

## A method to construct confidence interval for expected response to multi-trait selection

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**Summary.** Confidence intervals are constructed for the expected responses to three types of multi-trait selection. The influence of numbers of replicates and genotypes used in a progeny test experiment on the precision of response of multi-trait selection is discussed based on the structure of the established intervals. Special attention is paid to the characteristics of the intervals constructed for the conventional least square selection indices.

**Key words:** Multi-trait selection – Confidence interval – Index selection

### Introduction

One of the most serious problems in using index selection (Smith 1936; Hazel 1943) in breeding work is that the true population parameters are usually unknown and have to be estimated from samples.

The study of effect of sampling errors on the efficiency of index selection is difficult and often involves complicated statistical procedures (see e.g., Williams 1962a; Harris 1964; Hayes and Hill 1980). Tallis (1960) obtained a large sample variance of the index weights and predicted genetic gains. Harris (1963, 1964) examined the concept of progress from index selection and studied the joint distribution of the expected progress from selection for a calculated index and the predicted progress from this index. Hayes and Hill (1980) elaborated further on the definition of response to selection and study the sampling properties of the index weights by a reparameterization of the phenotypic and genetic covariances used in constructing the selection indices.

The aim of the present report is to propose a method to construct a confidence interval for the expected response to three types of multi-trait selection. The interval is then investigated for its various implications in selection work.

### General theory

Consider a set of  $n$  variables  $v_i$ ,  $i = 1, 2, \dots, n$ , which follows multivariate normal distribution  $MN(\mu, \Sigma)$  with

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{bmatrix} \quad \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \dots & \sigma_{nn} \end{bmatrix}$$

in which  $\mu_i$  is the mean,  $\sigma_{ii}$  ( $= \sigma_i^2$ ) the variance of  $i$ -th variable, and  $\sigma_{ij}$  the covariance of  $i$ -th and  $j$ -th variables. Let  $\mathbf{d}$  be a  $(n \times 1)$  vector of constants, i.e.,  $\mathbf{d}' = [d_1 \ d_2 \ \dots \ d_n]$ . A new composite variable  $z = \mathbf{d}'\mathbf{v}$  should have mean  $\mu_z = \mathbf{d}'\mu$  and variance  $\sigma_z^2 = \mathbf{d}'\Sigma\mathbf{d}$ . Also, for a random sample of size  $m$ ,

$$\frac{\mathbf{d}'\mathbf{S}\mathbf{d}}{\mathbf{d}'\Sigma\mathbf{d}} = \chi_{df}^2, \quad df = m - 1$$

where  $\mathbf{S}$  is the matrix of sample sum of squares and products. A  $(1 - \alpha)$  confidence interval for  $\mathbf{d}'\Sigma\mathbf{d}$  can be obtained as

$$P \left\{ \frac{\mathbf{d}'\mathbf{S}\mathbf{d}}{\chi_{\alpha/2; df}^2} \leq \mathbf{d}'\Sigma\mathbf{d} \leq \frac{\mathbf{d}'\mathbf{S}\mathbf{d}}{\chi_{1-\alpha/2; df}^2} \right\} \geq 1 - \alpha \quad (1)$$

where  $\chi_{\alpha/2; df}^2$  and  $\chi_{1-\alpha/2; df}^2$  are tabulated  $\chi^2$  value with  $m - 1$  degrees of freedom at the probability level  $\alpha/2$  and  $(1 - \alpha/2)$ , respectively.

Now assume that data of  $n$  traits are obtained from each of  $m$  genotypes tested in an experiment replicated  $r$  times according to a randomized complete block design. Let  $x_{ijk}$  be the observed value of  $j$ -th trait of

$i$ -th genotype in  $k$ -th block,

$$x_{ijk} = u_j + b_{jk} + g_{ij} + \varepsilon_{ijk}$$

$$i = 1, \dots, m; j = 1, \dots, n; k = 1, \dots, r,$$

where  $u$ ,  $b$ ,  $g$  and  $\varepsilon$  are, respectively, the population mean, and effects due to  $k$ -th block,  $i$ -th genotype and  $ik$ -th error deviate for the  $j$ -th trait. The phenotypic effect of  $j$ -th trait of  $i$ -th genotype is then

$$P_{ij} = \bar{x}_{ij} - \bar{x}_{.j} = g_{ij} + e_{ij}$$

where  $e_{ij} = \frac{1}{r} \sum_{k=1}^r \varepsilon_{ijk}$ . Let  $\mathbf{T}$  be the matrix of mean squares and products between genotypes and  $\mathbf{E}$  the corresponding matrix of error mean squares and products in the analysis of variance and covariance (VAR-COV) table for the  $n$  traits. Also let  $\mathbf{P}$ ,  $\mathbf{G}$  and  $\mathbf{E}$  be VAR-COV matrices for the phenotypic, genotypic and error effects,

$$\mathbf{P} = \begin{bmatrix} \sigma_{p11} & \sigma_{p12} & \dots & \sigma_{p1n} \\ \sigma_{p21} & \sigma_{p22} & \dots & \sigma_{p2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{pn1} & \sigma_{pn2} & \dots & \sigma_{pnn} \end{bmatrix}$$

$$\mathbf{G} = \begin{bmatrix} \sigma_{g11} & \sigma_{g12} & \dots & \sigma_{g1n} \\ \sigma_{g21} & \sigma_{g22} & \dots & \sigma_{g2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{gn1} & \sigma_{gn2} & \dots & \sigma_{gnn} \end{bmatrix}$$

$$\mathbf{E} = \begin{bmatrix} \sigma_{e11} & \sigma_{e12} & \dots & \sigma_{e1n} \\ \sigma_{e21} & \sigma_{e22} & \dots & \sigma_{e2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{en1} & \sigma_{en2} & \dots & \sigma_{enn} \end{bmatrix}$$

$\mathbf{P}$ ,  $\mathbf{G}$  and  $\mathbf{E}$  are estimated by

$$\hat{\mathbf{P}} = \frac{1}{r} \mathbf{T}, \quad \hat{\mathbf{G}} = \frac{1}{r} (\mathbf{T} - \mathbf{E}) \quad \text{and} \quad \hat{\mathbf{E}} = \frac{1}{r} \mathbf{E}.$$

Three types of expected response to selection are considered in the present paper:

### 1 Achieved response

Let  $\mathbf{a}$  and  $\mathbf{b}$  be two  $(n \times 1)$  vectors of constants whose elements are two sets of weights associated with the  $n$  traits.  $\mathbf{a}$  is used to weigh the genotypic effects of  $n$  traits of a genotype to obtain an aggregate genotypic value, i.e.,  $h_i = \sum_{j=1}^n a_j g_{ij}$ , whereas  $\mathbf{b}$  to obtain an index  $I_i = \sum_{j=1}^n b_j p_{ij}$ . The achieved response to selection based

on  $I_i$  is measured by  $R_a = \mathbf{i} \mathbf{a}' \mathbf{G} \mathbf{b} (\mathbf{b}' \mathbf{P} \mathbf{b})^{-1/2}$  where  $i$  is the intensity of selection.

### 2 Correlated response

The response of a trait to selection for another trait in the population is called correlated response (Falconer 1982). Let  $CR_{kl}$  be the correlated response of  $k$ -th trait to selection for  $l$ -th trait. We have  $CR_{kl} = i \sigma_{gkl} (\sigma_{p11})^{-1/2}$ . Let  $\mathbf{a}$  and  $\mathbf{b}$  be two vectors with null elements but the  $k$ -th and  $l$ -th elements, respectively, taking the value of unity. Then,  $CR_{kl} = R_a$ .

### 3 Maximum attainable response

In conventional least square index selection,  $\mathbf{a}$  is usually a set of "economic weights" whereas  $\mathbf{b}$  is obtained by  $\mathbf{b} = \mathbf{P}^{-1} \mathbf{G} \mathbf{a}$  (Smith 1936). The response to selection based on the index  $I_i = \sum_{j=1}^n b_j P_{ij}$  is measured by  $R = i (\mathbf{b}' \mathbf{P} \mathbf{b})^{1/2}$ . This represents the maximum attainable response when the genotypic effects are weighed by  $\mathbf{a}$ .

It is noted  $R_a$ ,  $CR$  and  $R$  can only be estimated using  $\hat{\mathbf{G}}$  and  $\hat{\mathbf{P}}$ . Also,  $R_a$  and  $CR$  can be either positive or negative measures, whereas  $R \geq 0$  when the intensity of selection ( $i$ ) is positive.

### Confidence intervals for expected response to multi-trait selection

#### Achieved response

The confidence interval for  $R_a$  can be derived by using the confidence intervals for  $(\mathbf{a} + \mathbf{b})' \mathbf{P} (\mathbf{a} + \mathbf{b})$ ,  $\mathbf{a}' \mathbf{P} \mathbf{a}$ ,  $\mathbf{b}' \mathbf{P} \mathbf{b}$ ,  $(\mathbf{a} + \mathbf{b})' \mathbf{E} (\mathbf{a} + \mathbf{b})$ ,  $\mathbf{a}' \mathbf{E} \mathbf{a}$ , and  $\mathbf{b}' \mathbf{E} \mathbf{b}$ . Let the six intervals with confidence limit  $(1 - \alpha)$  be  $(L_1, U_1)$ ,  $(L_2, U_2)$ ,  $(L_3, U_3)$ ,  $(L_4, U_4)$ ,  $(L_5, U_5)$  and  $(L_6, U_6)$ , respectively. The  $(1 - \alpha)$  interval  $(L_1, U_1)$ , for example, can be derived by putting  $\mathbf{d} = (\mathbf{a} + \mathbf{b})$ ,  $\mathbf{S} = (m - 1) \hat{\mathbf{P}}$ , and  $df = (m - 1)$  in (1), i.e.,

$$P \left\{ \frac{(m - 1) (\mathbf{a} + \mathbf{b})' \hat{\mathbf{P}} (\mathbf{a} + \mathbf{b})}{\chi^2_{\alpha/2; m-1}} \leq (\mathbf{a} + \mathbf{b})' \mathbf{P} (\mathbf{a} + \mathbf{b}) \leq \frac{(m - 1) (\mathbf{a} + \mathbf{b})' \hat{\mathbf{P}} (\mathbf{a} + \mathbf{b})}{\chi^2_{1-\alpha/2; m-1}} \right\} \geq 1 - \alpha.$$

Other five  $(1 - \alpha)$  intervals can be similarly derived. Since both  $\mathbf{P}$  and  $\mathbf{E}$  are positive semi-definite (see Searle 1966), the following two inequalities can be set up:

$$P \{ L_a \leq (\mathbf{a} + \mathbf{b})' \mathbf{P} (\mathbf{a} + \mathbf{b}) + \mathbf{a}' \mathbf{E} \mathbf{a} + \mathbf{b}' \mathbf{E} \mathbf{b} \leq U_a \} \geq 1 - \alpha$$

$$P \{ L_b \leq (\mathbf{a} + \mathbf{b})' \mathbf{E} (\mathbf{a} + \mathbf{b}) + \mathbf{a}' \mathbf{P} \mathbf{a} + \mathbf{b}' \mathbf{P} \mathbf{b} \leq U_b \} \geq 1 - \alpha$$

where  $L_a = L_1 + L_5 + L_6$ ,  $U_a = U_1 + U_5 + U_6$ ,  $L_b = L_2 + L_3 + L_4$  and  $U_b = U_2 + U_3 + U_4$ . Let  $\mathbf{A} =$

$\mathbf{a}'\mathbf{P}\mathbf{a} + (\mathbf{a} + \mathbf{b})'\mathbf{E}(\mathbf{a} + \mathbf{b})$ ,  $\mathbf{B} = \mathbf{b}'\mathbf{P}\mathbf{b}$  and  $\mathbf{C} = \mathbf{a}'\mathbf{G}\mathbf{b}$  and note that  $\mathbf{P} = \mathbf{G} + \mathbf{E}$ . We have

$$(\mathbf{a} + \mathbf{b})'\mathbf{P}(\mathbf{a} + \mathbf{b}) + \mathbf{a}'\mathbf{E}\mathbf{a} + \mathbf{b}'\mathbf{E}\mathbf{b} = \mathbf{A} + \mathbf{B} + 2\mathbf{C}$$

$$(\mathbf{a} + \mathbf{b})'\mathbf{E}(\mathbf{a} + \mathbf{b}) + \mathbf{a}'\mathbf{P}\mathbf{a} + \mathbf{b}'\mathbf{P}\mathbf{b} = \mathbf{A} + \mathbf{B}.$$

A Bonferroni inequality can then be formulated as follows (see Graybill 1976):

$$\begin{aligned} \mathbf{P}\{\mathbf{L}_a \leq \mathbf{A} + \mathbf{B} + 2\mathbf{C} \leq \mathbf{U}_a, \mathbf{L}_b \leq \mathbf{A} + \mathbf{B} \leq \mathbf{U}_b, \\ \mathbf{L} \leq \mathbf{C}^2/\mathbf{B} \leq \mathbf{U}\} \geq 1 - 3\alpha. \end{aligned}$$

That is,

$$\begin{aligned} \mathbf{P}\{\mathbf{L}_a \leq (\mathbf{a} + \mathbf{b})'\mathbf{P}(\mathbf{a} + \mathbf{b}) + \mathbf{a}'\mathbf{E}\mathbf{a} + \mathbf{b}'\mathbf{E}\mathbf{b} \leq \mathbf{U}_a, \\ \mathbf{L}_b \leq (\mathbf{a} + \mathbf{b})'\mathbf{E}(\mathbf{a} + \mathbf{b}) + \mathbf{a}'\mathbf{P}\mathbf{a} + \mathbf{b}'\mathbf{P}\mathbf{b} \leq \mathbf{U}_b, \\ \mathbf{L} \leq (\mathbf{a}'\mathbf{G}\mathbf{b})^2/\mathbf{b}'\mathbf{P}\mathbf{b} \leq \mathbf{U}\} \geq 1 - 3\alpha. \end{aligned} \quad (2)$$

The relationship in (2) can be used to obtain a  $(1 - 3\alpha)$  confidence interval for  $\mathbf{b}'\mathbf{P}\mathbf{b}$  according to the method given by Williams (1962b):

$$\mathbf{P}\{\mathbf{L}_c \leq \mathbf{b}'\mathbf{P}\mathbf{b} \leq \mathbf{U}_c\} \geq 1 - 3\alpha. \quad (3)$$

The structures of  $\mathbf{L}_c$  and  $\mathbf{U}_c$  are known,

$$\mathbf{L}_c = (m-1) \mathbf{b}'\hat{\mathbf{P}}\mathbf{b}/\chi_{3\alpha/2; m-1}^2,$$

$$\mathbf{U}_c = (m-1) \mathbf{b}'\hat{\mathbf{P}}\mathbf{b}/\chi_{1-3\alpha/2; m-1}^2.$$

Therefore, (2) and (3) can be used to find  $\mathbf{L}$  and  $\mathbf{U}$ . Let  $l_a$ ,  $l_b$  and  $l_c$  be the observed lower limits of  $\mathbf{L}_a$ ,  $\mathbf{L}_b$  and  $\mathbf{L}_c$ , respectively. We have

$$\begin{cases} l_a = (\mathbf{a} + \mathbf{b})'\mathbf{P}(\mathbf{a} + \mathbf{b}) + \mathbf{a}'\mathbf{E}\mathbf{a} + \mathbf{b}'\mathbf{E}\mathbf{b} \\ l_b = (\mathbf{a} + \mathbf{b})'\mathbf{E}(\mathbf{a} + \mathbf{b}) + \mathbf{a}'\mathbf{P}\mathbf{a} + \mathbf{b}'\mathbf{P}\mathbf{b} \\ l_c = \mathbf{b}'\mathbf{P}\mathbf{b} \\ l = (\mathbf{a}'\mathbf{G}\mathbf{b})^2/\mathbf{b}'\mathbf{P}\mathbf{b}. \end{cases}$$

Solving the equations for  $l$ ,

$$l = (l_a - l_b)^2/4l_c.$$

The general expression of  $\mathbf{L}$  is then

$$\begin{aligned} \mathbf{L} = \left[ \frac{(m-1) \mathbf{a}'\hat{\mathbf{P}}\mathbf{b}}{\chi_{3\alpha/2; m-1}^2} - \frac{(r-1)(m-1) \mathbf{a}'\hat{\mathbf{E}}\mathbf{b}}{\chi_{\alpha/2; (r-1)(m-1)}^2} \right]^2 \\ \cdot \left[ \frac{(m-1) \mathbf{b}'\hat{\mathbf{P}}\mathbf{b}}{\chi_{3\alpha/2; m-1}^2} \right]^{-1}. \end{aligned} \quad (4)$$

Similarly,

$$\begin{aligned} \mathbf{U} = \left[ \frac{(m-1) \mathbf{a}'\hat{\mathbf{P}}\mathbf{b}}{\chi_{1-\alpha/2; m-1}^2} - \frac{(r-1)(m-1) \mathbf{a}'\hat{\mathbf{E}}\mathbf{b}}{\chi_{1-\alpha/2; (r-1)(m-1)}^2} \right]^2 \\ \cdot \left[ \frac{(m-1) \mathbf{b}'\hat{\mathbf{P}}\mathbf{b}}{\chi_{1-3\alpha/2; m-1}^2} \right]^{-1}. \end{aligned}$$

The absolute size of  $\mathbf{R}_a$  falls between  $i\mathbf{L}^{1/2}$  and  $i\mathbf{U}^{1/2}$ . Let  $(\mathbf{L}_{\mathbf{R}_a}, \mathbf{U}_{\mathbf{R}_a})$  be the  $(1 - \alpha)$  confidence interval for  $\mathbf{R}_a$ .  $(\mathbf{L}_{\mathbf{R}_a}, \mathbf{U}_{\mathbf{R}_a})$  can be  $(i\mathbf{L}^{1/2}, i\mathbf{U}^{1/2})$ ,  $(-i\mathbf{L}^{1/2}, i\mathbf{U}^{1/2})$ ,

$(-i\mathbf{U}^{1/2}, i\mathbf{L}^{1/2})$  or  $(-i\mathbf{U}^{1/2}, -i\mathbf{L}^{1/2})$ . This can be determined by choosing the shortest one which covers the point estimate  $\mathbf{R}_a$ . It is interesting to note that  $\mathbf{R}_a \geq 0$  when  $\mathbf{a} = \mathbf{b}$  and  $i > 0$ . This is what Williams (1962a) referred to as the base index. In this case  $\mathbf{L}_R = i\mathbf{L}^{1/2}$  and  $\mathbf{U}_R = i\mathbf{U}^{1/2}$ .  $\mathbf{L}_R$  should be set to zero when  $(m-1) \mathbf{a}'\mathbf{P}\mathbf{b}/\chi_{\alpha/2; m-1}^2 < (r-1)(m-1) \mathbf{a}'\mathbf{E}\mathbf{b}/\chi_{\alpha/2; (r-1)(m-1)}^2$  whereas both  $\mathbf{L}_R$  and  $\mathbf{U}_R$  set to zero when  $(m-1) \mathbf{a}'\mathbf{P}\mathbf{b}/\chi_{1-\alpha/2; m-1}^2 < (r-1)(m-1) \mathbf{a}'\mathbf{E}\mathbf{b}/\chi_{1-\alpha/2; (r-1)(m-1)}^2$ .

### Correlated response

Consider two associated traits 1 and 2. Selection for trait 1 would bring up response of trait 2. The correlated response is measured by  $\mathbf{CR}_{21} = i \sigma_{g12}(\sigma_{p11})^{1/2}$ . Let

$$\begin{aligned} \mathbf{L} = \left[ \frac{(m-1) \hat{\sigma}_{p12}}{\chi_{\alpha/2; m-1}^2} - \frac{(r-1)(m-1) \hat{\sigma}_{e12}}{\chi_{\alpha/2; (r-1)(m-1)}^2} \right]^2 \\ \cdot \left[ \frac{\hat{\sigma}_{p11}}{\chi_{3\alpha/2; m-1}^2} \right]^{-1}, \\ \mathbf{U} = \left[ \frac{(m-1) \hat{\sigma}_{p12}}{\chi_{1-\alpha/2; m-1}^2} - \frac{(r-1)(m-1) \hat{\sigma}_{e12}}{\chi_{1-\alpha/2; (r-1)(m-1)}^2} \right]^2 \\ \cdot \left[ \frac{\hat{\sigma}_{p11}}{\chi_{1-3\alpha/2; m-1}^2} \right]^{-1}. \end{aligned} \quad (5)$$

Again  $(\mathbf{L}_{\mathbf{CR}}, \mathbf{U}_{\mathbf{CR}})$  can be  $(i\mathbf{L}^{1/2}, i\mathbf{U}^{1/2})$ ,  $(-i\mathbf{L}^{1/2}, i\mathbf{U}^{1/2})$ ,  $(-i\mathbf{U}^{1/2}, i\mathbf{L}^{1/2})$  or  $(-i\mathbf{U}^{1/2}, -i\mathbf{L}^{1/2})$ . The correct  $(1 - \alpha)$  interval should be the shortest one which covers the point estimate  $\mathbf{CR}_{21}$ .

### Maximum attainable response

The confidence interval for  $\mathbf{b}'\mathbf{P}\mathbf{b}$  can be expressed as

$$\mathbf{P}\left[ \frac{(m-1) \mathbf{b}'\hat{\mathbf{P}}\mathbf{b}}{\chi_{\alpha; m-1}^2} \leq \mathbf{b}'\mathbf{P}\mathbf{b} \leq \frac{(m-1) \mathbf{b}'\hat{\mathbf{P}}\mathbf{b}}{\chi_{1-\alpha; m-1}^2} \right] \geq 1 - 2\alpha$$

when the elements in  $\mathbf{b}$  are known constants. In the present case, however,  $\mathbf{b}$  is estimated by  $\hat{\mathbf{b}} = \hat{\mathbf{P}}^{-1} \hat{\mathbf{G}}\mathbf{a}$ . We are thus looking for two estimated vectors  $\mathbf{b}_1$  and  $\mathbf{b}_u$  such that  $\mathbf{b}_1'\hat{\mathbf{P}}\mathbf{b}_1 \leq \mathbf{b}'\hat{\mathbf{P}}\mathbf{b} \leq \mathbf{b}_u'\hat{\mathbf{P}}\mathbf{b}_u$  and

$$\mathbf{P}\left[ \frac{(m-1) \mathbf{b}_1'\hat{\mathbf{P}}\mathbf{b}_1}{\chi_{\alpha; m-1}^2} \leq \mathbf{b}'\mathbf{P}\mathbf{b} \leq \frac{(m-1) \mathbf{b}_u'\hat{\mathbf{P}}\mathbf{b}_u}{\chi_{1-\alpha; m-1}^2} \right] \geq 1 - 2\alpha. \quad (6)$$

Let  $\mathbf{I}$  be a  $(n \times n)$  unit matrix. We have

$$\mathbf{P}\mathbf{b} = \mathbf{G}\mathbf{a} = \mathbf{I}\mathbf{G}\mathbf{a} = \begin{bmatrix} \mathbf{I}'_1 \mathbf{G} \mathbf{a} \\ \vdots \\ \mathbf{I}'_i \mathbf{G} \mathbf{a} \\ \vdots \\ \mathbf{I}'_n \mathbf{G} \mathbf{a} \end{bmatrix}$$

where  $\mathbf{I}_i$  is a vector having zero for all its elements but the  $i$ -th one unity. Let  $(L_i, U_i)$  be the  $(1-2\alpha)$  confidence interval for  $\mathbf{I}_i' \mathbf{G} \mathbf{a}$  such that

$$P \left[ \sum_{i=1}^n b_i L_i \leq \mathbf{b}' \mathbf{G} \mathbf{a} \leq \sum_{i=1}^n b_i U_i \right] \geq 1 - 2\alpha. \quad (7)$$

$L_i$  and  $U_i$  can be derived by establishing the following Bonferroni inequality:

$$\begin{aligned} P[L_{1i} &\leq (\mathbf{I}_i + \mathbf{a})' \mathbf{P} (\mathbf{I}_i + \mathbf{a}) + \mathbf{I}_i' \mathbf{E} \mathbf{I}_i + \mathbf{a}' \mathbf{E} \mathbf{a} \leq U_{1i}, \\ L_{2i} &\leq (\mathbf{I}_i + \mathbf{a})' \mathbf{E} (\mathbf{I}_i + \mathbf{a}) + \mathbf{I}_i' \mathbf{P} \mathbf{I}_i + \mathbf{a}' \mathbf{P} \mathbf{a} \leq U_{2i}] \\ &\geq 1 - 2\alpha, \quad i = 1, 2, \dots, n. \end{aligned}$$

Based on the same procedure as described in (1) ~ (4), we obtain

$$\begin{aligned} L_i &= (L_{1i} - L_{2i})/2 \\ &= \left[ \frac{(m-1) \mathbf{I}_i' \hat{\mathbf{P}} \mathbf{a}}{\chi_{\alpha/2; m-1}^2} - \frac{(r-1)(m-1) \mathbf{I}_i' \hat{\mathbf{E}} \mathbf{a}}{\chi_{\alpha/2; (r-1)(m-1)}^2} \right] \end{aligned}$$

$$\begin{aligned} U_i &= (U_{1i} - U_{2i})/2 \\ &= \left[ \frac{(m-1) \mathbf{I}_i' \hat{\mathbf{P}} \mathbf{a}}{\chi_{1-\alpha/2; m-1}^2} - \frac{(r-1)(m-1) \mathbf{I}_i' \hat{\mathbf{E}} \mathbf{a}}{\chi_{1-\alpha/2; (r-1)(m-1)}^2} \right] \\ &\quad i = 1, 2, \dots, n. \end{aligned}$$

Let  $\mathbf{L}' = [L_1 \dots L_i \dots L_n]$  and  $\mathbf{U}' = [U_1 \dots U_i \dots U_n]$ . Then (7) can be rewritten as

$$P[\mathbf{b}' \mathbf{L} \leq \mathbf{b}' \mathbf{P} \mathbf{b} \leq \mathbf{b}' \mathbf{U}] \geq 1 - 2\alpha. \quad (8)$$

Obviously, by examining (8) we can also request that the two vectors  $\mathbf{b}_1$  and  $\mathbf{b}_u$  fulfil the following relation:

$$P[\mathbf{b}_1' \mathbf{L} \leq \mathbf{b}' \mathbf{P} \mathbf{b} \leq \mathbf{b}_u' \mathbf{U}] \geq 1 - 2\alpha. \quad (9)$$

Comparing (9) with (6), we have

$$\mathbf{b}_1' \mathbf{L} = \frac{(m-1) \mathbf{b}_1' \hat{\mathbf{P}} \mathbf{b}_1}{\chi_{\alpha/2; m-1}^2}$$

$$\mathbf{b}_u' \mathbf{U} = \frac{(m-1) \mathbf{b}_u' \hat{\mathbf{P}} \mathbf{b}_u}{\chi_{1-\alpha/2; m-1}^2}$$

$\mathbf{b}_1$  and  $\mathbf{b}_u$  are then obtained as

$$\begin{aligned} \mathbf{b}_1 &= \chi_{\alpha/2; m-1}^2 \hat{\mathbf{P}}^{-1} \mathbf{L} / (m-1) \\ \mathbf{b}_u &= \chi_{1-\alpha/2; m-1}^2 \hat{\mathbf{P}}^{-1} \mathbf{U} / (m-1) \end{aligned} \quad (10)$$

respectively. Bringing (10) into (9), the confidence interval for  $\mathbf{b}' \mathbf{P} \mathbf{b}$  can be established as:

$$\begin{aligned} P \left[ \frac{\chi_{\alpha/2; m-1}^2 \mathbf{L}' \hat{\mathbf{P}}^{-1} \mathbf{L}}{m-1} \leq \mathbf{b}' \mathbf{P} \mathbf{b} \leq \frac{\chi_{1-\alpha/2; m-1}^2 \mathbf{U}' \hat{\mathbf{P}}^{-1} \mathbf{U}}{m-1} \right] \\ \geq 1 - 2\alpha. \end{aligned} \quad (11)$$

The confidence interval for the maximum attainable response can be easily constructed using (11). Let  $(L_R, U_R)$  be the interval

$$P(L_R \leq R \leq U_R) \geq 1 - 2\alpha$$

where

$$\begin{aligned} L_R &= i [\chi_{\alpha/2; m-1}^2 \mathbf{L}' \hat{\mathbf{P}}^{-1} \mathbf{L} / (m-1)]^{1/2} \\ U_R &= i [\chi_{1-\alpha/2; m-1}^2 \mathbf{U}' \hat{\mathbf{P}}^{-1} \mathbf{U} / (m-1)]^{1/2}. \end{aligned} \quad (12)$$

## Discussion

An inspection of the intervals in (4), (5) and (11) would reveal the influence of the sizes of  $r$  and  $m$  on the precision of response to multi-trait selection. Tai (1983) pointed out that the use of a small number of genotypes in an elaborate experiment of many replicates may lead to imprecise genetic information on quantitatively inherited traits. The same conclusion can be made here with regard to response to multi-trait selection. It is important to have a large sample of genotypes tested in an experiment to ensure the precision of the estimate of response to multi-trait selection.

Of the three types of multi-trait selection studied here, the most important one is, of course, the conventional least square index selection. Many theoretical works (Tallis 1960; Williams 1962a; Harris 1964; Sales and Hill 1976a, b; Hayes and Hill 1980) were focused on locating the sampling properties of the index weights and identifying factors which may affect the effectiveness of index selection. The confidence intervals obtained in (12) can obviously be used for the same purpose. The lower confidence limit  $L_R$ , for example, can be expressed as follows:

$$L_R = i \{k_1 \mathbf{a}' [k_2 \hat{\mathbf{P}} - k_3 \hat{\mathbf{E}}] \hat{\mathbf{P}}^{-1} [k_2 \hat{\mathbf{P}} - k_3 \hat{\mathbf{E}}] \mathbf{a}\}^{1/2}$$

where

$$\begin{aligned} k_1 &= \chi_{\alpha/2; m-1}^2 (m-1), \quad k_2 = (m-1) / \chi_{\alpha/2; m-1}^2 \quad \text{and} \\ k_3 &= (r-1)(m-1) / \chi_{\alpha/2; (r-1)(m-1)}^2. \end{aligned}$$

This expression is comparable to that of the point estimate  $R$ , i.e.,

$$R = i \{ \hat{\mathbf{b}}' \hat{\mathbf{P}} \hat{\mathbf{b}} \}^{1/2} = i \{ \mathbf{a}' (\hat{\mathbf{P}} - \hat{\mathbf{E}}) \hat{\mathbf{P}}^{-1} (\hat{\mathbf{P}} - \hat{\mathbf{E}}) \mathbf{a} \}^{1/2}.$$

For  $r=2$ ,  $k_2 = k_3 = (m-1) / \chi_{\alpha/2; m-1}^2$  and

$$\begin{aligned} L_R &= i \left\{ \frac{(m-1) \chi_{\alpha/2; m-1}^2}{[\chi_{\alpha/2; m-1}^2]^2} \mathbf{a}' (\hat{\mathbf{P}} - \hat{\mathbf{E}}) \hat{\mathbf{P}}^{-1} (\hat{\mathbf{P}} - \hat{\mathbf{E}}) \mathbf{a} \right\}^{1/2} \\ &= \frac{[(m-1) \chi_{\alpha/2; m-1}^2]^{1/2}}{\chi_{\alpha/2; m-1}^2} \cdot R. \end{aligned}$$

The above relation reveals  $L_R \leq R$  for  $m \geq 2$ . The difference between them, however, would decline when increasingly larger  $m$  is used. The gap between  $L_R$  and  $R$  is getting larger when a greater number of replicates is used in an experiment. The trend can be checked by using a larger sample of genotypes in the experiment.

The above expression of  $L_R$  also indicates that the relative sizes of economic weights in  $\mathbf{a}$  and the esti-

mates of VAR-COV components in **P** and **E** would influence the difference between  $L_R$  and  $R$ . It is thus possible to use the interval constructed in (12) to study the impact of various factors, i.e., numbers of genotypes and replicates, sizes of estimates of genotypic and phenotypic VAR-COV components, and economic weights, on the precision of index selection.

It is interesting to observe that, for a single trait,

$$L_R = i \left\{ \frac{(m-1) \hat{\sigma}_p^2}{\chi^2_{\alpha/2; m-1}} - \frac{(r-1)(m-1) \hat{\sigma}_e^2}{\chi^2_{\alpha/2; (r-1)(m-1)}} \right\} \cdot \left\{ \frac{(m-1) \hat{\sigma}_p^2}{\chi^2_{\alpha; m-1}} \right\}^{-1/2}$$

according to (12). This is larger than and thus an improved lower limit over the one obtained by Tai (1979, 1983) for single-trait selection, i.e.

$$L_R = \left\{ \frac{(m-1) \hat{\sigma}_p^2}{\chi^2_{\alpha; m-1}} - \frac{(r-1)(m-1) \hat{\sigma}_e^2}{\chi^2_{\alpha; (r-1)(m-1)}} \right\} \cdot \left\{ \frac{(m-1) \hat{\sigma}_p^2}{\chi^2_{\alpha; m-1}} \right\}^{-1/2}$$

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