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Combined BLUP selection indexes with parents and F² populations in soybean (*Glycine max*) breeding

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Abstract: This study aimed to apply selection indexes in situations in which F_2 populations and their parents are evaluated simultaneously in field trials to predict population genotypic values and selecting the best populations. Fifteen F_2 soybean populations were evaluated for number of days to flowering and to maturity and grain yield. The data was analyzed using restricted maximum likelihood/best linear unbiased prediction (REML/BLUP) to obtain genotypic effects, variance components and accuracies. Four selection methods were compared: genotypic values of the F_2 populations (g_{F2}), combined index with the mean genotypic value of parents and F_2 population (I_{a}) and two indexes that add (to g_{F2} and to I_a) and consider genetic variability within populations (I_b and I_c). The index I_a presented a result similar to that obtained with the g_{F2} selection method. Selection indexes (I_b and I_c) based on several sources of information were more efficient than selection based on g_{F2} values only.

Keywords: Grain yield, selection gain, early selection, days to maturity

INTRODUCTION

Soybean breeding programs obtain many segregating populations annually, mainly from converging crosses. Due to the demand for resources and time, breeders should focus on the significantly superior populations, because these have a higher probability of generating lines superior to the parents or a certain standard, which is usually the best commercial cultivar. However, the efficiency of breeding programs has been low, as parental crosses that do not result in new cultivars consume more than 99% of the resources (Witcombe et al. 2013).

In the breeding of autogamous plants, such as soybeans, selection has been performed from the evaluation of $F_{2:4}$ progenies or more advanced generations (Ramalho et al. 2012). In addition, the selection procedures have taken as reference only the last generation in which the progenies were evaluated. According to Resende et al. (2015), the selection could be made using information from previous generations (Wricke and Weber 1986, Resende 2002, Resende et al. 2016).

Resende (2002) proposed the use of mixed model methods, through the best linear unbiased prediction (BLUP) (Henderson 1975) in the sequential

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analysis of successive generations, according to the genealogical method. Later, a multigeneration index that considers all information across generations and covariance between generations, aiming to identify the best progenies, was proposed (Resende et al. 2015). This multigeneration index was successfully applied to common bean breeding by Batista et al. (2017). Another method called selection index with parents, populations, progenies and effects of generations (SIPPPG) was recommended for selection in the breeding of autogamous species (Resende et al. 2016). This index includes not only the effects of progenies in different generations, but also the effects of populations in all generations, parental data and F_1 and F_2 generations all simultaneously.

There are no reports in the literature of a specific index for selecting F_2 populations. Previous studies were carried out focusing only on population's data without consider the parents information. In this context, this study applied new selection methods that can be used in situations in which F_2 populations and their parents are simultaneously evaluated in an experiment, aiming to estimate the genetic gain by selecting the best populations for earliness and grain yield in soybean.

MATERIAL AND METHODS

Obtaining phenotypic data

Fifteen F, populations from biparental crosses, obtained from balanced complete diallel cross between six parents (Table 1), was performed in the soybean breeding program of the Universidade Federal de Viçosa (UFV), at Viçosa, Minas Gerais, Brazil, in the 2013/2014 crop season. In the following year (2014/2015), the progenies were assessed at the Teaching, Research, and Academic-Extension Units at UFV (lat 20° 46' 08" S, long 42° 52' 14" W, alt 663 m asl). The experiment was laid out in a randomized complete block design with three replications. Populations and parents were evaluated in plots of three 6.0 m rows, spaced 0.7 m apart. In each plot 140 seeds were distributed, resulting in a sowing density of approximately 8 seeds per linear meter. All plant management operations were undertaken in accordance with the requirements of the crop in the region (Sediyama et al. 2022).

The traits evaluated at individual level were grain yield (g plant⁻¹), number of days to flowering and days to maturity. Days to flowering is the period between the emergence of the seedling and the appearance of the first flower on the main stem; days to maturity is the number

Table 1. Description of segregating soybean populations, with
their respective parents and number of F, individuals evaluated
for grain yield, days to flowering and days to maturity

Population	Parents	Number of F ₂ individuals
1	MSOY6001 x RSF6563IPRO	236
2	MSOY6001 x TMG123RR	265
3	MSOY6001 X SYN9078RR	197
4	MSOY6001 X TMG801	211
5	MSOY6001 X MSOY9144RR	262
6	RSF6563IPRO X TMG123RR	187
7	RSF6563IPRO X SYN9078RR	235
8	RSF6563IPRO X TMG801	226
9	RSF6563IPRO X MSOY9144RR	211
10	TMG123RR X SYN9078RR	209
11	TMG123RR X TMG801	240
12	TMG123RR X MSOY9144RR	221
13	SYN9078RR x TMG801	213
14	SYN9078RR X MSOY9144RR	188
15	TMG801 X MSOY144 RR	222
Total		3323

of days between the emergence of the seedling and full maturity (plants with 95% of pods that have reached the ripe pod color). For the number of days to flowering and maturity, selection was carried out in both directions, that is, for selection of early and late plants.

Statistical analyses

Data were analyzed using restricted maximum likelihood/best linear unbiased prediction (REML/BLUP). REML developed by Patterson and Thompson (1971) was used to estimate variance components and BLUP (Henderson 1975) was used to predict genotypic values. The analysis strategy adjusted simultaneously one model for crosses and another for parents (that were included in the experiments as controls) in the same analysis (Resende et al. 2014, Resende and Alves 2020). In this case, a special encoding in the column "Fixed Effect", separating crosses and parents, became necessary and was possible using Selegen-REML/BLUP software (Resende 2016), model 189. Thus, we have the implicit model for data of crosses:

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$$y = Xc + Zm + Wf + Sd + Tp + e$$
(1)

where y is the vector of phenotypic data; c is the fixed effect of the combination of the average of the cross in each block; m is the vector of the effects of general combining abilities of the male parents (assumed as random), in which $m \sim N(0, I\sigma_m^2)$; f is the vector of the effects of the general combining abilities of the female parents (assumed as random), in which $f \sim N(0, I\sigma_f^2)$; d is the vector of the effects of the specific combining abilities of the crosses (assumed as random), in which $d \sim N(0, I\sigma_f^2)$; d is the vector of the effects of plots (assumed as random), in which $d \sim N(0, I\sigma_d^2)$; p is the vector of the effects of plots (assumed as random), in which $p \sim N(0, I\sigma_g^2)$; e is the vector of the effects of plots (assumed as random), in which $p \sim N(0, I\sigma_g^2)$; e is the vector of the effects of the effects of plots (assumed as random), in which $p \sim N(0, I\sigma_g^2)$; e is the vector of the effects of plots (assumed as random), in which $p \sim N(0, I\sigma_g^2)$; e is the vector of the effects of plots (assumed as random). The capital letters (X, Z, W, S and T) represent the incidence matrices for c, m, f, d and p effects, respectively. The total genotypic effect of each F, population was given by:

$$\hat{g}_{F2ii} = \hat{m}_i + \hat{f}_i + \hat{d}_{ii}$$
 (2)

Implicit model for parents' data:

$$y = Xu + Hg + Tp + e \tag{3}$$

where y is the vector of phenotypic data; u is the fixed effect of the overall mean of the parents in each block; g is the vector of the additive genetic effects of the parents (assumed as random), in which $g \sim N(0, I\sigma_g^2)$; p is the vector of the effects of plots (assumed as random), in which $p \sim N(0, I\sigma_g^2)$; e is the vector of the effects of error, in which $e \sim N(0, I\sigma_g^2)$. The capital letters (X, H and T) represent the incidence matrices for u, g and p effects, respectively.

The BLUP index I₂, which considers the effects of populations and parents, has the following form (Resende 2015):

$$I_{a} = \hat{b}_{1} \left[\frac{(g_{1} + g_{2})}{2} \right] + \hat{b}_{2} g_{F2}$$
(4)

In which g_1 and g_2 refer to the predicted additive genetic values of the parents 1 and 2, respectively; g_{F2} is equivalent to the predicted additive genetic value of the F₂ population. The weights are given by: $\hat{b} = P^{-1}C$, where:

$$P = \begin{bmatrix} r_{\partial a \rho a r}^{2} & r_{\partial a \rho a r}^{2} \\ r_{\partial a r r}^{2} r_{\partial a \rho a r}^{2} r_{\rho a r r 2}^{2} & r_{\partial a \rho a r}^{2} \end{bmatrix}$$
(5)

In which r_{aaPar}^2 is the reliability of the parents information and r_{aaF2}^2 is the reliability of the F₂ populations information. However, under a completely additive genetic model, the correlation (r_{ParF2}^2) between the standardized predicted F₂ population genotypic values and the standardized predicted mean of parents genotypic values is equal to 1 (F₂ population and mean of parents seeks for the same quantity, i.e., the parametric genotypic mean of a population coming from crossing of the pair of parents), then we have $r_{ParF2}^2 = 1$, and consequently:

$$P = \begin{bmatrix} r_{\partial \alpha P \alpha r}^{2} & r_{\partial \alpha P \alpha r}^{2} r_{\partial \alpha F 2}^{2} \\ r_{\partial \alpha F 2}^{2} r_{\partial \alpha F 2}^{2} & r_{\partial \alpha F 2}^{2} \end{bmatrix}$$
(6)

and
$$C = \begin{bmatrix} r_{\hat{a}aPar}^{r} & r_{ParF2}^{r} \\ r_{\hat{a}aF2}^{2} & 1 \end{bmatrix} = \begin{bmatrix} r_{\hat{a}aPar}^{r} \\ r_{\hat{a}aF2}^{2} \end{bmatrix}$$
 (7)

The weights of the index are:

$$\hat{b}_{1} = \frac{(1 - r_{daF2}^{2})}{1 - r_{daF2}^{2} r_{daF2}^{2}}$$
(8)

$$\hat{b}_{2} = \frac{(1 - r_{doPar}^{2})}{1 - r_{doPar}^{2} r_{doF2}^{2}}$$
(9)

The accuracy of the index is given by $r_{\hat{a}al}^2 = \sqrt{1 - \frac{(1 - r_{\hat{a}aPar}^2)(1 - r_{\hat{a}aF2}^2)}{1 - r_{\hat{a}aPar}^2 r_{\hat{a}aF2}^2}}$.

where, according to Resende (2017), $r_{aaParents}^{2} = (1/2)(r_{aaMother}^{2} + r_{aaFather}^{2})$ is the square of accuracy of the genetic value predicted from the mean of the two parents, based on the performance of the parents in the experiment; $r_{aaMother}^{2}$: square of accuracy of the genetic value predicted from the parent used as a mother; $r_{aaFather}^{2}$; square of accuracy of the genetic value predicted from the parent used as a mother; $r_{aaFather}^{2}$; square of accuracy of the genetic value predicted from the parent used as a father; r_{aaF2}^{2} : square of the accuracy of the genetic value predicted from the parent used as a father; r_{aaF2}^{2} : square of the accuracy of the genetic value predicted from the populations in the experiment. This accuracy is given by: $r_{aaF2}^{2} = 2F_{sT}^{2}\sigma_{o}^{2}/V_{phenot/F2'}$ in which F_{sT}^{2} : square of the inbreeding coefficient due to the differentiation between populations; σ_{a}^{2} : additive genetic variance; and $V_{phenot/F2}$: total phenotypic variance; and $F_{sT} = Var_{g(F2)}/Var_{g(Par)}$ where $Var_{g(F2)}$ and $Var_{g(Par)}$ are the genotypic variances among F_{2} and among parents, respectively. The definitions of the squared accuracy presented are valid at generation $F\infty$.

To obtain the accuracies r_{daPar}^2 and r_{daF2}^2 we divided the accuracies from the output file with extension '.fam' of the Selegen-REML/BLUP software (Resende 2016) by 4 and 1/F_{st}, respectively. The second index (I_b) for population selection, which considers the additive genetic value of the population and genetic variability within the population, as described by Resende (2015, 2017) is:

$$I_{b} = F_{2\rho\rho\rho_{i}} + 3.09 \sqrt{(1 - F_{sT})2\sigma_{a0}^{2} \frac{Var_{(Residual_{i})}}{Var_{(Residual)}}}$$
(10)

where F_{2pop_i} is the BLUP of the population i effect, and the expression within the root refers to the magnitude of genetic variability within population i; σ_{a0}^2 represents the original additive genetic variance of parent's population and $Var_{(Residual_j)}$ is the phenotypic variability within population i and $Var_{(Residual_j)}$ corresponds to the residual variance of the experiment considering the population data. Finally, the value of the index I_b is an estimate of the genetic value of the best line to be selected at the end of the selection process and the constant 3.09 refers to the number of standard deviations in the normal distribution curve, associated with the selection of one in thousand lines. The sum of three standard deviations represents 99.7% of the data of a normal distribution. The accuracy of the index corresponds to the estimation accuracy of the genetic effects of the F₂ population, as discussed earlier.

The third index (I_c) was presented by Resende (2015) how an improved index and the same purpose of I_b , it uses the combined selection of F_2 parents and variability among individuals within the F_2 population. The index can be obtained as follows:

$$h_{c} = \hat{b}_{1} \left[\frac{(g_{1} + g_{2})}{2} \right] + \hat{b}_{2} g_{F2} + 3.09 \sqrt{(1 - F_{ST}) 2\sigma_{a0}^{2} \frac{Var_{(Residual_{i})}}{Var_{(Residual_{i})}}}$$
(11)

The definitions of the terms are the same as presented above and the accuracy of the index is equal the accuracy of the index I_a . Statistical analyses were processed using the Selegen-REML/BLUP software (Resende 2016). Spearman's rank correlation coefficients were calculated among the ranking given by the F_2 genotypic values, I_a , I_b and I_c . The analyses were performed in R software (R Core Team 2023) and the figures created with package ggplot2 (Wickham 2016).

RESULTS AND DISCUSSION

The predicted genotypic values, phenotypic variances within population and selection for grain yield are presented in Table 2. According to the genotypic value, the best populations were 8, 6, 7, 9, 13, 11, 10, 1 and 15, because they showed values above the overall mean of the experiment (57.32 g). The phenotypic variance within the population ranged from 808.76 (population 2) to 1896.78 (population 8).

F ₂ average		Index I _a with	Parents and F ₂	Index I _b with F	2 and variance of F2	Index I _c with Pare	nts, F ₂ and variance of F ₂	
Рор	Gv	Var _(Res)	Рор	I _a	Рор	I _b	Рор	I _c
8	64.26	1896.78	8	68.30	8	75.54	8	79.59
6	62.45	1250.04	6	64.85	6	71.61	6	74.01
7	60.57	868.01	7	63.41	9	68.62	7	71.04
9	59.24	1311.37	9	60.59	7	68.21	9	69.97
13	59.04	1085.99	13	60.55	15	68.09	13	69.09
11	58.25	1336.56	11	59.36	11	67.72	11	68.84
10	58.19	1074.60	1	58.06	13	67.58	15	68.11
1	57.96	1145.63	10	58.02	4	67.05	1	66.84
15	57.88	1551.35	15	57.90	1	66.73	10	66.52
4	56.31	1716.06	4	55.09	10	66.69	4	65.83
12	55.51	1249.42	12	53.88	12	64.67	12	63.04
14	54.92	1097.43	14	53.71	3	63.59	14	62.30
3	54.76	1161.45	3	52.28	14	63.51	3	61.11
2	50.39	808.76	2	47.62	5	58.50	2	54.99
5	50.12	1046.14	5	46.25	2	57.76	5	54.64
r _{âal}	0.54			0.55		0.54		0.55

Table 2. Predicted genotypic value (Gv), phenotypic variance within population ($Var_{(Res)}$), accuracy (r_{dal}) and selection indexes applied to fifteen F_2 soybean populations for grain yield

The index based on the additive genetic value of parents and F_2 populations (I_a) showed a result similar to that obtained with the selection on the genotypic value of population. In this case, populations 11, 10 and 1 are considered in this order of superiority, while by index I_a , population 10 reversed position with population 1. In addition, the accuracy of the index I_a (0.55) was higher than the accuracy of the selection based on the genotypic value of the F_2 population (0.54), that is, the use of the index provided 1% more genetic gain in grain yield, due to the inclusion of information from the parents. In terms of magnitudes, these accuracies are classified as moderate (Resende and Duarte 2007, Resende and Alves 2022).

For grain yield the selection by genotypic values and index I_a has provided genetic gain similar to those obtained annually by breeding programs. Felipe et al. (2016) reported that the genetic gains obtained for soybean in Argentina in the period from 1980 to 2015 were on the order of 1.1%, which is also similar to the gains observed in the United States. In Brazil, Toledo et al. (1990) evaluated the efficiency of a soybean breeding program in the state of Paraná in the period from 1981 to 1986 and found that genetic gains were 1.8% in the early group and 1.3% for genotypes of the semi-early group. Recently a new study revealed an average rate of yield gain of 45.9 kg ha⁻¹ yr⁻¹ (2.1% ha⁻¹ yr⁻¹) over the past 50 years in southern Brazil (Umburanas et al. 2022).

The selection based on the index with additive values of population and phenotypic variance within population (I_b) classified the best populations similarly to the other indexes. However, through this index it is possible to obtain gains, when performing the selection, in all the studied populations, because all the values obtained were above the overall mean of the experiment. The value of the index I_b refers to an estimate of the genetic value of the best line to be selected in generation F ∞ . Taking as an example the best population, in this case, the population 8, when comparing with the overall mean, we have 75.54/57.32 = 1.32 and, therefore, the genetic gain will be 32%. When comparing with the mean of population 8, we have 75.54/64.26 = 1.18, so the genetic gain with selection within population 8 will be 18%. Thus, through this index it is possible to obtain gains of up to 32% with the selection between populations and ranging from 13 to 19% by selecting within populations (Table 3).

For grain yield, the genetic gains obtained with index I_b are considered satisfactory for the genetic improvement of soybeans, given that in the literature gains between 3 and 32.8% are reported in different generations of inbreeding (Reis et al. 2004, Costa et al. 2008, Bárbaro et al. 2013). The great advantage of the index I_b is the combination of genetic information from populations and variance within populations. According to Resende (2015), the best indexes include both high mean and wide genetic variability. As a disadvantage of the index, the cost of phenotyping of all individuals to estimate variance within the population can be cited.

	Grai	in yield		Days to flowering			Days to maturity		
Population	F ₂ mean/Overall mean	I _b /Overall mean	I _b /F₂ mean	F ₂ mean/Overall mean	I _⊾ /Overall mean	I₅/F₂ mean	F ₂ mean/Overall mean	I _⊾ /Overall mean	I _b /F ₂ mean
1	1.01	1.16	1.15	0.88	0.59	0.67	0.94	0.82	0.88
2	0.88	1.01	1.15	0.92	0.71	0.77	0.93	0.79	0.85
3	0.96	1.11	1.16	0.99	0.53	0.54	1.01	0.80	0.80
4	0.98	1.17	1.19	1.01	0.53	0.52	1.01	0.69	0.69
5	0.87	1.02	1.17	1.01	0.52	0.52	1.00	0.69	0.69
6	1.09	1.25	1.15	0.92	0.57	0.62	0.99	0.81	0.82
7	1.06	1.19	1.13	0.87	0.64	0.73	0.94	0.82	0.87
8	1.12	1.32	1.18	0.96	0.52	0.54	1.00	0.68	0.69
9	1.03	1.20	1.16	0.97	0.45	0.47	1.00	0.72	0.72
10	1.02	1.16	1.15	1.03	0.62	0.60	0.99	0.72	0.73
11	1.02	1.18	1.16	1.03	0.55	0.53	0.99	0.70	0.70
12	0.97	1.13	1.17	1.02	0.54	0.53	1.00	0.71	0.71
13	1.03	1.18	1.14	1.09	0.64	0.58	1.04	0.72	0.70
14	0.96	1.11	1.16	1.08	0.52	0.48	1.03	0.76	0.73
15	1.01	1.19	1.18	1.22	0.98	0.81	1.14	1.00	0.88

Table 3. Relative performance compared to the overall mean and population F_2 mean, obtained from the index I_p , which considers the additive genetic value and genetic variability within the population, for the traits grain yield, days to flowering and days to maturity

The index I_c is a projection of I_a in the normal distribution curve, in which the index is the genetic value of the best line to be selected in generation $F\infty$, and the interpretation is the same made for I_b . However, the information from individuals within populations included in I_c promoted minor changes in the order of the best populations, in relation to I_a , as can be observed for populations 1, 10 and 15 (Table 2).

For days to flowering, the best populations classified, based on genotypic value, in descending order, were 7, 1, 6, 2, 8, 9 and 3. The other populations showed means higher than the overall mean of the experiment (51.16 days), so the probability of obtaining gains when selecting these populations is lower. The variance within the population for the trait in question ranged from 12.22 to 85.06 (Table 4). The ranking made by the index with parents and F_2 populations (I_a) changed the order of the two best populations (1 and 7) and raised population 10 to three positions above the classification made by genotypic values. The population sthat, notably, can provide gains in reducing the time to flowering are the same identified by genotypic population values. Through the application of the index, the possibility of a reduction from 2 to 65% in the time to flowering was found (Table 3). In addition, the use of the index I_a can provide 6% more genetic gains compared to selection based on genotypic values, due to its greater selective accuracy (0.38).

The inclusion of variances between plants in the population, in the index $I_{b'}$ promoted considerable change in the ranking of populations (Table 4). Populations 1 and 7, for example, which occupied the first two positions in the order based on genotypic values and index with parents and $F_2(I_a)$, were reallocated in the 10th and 13th positions by including the variance of F_2 in the index (I_b) . Due to the low variance between plants in populations 1 (23.01) and 7 (14.71), these were penalized by the index. The same projection of gains made previously for the grain yield from the $I_{b'}$ can be applied to the number of days to flowering. The results showed that it is possible to obtain gains by performing selection in all populations, contrary to what was observed when the selection was performed from the genotypic value of the population and by the index I_a .

As verified for grain yield, the index I_b was also the one that had the highest selective accuracy for the number of days to flowering. In Table 3 we can see that the relative performance of the index I_b was higher compared to the overall mean of the experiment and compared to the mean of the F₂ population, that is, in the selection between and within populations, respectively.

The index I_c was the one that showed the greatest expectation of reducing the time to flowering, because it had a higher probability of selection of plants with greater potential to originate lines in F_{∞} with less time to flowering and,

F ₂ average		Index I_a with Parents and F_2		Index I _b with F ₂	Index $\rm I_{\rm b}$ with $\rm F_{\rm 2}$ and variance of $\rm F_{\rm 2}$		nts, F ₂ and variance of F ₂	
Рор	Gv	Var _(Res)	Рор	l	Рор	l _b	Рор	l _c
7	44.58	14.71	1	42.13	9	23.09	9	22.71
1	45.07	23.01	7	43.03	14	26.66	8	26.34
6	47.20	33.11	6	44.74	8	26.70	3	26.66
2	47.31	12.22	2	46.13	5	26.73	6	26.90
8	49.15	52.45	8	48.79	4	26.89	1	27.26
9	49.39	71.98	9	49.01	3	27.21	5	27.51
3	50.80	57.93	3	50.26	12	27.82	4	27.71
4	51.67	63.87	10	52.46	11	27.98	14	28.67
5	51.85	65.71	4	52.48	6	29.36	12	29.17
12	52.34	62.59	5	52.64	1	30.20	11	29.33
10	52.50	45.03	12	53.69	10	31.70	7	31.15
11	52.51	62.61	11	53.86	13	32.52	10	31.65
14	55.25	85.07	14	57.26	7	32.69	13	34.52
13	55.69	55.86	13	57.69	2	36.48	2	35.30
15	62.22	15.31	15	65.31	15	50.09	15	53.18
(r _{âal})	0.32			0.38		0.32		0.38

Table 4. Predicted genotypic value (Gv), phenotypic varia	ance within population (<i>Var</i> _{(Par}), accuracy (r _{âa}) and selection indexes ap	plied
in fifteen F ₂ soybean populations for days to flowering	(nes	,		

at the same time, it had selective accuracy superior to the genotypic value of population and index I_{b} , and equivalent to the index I_{a} .

The genotypic values, variances of each population and indexes obtained for number of days to maturity are presented in Table 5. It was found that the ordering of the populations most favorable to reduction of the characteristic was similar when the selection based on genotypic value of population and index with Parents and $F_2(I_a)$ was used. Regarding the index, the results showed that, although the change in the ranking of the best populations was modest, compared to genotypic values, the inclusion of information from the parents contributed to obtaining expected gains with the selection (Table 3). Considering the reduction of the number of days to maturity, through the application of the index I_a , it was possible to obtain genetic gains of up to 32% compared to the overall mean of the experiment and 31% compared to the population mean.

The ordering and genetic gain with the selection of the best populations based on the index I_c were similar to those obtained with the index I_b (Table 5 and Figure 1) and much higher than those obtained with the selection by genotypic

Table 5. Predicted genotypic value (Gv), residual variance ($Var_{(Res)}$), accuracy (r_{dal}) and selection indexes applied in fifteen F_2 soybean populations for days to maturity

F ₂ averag	age Index I _a with Parents and F_2 Index I _b with F_2 and variance of F_2 Index I _c with Parents, F_2 and v		ents, F ₂ and variance of F ₂					
Рор	Gv	Var _(Res)	Рор	I _a	Рор	I _b	Рор	I _c
2	121.09	24.77	2	119.23	8	88.95	8	89.91
1	122.23	18.19	1	119.85	5	90.01	5	91.20
7	122.43	18.97	7	121.66	4	90.36	4	91.43
6	128.43	40.03	6	126.13	11	90.50	11	91.95
10	128.83	96.02	10	128.30	12	92.16	10	93.34
11	129.21	117.75	3	129.88	10	93.88	12	93.64
8	129.46	128.93	8	130.41	9	93.99	9	94.98
5	129.79	124.31	11	130.66	13	94.19	13	96.72
9	130.44	104.45	5	130.97	14	98.37	14	100.99
12	130.46	115.24	9	131.43	2	103.33	2	101.48
4	130.80	128.52	4	131.87	3	104.20	3	103.27
3	130.81	55.66	12	131.93	6	105.86	6	103.56
14	134.42	102.13	14	137.04	7	106.90	1	104.64
13	134.89	130.19	13	137.42	1	107.02	7	106.13
15	147.62	22.78	15	151.73	15	130.59	15	134.70
r _{âal}	0.30			0.35		0.30		0.35



Figure 1. Spearman's rank correlations among ranking by F_2 genotypic values and selection indexes (I_a , I_b and I_c) applied in fifteen F2 soybean populations for days to flowering, days to maturity and grain yield. * Only significant values (p<0.05) are presented.

value and index I_a . The indexes that contemplate the variance between individuals within populations (I_b and I_c) provided greater gains compared to the selection based on the genotypic value of the population and the index that includes information of parents and F_2 (I_a).

Significant rank correlations were found between F_2 genotypic values and indexes, especially for grain yield (Figure 1). There was no correlation among index I_b and F_2 genotypic values and among I_b and I_a for days to flowering

Table 6. Inbreeding coefficient between populations (F_{sT}) , accuracies of parents $(r_{\hat{a}aParents}^2)$, $F_2(r_{\hat{q}aF2}^2)$ and selection index with parents and $F_2(r_{\hat{a}al}^2)$ for grain yield, days to flowering and maturity

Trait	r² âaParents	r² _{âaF2}	F _{st}	r ² _{âal}
Grain yield	0.18	0.54	0.75	0.55
Days to flowering	0.23	0.32	0.34	0.38
Days to maturity	0.21	0.30	0.31	0.35

and days to maturity (p>0.05). For all studied traits, the index I_a was highly correlated with F_2 genotypic values (0.918 to 0.996) and I_c with I_b . The weak correlations between I_c and F_2 genotypic values and between I_c and I_a for days to maturity confirm that the parents information has changed the population's raking. For traits with a greater contribution of additive effect, the F_2 average reflects the parental average, especially for traits controlled by few genes. In this way, indexes containing only information from parents and F_2 are sufficient for selecting individuals.

The traits number of days to flowering and days to maturity are controlled by several genes. To date, ten genes involved in the genetic control of these traits have been described (Zhao et al. 2016). So, from divergent crosses it is possible to obtain various allelic combinations, which result in different phenotypes in F_2 . In addition, the occurrence of transgressive segregants for the traits in question is common, especially when the crosses involve divergent parents. The presence of transgressive individuals may increase the variance within the population, as verified in the populations 4, 5, 8, 9, 10, 11, 12, 13 and 14 originated from the cross of contrasting parents as to the number of days to maturity. Transgressive segregants are commonly observed in soybeans (Carpentieri-Pípolo et al. 2000, Tasma et al. 2001, Carpentieri-Pípolo et al. 2002). The occurrence of transgressive segregation is attributed to dispersion of favorable alleles between parents (Mackay et al. 2021).

We observed in this work that parent's information was more important than the information of the means of F_2 populations, depending on the F_{sr} . The F_{sr} is the proportion of total variability that is distributed among populations and greater efficiency is expected in F_2 when there is large total variance, the greater the efficiency of F_2 . According to Resende (2015) combining the two sources of information in an index is the optimal procedure (via BLUP) to obtain high selection accuracy. For grain yield, Table 6 shows that the accuracy of the index I_a (0.55) was higher than the accuracy of F_2 (0.54) and of the parents (0.18). According to Resende (2015), these results are valid under model with completely additive inheritance.

The great advantage of the index I_a compared to the other methods presented is its ease of obtaining, because it requires only the genetic value of parents and populations. Such an index dispenses with the evaluation at individual level, which makes the breeding program slow and costly. Besides, the index provided 1%, 6% and 5% more genetic gain, compared to selection by population genetic value, for the characteristics grain yield, number of days to flowering and number of days to maturity, respectively.

Indexes based on BLUP joint analyses for parents, populations and individuals in a single experiment as reported in this work provide all necessary information to obtain the BLUP of the indexes combining parents and population BLUPs. This is the most precise and efficient approach to obtain an index, which takes into account the reliability of each information as well as the correlation between them. This is also in line with the standard procedure of obtaining a selection index based on multiple traits via multivariate BLUP. The referred joint model is also crucial in computing the reliabilities of the different indexes. A BLUP index combining predicted (BLUP) genetic values of several information sources in this way is as exact as a multivariate BLUP (Resende 2015, Resende et al. 2016). The resulting BLUP is produced as an estimable function of several BLUPs.

In summary, selection using indexes based on various sources of information was more efficient than selection based on genotypic population values and the inclusion of parental information and variance within populations increased the expectation of gains for all the traits studied. The index I_a , which includes the genotypic values of parents and F_2 populations, was the best strategy to increase the gains with selection. Combined BLUP selection indexes with parents and F2 populations in soybean (Glycine max) breeding

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