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An economic selection index should be used instead of independent culling in plant breeding programs with genomic selection

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Order of Authors:	Lorena G Batista Robert Chris Gaynor Gabriel R.A. Margarido Tim Byrne Peter Amer Gregor Gorjanc John M Hickey
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1 **An economic selection index should be used instead of independent culling in plant**
2 **breeding programs with genomic selection**

3

4 **Lorena G. Batista***, R. Chris Gaynor, Gabriel R. A. Margarido, Tim Byrne, Peter Amer,
5 **Gregor Gorjanc, John M. Hickey**

6 Lorena G. Batista and Gabriel R.A. Margarido: “Luiz de Queiroz” College of Agriculture
7 (University of São Paulo), Piracicaba, SP, 13418-900, Brazil. R. Chris Gaynor, Gregor Gorjanc
8 and John Hickey: The Roslin Institute and Royal (Dick) School of Veterinary Studies, University
9 of Edinburgh, Easter Bush Campus Research Centre, Midlothian EH25 9RG, UK. Tim Byrne:
10 Abacusbio, Roslin Innovation Centre, University of Edinburgh, Easter Bush Campus Research
11 Centre, Midlothian EH25 9RG, UK. Peter Amer: Abacusbio, Public Trust Building, Moray Place,
12 Dunedin 9016, New Zealand

13 Received _____ . * Corresponding author: loregbatista@gmail.com

14

15 **Abstract**

16 In the context of genomic selection, we evaluated and compared recurrent selection breeding
17 programs using either index selection or independent culling for selection of parents. We simulated
18 a clonally propagated crop breeding program for 20 cycles of selection using either independent
19 culling or an economic selection index with two unfavourably correlated traits under selection.
20 Cycle time from crossing to selection of parents was kept the same for both strategies. Our results
21 demonstrate that accurate knowledge of the economic importance of traits is essential even when
22 performing independent culling. This is because independent culling achieved its optimum genetic
23 gain when the culling threshold for each trait varied accordingly to the economic importance of
24 the traits. When gains from independent culling were maximised, the efficiency of converting
25 genetic diversity into genetic gain of both selection methods were equivalent. When the same
26 proportion selected of 10% for each trait was used instead of optimal culling levels, index selection
27 was 10%, 128% and 310% more efficient than independent culling when the second trait had a
28 relative economic importance of 1.0, 2.5 and 5.0, respectively. Given the complexity of estimating
29 optimal culling levels and the fact that the gains achieved with independent culling are, at most,
30 equivalent to index selection, the use of an economic selection index is recommended for multi-
31 trait genomic selection.

32 **Introduction**

33 Crop breeding seeks to develop improved cultivars. Besides high yield levels, a successful
34 cultivar in many crops must meet minimal standards for several other traits that are economically
35 important, such as pest and disease resistance and product quality. Traits are often unfavourably
36 correlated with each other (e.g., 1–5). When traits are antagonistically correlated, selection for one
37 trait causes an undesired economic response in the other trait (6,7). This makes breeding to
38 simultaneously improve multiple traits complicated.

39 Independent culling and the use of a selection index are two commonly used methods in
40 plant breeding programs for selecting on multiple traits (7). Independent culling involves
41 establishing minimum standards (i.e., culling levels) for each trait and only selecting individuals
42 that meet these minimum standards. The thresholds can be set according to a specific selection
43 intensity or a specific value, such as a value relative to an agronomic check. The application of
44 independent culling can be on multiple traits simultaneously or on individual traits sequentially.
45 The selection index method involves selection for all traits simultaneously based on a linear or
46 non-linear combination of individual traits weighted by their importance for the breeding objective
47 (8).

48 Theoretically, the selection index is the most effective method of selection for multiple
49 traits (8–10). Independent culling is less effective than index selection because, when strictly
50 applied, it will not select individuals below the threshold for only one trait despite being
51 exceptional for all other traits, while the use of a selection index makes it possible to retain those
52 individuals (7). However, independent culling can achieve nearly equivalent effectiveness using
53 optimised thresholds (11).

54 When cost is considered, independent culling can be more efficient than a selection index
55 (11). This is because independent culling does not require phenotypes for all individuals and traits
56 at one time, whereas strict application of a selection index requires phenotypes for all traits. This
57 benefit is particularly valuable to plant breeders, because early stages of the breeding program
58 often have a very large number of individuals. Phenotyping all individuals for all traits is likely to
59 be logistically and financially infeasible. For example, some traits have a high measurement cost,
60 such as bread quality in wheat, so that they cannot be measured on a large number of individuals.
61 Further, some traits can only be measured on older plants, such as lifetime production in sugarcane,
62 or on a plot or group basis. Delaying selection until these traits become available would be
63 effectively equivalent to random selection, because the breeder would have to reduce the overall
64 size of the early stage. Thus, practical constraints require at least some use of independent culling
65 on traits that can be phenotyped simply/quickly and at a lower cost in breeding programs utilising
66 phenotypic selection.

67 The use of genomic selection in plant breeding may render the cost efficiency benefit of
68 independent culling obsolete if all early generation individuals are genotyped. This is because
69 genomic selection allows for accurate prediction of all traits at once (12). While genotyping all
70 early generation individuals is not standard in most current breeding programs, it may become so
71 in the future. This is likely to be the case if breeding programs adopt a two-part strategy to breeding
72 that explicitly splits breeding programs into a rapid cycling, genomic selection guided, population
73 improvement part tasked with developing new germplasm and a product development part focused
74 on developing new varieties. Simulations of these breeding programs suggest they can deliver
75 considerably more genetic gain than more conventional breeding programs (13).

76 Several studies have already discussed the benefits of incorporating genomic selection

77 strategies into crop breeding programs (13–16). In addition, other studies have demonstrated that
78 combining index selection and genomic prediction can increase genetic gain in breeding programs
79 (17,18) and, in the long term, even higher genetic gains can be obtained when multi-trait
80 optimization strategies that also control for the loss of genetic diversity are used (19). However,
81 differences in how multi-trait selection methods can affect not only genetic gain but other
82 population parameters such as genetic diversity and genetic correlations over several cycles of
83 recurrent selection have not yet been thoroughly investigated. In order to provide a more detailed
84 account of population dynamics in the genomic selection framework, we used simulations of
85 recurrent breeding programs to evaluate and compare both index selection and the independent
86 culling method for 20 cycles of selection. The purpose of these simulations was to quantify the
87 magnitude of the difference between optimally set independent culling levels and an optimal
88 selection index. The simulations also investigated the sensitivity of independent culling to sub-
89 optimal culling levels.

90 **Material and Methods**

91 Stochastic simulations of entire breeding programs for multiple traits were used to compare
92 the genetic gains in a breeding program using independent culling levels and a breeding program
93 using an economic selection index for selection of parents. In the independent culling approach,
94 selection was performed for one trait at a time at each stage of selection. A clonally propagated
95 crop species was considered. Generally, in breeding programs for clonally propagated species,
96 several crosses are performed between highly heterozygous hybrids, and all the genotypes in the
97 resulting F₁ progenies are candidate clones to be released as cultivars or used as parents in the next
98 breeding cycle (20). The methods were compared using the average of fifty replicates, each
99 replicate consisting of: i) a burn-in phase shared by both strategies so that each strategy had an

100 identical, realistic starting point; and ii) an evaluation phase that simulated future breeding with
101 different breeding strategies. The burn-in phase consisted of 20 years of breeding using
102 independent culling for the selection of parents and the evaluation phase consisted of 20 cycles of
103 selection using either independent culling or index selection.

104 **Genome sequence**

105 For each replicate, a genome consisting of 10 chromosome pairs was simulated for the
106 hypothetical clonally propagated plant species. These chromosomes were assigned a genetic length
107 of 1.43 Morgans and a physical length of 8×10^8 base pairs. Sequences for each chromosome were
108 generated using the Markovian Coalescent Simulator (21) and AlphaSimR (22). Recombination
109 rate was inferred from genome size (i.e. $1.43 \text{ Morgans} / 8 \times 10^8 \text{ base pairs} = 1.8 \times 10^{-9}$ per base pair),
110 and mutation rate was set to 2×10^{-9} per base pair. Effective population size was set to 50, with
111 linear piecewise increases to 1,000 at 100 generations ago, 6,000 at 1,000 generations ago, 12,000
112 at 10,000 generations ago, and 32,000 at 100,000 generations ago.

113 **Founder genotypes**

114 Simulated genome sequences were used to produce 50 founder genotypes. These founder
115 genotypes served as the initial parents in the burn-in phase. This was accomplished by randomly
116 sampling gametes from the simulated genome to assign as sequences for the founders. Sites that
117 were segregating in the founders' sequences were randomly selected to serve as 1,000 causal loci
118 per chromosome (10,000 across the genome in total). To simulate genetic correlations between
119 traits, the traits were treated as pleiotropic and the additive effects of the causal loci alleles were
120 sampled from a multivariate normal distribution with mean $\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ and desired values of
121 correlation.

122 **Estimated breeding values**

123 The true genetic value of the simulated traits was determined by the summing of its causal
124 loci allele effects. The matrix **E** with the estimated breeding values of the traits for each individual
125 in the population was obtained according to the formula:

$$126 \qquad \qquad \qquad \mathbf{E} = \mathbf{Y}\mathbf{P}^{-1}\mathbf{G}$$

127 Where **Y** is the matrix of phenotypes simulated by adding random error to the true genetic values
128 of the traits, where rows correspond to individuals in the population and columns correspond to
129 traits. The random error was sampled from a multivariate normal distribution with mean $\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$
130 and zero covariance, with variance values tuned to achieve a target level of accuracy (r), which
131 we define as the correlation between true and estimated breeding values. **P** is the phenotypic
132 variance-covariance matrix of the traits, and **G** is the genetic variance-covariance matrix for the
133 traits.

134 **Breeding methods**

135 The simulations modelled breeding for two component traits (T1 and T2) that were
136 improved using either independent culling or an economic selection index. **With both strategies,**
137 **an F₁ population of 5,000 individuals** was generated by randomly crossing the individuals in the
138 crossing block (Parents). With independent culling, selection was carried out in two stages: a
139 proportion of individuals was selected first based on T1 and then, from this proportion, the parents
140 of the next breeding cycle were selected based on T2. With the selection index approach, the F₁
141 individuals with the highest values for the index trait were selected as parents of the next breeding
142 cycle. The index trait was the sum of the estimated breeding values for each trait weighted by their
143 economic importance. The number of selected parents (50 parents) and the cycle time from
144 crossing to selection of new parents was kept the same for both strategies, so the comparisons

145 between them reflect only the differences due to the method of selection. The overall selection
 146 scheme used for each method of selection is shown in Supplementary material 1 (Fig S1.1). For
 147 simulation of breeding programs, we used the R package AlphaSimR (22).

148 **Simulated scenarios**

149 The selection index and independent culling methods were compared in a set of scenarios
 150 that aimed to assess the relative performance of the methods under different levels of accuracy of
 151 selection, and relative economic importance of T2. We were only interested in investigating the
 152 relative performance of selection methods under challenging conditions for multi trait selection.
 153 Hence, only an unfavourable genetic correlation between traits was simulated. A summary of all
 154 simulated scenarios we used in this study is shown in Table 1.

155 Table 1. Summary of parameters simulated in all comparison scenarios of recurrent selection
 156 breeding programs using either independent culling or selection index with two traits

Scenario	Selected Proportion		Relative economic importance of Trait 2	Accuracy
	Trait 1	Trait 2		
1	Optimum	Optimum	1.0	0.3
2	Optimum	Optimum	1.0	0.5
3	Optimum	Optimum	1.0	0.99
4	Optimum	Optimum	1.0	0.7
5	Optimum	Optimum	2.5	0.7
6	Optimum	Optimum	5.0	0.7
7	10%	10%	1.0	0.7
8	10%	10%	2.5	0.7
9	10%	10%	5.0	0.7

157 For one set of scenarios we simulated four levels of accuracy (0.3, 0.5, 0.7, and 0.99),
 158 assigned the same economic importance for both traits. In another set of scenarios, we varied the
 159 relative economic importance of T2, but fixed selection accuracy to 0.7. Here, three levels of
 160 relative economic importance were simulated. T1 was given an economic importance of 1.0 and
 161 T2 an economic importance of either 1.0, 2.5 or 5.0. For each level of relative economic
 162 importance, we simulated: i) scenarios where the proportion selected was the same (10%) when
 163

164 selecting for both traits, and ii) scenarios where the proportions selected were set to achieve
165 optimal culling levels (i.e., optimal independent culling). To achieve optimal culling levels, in each
166 cycle of selection we chose the proportion selected for each trait that maximised the genetic gain.
167 Thus, over the cycles of selection, when using optimal culling levels, instead of a fixed proportion
168 selected of 10%, the proportion selected for each trait varied between cycles. To find the optimal
169 proportions at each cycle, we fixed the number of parents selected (50 parents) and found the
170 number of individuals to be selected in the first culling stage that maximized parents' economic
171 value (i.e., index trait).

172 **Comparison**

173 The comparisons were made in terms of: i) genetic gain ii) genetic diversity, iii) the
174 efficiency of converting genetic diversity into genetic gain for the index; and iv) genetic correlation
175 between traits. For genetic gain and genetic diversity, we report values based on the individuals in
176 the crossing block (parents) at each cycle of selection. We measured genetic gain as the increment
177 in genetic mean (average of true genetic values) compared to the genetic mean in year 20. We
178 measured genetic diversity with genetic standard deviation and genic standard deviation. We
179 calculated genetic standard deviation as standard deviation of true genetic values. We calculated

180 genic standard deviation as $\sigma_a = \sqrt{2 \sum_{i=1}^{n_q} p_i(1 - p_i)\alpha_i^2}$, where n_q is the number of causal loci and
181 p_i and α_i are, respectively, allele frequency and allele substitution effect at the i -th causal locus.

182 To measure efficiency, genetic mean and genic standard deviation were standardized to
183 mean zero and unit standard deviation in year 20. We measured efficiency of converting genetic
184 diversity into genetic gain by regressing the achieved genetic mean ($y_t = (\mu_{a_t} - \mu_{a_{20}})/\sigma_{a_{20}}^2$) on
185 lost genetic diversity ($x_t = 1 - \sigma_{a_t}/\sigma_{a_{20}}$), i.e., $y_t = \alpha + bx_t + e_t$, where b is efficiency (23).

186 We estimated efficiency with robust regression using function `rlm()` in R (24).

187 For genetic correlation, we report the correlation between the true genetic values of T1 and
188 T2. We calculated this metric on the individuals in the F₁ population at each cycle of selection.

189 **Results**

190 Overall the results show that index selection provided consistent genetic gains and was
191 equivalent to independent culling in terms of genetic gains and efficiency when optimal culling
192 levels were used. Index selection performed better than independent culling in scenarios where
193 independent culling levels were suboptimal.

194 We have structured the description of the results in two parts, corresponding to how the
195 relative performance of the selection methods was affected by: i) the accuracy of selection, and ii)
196 the relative economic importance of traits.

197 **Accuracy of selection**

198 The results show that increases in accuracy accentuated the differences in the genotypes
199 being selected by either independent culling or index selection. This is shown in Fig. 1, where the
200 genotypes selected as parents by each selection method are highlighted. Lower levels of accuracy
201 led to a more diffuse cluster of selected genotypes and, with increasing selection accuracy, the
202 cluster of selected genotypes approached what was expected for each method of selection (7).

203 **Fig 1. Scatterplots of true genetic values for Trait 1 (T1) and Trait 2 (T2) of the genotypes in**
204 **the F1 population (grey) and genotypes selected as parents (orange) in the third cycle of**
205 **selection using either independent culling (a) or a selection index (b) with different levels of**
206 **accuracy**

207 Fig. 2 shows the change in the genetic correlation between the component traits for both
208 independent culling and index selection over 20 cycles of selection at different levels of accuracy.
209 Both selection methods resulted in the correlation between traits becoming increasingly
210 unfavourable over the cycles of selection. For both methods, the change in the genetic correlation
211 was higher with higher values of accuracy. Compared to independent culling, index selection led

212 to larger changes in the genetic correlation between the two traits. After 20 cycles of selection with
213 accuracy of 0.3, independent culling led to a genetic correlation that was 9% more unfavourable
214 compared to the genetic correlation in cycle 0, while index selection led to a genetic correlation
215 that was 17% more unfavourable compared to the genetic correlation in cycle 0. After 20 cycles
216 of selection with accuracy of 0.99, independent culling led to a genetic correlation that was 29%
217 more unfavourable compared to the genetic correlation in cycle 0, while index selection led to a
218 genetic correlation that was 64% more unfavourable compared to the genetic correlation in cycle
219 0.

220 **Fig 2. Change in genetic correlation (mean and 95% confidence interval) between traits in**
221 **the F1 population over 20 cycles of selection using either optimal independent culling (IC) or**
222 **a selection index (SI) with different levels of accuracy, and Trait 2 relative economic**
223 **importance of 1.0**

224 The change of genetic mean in parents for the component traits and the index trait over the
225 cycles of selection using each method is shown in Fig. 3. For both methods, the genetic gains for
226 the component traits and the index trait increased with higher values of accuracy. In general, the
227 selection index method and independent culling with optimal culling levels led to equivalent
228 genetic gains for the component traits and the index trait. Only in the scenario with 0.99 accuracy
229 did index selection lead to a slightly higher genetic gain compared to that achieved with optimal
230 independent culling. For the index trait, after 20 cycles of selection with accuracy of 0.99, index
231 selection had a genetic gain 4% higher than the genetic gain achieved with independent culling.

232 **Fig 3. Change in genetic mean for Trait 1 (T1), Trait 2 (T2) and Index Trait (Index) over 20**
233 **cycles of selection using either optimal independent culling (IC) or a selection index (SI) with**
234 **different levels of accuracy, unfavourably correlated traits, and T2 relative economic**
235 **importance of 1.0**

236 Table 2 shows the genetic standard deviation of parents in cycle 20 and the loss in genetic
237 standard deviation in cycle 20 compared to the genetic standard deviation in cycle 0 for the
238 component traits and the index trait. The change of genetic diversity in parents for the component

239 traits and the index trait over the cycles of selection using each method is shown in Supplementary
240 material 1 (Fig S1.2). For the component traits, when using index selection, the genetic standard
241 deviation showed an initial increase in the first few cycles of selection followed by a gradual
242 decrease in the subsequent cycles. When using independent culling, the decrease in the genetic
243 standard deviation of the component traits was continual over the cycles of selection. Both of these
244 trends were more obvious with increasing values of accuracy. For all values of accuracy,
245 independent culling led to a higher loss in the genetic standard deviation of the component traits
246 compared to the index selection. For T1 and T2, independent culling with accuracy of 0.3 led to a
247 loss of genetic standard deviation that was 6% and 5% higher than the loss of genetic standard
248 deviation observed for index selection, respectively. With accuracy of 0.99, for T1 and T2
249 independent culling led to a loss of genetic standard deviation that was 65% and 51% higher than
250 the loss of genetic standard deviation observed for index selection, respectively. For the index trait,
251 both methods led to equivalent values of genetic standard deviation. With accuracies of 0.3 and
252 0.99, index selection led to a loss in the genetic standard deviation of the index trait that was 3%
253 higher compared to the loss of genetic standard deviation observed using independent culling,
254 respectively.

255 Table 2. Mean genetic standard deviation (Genetic SD) of parents in cycle 20 and loss in genetic
 256 standard deviation in cycle 20 in comparison to the genetic standard deviation in cycle 0 (Loss
 257 over cycle 0) for trait 1 (T1), trait 2 (T2) and the index trait using either optimal independent
 258 culling or index selection with different levels of accuracy, unfavourably correlated traits, and T2
 259 relative economic importance of 1.0

Independent culling						
	T1		T2		Index trait	
Accuracy	Genetic SD (cycle 20)	Loss over cycle 0	Genetic SD (cycle 20)	Loss over cycle 0	Genetic SD (cycle 20)	Loss over cycle 0
0.3	3.51 (0.08)*	-17%	3.68 (0.08)	-16%	3.57 (0.06)	-22%
0.5	2.56 (0.06)	-30%	2.45 (0.04)	-28%	2.69 (0.05)	-32%
0.7	1.65 (0.04)	-42%	1.64 (0.03)	-37%	1.88 (0.04)	-45%
0.99	0.45 (0.01)	-68%	0.45 (0.01)	-55%	0.74 (0.02)	-62%

Index Selection						
	T1		T2		Index trait	
Accuracy	Genetic SD (cycle 20)	Loss over cycle 0	Genetic SD (cycle 20)	Loss over cycle 0	Genetic SD (cycle 20)	Loss over cycle 0
0.3	3.80 (0.09)	-11%	4.00 (0.09)	-11%	3.66 (0.08)	-19%
0.5	3.19 (0.08)	-17%	3.19 (0.07)	-14%	2.57 (0.06)	-33%
0.7	2.69 (0.06)	-16%	2.60 (0.06)	-18%	1.86 (0.04)	-41%
0.99	1.93 (0.4)	-3%	1.91 (0.04)	-4%	0.51 (0.01)	-59%

260 * standard errors of the estimates are presented in parenthesis

261
 262 Table 3 shows the genic standard deviation of parents in cycle 20 and the loss in genic
 263 standard deviation in cycle 20 compared to the genic standard deviation in cycle 0 for the
 264 component traits and the index trait. The values of genic standard deviation of T1, T2, and the
 265 index trait were equivalent. The highest difference between methods in the loss in genic standard
 266 deviation was 1% for all values of accuracy, except with accuracy of 0.99. With 0.99 accuracy, for
 267 T1, T2 and the index trait, index selection led to a loss in the genic standard deviation that was 3%
 268 higher compared to the loss of genic standard deviation observed using independent culling.

269

270 Table 3. Genic standard deviation (Genic SD) of parents in cycle 20 and loss in genic standard
 271 deviation in cycle 20 in comparison to the genic standard deviation in cycle 0 (Loss over cycle 0)
 272 for trait 1 (T1), trait 2 (T2) and the index trait using either optimal independent culling or index
 273 selection with different levels of accuracy, unfavourably correlated traits, and T2 relative
 274 economic importance of 1.0

Accuracy	Independent culling					
	T1		T2		Index trait	
	Genic SD (cycle 20)	Loss over cycle 0	Genic SD (cycle 20)	Loss over cycle 0	Genic SD (cycle 20)	Loss over cycle 0
0.3	3.94 (0.06)*	-15%	4.11 (0.07)	-15%	4.04 (0.05)	-16%
0.5	3.48 (0.06)	-24%	3.41 (0.05)	-24%	3.44 (0.04)	-25%
0.7	2.94 (0.04)	-34%	2.89 (0.04)	-34%	2.89 (0.04)	-34%
0.99	2.35 (0.04)	-42%	2.35 (0.04)	-42%	2.33 (0.04)	-43%

Accuracy	Index Selection					
	T1		T2		Index trait	
	Genic SD (cycle 20)	Loss over cycle 0	Genic SD (cycle 20)	Loss over cycle 0	Genic SD (cycle 20)	Loss over cycle 0
0.3	3.92 (0.06)	-16%	4.08 (0.07)	-16%	4.02 (0.05)	-16%
0.5	3.44 (0.06)	-25%	3.37 (0.05)	-25%	3.39 (0.05)	-26%
0.7	2.92 (0.05)	-34%	2.88 (0.05)	-34%	2.87 (0.04)	-35%
0.99	2.21 (0.04)	-45%	2.22 (0.04)	-45%	2.17 (0.03)	-46%

* standard errors of the estimates are presented in parenthesis

275
276

277 Relative economic importance of traits

278 Fig. 4 shows the efficiency of converting genetic diversity into genetic gain for the index
 279 trait when the relative economic importance of T2 varies. Independent culling was compared to
 280 index selection using either optimal culling levels or selection with the same proportion of plants
 281 selected (10%) for each trait. Index selection had the highest efficiency and most gain for all levels
 282 of economic importance. The efficiency and gain for optimal independent culling levels was nearly
 283 equivalent to index selection. The efficiency and gain for selecting the same proportion of plants
 284 for both traits was worse than index selection for all levels of relative economic importance. Index
 285 selection was 10%, 128% and 310% more efficient than independent culling using the same
 286 proportion of selected plants for relative economic importance of 1.0, 2.5 and 5.0, respectively.

287 **Fig 4. Change of genetic mean and genic standard deviation for the index trait across 20**
 288 **cycles of selection using either independent culling (IC) or a selection index (SI) under three**
 289 **levels of relative economic importance (REI) and using either the same proportion selected**
 290 **(10%) for Trait 1 (T1) and Trait 2 (T2) or optimal culling levels for each level of relative**

291 economic importance of T2 (a); and proportion selected (mean and 95% confidence interval)
292 for T1 used to achieve optimal culling levels over the 20 cycles of selection (b). Traits are
293 unfavourably correlated (-0.5). Individual replicates are shown by thin lines and a mean
294 regression with a time-trend arrow. Values of genetic mean and genic standard deviation
295 shown are standardized to mean zero and unit standard deviation in cycle 0
296

297 Fig. 4 also shows the proportion of plant selected for T1 under optimal independent culling
298 over the different levels of economic importance for T2. The mean proportion selected for T1 only
299 varied slightly over the cycles of selection. The means were 29%, 93%, and 99% for relative
300 economic importance of 1.0, 2.5, and 5.0, respectively. The variation about those means was
301 largest with relative economic importance of 1.0 and smallest with relative economic importance
302 of 5.0.

303

304 Discussion

305 This study evaluated and compared recurrent selection breeding programs that either use
306 index selection or independent culling for the selection of parents by genomic selection. Overall
307 the results show that using index selection is either better or equivalent to independent culling in
308 this context. Index selection outperformed independent culling when sub-optimal culling levels
309 were used. Our results demonstrate that accurately assessing the economic importance of the traits
310 is essential regardless of the method of selection being used.

311 The main difference between index selection and independent culling is that, when using
312 index selection, genotypes that are exceptional for one of the traits under selection are more likely
313 to be selected even though their performance for other traits is average. This can be seen in Fig. 1,
314 with the cluster of individuals selected as parents with the index method including individuals that
315 are more contrasting for the two traits under selection compared to the individuals selected with
316 independent culling. The main implications of this are in the way each method affects the
317 correlation between traits and the genetic diversity over cycles of recurrent selection. We discuss

318 each of these aspects in the following two sections. In the third section, we discuss how the relative
319 economic importance of the traits can affect the relative performance of the methods. Lastly, we
320 discuss the implications of our results for modern plant breeding programs which deploy genomic
321 selection.

322

323 **Methods of selection and genetic correlation between traits**

324 The results show that, after only a few cycles of selection, index selection generates F_1
325 populations with a more unfavourable genetic correlation between traits than the F_1 populations
326 generated by independent culling (Fig 2). An explanation for the faster decrease of the genetic
327 correlation observed with index selection is that the index is a linear combination of component
328 traits. As shown by Bulmer (25), selection on a linear combination leads to negative covariances
329 between components (i.e., Bulmer effect). Consequently, the same principle applies to the
330 component traits and index selection, with index selection leading to an unfavourable genetic
331 correlation between the component traits (26,27).

332 In general, genetic gains in multi-trait selection, regardless of the method of selection, are
333 expected to be higher when the correlation between traits is favourable and lower when this
334 correlation is unfavourable (9). As index selection generated F_1 populations with more
335 unfavourable genetic correlation between traits than independent culling, the genetic gains for
336 index selection were potentially lower than for independent culling. Nevertheless, despite index
337 selection being carried out under increasingly unfavourable genetic correlations over the cycles,
338 the genetic gains obtained for the index trait were equivalent to the gains obtained using
339 independent culling (Fig. 3).

340 Unfavourable genetic correlations are the most challenging scenario for breeders. When

341 traits are unfavourably correlated, selection on one trait results in response in an undesired
342 direction for the other trait. When these correlations are due to pleiotropy, they cannot be broken
343 with repeated cycles of recombination. This case is likely pervasive in several crops, e.g., grain
344 yield and protein content in cereal crops (28–30), quality and disease resistance in forage crops
345 (31), and yield and disease resistance in barley (32). However, the extent of genetic correlation
346 and pleiotropy in these examples is unknown because unfavourable genetic correlations between
347 the traits could also be, at least partly, induced by selection, as demonstrated in this study.


348 **Methods of selection and genetic diversity over cycles of selection**

349 According to Bulmer (25), reduction in the genetic variance due to selection stems mostly
350 from the build-up of negative linkage disequilibrium between causal loci when selection is
351 performed. This can be seen by comparing genetic and genic variation (Table 2 and Table 3,
352 respectively). Genic variation is a function of the allele frequencies and the allele substitution
353 effect only, and thus is not affected by changes in linkage disequilibrium. The results in Table 3
354 show that the loss of genic standard deviation of the component traits and index trait are not greatly
355 affected by the method of selection. Also, the method of selection did not greatly affect the trait
356 means, as shown in Fig. 3. This indicates that, in terms of allele frequencies, there was little
357 difference in the parents selected by either independent culling or the selection index method in
358 situations similar to our simulation. Therefore, the difference between the selection methods
359 derives from how they induce and exploit linkage disequilibrium between the causal variants of
360 the component traits. Specifically, as shown in Table 2, independent culling induced a greater
361 degree of negative linkage disequilibrium between the causal variants of the component traits
362 resulting in those traits having less genetic variation. A deviation from this result is expected with
363 more intense selection schemes and more component traits selected in successive stages, which

364 would induce larger changes in allele frequencies due to drift. As a consequence, differences
365 between index selection and independent culling would be accentuated. In a previous study (33),
366 the authors simulated and compared wheat breeding programs using different selection strategies
367 under high and low selection intensities. They observed index selection resulted in higher
368 population coancestry over cycles of selection compared to independent culling, and the difference
369 between methods increased in scenarios with high selection intensity. Their results indicate index
370 selection leads to a higher loss of genic standard deviation.

371 Somewhat surprisingly, it is possible to make an argument for the superiority of
372 independent culling relative to a selection index on the basis of the differences observed in linkage
373 disequilibrium. This is because independent culling produced populations with nearly equivalent
374 mean performance, but with more consistent performance between individuals, which is
375 demonstrated by the lower variation observed for the component traits. This property could be
376 beneficial from a management perspective if differences in the component traits require variations
377 in management of individuals. Breeding for plant-architecture traits in outbreeding cultivars is a
378 good example where this property might be valuable, as having more uniform plants in the field
379 favours mechanical harvest. However, we believe this property is more of an academic curiosity
380 than something that will have practical application.

381 For simplicity and ease of implementation, our simulations consider the same genetic
382 architecture for both traits, with both traits being controlled by a high number (10,000) of causal
383 loci with small additive effects. Under different circumstances, such as at least one of the traits
384 being controlled by few causal loci with higher allele substitution effects, different results could
385 be expected. The results for the two-locus model in (34) show that independent culling tends to
386 eliminate genotypes that are homozygous for alleles with low effect for one of the traits. For one

387 pleiotropic causal locus, when both alleles are favourable for one trait and unfavourable for the
388 other trait, both homozygous genotypes tend to be culled, and independent culling would select
389 the heterozygous genotypes. If heterozygous genotypes were preferred, the fixation of alleles
390 would be slower and, therefore, the loss in genic standard deviation would be lower. Our results
391 indicate that, for highly polygenic traits, differences between methods of selection in the loss of
392 genetic diversity are mostly due to changes in linkage disequilibrium as opposed to distinctive
393 changes in allele frequencies. Therefore, in terms of conserving genetic diversity there was no
394 obvious advantage for either method. Other strategies such as optimal-cross selection
395 (23,33,35,36) or the multi-objective optimized approach (19) should be considered in order to
396 optimize gains while also controlling the loss of genetic diversity over cycles of selection. 

397 **Economic importance of the traits**

398 In general, when using the same selection intensity for both traits, the greater the difference
399 in the economic importance of the traits, the better index selection will perform compared to
400 independent culling (Fig. 4). This happens because there is a combination of selection intensities
401 for each trait that maximizes the genetic gain when performing independent culling (8). Finding
402 these selection intensities when selecting for two traits in two stages of selection is complex (37–
403 40), and becomes even more complex with increasing number of traits and stages of selection
404 (11,41,42).

405 The results in Fig. 4 show that independent culling approaches its maximal gain when a
406 higher selection intensity is used for the trait with higher economic importance and a lower
407 selection intensity is used for the trait with lower economic importance. In fact, when one trait had
408 5 times the economic importance of the other trait, the optimum was achieved when almost no
409 selection was carried out for the less important trait. These results demonstrate that accurately

410 assessing the economic importance of the traits is essential even when independent culling is
411 performed.

412 Regardless of the gains achieved with independent culling being maximised, when parents
413 are selected based on an index, equivalent gains are achieved by simply summing the values of the
414 traits weighted by their economic importance. Once the true economic weights of the traits are
415 quantified, index selection is much simpler than independent culling when using these weights for
416 optimizing the genetic gains in a plant breeding program.

417 **Index selection in modern plant breeding programs that use genomic selection**

418 There is little to no evidence suggesting plant breeders use analytical techniques to
419 determine optimal independent culling thresholds and/or constructing selection indices in most
420 plant breeding programs. More likely, the majority of breeders rely on their intuition for setting
421 thresholds and constructing indices. Their decisions are likely guided by the performance of
422 agronomic checks and are prone to fluctuations between seasons and individual breeders. This
423 model has clearly been successful, because plant breeding programs have continued to deliver
424 genetic gain. However, it is likely sub-optimal, and a more analytical approach should be adopted
425 in the future.

426 The value of a more analytical approach becomes greater as genomic selection is more
427 widely used. The results presented in this paper show a selection index is superior to independent
428 culling when using genomic selection. These results are further supported by earlier theoretical
429 work (8,9,43) and recent implementation of index selection in modern breeding programs of wheat
430 (18) and Miscanthus (17). This indicates a clear preference for implementing selection indices in
431 plant breeding.

432 The focus of plant breeders should be determining the economic weights for a selection
433 index. In this paper the economic model used to select weights was implicitly assumed to be known
434 and linear. The reality is that true economic model may be unknown to breeders and it is likely
435 non-linear. The presence of a non-linear model does not pose a problem, because linear economic
436 weights can be derived for improving the economic value of germplasm (44). However, this still
437 requires defining the economic model, which constitutes the main challenge for using selection
438 indices successfully.

439 The best way of determining economic weights has been a topic of extensive research and
440 scientific debate (45–51). Recently, multi trait strategies have been proposed that suggest selection
441 weights should be learned directly from the breeding population under selection. The authors in
442 (52) proposed an eigen selection index method that do not require economic weights to be
443 previously known and, instead, estimates them using genomic information from the breeding
444 population. On the strategy proposed in (19), breeding choices are carried based on optimization
445 of trade-offs across multiple traits as well as possible losses of genetic diversity in the population.

446 Given all the available tools, it is our opinion that plant breeders would benefit greatly from
447 an increased emphasis on understanding and quantifying the **economics** of their species and using
448 more analytical approaches when selecting for multiple traits. This would greatly aid breeders in
449 getting the most out of genomic selection.

450 **Conclusions**

451 We evaluated and compared recurrent selection breeding programs using either
452 independent culling or index selection for parent selection. The results show that, despite selection
453 being carried out under unfavourable genetic correlations when using the selection index instead
454 of independent culling, equivalent or higher genetic gains were achieved with index selection in

455 all simulated scenarios. In terms of genetic diversity, the differences between methods in the
456 studied system were driven mostly by differences in the generation of linkage disequilibrium
457 between causal loci induced and not differences in allele frequencies. When linkage disequilibrium
458 was not considered, both methods were equivalent in terms of loss of genetic diversity, and the
459 differences between methods in terms of efficiency of converting genetic diversity into genetic
460 gains mostly reflected the differences in the genetic gains obtained with each method. To obtain
461 higher genetic gains, accurately assessing the economic importance of the traits is essential even
462 when independent culling is performed, as optimal culling levels should be determined in order
463 for maximum gain to be achieved. Given that optimal culling levels are complex to estimate, once
464 the economic importance of each trait is known, maximum genetic gains are more easily achieved
465 with index selection. Therefore, the best choice for plant breeding programs is to select parents
466 using an economic selection index.

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473 **Conflict of interest**

474 On behalf of all authors, the corresponding author states that there is no conflict of interest.

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