# INCOMPLETE DATA IN SPLIT-PLOT, SPLIT-BLOCK, AND <br> OTHER SIMILAR DESIGNS* 

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#### Abstract

The general form of analyses for split-plot, split-block, and similar designs with missing observations is presented through the medium of a specific example. In the example one of the treatments was deleted from a split-block design wherein one set of treatments was arranged in a $4 \times 4$ latin square and the other set of treatments in a randomized complete blocks design with four replicates; the columns of the $4 \times 4$ latin square design represented the complete blocks for the randomized complete blocks design. An alternate analysis utilizing dummy variates and a covariance analysis is discussed.


[^0]In the course of consulting the following design came under consideration:**

Row 1

Row 2

Row 3

Row 4


Treatments 1, 2, 3, and 4 represent time of harvest and were laid out in a $4 \times 4$ latin square design. Treatments $a, b, c$, and d represent four varieties which were laid out in a randomized complete block design with the four columns of the latin square representing the four complete blocks or replicates for varieties.

[^1]We note that the lay-out is a split block design with the four harvests in a latin square design and the four varieties in a randomized complete block design. Therefore, the yield equation is of the form:

$$
Y_{g h i j}=n_{g h i j}\left(\mu+\rho_{g}+\lambda_{h}+\alpha_{i}+\epsilon_{g h i}+\beta_{j}+\alpha \beta_{i j}+\delta_{h j}+\pi_{g h i j}\right),
$$

where $\mu=$ an effect common to all observations, $\rho_{g}=$ row effect, $\lambda_{h}=$ column and complete block effect, $\alpha_{i}=$ harvest effect, $\beta_{j}=$ variety effect, $\alpha \beta_{i j}=$ harvest by variety interaction effect, $\epsilon_{\text {ghi }}=$ randomly distributed error effects for harvests with mean zero and common variance $\sigma_{\epsilon}^{2}, \delta_{h j}=$ randomly distributed error effects for varieties with mean zero and common variance $\sigma_{\delta}^{2}$, $\pi_{\text {ghij }}=$ randomly distributed error effects for harvest by variety interaction with mean zero and common variance $\sigma_{\pi}^{2}, g=1,2,3,4=k, h=1,2,3,4=b$, $i=1,2,3,4=v, j=1,2,3,4=t$, and $n_{\text {ghij }}=$ one if the $i j^{t h}$ harvest and variety combination occurs in the $g^{t h}$ row of the $h^{t h}$ column and $=$ zero otherwise.

Let $Y_{\ldots} \ldots=\sum_{g h 1 j} \sum_{\text {ghij }} Y_{\text {ghij }}=$ grand total, $Y_{g} \ldots=g^{t h}$ row total, $Y_{\cdot h} . .=$ $h^{t h}$ column total, $Y_{\ldots i}=i^{t h}$ harvest total, $Y \ldots j=j^{t h}$ variety total, $Y_{\text {ghi }}=$ $\sum_{j} n_{\text {ghij }} Y_{\text {ghij }}, Y_{._{i j}}=$ total of $i j^{t h}$ harvest and variety combination, and $Y_{\cdot h \cdot j}=$ total for variety $j$ in column (complete block) h. Then, the key-out of degrees of freedom and the sums of squares in the analysis of variance with bkt $=64$ observations are:

| Source of variation | d.f. |  |
| :---: | :---: | :---: |
| Correction for mean | 1 | $Y_{\text {2 }}{ }^{2} . . . / 64$ |
| Row | 3 | $\sum_{B=1}^{4} \frac{Y_{B}^{2} \ldots}{16}-\frac{Y_{\dot{2}}^{2} \ldots}{64}$ |
| Column | 3 | $\sum_{n=1}^{4} \frac{Y^{2} \cdot n}{1 \sigma}-\frac{Y^{2} \cdots . .}{64}$ |

Harvest

Error for harvest

Variety

Error for variety

Variety $\times$ harvest
$3 \quad \sum_{i=1}^{4} \frac{Y^{2} \cdot \dot{1} \cdot 0}{16}-\frac{Y^{2} \cdot \ldots}{64}$
$6 \quad \sum_{g} \sum_{h} \frac{Y_{g h 1}^{2}}{4}-\frac{\sum Y_{g}^{2} \ldots}{16}-\frac{\sum Y_{h}^{2} \ldots}{16}-\frac{\sum Y^{2} ._{1} \cdot}{16}+\frac{2 Y^{2} \cdot \ldots}{64}$
$3 \quad \sum_{j=1}^{4} \frac{Y^{2} \cdots 1}{16}-\frac{Y^{2} \cdots}{64}$
$9 \quad \sum_{n} \sum_{j} \frac{Y_{0}^{2} \cdot \cdot j}{4}-\frac{\sum_{n}^{2} Y_{n} \cdots}{16}-\frac{\sum Y^{2} \cdots j}{16}+\frac{Y^{2} \cdots . .}{64}$
$9 \quad \sum_{1} \sum_{1} \frac{Y^{2} \cdot 11}{4}-\frac{\sum Y^{2} \cdots_{1} \cdot}{16}-\frac{\sum Y^{2} \cdots 1}{16}+\frac{Y^{2} \cdots \cdots}{64}$

Error for var. X hear.
27
by subtraction
$64 \quad \sum_{g} \sum_{h} \sum_{i} \sum_{j} n_{g h_{1 j}} Y_{g h_{1 j}}^{2}$
Total

$$
\begin{aligned}
& +\sum_{j} n \ldots j_{j}^{\beta}+\sum_{i} \sum_{j} n{ }_{\cdots i j} \beta_{i j}+\sum_{h} \sum_{j} n_{\cdot h \cdot j} \delta_{h j}=Y \ldots . \\
& n_{g} \ldots\left(\mu+\rho_{g}\right)+\sum_{h} n_{g h} \cdot . \lambda_{h}+\sum_{i} n_{g} \cdot i \cdot \alpha_{i}+\sum_{h i} \sum_{n_{g h i}} \cdot \epsilon_{g h i} \\
& +\sum_{j} n_{g} \cdot \cdot j_{j} \beta_{j}+\sum_{i} \sum_{j} n_{g \cdot i j} \alpha_{i j}+\sum_{h} \sum_{j} n_{g h \cdot j} \delta_{h j}=Y_{g} \ldots \\
& n_{\cdot h} . .\left(\mu+\lambda_{h}\right)+\sum_{g} n_{g h} \cdot \rho_{g}+\sum_{i} n_{\cdot h i} \cdot \alpha_{i}+\sum_{g i} \sum_{g h i} \cdot \epsilon_{g h i} \\
& +\sum_{j} n \cdot h \cdot j\left(\beta_{j}+\delta_{h j}\right)+\sum_{i} \sum_{j} n \cdot h_{i j} \alpha \beta_{i j}=Y_{\cdot h} . \\
& n_{\cdot \cdot i} \cdot\left(\mu+\alpha_{i}\right)+\sum_{g} n_{g \cdot i} \cdot \rho_{g}+\sum_{h} n_{h i} \cdot \lambda_{h}+\sum_{g h} n_{g h i} \cdot \epsilon_{g h i} \\
& +\sum_{j} n ._{i j}\left(\beta_{j}+\alpha \beta_{i j}\right)+\sum_{h j} \sum_{n_{i j}} \delta_{h j}=Y .{ }_{\cdot i} . \\
& n_{g h i} \cdot\left(\mu+\rho_{g}+\lambda_{h}+\alpha_{i}+\epsilon_{g h i}\right)+\sum_{j} n_{g h i j}\left(\beta_{j}+\alpha \beta_{i j}+\delta_{h j}\right)=Y_{g h i} . \\
& n \ldots\left({ }_{n}\left(\mu+\beta_{j}\right)+\sum_{g} n_{g} \cdot \cdot{ }^{\rho}{ }_{g}+\sum_{h} n_{\cdot h \cdot j}\left(\lambda_{h}+\delta_{h j}\right)+\sum_{i} n_{\cdot \cdot i j}\left(\alpha_{i}+\alpha \beta_{i j}\right)\right. \\
& +\sum_{g h i} \sum_{i} n_{g h i j} \epsilon_{g h i}=Y \ldots j
\end{aligned}
$$

$$
\begin{aligned}
& n_{\cdot \cdot i j}\left(\mu+\alpha_{i}+\beta_{j}+\alpha_{i j}\right)+\sum_{g} n_{g \cdot i j} \rho_{g}+\sum_{h} n_{\cdot h i j}\left(\lambda_{h}+\delta_{h j}\right) \\
& \quad+\sum_{g h} \sum_{h h i j} n_{g h i}=Y_{\cdot \cdot i j} \\
& n_{\cdot h \cdot j}\left(\mu+\lambda_{h}+\beta_{j}+\delta_{h j}\right)+\sum_{g} n_{g h \cdot j} \rho_{g}+\sum_{i} n_{\cdot h i j}\left(\alpha_{i}+\alpha_{i j}\right) \\
& \quad+\sum_{g} \sum_{i} n_{g h i j} \epsilon_{g h i}=Y_{\cdot h \cdot j} \quad
\end{aligned}
$$

Utilizing the following restraint equations:

$$
\sum \rho_{g}=\sum \lambda_{h}=\sum \alpha_{i}=\sum \beta_{j}=\sum_{h \text { or } j} \delta_{h j}=\sum_{i \text { or } j} \alpha \beta_{i j}=\sum_{g, h, \text { or } i} \epsilon_{\text {ghi }}=0,
$$

solutions.for the effects are easily found if there are no missing observations.
 $\hat{\mu}+\hat{\beta}_{j}=\bar{y} \ldots_{j}, \hat{\mu}+\hat{\alpha}_{i}+\hat{\beta}_{j}+\hat{\alpha}_{i j}=\bar{y} ._{i j}$, and $\hat{\mu}+\hat{\lambda}_{h}+\hat{\beta}_{j}+\hat{\delta}_{h j}=\bar{y}_{\cdot h \cdot j}$, where the se are the ordinary arithmetic means of the previously defined totals.

When there are missing observations the solution to the normal and restraint equations may become difficult depending upon the distribution of the missing observations. Instead of considering all the constants let us consider the following constants and let us note that the remaining normal equations may be obtained as sums of normal equations for these constants:

$$
\mu+\rho_{g}+\lambda_{h}+\alpha_{i}+\epsilon_{g h i}=\epsilon_{g h i}^{*}
$$

$$
\begin{aligned}
& \mu+\alpha_{i}+\beta_{j}+\alpha \beta_{i j}=\alpha \beta_{i j}^{*} \\
& \mu+\lambda_{h}+\beta_{j}+\delta_{h j}=\delta_{h j}^{*}
\end{aligned}
$$

Then, the normal equations may be written as:

$$
\left(\begin{array}{ccc}
D_{\epsilon} & N_{1} & N_{2} \\
N_{1}^{\prime} & D_{\alpha \beta} & N_{3} \\
N_{2}^{\prime} & N_{3}^{\prime} & D_{\delta}
\end{array}\right)\left(\begin{array}{l}
\epsilon^{*} \\
\alpha \beta^{*} \\
\delta^{*}
\end{array}\right)=\left(\begin{array}{c}
Y_{\epsilon} \\
Y_{\alpha \beta} \\
Y_{\delta}
\end{array}\right)
$$

where $D_{\epsilon}$ is a bk $\times b k$ diagonal matrix with diagonal elements $n_{g h i}, D_{\alpha \beta}$ is a tv $\times$ tv diagonal matrix with diagonal elements $\mathrm{n}_{.} \mathrm{Hj}_{\mathrm{ij}}, \mathrm{D}_{\delta}$ is a bt x bt diagonal
 $\left.\epsilon_{133}^{*} \epsilon_{234}^{*} \epsilon_{331}^{*} \epsilon_{432}^{*} \epsilon_{144}^{*} \epsilon_{241}^{*} \epsilon_{342}^{*} \epsilon_{443}^{*}\right)^{\prime}, \quad \alpha \beta^{*}=\left(\alpha_{11}^{*} \alpha \beta_{12}^{*} \alpha \beta_{13}^{*} \alpha \beta_{14}^{*} \alpha \beta_{21}^{*} \alpha \beta_{22}^{*} \alpha \beta_{23}^{*} \alpha \beta_{24}^{*}\right.$ $\left.\alpha \beta_{31}^{*} \alpha \beta_{32}^{*} \alpha \beta_{33}^{*} \alpha \beta_{34}^{*} \alpha \beta_{41}^{*} \alpha \beta_{42}^{*} \alpha \beta_{43}^{*} \alpha \beta_{44}^{*}\right)^{\prime}, \delta^{*}=\left(\delta_{11}^{*} \delta_{12}^{*} \delta_{13}^{*} \delta_{14}^{*} \delta_{21}^{*} \delta_{22}^{*} \delta_{2}^{*} \delta_{2}^{*} \delta_{31}^{*} \delta_{32}^{*} \delta \delta_{33}^{*} \delta_{34}^{*}\right.$ $\left.\delta_{41}^{*} \delta_{42}^{*} \delta_{4}^{*} \delta_{4}^{*}\right)^{\prime}, Y_{\epsilon}$ is $b k \times I$ with elements $Y_{\text {ghi }}$. in the same order as $\epsilon^{*}$, $Y_{\alpha \beta}$ is tv $\times 1$ with elements $Y_{._{i j}}$ in the same order as $\alpha \beta^{*}, Y_{\delta}$ is bt $\times 1$ with elements $Y_{\cdot h \cdot j}$ in the same order as $\delta *$, and $N_{1}, N_{2}$, and $N_{3}$ are the corresponding coefficient matrices for the remaining constants in the normal equations. For example, for the design given above $N_{l}$ is the following $b k \times$ vt matrix:

$$
\left[\begin{array}{ccccccccccccccc} 
& \left(n_{112 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & & \left(n_{212 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{313 j}\right) & & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{414 j}\right) & \\
0 & 0 & 0 & 0 & & \left(n_{122 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{223 j}\right) & & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{324 j}\right) & \\
& \left(n_{421 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{133 j}\right) & & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{234 j}\right) & \\
& \left(n_{331 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & & \left(n_{432 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{144 j}\right) & \\
& \left(n_{241 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \left(n_{342 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 . & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{443 j}\right) & & 0 & 0 & 0 & 0
\end{array}\right]
$$

where the matrix $\left(n_{111 j}\right)$, e.g., is a one $\times t$ row vector of ones if there are no missing observations and has zeros substituted for the ones where there are missing observations, and similarly for the remaining row vectors ( $\mathrm{n}_{\mathrm{ghij}}$ ).

For the above design $N_{2}$ is a $b k \times b t=16 \times 16$ matrix of the form:

$$
\left[\begin{array}{ccccccccccccccc}
\left(n_{111 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
& \left(n_{212 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
& \left(n_{313 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
& \left(n_{414 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & & \left(n_{122 j}\right) & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \left(n_{223 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \left(n_{324 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \left(n_{421 j}\right) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{133 j}\right) & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \left(n_{234 j}\right) & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \left(n_{331 j}\right) & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \left(n_{432 j}\right) & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{144 j}\right) \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{241 j}\right) \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{342 j}\right) \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & \left(n_{443 j}\right)
\end{array}\right]
$$

For the above design $N_{3}$ is a $b k \times v t=16 \times 16$ matrix of the form:

$$
\left[\begin{array}{llllllllllllllll} 
& & & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
& \text { E } & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
& & & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & & & & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & & \text { F } & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & & & & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & & & & & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & & & & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & & & & & & 0 & 0 & 0
\end{array} 0\right.
$$

where

$$
\begin{aligned}
& E=\left[\begin{array}{llll}
n_{1111} & n_{4211} & n_{3311} & n_{2411} \\
n_{1112} & n_{4212} & n_{3312} & n_{2412} \\
n_{1113} & n_{4213} & n_{3313} & n_{2413} \\
n_{1114} & n_{4214} & n_{3314} & n_{2414}
\end{array}\right] \\
& F=\left[\begin{array}{llll}
n_{2121} & n_{1221} & n_{4321} & n_{3421} \\
n_{2122} & n_{1222} & n_{4322} & n_{3422} \\
n_{2123} & n_{1223} & n_{4323} & n_{3423} \\
n_{2124} & n_{1224} & n_{4324} & n_{3424}
\end{array}\right]
\end{aligned}
$$

$$
\begin{aligned}
& G=\left[\begin{array}{llll}
n_{3131} & n_{2231} & n_{1331} & n_{4431} \\
n_{3132} & n_{2232} & n_{1332} & n_{4432} \\
n_{3133} & n_{2233} & n_{1333} & n_{4433} \\
n_{3134} & n_{2234} & n_{1334} & n_{4434}
\end{array}\right] \\
& H=\left[\begin{array}{llll}
n_{4141} & n_{3241} & n_{2341} & n_{1441} \\
n_{4142} & n_{3242} & n_{2342} & n_{1442} \\
n_{4143} & n_{3243} & n_{2343} & n_{1443} \\
n_{4144} & n_{3244} & n_{2344} & n_{1444}
\end{array}\right]
\end{aligned}
$$

In order to solve for the $\epsilon^{*}, \alpha \beta^{*}$, and $\delta^{*}$ we may rewrite the normal equations as:

$$
\begin{aligned}
& \left(\begin{array}{ccc}
D_{\epsilon} & N_{1} & N_{2} \\
N_{1}^{\prime} & D_{\alpha \beta} & N_{3} \\
N_{2}^{\prime} & N_{3}^{\prime} & D_{\delta}
\end{array}\right)\left(\begin{array}{c}
\epsilon^{*} \\
\alpha \beta^{*} \\
\delta^{*}
\end{array}\right)=\left(\begin{array}{c}
Y_{\epsilon} \\
Y_{\alpha \beta} \\
Y_{\delta}
\end{array}\right) \\
& =\left(\begin{array}{ccc}
D_{\epsilon} & N_{1} & N_{2} \\
0 & D_{\alpha \beta}-N_{1}^{\prime} D_{\epsilon}^{-1} N_{1}=B_{\alpha \beta} & N_{3}-N_{1}^{\prime} D_{\epsilon}^{-1} N_{2}=N_{4} \\
0 & N_{3}^{\prime}-N_{2}^{\prime} D_{\epsilon}^{-1} N_{1}=N_{4} & D_{\delta}-N_{2}^{\prime} D_{\epsilon}^{-1} N_{2}=B_{\delta}
\end{array}\right)\binom{\epsilon^{*}}{\alpha^{*}}=\left(\begin{array}{c}
Y_{\epsilon} \\
Y_{\alpha \beta}-N_{1}^{\prime} D_{\epsilon}^{-1} Y_{\epsilon}=X_{\alpha \beta} \\
Y_{\delta}-N_{2}^{\prime} D_{\epsilon}^{-1} Y_{\epsilon}=X_{\delta}
\end{array}\right)
\end{aligned}
$$

$$
=\left(\begin{array}{ccc}
D_{\epsilon} & N_{2} & N_{2} \\
0 & B_{\alpha \beta} & N_{4} \\
0 & 0 & B_{\delta}-N_{4}^{\prime} B_{\alpha \beta}^{-1} N_{4}
\end{array}\right)\left(\begin{array}{c}
\epsilon * \\
\alpha \beta^{*} \\
\delta^{*}
\end{array}\right)=\left(\begin{array}{c}
Y_{\epsilon} \\
X_{\alpha \beta} \\
X_{\delta}-N_{4}^{\prime} B_{\alpha \beta}^{-1} X_{\alpha \beta}
\end{array}\right)
$$

The above implies that none of the diagonal elements of $D_{\epsilon}, D_{\alpha \beta}$, or $D_{\delta}$ is zero. If this is the case delete the corresponding row and column from the matrix and the corresponding constant. Also, implied in the above is that $B_{\alpha \beta}$ has an inverse but this is generally not the case and use must be made of a restraint equation of the form $\sum_{i j}\left(\alpha \beta_{i j}^{*}-\mu\right)=0$, prior to the last step above. Then, in order to solve for the $\delta^{*}$ one must impose a restraint of the form $\sum_{h j}\left(\delta_{h j}^{*}-\mu\right)=0$. Restraint equations of the form listed previously must be utilized if solutions (denoted by the constant with a caret as e.g. $\hat{\alpha}_{i}$ ) of the $\alpha_{i}, \rho_{g}, \lambda_{h}, \beta_{j}, \epsilon_{g h i}, \alpha \beta_{i j}$, and $\delta_{h j}$ are to be obtained. After obtaining solutions for all constants we may compute the residual sum of squares as $R=\sum_{g h i j} \sum_{\sum_{g h i j}}\left(Y_{g h i j}-\hat{\mu}-\hat{\beta}_{g}-\hat{\lambda}_{h} \hat{\alpha}_{i}-\hat{\epsilon}_{g h i}-\hat{\beta}_{j}-\hat{\alpha \beta}_{i j}-\hat{\delta}_{h j}\right)^{2}=\Sigma \Sigma \Sigma \Sigma n_{g h i j} Y_{g h i j}^{2}-$ S where $S=S S\left(\mu, \rho_{g}, \lambda_{h}, \dot{\alpha}_{i}, \epsilon \epsilon_{g h i}, \dot{\beta}_{j}, \alpha \beta_{i j}, \dot{\delta}_{j h}\right)=\hat{\mu} Y \ldots+\hat{\rho}_{g} Y_{g} \ldots+\sum \hat{\lambda}_{h} Y{ }_{h} \ldots+\Sigma \hat{\alpha}_{i} Y \ldots i \cdot$ $+\sum_{g h i} \sum_{g h i} \cdot \hat{\epsilon}_{g h i} Y_{g h i}+\sum_{j} \hat{\beta}_{j} Y \ldots \sum_{i j}+\sum_{i \beta_{j}} \hat{\beta}_{i j} Y_{i j}+\sum_{h j} \sum_{h j} \hat{X}_{h \cdot j}$. The sum of squares due to any set of constants, say $\epsilon_{g h i}$, eliminating all other effects, is equal to $S-\operatorname{SS}\left(\mu, \rho_{g}, \lambda_{h}, \alpha_{i}, \beta_{j}, \alpha \beta_{i j}, \delta_{h j}\right)=S_{1}$ with $f_{1}$ degrees of freedom. The sum of squares due to two sets of constants, say $\alpha_{i}$ and $\epsilon_{g h i}$, eliminating all other effects is $S-S S\left(\mu, \rho_{g}, \lambda_{h}, \beta_{j}, \alpha \beta_{i j}, \delta_{h j}\right)=S_{2}$ with $f_{2}$ degrees of freedom. Then we may utilize a general theorem from least squares theory which states that when the null hypothesis is true $\frac{\left(S_{2}-S_{1}\right) /\left(f_{2}-f_{1}\right)}{S_{1} / f_{1}}$ follows Snedecor's $F$ distribution with $f_{2}-f_{1}$ and $f_{1}$ degrees of freedom. From this result, one may obtain $F$
tests for harvests, for varieties, and for the harvest $\times$ variety interaction regardless of the balanced or unbalanced nature of the design.

For the particular case at hand, the experimenter did not obtain results for harvest number four. This means that additional restraint equations of the form $\alpha_{4}=0, \alpha \beta_{4 j}=0, \epsilon_{g h 4}=0$, and $n_{\text {gh4 }}=0$ for all cases where $n_{g h 4 j}$ was one with no missing observations. For this case the solutions to the normal equations become:

$$
\begin{aligned}
\hat{\mu} & =\overline{\mathrm{y}}, \hat{\alpha}_{i}=\overline{\mathrm{y}}_{\ldots i \cdot} \cdot-\overline{\mathrm{y}}, \hat{\beta}=\overline{\mathrm{y}}_{\ldots j}-\overline{\mathrm{y}}, \\
\hat{\alpha \beta}_{i j} & =\overline{\mathrm{y}}_{\ldots{ }_{i j}}-\overline{\mathrm{y}}_{\ldots i \cdot} \cdot-\overline{\mathrm{y}}_{\ldots j}+\overline{\mathrm{y}},
\end{aligned}
$$

solutions for $\rho_{g}$ are obtained from the equations

$$
\left(\begin{array}{cccc}
32 / 3 & 0 & 0 & 0 \\
0 & 32 / 3 & 0 & 0 \\
0 & 0 & 32 / 3 & 0 \\
\hdashline & 0 & 0 & 32 / 3
\end{array}\right)\left(\begin{array}{l}
\hat{\rho}_{1} \\
\hat{\rho}_{2} \\
\hat{\rho}_{3} \\
\hat{\rho}_{4}
\end{array}\right)=\left(\begin{array}{c}
Y_{1} \ldots-(Y \ldots-Y \cdot 4 \ldots) / 3=Q_{r 1} \\
Y_{2 \ldots} \ldots(Y \ldots-Y \cdot 3 \ldots) / 3=Q_{r 2} \\
Y_{3} \ldots-(Y \ldots-Y \cdot 2 \ldots) / 3=Q_{r 3} \\
Y_{4} \ldots-\left(Y \ldots . Y_{1} \ldots\right) / 3=Q_{r 4}
\end{array}\right),
$$

and the solutions for $\lambda_{h}$ are obtained from the equations
For the case where harvest number 4 is missing all effects are orthogonal
to each other except rows and columns. The analysis of variance table is:
$Y^{2} . . . / 48$
subtraction

With harvest 4 data deleted the analysis of variance and solution of effects remain simple. With other missing plot situations the results are likely to becone more complicated and the various effects are likely to be non-orthogonal, thus complicating the analysis. The procedure described above holds for all unbalanced situations. Also, deletion of the $\delta_{h j}$ from the above yield equations gives the yield equation for the splitmplot design. Addition of other constants in the yield equation results in the split-split plot design, split block design with split plots, etc. Missing observations in all these designs may be handled as described above.

Alternatively, one may include dummy independent variates in regression where the $X_{\text {fghij }}$ values take on one (or -1) when the yield is missing and zero otherwise. Then, a multiple covariance analysis of the yield $Y_{g h i j}$ on the independent variates $X_{f g h i j}$ is computed. The solutions for the constants and the sums of squares in the analysis of variance adjusted for the covariates are identical to those obtained from regression theory.


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