A COMPARISON OF ALTERNATE METHODS FOR THE CONTROL OF EXPERIMENTAL ERROR IN PERENNIAL CROPS

By

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THESIS

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CERTIFICATE

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I hereby declare that this thesis entitled A comparison of alternate methods for the control of experimental error in perennial crops" is a bonafide record of research work done by me during the course of research and that the thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or any other similar title, of any other University or Society.

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(SEENA, C.)

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Introduction

1. INTRODUCTION

An intrinsic phenomenon in replicated experiments is the variability in the measurements on different experimental units even when they receive the same treatment. A part of this variation is systematic and can be controllable where as the remainder is assumed to be of random type. The unexplained (random) part of the variation is termed as experimental error. This is a technical term which includes all types of extraneous variation due to the inherent variabilities in the experimental units, error associated with measurements made and the lack of representativeness of the sample to represent population under study. The experimental error provides a measure of precision and a basis for measuring the amount of confidence to be placed on the inferences to be drawn from the sample about the relevant population. Thus estimation and control of error can be considered to be one of the basic objectives in designing any field experiment in perennial crops. Apart from this variation on soil heterogeneity the inherent genetic diversity within the crop species constitute the major source of experimental error. Variation may also arise due to such causes as inaccuracy of weighing, loss of grain/unit at harvest, non uniformity in the distribution of solar radiation over the experimental field, weather abnormalities etc. But the effect of such factors seems to be secondary and less prominent.

Absence of prior information about experimental error is a feature of any agricultural experiment. There are two sources of error variation (1) environmental variation or positional variation arising from the variability of the experimental plots and (2) genetic variability ie variation due to the inherent genetic make up of the indiviual units within the experimental plot.

All the commonly employed experimental designs aim at controlling the environmental (positional) variation so as to give the treatments almost equal chances to show their merit. But they ignore the presence of inherent variation among the trees in the same experimental unit and does not provide ways and means to control its impact on the treatment effect. In perennial crops, most of which are cross pollinated, tree to tree variation (genetic variation) is more predominant than positional variation. For example in coconut genetic variation is such that the environmental differences are mostly negligible in comparision and this is the case with most of the other perennial crops. Thus in the layout of the experiment on such crops direct methods of control of error as preceived in the relevant design often fail to afford a satisfactory control of error which in turn might mask the real treatment effect. Further in tree crops, individual trees are of prime importance because each tree occupies a vast area and serves as the unit of measurement. They have very long juvenile phase and the time taken for flowering, duration of bearing period, the time taken for stabilisation of yield, resistance to pest and disease, etc vary from tree to tree. Some of the trees exhibit biennial tendency in their yielding behaviour. Thus in experiments with perennial crops the researcher has to deal with a highly heterozygous material. Several methods of controlling variability are available for the experimenter which include the use of vegetatively propagated material, seedlings raised from the same parental stock or tissue culture. But all these methods fail if an experimenter wants to superimpose a field trial on an existing plantation containing a bulk of trees of diverge genetic make up.

The direct methods of controlling error include in addition to replication and local control such devices as selection of uniform site for experimentation maintaining uniformity in the physical conduct of the experiment, replanting dead hills, controlling the incidence of pests and disease, proper orientation of plots and blocks, adoption of the optimum size of plot and provision for border plants for controlling border effect.

When the above mentioned direct methods for the control of experimental error are found to be less efficient or ineffective the experimenter may resort to certain indirect (statistical) methods for the control of error which include the technique of calibration and analysis of covariance. The technique can also be incorporated along with the direct methods for further reduction in experimental error. The procedure has been used for the analysis of data gathered from many perennial crops and the results were highly promising. But in such studies it was conventional to assume that the concomitant variable was linearly related to the study variate. The validity of this assumption is never warranted. No effort was made in such studies to examine the cosequence or violation from the assumed linear relationship between the variables. There are many instances where the concomitant variable show different types of non linear relations with the study variate and consequently the precision of estimates on treatment effects will be considerably increased by using appropriate nonlinear covariance adjustment by the concomitant variable.

The classical device for controlling local variation over the experimental area is to divide the land into blocks such that plots are less variable within a block than within the entire experimental area. The method has great potential and is commonly used. For example if an experiment is to be conducted on a slopy land it will certainly be advantageous to form blocks in bands that keep to a limited range of contours. In agricultural trials blocking can be successfully implemented only if the direction of the fertility gradient is known. Unless the nature, extent and pattern of field variability is known blocking can not be effective. Reduction of experimental error depends largely on the choice of a suitable criterion for blocking and proper orientation of blocks over the experimental field. A serious disadvantage of blocking is that it results in the reduction of degrees of freedom for error. Thus 'improper' blocking may lead to highly inflated error mean square and inaccurate estimates of treatment effects. On many occations, especially when the researcher tries to superimpose experiments on standing tree crops in an orchard he may not have any idea on the pattern of environmental variability and on the proper orientation of blocks to reduce its effects. This may prompt him to conduct the experiment in a completely randomised design and to control error through calibration and covariance analysis. In such cases the researcher may seek for certain alternative technique to stratification for the control of gradients. The same situation also encounters with experiments where no information is available on the pattern and direction of fertility variation.

It is true that data gathered from uniformity trial are useful for the construction of fertility contour maps of the experimental field with which the fertility pattern can be judged. In annual crops this results in unnecessary delay for starting the experiment in addition to the high cost to be incurred. For perennial crops uniformity trail consists in recording the data from each of the individual trees for one or two years before the start of the experiment. If such data are available they can be utilised for preparing fertility contour maps. But uniformity trial data in perennial crops can not solely indicate environmental variation. It indicates the soil diversity in the experimental material arising from genetic and environmental sources. As a result often fertility contour maps show irregular patterns and are not amenable to any kind of stratification.

When the fertility contour map does not show any kind of systematic trends of fertility variations of suitable lengths running along or across the field the researcher is confronted with the problem of reducing experimental error by employing methods other than 'stratification' or 'blocking'. Further, even in experiments where blocking was effective or could be made effective it would be worthwhile to try other elegant mathods along with stratification so as to bring down the error mean square as low as possible. In the modern world of electronic computers computational easiness can not be the guiding principle for the adoption of novel devices or techniques. The ultimate objective of the experimenter should be to enhance the efficiency of field experimentation at all costs.

Sometimes a concomitant variable is derived from the location of the plot. It is then called a psuedo variable. For example, if plots lie in a row it may be advisable to use the plot number as covariates to allow for a trend. Federer and Schlottfeldt (1954) tried this method to control an environmental gradient from the centre of the field. Since linear covariance was not successful they used quadratic covariance.

It is well known that if a plot is surrounded by neighbours that are doing well it can be expected to do well by itself. It is this simple fact that induced Papadaki's (1937) to think of an alternative approach to blocking which consists in judging each plot from the performance of its neighbours. On the basis of experimental data gathered from the completed field experiment he showed that his method - nearest neighbourhood analysis (NNA) - resulted in a considerable reduction of spatial heterogeneity. Bartlett (1978) developed an iterative alogarithm for covariance adjustment of Papadaki's NN analysis. Covariate value for each iteration was obtained by subtracting variate but not replicate effects from neighbouring plot values. Wilkinson and Kempton (1983) developed a new method of NN analysis called moving block method. According to them the method was more efficient than NN analysms and produced more reliable results.

Thus several methods are available in the literature for the control of error apart from the usual method of blocking or stratification. But the applicability of these methods are seldom evaluated on the basis of data generated from actual field trials and resultant gain in precision over the conventional methods assessed, Experiments are being planned, conducted, data generated, and interpreted through statistical analysis in the same routine manner as was done several years ago. In the light of the rapid development in theoretical as well as applied staistics and facilities for data processing and data analysis it is high time to examine the feasibility of these techniques over the conventional ones in increasing the efficiency of field experimentation. Anyhow, isolated studies incorporating one or two methods may not help the researcher in getting the best choice. A comprehensive investigation incorporating all the important direct and indirect methods for the control of experimental error alone can indicate the extent of reduction possible on the estimate of error and the resultant gain in precision on treatment effects from field experiments on perennial crops.

In view of the facts described in the above paragraphs the present study is aimed at the following objectives.

1) To estimate the relative contribution of genetic and environmental factors towards the total phenotype variation among trees.

2) To examine the applicability of non conventional methods of covariance analysis among trees for the control of genetic variability among trees.

3) To examine empirically the relative efficiences of various alternative procedures such as NN analysis, moving block method, iterative process etc. for the control of error in field experiments on perennial crops.

4) To examine the feasibility of using informations on neighbouring plots as an alternative to blocking in the analysis of experimental data.

5) To suggest a comprehensive procedure for the efficient control of error in the analysis of data generated from various perennial crops.

Review of Literature

2. REVIEW OF LITERATURE

Literature pertaining to the aspects investigated in this study reviewed here under the following heads.

1. Control of genetic variability in perennial crops - adjustment by concomitant variable.

2. Adjustment by neighbouring plots.

3. Other methods of adjustment.

2.1. Control of genetic variability in perennial crops - adjustment by concomitant variable.

Fairfield Smith (1938) proposed an empirical relationship between plot size (X) and variance of mean per plot (Vx) given by $Vx = V_1x^{-b}$, $0 \leq b \leq 1$ where V_1 is the variance of yields of plots of size one unit and 'b' is a measure of heterogeneity among contigous units. A value of 'b' in the neighbourhood of one indicated that genetic variation was more predominant than positional variation.

Pearse (1953) recommended calibration of plots before starting any experiment on established plants such as fruit trees as there could be observable differences among the genotypes which could not be controlled by direct methods.

Federer and Schlottfeldt (1954) illustrated with an example the use of covariance analysis instead of stratification to control variation and to indicate some possible application of the procedure. The use of covariance analysis to control gradients across the treatment plots approximately doubled the amount of information obtained from the experiment. According to them for the same level of precision about twice as many replications as would be required when the effect of the gradient was not removed. The finding of Outwaite and Rutherford (1955) were also on the same lines with those of Federer and Schlottfeldt (1954).

Pearce (1955) suggested a new empirical formulation to express the relation between plot size and varriability of mean/plot. His general model was of the form $V_x=V_1X^{-b} + V_2X^{-1}$ where V_x is the variance per unit area between plots of size x unit. V_1 is the variance among individual trees and b is a constant lying between 0 and 1. The second term of the expression indicated the amount of genetic variability in the material.

Iyer (1957) reported that in field experiments with coconut covariance analysis could effectively be used for reducing experimental error. For coconut Shrikhanda (1957) has found that the genetic and environmental components of variation were in the ratio of 2:1 or 3:2 and this could be reduced by covariance analysis.

Kulkarni and Abraham (1963) proposed the technique of multiple covariance analysis with several calibrating variables, instead of ordinary covariance analysis, for increasing the precision of estimate in the analysis of data from field experiment on perennial crops.

Freeman (1963) proposed a simple hypothesis as the relation between environmental and plant variation. His study was mainly concerned with the addition of one term for random component in the Smith's model using serial correlations between neighbouring trees. The hypothesis had the consequence that the serial correlation between neighbouring plants would satisfy an empirical relation of the form

$$\frac{V_x}{V_1} = \frac{\alpha}{x^b} + \frac{1-\alpha}{x}$$

where V_x = variance/unit area among plots of size x units
V_1 = variance among individual trees and
α = the proportion of variance due to environmental factors.
He had also described the method of estimation of the parameters of the model. On the basis of empirical data he had shown that the model was an improvement over the Fairfield Smith's law in describing the relation between the plot size and variance of mean/plot in perennial crops.

Narayanan (1966) showed that the degree of precision due to analysis of covariance declined gradually with an increase in the time between experimental yield and pre-experimental yield. On an average the increase in the precision varied from two fold in the first year to 1.5 fold in the third year.

Narayanan (1968) suggested that in Rubber trunk girth could behave as an additional calibrating variable apart from pre-experimental yield for increasing precision from field experiments through double covariance analysis.

Agarwal *et al* (1968) revealed that the maximum reduction of error could be obtained from covaraiance analysis where pre-experimental yield for a period of two years was used as a a concomitant vairable. Abeyawardane (1970) observed that in coconut 30 to 50% reduction in experimental error could be achieved by using two years pre-experimental yield as the calibrating variable.

Rai *et al* (1973) suggested a method for generating estimates of uniformity trial data from the yield of the experimental trees receiving different treatments in occurance with the experimental design.

Singh *et al* (1975) concluded that in experiments with mango one pre-experimental period or two cosecutive years was sufficient to control error to a minimum level.

Sunderaraj (1977) developed a procedure for removing the block effect from treatment effect, in the case of confounded and incomplete block designs.

Nair, (1981) observed that in cashew pre-experimental yield data for two years immediately prior to the start of the experiment was sufficient to reduce error through the use of covariance analysis.

Prabhakaran and Nair (1983) suggested that application of covariance analysis would result in a considerable gain in precision in field trials on cashew crop. Single tree plots in blocks of varying sizes were chosen for estimating the relative efficiency of covariance adjustment over no adjustment due to the fact that they provided maximum information per tree. Among the calibrating variables a composite index involving pre-experimental yield and certain biometric charactors such as trunk girth, canopy spread, and plant length served as a better calibrating variate than the individual charactors. They also found that the relative gain in precision due to covariance analysis with pre experimental yield as covariate over conventional analysis ranged from 35% to 44% in blocks of different sizes.

2.2 Adjustment by neighbouring plots

Papadaki's (1937, 1940) used informations from neighbouring plots for the removal of spatial heterogeneity. He worked out the performance of each plot as deviation from appropriate mean. Then for each plot a concomitant variable was worked out from the deviations of the neighbours that could be regarded as measure of the inherent fertility of the plot. Finally the treatment mean was adjusted for the effect of the covariate. Papadaki's method was also useful for coping with the possible intra plant competition and for the adjustment of competition effects.

Bartlett (1938) pointed out that the correlation between the performance of neighbouring plots was such that the covariance adjustment of the residuals proposed by Papadakis might remove too much variation. For that reason he recommended two degrees of freedom instead of one for the regression coefficient and that has remained as a standard procedure.

Pearce and Moore (1976) described a method of adjusting plots by their neighbours as a means of reducing experimental error independently of blocking structure. They found that the adjustment by neighbouring plots was more efficient with longer blocks than with smaller ones. When there were only few treatments to be compared the expected relative gain in precision due to the incorporation of NN method over the conventional method of blocking was found to be negligibly small. Adjustment was made by covariance analysis for the performance of ends. Two degrees of freedom was assigned for estimation of regression coefficient with single covariance instead of usual one degree of freedom. Adjustment was also made by double covariance for the performance of ends and sides regaring them as to independent variables. The process was repeated for neighbours and corners and three degrees of freedom was recommended for the estimation of regression coefficient. The method was applied to trials of various perennial fruit crops. Most of the trials had the experimental error reduced although there were few exceptions. The technique was perticularly successful in tea but unsuccessful with apple. Double covariance was in general superior to single covariance. They found that in most of the trials blocking resulted in inconsistant results. The use of residuals of neighbouring plots as covariates also gave similar results. In certain cases error was increased when all combinations of neighbouring plots were used. In certain others the results were encouraging. No single pattern of neighbouring plots emerged as the most succesful. When results from calibration trials were also used along with iterated NNA the reduction was greater.

Bartlett (1978) re-examined the method of adjusting plot values by covariance on neighbouring plots in randomised field experiment suggested by Papadaki's (1937) theretically and empirically for one dimensional and two dimensional layouts making use of the Markovian and autonormal models. He concluded that the gain in efficiency of the method over the conventional randomised block design could be appreciable when the number of treatments to be compared was fairy large and could be increased by iterating the analysis. Further when block effects were removed the advantage of the new method over the conventional method was negligibly small.

Plot values were adjusted by covariance on neighbouring plots in cocoa progeny trial by Lockwood (1980). He derived covariates directly from the observations on neighbouring plots, unadjusted for treatment effect rather than residuals but the results were inconsistant. There was no general recommendations on combination of neighbouring plots whose residuals would form an effective covariate. Adjustment by the residuals of the appropriate neighbouring plots was effective in cocoa often giving reduction in experimental error equvalent to those to be expected from a 50% increase in total area. He found that the standard error of the difference between the progenies was reduced by 10% and often by over 20% when the covariates were formed from the residuals of neighbouring plots and the analyses were iterated using successively improved estimates of treatment effects to derive fresh residuals.

Kempton and Howes (1981) applied the method of adjusting plot values by covariance on neighbouring plots for the analysis of data generated from plant breeding trials. They found that the method was very effective in reducing variation caused by spatial heterogeneity. They recommended one dimensional neighbour model where plots were long and narrow. According to them the Papadakis adjustment reduced error 5%. They also found that the method was very useful when plot values were affected by the performance of particular varities occuring in neighbouring plots. The additional reduction in error from adjusting for neighbours averaged around 13% and the technique appeared to be especially effective in trials with high coefficient of variation. Further blocking by replication appeared to be no more effective in reducing error in trials with higher variability, suggesting that the increased heterogeneity occured mainly from plots within replicate. Results obtained from trials with replicated standards showed that the reduction in the estimate of error variance truely reflected the increased accuracy of the estimates of variety means.

Green *et al* (1985) assumed a smooth trend plus independent error model to represent the environmental effect on the yield of a field plot experiment. Least square smoothing was applied to estimate both the treatment effect and the effect of linear trend. Treatment estimates were closely related to those resulted from a generalised least square analysis in which the covariance structure for the environmental effects had a particular form.

Besag and Kempton (1986) described a different application of the use of neighbouring plot values in the analysis of agricultural experiments. He proposed a method of analysis derived from the stochastic description of plot yields with randomness arising as a consequence of fertility model together with the superimposed ramdom error component.

2.3 Other methods of adjustment

Williams (1952) and Atkinson (1969) tried to express the fertility pattern of a random field in mathematical terms. They suggested simple linear auto regressive model for the purpose. But the random residuals of the model were not independently distributed of their neighbours although the process of parametric estimation involved such an assumption. Consequently the method suggested by them was not acceptable to the scientific community.

Besag (1972) proposed the auto logistic model to overcome these difficulties. But the model had also many other limitations and was not acceptable to most workers.

A new method of NN analysis known as 'moving block' which was analogous to the classical form of analysis for fixed blocks was developed by Wilkinson *et al* (1983). It was free from most of the defects of the Papadaki's procedure and produced approximate unbiased estimates. They pointed out that an iteration of the analysis as suggested by Bartlett (1981) resulted in a substantial positive bias in the treatment 'F' ratio and NN method was very inefficient when there were substantial trend effects in the data. A theoretical explanation of these results was also given in their paper. According to them the efficiency of

NN analysis could be represented as the product of two factors namely an efficiency factor for size of error variance and an average efficiency factor for treatment estimation relative to the specific error vairance. According to them a smooth trend + independent error model would be appropriate for field experiment. If there were no interplant competition effect, moving block method would be found to be more efficient than analysis of complete block and incomplete block experiments and standard analyses of latin or lattice square designs.

Materials and Methods

3. MATERIALS_AND_METHODS

3.1 Methods of collecting data

The experimental data required for the present study were gathered from the available records of Cashew Research Station, Madakkathara, Cadbury Co-operative Cocoa Research Project, College of Horticulture, Vellanikkara, Instructional Farm, Vellanikkara and Coconut Research Station, Balaramapuram under Kerala Agricultural University. As a whole, four sets of data pertaining to long term trials on cashew, coconut and cocoa were collected.

The relevant details of the data collected on cashew from the Cashew Research Station are given below.

Period of observation	-	8 years (1982-'89)
Observations	-	Yield/tree
Design	-	RBD
Number of treatments	-	16
Number of replications	-	3
Number of plants/treatment	-	9

Description of treatments (varieties of Cashew)

Treatment Code	Variety	Treatment Code	Variety
T1	ASR-1	T5	T-1-BLA
T2	VENG36-3	T6	T-40-BLA
T3	SWT1	T7	T56-BLA
T4	VENG-37-3	T8	T273-BLA

T9	M-10/4	T13	H-4-7
T10	M-6/1	T14	K-10-2
T11	K-27-1	T15	BLA-139-1
T12	M-76/1	T16	BLA-256-1

The details of data collected on cocoa from the Cadbury KAU Co-operative Cocoa Research Project are given below.

Period of observation	-	4 years (1989-92)
Design	-	RBD
Number of Treatments	-	7
Number of replications	-	4
Number of plants/treatment	-	10

Description of treatments

T1 - Training to 1-1.5m and developing single tire.

T2 - Training to 1.5-2m and developing single tire.

T3 - Training to 2-2.5m and developing single tire.

T4 - Training to 1-1.5m + second tire 1-1.5m above.

T5 - Training to 1.5-2m + second tire 2-2.5m above.

T7 - Central (without pruning)

Two sets of data were available on coconut. Of these one set obtained from Coconut Research Station, Balaramapuram consisted of the results of the spacing cum manuring trial and the other from the instructional Farm, Vellanikkara related to the results of a uniformity trial.

The details of the first experiment are given below.

Period of observation - 4 years (1986-89)

Design - FBD

Number of treatments - 9

Number of replications - 3

Description of treatments

Levels of Spacing-3; S_0-5m x 5m, S_1-7.5m x 7.5m, S_2-10m x 10m

Levels of fertilizer-3; M_0 - no fertilizer

M_1 - N:P:K at the rateof 340:225:450 gm/palm/year

M_2 - N:P:K at the rate of 640:450:900 gm/palm/year

Number of trees/net plot S_0 - 25, S_1-9, S_2-4

Four year yield data from the uniformly maintained bulk crop laid out as a rectangular arrangement of 28 rows each consisting of six lines consisted the material for the second sets of experiment on coconut.

3.2 Statical analysis

3.2 (a) Plot size estimation

Yield data generated from uniformity trials were arranged as a two way layout. Missing values were replaced by the average of the means of corresponding rows and columns to which they belonged.

Neighbouring units of the array were combined to from plots of various sizes and shapes, a tree being the basic unit. Coefficient of variation defined as C.V.=standard error/mean x 100 was calculated for each plot arrangement. The relation between plot size (x) and variance of mean/plot (V_x) suggested by Fairfield Smith (1938) was utilised in estimating plot size. This relation is given by

$$V_x = \frac{V_1 e^u}{x^b} \qquad \text{......... (3.2.1)}$$

Where x - Number of units (trees) in a plot

V_x - Variance of mean per plot of size x units

b - An index of soil heterogeniety and is a measure of correlation among contigous units.

e^u - Random error component where u is $N(O, \sigma^2)$

The relation is logarithmically linear and hence 'b' can be estimated by the principle of least squares.

Smith's model can also be alternatively expressed in terms of the average coefficient of variation as $Y = ax^{-g}$ where Y is the average coefficient of variation for a plot of size 'x' units and 'g' soil heterogeniety coefficient. This has the same form on the original Smith's model. The curvature C on any part of a curve is defined as

$$C = \frac{Y_2}{(1+Y_1{}^2)^{3/2}} \qquad \text{.........(3.2.2)}$$

where Y_1 and Y_2 are the first and second derivatives of the functional form. The point at which the average curvature attaining the maximum value is obtained by differentiating the expression setting

dc/dx = 0. The resulting equation is

$$x^{2(g+1)} = (ag)^2 \ (2g+1)/(g+2) \qquad \text{.......(3.2.3)}$$

where $g = b/2$, $a = \sqrt{V_1}/\overline{x}$ and $\overline{x}$ is the grand mean.

3.2. (b) Generation of uniformity traial data from the result of long term experiments.

The method suggested by Rai *et al* (1973) was used for generating estimates of uniformity trial data from the yield of experimental trees receiving different types of treatments in concurrence with an experimental design.

The linear model used for the analysis is of the form $Y_{ijk} = u + t_i + b_j + e_{ijk}$ ....(3.2.4)

$i = 1,2,-----,t$

$j = 1,2,-----,r$

$k = 1,2,-----,u$

Where Y_{ijk} = The yield of the $(ijk)^{th}$ plot

u = the general mean effect

t_i = effect of the i^{th} treatment,

b_j = effect of the j^{th} block.

e_{ijk} is the random error component which is assumed to be normally distributed with zero mean and constant variance.

Since the block effect does not come in to the picture in the case of uniformity trial data the same was ignored and the model was modified as

$y_{ijk} = u + t_i + e_{ijk}$ .... (3.2.5)

$t_i = T_i/n_i$ ....(3.2.6)

where t_i = estimate of the effect of the i^{th} treatment

T_i= total of 'n_i' observations receiving the i^{th}

treatment, $\mu = y.../N$ where $N= \sum_{i=1}^{t} n_i$

From this $y_{ijk} - \hat{t}_i = \hat{\mu} + e_{ijk}$ ....(3.2.7)

The resulting residuals indicated in (3.2.7) were analysed in the same way as was done in the case of uniformity trial data. In the case of confounded designs and incomplete block designs 't_i' will not be free from block effects. Hence block effects are to be removed from the estimate of t_i. For this, the procedure developed by Sunderaraj (1977) could be adopted.

3.2 (c) Preparation of fertility contour map

The data gathered from uniformity trials or such data generated from secondary sources through the statistical procedure described in the previous paragraph could be utilised in preparing fertility contour maps. Such diagrams are helpful in giving a visual impression about the soil fertility variation in the experimental field with a view to determine size, shape and orientation of plots and blocks. Fertility contour maps were prepared in the following way. Correspinding to each plot except the first and last columns and rows two dimensional moving averages of period three were worked out and a two way table was formed with these averages. These average values were plotted graphically and fertility bands prepared by means of lines passing through areas of equal fertility. In order to classify the gradietary in fertility status into a limited number of groups the well known stratification procedure developed by Dalenius and Hodges (1959) known as the cumulative $\sqrt{f}$ procedure was used. This method consists in locating stratum boundaries by equalising the cumulative $\sqrt{f(y)}$ distribution where f(y) is the frequency function of the random variable. Sethi (1963) has showed that this rule would provide optimum stratification even when the number of strata was as small as two or three.

3.2. (d) Estimation of the proportionate genetic variation.

Freeman (1963) suggested that the total variance per plant (V_x) of a plot of x plants could written as

$$V_x = V_1'/x^b + V''/x \qquad \text{.........} (3.2.8)$$

where V_1'/x^b is the variance per plant among plots of x plants (obtained from the Fairfield Smith law) and V''/x is the variance per plant within a plot of x plants where V'' is the variane of yields of single plant. If $V_1' = V_1\alpha$ and $V'' = V_1 (1 - \alpha)$, α being the proportion due to environment of a variance of a unit plot, Equation (3.2.8) can be rewritten as

$$V_x/V_1 = \alpha/x^b + (1 - \alpha)/x \qquad \text{...........}(3.2.9)$$

Freeman (1963) suggested a method by which the above relation between variance components could be expressed in terms of serial correlations among nearby plants. Thus if ρ_1 is the serial correlation between adjacent plants, ρ_2 is that between plants with one intermediate, ρ_3 is that between two intermediates and so on and assuming that all the plants are in one long row, the serial correlatives and variance can be related by the following equations.

$$V_2/V_1 = (1+\rho_1)/2$$
$$V_3/V_1 = (3+4\rho_1+2\rho_2)/9 \qquad \text{...........(3.2.10)}$$
$$V_4/V_1 = (2+3\rho_1+2\rho_2+\rho_3)/8$$

From this the value of α can be estimated as

$$\alpha = 2\rho_1^2/(2\rho_2+\rho_3+\rho_1) \qquad \text{......... (3.2.11)}$$

and $\log 3/\log(1+\rho_1/\alpha) = \log 2.\log(1+(4\rho_1+2\rho_2)/3\alpha)$ .....(3.2.12)

where $(1-\alpha)$ is the proportion or genetic variation and α, that of environmental variation.

3.2(e) Analysis of covariance.

The linear model for the analysis of covariance of a randomised block design is given by

$$y_{ij} = \mu+\tau_i+\rho_j+\beta(x_{ij}-\bar{x})+e_{ij} \qquad \text{........... (3.2.13)}$$

where μ, τ_i, ρ_j, β and e_{ij} are the general mean effect, the effect of the ith treatment, the effect of the jth block, average regression coefficient from the error line and random error component respectively. Y_{ij} is the yield of the plot of the j^{th} replication receiving i^{th} treatment and x_{ij} is the pre-experimental yield of the $(ij)^{th}$ observation and $(x_{ij} - \bar{x})$ represents the deviation of observed x_{ij} from the mean of the observations on the covariate. The structure of the analysis of co-variance for a randomized complete block design is presented in Table I. The average within treatment and replicate regression is estimated by the quantity b_{yx} where $b_{yx} = E_{xy}/E_{xx}$

Table I. Convariance analysis for a randomised complete block design.

Source of variation	df	Sum of Products y^2	xy	x^2	adjusted sum of squares df	ss
Replicate	r-1	R_{yy}	R_{xy}	R_{xx}		-
Treatment	v-1	T_{yy}	T_{xy}	T_{xx}		
Error	(r-1)(v-1)	E_{yy}	E_{xy}	E_{xx}	{(r-1)(v-1)-1}	$E_{yy}' = E_{yy} - \frac{E_{xy}^2}{E_{xx}}$
Treatment +error	r(v-1)	T_{yy} $+E_{yy}$	T_{xy} $+E_{xy}$	T_{xx} $+E_{xx}$	r(v-1)	$(T_{yy}+E_{yy})' = (T_{yy}+E_{yy}) - (T_{xy}+E_{xy})^2/(T_{xx}+E_{xx})$
Treatment adjusted for average error regression					v-1	$(T_{yy}+E_{yy})'-E_{yy}'=T_{yy}'$

The estimates and variance of the estimates of different treatment contrasts, $\hat{t}_i$ are obtained as

$$\hat{t}_i = \bar{y}_i - \bar{y} - b(\bar{x}_i - \bar{x}) \qquad \text{..........(3.2.14)}$$

and $V(\bar{t}_i - \bar{t}_m) = \sigma^2 (2/r + (\bar{x}_i - \bar{x}_m)^2 / E_{xx})$ .... (3.2.15)

σ^2 is estimated by the error mean square obtained from Table I as $\{(T_{yy}+E_{yy})'-T_{yy}'\}/\{(v-1)(r-1)-1\}$. It has been found that the variance of the estimate of difference between any pair of treatment means is not constant. Hence in order to make the standard error of the difference between treatments a constant for any pair of treatment, $(\bar{x}_i-\bar{x}_m)^2$ in the above variance was replaced by $T_{xx}/(k-1)$, where T_{xx} is the treatment mean square for the x variate (Snedecor and Cochran (1967)) Thus,

$$V(\bar{t}_i - \bar{t}_m) = \sigma^2 \{(2/r) + T_{xx}/[(k-1)E_{xx}]\} \qquad \text{.........(3.2.16)}$$

3.2.(f) Use of covariance to control gradients and quadratic covariance

Federer and Schlottfeldt (1954) used pseudo concomitant variables to control gradients through quadratic covariance. They assumed that the action of the environmental gradient was from the centre of the replicate towards the end. They assigned plot numbers to different plots within a replicate such that the sum of the plot numbers in each replication is equal to zero. If p_l and p_m are two plots which lie 'j' units apart from the centre of the plots on the right and left sides of the central part within the replicate the pseudo plot numbers assigned to them are j and -j respectively. If x_1 stands for the pseudo concomitant variable denoting the serial number of the plot with in the replicate and x_2 the square of the numbers in the sequence x_1, the linear model used for the analysis of quadratic covariance is given by

$$y_{ij} = \mu + t_i + b_j + \beta_1(x_{1ij} - \bar{x}_1) + \beta_2(x_{2ij} - \bar{x}_2) + \epsilon_{ij} \qquad \ldots\ldots(3.2.17)$$

where y_{ij} is the $(ij)^{th}$ observation of the study variate μ, t_i, b_j, β_1, β_2 and ϵ_{ij} respectively denote the mean effect of i^{th} treatment, the effect of j^{th} replicate, the average regression coefficient due to the linear trend, the coefficient due to the curvilinear relationship and a random error component. x_{1ij} and x_{2ij} respectively denote the values of the pseudo concomitant variable x_1 and those on its square x_2. $\bar{x}_1$ and $\bar{x}_2$ denote the means of x_1 and x_2 respectively.

3.2.(g) Adjustment by neighbouring plots.

The method of adjusting plots by their neighbours developed by Papadakis (1937) was applied to the empirical data to examine the feasibility of reducing experimental error independently of the blocking structure. It was assumed that the plots of the layout lie on a rectangular grid though the entire area could be of any shape and each plot can receive one or the other of the treatment in the experiment.

Treatment means were first worked out and appropriate plot means subtracted from plot yields to form residuals, some of which were positive others negative. The residuals were then arranged into a rectangular array in accordance with the plan of the experiment to show their spatial relation. The concomitant variables were identified as follows.

A	B	C
D	X	E
F	G	H

Let us denote a plote by X and those near to it by A B C D E F G and H. D and E could be termed as the ends(I), B and G the sides (J) and the all four together may be called as neighbours(IJ). Using lower case letter to indicate the residuals of the plot designated by the corresponding capital, a concomitant value for X derived by its ends would be (d+e)/2. But if the value for D were missing or if X came at the end so that D did not exist, the value would be taken as 'e'. The data were examined by the analysis of covariance and two d.f. were allowed for the estimation of the regression coefficient instead of usual one as suggested by Bartlett (1978)

3.2.(h) Iterative process.

In the iterative process new covariates were formed at each stage of iteration on the basis of the adjusted plot yields derived from the Papadakis procedure of the previous stage and the process is continued until two successive estimate of treatment effect more or less coincide.

The statistical theory of iterative process has been described by Wilkinson *et al*(1983) by using some set operations as follows:

Let N(i) denote the set of column neighbours of plot i, namely (i-1, i+1) if plots are serially indexed within columns. Let T(i) the treatment applied on the plot i and U(j) the set of internal plots with treatment j.

In particular UT(i) is the set of internal plot with the treatment on plot i. Let $\bar{y}_{N(i)}$ denote the NN mean for y_i namely $(y_{i-1}+y_{i+1})/2$ and $y_{UT(i)}$ denote the mean of r interal plots with treatment T(i) where r is the number of replication.

The NN adjustment for a variate value y is given by $y_i^*(b) = y_i - b(\bar{y}_{N(i)} - \bar{t}_{TN(i)})$ ..... (3.2.18)
where b is a coefficient which in practice will be so chosen as to minimize the residual variance of the adjusted value and t denote the estimate of treatment parameter τ . Hence $\bar{t}_{TN(i)}$ denote the mean of such estimates for the neighbours of i. This is the general form of Papadakis adjustment with prior correction of NN covariate for the treatment effect. In the first cycle of an iterative analysis the treatment means $\bar{y}_{U(i)}$ are used as the initial estimate of the treatment parameter τ_i and the Equation (3.2.18) can be rewritten as $y_{1i}^*(b) = y_i - b_i\ (\bar{y}_{N(i)} - \bar{y}_{UTN(i)})$ .....(3.2.19)
Note that the 2r elements in UTN(i) are all distinct and do not include i. From (3.2.19) the treatment estimates were obtained as

$$t_{1j} = \bar{y}_{U(j)} - b_1\ (\bar{y}_{NU(j)}) - \bar{y}_{UTNU(j)}) \qquad \text{........(3.2.20)}$$

Substitution of (3.2.20) in (3.2.19) given the form of the Papadaki's adjustment in the second cycle. The process is continued until two successive estimates of treatment effects becomes more or less same

3.2.(i) Moving block method

In this method a new variety y_{ij}' is defined as a linear function of y_{ij}, where y_{ij} is the yield of the i^{th} treatment in the j^{th} block.

$$y_{ij}' = y_{ij} - b(y_{nm}-y_t) \qquad \ldots\ldots (3.2.21)$$

where y_{nm} is the average of yields of the neighbouring plots and y_t is the corresponding treatment mean (averaged over blocks) The value of b is estimated iteratively such that the error mean square is minimized. The value of b is given in terms of within block variance and covariance by Wilkinsons *et al* (1983) as

$$b = \frac{Cov(y_i, \bar{y}_{N(i)})}{V(\bar{y}_{N(i)})} \qquad \ldots\ldots\ldots\ldots(3.2.22)$$

where $\bar{y}_{N(i)}$ is the NN mean for y_i namely $(y_{i-1} - y_{i+1})/2$

3.2.(j). Multiple covariance analysis

Let X and Z denote two ancillary variates highly correlated with the study variate Y. A suitable model for double covariance analysis is given by

$$Y_{ij} = u+t_i+b_j+\beta_1(x_{ij}-x)+\beta_2(z_{ij}-z)+e_{ij} \qquad \ldots\ldots (3.2.23)$$

where u, t_i, b_j, e_{ij}, y_{ij} have the same meaning as in the case of linear model for variance with one ancillary variable. x_{ij} and z_{ij} denote the set of observations of the covariates X and Z respectively. β_1 and β_2 are the partial regression coefficient of Y on X and Z respectively. An outline of the analysis of covariance table with two concomitant variables is furnished in Table II.

Table II. Outline of the table of double covariance analysis

Soure	d.f.	sum of products					
		xx	xz	zz	xy	zy	yy
Blocks	r-1	Bxx	Bxz	Bzz	Bxy	Bzy	Byy
Treatments	k-1	Txx	Txz	Tzz	Txy	Tzy	Tyy
Error	(r-1)(k-1)	Exx	Exz	Ezz	Exy	Ezy	Eyy
Treatment +Error	r(k-1)	Exx'= Exx +Txx	Exz'= Exz +Txz	Exy'= Ezz +Tzz	Ezy'= Exy +Txy	Ezy'= Ezy +Tzy	Eyy'= Eyy +Tyy

$\bar{\beta}_1$ and $\bar{\beta}_2$ are obtained by solving the following equations

$\bar{\beta}_1 E_{xx} + \bar{\beta}_2 E_{xz} = E_{xy}$ .... (3.2.24)

$\bar{\beta}_1 E_{xz} + \bar{\beta}_2 E_{zz} = E_{zy}$ .... (3.2.25)

and adjusted error sum of squares is obtained as

$E = E_{yy} - \bar{\beta}_1 E_{xy} - \bar{\beta}_2 E_{zy}$ .... (3.2.26)

with (r-1)(k-1) - 2 d.f

Adjusted treatment sum of squares is obtained as E_1-E with (k-1) d.f where $E_1 = E_{yy}' - \bar{\beta}_1' E_{xy}' - \bar{\beta}_2' E_{zy}'$ .... (3.2.27)

where $\bar{\beta}_1'$ and $\bar{\beta}_2'$ were obtained by solving

$\bar{\beta}_1' E_{xx}' + \bar{\beta}_2' E_{xz}' = E_{xy}'$ .... (3.2.28)

$\bar{\beta}_1' E_{xz}' + \bar{\beta}_2' E_{zz}' = E_{zy}'$ .... (3.2.29)

Estimate of treatment means are obtained as

$\hat{t}_i = \bar{y}_1 - \bar{y} - \bar{\beta}_1(\bar{x}_i - \bar{x}) - \bar{\beta}_2(\bar{z}_i - \bar{z})$ ...... (3.2.30) and $v(\bar{t}_i-\bar{t}_m) = 2\sigma^2/r + (\bar{x}_i-\bar{x}_m)^2\, V(\bar{\beta}_1) + (\bar{z}_i-\bar{z}m)^2\, V(\bar{\beta}_2) +$

$$(\bar{x}_i-\bar{x}m)(\bar{z}_i-\bar{z}m)\ Cov(\bar{\beta}_1,\bar{\beta}_2) \qquad .... (3.2.21)$$

where $$V(\bar{\beta}_1) = \frac{E_{zz}\sigma^2}{E_{xx}E_{zz}-E_{xz}} \qquad .... (3.2.32)$$

$$V(\bar{\beta}_2) = \frac{E_{xx}\ \sigma^2}{E_{xx}E_{zz}-E_{xz}^2} \qquad .... (3.2.33)$$

$$Cov(\bar{\beta}_1,\bar{\beta}_2) = \frac{-E_{xz}\ \sigma^2}{E_{xx}E_{zz}-E_{xz}^2} \qquad .... (3.3.34)$$

and σ^2 is estimated from the error mean square as

$$\sigma^2 = \frac{E}{\{(r-1)(k-1)-2\}} \qquad ....(3.3.35)$$

By algibraic identity in (3.3.31)

$$V(\bar{t}_i-\bar{t}_m) = \frac{2\sigma^2}{r} + \frac{T_{xx}}{k-1}\frac{E_{zz}\sigma^2}{E_{xx}E_{zz}-E_{xy}^2} + \frac{T_{zz}}{k-1}\frac{E_{xx}\sigma^2}{E_{xx}E_{zz}-E_{xy}^2} - \frac{T_{xz}}{k-1}\frac{E_{xz}\sigma^2}{E_{xx}E_{zz}-E_{xy}^2} \qquad ....(3.2.36)$$

The method can also be extended to the case of three auxiliary variable.

The suitable model for covariance analysis with three auxiliary variable is

$$y_{ij}=\mu+t_i+b_j+\beta_1(x_{ij}-\bar{x})+\beta_2(z_{ij}-\bar{z})+\beta_3(u_{ij}-\bar{u})+e_{ij} \qquad .....(3.2.37)$$

where X , Z and U denote the three ancillary variables affecting the study variable Y. $\bar{\beta}_1$, $\bar{\beta}_2$ and $\bar{\beta}_3$ are obtained by solving

$$\bar{\beta}_1E_{xx} + \bar{\beta}_2E_{xz} + \bar{\beta}_3E_{xu} = E_{xy} \qquad ....(3.2.38)$$

$$\bar{\beta}_1E_{xz} + \bar{\beta}_2E_{zz} + \bar{\beta}_3E_{zu} = E_{zy} \qquad ....(3.2.39)$$

$$\overline{\beta}_1 E_{xu} + \overline{\beta}_2 E_{zu} + \overline{\beta}_3 E_{uu} = E_{uy} \qquad \text{........(3.2.40)}$$

and adjusted error sum of square is obtained as

$$E = E_{yy} - \overline{\beta}_1 E_{xy} - \overline{\beta}_2 E_{zy} - \overline{\beta}_3 E_{uy} \qquad \text{........(3.2.41)}$$

with $\{(r-1)(k-1)-3\}$ d.f (where the symbols have their usual connotations)

Results and Discussion

4. RESULTS AND DISCUSSION

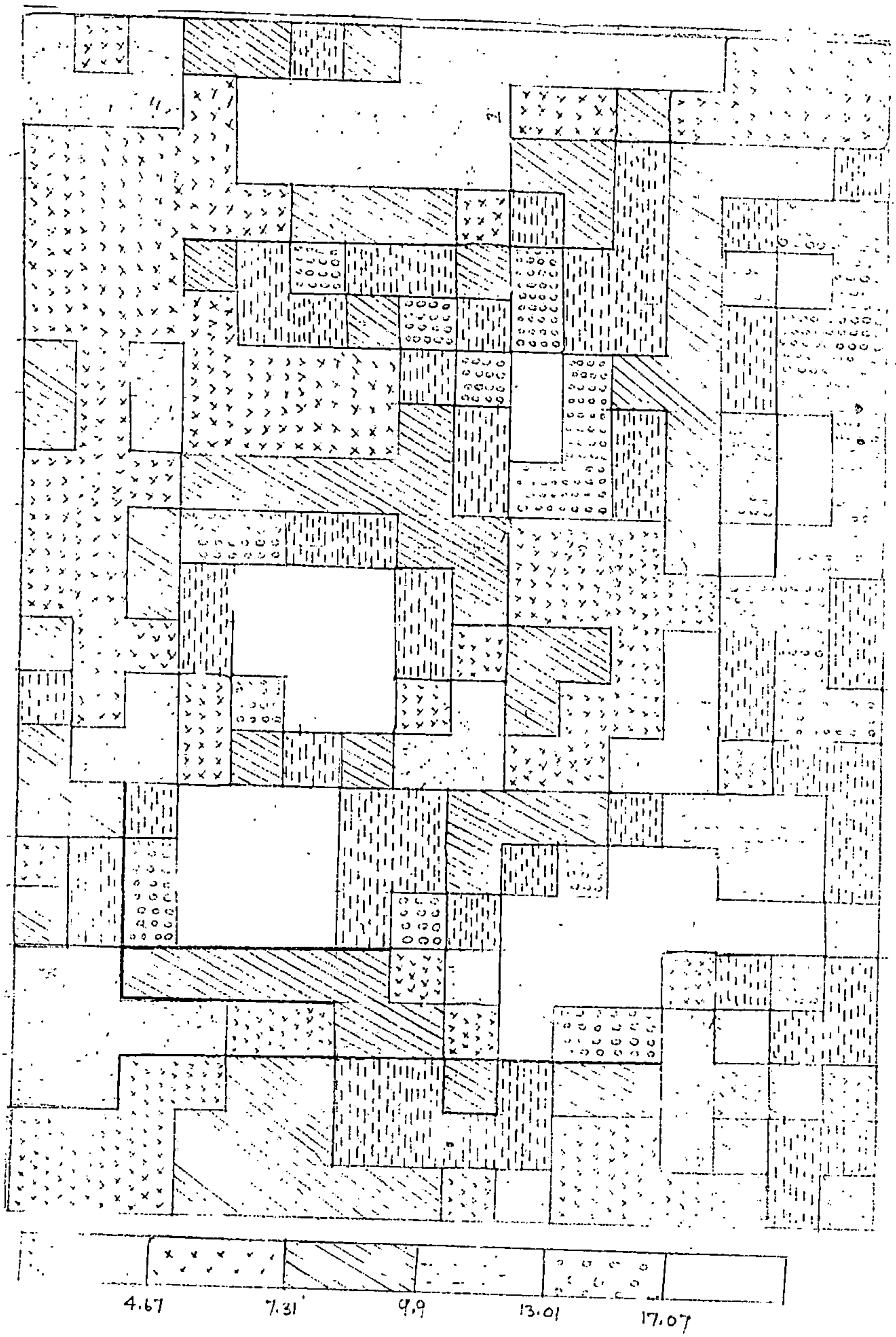
The results obtained from the analysis of experimental data gathered in the study are presented in the appended tables and discussed under the following heads.

1. Modelling of environmental variation
2. Relation between environmental and plant variation.
3. Indirect method of control of error through ANCOVA.
4. Nearest neighbourhood analysis.
5. Other methods

4.1 Modelling of environmental variation

Fertility contour map prepared from the data of the trial on cashew is presented in Fig.1. An inspection of the fertility contour map revealed that variation among the plots in the field did not follow any systematic pattern. But fertile patches were distributed all over the field in an almost erratic fashion. However there were few fertility bands running across the field indicating the possible orientation of blocks in that direction. Fertility contour maps prepared from the data on the other crops also exhibited more or less the same pattern. However, in a perennial crop, a part of variation depicted in fertility contour maps is due to the genetic make up of experimental material. Hence such diagrams are not efficient in detecting the true fertility pattern of the field. It only gives a description of the total variability among the units in the field.

Fig. 1. Fertility Contour Map from Data on Cashew



The extent of variability among plots of different sizes and shapes was estimated by calculating the value of coefficient of variation which is given in Table 1. In the case of coconut, the uniformity trial data collected from the Instructional Farm, Vellanikkara alone were used for the calculation of coefficient of variation. In general coefficient of variation was found to decrease consistantly with an increase in plot size. Maximum coefficient of variation was noticed in the case of single tree plots. The range of variation was from 11.77% to 55.58% in cashew. 62% to 433% in cocoa and 18.6 to 56.6% in coconut. From the results presented in Table 2. It could be infered that shape of the plot had no consistant effect on variability.

Fairfield Smith's model fitted to the uniformity trial data on the three crops are given in Table 3. Estimate of optimum plot size was determined mathematically for each crop by using the modified maximum curvature method. Average coefficient of variation was worked out for each plot size, details of which are presented in Table 1. Eight tree plots were found to be optimum for the conduct of yield trials on cashew and coconut. Field trial on cocoa demanded extremely large plot size. This may due to the high genetic variability of the material. The choice of a relatively large plot size will help in getting a more or less consistant result in the presence of wide variability. Mathew (1986) observed that in cashew the optimum plot size was six to seven trees. Sheela (1987) with the help of data

Table 1. Variance and Coefficient of Variation of Yields of Different Crops Corresponding to Plots of Different Sizes

Cashew			Cocoa			Coconut		
x	V_x	C_v	x	V_x	C_v	x	V_x	C_v
1	47.460	55.581	1	256.24	433.127	1	2680.989	56.60
2	101.115	40.562	2	546.095	316.148	2	1570.706	42.20
3	135.264	31.267	3	1000.010	285.212	3	1361.170	35.20
4	204.564	28.847	4	1034.822	217.601	4	900.295	32.40
6	284.175	22.666	6	1907.878	196.976	6	610.949	25.95
9	486.539	19.772	8	2236.107	159.936	8	459.434	22.80
12	571.869	16.077	10	2510.576	135.574	12	341.857	19.88
18	1173.247	15.352	12	3403.748	131.549	15	320.185	18.60
24	1226.919	11.774	20	3800.902	83.407			
			24	4985.413	79.603			
			30	4756.778	62.205			

x - Plot Size (Number of trees/plot)

V_x - Variance of mean yield per plot of 'x' trees.

C_v - Coefficient of variation (%) of yeild from plots of 'x' trees.

Table 2(a). Variance and Coefficient of Variation of Yields of Cashew Corresponding to Plots of Different Sizes and Shapes

Plot* Dimension	x	V_x	CV	Plot dimension	x	V_x	CV
1 x 1	1	47.460	55.581	2 x 12	24	970.645	10.473
1 x 2	2	99.715	40.842	3 x 1	3	138.025	31.594
1 x 3	3	132.504	30.955	3 x 2	6	269.04	22.055
1 x 4	4	187.943	27.65	3 x 3	9	332.289	16.092
1 x 6	6	299.120	23.255	3 x 4	12	353.238	12.636
1 x 8	8	407.973	20.369	3 x 6	18	814.017	12.788
1 x 12	12	618.081	16.714	3 x 8	24	982.285	10.535
1 x 24	24	1886.126	14.599	6 x 1	6	343.798	24.931
2 x 1	2	102.516	40.842	6 x 2	12	662.692	17.307
2 x 2	4	221.184	29.996	6 x 3	18	881.869	13.310
2 x 3	6	224.743	20.157	6 x 4	24	1062.619	10.989
2 x 4	8	330.744	18.34	9 x 1	9	640.081	16.714
2 x 6	12	653.464	17.186	9 x 2	18	1253.377	15.866
				18 x 1	18	1743.727	18.716

x - Number of trees per plot

V_x - Variance of mean yields per plot of 'x' trees

CV - Coefficient of variation (%) yield from plots of 'x' trees

* - A plot of dimension a x b indicates a rectangular arrangement with 'a' trees along rows and b trees along colums

Table 2(b). Variance and coefficient of variation of yields of cocoa corresponding to plots of different sizes and shapes.

Plot Dimension*	X	V_x	CV
1 x 1	1	256.243	433.127
1 x 2	2	548.514	316.850
1 x 3	3	1000.01	285.212
1 x 6	6	1893.411	196.227
1 x 10	10	2323.269	130.418
2 x 1	2	543.678	315.447
2 x 2	4	1016.046	215.618
2 x 3	6	1922.346	197.720
2 x 5	10	2697.883	140.539
2 x 6	12	2566.751	114.235
2 x 10	20	2270.646	64.4663
2 x 15	30	4756.778	62.205
4 x 1	4	1053.598	219.566
4 x 2	8	2065.415	153.711
4 x 3	12	4240.746	146.835
4 x 5	20	5331.158	98.780
4 x 6	24	4985.473	79.603
8 x 1	8	2406.709	165.927

X - Number of trees/plot

V_x - Variance of mean yield per plot of x trees

CV - Coefficient of variation (%) of yield of plots x trees

* - A plot of dimension a x b indicates a rectangular arrangement with 'a' trees along columns.

Table 2(c). Variance and coefficient of variation of yields of Coconut corresponding to plots of different sizes and shapes.

Plot Dimension*	X	V_x	CV
1 x 1	1	2680.98	56.6
1 x 2	2	1663.07	44.4
1 x 3	3	1154.35	34.8
1 x 4	4	984.16	33.16
1 x 6	6	541.72	25.02
1 x 8	8	520.05	24.12
2 x 1	2	1432.82	39.3
2 x 2	4	609.26	28.22
2 x 3	6	580.65	26.8
2 x 4	8	217.07	16.35
3 x 1	3	1407.71	36.76
3 x 2	6	683.27	27.31
3 x 4	12	449.56	23.29
3 x 5	15	326.18	18.6
4 x 1	4	834.37	29.71
4 x 2	8	261.63	20.56
4 x 3	12	234.99	16.84
8 x 1	8	180.57	15.8

x - Number of trees/plot

V_x - Variance of mean yield per plot of x trees.

CV - Coefficient of variation (%) of yeild of plots of 'x' trees.

* - A plot of dimension a x b indicates a rectangular arrangement with 'a' trees along row, and 'b' trees along columns.

Table 3. Fairfield Smith's models fitted to the experimental data on Cashew, Coconut and Cocoa

Crop	Equation	R^2
Cashew	$CV_x = 54.95\ x^{-0.473}$	0.991^{**}
Coconut	$CV_x = 56.23\ x^{-0.414}$	0.997^{**}
Cocoa	$CV_x = 489.78\ x^{-0.567}$	0.981^{**}

CV_x - The average coefficient of variation of yields of plots of 'x' trees.

x - Number of units (trees) in a plot.

R^2 - Coefficient of determination.

** - Significant at 1% level.

Table 4. Estimated serial correlation coefficients of varying order obtained from the uniformity trial data on Cashew, Coconut and Cocoa

Crop	ρ_1	ρ_2	ρ_3
Cashew	0.1351	0.0796	0.1390
Coconut	0.1586	0.1466	0.1673
Cocoa	0.1085	0.0228	0.0176

ρ_i - Serial correlation of i^{th} order (i = 1,2,3) which indicates the degree of spatial association between the yield of a tree and its i^{th} immediate neighbour.

on cocoa established that in the case of 10 plot blocks the optimum size was 18.

The estimated value of the coefficient of heterogeneity 'b' was relatively high indicating poor correlation among neighbouring trees. In other words genetic variation or tree to tree variation was expected to be more predominant than positional variation. It could be seen that the Smith's model gave an excellent representation of the environmental variation. The coefficient of determination (R^2) of the three fitted models ranging from 98.1% to 99.7%.

4.2 Relation between environmental and plant variation

Serial correlations (ρ_i) between neighbouring trees were calculated from the data gathered on each crop and are presented in Table 4 where ρ_i ($i = 1, 2, 3$) denote the serial correlation between the yields of trees and those of their ith immediate neighbours on the same row. The serial correlations satisfied the mathematical constraints suggested by Freeman (1963).

An attempt was also made to estimate the relative contribution of genetic and environmental components of variation to the total phenotypic variation between trees by modifying the Fairfield Smith's empirical law describing heterogeneity in yields of agricultural crops to include variation due to genetic factors as suggested by Freeman (1963). The component of within plot variation due to genetic and environmental factors was worked out for the three crops by choosing single tree plots as the basic unit of analysis. Serial correlations of varying orders were utilised in estimating the parameter, α which indicated the proportion of variability due to environment. The estimated values of α were 0.223, 0.116 and 0.546 for cashew, coconut and cocoa respectively.

The percentage of genetic variability given by $(1-\alpha)$ 100 was thus estimated to be 77.7, 83.4 and 45.4 in cashew, coconut and cocoa. Thus all the three crops exhibited large amount genetic diversity with coconut showing the maximum amount of heterozygosity. The results called for the use of calibrating variables and application of analysis of covariance for the control of inherent genetic variability among the trees in addition to the use of conventional or modified direct methods for the control of positional variation among the trees. Shrikhande (1957) with the help of data on coconut trees at Pilicode and Kasaragode experimental stations demonstrated that the inherent variability among coconut trees was as high as or even twice as high as the positional variation. Pankajakhshan (1960) also had estimated the genetic and environmental components of variation from data on coconut trees at Pilicode and found that they were in the ratio of 3:2 for the analysis based on yield data for the two years. The results on coconut obtained in the present study are in general agreement with the findings of these two earlier workers. But the estimated proportion of the genetic variability to the total variability in coconut was slightly high when compared to that reported in the earlier studies.

4.3 Indirect method of control of error through ANCOVA

The study emphasised the need for controlling tree to tree variation within each experimental plot caused by the genetic make up of the experimental trees through calibration and analysis of covariance.

Covariance analysis was attempted with pre-experimental yield or any of its transformed versions as concomitant variables. Two years yield data immediately prior to the start of the experiment were gathered from each tree to serve as an effective covariate. Error mean squares before and after application of the ANCOVA with different concomitant variables were determined and these were further utilised in estimating the percentage efficiency due to covariance analysis over conventional ANOVA of the relevant design. Since completely randomised design (CRD) and randomized block design (RBD) are the most common designs employed for experimentations with perennial crops and the available secondary data were from randomised block lay out, the present study was limited to the comparison of these two basic designs with and without the applications of ANCOVA. The relevant results are presented in Table 5. It could be seen that there had been considerable reduction in error variance in all the three sets of data relating to the three crops by the applications of ANCOVA. The linear regression coefficient of current year's yield records on pre-experimental yield data were found to be significant providing a logical explanation for the use of analysis of covariance. In the case of cocoa trial laid out in RBD analysis of covariance of the experimental yield data using pre-experimental yield data for one pre-experimental period as covariate resulted in as much as 325% efficiency. Consequently CV decreased from 37.88% to 20.99%. For cashew, the comparative efficiency of covariance analysis over conventional analysis of variance was over 200%. Similar results were also obtained in the values of coefficient of variation.

In coconut also covariance analysis assuming a completely randomised layout resulted in a substantial gain of precision (59%). In fact the relative efficiency of covariance analysis was directly proportional to the degree of heterozygosity of the crop species. It was most effective with cocoa which gave maximum coefficient of variation.

Covariance analysis fails when the study variate exhibits a non linear functional relationship with the concomitant variate. But even in such cases if the exact functional form is known the auxilliary information could be utilised for statistical control of error. In this study an attempt was made to know the effect of incorporating the various transformation on the ancillary variance such as $\sqrt{x}$, x^2 and log x in the linear model as covariates instead of x where x is the pre-experimental observation. The results are also given in Table 5. It could be seen that covariance analysis incorporating the transformed concomitant variables resulted in better error control than the one using conventional covariates. Of the four concomitant variables examined x, x^2, $\sqrt{x}$ and log x, $\sqrt{x}$ gave maximum efficiency for all the three crops. The percentage efficiency of covariance analysis with $\sqrt{x}$ as covariate over conventional analysis ranged from 150 to 345.

The maximum percentage gain in efficiency due to covariance analysis with $\sqrt{x}$ as the concomitant variate was recorded in yield trials on cocoa when there was blocking. The gain in efficiency achieved for this crop was as large as 340%. In coconut, percentage gain in efficiency due to covariance analysis with $\sqrt{x}$ as concomitant variate was larger (84%) with no blocking as compared to that with blocking (50%). Estimated percentage gain in efficiency through analysis of covariance of cashew yield with $\sqrt{x}$ as the covariate ranged from 91% to 102% in RBD to CRD. Prabhakaran and Nair (1983) found that in cashew the estimated efficiency of covariance analysis over conventional analysis with pre-experimental yield as the concomitant variable ranged from 35% to 44%. The estimated efficiency in the present study exceeded this range by a considerable margin. It was found that statistical control of error through covariance analysis after identifying a proper calibrating variable was better and more efficient method for the

Table 5. Efficiency of Covariance analysis in yield trials with or without blocking on Cashew, Coconut and Cococa by using pre-experimental yeild or its selected transformations ascovariate

Concomitant Variable(s) selected	Cashew						Coconut						Cocoa					
	CRD			RBD			CRD			RBD			CRD			RBD		
	MSE	CV	E	MSE	CV	E	MSE	CV	E	MSE	CV	E	MSE	CV	E	MSE	CV	E.
NA	11.568	41.38		10.714	39.82		270.15	13.92		233.27	12.93		39.76	40.7		34.42	37.88	
X	5.91*	29.57	196	5.78*	29.25	185	169.64*	11.03	159	174.04*	11.17	134	12.68*	22.99	314	10.58*	20.99	325
$\sqrt{x}$	5.72*	29.10	202	5.60*	28.79	191	146.37*	10.24	184	155.02*	10.54	150	13.01*	23.28	306	10.11*	20.53	340
log x	5.88*	29.50	197	5.92*	29.60	181	168.91*	11.01	160	171.60*	11.09	136	14.23*	24.37	279	10.36*	20.78	332
x $\sqrt{x}$	5.92	29.60	195	5.80	29.30	185	154.54	10.53	175	165.43	10.89	141	13.33	23.57	298	10.74	21.16	320
x log x	5.91	29.57	196	5.81	29.32	184	164.75	10.87	164	173.15	11.14	135	13.31	23.55	299	10.60	21.02	325
x x^2	6.03	29.87	192	5.89	29.52	182	130.00*	9.66	208	143.55	10.15	162	13.35	23.58	297	11.03	21.44	312

CRD - Completely Randomised Design

RBD - Randomised Block Design

MSE - Mean Square Error

CV - Coefficient of Variation in percentage

E - Percentage Efficiency

NA - No Adjustment

X - Pre-experimental Yield Data (Two Years)

* - Significant at 5% Level.

control of error than the ordinary method of blocking. Further, by the seperation of a large amount of non-environmental variability from error variance through ANCOVA, the effect of stratification on the control of error becomes secondary or non-significant and consequently blocked designs were found to be less efficient than the completely randomised designs. This is mainly due to the loss of degree of freedom for the estimation of the block contrast. Thus it appears that ANCOVA in CRD by taking $\sqrt{x}$ as the calibrating variable is a better method of controlling error than that of its application in RBD with the same calibrating variable.

Covariance analysis with $\sqrt{x}$ as the covariate resulted in an efficiency gain in the range of 6 - 25% over ordinary covariance analysis with x as the covariate. However double covariance analysis involving x or any of its functions as one of the covariate and any of the NN variables as the other covariate did not resulted substantial gain of precision of comparisons except in the case of yield data on coconut with no blocking. The percentage efficiency of quadratic covariance on coconut over conventional ANOVA was estimated to be 208 while that of conventional covariance analysis was low (159%). This result, though empirical, indicates the possibility of using quadratic covariance for the analysis of data on coconut for further reduction of error. In the case of the other two crops ANCOVA with $\sqrt{x}$ as auxiliary variate has resulted in better error control than the conventional procedure. Anyhow, the results definitely emphasise the need for using non conventional procedure, in the analysis and interpretation of data from experiments on perennial crops.

Often direct methods of control of error through blocking will not be sufficient to make sufficiently precise comparisons of treatment effects. The percentage variation removed through blocking could be negligibly small when compared to that which could be controlled through calibration and covariance analysis. Hence in the analysis and interpretation of data on perennial crops especially in those exhibiting large amount of genetic variability calibration of trees and application of linear or non-linear types of covariance analysis using appropriate concomitant variables shall be considered to be an important pre-requisite for increasing the efficiency of field experimentation.

In situations where the original covariates fail to satisfy a linear relationship with the study variate an appropriate transformed form of the original concomitant variables or non-linear covariance with a proper choice of the functional form has to be attempted for effective error control and for increasing the sensitivity of the experiment. As this requires no additional expenditure on the part of the researcher apart from efficient use of the available data efforts are to be made to develop appropriate computer softwares for the application of multiple covariance and non-linear covariance for the efficient analysis of experimental data and the approach should be popularised among researchers working on perennial crops.

An attempt was also made to indicate how the conclusions drawn from an experiment vary according to the type of the analysis chosen by the researcher and to emphasise the need of choosing the appropriate statistical tool in data analysis to arrive at a reliable interpretation from experimental data. Bar charts indicating multiple comparisons among treatments in the case of ordinary analysis and analysis of covariance with varying concomitant variables among with the estimated least significant difference and corresponding error means square are given in Fig.2. It could be seen that among the various covariates used $\sqrt{x}$ yielded the lowest CD for cashew and cocoa, while log x gave slightly better results with coconut.

4.4 NN analysis

Three different methods of NN analysis were applied to the yield data on the three perennial crops. These methods are :

1. Papadaki's procedure
2. Pearce's iterative process
3. Moving block method

4.4.1. Papadaki's Procedure

The concomitant variables used for the analysis constituted of the ends (I), sides (J) and neighbours (IJ) of each of the experimental plots. The effect of NNA was studied both in the case of grouping the plots into blocks and with no blocking. In each case the data were first subjected to ANCOVA, the auxiliary variate being the average of the residuals of the nearest neighbouring plots. The relevant results are presented in Table 6. It could be seen that in coconut and cocoa nearest neighbourhood analysis (NNA) resulted in a significant reduction of experimental error when ends were used as the NN covariates in the absence of blocking. The relative efficiency of NNA (with ends as covariate) was 125% as compared to ordinary analysis without blocking for coconut and it was 133% in the case of cocoa. In cashew NNA using ends as NN covariate resulted in 6% gain of precision over the conventional procedure and the reduction was not statistically significant. The three auxiliary variates I, J and (IJ) failed to exhibit consistant performance with all the crops. ~~Sides~~ ends (I) gave better results with experimental data on cocoa where as neighbours showed better performance in experimentation with coconut and cashew. From the summary table (Table 7) given, it could be seen that Papadaki's NN adjustment in CRD was more efficient than its application in RBD even when blocking was effective, but no general recommendation could be made about the choice of the

Table 6 . Estimates of MSE, CV, and efficiency gain (%) produced by covariance analysis with various combinations of a NN covariates and functions of preexperimental yield.

Concomitant	Cashew						Coconut						Cocoa					
Variable(s) selected	CRD			RBD			CRD			RBD			CRD			RBD		
	M.S.E	CV	E	M.S.E	CV	E	M.S.E	CV	E	M.S.E	CV	E	M.S.E	CV	E	M.S.E	CV	E
N.A.	11.568	41.38		10.714	39.82		270.15*	13.92		233.27	12.93		39.76*	40.7		34.42	37.88	
I	10.9	40.16	106	10.83	40.04	99	215.39	12.43	125	231.94	12.90	101	29.8	35.24	133	33.69	37.47	102
J	12.23	42.54	95	11.42	41.11	94	254.06*	13.50	106	228.99	13.63	90	43.85	42.75	91	38.53	40.07	89
IJ	10.51	39.43	110	11.00	40.35	97	205.109	12.13	132	229.21	12.86	98	36.17	38.82	109	38.55	40.08	89
X I	6.18	30.24	187	6.06	29.95	177	143.92	10.16	188	157.46	10.63	148	11.84	22.21	336	11.99	22.35	287
X J	6.22	30.34	186	6.13	30.12	175	169.90	11.03	159	190.66	11.69	122	13.98	24.14	284	11.98	22.34	287
X IJ	6.30	30.54	184	6.21	30.32	172	148.81	10.33	182	166.31	10.92	140	11.86	22.23	335	11.94	22.37	288
√X I	6.02	29.85	192	5.9	29.55	182	128.82	9.61	210	144.19	10.17	162	12.25	22.59	324	11.43	21.82	301
√X J	6.01	29.82	192	5.94	29.65	180	158.95	10.68	170	177.70	11.29	131	14.06	24.21	283	11.35	21.75	303
√X IJ	6.11	30.07	189	6.02	29.85	180	142.76	10.12	189	163.20	10.82	143	11.62	22.01	342	11.42	21.82	301
LogX I	6.17	30.22	187	6.23	30.36	172	141.11	10.06	191	160.06	10.73	146	13.41	23.64	296	11.61	21.99	296
LogX J	6.20	30.29	186	6.28	30.49	171	187.82	11.61	144	197.63	11.90	118	15.04	25.04	264	11.47	21.86	300
LogX IJ	6.26	30.44	185	6.35	30.66	169	167.31	10.95	161	189.56	11.66	123	12.09	22.45	329	11.72	22.10	294
X X^2 I	6.34	30.63	182	6.21	30.32	186	121.97	9.35	221	141.11	10.06	165	12.52	22.84	318	12.60	22.92	273
X X^2 J	6.34	30.63	182	6.25	30.41	185	147.19	10.27	184	167.46	10.96	139	14.80	24.84	269	12.54	22.86	274
X X^2 IJ	6.45	30.90	179	6.34	30.63	182	136.49	9.89	198	158.76	10.67	147	12.45	22.78	319	12.57	22.89	274
X √X I	6.23	30.36	186	6.12	30.10	189	137.07	9.92	197	156.08	10.58	149	12.54	22.86	317	12.24	22.58	281
X √X J	6.23	30.36	186	6.16	30.19	188	170.30	11.05	159	192.38	11.75	121	14.71	24.76	270	12.15	22.50	283
X √X IJ	6.33	30.61	183	6.24	30.39	185	152.66	10.46	177	175.5	11.22	133	12.28	22.62	324	12.24	22.58	281
X log XI	6.22	30.34	186	6.12	30.10	189	143.74	10.15	188	161.92	10.78	144	12.53	22.85	317	12.06	22.42	285
X log X J	6.22	30.34	186	6.17	30.22	187	177.80	11.29	152	200.44	11.99	116	14.67	24.73	271	11.98	22.34	287
X log XIJ	6.32	30.58	183	6.25	30.41	185	157.42	10.62	172	179.42	11.34	130	12.21	22.56	326	12.07	22.43	285

NA - No adjustment

MSE - Mean Square error.

E - Percentage efficiency.

CV - Coefficient of variation in percentage.

I - NN Cova riate namely ends.

J - NN covariate namely sides.

X - Preexperimental yield

* - Significants at 5% level

CRD - Complete Randemised design.

RBD - Randomised block design.

Table 7 Summary table indicating error mean squares in CRD and RBD with and without making Papadaki's NN adjustment using sides (I) and neighbours (IJ) as covariates.

Types of Analysis	Cashew		Coconut		Cocoa	
	EMS	CD	EMS	CD	EMS	CD
CRD	11.6	5.64	270.2	28.20	39.8	9.27
RBD	10.7	5.46	233.3	26.44	34.4	8.72
CRD-NN (I)	10.9	5.65	215.4	26.33	29.8	8.20
CRD-NN (IJ)	10.5	5.51	205.10	25.74	36.2	9.35
RBD-NN (I)	10.8	5.56	231.9	28.31	33.7	9.65
RBD-NN (IJ)	11.0	5.73	229.2	28.14	38.5	9.78

EMS - Error mean square

CD - Critical differenct at 5% level of significant

NN (I) - Papadaki's nearest neighbourhood adjustment using 'ends' as covariate.

NN (IJ)- Papadaki's nearest neighbourhood adjustment using 'neighbours' as covariate.

anciliary variate. In cashew choice of complete neighbours (IJ) resulted in lesser error variance than that due to blocking. This was also true in the case of coconut. But in cocoa trial the choice of side neighbours (I) produced better results. The percentage gain in efficiency of the NN method of Papadaki's over stratification as obtained from the experemental data on coconut was found to be 13.7 while that in the case of cocoa was over 16. However Papadaki's NN method did not yield any significant additional gain of precision in the analysis of the experimental data on cashew.

The results also emphasised the need for restricting Papadaki's NN method to the analysis and interpretation of data generated from experiments laid out in completely randomnised design unless unusually larger number of treatments are to be tested. In the case of data generated from block designs the added advantage of the method over the conventional method of analysis had been negligibly small on either direction. This empirical result is in close agreement with the findings of Bartlett (1978) on the use of NNA in block design.

Chetty (1989) has shown that in dryland experiments the relative efficiency of NNA over coventional procedure ranged from 85% to 198%. The results obtained in the present study are also included in the above efficiency range.

It is also interesting to examine empirically whether adjustment by neighbouring plots could be regarded as an effective alternative for stratification on blocking. In case it was found to serve as an effective alternative for blocking or stratification a completely randomised layout would generate useful data for the analysis and interpretation in place of the usual two way randomised lay out. Randomised block design would provide effective control of error through blocking only in such experimental situation where the direction of the environmental variation was known or could be identified by the experimenter. In perennial crops environmental variation would be usually negligibly small when compared to genetic variation and consequently gain in precision through stratification would be relatively small. Hence it would be worthwhile in such situation to use CRD for the layout of the experiment and apply NNA for reducing error and enhancing the precision of treatment comparisons as far as possible.

Bar diagrams indicating multiple comparisons among mean value, the error mean squares and critical difference estimated from the three sets of experimental data using Papadaki's NNA with ends sides or neighbours as NN covarites in randomised complete block layout is also presented in Fig.2. It could be seen that different methods of analysis had given rise to different inferences and logical interpretations of data, though there had been a high degree of overall uniformity among the findings.

Fig. 2(a) Multiple comparisons among treatment means by Papadaki's NN method f[...] different crops. Design : RBD Crop: Cashew.

Concomitant Variable	Array of treatment means with line diagram	MSE	CD
NA	T_{15} T_5 T_6 T_8 T_7 T_{10} T_{12} T_3 T_9 T_{16} T_2 T_1 T_{13} T_{11} T_4 T_{14}	10.7	5.4
X	T_{15} T_5 T_6 T_8 T_{10} T_3 T_9 T_7 T_{12} T_{16} T_{13} T_1 T_2 T_4 T_{11} T_{14}	5.78	4.0
log X	T_{15} T_5 T_6 T_8 T_7 T_{10} T_3 T_9 T_{12} T_1 T_{16} T_{13} T_2 T_4 T_{11} T_{14}	5.92	4.1
$\sqrt{x}$	T_{15} T_5 T_6 T_8 T_{10} T_3 T_7 T_9 T_{12} T_{16} T_1 T_{13} T_2 T_4 T_{11} T_{14}	5.6	4.0
I	T_{15} T_5 T_6 T_8 T_7 T_{12} T_3 T_{10} T_9 T_{16} T_1 T_2 T_{13} T_{11} T_4 T_{14}	10.83	5.5
J	T_{15} T_5 T_6 T_8 T_7 T_{10} T_{12} T_3 T_9 T_2 T_{16} T_1 T_{13} T_{11} T_4 T_{14}	11.42	5.8
IJ	T_{15} T_5 T_6 T_7 T_8 T_{10} T_{12} T_3 T_{16} T_9 T_2 T_1 T_{13} T_{11} T_4 T_{14}	11.00	5.7

N. A. - no adjustment

X - pre-experimented yield

I - ends of the plot as NN covariate

J - sides of the plot as NN covariate

IJ - neighbours of the plot S NN covariate

MSE - mean square error

CD - critical difference

T_1 - T_{16} - treatment codes

Fig.2(b) Multiple comparisons among treatment means by Papadaki's NN method for different crops. Design : RBD Crop: coconut.

Concomitant Variable	Array of treatment means with line diagram	MSE	CD
NA	T_9 T_6 T_8 T_5 T_3 T_2 T_4 T_7 T_1	233.27	26.44
X	T_6 T_9 T_5 T_8 T_3 T_2 T_4 T_7 T_1	174.04	51.81
log X	T_6 T_9 T_8 T_5 T_3 T_2 T_4 T_1 T_7	171.6	44.65
$\sqrt{x}$	T_6 T_9 T_5 T_8 T_3 T_2 T_4 T_1 T_7	155.02	48.16
I	T_9 T_6 T_8 T_5 T_3 T_2 T_4 T_7 T_1	231.94	28.31
J	T_9 T_6 T_8 T_5 T_3 T_2 T_4 T_7 T_1	258.99	29.25
IJ	T_9 T_6 T_8 T_5 T_3 T_2 T_4 T_7 T_1	229.21	28.14

N. A. - no adjustment

x - pre-experimented yield

I - ends as NN covariate

J - sides as NN covariate

IJ - neighbours as NN covariate

MSE - mean square error

CD - critical difference

T_1 - T_9 - treatment codes

Fig. 2(c) Multiple comparisons among treatment means by Papadaki's NN method for different crops. Design : RBD Crop: cocoa.

Concomitant Variable	Array of treatment means with line diagram							MSE	CD
NA	T_4	T_5	T_7	T_1	T_2	T_6	T_3	34.42	8.72
x	T_4	T_5	T_1	T_6	T_2	T_3	T_7	10.58	5.13
log x	T_4	T_5	T_1	T_2	T_7	T_6	T_3	10.36	5.04
$\sqrt{x}$	T_4	T_5	T_1	T_2	T_6	T_7	T_3	10.11	4.996
I	T_4	T_5	T_7	T_2	T_1	T_3	T_6	33.69	9.05
J	T_4	T_5	T_7	T_1	T_2	T_6	T_3	38.53	9.78
IJ	T_4	T_5	T_7	T_1	T_2	T_6	T_3	38.55	9.78

N. A. - no adjustment

x - pre-experimented yield

I - ends as NN covariate

J - sides as NN covariate

IJ - neighbours as NN covariate

MSE - mean square error

CD - critical difference

T_1 - T_7 - treatment codes

.pa

Double covariance analysis was attempted with selected NN variables (I, J or IJ) and functions of pre-experimental yield (x, $\sqrt{x}$ or log x) as auxiliary variates with a view to reduce experimental error to the minimum possible level. The results are also presented in Table 6. It could be seen that in coconut double covarance analysis using $\sqrt{x}$ and 'I' as concomitant variables produced more precise estimates than those of the conventional analysis in the presence of blocking and with no blocking. The obtained gain in precision was substantially higher than that in ordinary ANCOVA with x or $\sqrt{x}$ as covariates. The percentage gain in precision was also slightly higher than that obtained in the case of quadratic covariance. Similar was the case with cocoa. Double covariance with $\sqrt{x}$ and (IJ) as covariates resulted in an efficiency gain of 242% over conventional analysis in CRD when compared to an efficiency gain of 214% for ordinary covariance analysis in CRD with pre-experimental yield as the sole covariate. Similarly when experimental data on cashew were analysed using double covariance technique in CRD incorporating NN covariates along with a suitable function of pre-experimental yield there was a slight improvement in precisions. However when data were analysed as in RBD multiple covariance analysis did not give rise to any substantial gain in precision. This may be due to the loss of degrees of freedom in RBD for making block comparisons which might have adversly affected the precision of estimates of treatment contrasts.

The possibility of using triple covariance analysed for the control of error was also examined with the help of the empirical data. It was found that triple covariance analysis on the data on coconut using x, x^2 and NN (I) as covariates reduced CV from 13.92 to 9.35 in CRD. The percentage gain in efficiency was 121%. The same procedure led to an efficiency gain of 65% with RBD. With other two crops triple covariance analysis did not yield any promising results (Table 6).

4.4.2 Iterative procedure

Pearce's iterative procedure was also tried for the interpretation of experimental data on the three perennial crops with a view to reduce the environmental variation. The concomitant variable used for the analysis constituted the ends and neighbours of each of the experimental plots. The relevant results are presented in Table 8. It could be seen that in all the three crops iterative procedure resulted in a significant reduction in experimental error in the absence of blocking. When both ends and neighbours were used as covariates, the relative efficiency of iterative procedure in cashew over the conventional procedure with no blocking was 124% and 122% respectively. In the case of cocoa the percentage gain in precision due to iterative procedure over the conventional method was still higher (43%). But maximum percentage gain in efficiency was noted in coconut trials. When there was no blocking the percentage gain in efficiency of the iterative

TABLE 8. Error Mean Squares(E.M.S.) before and after the application of Pearce's iterative procedure along with the relative efficiencies of the process for different crops and NN covariates.

Crop	Design Selected	Concomitant Variable selected	E.M.S. Before	E.M.S. After	Percentage Efficiency Pearce	Percentage Efficiency Papadakis	Percentage Efficiency Wilkinson
Cashew	CRD	I	11.568	9.31	124	106	157
		IJ	11.568	9.48	122	110	
	RBD	I	10.714	9.56	112	99	
		IJ	10.714	10.53	102	97	
Cocoa	CRD	I	39.76	27.81	143	133	114
		IJ	39.76	34.42	116	109	
	RBD	I	34.42	31.8	108	102	
		IJ	34.42	38.51	89	89	
Coconut	CRD	I	270.15	168.24	160	125	137
		IJ	270.15	127.76	211	132	
	RBD	I	233.27	178.03	131	101	
		IJ	233.27	137.31	178	98	

'I', 'IJ' are the NN covariates namely ends and neighbours.

process with neighbours (IJ) as covariates over the conventional method was as high as 111%.

It could be further observed from the empirical analysis that there was no additional gain due to stratification when the iterative process was used. It could be better to layout the experiment in CRD (unless there was a strong ground for thinking in the other way), before attempting the iterative NNA process for the reduction of error. In the case of coconut the procedure results in comparatively high efficiency (160% and 211%). In the present study the number of iteration required to stabilize the treatment means ranged from five to eight in all cases under study. An illustration of the process is given in Table 9. In cashew and cocoa maximum efficiency of iterative NNA was observed when 'ends' were used as covariates in the absence of blocking. But in coconut maximum gain of precision by NNA was recorded when neighbours were used as covariates. Chetty (1989) has shown that in dryland experiments the relative gain in efficiency of iterative procedure over conventional method ranged from 70% to 325%. The results obtained in the present study are in general conformity with the above finding. The percentage gain of efficiency in the present study ranged from 89% to 211%. Results presented in Table 8 clearly indicated the consistant superiority of the iterative NNA process over the Papadaki's procedure.

Table: 9 Error Mean Squares (E.M.S.) and estimated treatment means obtained from Pearce's iterative Procedure.

Treatments	Initial Treatment means	Estimated Treatment means after each iteration					
		1	2	3	4	5	6
T_1	13.56	13.4	13.11	13.12	13.10	13.10	13.10
T_2	12.57	13.5	13.52	13.53	13.52	13.52	13.52
T_3	11.10	10.56	10.71	10.71	10.72	10.72	10.72
T_4	21.4	21.62	20.64	21.72	21.73	21.74	21.74
T_5	20.36	19.65	19.53	19.48	19.47	19.47	19.47
T_6	11.58	10.54	10.54	10.45	10.45	10.44	10.44
T_7	17.78	19.06	19.31	19.37	19.37	19.38	19.38
E.M.S.	36.17	34.76	34.54	34.45	34.42	34.42	34.42

T_1-T_7 - Treament Codes

4.4.3 Moving Block Method

Moving block method was also applied to the three sets of data and the relative efficiencies of the method over the other methods arrived at. Moving block method gave a significantly higher reduction in error mean square over conventional analysis of variance and that involving Papadaki's NN adjustment (Table 8). Among the three crops the estimated gain in efficiency through moving block method was highest (57%) in cashew followed by coconut (37%) and cocoa (14%). Of the three NN methods in cashew, moving block method produced the most precise estimate.

4.5 Other Methods

The quadratic covariance method involving the use of pseudo plot numbers as covariates suggested by Federer and Schlottfeldt (1954) to control gredients was also applied to the three sets of data to examine its suitability. The estimated error mean squares for the three sets (Table 10) were 10.73, 168.96 and 36.22 respectively. The methods gave a slight reduction in error mean square when applied to the data on coconut and the estimated gain in efficiency was around 28%. But in the case of the other two crops the method failed to record any appreciable reduction in error sum of square. This was due to non-significance of the regression relation indicating the improper choice of the auxiliary variables. In fact, the suitability of the method depends largely on the particular

Table 10(a). Results of quadratic covariance analysis to control gradients Crop: Cashew

Source of Variation	d.f.	X_1^2	$X_1 X_2$	X_2^2	X_1Y	X_2Y	Y^2
		Sums of products					
Total	47	360	0	1548	37.29	-359.68	974.31
Replication	2	0	0	0	0	0	48.75
Treatment	15	156.67	32.67	424.67	43.01	-207.62	604.14
Error	30	203.33	-32.67	1123.33	-5.72	-152.07	321.42

Source of Variation	Error of estimate D.F.	S.S.	M.S	F
Treatment + Error	43	838.12	21.49	
Regression	2	21.09	10.55	
Error	28	300.133	10.73	

X_1 - Concomitant variable (Pseudo plot number)

X_2 - Square of X_1

Table 10 (b). Results of quadratic covariance analysis to control gradints. Crop : Coconut.

Source of Variation	D.F.	X^2_1	$X1\ X_2$	X_2^2	X_1Y	X_2Y	Y^2
		Sums of products					
Total	26	59.41	19.11	118.67	691.42	1000.28	1100441.5
Replication	2	2.07	3.56	10.67	-44.91	-103.68	1128.30
Treatment	8	17.41	-0.89	40.67	507.01	951.89	105576.4
Error	16	39.92	16.44	67.33	229.27	152.06	3736.906

Source of Variation	D.F.	S.S.	M.S	F
	Error of estimate			
Treatment + Error	22	91979.03	5109.947	
Regression	2	1371.432	685.715	3.77*
Error	14	2365.47	168.96	

X_1 - Concomitant variable (Pseudo plot number)

X_2 - Square of X_1

* - Significance at 5% level

Table 10 (c). Results of quadratic covariance analysis to contral gradints. Crop : Cocoa.

Source of		Sums of products					
Variation	D.F.	X^1	$X1\ X_2$	X_2^2	X_1Y	X_2Y	Y^2
Total	27	16.68	-1.18	6.68	0.22	5.95	1281.63
Replication	3	0.39	-0.03	0.11	2.78	1.96	215.30
Treatment	6	6.93	0.07	0.93	11.32	-8.13	446.76
Error	18	9.35	-1.21	5.64	-13.88	12.11	619.57

Source of		Error of estimate		
Variation	DF	S.S.	M.S	F
Treatment + Error	22	1063.69	66.48	
Regression	2	39.99	19.99	
Error	16	579.58	36.22	

X_1 - Concomitant variable (Pseudo plot number)

X_2 - Square of X_1

choice of plot numbers along the rectangular grid which was rather a matter of speculation and contraversy. So there is nothing unusual to comment on it if it so happened that in a particular case the method failed to provide with a substantial reduction of error sum of squares. The method is to be applied with atmost care and its reliability is to be examined in the light of stronger evidence.

Summary

5. SUMMARY

The feasibility of using certain alternative techniques for the control of experimental error in experiments on perennial crops such as adjustments by neighbouring plots, modelling of soil heterogeneity, adjustments using pseudo concomitant variable, moving block method, etc. was studied on actual experimental data of three ongoing experiments on important perennial crops, coconut cashew and cocoa. The results obtained in the study are summarized below.

1. Optimum plot size for conducting comparative yield trials was estimated by using modified maximum curvature method. Eight tree plots were found to be optimum for conducting field trials on coconut and cashew. Trials on cocoa required unusually large plot size of 32 trees.
2. An attempt was also made to estimate the relative contribution of genetic and environmental components of variation to the total phenotypic variability in the yields of the three perennial crops by employing the method suggested by Freeman (1963). The percentage of genetic variability in total phenotypic variability in the yield of cashew, coconut and cocoa was estimated to be 77.7, 83.4 and 45.4 respectively. The result called for the use of calibration of the plots and analysis covariance (ANCOVA) for the reduction of experimental error.

3. A considerable amount of reduction in error variance was achieved in all the three sets of data by the application of ANCOVA with pre-experimental yield as concomitant variable. It was also found that the application of covariance analysis utilising the transformed concomitant variable, namely $\sqrt{x}$, where x is the pre-experimental observation, resulted in better error control than the one using conventional covariates. The efficiency of the procedure over conventional analysis without using any covariance adjustment ranged from 150% to 345%.

4. By the seperation of large amount of variability from error variance through ANCOVA the effect of stratification has become often non-significant. Thus analysis of covariance in CRD by taking $\sqrt{x}$ as the calibrating variable was found to be a better method of controlling error than that of its application in RBD.

5. Application of quadratic covariance for the analysis of data on coconut resulted in a substantial gain in precision while for the other two crops, the method failed to give any promising result. The percentage efficiency of quadratic covariance on coconut over conventional analysis of variance was estimated to be 208% while that of conventional covariance analysis was low (159%). The result, though empirical, indicates the possibility of using quadratic covariance for the analysis of data on coconut.

6. Nearest neighbourhood analysis (NNA) resulted in a significant reduction of error in experiments on coconut and cocoa when no restriction was imposed on randomisation. Where as on cashew the reduction of error through NNA was non-significant. No simple pattern of neighbouring plots emerged consistently as the most successful covariate in reducing experimental error. The relative efficiency of Papadaki's NNA over ordinary analysis without blocking was 125% for coconut and it was 133% in the case of cocoa.

7. Double covariance analysis involving suitable function of pre-experimental yield and nearest neighbourhood variable resulted in a substantial reduction of error. In coconut, double covariance analysis involving $\sqrt{x}$ and `ends' as covariate resulted in a 110% gain of efficiency. In cocoa double covariance analysis with $\sqrt{x}$ and `neighbour' as covariate resulted in an efficiency of 242% over conventional analysis. The application of triple covariance analysis did not yield any promising results.

8. Pearce's iterative NN procedure resulted in a significant reduction of error mean square over Papadaki's NN method or conventional analysis of variance. The percentage efficiency of the procedure ranged from 89 to 211 for the three crops under study. The rate of reduction was less substantial in the case of blocking as compared to that with no blocking.

9. Moving block method also gave a significant reduction in error mean square over conventional analysis of variance. The percentage gain of the method over conventional ANOVA ranged from 14 to 57.

10. The quadratic covariance with pseudo plot numbers as concomitant variables gave a slight reduction in error sum of squares when applied to the data on coconut. But for the other two crops, the method failed to record any appreciable reduction in error sum of squares.

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Appendices

APPENDIX-I

Yield Data on Cashew

Treatment Code	Replication					
	1		2		3	
	Y	X	Y	X	Y	X
T_1	2.45	1.55	7.62	12.66	9.82	15.70
T_2	3.28	4.85	10.11	14.53	7.53	15.2
T_3	7.02	5.91	7.63	5.08	8.07	9.29
T_4	6.06	8.56	8.01	7.00	2.61	9.13
T_5	17.61	10.25	12.04	4.59	13.31	12.88
T_6	11.88	7.64	6.04	12.85	15.23	9.35
T_7	3.73	3.86	8.41	6.96	17.80	25.95
T_8	9.32	5.23	16.12	7.98	5.38	7.28
T_9	4.69	4.81	6.98	8.02	9.79	8.73
T_{10}	6.65	7.34	11.75	6.94	9.67	13.61
T_{11}	6.00	13.58	2.69	13.77	4.55	13.23
T_{12}	4.33	9.78	10.70	11.07	10.62	9.25
T_{13}	3.75	4.32	7.59	9.45	5.95	11.06
T_{14}	1.42	9.55	3.78	13.84	1.55	18.53
T_{15}	14.09	5.64	18.75	13.02	16.11	10.99
T_{16}	7.00	8.91	5.07	5.49	9.01	8.96

Y - current year yield data

X - pre-experimental yield data

APPENDIX-II

Yield Data on Coconut

Treatment Code	Replication					
	1		2		3	
	Y	X	Y	X	Y	X
T_1	22.16	7.80	23.64	14.72	20.92	10.48
T_2	101.20	60.72	102.60	49.80	94.40	50.60
T_3	117.44	72.36	112.60	65.52	98.64	55.48
T_4	77.22	56.55	106.22	65.23	38.33	29.56
T_5	154.77	103.67	162.88	135.11	173.78	121.22
T_6	220.11	120.70	167.66	105.22	177.66	108.89
T_7	49.00	48.75	27.50	15.07	24.00	19.50
T_8	177.75	147.75	180.00	170.00	167.75	133.25
T_9	205.25	154.75	195.25	174.25	189.50	121.75

Y - Current Year yield data

X - Pre-experimental yield data

APPENDIX-III

Yield Data on Cocoa

Treatment Code	Replication							
	1		2		3		4	
	Y	X	Y	X	Y	X	Y	X
T_1	21.8	43.24	12.14	15.14	10.28	15.12	10.00	18.67
T_2	11.25	44.00	4.33	8.57	8.89	15.20	25.80	44.20
T_3	6.78	12.11	16.75	29.88	10.44	22.34	10.44	18.00
T_4	17.20	10.44	29.20	32.78	18.11	7.25	21.40	29.80
T_5	21.30	31.67	23.90	23.40	17.11	56.00	19.14	40.50
T_6	4.38	9.11	19.20	30.80	7.56	22.11	15.20	19.30
T_7	9.11	19.45	27.11	53.81	14.70	28.50	20.20	45.60

Y - Current Year Yield Data

X - Pre-experimental Yield Data

APPENDIX IV

Computer Program for the Calcuation Variance and Coefficient of Variation for Different Plot Dimensions

```
10 DIM X(75,75)
20 INPUT "file name",N$
30 OPEN "i", #1, N$
40 INPUT "column,row,", N,K
50 INPUT "plot size column*row",R,C
60 A=INT(N/R)
70 B=INT(K/C)
80 FOR I=1 TO N
90 FOR J=1 TO K
100 INPUT #1,X(I,J)
110 NEXT J
120 NEXT I
130 SUM=0
140 SS=0
150 T=A*B
160 DIM S(75,75)
170 FOR N=1 TO A
180 FOR K=1 TO B
190 S(N,K)=0
200 FOR I=1+(N-1)*R TO N*R
210 FOR J=1+(K-1)*C TO K*C
220 S(N,K)=S(N,K)+X(I,J)
230 NEXT J
240 NEXT I
250 SS=SS+S(N,K)*S(N,K)
260 SUM=SUM+S(N,K)
270 NEXT K
280 NEXT N
290 PRINT "sum",SUM
300 CSS=SS-SUM*SUM/T
310 VAR=CSS/A/B
320 PRINT "css",CSS
330 PRINT "var",VAR
340 S=0
350 FOR N=1 TO A
360 FOR K=1 TO B
370 S=S+S(N,K)
380 NEXT K
390 NEXT N
400 M=S/A/B
410 PRINT "mean",M
420 PRINT "cv", SQR(VAR)/M
```

APPENDIX V

Computer Program for the Calculation of Moving Average in Two Dimension

```
10 REM "calculation of moving average in two dimension"
20 DIM X(50,50)
30 INPUT "row,column",R,C
40 INPUT "size",Z
50 FOR I=1 TO R
60 FOR J=1 TO C
70 INPUT X(I,J)
80 NEXT J
90 NEXT I
100 FOR I=1 TO (R-Z+1)
110 FOR J=1 TO (C-Z+1)
120 S(I,J)=0
130 FOR N=I TO I+Z-1
140 FOR K=J TO J+Z-1
150 S(I,J)=S(I,J)+X(N,K)
160 NEXT K
170 NEXT N
180 PRINT I,J,S(I,J)/Z/Z
190 NEXT J
200 NEXT I
```

APPENDIX VI

Computer Program for the Calculation of Serial Correlations of Different Orders

```
10 REM "calculation of serial correlation of given order"
20 DIM X(50,50), U(50)
30 INPUT "row, column",R,C
40 FOR I=1 TO R
50 FOR J=1 TO C
60 INPUT X(I,J)
70 NEXT J
80 NEXT I
90 SUM=0
100 FOR I=1 TO R
110 FOR J=1 TO C
120 SUM=SUM+X(I, J)
130 NEXT J
140 NEXT I
150 M=SUM/R/C
160 FOR I=1 TO R
170 FOR J=1 TO C
180 K=J+(I-1)*C
190 U(K)=X(I,J)
200 NEXT J
210 NEXT I
220 S=0
230 FOR K=1 TO R*C
240 S=S+U(K)
250 NEXT K
260 PRINT "s", S/R/C
270 NR=0
280 INPUT "laq",L
290 FOR I=1 TO R*C-1
300 J=I+L
310 NR=NR+(U(I)-M)*(U(J)-M)
320 NEXT I
330 DR=0
340 FOR I=1 TO R*C
350 DR=DR+(U(I)-M)^2
360 NEXT I
370 PRINT "nr,dr", NR, DR
380 PRINT "ser.corr=";NR/DR
```

APPENDIX VII

Computer Program for Covariance Analysis in RBD

```
10 DIM X1(25,25),X(50,50),Y(50,50),SX(50),TX(50),TY(50)
20 INPUT "file name (y)",N$
30 OPEN "i",#1,N$
40 REM "anacova"
50 READ SY,SSY,SX,SSX,SP,SSBX,SSBY,SPB,SSVX,SSVY,SPV
60 DATA 0,0,0,0,0,0,0,0,0,0,0
70 INPUT "no of replication, no of treatment.",R,K
80 INPUT "file name (x)",M$
90 OPEN "i",#2,M$
100 FOR I=1 TO R
110 FOR J=1 TO K
120 INPUT #1,Y(I,J)
130 SY=SY+Y(I,J)
140 SSY=SSY+Y(I,J)*(I,J)
150 NEXT J
160 NEXT I
170 FOR I=1 TO R
180 FOR J=1 TO K
190 INPUT #2,X1(I,J)
200 X(I,J)=X1(I,J)
210 SX=SX+X(I,J)
220 SSX=SSX+X(I,J)*X(I,J)
230 SP=SP+X(I,J)*Y(I,J)
240 NEXT J
250 NEXT I
260 X..=SX/R/K
270 CFX=SX*SX/R/K
280 CFY=SY*SY/R/K
290 CFXY=SX*SY/R/K
300 TXX=SSX-CFX
310 TYY=SSY-CFY
320 TXY=SP-CFXY
330 FOR I=1 TO R
340 SY(I)=0
350 SX(I)=0
360 NEXT I
370 FOR I=1 TO R
380 FOR J=1 TO K
390 SY(I)=SY(I)+Y(I,J)
400 SX(I)=SX(I)+X(I,J)
410 NEXT J
420 SSBY=SSBY+SY(I)*SY(I)
430 SSBX=SSBX+SX(I)*SX(I)
440 SPB=SPB+SX(I)*SY(I)
450 NEXT I
460 BXX=SSBX/K-CFX
470 BYY=SSBY/K-CFY
480 BXY=SPB/K-CFXY
```

```
490 FOR J=1 TO K
500 TY(J)=0
510 TX(J)=0
520 NEXT J
530 FOR J=1 TO K
540 FOR I=1 TO R
550 TY(J)=TY(J)+Y(I,J)
560 TX(J)=TX(J)+X(I,J)
570 NEXT I
580 SSVX=SSVX+TX(J)*TX(J)
590 SSVY=SSVY+TY(J)*TY(J)
600 SPV=SPV+TX(J)*TY(J)
610 NEXT J
620 VXX=SSVX/R-CFX
630 VYY=SSVY/R-CFY
640 VXY=SPV/R-CFXY
650 EXX=TXX-BXX-VXX
660 EYY=TYY-BYY-VYY
670 EXY=TXY-BXY-VXY
680 EXX1=VXX+EXX
690 EYY1=VYY+EYY
700 EXY1=VXY+EXY
710 E1=EYY1-EXY1*EXY1/EXX1
720 E=EYY-EXY*EXY/EXX
730 F=(E1-E)/E*((R-1)*(K-1)/(K-1)
740 LPRINT "source","df","ssx","spxy","ssy"
750 LPRINT "--------------------------------------------"
760 LPRINT "total",R*K-1,TXX,TXY,TYY
770 LPRINT "replication",R-1,BXX,BXY,BYY
780 LPRINT "treatment",K-1,VXX,VXY,VYY
790 LPRINT "error",(R-1)*(K-1),EXX,EXY,EYY
800 LPRINT "------------------------------------------"
810 ER2=E/((R-1)*(K-1)-1)
820 ER1=EYY/(R-1)/(K-1)
830 LPRINT "treat+error",R*(K-1),EXX1,EYY1
840 LPRINT "----------------------------------------------------"
850 LPRINT "source","df","ss","mss","f"
860 LPRINT "treatment",K-1,E1-E,(E1-E)/(K-1),F
870 LPRINT "reqression",1,EXY*EXY/EXX,EXY*EXY/EXX,EXY*EXY/EXX/ER2
880 LPRINT "error",(R-1)*(K-1)-1,E,E/((R-1)*(K-1)-1)
890 LPRINT "reqression coefficient from error line b^=",EXY/EXX
900 LPRINT "error=",ERI
910 LPRINT "error(adj)="ER2
920 LPRINT"% reduction in error=",(ER1-ER2)/ER2*100
```

APPENDIX VIII

Computer Program for the Multiple Covariance Analysis with two Anciliary Variate in RBD

```
10 REM "multiple covariance"
20 DIM X1(25,25), Z1(25,25), X(25,25), Z(25,25), Y(25,25)
30 DIM A(500), B(500), C(500)
40 INPUT "file name(x)",N$
50 OPEN "i", #1, N$
60 INPUT "no of replications, no of treatments", T,R
70 READ SUMX,SUMY,SUMZ,SSX,SSZ,SSY,X,Z,Y,XZ,XY,ZY,SXY,SXZ,SZY
80 DATA 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
90 FOR I=1 TO T
100 FOR J=1 TO R
110 INPUT #1,X1(I,J)
120 X(I,J)=X1(I,J)
130 NEXT J
140 NEXT I
150 INPUT "file name(z)",M$
160 OPEN "i",#2,M$
170 FOR I=1 TO T
180 FOR J=1 TO R
190 INPUT #2,Z1(I,J)
200 Z(I,J)=Z1(I,J)
210 NEXT J
220 NEXT I
230 INPUT "f.name(y)",L$
240 OPEN "i",#3,L$
250 FOR I+1 TO T
260 FOR J=1 TO R
270 INPUT #3, Y(I,J)
280 NEXT J
290 NEXT I
300 FOR I=1 TO T
310 FOR J=1 TO R
320 SUMX=SUMX+X(I,J)
330 SSX=SSX+X(I,J)*X(I,J)
340 SUMZ=SUMZ+Z(I,J)
350 SSZ=SSZ+Z(I,J)*Z(I,J)
360 SUMY=SUMY+Y(I,J)
370 SSY=SSY+Y(I,J)*Y(I,J)
380 SXZ=SXZ+X(I,J)*Z(I,J)
390 SXY=SXY+X(I,J)*Y(I,J)
400 SZY=SZY+Y(I,J)*Z(I,J)
410 NEXT J
420 NEXT I
430 PRINT SUMX,SUMZ,SUMY
440 CFX=SUMX*SUMX/T/R
450 CFZ=SUMZ*SUMZ/T/R
460 CFY=SUMY*SUMY/T/R
470 CFXZ=SUMX*SUMZ/T/R
```

```
480 CFXY=SUMX*SUMY/T/R
490 CFZY=SUMZ*SUMY/T/R
500 FOR I=1 TO T
510 A(I)=0
520 B(I)=0
530 C(I)=0
540 NEXT I
550 FOR I=1 TO T
560 FOR J=1 TO R
570 A(I)=A(I)+X(I,J)
580 B(I)=B(I)+Z(I,J)
590 C(I)=C(I)+Y(I,J)
600 NEXT J
610 X=X+A(I)*A(I)
620 Z=Z+B(I)*B(I)
630 Y=Y+C(I)*C(I)
640 XZ=XZ+A(I)*B(I)
650 XY=XY+A(I)*C(I)
660 ZY=ZY+B(I)*C(I)
670 NEXT I
680 DIM AA(50),BB(50),CC(50)
690 READ VX,VZ,VY,VXY,VZY,VXZ
700 DATA 0,0,0,0,0,0
710 FOR J=1 TO R
720 AA(J)=0
730 BB(J)=0
740 CC(J)=0
750 NEXT J
760 FOR J=1 TO R
770 FOR I=1 TO T
780 AA(J)=AA(J)+X(I,J)
790 BB(J)=BB(J)+Z(I,J)
800 CC(J)=CC(J)+Y(I,J)
810 NEXT I
820 VX=VX+AA(J)*AA(J)
830 VZ=VZ+BB(J)*BB(J)
840 VY=VY+CC(J)*CC(J)
850 VXZ=VXZ+AA(J)*BB(J)
860 VXY=VXY+AA(J)*CC(J)
870 VZY=VZY+BB(J)*CC(J)
880 NEXT J
890 CSSX=SSX-CFX
900 CSPXZ=SXZ-CFXZ
910 CSPXY=SXY-CFXY
920 CSSZ=SSZ-CFZ
930 CSPZY=SZY-CFZY
940 CSSY=SSY-CFY
950 RX=VX/T-CFX
960 RZ=VZ/T-CFZ
970 RY=VY/T-CFY
980 RXZ=VXZ/T-CFXZ
990 RXY=VXY/T-CFXY
1000 RZY=VZY/T-CFZY
1010 TX=X/R-CFX
1020 TXZ=XZ/R-CFXZ
```

```
1030 TXY=XY/R-CFXY
1040 TZ=Z/R-CFZ
1050 TZY=ZY/R-CFZY
1060 TY=Y/R-CFY
1070 EX=CSSX-TX-RX
1080 EXZ=CSPXZ-TXZ-RXZ
1090 EXY=CSPXY-TXY-RXY
1100 EZ=CSSZ-TZ-RZ
1110 EZY=CSPZY-TZY-RZY
1120 EY=CSSY-TY-RY
1130 EY1=EY+RY
1140 EZ1=EZ+RZ
1150 EX1=EX+RX
1160 EXZ1=EXZ+RXZ
1170 EXY1=EXY+RXY
1180 EZY1=EZY+RZY
1190 LPRINT "total", "block", "treatment", "error"
1200 LPRINT "d.f",R*T-1, T-1, R-1, (R-1)*(T-1)
1210 LPRINT "ssx",CSSX,TX,RX,EX
1220 LPRINT "spxz",CSPXZ,TXZ,RXZ,EXZ
1230 LPRINT "ssz",CSSZ,TZ,RZ,EZ
1240 LPRINT "spxy",CSPXY,TXY,RXY,EXY
1250 LPRINT "spzy",CSPZY,TZY,RZY,EZY
1260 LPRINT "ssy",CSSY,TY,RY,EY
1270 C=EX1*EZ1-EXZ1*EXZ1
1280 C11=EZ1/C
1290 C12=-EXZ1/C
1300 C22=EX1/C
1310 B1=C11*EXY1+C12*EZY1
1320 B2=C12*EXY1+C22*EZY1
1330 CC=EX*EZ-EXZ*EXZ
1340 CC11=EZ/CC
1350 CC12=-EXZ/CC
1360 CC22=EX/CC
1370 CB1=CC11*EXY+CC12*EZY
1380 CB2=CC12*EXY+CC22*EZY
1390 RE=B1*EXY1+B2*EZY1
1400 R1=CB1*EXY+CB2*EZY
1410 ER1=(EY-R1)/((T-1)*(R-1)-2)
1411 LPRINT "  "
1412 LPRINT "source", "df", "ss", "mss", "f"
1413 LPRINT "--------------------------------------------------"
1420 LPRINT "treat+error(adj)",T*(R-1)-2,EY1-RE,(EY1-RE)/T/((R-1)-2)
1430 LPRINT "treat (adj)", R-1, EY1-RE-EY+R1, (EY1-RE-EY+R1)/(R-1)
1435 LPRINT "regression", 2, R1,R1/2,R1/2/ER1
1440 LPRINT "error", (T-1)*(R-1)-2,EY-R1,(EY-R1)/(T-1)*(R-1)-2)
1450 LPRINT "b1,b2",CB1,CB2
1460 ER2=EY/(R-1)/(T-1)
1470 LPRINT "% reduction in error", (ER2-ER1)/ER1*100
```

ABSTRACT

The feasibility of using certain novel devices for the control of error in experiments on perennial crops was examined on the basis of actual experimental data and the resulting efficiency gain evaluated.

A considerable amount of reduction in error variance was achieved by the application of analysis of covariance with suitable functions of pre-experimental yield as concomitant variable. Application of quadratic covariance resulted a substantial gain of precision in the analysis of data on coconut. Nearest neighbourhood analysis (NNA) resulted in a significant improvement of precision in the analysis of data in most of the experiments. Double covariance analysis involving suitable functions of pre-experimental yield and NN variable as covariates resulted in further reduction of experimental error. Pearce's iterative NN procedure was found to be the best alternative method for reduction of error over the coventional method of stratification. A plot of eight trees was found to be optimum for conducting yield trails on coconut and cashew. The percentage of genetic variability to the total phenotypic variability in the yields of cashew, coconut and cocoa was estimated to be 77.7, 83.4 and 45.4 respectively. The result called for the use of calibration of the plots and choice of appropriate concomitant variables for the reduction of experimental error in designing experiments on perennial crops.