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# Stability Variance and its Bayesian Estimation for Genotype × Environment Interaction in $m \times m$ Gracro-latin Square Layout

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## ABSTRACT

**Background:** In agricultural, the field experimenters have been bona fide way of verifying the test result when researchers have developed new cultivating method in order to improve the overall crop production. To meet this requirement experimenters have continuously be measured in thinking the new and/or modified techniques and methodologies.

**Methods:** To estimate stability variance with two treatments through Graceo-latin square layout apart from prevailing Latin square layout with one treatment. The maximal data information prior and asymptotically locally invariant prior are also studied for the obtained stability variance in such layout.

**Result:** The Graceo-latin square design layout with two different treatments has been proposed to study genotype × environment (G × E) interaction. Statistical model for the design and ANOVA is also developed and simultaneous methods are proposed to diagrammatize the respective stability variance.

**Key words:** ANOVA, Genotype × environment (G × E) interaction, Graceo-latin square design, Latin square design, Stability variance.

## INTRODUCTION

In the plant breeding experiments, researchers always keen to develop new as well as modified varieties or genotypes which are favorable to the diverse environmental under consideration. The study of genotype × environment (G × E) Interaction plays a vital role along with prior information on the exiting genotype to estimate its stability in particular environment. Cotes *et al.* (2006) used the Bayesian methodology for computing Shukla's phenotypic stability variance Shukla (1972) and incorporate prior information on the parameter for better estimation. Edwards and Jannink (2006) tested a Bayesian approach to estimate heterogeneous error and (G × E) interaction variance. Their results show that error variances were highly heterogeneous among environments and the (G×E) interaction variances were heterogeneous among environment and genotypes. Elizalde *et al.* (2011) studied usefulness of general Bayesian approach for breeding trials and detection of genotypes groups and environments that showed significance in (G × E) interaction. They also advocated that they may be extended to other linear-bilinear models by fixing certain conditions. Birla and Ramgiry (2015) used AMMI analysis to comprehend genotype by environment (G × E) interaction in rain fed grown soybean [*Glycine max* (L.) Merrill]. Bhushan and Samnotra (2017) studies the stability for yield and quality trails in brinjal (*Solanum melongena* L). In that particular experiment, the performance of genotypes in terms of yield as well as quality across seasons and years under wide range of environments through phenotypic stability studies using Eberhart and Russell regression model.

In general, in many plant breeding programmes, new genotypes are developed in controlled conditions and as well as in open environmental conditions where it is very important to study the behavior and stability of genotypes under consideration. The new genotype under various situation and conditions received different treatments, Chetan *et al.* (2018) studies the stability variance obtained through (G × E) interaction in $m \times m$ Latin square layout with one treatment effect. Mamata *et al.* (2019) proposed new index for evaluation of G × E interaction in pearl millet using AMMI and GGE bilot analysis. Chetan *et al.* (2019) studied the general Bayesian estimation for (G × E) interaction in $m \times m$ Latin square layout with one treatment effect. Still there are many situations where the experimenters need to study more than one treatment. Therefore, in the present study, an attempt is made to study the situation where two treatments are act simultaneously with $m \times m$ Graceo Latin Square layout with two treatment effects. For estimating the new explanatory power about the unknown parameters, the maximal data information prior and asymptotically locally invariant prior are also studied for the obtained stability variance in such layout.

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## MATERIALS AND METHODS

The present study was carried out at Department of Statistics, M.D. University, Rohtak and Department of Statistics, Sri Venkateswara College, University of Delhi during 2020-21. Let $y_{jkr}$ (i, j, k, r = 1, 2........m) denote the observation on the experimental unit of the ith genotype in the jth environment receiving two different treatments *i.e.* kth and rth. In this situation, general least square layout is most suitable one with $m^2$ experimental units to be used in the experiment instead of $m^5$ possible experimental units needed in a complete layout. Therefore, the following model may be considered for such experiment.

$$y_{ijkr} = \mu + d_i + e_j + t_k + y_r + g_{ijkr} + \varepsilon_{ijkr} \ (i, j, k, r = 1, 2,.....m)$$

Where,

$\mu$ is the general mean effect.

$d_i$ is the additive effect of ith genotype.

$e_j$ is the effect of jth environment.

$t_k$ is the effect due to kth treatment on the ith genotype in the jth environment.

$y_r$ is the effect due to rth treatment on the ith genotype in jth environment.

$g_{ijkr}$ is the genotype environment interaction receiving kth and rth treatments.

$e_{ijkr}$ is the random error term which is assumed to be NID $(0, \sigma^2)$.

If $\delta$ represent the set of $m^2$ values, then $(i, j, k, r) \in \delta$; $\delta_i$ is the possible pair (j, k, r) associated with a fixed value of i and similarly $\delta_j$, $\delta_k$ and $\delta_r$, then parameters involved in the above model may be obtained by minimizing the sum of square error.

$$E = \sum\nolimits^{m}_{i,j,k,r=1} \varepsilon_{ijkr}{}^2 = \sum\nolimits^{m}_{i,j,k,r=1} (y_{ijkr} - \mu - d_i - e_j - t_k - y_r - g_{ijkr})^2$$

and

$$\frac{\delta E}{\delta \mu} = \frac{\delta E}{\delta d_i} = \frac{\delta E}{\delta e_j} = \frac{\delta E}{\delta t_k} = \frac{\delta E}{\delta y_r} = \frac{\delta E}{\delta g_{ijkr}} = 0$$

If it is assumed that

$$\sum_{i=1}^{p} d_i = \sum_{j=1}^{p} e_j = \sum_{k=1}^{p} t_k = \sum_{i=1}^{p} y_r = \sum_{i,j,k,r=1}^{p} g_{ijkr} = 0$$

then

$$\sum_{i=1}^{m} y_{ijkr} - m^2 \hat{\mu} = \sum\nolimits^{m}_{i,j,k,r=1} y_{ijkr} - m\hat{\mu} - m\hat{d}_i = \sum_{i,j,k,r=1}^{m} y_{ijkr} - m\hat{\mu} - P\hat{e}_j$$

$$= \sum_{i=1}^{m} y_{ijkr} - m\hat{\mu} - P\hat{t}_k = \sum_{i=1}^{m} y_{ijkr} - m\hat{\mu} - P\hat{y}_r$$

$$= \sum_{i=1}^{m} \gamma_{ijkr} - \hat{\mu} - \hat{d}_i - \hat{e}_j - \hat{t}_k - \hat{\gamma}_r - \hat{g}_{ijkr} = 0$$

on solving above equations simultaneously

$$\hat{\mu} = \bar{y}_{...}; \ \hat{d}_i = \bar{y}_{i...} = \bar{y}_{...}; \ \hat{e}_j = \bar{y}_{.j..} - \bar{y}_{...}; \ \hat{t}_k = \bar{y}_{..k.} - \bar{y}_{...} \ \hat{y}_r = \bar{y}_{...r} - \bar{y}_{...} \text{ and}$$

$$\hat{g}_{ijkr} = \frac{1}{m^2} [(m^2 + 3)\bar{y}_{...} - (\bar{y}_{i...} + \bar{y}_{.j..} + \bar{y}_{..k.} + \bar{y}_{...r})]$$

Since the algebraic sum of deviation of a set of observation about their mean is zero and other product term also zero. Therefore, the analysis of variance may be given as:

$$\sum_{i,j,k,r=1}^{m} (y_{ijkr} - \bar{y}_{...})^2 = \sum_{\delta_i} (\bar{y}_{i...} - \bar{y}_{...})^2 + \sum_{\delta_j} (\bar{y}_{.j..} - \bar{y}_{...})^2 + \sum_{\delta_k} (\bar{y}_{.k..} - \bar{y}_{...})^2 + \sum_{\delta_r} (\bar{y}_{...r} - \bar{y}_{...})^2 + \frac{1}{4} \sum_{i,j,k,r=\delta} (\bar{y}_{ijkr} - \bar{y}_{i...} - \bar{y}_{.j..} - \bar{y}_{.k..} - \bar{y}_{...r})^2$$

$$+ \sum_{i,j,k,r \in \delta} \left\{ \frac{1}{2} (y_{ijkr} - \bar{y}_{i...} - \bar{y}_{.j..} - \bar{y}_{.k..} - \bar{y}_{...r}) + 2\bar{y}_{...} \right\}^2$$

Or may be portioned as:

$$T.SS = SS.G + SS.E_n + SS.T_1 + SS.T_2 + SS.I + SS.E_r$$

Where,

The total sum of square (TSS) into its component parts, the sum of square for genotype (SSG), sum of square for environment ($SSE_n$), sum of square for treatment ($SST_1$), the sum of square for another treatment ($SST_2$), the sum of square for interaction (SSI) and the sum of square for error ($SSE_r$). The ANOVA for such layout may be framed as:

| Source of variation | Degree of freedom | Sum of square (SS) |
|---|---|---|
| Genotype | $(m-1)$ | $m\sum_{\delta_i}(\bar{y}_{i...}-\bar{y}_{...})^2$ |
| Environment | $(m-1)$ | $m\sum_{\delta_j}(\bar{y}_{.j..}-\bar{y}_{...})^2$ |
| Treatment (First) | $(m-1)$ | $m\sum_{\delta_k}(\bar{y}_{..k.}-\bar{y}_{...})^2$ |
| Treatment (Second) | $(m-1)$ | $m\sum_{\delta_r}(\bar{y}_{...r}-\bar{y}_{...})^2$ |
| Interaction | $\frac{1}{2}(m-1)(m-3)$ | $\frac{1}{4}\sum_{i,j,k,r=\delta}(y_{ijkr}-\bar{y}_{i...}-\bar{y}_{.j..}-\bar{y}_{..k.}-\bar{y}_{...r})^2$ |
| Error | $\frac{1}{2}(m-1)(m-3)$ | $\frac{1}{4}\sum_{i,j,k,r=\delta}\{(y_{ijkr}-\bar{y}_{i...}-\bar{y}_{.j..}-\bar{y}_{..k.}-\bar{y}_{...r})+2\bar{y}_{...}\}^2$ |
| Total | $(m^2-1)$ | |

A stable genotype possesses an unchanged performance regardless of any variation of environmental conditions. The stability is termed as stability variance and can be estimated as:

$$\hat{g}_{ijkr}=\gamma_{ijkr}-\hat{\mu}-\hat{d}_i-\hat{e}_j-\hat{t}_k-\hat{y}_r$$

By using the estimated values

$$V(\hat{g}_{ijkr})=E[\hat{g}_{ijkr}-E(\hat{g}_{ijkr})]^2=E[\hat{g}^2_{ijkr}+E(\hat{g}^2_{ijkr})-2\hat{g}^2_{ijkr}E(\hat{g}^2_{ijkr})]$$

$$\sigma_i^2=\frac{1}{m^2-1}\left[\sum_{j,k,r\in\delta}(m\bar{y}_{ijk.}-\bar{y}_{....}-\bar{y}_{i...}-\bar{y}_{.j..}\pm\bar{y}_{..k.}\pm\bar{y}_{...r}+3\bar{y}_{...})^2+\frac{1}{m^4}\sum_{j,k,r\in\delta}[(m^2+3)\bar{y}_{...}-(\bar{y}_{i...}+\bar{y}_{.j..}+\bar{y}_{.k..}+\bar{y}_{...r})]^2\right]$$

or

$$\sigma_i^2=\frac{1}{(m^2-1)}Z_i$$

is the stability variation for the ith genotype under experimental conditions. If it is assume that stability variance is equal to the within environment at variance $\sigma^2$ *i.e.* $\sigma_i^2=0$, then it can be a stable genotype. The variance of the estimated parameters for the proposed model may be given by

$$V(\hat{\mu})=E[\hat{\mu}-E(\hat{\mu})]^2$$

$$=E[\bar{y}_{...}-E(\bar{y}_{...})]^2$$

$$E[\bar{y}_{...}-E(\bar{y}_{...})]^2 \text{ as } E(\bar{y}_{...})=\mu \text{ and } \bar{y}_{...}-\mu=\in_{...} \text{ then}$$

$$E[\bar{y}_{...}-\mu]^2=E(\in_{...})^2=V(\in_{...})=\frac{\sigma_e^2}{m^2}$$

Similarly,

$$V(\hat{d}_i)=V(\hat{e}_j)=V(\hat{y}_r)=\frac{(m-1)}{m^2}\sigma_e^2$$

$$V(\hat{g}_{ijkr})=[\hat{g}_{ijkr}-E(\hat{g}_{ijkr})]^2$$

$$\hat{g}_{ijkr}=\frac{1}{m^2}[(m^2+3)(\mu+\in_{...})-(\mu+d_i+\bar{g}_{i...}+\bar{\in}_{i...}+\mu+e_j+\bar{g}_{.j..}+\bar{\in}_{.j..}+\mu+t_k+\bar{g}_{..k.}+\bar{\in}_{..k.}+\mu+y_r+\bar{g}_{...r}+\bar{\in}_{...r})]$$

$$\hat{g}_{ijkr}=\frac{1}{m^2}[(m^2-1)(\mu)+(m^2+3)\in_{...}-(d_i+\bar{g}_{i...}+\bar{\in}_{i...}+e_j+\bar{g}_{.j..}+\bar{\in}_{.j..}+t_k+\bar{g}_{..k.}+\bar{\in}_{..k.}+y_r+\bar{g}_{...r}+\bar{\in}_{...r})]$$

$$V(\hat{g}_{ijkr})=\Bigg[\frac{1}{m^2}[(m^2-1)(\mu)+(m^2+3)\in_{...}-(d_i+\bar{g}_{i...}+\bar{\in}_{i...}+e_j+\bar{g}_{.j..}+\bar{\in}_{.j..}+t_k+\bar{g}_{..k.}+\bar{\in}_{..k.}+y_r+\bar{g}_{...r}+\bar{\in}_{...r})]$$

$$-E\left\{\frac{1}{m^2}[(m^2-1)(\mu)+(m^2+3)\bar{\in}_{...}-(d_i+\bar{g}_{i...}+\bar{\in}_{i...}+e_j+\bar{g}_{.j..}+\bar{\in}_{.j..}+t_k+\bar{g}_{..k.}+\bar{\in}_{..k.}+y_r+\bar{g}_{...r}+\bar{\in}_{...r})]\right\}\Bigg]^2$$

Maximal sata information prior (MDIP) for the conditions under consideration may be given by

$$y_{ijkr}\sim N(\mu,\sigma_i)$$

It is well known that

$$\log[f(y_{ijkr}|\mu,\ \sigma_i)] = -\frac{1}{2}\log 2\pi - \log\sigma_i - \frac{1}{2\sigma_i^2}(y_{ijkr}-\mu)^2$$

then

$$I(\mu,\ \sigma_i) = \int_{-\infty}^{\infty} f(y_{ijkr}|\mu,\ \sigma_i)\ \log[f(y_{ijkr}|\mu,\ \sigma_i)]\ dy$$

$$= \int_{-\infty}^{\infty}\left(\frac{1}{2}\log 2\pi - \log\sigma_i - \frac{1}{2\sigma_i^2}(y_{ijkr}-\mu)^2\ f(y_{ijkr}|\mu,\ \sigma_i)\right)dy$$

$$= -\frac{1}{2}\log 2\pi - \log\sigma_i - \frac{1}{2}$$

$$= -\frac{1}{2}(1+\log 2\pi) - \log\sigma_i$$

is the data information averaged over the value $(\mu,\ \sigma_i)$ with $g(\mu,\ \sigma_i)$ prior this average may aso given by

$$I(\mu + Z_i) = -\frac{1}{2}(1+\log 2\pi) - \log\sqrt{\frac{Z_i}{m^2-1}}$$

The average information in the data density minus the information in the prior density therefore,

$$D = \int_{-\infty}^{\infty} I(\theta)\ g(\theta)\ d(\theta) - \int_{-\infty}^{\infty} g(\theta)\log g(\theta)\ d\theta$$

$$= \int_{-\infty}^{\infty} I(\mu,\ Z_i)\ g(\mu,\ Z_i)\ d\mu\ dZ_i - \int_{-\infty}^{\infty} g(\mu,\ Z_i)\log g(\mu,\ Z_i)\ d\mu\ dZ_i$$

$$= -\frac{1}{2}(1+\log 2\pi) - \int_0^{\infty}\int_{-\infty}^{\infty}\log\sqrt{\frac{Z_i}{m^2-1}}\ g(\mu,\ Z_i)\ d\mu\ dZ_i - \int_0^{\infty}\int_{-\infty}^{\infty} g(\mu,\ Z_i)\log g(\mu,\ Z_i)\ d\mu\ dZ_i$$

Lagrangian expression is

$$L = -\left[\left\{\int_0^{\infty}\int_{-\infty}^{\infty}\log\sqrt{\frac{Z_i}{m^2-1}}\ g(\mu,\ Z_i)\ g(\mu,\ Z_i)\log g(\mu,\ Z_i) - \lambda g(\mu,\ Z_i)\right\}d\mu dZ_i\right] - \lambda$$

According to the Euler-Lagrange equation

$$F = g(\mu,\ Z_i)\left\{\log\sqrt{\frac{Z_i}{m^2-1}} + \log g(\mu,\ Z_i) - \lambda\right\}$$

$$\frac{\delta F}{\delta g(\mu,\ Z_i)} = \log\sqrt{\frac{Z_i}{m^2-1}} + \log g(\mu,\ Z_i) + 1 - \lambda = 0$$

Gives

$$\log\left\{\sqrt{\frac{Z_i}{m^2-1}}\ g(\mu,\ Z_i)\right\} = \lambda - 1$$

$$\sqrt{\frac{Z_i}{m^2-1}}\ g(\mu,\ Z_i) = \exp^{\lambda-1}$$

$$g(\mu,\ Z_i) = \exp^{\lambda-1}\sqrt{\frac{m^2-1}{Z_i}}$$

Asymptotically locally invariant (ALI) prior for the conditions under consideration may be given by

$$L(\mu,\ Z_i) = -\frac{1}{2}\log 2\pi - \log\sqrt{\frac{Z_i}{m^2-1}} - \frac{m^2-1}{2Z_i}(y_{ijkr}-\mu)^2$$

$$\frac{\delta L(\mu,\ Z_i)}{\delta\mu} = \frac{m^2-1}{Z_i}(y_{ijkr}-\mu)$$

$$\frac{\delta L(\mu, Z_i)}{\delta Z_i} = -\frac{m^2-1}{2Z_i} + \frac{m^2-1}{2Z_i^2}(y_{ijkr}-\mu)^2$$

$$\frac{\delta^2 L(\mu, Z_i)}{\delta\mu\delta Z_i} = \frac{m^2-1}{2Z_i^2}(y_{ijkr}-\mu)$$

Since the conditions of ALI prior are satisfied. Therefore, ALI prior for $(\mu, Z_i)$ may be estimated by

$$\frac{\delta \log g(\mu, Z_i)}{\delta\mu} = -E\left[\left\{\frac{\delta^2}{\delta\mu^2}L(\mu, Z_i)\right\}\left\{\frac{\delta L(\mu, Z_i)}{\delta\mu}b_{11}\right\}\right] - E\left[\left\{\frac{\delta^2 L(\mu, Z_i)}{\delta\mu\delta Z_i}\right\}\left\{\frac{\delta L(\mu, Z_i)}{\delta\mu}\right\}b_{22}\right]$$

$$= E\left[\left\{-\frac{m^2-1}{Z_i}\right\}\left\{\frac{m^2-1}{Z_i}(y_{ijkr}-\mu)\right\}\frac{Z_i}{m^2-1}\right] + \left[\left\{-\frac{m^2-1}{Z_i}(y_{ijkr}-\mu)\right\}\left\{-\frac{m^2-1}{2Z_i} + \frac{m^2-1}{2Z_i^2}(y_{ijkr}-\mu)^2\frac{Z_i^2}{m^2-1}\right]$$

$$= E\left[\left\{\frac{m^2-1}{Z_i}(y_{ijkr}-\mu)\right\} + \left\{-\frac{m^2-1}{Z_i^2}(y_{ijkr}-\mu)\right\} + \left\{-\frac{Z_i}{2} + \frac{Z_i}{2}(y_{ijkr}-\mu)^2\right\}\right]$$

Where,

$$B = \begin{bmatrix} -\dfrac{m^2-1}{Z_i} & 0 \\ 0 & \dfrac{m^2-1}{Z_i} \end{bmatrix}$$

$$B^{-1} = \begin{bmatrix} -\dfrac{Z_i}{m^2-1} & 0 \\ 0 & \dfrac{Z_i^2}{m^2-1} \end{bmatrix}$$

Since the $g(\mu, Z_i)$ is a function of $Z_i$ and independent of μ, therefore

$$\frac{\delta \log g(\mu, Z_i)}{\delta Z_i} = -E\left[\left\{\frac{\delta^2}{\delta Z_i^2}L(\mu, Z_i)\right\}\left\{\frac{\delta L(\mu, Z_i)}{\delta Z_i}b_{11}\right\}\right] - E\left[\left\{\frac{\delta^2 L(\mu, Z_i)}{\delta\mu\delta Z_i}\right\}\left\{\frac{\delta L(\mu, Z_i)}{\delta\mu}\right\}b_{22}\right]$$

$$= E\left[\left\{-\frac{m^2-1}{2Z_i^2} + \frac{m^2-1}{Z_i^3}(y_{ijkr}-\mu)^2\right\}\left\{-\frac{m^2-1}{2Z_i} + \frac{m^2-1}{2Z_i^2}(y_{ijkr}-\mu)^2\right\}\frac{Z_i}{m^2-1}\right]$$

$$= -E\left[\left\{-\frac{m^2-1}{Z_i^2}(y_{ijkr}-\mu)\right\}\left\{\frac{m^2-1}{Z_i}(y_{ijkr}-\mu)\right\}\frac{Z_i^2}{m^2-1}\right]$$

$$= \left[\left\{\frac{m^2-1}{2Z_i^2} + \frac{m^2-1}{Z_i^3}\mathrm{Var}(y_{ijkr})\right\}\left\{-\frac{1}{2} + \frac{1}{2}\mathrm{Var}(y_{ijkr})\right\}\right] - \left[\left\{-\frac{m^2-1}{Z_i^2}E(y_{ijkr}-\mu)\right\}\{Z_i\ E(y_{ijkr}-\mu)\}\right]$$

$$= \left[\left\{\frac{m^2-1}{2Z_i^2} + \frac{m^2-1}{Z_i^3}\sigma_i^2\right\}\left\{-\frac{1}{2} + \frac{\sigma_i^2}{2}\right\}\right]$$

or

$$= \left[\left\{\frac{m^2-1}{2Z_i^2} + \frac{1}{2Z_i^2}\right\}\left\{-\frac{1}{2} + \frac{Z_i}{2(m^2-1)}\right\}\right]$$

Hence,

$$g(\mu, Z_i) = \left[\left\{\frac{m^2-1}{2Z_i^2} + \frac{1}{2Z_i^2}\right\}\left\{-\frac{1}{2} + \frac{Z_i}{2(m^2-1)}\right\}\right]$$

## RESULTS AND DISCUSSION

Genotype × Environment (G × E) interaction play a key role in identifying adaptability and stability for any genotype for obtaining high yield over a wide range of diverse environmental conditions around the world. The variability between the environments is smaller genotype is considered to be more stable. In plant breeding programmes, (G × E) interaction and its analyses along with its interpretation are still an intensive and extensive focused area. Numerous stability measures with different approaches are present in the literature. Apart from existing literature, method of analysis Graceo-Latin square design when experiments are conducted in environment with two different treatments has been proposed. Also, statistical model for the design is presented the estimates of parameters in the model is derived, ANOVA is developed and stability variance is also developed and simultaneous methods are proposed to diagrammatize the respective stability variance ($\sigma_i^2$).

**Conflict of interest:** None.

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