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1 Blueberry supply chain: critical steps impacting fruit quality and application of a boosted
2 regression tree model to predict weight loss
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12 Highlights

- 13 • Shipping, store display and consumer are critical steps, impacting quality and waste
- 14 • Boosted regression tree model predicted weight loss at the end of storage
- 15 • Vapour Pressure Deficit, time, and point in the supply chain influence weight loss

17 Abstract

18 Blueberries have increased in popularity in recent years due to their nutritional benefits and
19 sensory characteristics. However, to preserve quality and extend shelf-life, they need to be
20 maintained at refrigerated temperatures and high relative humidity, conditions that are not
21 routinely met along the supply chain. Poor temperature management leads to quality
22 deterioration, increasing waste/losses along the supply chain. This study examined the impact of
23 each step along the supply chain on the physicochemical quality and shelf-life of blueberries,
24 identifying the most critical steps from field to consumption. The following steps were identified
25 as critical in the blueberry supply chain: shipping to distribution centre (DC) (72 h at 5 °C), store

26 display (48 h at 15 °C), and consumer (48 h at 20 °C). Given the economic importance of weight
27 loss and its link to fruit quality and shelf-life, a boosted regression tree (BRT) model was built to
28 predict weight loss using the post-harvest environmental conditions of a simulated supply chain
29 applying different temperature-time scenarios. The model explained 84 % of the variance on the
30 test set and highlighted the interactions of supply chain conditions on weight loss.

31

32 Keywords: Cold chain; Shelf-life; Machine learning; Biochemical properties; Post-harvest storage

33

34 1. Introduction

35 Food security is a worldwide challenge faced by the uncertainty of meeting future food
36 demand for an increasing population. Increasing food production is challenging, and reports have
37 revealed that reducing food waste can address food security challenges (Gustavsson et al., 2011).
38 Fresh fruit and vegetables are among the most frequently wasted foods (Kelly et al., 2019).
39 Emphasis has been placed on temperature management as one of the major causes of fresh
40 produce losses (FAO, 2019; Lai et al., 2011). Improper display conditions, limited shelf-life, and
41 aesthetic standards have been linked to waste occurring at the retail level. At the consumer level,
42 waste occurs, among other reasons, due to improper storage (FAO, 2019; Porat et al., 2018).

43 Blueberries are now the second most economically important soft fruit grown worldwide
44 (Giongo et al., 2013), labeled as "superfoods" (Peano et al., 2017) due to their nutritional value
45 and benefits to human health (Manganaris et al., 2014; Wang et al., 2017). Their shelf-life ranges
46 from one to five (Matiacevich et al., 2013) or a maximum of eight weeks (Duan et al., 2011),
47 depending on several preharvest and post-harvest factors. Commonly, blueberries are being

48 exported via long supply chains (Paniagua et al., 2014), 95 % of which is shipped by ocean
49 transport (Beaudry et al., 1998; Moggia et al., 2016). Lobos et al. (2018) reported an increase in
50 rejected Chilean blueberries at the destination over the last decade. Peano et al. (2017) reported
51 blueberries kept under normal atmosphere conditions results in wastage in the range of 6-10 %
52 per pallet unit.

53 Optimum storage conditions for blueberries are 0 °C and high relative humidity (RH)
54 (Cantwell, 2002), while blueberries are often stored under a controlled atmosphere to maximise
55 their shelf-life (Falagan et al., 2020; Terry et al., 2009). Deviations from optimum conditions occur
56 due to logistical constraints of precooling, sorting, and transport (Paniagua et al., 2014) and at
57 the retail and consumer level (Nunes et al., 2009; Porat et al., 2018; WRAP, 2008). Non-optimal
58 conditions lead to increased weight loss, decay incidence, and softening (Paniagua et al., 2014)
59 and affect biochemical characteristics of fresh fruit, such as vitamin C, sugars, and soluble solids
60 content (Chiabrando et al., 2009; Kelly et al., 2019).

61 Weight loss is a key factor influencing the shelf-life of blueberries, as it causes shriveling, loss
62 of brightness (Chiabrando & Giacalone, 2011), and softening (Bai et al., 2019; Moggia et al.,
63 2016). Weight loss (primarily due to water loss) directly causes economic losses when sold based
64 on fruit weight (Bai et al., 2019). Blueberries can suffer high water loss due to their small size
65 (high surface area/volume ratio) (Wills et al., 1981). Sanford et al. (1991) reported that
66 blueberries become non-saleable when weight loss is higher than 5-8 %. Another study reports
67 that the maximum acceptable weight loss during a 2-3-week period (14-21 days) is between 5-7
68 % (Paniagua et al., 2014). Non-optimal temperature and/or RH conditions result in higher water

69 loss due to increased transpiration caused by a larger water vapour pressure deficit (VPD)(Laurin
70 et al., 2005).

71 Extensive literature exists in mathematical models used to describe the moisture and weight
72 loss of fresh produce (Bovi et al., 2018; Joshi et al., 2018; Lufu et al., 2019; Xanthopoulos et al.,
73 2017). They provide detailed information on all the process variables and have been paramount
74 in describing the phenomena associated with weight loss and how they are influenced by
75 environmental conditions such as storage temperature and RH. Application of such models can
76 be found in designing efficient packaging, designing strategies for controlling weight loss,
77 designing and studying MAP packaging and efficiency, etc. (Joshi et al., 2019; Mahajan et al.,
78 2016; Song et al., 2002). These models often require the estimation of many experimental
79 parameters, application of advanced calculation methods, and in-depth knowledge of the
80 process mechanisms (Omari et al., 2018).

81 In recent years, artificial intelligence and machine learning algorithms have empowered
82 data analysis in the agri-food sector. The learning ability of such algorithms is suitable for
83 identifying the complexity of biological responses. Modeling and predicting biological functions
84 is difficult due to non-linear responses and complicated relationships among input variables (Lin
85 and Block, 2009) to which mathematical approaches are not easily applied. These data-driven
86 models, although they lack the ability equation-driven mathematical models have, to describe
87 process parameters such as heat or mass transfer coefficients or reaction kinetics (Zhang,
88 2010), are derived from measurements using system identification techniques and are ideal for
89 control purposes (Farkas et al., 2000). Such algorithms' applicability is becoming prevalent due
90 to their ability to learn, adapt and improve continuously, ease of use, and high accuracy

91 (Ojediran et al., 2020). They have been used in agri-food quality evaluation and shelf-life
92 determination (Ktenioudaki et al., 2019; Meng et al., 2012; Santos Pereira et al., 2018; Zhang et
93 al., 2016), modeling and controlling drying processes (Chen et al., 2020; Erenturk and Erenturk,
94 2007; Farkas et al., 2000; Qadri et al., 2020) and various other applications in food engineering
95 (Wang et al., 2012; Younis et al., 2019).

96 Little information is available in the literature regarding the relative importance of each step
97 of the supply chain on the quality and shelf-life of blueberries. Knowledge of the impact of each
98 step on the overall quality and shelf-life of blueberries would allow proper decision making to
99 address/prevent waste and facilitate actions so that high quality and nutritious food products
100 reach the consumer. The objectives of the study were: i) to identify critical supply chain steps
101 where a significant decline in physical and/or biochemical quality occurred by determining the
102 impact level of each step along the supply chain, and ii) given the importance of weight loss in
103 the blueberry industry to build a machine learning model predicting weight loss taking into
104 account post-harvest environmental conditions.

105

106 2. Material and Methods

107 2.1 Plant material and experimental setup

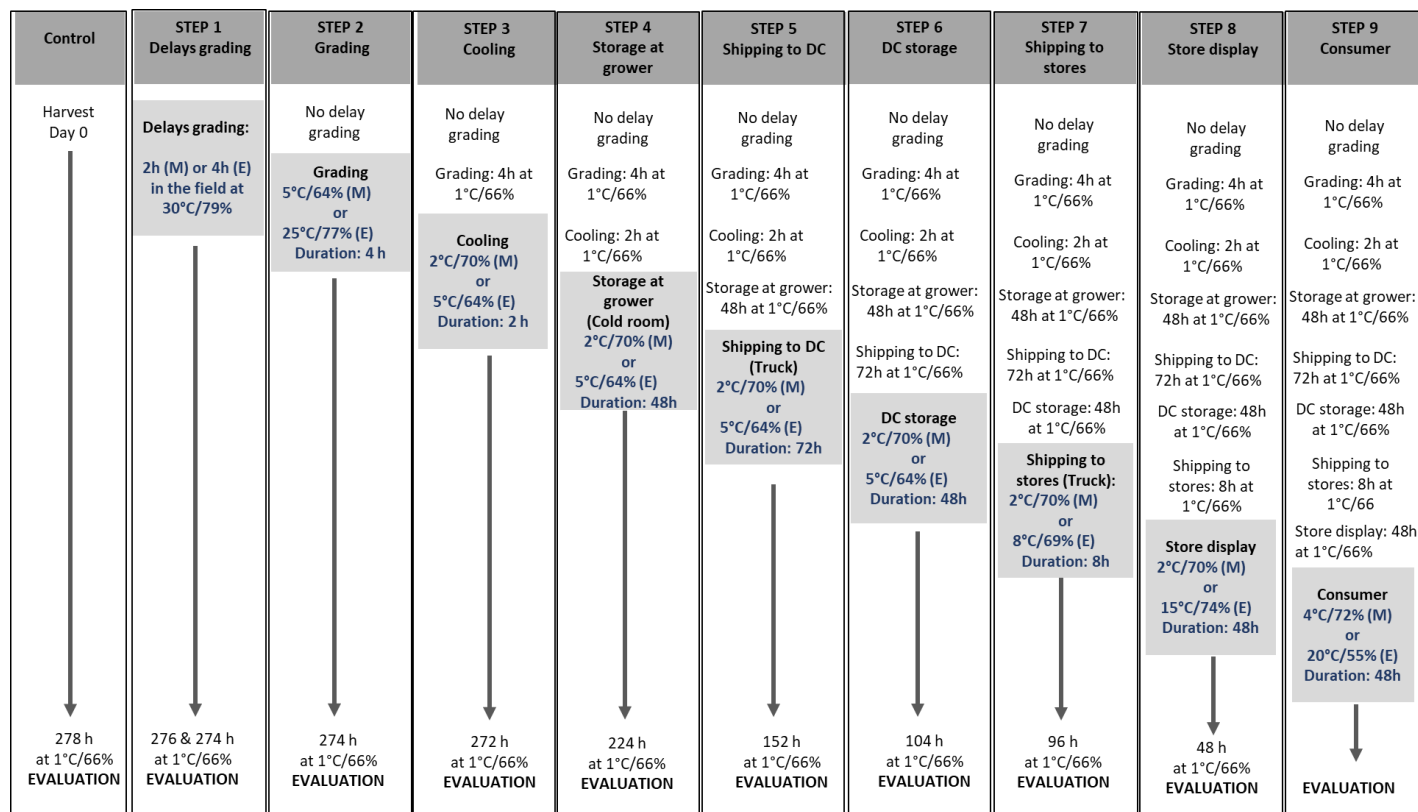
108 'Jewel' blueberries were harvested on two occasions during the production season (April
109 and May) from commercial fields in Florida, USA. Within one hour of harvest, approximately 28
110 kg of blueberries were brought to the USF-Food Quality Laboratory (transit temperature of
111 approximately 15 °C), where 21 kg were randomly selected for uniformity of colour and freedom
112 from defects.

113 The blueberry supply chain was divided into nine steps to include all steps from
114 production to consumer. Each step was split into two conditions: Moderate (M) and Extreme (E).
115 *Moderate* being conditions of small temperature deviation from optimum or shorter duration
116 and *Extreme* being conditions of higher temperature deviation or longer duration (Fig.1).
117 Simulated supply chain conditions were selected based on previous observations during
118 blueberry handling: Blueberry optimum temperature storage conditions (1.0 °C) were selected
119 based on published data (Nunes, 2008; Perkins-Veazy, 2016). Grading delays, grading
120 temperatures were estimated based on previous observations during field operations; field
121 temperatures (30 °C) were selected based on the average field temperatures measured in Florida
122 between April and May (<https://fawn.ifas.ufl.edu/>); cooling times and temperatures (2 or 5 °C
123 for 2 h), storage at the grower's facilities (2 or 5°C for 24 h), shipping to distribution centre (DC)
124 (2 or 5 °C for 72 h), DC storage (2 or 5 °C for 24 h), shipping to stores (2 or 8 °C for 8 h) and store
125 display (2 or 15 °C for 24 h) were selected based on previous observations during field operations.
126 The time (104 h) used to simulate shipping from grower to distribution center (DC) was chosen
127 based on the farthest distance in time from Florida to the Midwestern States or Eastern Canada.
128 Finally, conditions used for consumer handling (4 or 20 °C for 24 h) were chosen based on the
129 standard household refrigerator (Godwin et al., 2007) and countertop conditions (temperature
130 and RH). Target RH for most steps (except Step 9E-Consumer at 20 °C) was set at 80 %. However,
131 the achievable RH was dependant on the temperature as it was difficult, due to equipment
132 limitations, to maintain a high RH at temperatures close to freezing point. Recorded RH and
133 temperature conditions are shown in Figure 1 and Table 1. RH at Consumer(20 °C) step was 55 %
134 to simulate countertop conditions.

135 The experiment consisted of 19 treatments [9 simulated supply chain steps x 2 conditions
136 each (M + E) and 1 Control]. Temperature and humidity-controlled chambers (Forma
137 Environmental Chambers Model 3940 Series, Thermo Electron Corporation, OH, USA) were used
138 to store the samples. Control samples were kept at optimum temperature conditions (1.0 °C) and
139 66 % RH. As mentioned earlier, optimum RH conditions of above 80 % were challenging to attain
140 due to the limited capability of the equipment used in maintaining high RH values at this low
141 temperature. Each step (Fig. 1) is an individual supply chain condition, as only that step differed
142 from the control. Before and after each of those different time-temperature treatments, the
143 blueberries were kept at constant optimum temperature conditions. The quality of the fruit was
144 evaluated initially (day 0) and at each step individually, after a total supply chain length of 278 h
145 (\approx 12 d).

146 In total, 133 clamshells of 150 g of fruit were prepared and distributed to the chambers
147 set at different temperatures and RH conditions depending on the supply chain step (Fig. 1 and
148 Table 1). Four clamshells were taken from each treatment/step (4 replicates) after 278 h and
149 were used for weight loss, appearance, colour, and texture evaluation; and three additional
150 clamshells per treatment (3 replicates) were homogenized in a laboratory blender, and the
151 resulting puree was immediately frozen and kept at -30 °C for biochemical analysis. On the day
152 of harvest (day 0), four replicates of 150 g fruit were used for appearance, colour, and texture

153 evaluation. Additional three replicates of 150 g fruit were immediately blended and frozen and
 154 subsequently used for biochemical analysis.



155 Fig. 1 Blueberry supply chain simulations from field to consumer. Each column represents a supply chain step, and within each
 156 step, moderate (M) and extreme conditions (E) were tested. DC: Distribution Centre
 157

158 Table 1 Conditions of simulated supply chain steps

Samples/Steps	Conditions (Duration /Temperature/RH)	VPD* (kPa)	Point (h)	Time (h)
Control	278h / 1°C/ 66%	0.22 ± 0.00	0	0
Simulated supply chain steps				
1M	Delays grading	0.934 ± 0.02	0	2
1E				
2M	Grading	0.31 ± 0.05	0	4
2E				
3M	Cooling	0.23 ± 0.02	4	2
3E				
4M	Storage at grower	0.23 ± 0.02	6	48
4E				

5M	Shipping to DC	72h / 2°C / 70%	0.23 ± 0.02	54	72
5E		72h / 5°C / 64%	0.31 ± 0.05	54	72
6M	DC storage	48h / 2°C / 70%	0.23 ± 0.02	126	48
6E		48h / 5°C / 64%	0.31 ± 0.05	126	48
7M	Shipping to stores	8h / 2°C / 70%	0.23 ± 0.02	174	8
7E		8h / 8°C / 69%	0.34 ± 0.01	174	8
8M	Store display	48h / 2°C / 70%	0.23 ± 0.02	182	48
8E		48h / 15°C / 74%	0.44 ± 0.03	182	48
9M	Consumer	48h / 4°C / 72%	0.23 ± 0.04	230	48
9E		48h / 20°C / 55%	1.05 ± 0.02	230	48

159 * M - moderate conditions of small temperature deviation from optimum or shorter duration, E - extreme
160 conditions of higher temperature deviation from optimum or longer duration, VPD – Vapour Pressure Deficit,
161 Point - point in the supply chain when a deviation from optimum conditions occurred (breach), Time - duration of
162 breach

163 * VPD results shown are the mean (± standard deviation) of two harvests. VPD calculations were based on actual
164 temperature and RH conditions recorded by the data loggers.

165

166 2.2 Temperature and relative humidity (RH) monitoring

167 Temperature and RH inside the chambers were monitored throughout the study using
168 HOBO® brand U12 data loggers (Onset Computer Corporation, Pocasset, MA, USA), which
169 records within an accuracy of ± 0.35 °C ± 2.5 % respectively.

170

171 2.4 Vapour pressure deficit (VPD)

172 VPD was calculated for all treatments based on the temperature and RH recordings of the
173 data loggers. VPD was calculated according to equation 1:

$$174 \text{ VPD} = u_{\text{sat}} * (1 - \text{RH}/100), \text{ (eq.1)}$$

175 Where u_{sat} is the saturation vapour pressure in kPa (obtained from psychrometric charts), RH is
176 the relative humidity.

177 VPDt, the combination of VPD and Time (duration of breach), was calculated to show
178 accumulated VPD during breach. The cumulative VPD (VPDt_total), which is the sum of the VPDt
179 for the duration of the simulated supply chain (278 h), to express accumulated VPD during breach
180 and control conditions.

181

182 2.5 Quality evaluation

183 *Weight loss and dry weight.* Weight loss was calculated from the initial weight of the fruit and
184 after each supply chain (278 h). Weight loss was calculated as the percentage difference between
185 the initial and the final net weight of the fruit in each clamshell. A digital balance (Denver
186 Instruments, Timberline Series Model TP-3102) of 0.01 g of precision was used for this weight
187 measurement.

188 The following formula was used for water loss corrections: $[\text{chemical components (fresh weight)} \times 100 \text{ g} / (\text{dry weight} + \text{weight loss during storage (g)})]$. The dry weight was determined by
189 drying three weighed aliquots of homogenized fruit tissue at 80 °C until the weight stabilized.
190 Concentrations of chemical constituents were expressed in dry weight to show the differences
191 between treatments that might be obscured by differences in water content and water loss
192 during storage (Kelly et al., 2018).

194

195 *Overall appearance.* Subjective quality evaluation of blueberry was performed at harvest (initial)
196 and the end of each supply chain step (278 h), always by the same trained personnel. Four
197 replicated samples of 150 g were evaluated for overall appearance/marketability based on
198 colour, firmness, shrivelling, and decay (Table 2). A score of 3 was considered the lower limit of

199 acceptability for sale (Sanford et al., 1991; Nunes, 2015). The time (days) between harvest and
 200 this lower limit of acceptability (score of 3) determined the shelf-life of the fruit.

201

202 *Table 2. Visual quality scores and descriptors for blueberry*

	Scores and description				
	1	2	3 ^a	4	5
	Very poor	Poor	Acceptable	Good	Excellent
Colour ^b	Extremely dark; overripe or senescent	Very dark blue/purplish	Fully dark blue	Bluer, less bright	Bright blue colour
Firmness ^c	Berry rupture on touch	Berry surface very depressed on touch but no rupture	Berry surface depressed on touch, softer than firmer	Slight depression on touch	Firm berry, not yielding to touch
Shrivelling ^d	Extremely wilted and dry	Severe shrivelling	Shrivelling evident but not serious	Slight signs of shrivelling	Field-fresh, fruit appear very fresh and turgid
Decay ^d	76 -100% decay, severe to extreme decay	51-75% decay, moderate to severe decay	26-50% decay, slight to moderate decay	1-25% decay, probable decay (brownish/greyish sunken minor spots)	0%, no decay

203 ^a Score of 3 was the minimum acceptable quality before blueberries become unmarketable.

204 ^b Modified from Jackson et al. (1999); Sapers et al. (1984).

205 ^c Modified from Sanford et al. (1991).

206 ^d Nunes et al. (2004).

207

208 *Instrumental colour (L*a*b*) analysis.* Ten surface measurements (L*a*b*) were taken directly
 209 in the bulk of blueberries with a hand-held tristimulus reflectance colorimeter (Model CR-400,
 210 Konica Sensing Americas, NJ, USA) using standard illuminant D65. The measurement took place
 211 directly from the clamshell. The blueberries were spread out evenly throughout the clamshell.
 212 Colour was recorded using the CIE-L*a*b* uniform colour space (CIE-Lab), L* (lightness), a*
 213 (redness), and b* (yellowness) values. Numerical values of a* and b* were converted into hue
 214 angle and chroma using the CR-400 Utility Software (Konica Minolta Sensing Americas, NJ, USA).

215 *Texture analysis.* Firmness of blueberries was measured after conditioning the samples at room
216 temperature for approximately one hour, using a TA.XT Plus Texture Analyzer (Texture
217 Technologies Corp., NY, USA) equipped with a 50 kg load cell. Three replicated samples of 30 g
218 each were placed into three-100 mL plastic beakers. The fruit was then compressed to a depth
219 of 30 mm using a 38 mm diameter and 20 mm high acrylic cylinder probe, driven at 1 mm/sec
220 crosshead speed, and the compression force was recorded in N (Sanford et al. 1991; Nunes,
221 2015).

222
223 *Biochemical analysis.* Frozen pureed samples were thawed at 4 °C overnight, and samples were
224 analysed for sugar content, ascorbic acid (AA), total phenol content (TPC), and total anthocyanins
225 (ANC) content as described by Kelly et al.(2019). All values are expressed in g kg⁻¹ on a dry weight
226 basis. Total sugars were calculated as the sum of individual sugars. TPC is expressed as g kg⁻¹ gallic
227 acid equivalents (GAE), ANC is expressed as g kg⁻¹ pelargonidin 3-glucoside equivalents.
228 Titratable acidity (TA), pH, and soluble solids content (SSC) were determined, according to Kelly
229 et al. (2019). TA and SSC are expressed in % on a dry weight basis.

230

231 2.6 Boosted Regression Tree

232 A boosted regression tree model (BRT) was used to predict fruit weight loss using the
233 recorded simulated supply chain storage conditions. Decision tree algorithms are popular as they
234 present information in the form of a tree and are easy to visualize with straightforward rules
235 (Elith et al., 2008; Santos Pereira et al., 2018). BRT combines a large number of simple tree models
236 adaptively to improve the performance of the model (Elith et al., 2008).

237 The objective was to explore whether the BRT model can be used to predict weight loss
238 by using commonly recorded storage conditions (temperature and RH). Cumulative VPD was
239 calculated, showing the total VPD the fruit was subjected to during the simulated supply chain.
240 Cumulative VPD and Point - point in the supply chain when a deviation from optimum conditions
241 (breach) occurred were the two independent variables of the model.

242 The model was fitted in R version 3.4.4 and R Studio 1.2.5001 (R Core Team, 2017) using
243 the Caret and gbm packages. The hyperparameters were tuned using a 10fold cross-validation
244 technique. These hyperparameters (n.trees = 150, interaction depth = 3, shrinkage = 0.1,
245 n.minobsinnode = 3) were then used to fit a model with and to acquire the partial plots using the
246 gm.plot function. The data was divided through random stratified sampling in training and test
247 set (75:25 split ratio) and Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-
248 squared (R^2) were used as model metrics. The gbm library was used to identify variable
249 importance and build the partial effect plots. The model was tested on new splits (n=10) to
250 examine data randomness, and the mean and standard deviations of RMSE, MAE, and R^2 are
251 presented.

252

253 2.5 Statistical and data analysis

254 One-way ANOVA analysis was carried out using R version 3.4.4 and R Studio 1.2.5001 (R
255 Core Team, 2017). Where ANOVA indicated significant differences were present, the Tukey
256 pairwise comparison of the means (and 95% confidence intervals) was used to identify where the
257 sample differences occurred. Significant differences in the physicochemical properties were
258 identified between the two harvests, and the results were treated separately. Algorithms

259 investigated included regression trees, support vector regression (SVR) and generalised additive
260 models (GAMs), but the boosted regression tree had the best performance in this study. The
261 following R packages were used to perform the data analysis: Agricolae (Mendiburu, 2015), Caret
262 (Kuhn, 2019), gbm (Greenwell et al., 2019), pdp (Greenwell, 2017), caTools (Tuszynski, 2019),
263 Metrics (Hammer & Frasco, 2018), writexl (Ooms, 2018).

264

265 3. Results & Discussion

266 Significant differences in the initial biochemical properties of blueberries were observed
267 between the two harvests, possibly due to variability in pre-harvest conditions that can affect
268 the concentration of chemical components in fruit or variability in the degree of ripeness.

269 Overall, fruit from the first harvest H1 exhibited higher acidity, TPC, ANC, total sugars, and AA;
270 and lower pH and SSC (see section 3.3).

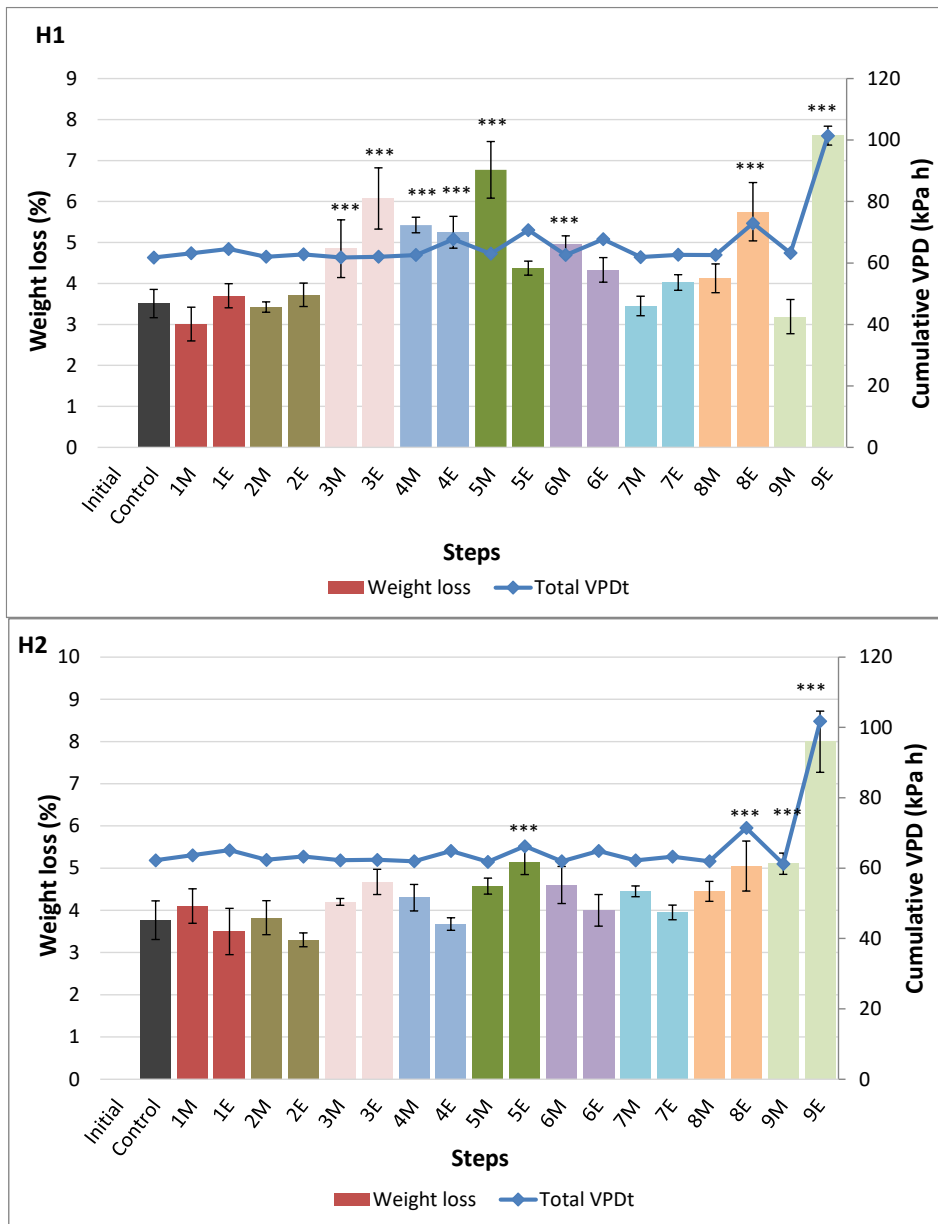
271

272 3.1 Impact of supply chain steps on weight loss

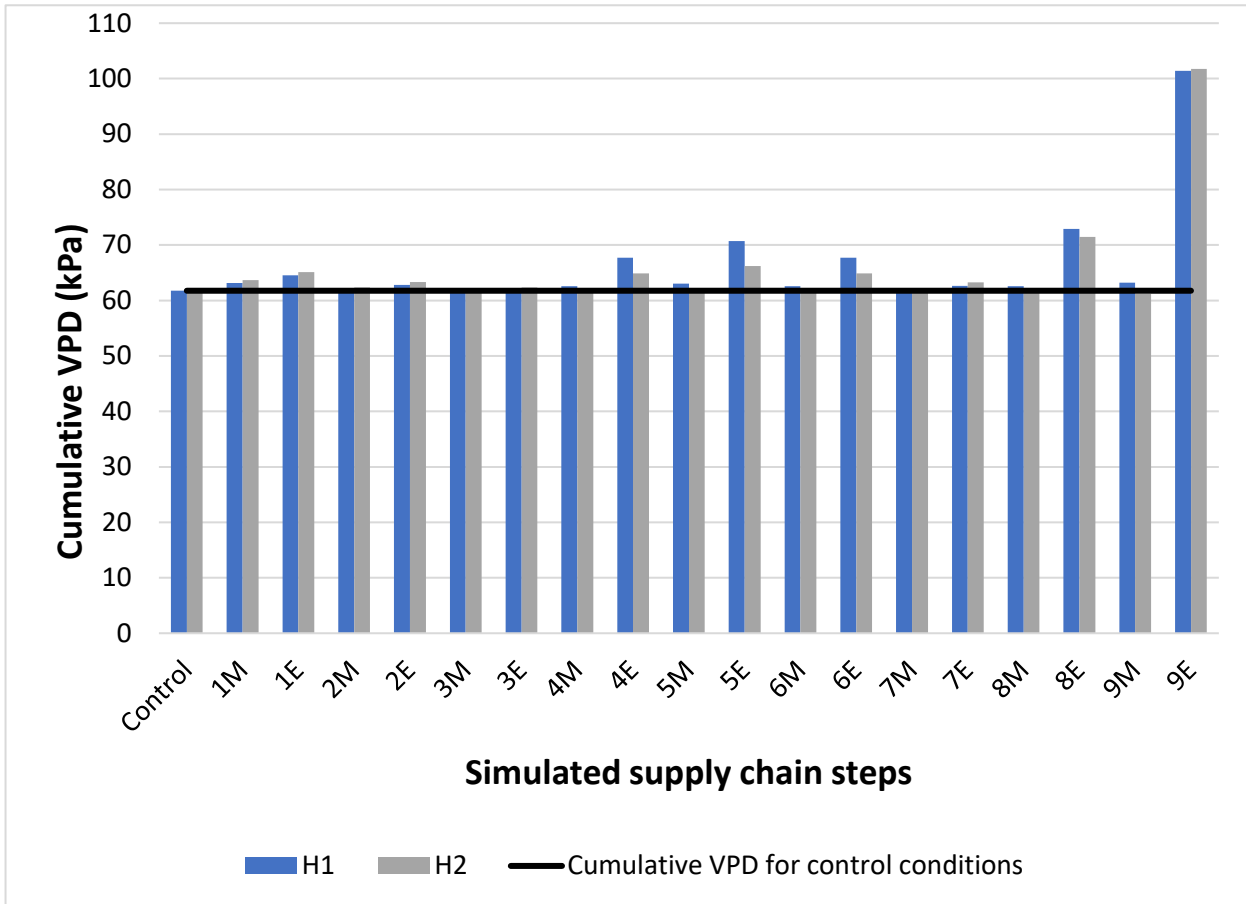
273 Weight loss of blueberries was observed regardless of the storage conditions (Fig. 2). The
274 conditions in many steps of the simulated supply chain resulted in significantly higher weight loss
275 than the control (3.5 ± 0.4 % and 3.8 ± 0.5 % in H1 and H2, respectively). Differences in weight
276 loss between moderate and extreme conditions within each step were not significant except for
277 steps 3, 8, and 9 in H1 and step 9 in H2. In these cases, blueberries stored in extreme conditions
278 (higher temperatures and/or longer exposure times) exhibited higher weight loss. In H1 and step
279 5, the weight loss was significantly higher in moderate conditions (lower temperature) and the
280 highest observed in the study. Due to this unjustified and unusual high value, data from this step

281 was considered an outlier and excluded from further analysis. Our results are within the range
282 of weight loss values reported in previous studies. For example, Chiabrand and Giacalone (2011)
283 reported a weight loss of 1.55 and 2.64 % on years 1 and 2, respectively, for blueberries stored
284 at 0 °C and 90-95 % RH. In contrast, Paniagua et al. (2013a) reported a 10 % weight loss after 21
285 days of storage at 0 °C. Temperature and RH and their interaction affect weight loss.
286 Furthermore, the rate of weight loss has been linked to VPD, based on the principle that
287 transpiration rate is dependent on VPD (Lufu et al., 2019); and higher VPD will lead to higher
288 rates of water loss. All supply chain steps caused an increase in VPD compared to the control.
289 During step 9E-Consumer, for example, VPD increased to 1.05 kPa, resulting in an approximately
290 5 times higher rate of water loss than control (VPD= 0.22 kPa). Fig. 3 shows the cumulative VPD
291 for each step of the simulated supply chain and the deviation from control. There were significant
292 increases in cumulative VPD during steps 8E-Store Display and 9E-Consumer, and smaller
293 increases in steps 4E-Storage at the grower, 5E-Shipping to DC, 6E-DC Storage for both harvests.

294 Similarly, in steps 8E-Store Display and 9E-Consumer, significantly higher weight loss was
295 noted compared to control in both harvests. The cumulative VPD variation alone did not explain
296 the weight loss results because weight loss is a complex process influenced by many physiological
297 and environmental factors. However, as discussed further in section 3.5, cumulative VPD could
298 indicate with accuracy where and when the most water loss will occur, which is valuable
299 information for perishable goods moving through a cold supply chain.



301 Fig. 2 Impact of simulated supply chain steps (moderate (M) and extreme conditions (E)) on weight loss
 302 of fresh blueberries after 278 h of storage in harvest 1 (H1) and harvest 2 (H2). Error bars show standard
 303 deviation between replicates (n = 4). Asterisks indicate significant differences ($p \leq 0.0001$) between
 304 control and supply chain steps. Cumulative Vapour Pressure Deficit (VPD) in each step is also shown.



305

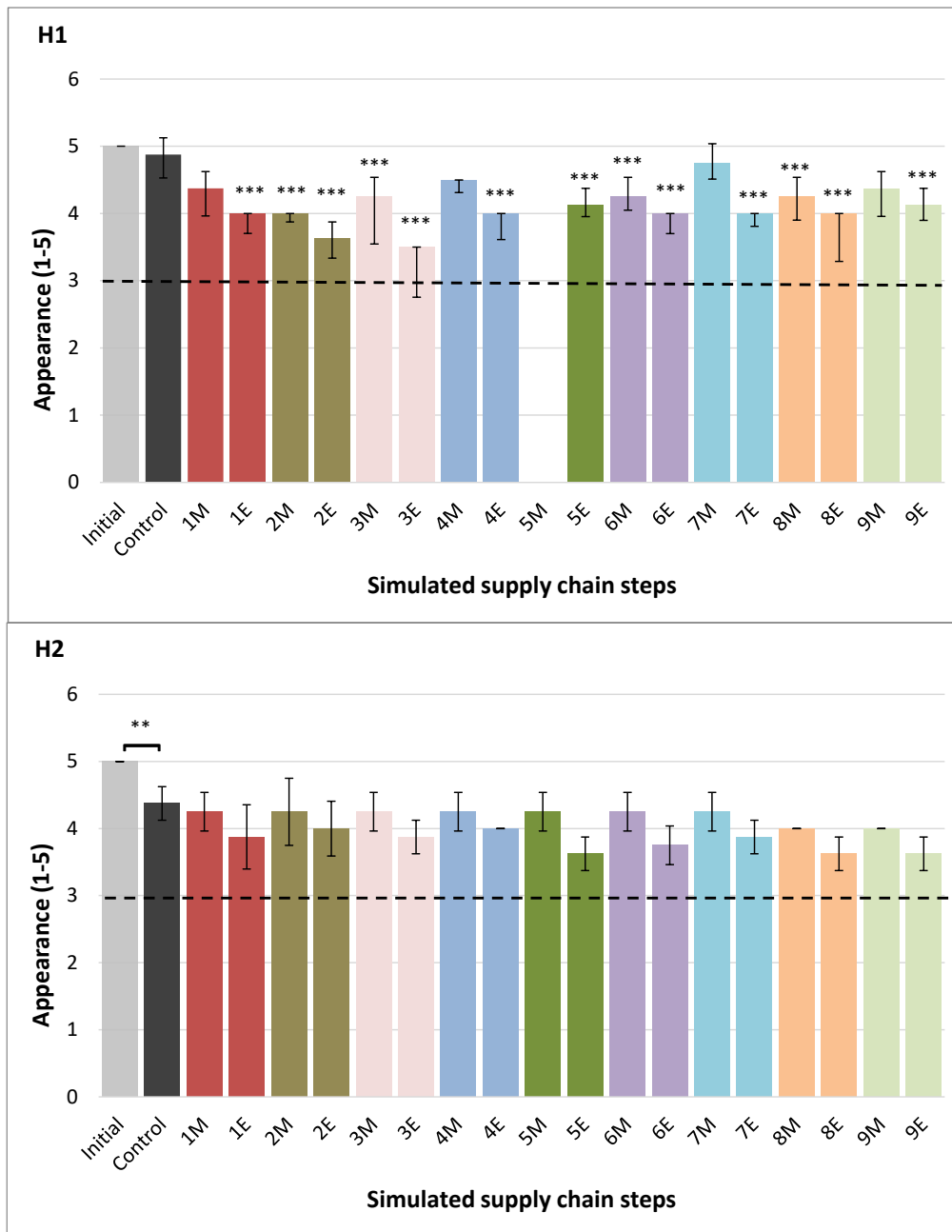
306 **Fig. 3.** Cumulative Vapour Pressure Deficit (VPD) for each step (moderate (M) and extreme conditions (E))
 307 of simulated supply chain. Results from two harvests are shown (Harvest 1 - H1 and harvest 2 - H2).

308

309 3.2 Impact of supply chain steps on physical quality attributes

310 Fruit appearance, an important quality attribute that influences shelf-life and waste,
 311 declined during storage for all treatments. Blueberries kept at control conditions scored higher
 312 in both harvests (mean score of 4.6) than the fruit exposed to simulated supply chain conditions
 313 (scores ranged between 3.6 to 4.5, Fig. 4). Most blueberries exposed to extreme (E) simulated
 314 supply chain conditions received lower scores, but not all differences were significant.

315



316 **Fig. 4.** Impact of simulated supply chain steps (moderate (M) and extreme conditions (E)) on appearance
 317 of fresh blueberries after 278 h of storage in harvest 1 (H1) and harvest 2 (H2). Error bars show standard
 318 deviation between replicates (n = 4). Asterisks indicate significant differences (** $p \leq 0.001$, *** $p \leq 0.0001$)
 319 between control and supply chain steps. Dashed straight line represents the minimum acceptable quality
 320 before blueberries become unmarketable (rating 3).

321

322 The colour of blueberries depends on maturity level, and the colour-appearance of the

323 fruit is affected by the presence of bloom. Higher L^* values were generally observed for fruit on

324 day 0 than the control samples after 278 hours of storage, indicative of a lighter color or presence
325 of bloom (Eum et al., 2013). There was variability in L* for samples exposed to simulated supply
326 chain conditions varied from 27.8 to 33.6 in H1 and 23.3 to 34.4 in H2 (results not shown). Hue
327 values slightly increased during storage, indicating a change to a blue-purple colour.

328 Firmness changes during storage have been linked to changes in the primary cell wall
329 components (Liu et al., 2019). Variable behaviour was observed with most steps leading to a
330 decrease in firmness compared to the control and initial values; however, in some cases increase
331 in firmness was also noted. Significantly lower firmness was observed between step *2-Grading(E)*
332 (10.2 ± 1.6 N), *3-Cooling(E)* (11.0 ± 3.1 N), and control samples (21.8 ± 6.6 N) in H1, whereas the
333 increase in firmness observed was not significant. No significant differences were observed in H2;
334 firmness varied between 9.12 ± 1.7 N (step *2-Grading(E)*) and 15.2 ± 3.5 N (Initial). The firmness
335 of control blueberries was 13.3 ± 2.15 after 278 hours. Variable firmness behaviour during
336 storage has also been reported previously (Paniagua et al., 2013b). Many studies have linked
337 weight loss to the decrease of firmness (Chen et al., 2017;Paniagua et al., 2013b) with Paniagua
338 et al. (2013b), suggesting a threshold of 8 % weight loss over which extensive softening can occur.
339 An increase in firmness during storage has also been observed and associated with low weight
340 loss (Paniagua et al., 2013b). Different theories have been proposed to explain this phenomenon
341 (i.e., thickening of parenchyma and epidermal cell wall (Allan-Wojtas et al., 2001) due to moisture
342 loss reduction on the outer cell layers (Paniagua et al., 2013b)

343

344 3.3 Impact of supply chain steps on biochemical quality attributes

345 Soluble solids content (SSC) decreased from day 0 for all samples regardless of the
 346 simulated supply chain conditions (Table 3). There was variability during H1, as blueberries
 347 exposed to simulated supply chain conditions showed both significantly higher and lower
 348 contents compared to the control. Variability in the maturity of harvested blueberries could be
 349 the reason for the variability in the responses observed. Eum et al. (2013) did not report any
 350 significant differences in the SSC of blueberries due to temperature treatments, while
 351 Chiabrando and Giacalone (2011) found a slight increase in SSC for the first weeks followed by a
 352 decline, but overall no consistent change was found.

353 Acidity was significantly lower for all samples exposed to simulated supply conditions
 354 compared to the control in H1, and five steps significantly impacted blueberry acidity in H2 (lower
 355 than control) (Table 3). A decrease in titratable acidity during storage has been associated with
 356 organic acids being substrates for respiratory metabolism (Gol et al., 2013). This is a possible
 357 explanation for the lower TA observed in the samples subjected to the simulated supply chain
 358 conditions. On average, in both harvests, pH varied from 2.74 to 3.41.

359 Table 3 Soluble solids content (SSC) and acidity values for samples measured on day 0 (Initial)
 360 and after 278 hours (control and simulated supply chain steps)

Treatment / Step	Harvest 1		Harvest 2	
	SSC (%)	Acidity (%)	SSC (%)	Acidity (%)
Initial (Day 0)	89.5 ± 0.8 *	8.05 ± 0.1	82.4 ± 1.3 *	6.69 ± 0.2 *
Control	64.2 ± 6 ^{efg}	8.7 ± 0.4 ^a	59.8 ± 1.4 ^{abcd}	5.6 ± 0.2 ^a
1M	82.2 ± 0.6 ^a	7.6 ± 0.1 ^b	57.1 ± 1.5 ^{bcdef}	5.6 ± 0.5 ^a
1E	70.7 ± 0.3 ^{cd}	5.5 ± 0.1 ^{fgh}	60.4 ± 3.8 ^{abc}	5.9 ± 0.3 ^a
2M	74.6 ± 0.6 ^{bc}	5.8 ± 0.0 ^{efg}	57.2 ± 1.9 ^{bcdef}	5.9 ± 1.1 ^a
2E	82.3 ± 0.6 ^a	6.5 ± 0.1 ^{cd}	57.8 ± 2.7 ^{bcdef}	5.6 ± 0.9 ^a
3M	67.8 ± 0.6 ^{def}	5.9 ± 0.1 ^{defg}	55.3 ± 1.2 ^{cdefg}	5.4 ± 0.2 ^a

3E	77.9 ± 1.4 ^{ab}	6.1 ± 0.1 ^{def}	51.7 ± 1.3 ^g	5.4 ± 0.4 ^a
4M	62.3 ± 0.3 ^{gh}	4.2 ± 0.2 ^j	57.6 ± 0.6 ^{bcdef}	5.0 ± 0.2 ^a
4E	62.6 ± 0.5 ^{fgh}	4.0 ± 0.2 ^{jk}	59.4 ± 3.4 ^{abcde}	5.1 ± 0.2 ^a
5M	-	-	54.4 ± 0.9 ^{defg}	5.0 ± 0.1 ^a
5E	58.8 ± 0.6 ^{hi}	6.1 ± 0.3 ^{def}	52.4 ± 1.0 ^{fg}	4.8 ± 0.1 ^a
6M	61.9 ± 0.5 ^{gh}	4.1 ± 0.0 ^j	55.7 ± 2.4 ^{cdefg}	4.5 ± 0.9 ^{abc}
6E	63.3 ± 1.7 ^{fgh}	4.3 ± 0.1 ^{ij}	56.2 ± 1.1 ^{cdefg}	5.2 ± 0.4 ^a
7M	62.4 ± 0.3 ^{fgh}	6.4 ± 0.2 ^{cde}	62.3 ± 1.9 ^{ab}	3.5 ± 0.2 ^{bcd}
7E	58.6 ± 1.5 ^{hi}	6.5 ± 0.2 ^{cde}	64.6 ± 0.8 ^a	3.3 ± 0.2 ^{cd}
8M	76.9 ± 1.5 ^{ab}	3.2 ± 0.1 ^l	54.1 ± 0.4 ^{efg}	5.3 ± 0.1 ^a
8E	69.1 ± 3.0 ^{de}	3.4 ± 0.5 ^{kl}	61.9 ± 1.1 ^{ab}	2.6 ± 0.2 ^d
9M	67.3 ± 1.6 ^{defg}	6.8 ± 0.2 ^c	59.5 ± 1.0 ^{abcde}	3.4 ± 0.2 ^{cd}
9E	53.9 ± 0.3 ⁱ	4.9 ± 0.1 ^{hi}	53.2 ± 0.6 ^{fg}	2.5 ± 0.1 ^d

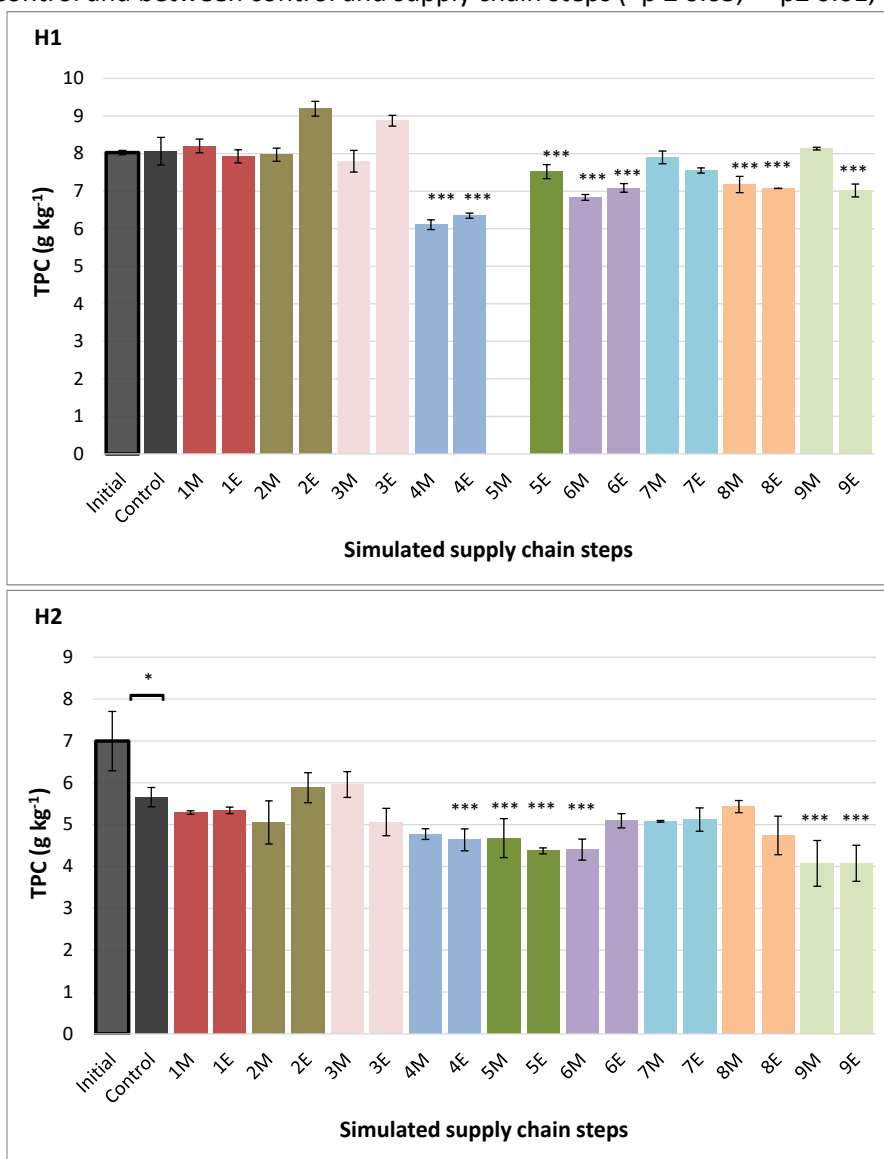
361 M - moderate conditions of small temperature deviation from optimum or shorter duration, E - extreme
362 conditions of higher temperature deviation from optimum or longer duration. Values with different
363 letters indicate significant difference (p<0.05). Asterisk (*) indicates significant difference between initial
364 and control.

365

366 Eight supply chain steps in H1 and six steps in H2 impacted total phenolic content (TPC),
367 resulting in significantly lower values compared to the control (Fig. 5). In H1, the TPC of control
368 samples did not change significantly from day 0, whereas a significant decrease was observed in
369 H2. In some cases, blueberries exposed to simulated supply chain conditions showed higher TPC.
370 This could be due to sample variation or a result of the stress response (Van de Velde et al., 2017).
371 The highest decrease in TPC was observed for step 9E-Consumer in both harvests. This was the
372 most abusive step in Point, Time, and Temperature and was also the step with the highest weight
373 loss. Duan et al. (2011) also reported a decrease in TPC after one week of cold storage. However,
374 results were dependant on variety. The decrease in TPC has been attributed to the oxidation of
375 phenolic compounds catalyzed by polyphenol oxidase and peroxidase (Verma and Joshi, 2000)

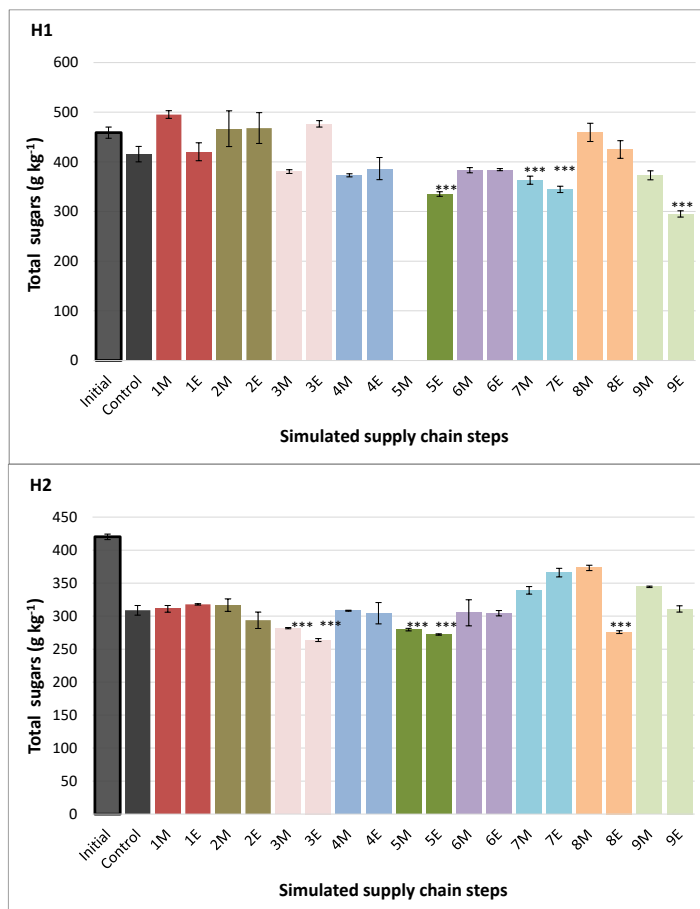
376 during post-harvest storage. Loss of water leads to membrane collapse, which allows for
 377 enzymes like polyphenol oxidase to come in contact with polyphenols; hence a reduction in TPC
 378 is observed (Nunes et al., 2005). This could explain the higher decrease in TPC observed in step
 379 9E-Consumer.

380 Fig. 5. Impact of simulated supply chain steps (moderate (M) and extreme conditions (E)) on TPC of fresh
 381 blueberries after 278 h of storage in harvest 1 (H1) and harvest 2 (H2). Error bars show standard deviation
 382 between replicates (n = 3). Asterisks indicate significant differences between initial quality at harvest and
 383 control and between control and supply chain steps (*p ≤ 0.05, **p ≤ 0.01, ***p ≤ 0.001).



384

385 The main sugars present in blueberries were fructose and glucose (data not shown).
 386 Falagan et al. (2020) found a sharp decrease in sucrose and fructose content during the storage
 387 of blueberries at 0 °C, whereas glucose showed a small increase. In our study, total sugars
 388 decreased with time for most samples with significantly lower values than the control in H1 and
 389 H2 (Fig. 6). Sugars are substrates in the respiratory metabolism (Falagan et al., 2020); Saltveit,
 390 2019). The significantly lower sugar content in blueberries in the simulated supply chain was most
 391 likely caused by differences in the respiratory behaviour due to the different storage conditions.
 392 In four supply chain steps in H1 total sugar content was higher than the initial value on day 0, but
 393 none of the differences was significant. An increase in sugars during storage has been previously
 394 reported due to sucrose metabolism and decomposition into glucose and fructose (Wang et al.,
 395 2020). However, in this experiment, sucrose content was low; the increase observed was not
 396 significant and most likely due to sampling variability during harvest.



397 **Fig. 6.** Impact of simulated supply chain steps (moderate (M) and extreme conditions (E)) on total sugars
398 content of fresh blueberries after 278 h of storage in harvest 1 (H1) and harvest 2 (H2). Error bars show
399 standard deviation between replicates (n = 3). Asterisks indicate significant differences between initial
400 quality at harvest and control and between control and supply chain steps (*p ≤ 0.05, **p ≤ 0.01, ***p ≤
401 0.001).

402
403 Ascorbic acid (AA) decreased significantly in both harvests with storage, regardless of the
404 supply chain step. In H1, AA decreased by 41.7% in the control and, on average, by 46.4% in
405 blueberry samples subjected to simulated supply chain conditions. In H2 initial ascorbic acid
406 levels were significantly lower than H1 (0.6 g kg⁻¹ compared to 1.06 g kg⁻¹), and it decreased by
407 14.2% and 15.7% for the control and samples subjected to the simulated supply chain,
408 respectively. Many studies have reported a loss of AA during storage for fresh fruits (Falagan et
409 al., 2020; Ktenioudaki et al., 2019) and have been attributed to tissue degradation, cell wall
410 damage, enzymatic oxidation, and water loss (Nunes et al., 1998; Klein, 1987). The lowest AA
411 content was observed for step 9E-Consumer (0.49 g kg⁻¹) of the supply chain in H1 and step 2M-
412 Grading (0.47 g kg⁻¹) of the supply chain in H2. Blueberries exposed to the simulated supply chain
413 conditions had lower AA content compared to control samples. Still, only two steps in H1 was the
414 decline significant (5E-Shipping to DC, and 9E-Consumer, data not shown).

415 Anthocyanin (ANC) content varied from 3 ± 0.2 g kg⁻¹ to 6.1 ± 0.5 g kg⁻¹ in H1 and
416 decreased after 278 h of storage for most samples. In H2 there was no significant change in ANC
417 content; it varied from 3.1 ± 0.3 g kg⁻¹ to 5.6 ± 0.1 g kg⁻¹. There were no significant differences
418 between the ANC content of the control and the samples subjected to the simulated supply chain

419
420 3.4 Critical supply chain steps

421 A supply chain step was deemed critical based on whether a blueberry quality attribute
422 had significantly declined after 278 hours of storage compared to the control. Table 4 shows the
423 critical steps listed in order of importance, depending on the number of attributes they affected
424 and the affected quality attributes. Only the steps that impacted at least three quality attributes
425 are listed. In H1, the top critical step was *9E-Consumer*, affecting seven quality attributes, and in
426 H2, the top critical steps were *5E-Shipping to DC* and *9E-Consumer*, affecting four quality
427 attributes each.

428 Steps *5E-Shipping to DC*, *8E-Store Display*, and *9E-Consumer* were common in both
429 harvests and were thus considered the most critical steps of the supply chain under the
430 conditions used in our study. Step 5E was characterised by a considerably small temperature
431 deviation from optimum (4 °C); however, the duration of the steps is high (72 h). Steps 8E and 9E
432 were characterised by high deviations from optimum temperature and equally high durations (48
433 h). The most common negatively impacted quality attributes in both harvests were weight loss,
434 acidity, SSC, total sugars, and TPC. The effect of various individual supply chain steps on quality
435 attributes has been previously considered but separately. For example, Paniagua et al. (2013a)
436 reported that delays of 20 h at 10 °C cause a significant effect in softening and weight loss in
437 blueberries, whereas Eum et al. (2013) reported that fruit was not suitable for sale after 6 days
438 at room temperature or 16 days at 10 °C during transport. A similar methodology as presented
439 in our study was applied to strawberries (Kelly et al., 2019) and the critical supply chain steps
440 identified were storage at consumer (20 °C), shipping to stores (8 °C), and storage at the grower
441 (5 °C). The last step in the supply chain (i.e., consumer) has been highlighted as the step with

442 higher losses than retail (Golan and Buzby, 2015) as over 65 % of consumers store fresh produce
 443 at unsuitable temperatures (i.e., ambient temperatures) (WRAP 2008).

444

445 Table 4 Critical supply chain steps based on the number of quality attributes impacted

Step	N° of quality attributes impacted	Quality attributes impacted
Harvest 1		
9E - Consumer (48 h at 20°C) *	7	Appearance, weight loss, AA, TS, TPC, Acidity, SSC
5E - Shipping to DC (72 h at 5 °C) *	5	Appearance, AA, TS, Acidity, SSC
8E - Store Display (48 h at 15°C) *	4	Appearance, weight loss, TPC, Acidity
3E - Cooling (2 h at 5 °C)	4	Appearance, weight loss, Texture, Acidity
4E - Storage at grower (48 h at 5°C)	4	Appearance, weight loss, TPC, Acidity
6M – DC Storage DC (48 h at 2°C)	4	Appearance, weight loss, TPC, Acidity
7E- Shipping to stores (8 h at 8°C)	4	Appearance, TS, Acidity, SSC
4M - Storage at grower (48 h at 2°C)	3	Weight loss, TPC, Acidity
3M - Cooling (2 h at 2 °C)	3	Appearance, weight loss, Acidity
6E - DC Storage DC (48 h at 5°C)	3	Appearance, TPC, Acidity
8M - Store Display (48 h at 2°C)	3	Appearance, Acidity, SSC
3M- Cooling (2 h at 2°C)	3	Appearance, Acidity, Weight loss
Harvest 2		
9E - Consumer (48 h at 20°C) *	4	Weight loss, TPC, Acidity, SSC
5E - Shipping to DC (72 h at 5 °C) *	4	Weight loss, TS, TPC, SSC
8E - Store Display (48 h at 15°C) *	3	Weight loss, TS, Acidity
9M - Consumer (48 h at 4°C)	3	Weight loss, TPC, Acidity

446 ^a AA = ascorbic acid content (AA), TS = total sugar content, TPC = total phenolics content, SSC = soluble
 447 solids content.

448 ^b E = extreme conditions of higher temperature deviation from optimum or longer duration.

449 ^c M = moderate conditions of small temperature deviation from optimum or shorter duration

450 * Asterisk indicates common steps in both harvests.

451

452 3.5 BRT model

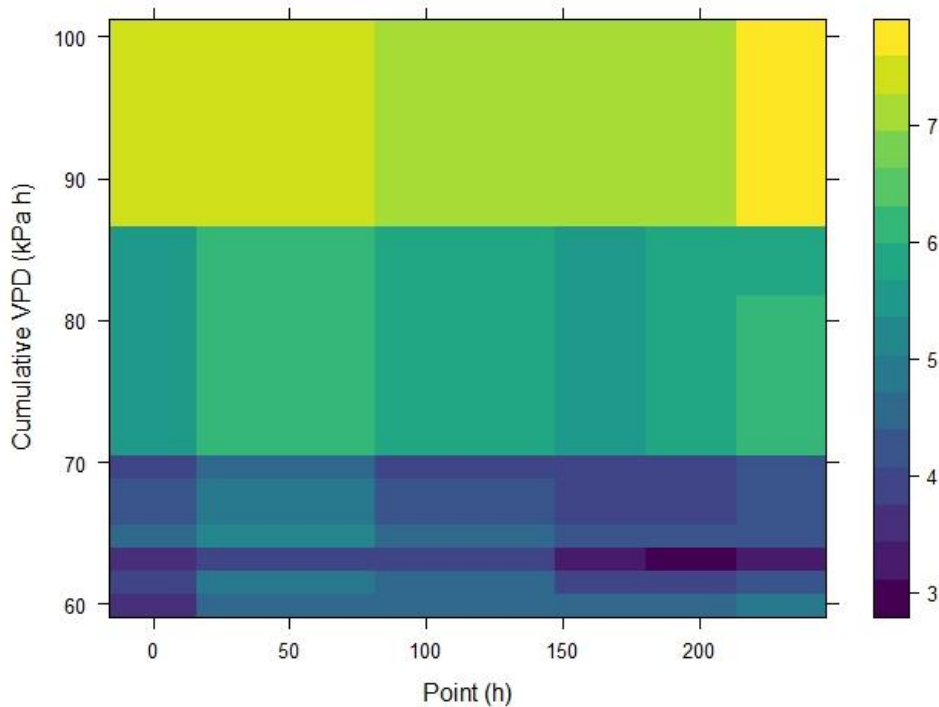
453 A gradient boosted model was built to predict weight loss using environmental data from

454 the simulated supply chain conditions. The BRT model explained 84 % of the variance in weight

455 loss on the test set ($R^2 = 0.84 \pm 0.02$, RMSE = 0.44 ± 0.05 , MAE= 0.40 ± 0.04) and 89 % on the

456 training set ($R^2 = 0.89 \pm 0.01$, $RMSE = 0.37 \pm 0.01$, $MAE = 0.28 \pm 0.01$). Cumulative VPD and Point
457 (point in the supply chain when a breach occurred) were the two predictors used in the model,
458 and the results showed that Point had a 23 % influence on the model, noting it as an important
459 factor in the estimation of weight loss.

460 Fig. 7. shows the Partial Dependency Plot (PDP) with the marginal effect of the two
461 variables on weight loss. It can be observed that blueberries exposed to cumulative VPD between
462 approximately 60 and 70 kPa h will lose less than 5 % of their weight in 278 hours, those exposed
463 to cumulative VPD of 70 – 87 kPa h approximately will lose between 5 and 6.5 % of their weight,
464 whereas finally at higher cumulative VPD ranges weight loss will be over 7 %. This information
465 can be useful in extended supply chains where due to logistic constraints, storage/ shipping
466 conditions deviate from optimum, and blueberries can become unsalable by the time they reach
467 their destination.

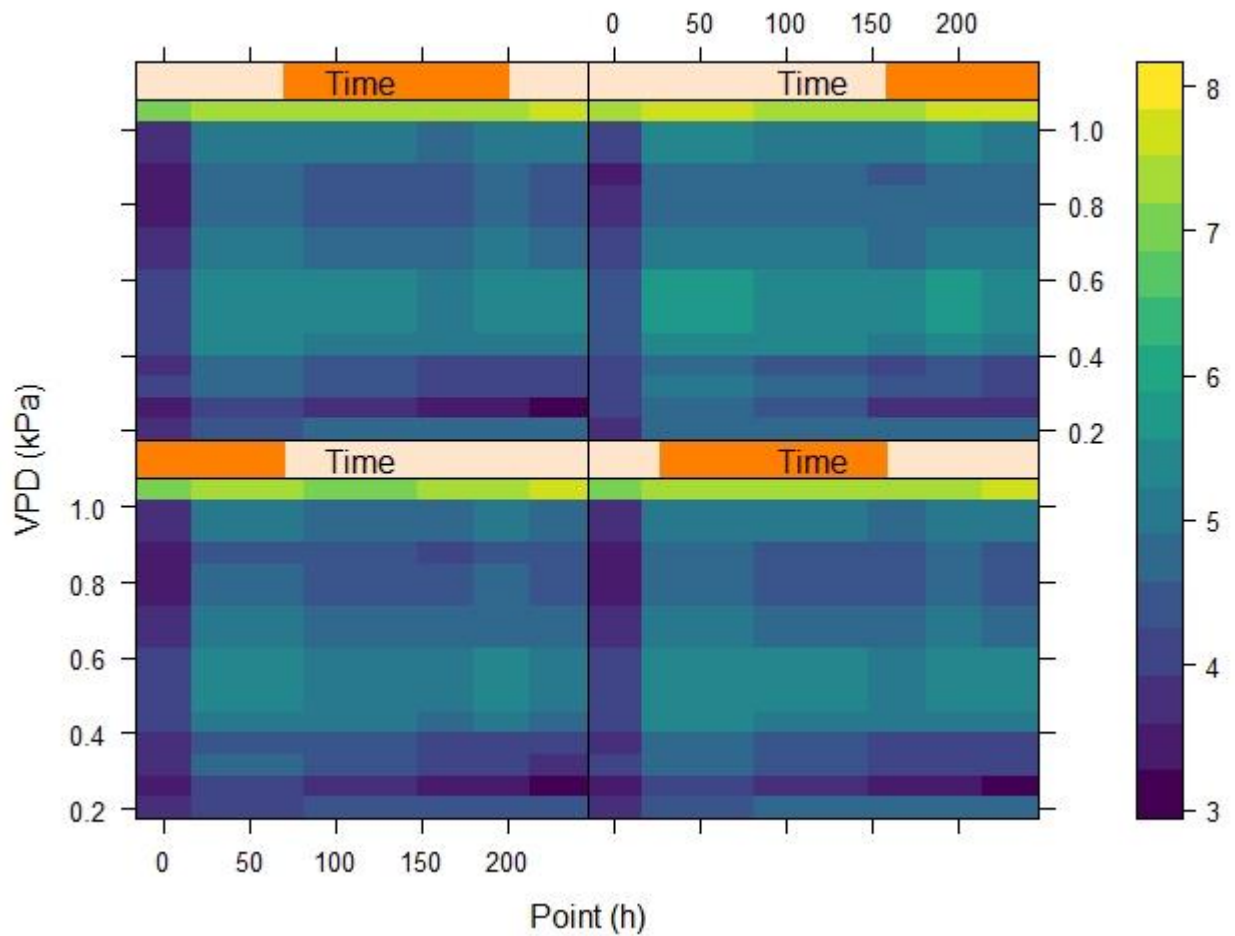


468

469 **Fig. 7.** Partial dependency plot showing the marginal effect of cumulative Vapour Pressure Deficit (VPD)
 470 and Point - point in the supply chain when a deviation from optimum conditions occurred (breach) on
 471 predicted weight loss. Colour scale refers to % weight loss.
 472

473 The effect of Point in the supply chain on weight loss is not apparent from Fig. 7. To
 474 investigate this further, and since there was a significant relative influence on the model, the BRT
 475 model was built using the following variables: VPD (as in VPD at point of breach), Point (point in
 476 the supply chain where a breach occurred) and Time (duration of breach). Fig. 8 shows the PDP
 477 plots of the three variables and the marginal effect on weight loss. It can be observed that if a
 478 breach occurred in the first 24 hours, regardless of the duration, it is unlikely that it will have a
 479 significant effect on the weight loss. At later stages of the supply chain, when VPD was > 0.4 kPa,
 480 weight loss was likely to be higher than 6-7 %, especially when the duration of the unfavourable
 481 conditions is longer (top and bottom right boxes). Finally, VPD values > 1 are likely to lead to

482 maximum weight loss > 8 % regardless of time and duration of the breach. However, these results
483 were influenced by the design of the simulated supply chain used in the study, where the last
484 step (9E-Consumer) was the most abusive in terms of temperature, RH, and duration. Hence, it
485 can influence this representation. More data would be required to verify the effect of Point on
486 weight loss.



487 **Fig. 8.** Partial dependency plot showing the marginal effect of VPD, Point, and Time on predicted weight
488 loss. Time is continuous, therefore it is first converted to a shingle; in this case, four groups with 10%
489 overlap. Colour scale refers to % weight loss.

490

491 Respiration and transpiration have long been identified as the primary sources of weight
492 loss in fresh fruit and vegetables (Bovi et al., 2018). Maguire et al. (2000) described weight loss
493 in apples as a function of initial weight, respiration and transpiration rates, fixed water vapour
494 permeance, saturated water pressure at air temperature, and fruit surface area. The model
495 highlighted the importance of transpiration and respiration in weight loss and identified more
496 factors (e.g., respiration dependence on RH, variable water vapour permeance) to be accounted
497 for weight loss predictions. Hertog (2002) expanded this model to include fruit-to-fruit variation
498 accounting for individual fruit differences in skin permeate to water. Another study (Lufu et al.,
499 2019) reported that most of the weight loss in fresh pomegranate was explained by the vapour
500 pressure deficit (VPD) and concluded that temperature, RH, and time must be considered in
501 weight loss predictive models.

502 The analysis used in this study showed that the BRT algorithm could be used to accurately
503 predict the expected weight loss of blueberries depending on the supply chain conditions. The
504 model was also effective in identifying and explaining the influence of each variable and their
505 interactions on weight loss.

506

507 4. Conclusions

508 This study shows the importance of monitoring and maintaining appropriate conditions
509 throughout each step along the supply chain to minimise waste and ensure a good quality
510 product reaches the consumer. The critical steps identified in this study with the highest impact
511 on the quality (physical and biochemical) of blueberries were Shipping to DC (72 h at 5 °C), Store
512 Display (48 h at 15°C), and Consumer (48 h at 20 °C).

513 Furthermore, from this study, a BRT model was developed to predict weight loss. The
514 model used data suitable for supply chain control purposes (i.e., temperature, RH, duration,
515 expressed as cumulative VPD, and point of breach) and accurately predicted the range of weight
516 loss expected at the end of the simulated supply chain. Cumulative VPD did not explain all the
517 variation in weight loss, so more data from diverse simulated supply chain scenarios are needed
518 to verify the predictive power of cumulative VPD and the model. The advantage of the BRT model
519 is that it can adapt and improve continuously as more data is accumulated.

520 The analysis presented in this study provides valuable insightson which blueberry quality
521 attributes are impacted along the supply chain. It also highlights the importance of supply chain
522 monitoring and the potential benefits of real-time data analysis to aid stakeholders in making
523 informed decisions concerning required actions to prevent product, quality, and monetary losses.

524

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529

530 **Declaration of interests**

531 The authors declare that they have no known competing financial interests or personal
532 relationships that could have appeared to influence the work reported in this paper.

533

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