic characteristics, but the truth is that numerous populations of
603 landraces have lost during their evolution their valued flavor. It is necessary to continue with
604 deputation programs to consolidate their presence in high quality markets and their on-farm
605 conservation. But in the process, it should be considered that extremely high yields would highly
606 impact the sensory profile of tomatoes.

607

608 **Credit authorship contribution statement:**

609 **Jaime Villena:** methodology & formal analysis, review & editing. **Carmen Moreno:**
610 conceptualization, methodology, review & editing, supervision & project administration. **Marta**
611 **M. Moreno:** conceptualization, methodology, review & editing, supervision & project
612 administration. **Joaquín Beltrán:** methodology & formal analysis. **Salvador Roselló:**
613 methodology & formal analysis, visualization, review and editing. **Jaime Cebolla-Cornejo:**
614 visualization, writing original draft, writing review & editing.

615

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618 reported in this paper.

619

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624

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626

627 **Supplementary materials:** Supplementary material associated with this article can be
628 found, in the online version.

629

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