A MODIFIED AUGMENTED DESIGN (TYPE 2) FOR RECTANGULAR PLOTS

CHUANG-SHENG LIN and GREG POUSHINSKY

Engineering and Statistical Research Institute, Agriculture Canada, Ottawa, Ontario K1A 0C6. *Contribution no. I-570, received 15 July 1984, accepted 18 Jan. 1985.*

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A modified augmented design (type 2) is presented for the situation where subplots are long and narrow (rectangular plots). The arrangement of the whole plots is the same as in the type 1 modified augmented design, but the subplots are laid out in rows within whole plots. The number of subplots per whole plot is 5, where the centre plot is the control plot. Twelve sets of data generated from three hypothetical fertility maps were used to investigate (i) the choice of adjustment method based on ANOVA of control plots and (ii) the estimated relative efficiencies of the methods. The results showed that the choice of adjustment method based on ANOVA is satisfactory and, although the estimates of relative efficiency differed from the population values, the ranking of the estimates and that of population values was nearly identical.

Key words: Augmented design, non-replicated experiment, control of soil heterogeneity

[Un dispositif enrichi modifié (type 2) pour les parcelles rectangulaires.]
Titre abrégé: Dispositif enrichi modifié de type 2.
L'article présente un dispositif enrichi modifé (type 2) à utilizer dans le cas de sous-parcelles longues et étroites (parcelles rectangulaires). La disposition des grandes parcelles est la même que dans le dispositif enrichi modifé de type 1, mais les sous-parcelles sont disposées en lignes à l'intérieur des grandes parcelles. Il y a cinq sous-parcelles par grande parcelle et la sous-parcelle centrale sert de témoin. Douze ensembles de données produites à partir de trois cartes de fertilité hypothétiques ont été utilisées pour étudier (i) le choix d'une méthode de correction basée sur l'analyse de la variance des parcelles témoins et (ii) les efficacités relatives estimées des méthodes. Les résultats ont indiqué que le choix d'une méthode de correction basée sur l'analyse de la variance est satisfaisant et, bien que les estimations d'efficacité relative différaient des valeurs de la population, l'ordre des estimées et celui des valeurs de population étaient presque identiques.

Mots clés: Dispositif enrichi, expérience à répétition unique, contrôle de l'hétérogénéité du sol

In the early stage of plant selection program, breeders are frequently faced with the situation of having a large number of test lines without sufficient seed for replicated experiments. To cope with such experimental conditions, Lin and Poushinsky (1983) proposed a modified augmented design (MAD) for a non-replicated experiment. Two restrictions of the design were that the shape of plot needs to be square or near square and the subplots within a whole plot should be in a 3×3 layout. These restrictions were aimed at achieving approximate uniformity of distance between a control plot and its surrounding eight subplots so that homogeneity of within-whole-plot correlations can be better maintained. A subsequent simulation study (Lin et al. 1983) confirmed that this property was well preserved for 12 fertility maps studied, suggesting that the design is robust in fulfilling the assumption of homogeneity of subplots within whole plots.

However, crops such as cereals or soybeans are planted in rows. If a rectangular plot is to be used, then the 3×3 arrangement of subplots within a whole plot used in the MAD may not provide homogeneity of distances and new arrangements must be considered.

In this paper we propose a type 2 MAD for rectangular plots. The major change from the earlier MAD (which we will call type 1 MAD) is to use five rectangular plots arranged in parallel rows within a whole plot. A 5×6 row-column design was used as an example to demonstrate the basic idea of the design and 12 sets of data generated from three hypothetical maps were used to investigate (i) if ANOVA of control plots will indicate an adequate adjustment method and (ii) if the relative efficiency of adjustment calculated from part of the data can represent that calculated from the population.

DESIGN

The design is structured in a split plot with whole plots arranged in rows and columns as in the type 1 MAD (Lin and Poushinsky 1983). Each whole plot contains five rectangular subplots; the center subplot is called a control plot and is assigned to the control line. For estimating subplot error, an arbitrary number of whole plots (10 in our example) is randomly chosen and the control line (or lines) is assigned to randomly selected subplots in each of these 10 whole plots; these are called control subplots. After these two types of plots are assigned, the test lines are then randomly allocated to the remaining subplots. Note that if some test lines (say n) have sufficient seed for two plots, they can be treated as $2n$ test lines and the data from these duplicated test lines can be used to assess the relative efficiency of the adjustment. In the present example, one control line was allocated to all control plots and two other control lines to the control subplots. However, all control lines can be allocated jointly to both types of plots as described in Lin and Poushinsky (1983). The present assignment of control lines is more suitable for the situation where breeders place more importance on comparisons involving one of the check cultivars, i.e., put the cultivar of major interest in the control plots and the cultivars of minor interest in the control subplots. The field layout for a 5×6 arrangement is shown in Fig. 1.

SIMULATION AND ADJUSTMENTS

Data were generated based on the model given in Lin et al. (1983) with the observed response (Y_{irck}) being the sum of a genetic value (μ_i), a plot value (ρ_{rck}) and a random error (e_{rck}). The genetic values for 100 test lines were fixed with mean of 22.89 and variance of 7.02. Three check cultivars, designated A, B, and C, were used as control lines. Cultivar A held the major interest for comparison and was assigned to the 30 control plots (see Fig. 1), while cultivars B and C were of minor interest and were assigned to one subplot in each of 10 randomly chosen whole plots. Note that of the 100 test lines, 60 lines had one replicate and 20 lines had duplicates. The simulated data from the latter group were used to check the relative efficiency of the adjustment methods. Three hypothetical soil fertility maps were used to represent various soil conditions. Each map was made up of 50×48 units and the fertility level of each unit was expressed as a number from 1 to 9 (Fig. 2). A map was divided into 25×6 subplots (i.e., a 5×6 whole plot arrangement) with subplots being 2×8 units. The mean of the fertility values within each plot was considered to be the plot value (ρ). Four sets of random error (e) were generated randomly for each map in such a way that R^2 (the percentage of environmental variance attributable to soil effects, defined as

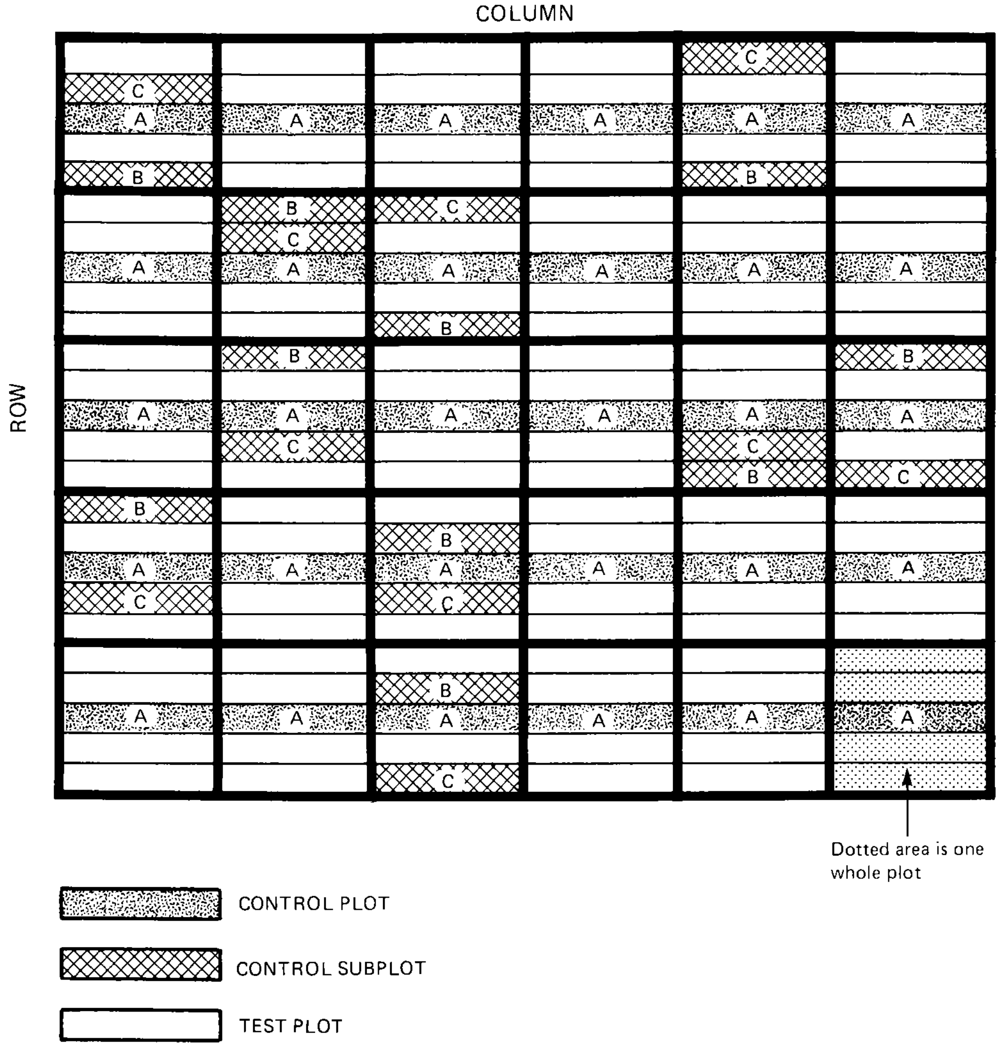

Fig. 1. Field layout of 5 × 5 type 2 MAD.

$$R^2 = \sigma_\rho^2/(\sigma_\rho^2 + \sigma_e^2)$$

where $\sigma^2\rho$ and σ^2_e are the variance of ρ and e values, respectively) was in the range 48–100% (see Table 1). Both plot values and error values were adjusted for their overall mean to eliminate map effects, i.e.

$$\sum_{i=1}^{100} \rho_i = \sum_{i=1}^{100} e_i = 0.$$

Note that allocations of control subplots, test lines and the e values were all randomized independently for each set of data.

Three adjustment methods were applied to each set of data. Let $Y_{ij(k)}$ denote the observed value of the kth test line in the whole plot of the ith row ($i = 1,\ldots,r$) and the jth column ($j = 1,\ldots,c$) and let $X_{ij(A)}$ denote the observed value of the control plot (cultivar A) in the ijth whole plot. Then the adjusted

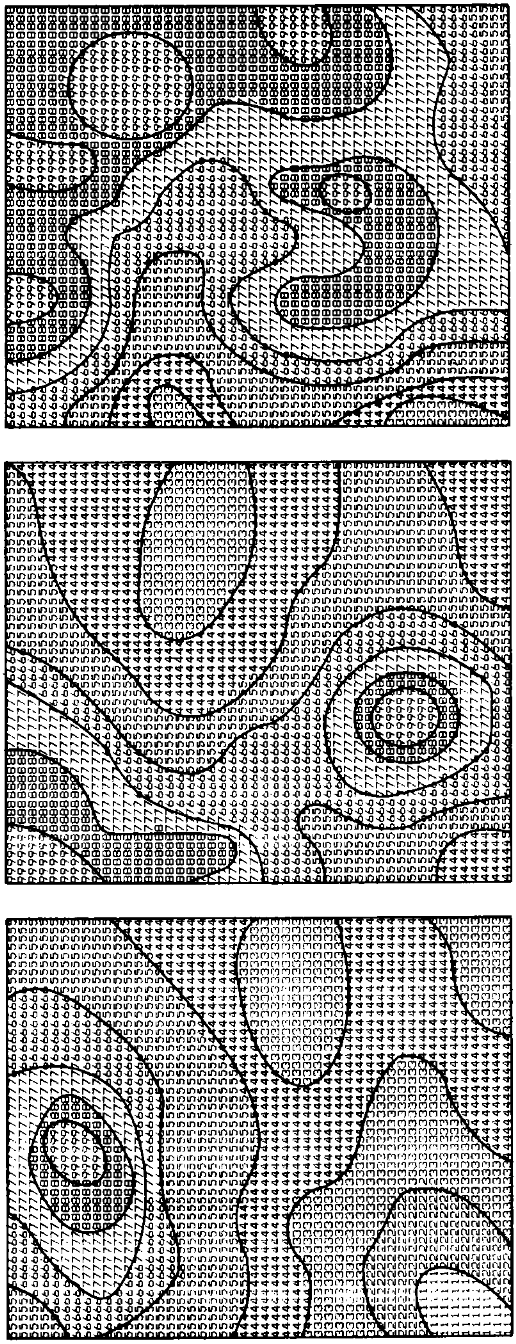

Fig. 2. Three soil fertility maps used in simulating soil fertility values (ρ).

Table 1. Summary of analyses of simulated data

		Map 1				Map 2				Map 3			
	Set:	1	2	3	4	5	6	7	8	9	10	11	12
	(R^2 in %)†:	(100)	(81.5)	(62.9)	(56.0)	(100)	(77.5)	(59.3)	(55.1)	(100)	(73.7)	(62.1)	(48.5)
		I. ANOVA											
Source	*DF*	MS											
Row	(4)	1.34*	1.24	1.94	5.17	8.52*	11.86*	6.89*	12.72*	7.82*	5.72*	5.48*	6.32
Column	(5)	11.17*	10.09*	16.08*	13.58*	1.51*	0.76	3.38*	5.88*	2.10*	3.83*	5.01*	4.69
R×C	(20)	0.66*	1.11*	2.37	2.46	1.16*	1.21*	1.79*	3.50	0.63*	1.48	1.62	3.69
Subplot error	(18)	0.12	0.50	1.54	2.13	0.18	0.55	0.38	1.98	0.21	0.76	1.08	3.80
		II. Actual relative efficiency measured by 100 test lines (%)											
Method 1		340.9	**258.6**‡	**172.0**	**157.7**	236.8	168.9	142.9	**90.4**	133.2	**127.4**	108.9	**102.2**
Method 2		**623.7**	229.2	133.8	133.6	655.1	181.0	159.4	56.7	**141.5**	114.7	98.3	81.1
Method 3		606.9	229.7	163.3	147.0	**669.8**	**192.1**	**165.9**	67.1	141.2	120.0	**109.8**	101.1
		III. Estimated relative efficiency measured by 20 pairs of duplicates (%)											
Method 1		1097.0	**682.8**	**171.1**	96.9	260.5	155.6	**147.6**	**48.7**	314.5	**316.8**	**137.3**	**129.8**
Method 2		2003.8	309.6	92.0	84.7	**1221.7**	151.3	130.8	30.1	**871.4**	139.5	114.3	76.9
Method 3		**2281.3**	287.9	116.5	**145.0**	997.7	**221.6**	139.5	36.7	838.4	177.3	130.9	101.9

†Percentage of total variation attributable to the fertility factor, see the text.
‡Boldface indicates the method that is most efficient.
*$P \leqslant 0.05$.

value $Y'_{ij(k)}$ was defined as

Method 1 (adjustment by design structure):

$$Y'_{ij(k)} = Y_{ij(k)} - R_i - C_j$$

$$\text{where } R_i = \sum_{j=1}^{c} X_{ij(A)}/c - \overline{X}_A$$

$$C_j = \sum_{j=1}^{r} X_{ij(A)}/r - \overline{X}_A$$

$$\text{and } \overline{X}_A = \sum_i \sum_j X_{ij(A)}/rc$$

Method 2 (adjustment by fertility index):

$$Y'_{ij(k)} = Y_{ij(k)} - (X_{ij(A)} - \overline{X}_A)$$

Method 3 (adjustment by regression):

$$Y'_{ij(k)} = Y_{ij(k)} - b(X_{ij(A)} - \overline{X}_A)$$

where b is the regression coefficient of the mean of two control subplots (cultivars B and C) regressed on the corresponding control plot.

The relative efficiency (RE) of each method, as compared with nonadjustment, was calculated based on the sums of squares (SS) for bias as shown in Eq. 2 of Lin et al. (1983). In addition, RE based on the SS of differences between duplicates (20 pairs) for both adjusted and unadjusted was calculated for each method.

RESULTS

An analysis of variance for row, column and row-column interaction, based on 30 control plots, and the mean square for subplot error measured from the 10 whole plots (total 30 observations for A, B, C) are summarized in Analysis I of Table 1. Set 12 shows no main effect nor interaction effect, indicating that for this set of data, environmental variations can be considered random and no adjustment was necessary. Sets 3, 4, 8, 10, 11 show significant main effects but no interaction, indicating that the adjustment by method 1 was probably adequate. For sets 1, 2, 5, 6, 7, 9, the row-column interaction was significant, thus for these sets adjustment by method 3 would probably be more appropriate. The actual RE shown in Analysis II of Table 1 (except set 2) supports these conclusions (see method in bold face, Table 1). In general, effectiveness of adjustment depends on the field fertility pattern and the size of R^2 (Lin et al. 1983). For the present simulation, adjustment was most effective for map 1, and then map 2 and map 3 in that order. When R^2 was 100%, method 2 was superior to method 1; but as R^2 decreased ($R^2 \leq 80\%$) method 1 was superior. At low levels of R^2 ($R^2 \leq 50\%$) there was an indication that method 2 may be worse than no adjustment. Although RE based on a sample variance estimated from 20 pairs of duplicates (Analysis III of Table 1) differed considerably from that based on the entire population, the rankings of the methods with respect to RE were fairly consistent for both sets of data.

DISCUSSION AND CONCLUSIONS

The major purpose of arranging rectangular subplots in parallel is to keep the distances between a control plot and its surrounding test plots as uniform as possible, so that the homogeneity of a whole plot can be better preserved. To investigate this, simple correlations between the ρ values of control plots and neighbouring plots in four distance classes (i.e., 2, 4, 6, and 8 units from the control) were investigated. Table 2 shows that the correlation patterns differed from map to map. However, high correlation coefficients were always maintained for classes 1 and 2, suggesting that the use of five subplots per whole plot was fairly safe for maintaining homogeneity of the subplots.

Although in the present example we have used five subplots, this number can be adjusted (in odd numbers, i.e. 7, 9, etc.) depending on the shape of the rectangular plot. For example, if the ratio of width to length is 1:4 as in the present example, five

Table 2. Simple correlation between the control plots and four classes of neighbouring plots based on ρ values

Class	Unit distance from the control plot	No. of observations	Map 1	Map 2	Map 3
1	2	60	0.99	0.97	0.96
2	4	60	0.97	0.93	0.88
3	6	48	0.95	0.80	0.70
4	8	48	0.90	0.70	0.53

plots should be appropriate; on the other hand if the ratio is 1:7, seven subplots per whole plot should be considered. Naturally, the greater the number of subplots, the less accurate will be the adjustment as indicated by the correlation study (but more economical since the percentage of plots required for control plots will be smaller). However, the important point in this regard is that shape of the whole plot should be maintained relatively square so that a more balanced two-way adjustment is possible.

In the previous simulation study, Lin et al. (1983) concluded that if the soil fertility appears to vary along rows or columns or in both directions in an additive way, they recommend method 1, otherwise they recommend method 3. Method 2 need not be considered because it is usually inferior to the other two and because the danger of loss of efficiency is greater. This conclusion is still valid with respect to these 12 sets of data. Although method 2 in the present analyses shows superiority when $R^2 = 100$, it was concluded in the previous study that R^2 is likely to be less than 70% in most fields. Thus, the chance of getting better estimates by method 2 is slim.

An important feature of both type 1 and type 2 MAD, as compared to the classical control method, is that these new designs allow researchers to investigate the general pattern of soil variation and through ANOVA answer such important questions, as: (i) is soil variation in the field homogeneous? (ii) is soil variation in one or two directions? and (iii) if it is two directional, are these effects additive? Depending on the answers to these questions, the best strategy for adjustment can be selected. For example, if no apparent row and column effects were observed and the whole-plot error (i.e. row × column interaction) was about the same magnitude as the subplot error, then the field can be considered homogeneous and no adjustment is necessary. On the other hand, if either or both of these effects are significant and they are additive then design correction (method 1) should be used. If the interaction is significant (i.e. non-additive main effects) then the regression method (method 3) should be used. The MAD design (both types) provides the information required to determine the better adjustment method. Furthermore, the design allows the investigator to estimate the relative efficiency of the different adjustment methods. Although the RE measured from the partial data differ considerably from those from the population as shown in the present simulation, the patterns of relative superiority of the method were generally in good agreement. This is encouraging, because when the results from the ANOVA are inconclusive, RE based on control subplots or duplicated test lines can provide supplementary information as to which adjustment method is better.

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