STUDIES ON OPTIMUM SIZE AND SHAPE OF PLOTS AND BLOCKS FOR FIELD TRIALS ON RICE AND JUTE CROPS IN TERAI AGROCLIMATIC ZONE OF NORTH BENGAL AND ON THE EFFICIENT MODELLING OF DATA THROUGH CONVENTIONAL AND SPATIAL METHODOLOGY

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in

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By

Satyananda Basak

DEPARTMENT OF AGRICULTURAL STATISTICS
FACULTY OF AGRICULTURE
BIDHAN CHANDRA KRISHI VISWAVIDYALAYA
MOHONPUR, NADIA, WEST BENGAL

2004

Dedicated

to

my beloved little daughter

Sailee

and my beloved wife

Babita

CERTIFICATE OF APPROVAL

We, the undersigned, having been satisfied with the performance of Shri Satyananda Basak, in the Viva-Voce Examination, conducted today, the......16/02/05......, ~~2004~~, recommended that the thesis be accepted for the award of the Degree of Doctor of Philosophy in Agricultural Statistics of Bidhan Chandra Krishi Viswavidyalaya.

Name	Board of Research Studies Examiners	Signature
1. Prof. S. Pal	Chairman, Advisory Committee	....
2. Dr.	External Examiner	Vijay Katyal ....
3. Dr. A. K. Pal	Member, Advisory Committee	.... 16/02/05
4. Dr. N. R. Majumdar	Member, Advisory Committee	....
5. Dr. A. Majumdar	Member, Advisory Committee	....
6. Dr. S.K. Mukhopadhyay	Departmental Nominee	S.K. Mukhopadhyay

Bidhan Chandra Krishi Viswavidyalaya

FACULTY OF AGRICULTURE
DEPARTMENT OF AGRICULTURAL STATISTICS
Mohanpur, Nadia, West Bengal; Pin – 741252.
Phone (O): +91-3473-278605

Prof. Satyabrata Pal
Ph. D., F.I.F.I., F.A.Sc.T., F.I.A.H., M. N. A. Sc.

Dean
Post-Graduate Studies
and Professor in Agricultural Statistics

Residence: 101/B Bakul Bagan Road
Kolkata – 700025
Phone (Residence): 033-2485-2160
033-2475-9048

E-mail: satbrpal@vsnl.net
E-mail: satyabratpal@hotmail.com

Ref. No.*: *Ag. Stat / ***Date*: ..23... / 08 / 2004.**

CERTIFICATE

This is to certify that the work, recorded in the thesis, entitled "Studies on optimum size and shape of plots and blocks for field trials on rice and jute crops in terai agroclimatic zone of North Bengal and on the efficient modeling of data through conventional and spatial methodology" submitted by Shri Satyananda Basak for the award of the degree of Doctor of Philosophy in Agricultural Statistics of the Bidhan Chandra Krishi Viswavidyalaya, is a record of faithful and bonafide research work carried out by Shri Basak under my direct supervision and guidance. The results of the investigation, reported in this thesis, have not so far been submitted for any other Degree or Diploma. The assistance and help received during the course of investigation have been duly acknowledged.

(SATYABRATA PAL)
Chairman, 23/08/04
Advisory Committee

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Satyananda Basak

(Satyananda Basak)

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Chapter 1

INTRODUCTION

1.1 HISTORICAL BACKGROUND:

One of the chief difficulties in obtaining reliable results in field trials is the natural variability of the material with which we are dealing. Crops are living organisms with inherent tendencies to vary even though it was possible to make their environmental conditions identical. Further, variation is induced as a result of many environmental factors which are beyond the control and recognition of the experimenter. Lack of uniformity in both the physical and chemical characteristics of the soil is one of the foremost factors causing variation in productivity of plants. Apparently, uniform surface soils may be underlain with a heterogeneous subsoil. Differences also occur which are not evident on a careful inspection of both the soil and the crops, but which are easily measured by weighing the yields. In other words, the weighing machine is more sensitive than the eye and reveals differences that mere inspection can not detect. The past treatment of the soil brings in variables the significance of which may not be comprehended at the time a field trial is begun. The persistent effects left by the application of manure in some field plots can show how large a part is played by the past history of the field. Unequal prevalence of diseases and insects may bring about further errors in the results. Besides the above sources of variation and possibly outweighing them at times is the effect of season. No season is entirely normal.

Holtsmark and Larsen (1906) are among the first to call attention to the errors of field trials. They recognize the inevitable variation of field results, and show how it may be estimated by the use of the standard deviation and the coefficient of variability. They also show that the coefficient of variability decreases as the plots are enlarged, but not proportionally to the size of the plot. The limitations of field experiments are discussed by Carleton (1909), who call the attention of experimenters to the various uses of control plots, and to the general precautions necessary to obtain reliable results. Hall (1909), Mercer and Hall (1911) and Hall and Russel (1911) record extensive studies of the soil variations in experimental grounds and the influence of size and repetition of plots upon accuracy. The above work was done largely with the yields of wheat, mangel and hay crops. The conclusions from the above work are that the error in field trials diminishes as the size of the plot increases, but that the reduction is small when the plot is enlarged to a size greater than one-fortieth of an acre. The error may be further diminished by increasing the number of plots similarly treated and scattering them about the area under experiment; but there is not much to be gained by increasing the number of plots above five. Wood and Stratton (1910) sound notes of caution concerning the interpretation of experimental results. Frequency distribution is discussed from the point of view of its bearing on the reliability of averaging results. The applications of the probable-error methods to questions of sampling for analysis, to field experiments, and to feeding experiments are illustrated. The probable-error of field experiments is investigated by two independent methods and found to be about five percent of the mean yield. It is shown that more accurate results may be obtained by employing large numbers of small scattered plots than by using one large plot. The estimation of errors in field plot tests has been given considerable attention by Lyon (1912) and coworkers. It is shown that it is not possible to established a schedule of relative yields for a series of plots, even after several years' comparison. Also, there seems to be little gain by using plots larger than one-fiftieth of an acre in size when the comparative yield of the crops is made the criterion. An area of one-twenty-fifth of an acre of land distributed in four widely separated plots, devoted to any one test, secures a much greater degree of accuracy than the same area of land in one body. The probable-error is reduced from 4.5 to 2.0 percent by such distribution. Pickering (1911), from studies on apples and pears, conclude that experimental plots should include 6 to 12 fruit trees. Precautionary advice is also given concerning the measurement of results by crop production, foliage and tree characteristics. In comparing the results on the treated plots with the controls, instead of taking the average of the controls, he prefers to plot these results out and to draw a smoothed curve through them, and then to compare the results of the experimental plots with readings taken at corresponding points of this curve. Wood (1911) shows how the degree of reliance can be determined for any set of experimental results by the use of the probable error. The use of this constant is demonstrated in interpreting laboratory analysis, as well as both plot and feeding experiments. Working with mangel yields, the author calculates the number and size of plots required to attain any desired precision, and working with the probable error of live weight increase of sheep, tables are given showing the number of animals required in an experiment to attain various degrees of reliability. Several papers by Harris (1912, 1913a, 1913b, and 1915) have drawn our attention to several phases of the experimental error in field tests. A measure of the variability of the soil productivity is obtained by determining the correlation between the yields of ultimate small plots and the yields of various groups of adjacent plots. The more nearly this correlation approaches zero, the more homogeneous the soil. This method of measurement does not seem to provide as definite a means of obtaining a corrective term as the use of the coefficient of variability and the probable error as used by Wood, Wood and Straton, Mercer and Hall, etc., or the contingency method of correction as used by Surface and Pearl (1916). Montgomery (1912) has also discussed the comparative variability resulting from increasing the size of the plot and from distributing small ultimate plots over the area. The later method is found to be more accurate. In a subsequent paper (1913) the relative reliability of yields of wheat planted in rows and in square blocks is discussed. An exhaustive and discriminating discussion of the nature and magnitude of variability in the results of feeding experiments has been given by Mitchell and Grindley (1913). Much of their discussion is equally applicable to experimentation with plants. Olmstead (1914) applies the method of least squares in calculating the reliability of the yields of the mangel and wheat crop records of Mercer and Hall, the potato records of Lyon and the wheat yields of Montgomery. The author concludes that the estimation of the probable error of a large number of small duplicate plots well distributed in the area devoted to a field experiment indicates that the precision of agricultural experiments can be increased by replicating the experiment on small plots. Coombs and Grantham (1916) have studied the variation in the yields of rice and coconuts for one year, and discussed the range and interpretation of the probable error. They showed that the yields from any two single plots could only be significant when the difference amounted to 22.8 percent of the mean. They also introduced calculations to show the odds that any increase is a real increase and not a probable error. The use of controls and repeated plantings in varietals tests was studied by Pritchard (1916) in breeding work with sugar beets. His studies lead to the conclusion that the practice of dispensing with control rows and using the mean of all progeny rows as a standard of comparison appears to be less accurate than the employment of frequent controls. However, the employment of every alternate row as a control was not sufficient to offset the variability in yield arising from irregularities of soil. Stockberger (1916) discusses the value of a number of the common methods for determining the normal yield of treated plots based upon the yields of hops. Normal yields for various plots varied widely according to the method of computation, the values in some cases differing from the actual yield by as much as 40 percent. Repetition brought about a very marked reduction in variability, although with only five repetitions the error is still relatively large. The work of Surface and Pearl (1916) shows an advance in the refinement of methods of conducting field trials. With the realization that the use of frequent control plots often produces results far from satisfactory, these workers have calculated by the contingency method the probable yield of each plot of ground in their grain testing series. This calculated yield represent the most probable yield of each plot on the supposition that they have all been planted with a hypothetical variety whose mean yield is the same as the observed mean of the field. This "calculated" yield may then be used as a basis for determining a correction factor, whereby each area must be given a handicap plus or minus the actual yield, depending upon whether the plot in question is calculated to be a low or a high producing area. This method of correcting the soil variation is combined with four systematically repeated plots of one-fortieth acre of each variety, and gives a high degree of accuracy. Batchelor and Reed (1918) study the nature and extent of the variability of the yields of fruit trees under field conditions and its bearing on the reliability of plot trials. The orchards studied are selected on account of uniformity of treatment and appearance, yet the variability in productivity was considerable. The effect upon variability of combining trees into plots of various sizes and shapes has been investigated. As the number of trees per plot is increased, the coefficient of variability decreases. However there is little gain in accuracy by increasing the plot to include more than eight adjacent trees. Greater reliability may be secured by a systematic repetition and distribution of plots through the experimental area. A 16 tree plot can be expected to give more reliable results if divided into four equal plots and repeated at four regularly placed intervals than can either two eight tree plots or 6 adjacent trees. The fact that marked soil variations occur which tend to make adjacent trees or adjacent plots yield alike, even on soils which are chosen because of their apparent uniformity, is well shown by applying the formula proposed by Harris (1915) for measuring the coefficient of correlation between neighboring plots of the field. Computations made on the yields of fruit trees for several consecutive years showed little annual fluctuation in their variability. Kalamkar (1932) studies the uniformity trial on potato. In his study the standard error in percent of the mean yield decreased slightly with increase in the widths up to plots 5 rows wide, but any further increase in the width of the plot results in the higher standard error. Given a piece of land of certain size, it is advantageous to have a greater replication of smaller plots than a smaller number of larger plots. Four-row plots proves to be the most efficient when the border rows are discarded. The superiority of long and narrow plots over shorter and wider ones is demonstrated.

For efficient conduct of Agricultural field trials knowledge of the proper size & shape of experimental plots and their arrangement in blocks is essential. One major problem encountered in experimental yield trials on field crops is that their exists variation in yield estimates regardless of how the trial is designed/ laid out taking the variety (or treatment). The usual method of finding out the heterogeneity structure of a piece of land is to construct a fertility contour map by conducting uniformity trial. The uniformity trial consists of growing the same crop under uniform treatment and management practices on a piece of land. When the crop is ready for harvest, the entire field is divided into suitable small units and the produce of each unit is recorded separately along with the row and column positions of the selected units. By combining these units suitably, different sizes and shapes of plots are obtained and their variability's for each size and shape can be worked out and compared efficiently.

The effect of inherent soil heterogeneity (without application of fertilizer) upon crop yield has been recognized since long age. In an early study to determine experimental error of field trials, Mercer and Hall (1912), working with mangels used the concept of probable error to analyse variation in field experiments. They determined optimum plot size on the basis of a curve relating plot size and percent deviation. Under the procedure a field growing the crop under uniform treatment is harvested in small units of suitable size, usually 1m X 1m. The small units are then combined into various sizes. The sum of squares among the various plots are divided by the degrees of freedom to obtain the variances. The mean against various plot sizes are also computed together with the values of the coefficient of variation. These values of the coefficient of variation are plotted against the respective plot sizes. A free hand curve is drawn through the ordinates. It can be seen that the ordinates decrease with increase in plot size but after a particular plot size, the C.V. values do not decrease any further. The plot size above which the corresponding C.V. values become more or less steady and do not decrease further is called the optimum plot size.

1.2 SCOPE OF THE WORK:

One major problem encountered in experimental yield trials on field crops is that there exists variation in observed yields regardless of how the trial is designed/ laid out taking the variety (or treatment). The usual method of finding out the heterogeneity structure of a piece of land is to construct a fertility contour map by conducting uniformity trial. The uniformity trial consists of growing the same crop under uniform treatment and management practices on a piece of land. When the crop is ready for harvest, the entire field is divided into suitable small units and the produce of each unit is recorded separately along with the row and column positions of the selected units. By combining these units suitably, different sizes and shapes of plots are obtained and variability with respect to each size and shape can be worked out and compared efficiently.

The particular experimental material under study determines the plot size to a large extent. Certain types of variabilities and cultural operations are associated with the kind of crop considered under experimentation. The optimum plot size for a variety yield trial for rice is different from that for jute. Hence, for efficient conduct of Agricultural field trials a knowledge of the proper size & shape of experimental plots and their arrangement in blocks is essential. The effect of inherent soil heterogeneity (without application of fertilizer) upon crop yield has been recognized since centuries ago. In an early study to determine experimental error of field trials, Mercer and Hall (1912), working with mangels used the concept of probable error to analyse variation in field experiments. They determined optimum plot size on the basis of a curve relating plot size and percent deviation. Under the procedure a field growing the crop under uniform treatment is harvested in small units of suitable size usually 1m X 1m. The small units are then combined into various sizes. The sum of squares among the various plots are divided by the degrees of freedom to obtain the variances. The mean against various plot sizes are also computed together with the values of the coefficient of variation. These values of the coefficient of variation are plotted against the respective plot sizes. A free hand curve is drawn through the ordinates. It can be seen that the ordinates decrease with increase in plot size but after a particular plot size, the C.V. values do not decrease any further. The plot size above which the corresponding C.V. values become more or less steady and do not decrease further is called the optimum plot size. Many workers used the above method to determine the optimum plot size. Federer (1955) however, pointed out that this method had a weakness in that the above method of determination of the point of optimum plot size was not independent of the smallest unit selected or of the scale of measurement used. Also this method did not consider the relative cost of various plot sizes.

An unscientific approach is again usually adopted when comparing the reduction of variability due to increasing the size of plot with the reduction which is to be expected if the fertilities of the adjacent areas/ plots of the land were uncorrelated or which is attainable by random replication of unit plots. But since an hypothesis of zero correlation between adjacent areas/ plots can not be regarded as probable (as was demonstrated by Harris, 1915, 1920) it is misleading to speak of it as "theoretically expected".

No satisfactory quantitative measure of soil heterogeneity was devised till the first decade of twentieth Century. Harris (1915) proposed using the intraclass correlation coefficient of yields from adjacent areas as a "coefficient of heterogeneity". But although numerous workers have taken the trouble to evaluate such coefficients for their data it does not appear to serve any other purpose than to demonstrate that the fertilities of adjacent areas are correlated. Thereafter Smith (1938) suggested an empirical model relating variability to plot size and shape. He recognized the presence of association between adjacent plots and included a factor '*b*' (called soil heterogeneity) in his proposed model. His model has been the basis for analysis of uniformity studies for many decades.

To the best of the knowledge, no uniformity studies have been reported for Terai agro-climatic zone of North Bengal in the literature. It is expected that this study will be the first of its kind. Keeping these facts in view, it has now become necessary to understand in detail the nature of variation, association, similarity and dissimilarity among data points in different directions and their relation in determining optimum plot and block size and shape. Thus the present studies will be carried out with the following objectives:

OBJECTIVES:

1. To find optimum plot size for rice and jute crops (by Smith's and Sehti's methods).
2. To find optimum plot shape for rice and jute crops.
3. To find optimum block size and shape for rice and jute crops.
4. To find optimum plot size by variogram analysis.

1.3 Overview of results: The works embodied under the research investigation have been carried out on the objectives mentioned as above. The chapters have been prepared keeping an eye to the important and latest reviews available in the literature concerned with optimum plot size. The findings obtained against the above objectives have been delineated precisely below.

Chapter 2

Chapter 2 presents an introduction pertaining to the works on optimum plot size and shape based on the Smith's model. Using the cost considerations optimum plot sizes for jute and rice crops are 12.42 sq.m. and 5.51 sq.m. respectively. By relating C.V. to the plot sizes the method of maximum curvature gives the plot sizes of 6.5 sq.m. (1.12m. X 5.76m.) and 15.86 sq.m. (7.84m. X 2.02 m.) for jute and rice crops respectively. For jute data it is observed that blocks should run row wise i.e., along E→W direction, and the larger dimension of the plot should be in the column i.e., along N→S direction. However, for rice data the plot and block orientation should be just the opposite i.e., the blocks should run column wise i.e., along N→S direction, and the larger dimension of the plot should be along the row direction i.e., along E→W direction.

Chapter 3

The uniformity data are analysed to study the two way spatial correlations present in the field. In the Smith's model we have not considered the spatial covariance aspect while calculating the variance for different plot sizes and shapes. But in this chapter the covariance among plot observations both in the diagonal and off diagonal directions is considered (vide Modjeska and Rawlings, 1983). The optimum plot size is found by using the Smith's cost concept i.e. minimizing the cost per unit of information. However for finding suitable heterogeneity index *b* a few criteria like (i)symmetry of diagonal spatial correlation with the off diagonal one (ii) heterogeneity in the row and column directions (iii) plot of ln(STMSE/plot size) vs. ln(plot size) for the first and last row and first and last column of the STMSE matrix are considered. For both of my Jute and Rice data neither of Smith's one dimensional nor Smith's two dimensional model can be best fitted to the respective STMSE matrices so that a suitable heterogeneity index and thereby the optimum plot sizes can be found. However by studying the cost per unit of information for the minimum value it is found that optimum plot size is 15 sq.m. (3m. X 5m.) for jute data and 11 sq.m. (11m. X 1m.) for rice data.

Chapter 4

Here uniformity data are studied in great detail to observe the nature and amount of spatial dependence present in the data. The variogram analysis has been done for different row and column lags at the diagonal and off diagonal directions. The change in spatial dependence with the increase in lag distance among observations is studied using the models, namely, spherical, exponential, Gaussian, Michaelis-Menton & VB. For both Jute and Rice data all of the above mentioned five models provides reasonably good fit ($R^2 \cong 0.75$). However, the amount of dependency among the estimated parameters is found to be least for exponential and VB models. From the fitted models we observe the values of the three parameters of the variogram model: the range, the sill, and the nugget effect. Here it is understood that the range is the separation distance beyond which two observations are independent of each other. The sill is the variogram value corresponding to the range. The discontinuity at the origin is called the nugget effect and arises from a combination of random errors and sources of variation at distances smaller than the shortest sampling interval (Goovaerts, 1998). Optimum plot size is studied using nugget to sill ratio of the fitted variogram model as one criterion indicating the extent to which the experimental errors between plots were randomly distributed in space (Bhatti *et al.*, 1991; Ersboll, 1996).

Chapter 5

Here we suggest a totally new method whereby we observe the amount of maximum curvature of variogram curves for each plot size and shape.

Chapter 6

In this chapter we study the historically renowned wheat grain yield uniformity data of Mercer and Hall (1911). Applying the method of maximum curvature to the data relating C.V. to plot sizes we find that optimum plot size is 19.14 sq.m. (1.33 m. X 14.39 m.).

Chapter 7

In this last chapter we summarise all of the methods studied.

Chapter 2

SMITH'S MODEL AND ITS DEVELOPMENT

2.1 Optimum plot size for isotropic field: Smith (1938) pointed out that the regression of variability on plot size can be more easily interpreted when the observations are plotted on double logarithmic paper. It becomes linear. Thus the relationship can be described by an equation of the form $\log(V_x) = \log(V_1) - b.\log(x)$ where V_x = variance of yield per unit area for plots of x units of area. Since the variances have been estimated from varying numbers of plots it is desirable that, when fitting a regression equation, each point should be weighted inversely by its variance.

But size of the field is purely arbitrary, and any given field may be considered as a single block of a larger field. Let the variance of the mean yield per unit area, of plots of x units of area over a block of m plots be $(V_x)_m$. Then the regression which has been empirically observed for a field having n plots is $\log(V_x)_{n/x} = \log(V_1)_n - b'\log x$. But the size of the field, n, is arbitrarily fixed, and if this regression is theoretically sound it should hold good for any alternative size of field which we may wish to consider as the area over which variances should be measured. But if n be varied the above regression becomes curved for any value other than that originally assigned. The regression is therefore inconsistent with the requirement that the law shall be unaffected by variation in the size of the field. This difficulty is overcome if we postulate an infinitely large field of which an observed field may represent a single block and suppose that the law be $\log(V_x)_\infty = \log(V_1)_\infty - b.\log x$, or $(V_x)_\infty = \frac{(V_1)_\infty}{x^b}$. When $b = 1$ this gives the ordinary formula for the variance of the mean of x independent units. Since a block is merely a large size plot the variance between blocks can be estimated from the same equation, and thence the variance of plots of x units within blocks of *m* plots is given by an analysis of variance, where λ tends to 4, as follows:

	d.f.	M.S.
Between blocks	$(\lambda-1)$	$m.(V_{xm})_\lambda$
Within blocks	$\lambda.(m-1)$	$(V_x)_m$
Total	$(\lambda.m-1)$	$(V_x)_{\lambda m}$

Thus in the limit: $(V_x)_m = \frac{m.(V_x)_\infty - m.(V_{xm})_\infty}{m-1} = \frac{m.(1-m^{-b})(V_x)_\infty}{m-1}$. Here for given values of m and b, $(V_x)_m / (V_x)_\infty$ is a constant irrespective of x. Thus the association between neighboring plots is of such a type that the variance per plot within a block of m plots bears the same ratio to the total variance per plot in an infinite field whatever the plot size.

First we combine r X c basic units to simulate plots of different sizes and shapes. Here we use only those combinations that fit exactly into the whole area. Now for each of simulated plots we compute yield total T as the sum of the x basic units combined to construct that plot. Now we compute between plot variance $V_{(x)} = \Sigma T_i^2 / w - \bar{T}^2$ where $w = (r.c / x)$ is the total number of simulated plots of size x basic units. For each plot size and shape, compute the variance per unit area as $V_x = V_{(x)} / x^2$. For each plot size having more than one shape, we test the homogeneity of between plot variances $V_{(x)}$, to determine the significance of plot orientation i.e. plot shape effect, by using F-test or the chi-square test. For each plot size whose plot shape effect is insignificant, we compute the average of V_x values over all plot shapes. However, when plot shape effect is significant we use the lowest V_x value.

Now using the values of variance per unit area V_x and plot size x we compute the regression coefficient b. As explained by Smith (1938) the relationship between V_x and x is not linear but log linear. As $V_x = \frac{V_1}{x^b}$ the first step is to linearise the function into a linear form as Y = c.X where Y = log V_x – log V_1, c = -b and X = log x. Now minimizing weighted sum of square of residuals i.e. RSS = $\sum_i w_i.(Y_i - c.X_i)^2$ with respect to c we get $\frac{\partial RSS}{\partial c} = 0$ or,

$$2.\sum_i w_i.(Y_i - c.X_i).X_i = 0 \text{ or, } c = \frac{\sum_{i=1}^{m} w_i.X_i.Y_i}{\sum_{i=1}^{m} w_i.X_i^2}$$

Thus b = -c. Here w_i = the d.f. associated with a given variance. Here the weights are proportional to the reciprocal of the variances. As we have s.d. of s i.e. $\partial s = \frac{s}{\sqrt{2n}}$ to a first approximation the variance of the logarithm of a variance may be taken as:

$\{\partial(\log_e s^2)\}^2 = \left\{\frac{2.s.\partial s}{s^2}\right\}^2 = \frac{2}{n}$ where n is the number of degrees of freedom upon which the estimate of variance is based.

The contribution of soil heterogeneity to experimental error stems from differences in soil fertility between plots within a block. The smaller this difference is, the smaller is the experimental error. The choice of suitable plot size and shape, therefore, should reduce the differences in soil productivity from plot to plot within a block and consequently reduce experimental error. Two major considerations are involved in choosing plot size, namely, practical considerations and the nature and size of variability. Practical considerations generally include ease of management in the field. The nature and size of variability is generally related to soil heterogeneity. From the empirical relationship between plot size and between plot variance, it can be seen that while variability becomes smaller as plot size becomes larger, the gain in precision decreases as plot size becomes increasingly large. Furthermore, higher costs are involved when large plots are used. Hence, the plot size that a researcher should aim for is one that balances precision and cost. This is conventionally referred to as *optimum plot size.*

To obtain optimum plot size we assume that cost per unit is known. Let the cost function be of the following linear form $K_t = K_1 + K_2.x$, where K_t = total cost for the experimental unit, K_1 = part of the cost associated with the number of plots only. K_2 = cost per unit area, x = size of plot. Then C = cost / unit of information is given by C = $\frac{K_1 + K_2.x}{\frac{1}{V_x}} = \frac{V_1.(K_1 + K_2.x)}{x^b}$. Now the value of x which minimizes the cost (C) is given by the equation $\frac{dC}{dx} = 0$. Solving the equation for x we obtain $x_{opt} = \frac{b.K_1}{(1-b).K_2}$, which gives the optimum plot size. The value of b i.e., the index of soil heterogeneity, is used primarily to derive optimum plot size. The value of b indicates also the degree of correlation between adjacent experimental plots. Its value varies between unity and zero. The larger is the value of the index b, the lower is the correlation between adjacent plots, indicating that fertile spots are distributed randomly or in patches.

The value of 'b' in the range 0.3 to 0.7 does not greatly effect the increase in cost or in variance when plots of size ¼ to 4 times the optimum plot size are used. On the basis of these results plot size of ½ to 2 times the optimum plot size can be taken without any loss in efficiency. However, for plot size ¼ to 4 times the optimum size, a loss in efficiency of 20% results because of the increased variance.

A UNIFORMITY TRIAL ON JUTE: A uniformity trial with JRO 524 (Naveen, a variety of jute) was conducted (1999) at the Barokodali State Government Farm (approximately 7 Km from Tufanganj Subdivision of Cooch Behar District). The seeds were sown in continuous lines. The distance between line to line was kept 20 cm leaving a border on each side. Uniform management practices were undertaken throughout the field. The field was harvested in continuous units of 448 basic units. There was in total 32 rows each of which were along N – S direction and 14 columns each of which were along E – W direction. Yield of dried fiber was calculated from each basic unit of 1mt. X 1mt. The units were combined by taking 1 to 9 units along N→S with 1 to 9 units across E→W to from plots of different sizes & shapes.

A UNIFORMITY TRIAL ON RICE: A uniformity trial with MW10 (a variety of rice) as Aus paddy was conducted (1999) at the RRS, Terai zone, Pundibari. The seedlings were transplanted in lines with a hill to hill spacing of 20 c.m. The distance between line to line was kept 20 cm leaving a border on each side. Uniform management practices were undertaken throughout the field. There was in total 22 rows each of which were along N –> S direction and 18 columns each of which were along E –>W direction.The field was harvested in units of 1 mt x 1mt there being 22 mt x 18 mt i.e. 396 such units. The yields of these units were separately dried & weighed correct to the nearest gram.

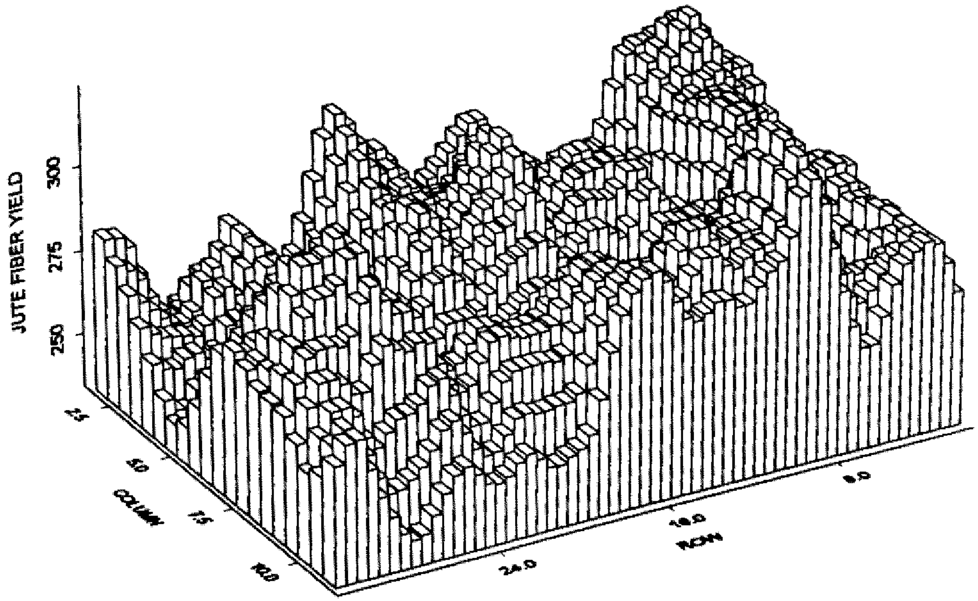


Fig.2.1.1 Jute field fertility contour surface based on moving average of 3X3 basic units.

On Eastern end of the field was dominated by very high yields, the middle region by a mixture of intermediate yields, and the Western end by low yield. Yield was not constant within any of these regions and appeared to change along both row and column.

The Jute uniformity data was analysed based on a two way ANOVA. The result shows that the Row mean square is 1.63 times higher than the Column mean square, indicating that the trend of soil fertility was slightly more pronounced along the row i.e. E->W direction than along the column i.e. N->S direction.

ANOVA FOR JUTE UNIFORMITY DATA

S.O.V.	d.f.	M.S.	Fcal.
Row	31	218.4804	0.1735587
Column	11	133.1731	0.1057914
Error	341	1258.827	
Total	383	1610.48	

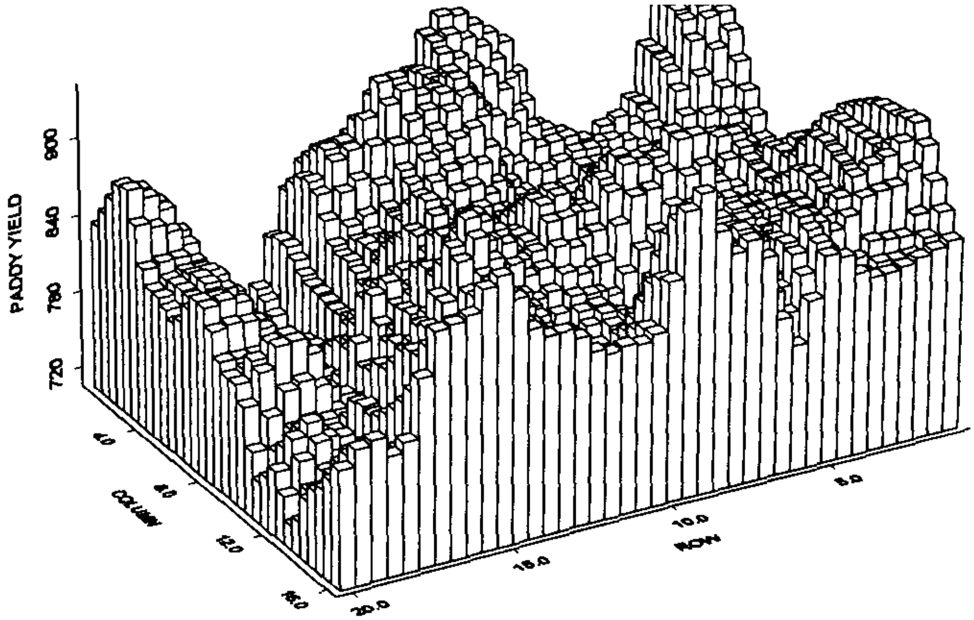


Fig. 2.1.2 Rice field fertility contour surface based on moving averages of 3X3 basic units.

On the borders of Eastern, Northern & Southern ends of the Rice field are dominated by very high yields, the middle region by a mixture of high and intermediate yields and Western borders by low yields. Yield was not constant within any of these regions and appeared to change along both row and column.

The Rice uniformity data was analysed based on a two way ANOVA. The result shows that the Row mean square is more than four times higher than the Column mean square, indicating that the trend of soil fertility was more pronounced along the row i.e. E->W direction than along the column i.e. N->S direction.

ANOVA FOR RICE UNIFORMITY DATA

S.O.V.	d.f.	M.S.	Fcal.
Row	21	1978.732	0.1717749
Column	17	490.308	0.04256392
Error	357	11519.33	
Total	395	13988.38	

Smith's optimum: The basic units were combined by taking 1 to 9 units along N→S with 1 to 9 units across E→W to from plots of different sizes & shapes for rice and jute data individually. Based on this between plot variance $V_{(x)}$, Variance per unit area V_x and coefficient of variability C.V. are calculated for plots of various size and shapes. These are shown in the following tables:

TABLE:2.1.1(Jute data)

PLOT SIZE	Wid-th	Len-gth	No.of Plots	PLOT MEAN	VARIANCE	VARIANCE /SQ.MT	C.V.
1	1	1	384	276.2578	1610.48	1610.48	14.52657
2	2	1	192	552.5156	3850.241	962.5602	11.23051
2	1	2	192	552.5156	3683.476	920.8691	10.9846
3	3	1	120	829.7584	6892.605	765.845	10.00553
3	1	3	128	828.7734	6039.638	671.0709	9.377122
4	4	1	96	1105.031	9688.674	605.5421	8.907537
4	2	2	96	1105.031	9145.685	571.6053	8.654332
4	1	4	96	1105.031	7038.905	439.9316	7.592381
5	5	1	72	1382.931	14923.21	596.9285	8.833459
5	1	5	64	1396.563	10267.3	410.6921	7.255507
6	6	1	60	1659.517	20687.05	574.6403	8.666978
6	3	2	60	1659.517	18360.54	510.0151	8.165094
6	2	3	64	1657.547	13024.32	361.7866	6.885124
6	1	6	64	1657.547	13992.95	388.6931	7.136559
7	7	1	48	1940.917	27332.13	557.7985	8.517846
7	1	7	32	1935.281	22072.06	450.4503	7.67675
8	8	1	48	2210.063	28331.91	442.6862	7.616113
8	4	2	48	2210.063	25416.85	397.1383	7.213671
8	2	4	48	2210.063	13128.51	205.133	5.184456
8	1	8	32	2211.531	20612.64	322.0726	6.491929
9	9	1	36	2496.556	35958.69	443.9344	7.595576
9	3	3	40	2489.275	26544.72	327.7126	6.545098
9	1	9	32	2492.063	21952.26	271.0155	5.945395
10	5	2	36	2765.861	42883.43	428.8343	7.487113
10	2	5	32	2793.125	17482.84	174.8284	4.733862
12	6	2	30	3319.033	59150.9	410.7701	7.327724
12	4	3	32	3315.094	33146.07	230.181	5.491868
12	3	4	30	3319.033	28774.07	199.8199	5.110801
12	2	6	32	3315.094	32910.71	228.5466	5.472336
14	7	2	24	3881.833	76620.7	390.9219	7.130765
14	2	7	16	3870.563	41125.6	209.8245	5.239406
15	5	3	24	4148.792	54537.22	242.3876	5.628918
15	3	5	20	4195.6	43627.47	193.8999	4.978356
16	8	2	24	4420.125	80681.74	315.1631	6.426183
16	4	4	24	4420.125	27894.26	108.962	3.77853
16	2	8	16	4423.063	34289.07	133.9417	4.186535
18	9	2	18	4993.111	93382.82	288.2186	6.120153
18	6	3	20	4978.55	81695.58	252.1469	5.741117
18	3	6	20	4978.55	76373.48	235.7206	5.550964

PLOT SIZE	Wid-th	Len-gth	No.of Plots	PLOT MEAN	VARIANCE	VARIANCE /SQ.MT	C.V.
20	4	5	16	5586.25	46513.07	116.2827	3.860709
21	7	3	16	5822.75	100332.1	227.5105	5.439911
21	3	7	10	5807.4	127643.8	289.4417	6.152025
24	8	3	16	6630.188	109432.5	189.987	4.98939
24	6	4	15	6638.067	80592	139.9167	4.276657
24	4	6	16	6630.188	75986.13	131.9204	4.157587
24	3	8	10	6630	111061.3	192.8148	5.026526
25	5	5	12	6992.667	100211.5	160.3383	4.527056
27	9	3	12	7489.667	104260.2	143.0181	4.311186
27	3	9	10	7478.3	91430.22	125.4187	4.043356
28	7	4	12	7763.667	113961.5	145.359	4.348226
28	4	7	8	7741.125	112005.7	142.8644	4.323306
30	6	5	10	8391.2	132592.4	147.3249	4.339457
30	5	6	12	8297.583	157490.2	174.9891	4.782722
32	8	4	12	8840.25	84834.91	82.84659	3.294752
32	4	8	8	8846.125	100269.7	97.91964	3.579578
35	7	5	8	9824.75	166125.1	135.6124	4.148549
35	5	7	6	9679	249047.6	203.3042	5.155973
36	9	4	9	9986.223	139181	107.3927	3.735844
36	6	6	10	9957.1	231927.1	178.9561	4.83663
36	4	9	8	9968.25	77691.43	59.94709	2.796196
40	8	5	8	11172.5	148498.3	92.81142	3.449136
40	5	8	6	11050	236774.4	147.984	4.403572
42	7	6	8	11645.5	293894.3	166.6067	4.65519
42	6	7	5	11614.8	339805	192.6332	5.018838
45	9	5	6	12620.67	150843.2	74.49047	3.077376
45	5	9	6	12463.83	171169.6	84.5282	3.319416
48	8	6	8	13260.38	252347.4	109.5258	3.788294
48	6	8	5	13260	316752	137.4792	4.244399
49	7	7	4	13620.25	582604	242.6506	5.604045
54	9	6	6	14979.33	311084	106.6818	3.723457
54	6	9	5	14956.6	217356	74.53909	3.117116
56	8	7	4	15482.25	341125.3	108.7772	3.772445
56	7	8	4	15534.75	546352	174.2194	4.758083
63	9	7	3	17502.33	529995	133.5336	4.159488
63	7	9	4	17513.5	437853.3	110.3183	3.778256
64	8	8	4	17692.25	286378.7	69.91666	3.024734
72	9	8	3	19942.33	639336	123.3287	4.009485
72	8	9	4	19936.5	233408	45.02469	2.42331
81	9	9	3	22465.67	477797	72.82381	3.076822

TABLE:2.1.1A(Jute data) average values for same plot sizes but different shapes.

PLOT SIZE	No.of Plots	PLOT MEAN	VARIANCE	VARIANCE /SQ.MT	C.V.
1	384	276.2578	1610.48	1610.48	14.52657
2	192	552.5156	3766.859	941.7147	11.10756
3	124	829.2659	6466.122	718.458	9.691326
4	96	1105.031	8624.421	539.0263	8.38475
5	68	1389.747	12595.26	503.8103	8.044483
6	62	1658.532	16516.22	458.7838	7.713439
7	40	1938.099	24702.1	504.1244	8.097298
8	44	2210.43	21872.48	341.7575	6.626542
9	36	2492.631	28151.89	347.5542	6.695356
10	34	2779.493	30183.14	301.8314	6.110488
12	31	3317.064	38495.44	267.3294	5.850682
14	20	3876.198	58873.15	300.3732	6.185086
15	22	4172.196	49082.35	218.1438	5.303637
16	21.33	4421.104	47621.69	186.0223	4.797083
18	18.5	4983.584	69286.7	213.8479	5.157093
20	17	5558.986	51886.65	129.7167	4.093254
21	13	5815.075	113988	258.4761	5.795968
24	14.25	6632.111	94267.98	163.6597	4.61254
25	12	6992.667	100211.5	160.3383	4.527056
27	11	7483.984	97845.21	134.2184	4.177271
28	10	7752.396	112983.6	144.1117	4.335766
30	11	8344.392	145041.3	161.157	4.56109
32	10	8843.188	92552.31	90.38312	3.437165
35	7	9751.875	207586.4	169.4583	4.652261
36	9	9970.524	149599.8	115.432	3.789557
40	7	11111.25	192636.4	120.3977	3.926354
42	6.5	11630.15	316849.7	179.62	4.837014
45	6	12542.25	161006.4	79.50934	3.198396
48	6.5	13260.19	284549.7	123.5025	4.016347
49	4	13620.25	582604	242.6506	5.604045
54	5.5	14967.97	264220	90.61045	3.420287
56	4	15508.5	443738.7	141.4983	4.265264
63	3.5	17507.92	483924.2	121.926	3.968872
64	4	17692.25	286378.7	69.91666	3.024734
72	3.5	19939.42	436372	84.1767	3.216398
81	3	22465.67	477797	72.82381	3.076822

TABLE 2.1.2: Rice data

Plot Size	Wid-th	Len-gth	No.of Plots	Plot MEAN	VARIANCE	Variance /sq.mt.	C.V.
1	1	1	396	835.1843	13988.38	13988.38	14.16124
2	2	1	198	1670.369	27349.12	6837.279	9.90055
2	1	2	198	1670.369	35538.84	8884.711	11.28598
3	3	1	126	2515.262	39960.83	4440.092	7.947564
3	1	3	132	2505.553	60863.75	6762.639	9.846361

Plot Size	Wid-th	Len-gth	No.of Plots	Plot MEAN	VARIANCE	Variance /sq.mt.	C.V.
4	4	1	90	3357.145	53770.79	3360.674	6.907218
4	2	2	99	3340.737	80709.23	5044.327	8.503922
4	1	4	88	3333.386	95908.78	5994.299	9.290595
5	5	1	72	4196.431	62910.65	2516.426	5.976983
5	1	5	66	4157.091	123822.5	4952.901	8.464675
6	6	1	54	5050.056	79760.91	2215.581	5.592408
6	3	2	63	5030.524	106220.4	2950.566	6.478743
6	2	3	66	5011.106	136336.7	3787.132	7.368395
6	1	6	66	5011.106	153177.6	4254.933	7.810233
7	7	1	54	5868.944	107111.2	2185.944	5.576447
7	1	7	44	5813.364	193632.8	3951.689	7.569408
8	8	1	36	6807.583	89870.63	1404.229	4.403682
8	4	2	45	6714.289	170132.4	2658.318	6.143183
8	2	4	44	6666.773	236410	3693.907	7.293186
8	1	8	44	6666.773	269960.9	4218.14	7.79354
9	9	1	36	7575.083	92057.6	1136.514	4.005367
9	3	3	42	7545.786	187989.1	2320.853	5.74595
9	1	9	44	7516.659	292946.6	3616.625	7.200611
10	5	2	36	8392.861	169155.7	1691.557	4.900419
10	2	5	33	8314.182	334565	3345.65	6.956979
12	6	2	27	10100.11	240029.5	1666.872	4.85072
12	4	3	30	10071.43	287783.7	1998.498	5.326499
12	3	4	28	10034.93	334312.3	2321.613	5.761849
12	2	6	33	10022.21	376188	2612.417	6.119823
14	7	2	27	11737.89	306715.1	1564.873	4.718213
14	2	7	22	11626.73	534253.7	2725.784	6.286607
15	5	3	24	12589.29	263770.4	1172.313	4.079545
15	3	5	21	12519.9	481429.6	2139.687	5.541985
16	8	2	18	13615.17	286930.8	1120.823	3.934283
16	4	4	20	13403.4	520879.2	2034.684	5.384601
16	2	8	22	13333.55	707925.3	2765.333	6.310272
18	9	2	18	15150.17	257340.2	794.26	3.348393
18	6	3	18	15150.17	373504	1152.79	4.033947
18	3	6	21	15091.57	535516.8	1652.83	4.849
18	2	9	22	15033.32	761731.1	2351.022	5.805585
20	5	4	16	16754.25	513668.3	1284.171	4.27776
20	4	5	15	16709.2	757961.1	1894.903	5.210361
21	7	3	18	17606.83	508176.9	1152.329	4.048799
21	3	7	14	17494.86	787478.1	1785.665	5.072346
24	8	3	12	20422.75	332171.6	576.6868	2.822066
24	6	4	12	20164.83	699194.2	1213.879	4.146715
24	4	6	15	20142.87	727899.4	1263.714	4.235595
24	3	8	14	20069.86	1052416	1827.111	5.111513
25	5	5	12	20886.5	611211.6	977.9386	3.743089
27	9	3	12	22725.25	366964.4	503.3805	2.665651
27	3	9	14	22637.36	1224071	1679.11	4.887397

Plot Size	Wid-th	Len-gth	No.of Plots	Plot MEAN	VARIANCE	Variance /sq.mt.	C.V.
28	7	4	12	23414.83	1006976	1284.408	4.285667
28	4	7	10	23345.8	1167239	1488.825	4.627764
30	6	5	9	25112	910596	1011.773	3.799982
30	5	6	12	25178.58	589410.9	654.9011	3.049143
32	8	4	8	27253.5	597357.7	583.3571	2.835926
32	4	8	10	26806.8	1635726	1597.389	4.77101
35	7	5	9	29213.11	1497438	1222.398	4.188868
35	5	7	8	29182.25	905826.3	739.4501	3.261397
36	9	4	8	30247.25	569828.6	439.6825	2.495665
36	6	6	9	30300.33	886656	684.1481	3.107636
36	4	9	10	30214.3	1573305	1213.97	4.151393
40	8	5	6	33976.33	673126.4	420.704	2.414748
40	5	8	8	33508.5	1586304	991.44	3.758705
42	7	6	9	35213.67	1250952	709.1564	3.176209
42	6	7	6	35068	1140448	646.5125	3.045276
45	9	5	6	37668	554096	273.6277	1.97615
45	5	9	8	37767.88	1761659	869.9553	3.514297
48	8	6	6	40845.5	107212.8	46.53333	0.80164
48	6	8	6	40329.67	1812224	786.5555	3.337961
49	7	7	6	40821.33	1871699	779.5499	3.351435
54	9	6	6	45450.5	279961.6	96.00877	1.164154
54	6	9	6	45450.5	2289459	785.1369	3.329107
56	8	7	4	47494.5	256170.7	81.68707	1.065667
56	7	8	6	46829.67	3119360	994.6938	3.771479
63	9	7	4	52602	149552	37.68002	0.73518
63	7	9	6	52820.5	3264122	822.404	3.420429
64	8	8	4	54507	1319936	322.25	2.107774
72	9	8	4	60494.5	1730773	333.8683	2.174724
72	8	9	4	61268.25	736341.3	142.0412	1.400568
81	9	9	4	68175.75	2025472	308.7139	2.087532

TABLE 2.1.2A: (Rice data) average values for same plot sizes but different shapes.

Plot Size	No.of Plots	Plot MEAN	VARIANCE	Variance /sq.mt.	C.V.
1	396	835.1843	13988.38	13988.38	14.16124
2	198	1670.369	31443.98	7860.995	10.59327
3	129	2510.408	50412.29	5601.366	8.896963
4	92.3	3343.756	76796.267	4799.767	8.233912
5	69	4176.761	93366.575	3734.664	7.220829
6	62.3	5025.698	118873.9	3302.053	6.812445
7	49	5841.154	150372	3068.817	6.572928
8	42.3	6713.855	191593.48	2993.649	6.408398
9	40.7	7545.843	190997.77	2357.997	5.650643
10	34.5	8353.522	251860.35	2518.604	5.928699
12	29.5	10057.17	309578.38	2149.85	5.514723
14	24.5	11682.31	420484.4	2145.329	5.50241

Plot Size	No.of Plots	Plot MEAN	VARIANCE	Variance /sq.mt.	C.V.
15	22.5	12554.6	372600	1656	4.810765
16	20	13450.71	505245.1	1973.613	5.209719
18	19.8	15106.31	482023.03	1487.726	4.509231
20	15.5	16731.73	635814.7	1589.537	4.744061
21	16	17550.85	647827.5	1468.997	4.560573
24	13.3	20200.08	702920.3	1220.348	4.078972
25	12	20886.5	611211.6	977.9386	3.743089
27	13	22681.31	795517.7	1091.245	3.776524
28	11	23380.32	1087107.5	1386.617	4.456716
30	10.5	25145.29	750003.45	833.3371	3.424563
32	9	27030.15	1116541.9	1090.373	3.803468
35	8.5	29197.68	1201632.2	980.9241	3.725133
36	9	30253.96	1009929.9	779.2669	3.251565
40	7	33742.42	1129715.2	706.072	3.086727
42	7.5	35140.84	1195700	677.8345	3.110743
45	7	37717.94	1157877.5	571.7915	2.745224
48	6	40587.59	959718.4	416.5444	2.0698
49	6	40821.33	1871699	779.5499	3.351435
54	6	45450.5	1284710.3	440.5728	2.246631
56	5	47162.09	1687765.4	538.1904	2.418573
63	5	52711.25	1706837	430.042	2.077805
64	4	54507	1319936	322.25	2.107774
72	4	60881.38	1233557.2	237.9548	1.787646
81	4	68175.75	2025472	308.7139	2.087532

From the above table it is observed that both variance per unit area and C.V. decrease with the increase in size of plot. For calculating Smith's heterogeneity coefficient b we consider only those plot shapes which fit exactly into the whole field. For Jute data the Smith's coefficient is 0.715 and its corresponding optimum plot size is 12.42 sq.mt. However for rice data Smith's coefficient is 0.54 and its corresponding optimum plot size is 5.51 sq.mt. The relatively high value of heterogeneity index for jute data indicate that the jute data are relatively random than rice field data.

2.2 Heterogeneity for non-isotropic field: Smith's empirical law relating the variance of crop yields per unit area to plot size is $V_n = V_1 / n^b$ where V_n is the variance among plots with an area of n units and V_1 is the variance among plots of unit size. The factor b is an index of heterogeneity. If the plots are spatially uncorrelated, then b will be 1. It can approach a limiting value of zero if no heterogeneity exists. If n corresponds to an area W and the size of the basic plot is w we can rewrite the above equation as $V_W = V_w.[w/W]^b$ where V_W and V_w are the two corresponding variances. Smith's empirical law is applicable only under the broad assumption of an isotropic field. However, in field it is often encountered that the fertility pattern shows a directional trend. To take anisotropy into account, a general variance relationship similar to Smith's law may be written as $V_{n,s} = V_1 /(n_1^{b_1}.n_2^{b_2})$ .....(i) where n_1, n_2 are the numbers of basic plots taken along the row, column directions respectively. V_1 is the variance of the basic plots, $V_{n,s}$ is the variance of plots each of which has $n = n_1.n_2$ basic plots. b_1 and b_2 are the indices which characterize the heterogeneity in the X, Y directions of a 2-D field, respectively. Such anisotropic models are used by Modjeska and Rawlings (1983), Sethi (1985), Zhang *et al.* (1994) etc. For an isotropic field, $b_1 = b_2$ resulting in $V_{n,s} = V_1 /(n_1.n_2)^{b_1}$ which is essentially the same as given by Smith. For a completely uniform field $b_1 = b_2 = 0$; and for a field with no spatial correlation, $b_1 = b_2 = 1$. In a logarithmic form we can write $\log(V_{n,s} / V_1) = -b_1 \log(n_1) - b_2 \log(n_2)$ ....(ii) which will be used to compute the indices of heterogeneity, i.e. b_1 and b_2 from available data. V_1 is calculated from the basic units (the original data) while $V_{n,s}$ is estimated from reconstructed plots each of which consists of $n = n_1.n_2$ basic units. During the reconstruction of the plots, if n_2 is fixed (e.g. n_2=1) and n_1 is varied i.e. n_1= 1,2,3,......, $V_{n,s}$ is a function of n_1 only. Therefore, the second term i.e. $b_2 \log(n_2)$ is constant and we can compute b_1 from the $\log(V_{n,s} / V_1)$ vs. $\log(n_1)$ relationship. Similarly, if n_1 is fixed and n_2 is varied, b_2 can be computed from the relationship of $\log(V_{n,s} / V_1)$ vs. $\log(n_2)$. If the same number of units are taken in the X and Y directions, or $n_1 = n_2$, we have $\log(V_{n,s} / V_1) = -(b_1 + b_2).\log(n_1) = -b_s.\log(n_1)$...(iii) Thus b_s can be obtained from the linear regression of $\log(V_{n,s} / V_1)$ on $\log(n_1)$. Now to verify whether the equation $V_{n,s} = V_1 /(n_1^{b_1}.n_2^{b_2})$ is a reasonable mathematical form to characterize heterogeneity in two directions, the sum of b_1 and b_2 computed from equation (ii) should be close to b_s independently computed from equation (iii). To study the effect of plot shapes on variances Zhang *et al.* (1994) have used an index called relative difference of variance i.e. RV = $100.(V_{n,s} - V_n)/V_n$ where $V_{n,s}$ is computed using equation (i) and $V_n = V_1/(n_1.n_2)^{0.5(b_1+b_2)}$ which represents the variance assuming that the field is isotropic. Less RV value will indicate a more efficient plot. Earlier optimum plot size has been defined as the size which balances between precision and sampling cost. The cost per plot is given by a linear relation (Smith, 1938; Weber and Horner, 1957) $K_1 + K_2.n$. Thus an objective function accounting for both cost and variance in an isotropic field can be expressed by $C = (K_1 + K_2.n).\frac{V_1}{n^b}$ where n is the number of units in the chosen plot and K_1, K_2 are the cost components as defined earlier. This objective function is minimized when $n_0 = \frac{K_1.b}{K_2.(1-b)}$ where n_0 is the optimum plot size in terms of the number of basic units. Let, $K = \frac{K_2}{K_1}$, we have $n_0.K = \frac{b}{1-b}$. Again let, $z = \frac{n}{n_0}$ (i.e. the ratio of plot size of n units to the most efficient size of n_0 units), then the objective function can be rewritten as $C = K_1.\left[1 + \frac{b}{1-b}.z\right].\frac{V_1}{n^b}$. Now if C is the cost related to variance for a specified plot size n and C_{min} is the cost related to variance for the optimum plot size n_0 then using Smith's (1938) definition the relative cost is $y = \frac{C}{C_{min}} = b.z^{(1-b)} + (1-b).z^{-b}$. In non-isotropic fields, the cost per plot may be given by $K_1 + K_2.n_1.n_2$ (Zhang *et al.*, 1994). Here the objective function accounting for both cost and variance is $C_s = (K_1 + K_2.n_1.n_2).\frac{V_1}{n_1^{b_1}.n_2^{b_2}}$ where $n_1.n_2$ is the number of basic units in a chosen plot. When $b_1 \le 0.5$ and $b_2 \le 0.5$, C_s is a monotone increasing function of n_1 and n_2. When b_1 or / and b_2 are greater than 0.5, the minimum value of C_s depends on the larger value of the heterogeneity indices. If $b_1 > b_2$, C_s has a minimum value when $n_1 = \frac{K_1.b_1}{[k_2.(1-b_1)]}$ and n_2=1. Similarly, if $b_2 > b_1$, C_s is minimum when $n_2 = \frac{K_1.b_2}{[k_2.(1-b_2)]}$ and $n_1 = 1$.

TABLE 2.2.1 : Indices of heterogeneity b_1, b_2 and b_s for the Jute data.

Shape	Jute data Variance per Unit area	LOG(VAR)	Plot size	SHAPE	JUTE DATA VARIANCE PER UNIT AREA	LOG(SIZE)	LOG(VAR)
1X1	1610.48	0	1	1X1	1610.48	0	0
1X2	920.8691	-0.55897	2	2X1	962.5602	0.6931472	-0.5146909
1X3	671.0709	-0.87541	3	3X1	765.845	1.0986123	-0.7433078
1X4	439.9316	-1.29767	4	4X1	605.5421	1.3862944	-0.9781635
1X5	410.6921	-1.36644	5	5X1	596.9285	1.6094379	-0.9924902
1X6	388.6931	-1.4215	6	6X1	574.6403	1.7917595	-1.0305433
1X7	450.4503	-1.27404	7	7X1	557.7985	1.9459102	-1.0602898
1X8	322.0726	-1.60951	8	8X1	442.6862	2.0794416	-1.2914264
1X9	271.0155	-1.78211	9	9X1	443.9344	2.1972246	-1.2886108
Intercept=	-0.0498954			Intercept=	-0.08147225		
Slope=	-0.7605628	b_2=0.76		Slope=	-0.55978509	b_1=0.56	
Corr. Coeff.	-0.9761098			Corr. Coeff.	-0.98372046		

Jute Plot size	SHAPE	Variance per Unit area	LOG(SIZE)	LOG(VAR)
1	1X1	1610.48	0	0
2	2X2	571.6053	0.6931472	-1.0358388
3	3X3	327.7126	1.0986123	-1.5921506
4	4X4	108.962	1.3862944	-2.6932884
5	5X5	160.3383	1.6094379	-2.3070016
6	6X6	178.9561	1.7917595	-2.197147
7	7X7	242.6505	1.9459102	-1.8926654
8	8X8	69.91666	2.0794416	-3.1369836
9	9X9	72.82381	2.1972246	-3.0962446
	Intercept=	-0.16429954		
	Slope=	-1.28674004	b_s=1.28	
	Corr. Coeff.	-0.91328668		

TABLE 2.2.2 : Indices of heterogeneity b_1, b_2 and b_s for the rice data.

Rice data							
Shape	Variance per Unit area	Log(var)	Plot size	Shape	Rice data Variance per Unit area	Log(size)	Log(var)
1X1	13988.38	2.161695	1	1X1	13988.38	0	2.161695
1X2	8884.711	1.7078	2	2X1	6837.279	0.693147	1.445858
1X3	6762.639	1.434881	3	3X1	4440.092	1.098612	1.014143
1X4	5994.299	1.314277	4	4X1	3360.674	1.386294	0.735609
1X5	4952.901	1.123441	5	5X1	2516.426	1.609438	0.446307
1X6	4254.933	0.971547	6	6X1	2215.581	1.791759	0.318982
1X7	3951.689	0.897611	7	7X1	2185.944	1.94591	0.305516
1X8	4218.14	0.962862	8	8X1	1404.229	2.079442	-0.13704
1X9	3616.625	0.809009	9	9X1	1136.514	2.197225	-0.34857
Intercept=	2.1357619			Intercept=	2.2010865		
Slope=	-0.6123138	b_2=0.61		Slope=	-1.0832265	b_1=1.08	
Corr. Coeff.	-0.9936021			Corr. Coeff.	-0.9910984		

PLOT SIZE	SHAPE	Variance per Unit area	LOG(SIZE)	LOG(VAR)
1	1X1	13988.38	0	2.161695
2	2X2	5044.327	0.693147	1.141732
3	3X3	2320.853	1.098612	0.365403
4	4X4	2034.684	1.386294	0.233808
5	5X5	977.9386	1.609438	-0.49884
6	6X6	684.1481	1.791759	-0.85611
7	7X7	779.5499	1.94591	-0.72557
8	8X8	322.25	2.079442	-1.60896
9	9X9	308.7139	2.197225	-1.65187
	Intercept=	2.3011417		
	Slope=	-1.730143	b_s=1.73	
	Corr. Coeff.	-0.985333		

The above tables show the values of b_1, b_2 and b_s for the jute and rice data. The index heterogeneity is more pronounced along column than along row in case of Jute data. In Rice field the heterogeneity is nearly double along row than along column direction. The sum of b_1 and b_2 is close to b_s for both rice and jute data. Smith's b found for both rice and jute data is some sort average of b_1 and b_2.

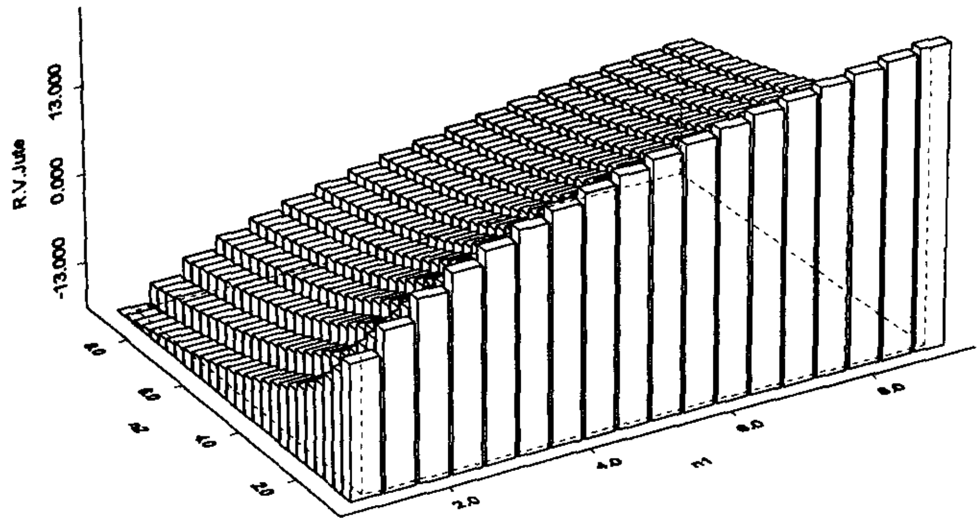


Fig. 2.2.1: Relative difference of variances R.V. as a function of plot shapes i.e. units along row and column directions n_1 and n_2 respectively for jute data.

The effect of plot shapes on the variance is shown in the fig.2.2.1For Jute data the relative difference in variance increases i.e. efficiency decreases considerably as the number of units taken along row increases as compared to the number units taken along the column direction. In case of Rice data the efficiency decreases considerably as we increase the number of units along column direction as compared to the number units taken along the row direction.

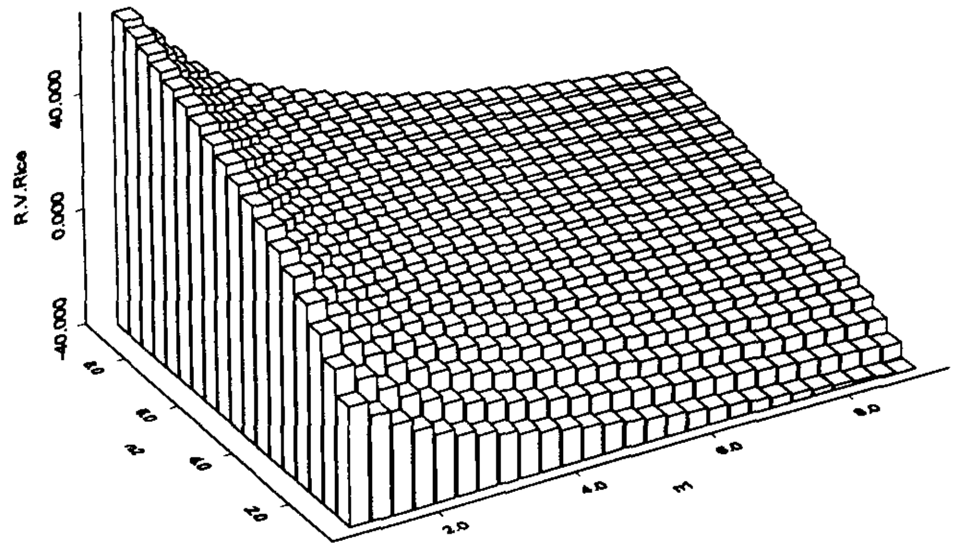
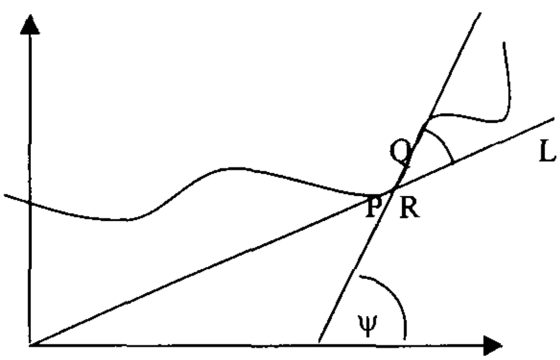
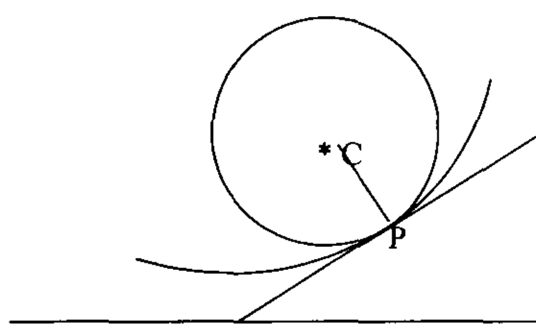


Fig. 2.2.2: Relative difference of variances R.V. as a function of plot shapes i.e. units along row and column directions n_1 and n_2 respectively for Rice data.

2.3 Maximum curvature: The method of maximum curvature is useful for determining optimum size and shape of plots in field experiments. Sethi (1985) suggested that Smith's law can be employed to relate C.V.(y) of a plot to its size(x) as $y = a.x^{-b}$. Now method of maximum curvature uses the general result of curvature of any curve. Let there be any curve AB on which PQ is any arch.We draw two tangent lines at P &Q respectively.Let $\angle QRL = \Delta\psi$ where $\Delta\psi$ is the





change in the inclination of the tangent line as the point of contact of the tangent line describes the arc PQ = ΔS. Here, $\frac{\Delta\Psi}{\Delta S}$ is called the average curvature of the arch PQ. When Q → P (from either side) along the curve, as a limiting position curvature at P is $\underset{\Delta S \to 0}{Lt}\frac{\Delta\Psi}{\Delta S} = \frac{d\Psi}{dS}$. Thus curvature is the rate of change of direction of the curve with respect to the arc or roughly the curvature is the "rate at which the curve curves". The reciprocal of the curvature at any point P is called the radius of curvature at P and it is denoted as $\frac{dS}{d\Psi}$. If a length PC is measured from P along the positive direction of the normal, the point C is called the centre of curvature at P and the circle with centre C and radius CP (i.e. ρ) is called the circle of curvature at P. Any chord of this circle through the point of contact is called a chord of curvature. The line PC which makes an angle +90° with the positive direction of the tangent (i.e. the direction in which S increases) is called the positive direction of the normal at P. ρ is +ve or –ve according to C is on the +ve or –ve side of the normal. For y = f(x) $\frac{dy}{dx} = \tan(\Psi)$ and $\frac{d^2y}{dx^2} = Sec^2\Psi.\frac{d\Psi}{dx} = Sec^2\Psi.\frac{d\Psi}{ds}.\frac{ds}{dx} = Sec^3\Psi.\frac{d\Psi}{ds}$. As we see that $\left[\frac{ds}{dx} = Sec\Psi\right]$. Hence ρ = $\frac{ds}{d\Psi} = \frac{Sec^3\Psi}{\frac{d^2y}{dx^2}}$. Since Secψ = $(1+\tan^2\Psi)^{1/2}$ we can write that $Sec\Psi = \left\{1+\left(\frac{dy}{dx}\right)^2\right\}^{1/2}$. Finally

$$\rho = \frac{\left\{1+\left(\frac{dy}{dx}\right)^2\right\}^{3/2}}{\frac{d^2y}{dx^2}} = \frac{(1+y_1^2)^{3/2}}{y_2}$$

. ρ is +ve or –ve accordingly as y_2 is +ve or _ve. If we denote it by ρ then ρ = $\frac{(1+y_1^2)^{3/2}}{y_2}$ where $y_1 = \frac{dy}{dx}$ and $y_2 = \frac{d^2y}{dx^2}$. Now using the property of maxima minima we have $\frac{d\rho}{dx} = 0$ or, $\frac{d}{dx}\left\{\frac{(1+y_1^2)^{3/2}}{y_2}\right\} = 0$ which gives rise to the following equation:-

$3.y_1.y_2^2 - y_1^2.y_3 - y_3 = 0$ where $y_1 = -a.b.x^{-(1+b)}$, $y_2 = a.b.(1+b).x^{-(2+b)}$,

$y_3 = -a.b.(1+b).(2+b).x^{-(3+b)}$. Putting the values and solving for x gives $x_{opt} = \left\{ \frac{a^2.b^2.(1+2.b)}{(2+b)} \right\}^{\frac{1}{2.(1+b)}}$.

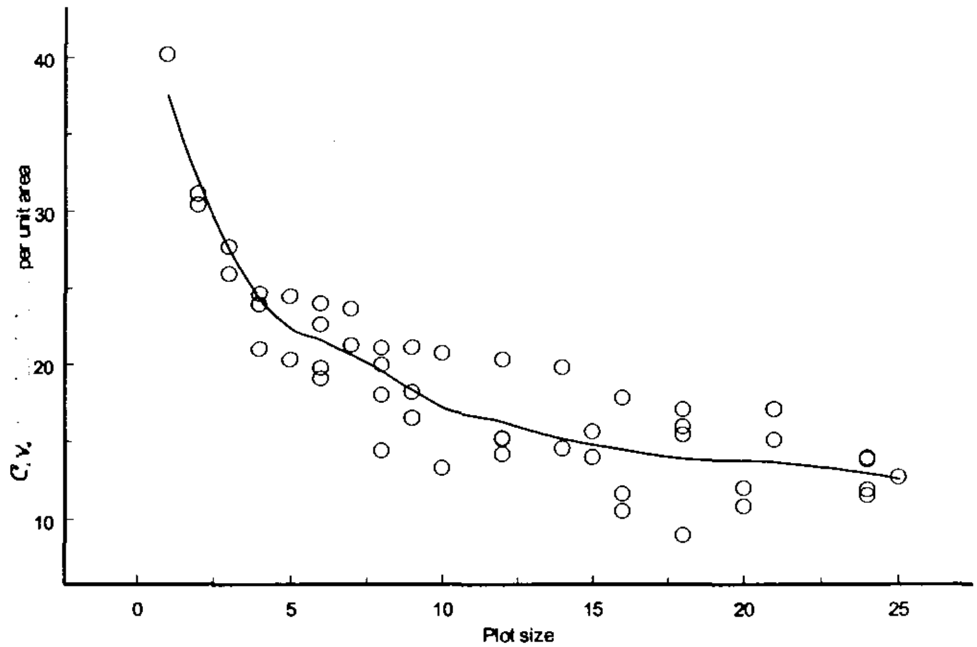


Fig.2.3.1: Smoothing Loess plot of C.V. as a function of plot size for Jute data.

Once the optimum plot size is determined, the choice of *plot shape* is governed by the following considerations. Long and narrow plots should be used for areas with distinct fertility gradient, with the length of the plot parallel to the fertility gradient of the field. When the fertility pattern of the field is spotty or not known plots should be as square as possible. For determining optimum shape of plots y was further related to x as $y = a'.x_1^{-b_1}.x_2^{-b_2}$ where x_1 and x_2 denote the number of units combined in row (E →W) and column (N→S) directions respectively, to make a plot of size x. Now the value of x_2 (say x_{02}) which conditionally maximizes curvature of y at a fixed x_1 is given by $x_{02} = \left\{ \frac{b_2^2.c_1^2.(1+2.b_2)}{(2+b_2)} \right\}^{\frac{1}{2.(1+b_2)}}$ where $c_1 = a'.x_1^{-b_1}$. The conditional maxima of x_1 at a fixed x_2 was similarly obtained. Now x_{02} was expressed as a function of x_1 as $x_{02} = d.x_1^{-e}$. The above function was solved for the values of x_1 (say x_{1opt}) and x_2 (say x_{2opt}) under the constraint $x_{opt} = x_{1opt}.x_{2opt}$ thereby providing optimum dimensions of the plot of size x_{opt}. The unknown parameters *a*, *b* are estimated through regression analysis. The goodness of a fitted function is indicated by the closeness of a statistic ϕ,

given by $\phi = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$ to 1, where $\hat{y}_i$ is the estimate of an observed y_i from the function

and $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

Maximum curvature: **Jute data**: The pooled values of C.V. decreases with an increases in plot size. The relation $y = a\,x^{-b}$ in estimated form was $y = 40.2\,x^{-0.38}$ with $\phi = 0.98$, thus indicating a good fit. From relation 2 it was found that $x_{opt} = 6.5$ units i.e. $X_{opt} = 7$ sq. m. when units plots were 1 m. x 1 m. Model 3 i.e. $y = a' .x_1^{b_1}.x_2^{b_2}$ applied to C. V. data resulted in $y = 40.2\ x_1^{-0..31}.x_2^{-0.45}$, which too was a good fit since $\phi = 0.987$. The relative magnitude of b_1 and b_2 again indicate the C.V values to expectedly fall at a higher rate as the plot size was increased along length along width of the Jute field. For attaining $x_2 > x_1$ with $x_1x_2 = 6.5$ it is sufficient to evaluate conditional maxima of x_2 at different x_1,s which be possibly due to $b_2 > b_1$. The equation $x_{02} = 6.75\ x_1^{-0.21}$ gave an excellent fit to the underlying relationship between x_{02} & x_1. its solution provided $x_{1opt} = 1.122$ m., $x_{2opt} = 5.762$ m. meaning thereby that the optimum plot size was 7 sq. m. with 1.12 m. along the width and 5.76 m. along the length of the Jute field.

Rice data: The pooled values of C.V. decreases with an increases in plot size. The relation $y = a\,x^{-b}$ in estimated form was $y = 139.86\ x^{-.0.48}$ with $\phi = 0.96$, thus indicating a good fit. From relation 2 it was found that x opt = 15.86 mt.^{2} when units plots were 1 mt x 1 mt. model 3 i.e. $y = a' .x_1^{b_1}.x_2^{b_2}$ applied to C. V. data resulted in $y = 139.87\ x_1^{-0.63}\ x_2^{-0.32}$ which too was a good fit since $\phi = 0.96$ the relative magnitude of b_1 and b_2 again indicate the C.V values to expectedly fall at a higher rate as the plot size was increased along width than along length of the Rice field. For attaining $x_1 > x_2$ with $x_1 . x_2 = 15.86$. it is sufficient to evaluate conditional maxima of x_1 at different x_2's which be possibly due to $b_1 > b_2$. The equation $x_{01} = 14.87.\ x_2^{-0.196}$ gave an execellent fit to the underlying relationship between x_{01} & x_2. Its solution provided $x_{1opt} = 7.842$

mt. x_{2opt}= 2.022 mt. meaning thereby that the optimum plot size was 15.86 sq. mt. with 7.842 mt. along width and 2.022 mt. along length of the Rice field.

2.4 Block size: Block size is governed by the plot size chosen, the number of treatments tested and the experimental design used. The primary objective in choosing the shape of blocks is to reduce the differences in productivity levels among plots within a block so that most of the soil variability in the experimental area is accounted for by variability between blocks. Information on the pattern of soil heterogeneity in the area is helpful in making this choice. When the fertility pattern of the area is known, orient the blocks so that soil differences between blocks are maximized and those within the same block are minimized. For example, in an area with a unidirectional fertility gradient, the length of the block should be oriented perpendicular to the direction of the fertility gradient. In an area with bidirectional fertility gradient a row-column design is appropriate. On the other hand, when the fertility pattern of the area is spotty or is not known to the researcher blocks should be kept as compact or as nearly square as possible. Again block size, for most experimental designs, increases proportionately with the number of treatments and because it is difficult to maintain homogeneity in large blocks, a researcher must also be concerned with the number of treatments. If the number of treatments is so large that uniform area within a block can not be attained, incomplete block designs may be used.

To find out the size and shape of plots and blocks that will give the maximum accuracy for the mean with a given amount of experimental area, it is necessary to have a knowledge of the probable magnitude of the coefficient of variation for different sizes and shapes of the plots and blocks. This information is generally obtained from the data of a uniformity trial. In India earlier such studies have been made by Hutchinson and Panse (1935) for cotton, Ghose and Sanyal (1945) for jute and by a large number of workers for sugarcane and wheat. Similar work on rice has been done by Bose et al (1936), Narasinga Rao (1937), Abraham et al (1964).

In our work both the crops (rice and jute) are harvested in contiguous units of 1mt. X 1mt. Plots of various sizes are obtained by combining the units along North-South and West-East directions. The plots are grouped into blocks of 2 to 12 plots as found feasible for our data. Plots are grouped both in North-South and West-East directions separately. The coefficient of variation (C.V.) for each arrangement is calculated separately and the optimum size and shape of the plots and their arrangement in blocks are found out on the basis of observed C.V.

RESULT: *Optimum block size and shape*: For Jute data Table 2.4.1 & 2.4.2 give the C.V. for the different size and shapes of plots after arranging them into blocks of 3 to12 plots some of the combinations of the plot sizes and blocks are not possible. The blanks in Table correspond to such combinations.

For Jute data C.V. in general decreased with increase in plot size in either direction, the decrease being greater when the larger dimension is in N→S direction and when the blocks run E→W direction. The reduction in C.V. with increased plot size is comparatively less when the increase in plot size was beyond 6 units or 6 mt. along E→W direction. For optimum plot size of 2mt.X5mt. the 9 plot blocks give lowest C.V. than 3 plot blocks and 6 plot and 12 plot blocks.However when blocks run in N→S direction the decrease in C.V. with increase in plot size is more or less equal in both directions. The 12 plot blocks gave a higher C.V. than the 6 plot blocks with larger plots.The decrease in C.V. is reasonably greater when blocks run E→W direction than when blocks run N→S direction.

EFFECT OF PLOT SHAPE ON VARIABILITY: In general plots elongated along N→S direction showed less variability than plots elongated along E→W direction. Compact or square plots in general showed slightly less or approximately equal variability than plots elongated in N→S direction. However, plots elongated along E→W direction are more variable than square plots.

TABLE 2.4.1: (Jute data) Within block C.V. for different plot sizes when blocks run row (E→W) direction

3 plot blocks:

row	no. of units along column(N→S) direction								
E→W	1	2	3	4	5	6	7	8	9
1	10.62	7.50	6.91	5.67	5.52	4.86	5.16	4.55	4.67
2	7.35	4.92	4.05	3.10	2.41	3.08	2.70	**1.75**	**1.60**
3	6.62	5.41	4.52	3.59	3.65	4.16	4.89	3.71	3.13
4	6.14	4.71	3.15	2.98	2.29	2.53	2.78	2.64	**2.12**
5	6.68	5.72	4.69	3.37	3.59	3.83	3.81	3.11	2.30
6	5.26	4.40	2.75	2.89	2.26	2.30			
7	5.26	4.18	2.87	2.39	2.17	2.19			
8	5.04	4.14	2.87	2.53	**1.52**	2.29			
9	5.81	4.51	3.99	3.52	2.69	3.31			

of variation (C.V.) for each arrangement is calculated separately and the optimum size and shape of the plots and their arrangement in blocks are found out on the basis of observed C.V.

RESULT: *Optimum block size and shape*: For Jute data Table 2.4.1 & 2.4.2 give the C.V. for the different size and shapes of plots after arranging them into blocks of 3 to12 plots some of the combinations of the plot sizes and blocks are not possible. The blanks in Table correspond to such combinations.

For Jute data C.V. in general decreased with increase in plot size in either direction, the decrease being greater when the larger dimension is in N→S direction and when the blocks run E→W direction. The reduction in C.V. with increased plot size is comparatively less when the increase in plot size was beyond 6 units or 6 mt. along E→W direction. For optimum plot size of 2mt.X5mt. the 9 plot blocks give lowest C.V. than 3 plot blocks and 6 plot and 12 plot blocks.However when blocks run in N→S direction the decrease in C.V. with increase in plot size is more or less equal in both directions. The 12 plot blocks gave a higher C.V. than the 6 plot blocks with larger plots.The decrease in C.V. is reasonably greater when blocks run E→W direction than when blocks run N→S direction.

EFFECT OF PLOT SHAPE ON VARIABILITY: In general plots elongated along N→S direction showed less variability than plots elongated along E→W direction. Compact or square plots in general showed slightly less or approximately equal variability than plots elongated in N→S direction. However, plots elongated along E→W direction are more variable than square plots.

TABLE 2.4.1: (Jute data) Within block C.V. for different plot sizes when blocks run row (E→W) direction

3 plot blocks:

row	no. of units along column(N→S) direction								
E→W	1	2	3	4	5	6	7	8	9
1	10.62	7.50	6.91	5.67	5.52	4.86	5.16	4.55	4.67
2	7.35	4.92	4.05	3.10	2.41	3.08	2.70	**1.75**	**1.60**
3	6.62	5.41	4.52	3.59	3.65	4.16	4.89	3.71	3.13
4	6.14	4.71	3.15	2.98	2.29	2.53	2.78	2.64	**2.12**
5	6.68	5.72	4.69	3.37	3.59	3.83	3.81	3.11	2.30
6	5.26	4.40	2.75	2.89	2.26	2.30			
7	5.26	4.18	2.87	2.39	2.17	2.19			
8	5.04	4.14	2.87	2.53	**1.52**	2.29			
9	5.81	4.51	3.99	3.52	2.69	3.31			

4 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	11.49	8.31	7.62	6.58	6.15	5.83	6.38	5.44	5.23
2	8.29	5.88	4.83	4.05	3.36	4.06	3.88	3.09	2.30
3	7.76	5.84	4.85	4.37	3.73	4.32	4.92	4.05	3.40
4	6.83	5.47	4.33	2.69	2.96	3.15	3.18	2.49	**1.94**
5	6.00	4.79	3.17	2.90	2.58	2.86			
6	6.42	5.15	3.94	3.73	2.91	3.56			
7	7.04	5.75	5.20	4.16	3.77	4.28			
8	6.27	5.30	4.76	3.13	2.95	3.53			

5 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	11.63	8.21	7.69	6.30	5.94	5.65	6.20	5.23	5.23
2	8.82	6.45	5.20	4.01	3.42	4.08	3.23	2.29	**1.79**
3	8.18	6.62	5.78	4.35	4.20	4.79	5.14	4.03	3.29
4	6.01	4.80	2.90	2.43	**1.99**	**2.18**			
5	6.92	5.52	4.27	4.08	3.54	3.93			
6	7.40	6.21	5.57	4.11	3.89	4.58			

6 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	11.76	8.36	7.63	6.35	6.09	5.65	6.36	5.39	5.36
2	9.33	6.77	5.33	4.63	3.63	4.42	4.22	3.44	2.70
3	7.06	5.09	3.64	3.32	**2.62**	**2.89**			
4	6.74	5.29	3.62	3.28	**2.64**	3.09			
5	7.61	6.41	5.48	4.19	4.12	4.57			

7 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	11.79	8.53	7.62	6.33	5.89	5.65	5.91	5.02	4.93
2	9.64	7.28	6.16	4.64	3.86	4.72	4.48	**3.40**	**2.52**
3	7.51	5.65	4.29	3.54	2.83	3.66			
4	7.63	6.10	5.15	3.75	3.27	3.90			

8 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	12.40	8.97	7.99	6.86	6.44	6.13	6.81	5.83	5.46
2	9.68	7.29	6.02	4.46	4.06	4.77	4.42	**3.38**	**2.57**
3	8.25	6.31	5.17	4.59	3.95	4.67			
4	7.81	6.28	5.34	3.68	3.50	4.02			

9 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	12.16	9.15	7.87	6.57	6.57	6.41	7.01	5.70	5.36
2	9.13	6.69	4.95	4.23	**3.30**	3.87			
3	8.81	7.04	6.03	5.03	4.53	5.32			

10 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	12.73	9.35	8.30	6.84	6.56	6.25	6.60	5.59	5.42
2	9.28	6.88	5.42	4.51	**3.55**	4.44			
3	8.95	7.23	6.44	5.01	4.66	5.41			

11 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	12.03	8.88	7.66	6.58	5.97	6.07	6.16	4.91	4.71
2	9.29	7.01	5.46	4.57	**3.54**	4.52			

12 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	12.56	9.19	7.93	6.75	6.20	6.32	6.68	5.44	5.06
2	9.74	7.19	5.62	4.83	**3.86**	4.76			

TABLE 2.4.2: (Jute data) Within block C.V. for different plots when blocks run column (N→S) direction.

3 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4
1	11.10	8.36	6.98	5.33
2	8.88	6.72	5.42	3.68
3	7.58	6.02	5.18	3.20
4	7.02	5.89	4.36	2.07
5	6.83	5.79	4.81	2.66
6	6.52	5.55	4.52	2.50
7	6.58	5.46	3.57	2.10
8	5.78	5.20	4.09	1.73
9	6.25	4.88	2.23	1.25

4 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3
1	12.39	8.35	7.66
2	9.96	6.65	5.82
3	8.60	6.49	5.17
4	8.05	5.57	4.45
5	7.70	6.04	4.44
6	7.54	5.60	4.53
7	7.33	5.01	3.85
8	6.84	5.21	4.05
9	6.61	3.74	2.49

	5 plot		*6 plot blocks*	
row	no. of units along column(N→S) direction			
E→W	1	2	1	2
1	12.28	8.95	12.66	9.56
2	9.52	7.14	9.82	7.83
3	8.4	6.95	8.37	7.11
4	7.49	5.95	7.89	6.45
5	7.14	6.49	7.48	6.62
6	7.01	6.18	7.27	6.41
7	6.82	5.59	7.22	5.98
8	6.28	5.26	6.65	5.71
9	6.14	4.37	6.67	4.95

row	*7 plot*	*8 plot*	*9 plot*	*10 plot*	*11 plot*	*12 plot blocks*
single unit along column(N→S) direction						
1	11.83	12.21	12.2	13.07	13.18	13.48
2	9.07	9.52	9.61	10.11	10.35	10.61
3	7.94	8.39	8.51	9	9	9.18
4	7.21	7.33	7.41	7.93	8.01	8.31
5	6.87	7.23	7.44	7.85	7.86	8.14
6	6.61	6.71	6.97	7.64	7.73	7.94
7	6.09	6.14	6.3	7.18	7.29	7.62
8	6.11	6.3	6.14	6.7	6.82	7.06
9	5.34	5.17	5.36	6.22	6.39	6.73

BLOCK EFFICIENCY: For investigating the influence of size and shape of plots and blocks on block efficiency 24 units along E→W and 18 units along N→S are taken to have as many convenient combinations as possible.

If V_B denotes variance with blocks & V the variance without block restriction, the efficiency of block is defined as $\frac{V}{V_B}$. For selected plot sizes & shapes, block efficiencies for various number of plots per block are given in Table 5 & 6

From the following Table 2.4.3 for Jute data we see that with blocks of same size but different shapes formed from plots of the same size, there was detectable change in blocking efficiency. As in general for all plot sizes & shapes blocks running E→W showed higher blocking efficiency than the blocks running in N→S direction. The highest blocking efficiency value 5.71 was found for 3 plot blocks containing plots of size 16 sq. mt. & shape 2 x 8 (i.e. 2 mt. in E→W & 8 mt in N→S direction). For the same B.E. block size was 48 sq. mt. & shape was 3 : 4 (i.e. 6 mt. in E→W direction & 8 mt. in N→S direction). The second highest blocking efficiency was 4.05 was found for 3 plot blocks containing plot of size 18 sq. mt. & shape 2 :9 (i.e. 2 mt. in E→W direction & 9 mt. in N→S direction). For the same B.E. block size was 54 sq. mt. & block shape was 2 : 3 (i.e. 6 mt. in E→W direction & 9 mt. in N→S direction).

TABLE 2.4.3: (Jute data) Blocking Efficiencies when blocks run row(E->W) direction

3 plot blocks:

row	no. of units along column(N→S) direction								
E→W	1	2	3	4	5	6	7	8	9
1	1.88	2.16	1.87	1.79	1.77	2.24	2.28	2.10	1.68
2	2.37	3.14	2.91	2.78	3.93	3.21	3.77	**5.71**	**4.05**
3	2.28	2.21	1.83	1.96	1.59	1.67	1.48	1.78	1.64
4	1.89	2.00	1.65	1.22	1.35	1.79	1.10	1.20	1.23
5	1.72	1.66	1.38	1.56	1.46	1.43	1.53	1.67	1.73
6	1.87	1.46	1.40	1.04	1.18	1.06			
7	2.00	1.90	1.51	1.01	1.03	1.49			
8	2.02	1.96	1.39	1.00	1.05	1.37			
9	1.66	1.74	1.07	1.00	1.09	1.06			

4 plot blocks:

row	no. of units along column(N→S) direction								
E→W	1	2	3	4	5	6	7	8	9
1	1.60	1.74	1.50	1.32	1.37	1.48	1.40	1.38	1.25
2	1.83	**2.15**	2.00	1.61	1.92	1.76	1.71	1.72	1.83
3	1.56	1.65	1.27	1.10	1.13	1.27	1.03	1.08	1.09
4	1.68	1.70	1.56	1.89	1.60	1.63	1.62	1.81	1.82
5	1.65	1.51	1.34	1.01	1.03	1.20			
6	1.63	1.62	1.21	1.00	1.01	1.15			
7	1.43	1.48	1.02	1.00	1.06	1.03			
8	1.44	1.41	1.03	1.01	1.20	1.01			

5 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.57	1.81	1.51	1.45	1.53	1.66	1.58	1.59	1.34
2	1.64	1.83	1.77	1.65	1.94	1.83	2.63	**3.32**	**3.22**
3	1.48	1.50	1.25	1.34	1.34	1.28	1.29	1.40	1.36
4	1.65	1.50	1.40	1.02	1.05	1.34			
5	1.48	1.52	1.14	1.00	1.01	1.10			
6	1.35	1.35	1.01	1.01	1.12	1.00			

6 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.53	1.74	1.54	1.42	1.46	1.66	1.50	1.50	1.27
2	1.39	1.49	1.23	1.09	1.14	1.26	1.04	1.12	1.14
3	1.49	1.35	1.23	1.03	1.13	1.04			
4	1.57	1.59	1.25	1.00	1.02	1.20			
5	1.33	1.32	1.01	1.01	1.11	1.00			

7 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.51	1.67	1.48	1.43	1.43	1.59	1.67	1.67	1.44
2	1.36	1.42	1.16	1.22	1.25	1.24	1.25	1.38	1.42
3	1.49	1.49	1.23	1.00	1.02	1.18			
4	1.37	1.42	1.03	1.00	1.08	1.04			

8 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.37	1.49	1.37	1.21	1.25	1.33	1.23	1.20	1.15
2	1.34	1.39	1.29	1.32	1.32	1.28	1.32	1.44	1.47
3	1.38	1.41	1.12	1.00	1.01	1.09			
4	1.29	1.29	1.03	1.01	1.14	1.00			

9 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.38	1.42	1.27	1.29	1.18	1.28	1.23	1.33	1.22
2	1.29	1.20	1.12	1.02	1.08	1.02			
3	1.29	1.30	1.03	1.00	1.03	1.02			

10 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.31	1.40	1.30	1.23	1.26	1.36	1.39	1.39	1.24
2	1.27	1.24	1.12	1.00	1.02	1.08			
3	1.24	1.26	1.01	1.01	1.08	1.00			

11 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.27	1.31	1.13	1.01	1.02	1.12	1.00	1.01	1.01
2	1.33	1.32	1.12	1.00	1.02	1.10			

12 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3	4	5	6	7	8	9
1	1.21	1.26	1.10	1.04	1.05	1.13	1.02	1.05	1.04
2	1.27	1.32	1.10	1.00	1.01	1.08			

For Rice data C.V.(TABLE 2.4.4 & 2.4.5) in general decreased with increase in plot size in either direction, the decrease being greater when the larger plot dimension is in E→W direction and when the blocks run N→S direction. The reduction in C.V. with increased plot size is comparatively less when the increase in plot size was beyond 6 units or 6 mt. along E→W direction. For optimum plot size of 8mt. X 2mt. the 5 plot blocks give lowest C.V. than 3 plot blocks and 6 plot and 12 plot blocks. However when blocks run in E→W direction the decrease in C.V. with increase in plot size is more in E→W directions. The decrease in C.V. is reasonably greater when blocks run N→S direction than when blocks run E→W direction.

EFFECT OF PLOT SHAPE ON VARIABILITY: Plots elongated along N→S direction showed less variability than plots elongated along E→W direction. Compact or square plots in general showed slightly less variability than plots elongated in N→S direction. However, plots elongated along E→W direction are more variable than square plots.

TABLE 2.4.4: (Rice data) C.V. for different plots when blocks run row(E->W) direction

3 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	11.70	9.21	7.92	7.31	6.26	6.01	5.64	5.85	5.11
2	8.25	7.12	6.38	6.17	6.03	5.45	5.81	5.38	4.87
3	6.96	5.63	5.28	5.12	5.30	4.74	5.10	4.56	4.55
4	5.94	5.25	4.41	4.29	4.36	3.19	3.15	3.53	2.72
5	4.62	3.61	2.25	2.67	2.20	1.42	1.12	2.16	1.64
6	4.67	4.03	3.20	3.42	3.36	2.79	2.75	2.62	2.52
7	4.79	4.10	3.38	3.80	3.86	2.97	3.06	3.34	2.89

4 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	12.20	9.36	8.37	7.63	6.70	6.62	6.13	6.16	5.86
2	7.97	6.59	5.63	5.37	5.16	4.49	4.52	4.28	3.94
3	7.14	5.48	4.78	4.42	4.83	3.96	4.37	3.84	3.75
4	5.50	4.89	3.97	3.83	3.93	2.87	2.89	3.09	2.38
5	5.26	4.29	3.37	3.77	3.47	2.87	3.04	3.31	2.98

5 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	12.68	10.06	9.03	8.28	7.58	7.21	6.90	6.79	6.25
2	8.85	7.55	6.65	6.48	6.33	5.75	5.90	5.48	5.09
3	6.82	5.23	4.38	4.06	4.39	3.57	3.93	3.52	3.39
4	6.30	5.65	4.78	4.96	4.95	4.05	4.38	4.37	3.68

6 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	13.22	10.36	9.42	8.67	7.89	7.45	7.40	7.32	6.68
2	9.10	7.64	6.46	6.06	5.85	4.99	5.00	4.82	4.31
3	7.42	5.99	5.41	5.25	5.45	4.78	5.12	4.68	4.59

7 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	13.00	10.24	8.91	8.28	7.27	7.04	6.81	6.83	6.21
2	8.89	7.45	6.11	5.78	5.53	4.66	4.63	4.55	4.06
3	7.42	6.05	5.31	5.44	5.34	4.72	4.89	4.86	4.56

8 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	12.83	9.77	8.81	7.80	7.22	6.45	6.22	6.30	5.77
2	8.57	7.16	5.92	5.63	5.49	4.55	4.61	4.54	4.03

9 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	13.78	10.93	9.88	9.25	8.48	7.93	7.88	7.71	7.11
2	9.48	8.18	7.14	7.05	6.90	6.12	6.43	5.98	5.49

10 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	13.42	10.60	9.43	8.78	8.04	7.57	7.35	7.25	6.71
2	9.31	8.01	6.94	6.91	6.70	5.99	6.14	5.87	5.37

11 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	13.51	10.64	9.31	8.65	7.94	7.41	7.15	7.19	6.70
2	9.51	8.21	7.08	7.07	6.80	6.02	6.14	6.13	5.60

12 plot blocks:

row E->W	no. of units along column(N->S) direction 1	2	3	4	5	6	7	8	9
1	13.99	10.75	9.64	8.36	8.03	7.00	6.79	6.85	6.36

TABLE 2.4.5: (Rice data) Within block C.V. when blocks run col.(N $\rightarrow$ S) direction

row *3 plot blocks*: no. of units along column(N→S) direction

E→W	1	2	3	4	5	6
1	10.19	8.16	6.75	5.80	5.55	5.63
2	6.64	5.94	4.61	4.39	4.42	4.11
3	5.52	4.35	3.17	3.32	3.85	3.56
4	4.44	4.49	3.45	3.42	3.24	2.40
5	4.39	3.85	2.27	2.87	2.39	1.85
6	3.92	3.75	2.48	2.75	2.93	2.43
7	3.88	3.53	2.39	2.18	3.02	2.11
8	3.40	3.75	2.41	2.59	2.20	0.67
9	3.01	3.08	1.80	2.25	1.66	0.91

row *4 plot blocks*: no. of units along column(N→S) direction

E→W	1	2	3	4
1	10.68	8.19	6.95	6.98
2	6.60	5.83	4.73	5.14
3	5.61	4.45	4.13	4.37
4	4.31	4.04	3.73	3.51
5	4.28	3.48	3.25	3.02
6	3.67	3.76	3.02	3.41
7	3.76	3.23	2.53	3.07
8	3.04	3.01	2.62	2.63
9	3.20	2.75	2.63	2.15

row *5 plot blocks*: no. of units along column(N→S) direction

E→W	1	2	3
1	11.36	8.94	7.68
2	7.07	6.35	5.29
3	5.67	4.24	4.66
4	4.55	4.33	3.85
5	4.59	3.60	3.27
6	3.87	3.51	3.51
7	3.77	2.51	3.33
8	3.26	**2.63**	2.68
9	3.22	2.21	2.36

row *6 plot blocks*: no. of units along column(N→S) direction

E→W	1	2	3
1	11.83	8.90	8.24
2	7.82	6.39	5.83
3	6.35	4.62	4.75
4	5.52	4.52	4.06
5	5.17	3.74	3.29
6	4.70	3.72	3.57
7	4.64	3.03	3.31
8	4.28	3.21	2.69
9	3.80	2.80	2.49

row	*7 plot*		*8 plot*		*9 plot blocks*	
	no. of units along column(N→S) direction					
E→W	1	2	1	2	1	2
1	12.17	9.24	11.83	9.47	12.22	9.92
2	7.77	6.54	7.58	6.82	8.08	7.22
3	6.24	5.04	6.26	5.58	6.36	5.62
4	5.23	4.58	5.06	4.65	5.63	5.09
5	4.9	3.72	4.81	4.06	4.94	4.27
6	4.47	4.04	4.47	4.4	4.63	4.47
7	4.44	3.58	4.37	3.86	4.56	4.11
8	3.71	3.22	3.6	3.5	4.17	3.81
9	3.46	2.66	3.49	3.21	3.51	3.21

Row	Single unit along column(N→S) direction		
E→W	*10 plot*	*11 plot*	*12 plot blocks*
1	12.89	12.65	12.54
2	8.03	7.95	8.07
3	6.31	6.32	6.54
4	5.45	5.35	5.55
5	5.12	4.96	5.22
6	4.27	4.21	4.38
7	3.77	3.73	4.29
8	3.34	3.36	3.84
9	3.18	3.25	3.52

From the following Table 2.4.6 for Rice data we see that with blocks of same size but different shapes formed from plots of the same size, there was detectable change in blocking efficiency. As in general for all plot sizes & shapes blocks running N→S showed higher blocking efficiency than the blocks running in E→W direction. The highest blocking efficiency value 3.21 was found for 3 plot blocks containing plots of size 9 sq. mt. & shape 3 x 3 (i.e. 3 mt. in E→W & 3 mt in N→S direction). For the same B.E. block size was 27 sq. mt. & shape was 1 : 3 (i.e. 3 mt. in E→W direction & 9 mt. in N→S direction). The second highest blocking efficiency was 3.10 was found for 3 plot blocks containing plot of size 15 sq. mt. & shape 5 :3 (i.e. 5 mt. in E→W direction & 3 mt. in N→S direction). For the same B.E. block size was 45 sq. mt. & block shape was 5 : 9 (i.e. 5 mt. in E→W direction & 9 mt. in N→S direction). For 5 plot block highest blocking efficiency was 2.73 for plot of size 14 sq. mt. & shape 7 : 2 (i.e. 7 mt. in E→W direction & 2 mt. in N→S direction). For the same B.E. block size was 70 sq. mt. & block shape was 7 : 10 (i.e. 7 mt. in E→W direction & 10 mt. in N→S direction).

TABLE 2.4.6: (Rice data) Within block Blocking Efficiencies for different plot sizes when blocks run col.(N $\rightarrow$ S) direction

3 plot blocks:

row E $\rightarrow$ W	no. of units along column(N $\rightarrow$ S) direction 1	2	3	4	5	6
1	1.93	1.90	2.11	2.43	2.29	1.89
2	2.21	2.03	2.51	2.75	2.40	2.15
3	2.06	2.18	**3.21**	2.81	1.98	1.76
4	2.39	1.83	2.30	2.44	2.42	2.90
5	1.83	1.58	**3.10**	2.07	2.25	2.50
6	2.00	1.61	2.51	2.17	1.50	1.45
7	2.03	1.72	2.70	2.91	1.71	2.01
8	1.63	1.04	1.25	1.03	1.01	1.19
9	1.72	1.12	2.01	1.07	1.18	1.38

4 plot blocks:

row E $\rightarrow$ W	no. of units along column(N $\rightarrow$ S) direction 1	2	3	4
1	1.75	1.89	2.00	1.75
2	2.19	2.12	2.51	1.96
3	2.02	2.22	2.17	1.68
4	2.48	2.25	2.21	2.24
5	1.93	2.02	1.83	1.88
6	2.17	1.66	1.98	1.35
7	2.19	2.13	2.42	1.79
8	1.76	1.37	1.02	1.02
9	1.53	1.47	1.05	1.17

5 plot blocks:

row E $\rightarrow$ W	no. of units along column(N $\rightarrow$ S) direction 1	2	3
1	1.55	1.66	1.68
2	1.94	1.88	1.98
3	1.91	2.50	1.67
4	2.22	1.89	2.00
5	1.61	1.73	1.67
6	1.86	1.89	1.35
7	2.10	**2.73**	1.58
8	1.46	1.19	1.00
9	1.31	1.00	1.09

6 plot blocks:

row E→W	no. of units along column(N→S) direction 1	2	3
1	1.43	1.61	1.42
2	1.59	1.83	1.57
3	1.56	1.94	1.43
4	1.55	1.82	1.67
5	1.32	1.63	1.47
6	1.39	1.64	1.21
7	1.42	1.99	1.41
8	1.03	1.02	1.01
9	1.08	1.04	1.05

	7 plot		*8 plot*		*9 plot blocks*	
row	no. of units along column(N→S) direction					
E→W	1	2	1	2	1	2
1	1.38	1.5	1.42	1.41	1.34	1.29
2	1.63	1.69	1.66	1.55	1.49	1.37
3	1.61	1.65	1.62	1.41	1.55	1.31
4	1.71	1.73	1.8	1.7	1.49	1.42
5	1.39	1.52	1.53	1.49	1.44	1.28
6	1.39	1.3	1.47	1.21	1.43	1.13
7	1.47	1.53	1.62	1.5	1.47	1.27
8	1.06	1	1.26	1.01	1.08	1.01
9	1.03	1.03	1.29	1.08	1.27	1.03

Row	Single unit along column(N→S) direction		
E→W	*10 plot*	*11 plot*	*12 plot blocks*
1	1.32	1.31	1.31
2	1.55	1.57	1.52
3	1.68	1.62	1.47
4	1.56	1.63	1.55
5	1.36	1.43	1.32
6	1.6	1.56	1.46
7	1.77	1.85	1.5
8	1.11	1.08	1.01
9	1	1.01	1.03

Chapter 3

TWO WAY SPATIAL CORRELATION STUDY:

3.1 Introduction: The empirical model developed by Smith (1938) gives a measure of correlation between adjacent units in terms of a soil heterogeneity index '*b*'. Here $b = 0$ indicates perfect positive correlation and $b = 1$ indicates no correlation between adjacent units. An alternative approach to the analysis based on Smith's model is a direct study of the correlation structure among experimental units. Li and Keller (1951) estimated lag-one serial correlations to obtain information on the randomness of a set of uniformity data and to compare relative efficiencies of different sizes and shapes of plots. However, a more complete analysis of the correlation structure would include the estimation of two dimensional spatial correlations of various lags. Whittle (1954) computed the spatial correlations for several uniformity studies as a model fitting and testing exercise on the nature of the two dimensional autoregressive models operating in the field, but he did not attempt to use the correlation structure to infer on the optimum plot size and shape. In 1983 Modjeska and Rawlings presented the spatial correlation analysis of uniformity data as an alternative to the conventional method of analysis based on Smith's model. Here the spatial correlation model permits arbitrary patterns of behavior of the correlations, in contrast to the strict monotonic decrease required in Smith's model. It also provides more information about the nature of the variation in the uniformity trial.

3.2 Material and method: Let $Y = \{ Y_{ij} \}$ be a matrix of crop yield from a uniformity trial of R X C units in size where $i = 1,2,\ldots\ldots,R$ and $j = 1,2,\ldots\ldots,C$ designate row and column numbers. Here the spatial correlation model assumes that all pairs of observations having same spatial relationship have the same correlation. Thus $Y_{ij} = \mu + \varepsilon_{ij}$ and $\frac{E(\varepsilon_{ij},\varepsilon_{i'j'})}{\sigma^2} = \rho(l,k)$ where $l = i' - i$ and $k = j' - j$ define the two dimensional lags or the number of unit plots from plot (i,j) acoross rows and across columns respectively, to plot (i',j'). Because of symmetry of correlation $\rho(l,k) = \rho(-l,-k)$ and $\rho(l,-k) = \rho(-l,k)$. Three spatial correlation matrices of dimension m X n are defined as $\rho^+ = \{\rho(l,k)\}$ $\rho^- = \{\rho(l,-k)\}$ and $\bar{\rho} = \frac{1}{2}(\rho^+ + \rho^-)$ where $0 \le l \le m-1$ and $0 \le k \le n-1$. Here m X n is the maximum plot size to be considered. For $l,k > 0$, ρ^+ and ρ^- contain spatial correlations for lags in different diagonal directions. The first row and first column ($l = 0$ or $k = 0$) of ρ^+ and ρ^- will be identical. No constraints are imposed on the manner in which $\rho(l,k)$ changes with l and k; in particular $\rho(l,k)$ can be negative and need not be monotonic function of l and k. If the field consists of regular cycles of fertility with axes coinciding with the axes of the field, $\rho^+ = \rho^-$ and the spatial correlations will cycle between +1 and -1 with a frequency corresponding to the frequency of the fertility cycles. That is, the spatial correlations reproduce the soil fertility patterns. If the axes of the fertility cycles are not parallel to the field axes, $\rho^+ \neq \rho^-$. If the fertility cycles are not regular, the cycle length of the spatial correlations will reflect an averaging of the lengths of the fertility cycles and the spatial correlations will not approach ± 1. If the field is uniform with random error attached to all unit plots, the true spatial correlations will be zero. The spatial covariances, $\text{cov}(l,k)$, are defined similarly as the three m X n spatial covariance matrices, cov^+, cov^- and $\overline{\text{cov}}$. The variance among plots r X c units in size in a field of size R X C is:

$$MSE(rc/RC) = \frac{\left\{ rc\overline{\text{cov}}(0,0) + 2r.\sum_{k=1}^{c}(c-k)\overline{\text{cov}}(0,k) + 2c.\sum_{l=1}^{r}(r-l)\overline{\text{cov}}(l,0) + 4.\sum_{l=1}^{r}\sum_{k=1}^{c}(c-k).(r-l)\overline{\text{cov}}(l,k) \right\}}{r.c}$$

Here **MSE(RC)** = {MSE(rc / RC)} is the m X n matrix of variances among plots of size r X c, where r and c designate the row and column positions in the **MSE** matrix as well as the plot size and can be expressed in terms of $\overline{\text{cov}}$ as $MSE(RC) = k_m * \overline{\text{cov}} * k_n'$, where, $k_m = (L_m^{\ 2} * D_m)\#/(L_m *_m J_m)$, L_m = m X m lower triangular matrix of 1's, D_m = diag(1,2,............,2) of dimension m X m, $_m J_m$ = m X m matrix of 1's and '#/' denotes element wise division. The spatial covariances and correlations are computed for $0 \le l \le \frac{1}{2}.R - 1$, $0 \le |k| \le \frac{1}{2}.C - 1$. The estimate $\hat{\text{cov}}^+$ is computed as the $\frac{1}{2}.R \times \frac{1}{2}.C$ matrix whose elements are :

$$\hat{\text{cov}}^+(l,k) = \frac{\sum_i\sum_j Y_{ij}.Y_{i+l,j+k} - (\sum_i\sum_j Y_{ij}).(\sum_i\sum_j Y_{i+l,j+k})/(R-l).(C-k)}{\{(R-l).(C-k)-1\}}$$

with summations over all combinations of $1 \le i \le R-l$ and $1 \le j \le C-k$, $k \ge 0$. Similarly $\hat{cov}^-$ is computed as the $\frac{1}{2}.R \times \frac{1}{2}.C$ matrix whose elements are:

$$\hat{cov}^-(l,k) = \frac{\sum_i \sum_j Y_{i,j-k}.Y_{i+l,j} - (\sum_i \sum_j Y_{i,j-k}).(\sum_i \sum_j Y_{i+l,j})/(R-l).(C+k)}{\{(R-l).(C+k)-1\}}$$

with summations over $1 \le i \le R-l$ and $1 \le j \le C+k$, $k \le 0$. Then $\overline{cov} = \frac{1}{2}\left(\hat{cov}^+ + \hat{cov}^-\right)$. The spatial correlations are computed by dividing each $\hat{cov}(l,k)$ by the geometric mean of covariances of the two subsets of Y_{ij} involved, rather than by $\hat{cov}(0,0)$. This procedure appears to give more stability to $\hat{\rho}(l,k)$ as l and k become large.

Comparison of the elements of **MSE(RC)** gives the reative efficiencies of plots of r X c within blocks of R X C. Thus the matrix of variances among plots of all possible sizes up to $\frac{1}{2}R \times \frac{1}{2}C$ is computed as $M\hat{S}E(RC) = K_m * \widehat{\overline{cov}} * K_n{}'$, where $m = \frac{1}{2}R$ and $n = \frac{1}{2}C$, and is standardized by dividing all elements by the variance among unit plots. Thus, $\widehat{\mathbf{STMSE}}$**(RC)** = $M\hat{S}E$ **(RC)** / $M\hat{S}E$ **(11/RC)**. The quantity $M\hat{S}E$ (rc/RC)/rc is equal to $(V_{rc})_{RC}$ in Smith's notation. Behavior of the MSE is shown by plotting $\ln\{M\hat{S}E(rc/RC)/rc\}$ against $\ln(r.c)$. If Smith's original model holds, a linear relationship is obtained; because of the density of points, a graphical estimate of b appears adequate. If the two dimensional model holds, the graph would be a parallelogram with the slopes for all columns being $-b_1$ and those for all rows being $-b_2$.

A two dimensional version of Smith's model and its implications for the spatial correlation structure: Smith (1938) recognized that the index of soil heterogeneity need not be the same for plots oriented in different directions in the field and that the longer axis of the plots should cover the greatest variability. In Smith's analysis this can be taken into account by computing variances and estimating b separately for different plot orientations. For our purposes it is more convenient to define a two-dimensional version of Smith's model for variances of plots of size r x c as $V_{rc} = \frac{V_1}{r^{b_1}c^{b_2}}$, where b_1 and b_2 are indices of soil heterogeneity across rows and across columns, respectively. If $b_1 = b_2$, Smith's one-dimensional model holds as a special case. If two-dimensional version of Smith's model holds the following relationships among the spatial correlations exist:

(i) $\rho(l,0)=\frac{1}{2}\left\{(l+1)^{2-b_1}-2l^{2-b_1}+(l-1)^{2-b_1}\right\}$, $l \geq 1$. By symmetry, $\rho(0,k)$ is obtained by substituting $|k|$ for l and b_2 for b_1. From this it can be seen that $\rho(0,k)$ and $\rho(l,0)$ are monotonically decreasing functions of k and l, respectively, approaching zero in the limit for acceptable values of b_1 and b_2.

(ii) $\rho(l,k)=\rho(l,0).\rho(0,k)$, which implies that all spatial correlation matrices are rank –one matrices. This in turn implies that **MSE(RC)** and **STMSE(RC)** also must be rank –one matrices.

(iii) $\rho^{+}=\rho^{-}$.

Thus, inspection of the similarity of $\hat{\rho}^{+}$ and $\hat{\rho}^{-}$ and degree to which $\hat{\bar{\rho}}$ can be 'fitted' by a rank one matrix (via a singular value decomposition, SVD) provide a convenient first step in the assessment of whether the two dimensional model is potentially acceptable. Verification that the two-dimensional model does hold requires checking the behavior of $\hat{\rho}(0,k)$ and $\hat{\rho}(l,0)$ against condition (i) above. If the SVD shows that $\hat{\bar{\rho}}$ is reasonably close to rank one, the elements of the left and right eigenvectors corresponding to the largest singular value are scaled values of $\hat{\rho}(l,0)$ and $\hat{\rho}(0,k)$, respectively, and provide a convenient basis for checking condition (i). If Smith's model holds (i.e. b_1=b_2), then, in addition to the above relationships, $\rho(l,0)=\rho(0,k)$ for $l=k$ and the two eigen vectors have the same form.

3.3 Optimum plot size: Determining optimum plot size (and shape) using the spatial correlation analysis is dependent on as follows:

(i) Smith's original model holds (b_1=b_2). In this case, plots of $\ln\{M\hat{S}E(rc/RC)/rc\}$ vs ln(rc) are linear and coincident, plot and block shape are immaterial, and Smith's(1938) formula for optimum plot size can be applied.

(ii) The two-dimensional version of Smith's model holds ($b_1 \neq b_2$). The shape of the plot now becomes important. Let plot size be $r \times c = p$ and block size smaller than $R \times C$ be $\alpha.r \times \gamma.c$, where α and γ are integers such that α.γ = t, the number of plots per block. Now we can adjust MSE(rc/RC) for block size by

$MSE(p/tp) = \{t.MSE(p/N) - MSE(tp/N)\}/(t-1) + \frac{\beta}{t-1}\{MSE(tp/N) - MSE(p/N)\}$ ..1)where $N = R \times C$, p = number units per plot, t = number of plots per block and $\beta = tp/N$, the size of the new block relative to the size of the original block. If $\frac{\alpha}{t-1}$ is small enough to enable the second term to be ignored, and if Smith's model holds i.e. $\frac{MSE(p/N)}{p} = \frac{(V_1)_N}{p^b}$, then equation 1) becomes $\frac{MSE(p/tp)}{p} = \frac{t.(1-t^{-b})(V_p)_N}{(t-1)}$ which is the Smith's (1938) result after adjustment for block size. However the mean square among plots of dimension $r \times c = p$ within blocks of dimension $\alpha.r \times \gamma.c$ is, approximately, $MSE(rc/\alpha r \times \gamma c) = \{MSE(rc/RC) - MSE(\alpha r \times \gamma c/RC)\}/(t-1)$.

Substitution of the two-dimensional version of Smith's model gives $V(rc/\alpha r \times \gamma c) = \frac{t.(V_1)_N}{(t-1)r^{b_1}c^{b_2}}(1 - \alpha^{b_2 - b_1}t^{-b_2})$. If cost is a function of only plot size, p, and not of plot shape, the variance is minimized for given $p = r \times c$ by making $r = p$, $c = 1$ if $b_1 > b_2$, or $r = 1$, $c = p$ if $b_2 > b_1$. The optimum plot is one unit wide and p units long with longer axis of the plot running in the direction of the larger b; that is, in the direction of greater variability as indicated by Smith (1938). Further, the optimum block shape is given by $\alpha = 1$, $\gamma = t$ if $b_1 > b_2$, or $\alpha = t$, $\gamma = 1$ if $b_2 > b_1$, that is, the optimum block shape will contain t optimum plots side by side. Assuming without loss of generality that $b_2 > b_1$, then $r_{opt} = 1$, $c_{opt} = p$ and $\alpha_{opt} = t$ and the cost per unit information is $\frac{t(V_1)_N}{(t-1)p^{b_2}}(1 - t^{-b_1})(k_1 + k_2 p)$, where k_1 and k_2 are costs as defined by Smith (1938). Minimization with respect to p gives $p_{opt} = \frac{b_2.k_1}{(1-b_2).k_2}$ which is the Smith's original formula for optimum plot size except that the larger b in this case b_2 determines optimum plot size. However in the conventional analysis of uniformity data we obtain some sort of average of b_1 and b_2 as the measure of soil heterogeneity causing underestimation of the optimum plot size.

(iii) The two dimensional model does not hold. In this general case a matrix of costs per unit of information can be computed as $Cost/I = [(k_{1\,m}J_n + k_2N)\#MSE(RC)]\#/N$ where $N = L_m *_m J_n * L_n' = \{(\text{number of unit plots per plot})\}$, and the symbol '#' means element wise multiplication. Inspection of $Cost / I$ for the minimum value will reveal the optimum plot size within a block of size R X C.

3.4 Result and discussion: Yield was not constant within any of these regions and appeared to change along both row and column. The only obvious patter was a cycling across rows, but because the pattern lacked regularity no cycle length could be ascertained from a visual inspection of the field response surface.

The spatial correlations started at relatively low values and remained fairly constant within the rows of Table 3.4.1. Within the columns of Table 3.4.1, correlations decreased to a negative correlation at about lag 12 as large in absolute value as the positive lag-one correlations. This suggested that there was a major micro-environmental cycle in the field with a half-cycle length of about 12 units, and that conditions with a row remained relatively constant.

TABLE 3.4.1: Jute data: Spatial correlation left =>R-(l, k) right =>R+(l, k)

					k						
l	-5	-4	-3	-2	-1	0	1	2	3	4	5
0	0.156	0.111	0.005	-0.068	0.192	1	0.192	-0.068	0.005	0.111	0.156
1	0.012	-0.008	-0.062	-0.191	0.081	0.245	0.056	-0.154	-0.048	0.099	0.145
2	0.158	0.174	-0.038	-0.089	0.161	0.109	-0.007	-0.139	0.016	0.186	0.1
3	0.173	0.121	-0.101	-0.065	0.136	0.245	0.02	-0.178	-0.061	0.176	0.108
4	0.11	-0.032	-0.126	-0.023	0.119	0.186	0.022	-0.216	-0.063	0.106	0.059
5	0.108	0	0.001	0.005	0.065	0.182	-0.037	-0.142	0.021	0.248	0.119
6	0.036	-0.136	-0.052	-0.089	0.019	0.123	-0.099	-0.169	0	0.12	0.077
7	0.078	0.02	-0.062	0.015	0.081	0.133	-0.07	-0.165	0.137	0.12	0.096
8	0.025	0.014	0.02	0.026	0.099	0.078	-0.074	-0.008	0.1	0.189	0.055
9	0.009	-0.08	-0.004	-0.055	0.056	0.019	-0.161	-0.027	0.073	0.184	0.016
10	-0.029	0.019	-0.065	0.012	-0.023	-0.061	-0.104	-0.15	-0.035	0.07	-0.052
11	0.002	-0.012	0.064	0.103	0.112	-0.049	-0.059	-0.016	0.128	0.13	-0.07
12	-0.106	-0.126	-0.007	-0.016	0.01	0.03	-0.052	0.004	0.189	0.107	-0.008
13	-0.025	-0.023	-0.012	0.023	-0.014	0.003	-0.101	0.01	0.133	0.067	-0.108
14	-0.07	0.02	0.103	0.114	0.129	-0.047	-0.084	0.066	0.133	0.081	-0.032
15	-0.158	-0.119	0.029	0.045	0.036	0.003	-0.086	0.056	0.094	-0.01	-0.138

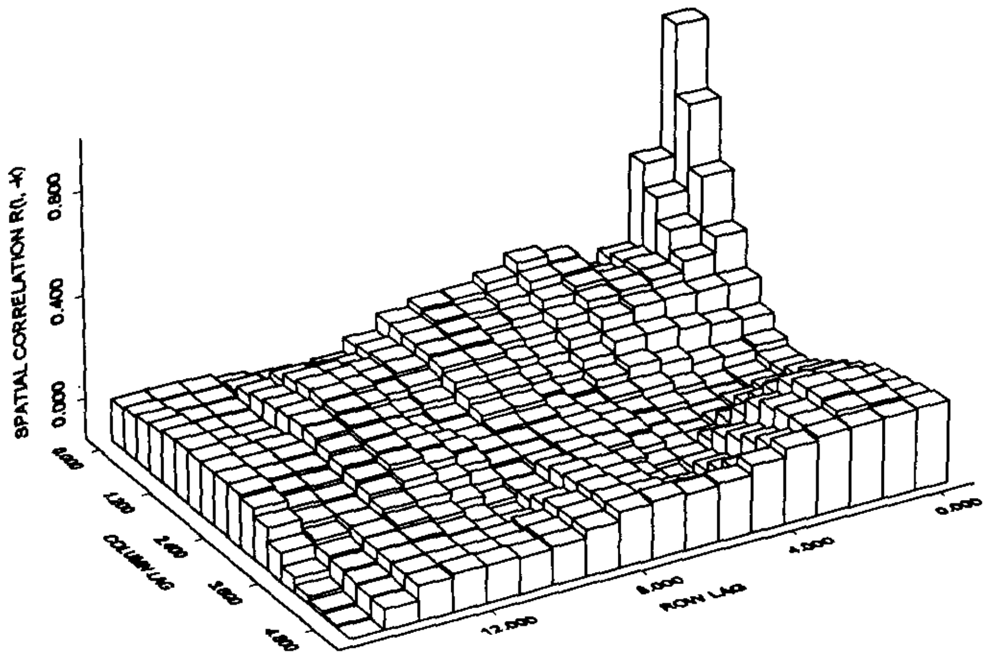


Fig. 3.4.1 (Jute data) Spatial correlation surface R-(l, k) for different row and column lags.

The patterns of change in $\hat{\rho}^+$ and $\hat{\rho}^-$ differ appreciably. There are sizeable negative correlations in $\hat{\rho}^+$ than in $\hat{\rho}^-$. For lag columns 4 & 5 there is a clear tendency for the +ve correlations to cycle to negative values as large as the lag zero correlations. However in general correlation values with increase in lag both in row and column directions. But the decay is more uniform in $\hat{\rho}^-$ than in $\hat{\rho}^+$ as obvious from fig.4 and fig.5. The first column of $\hat{\rho}^-$ showed a slow decay relative to the decay from $\hat{\rho}\,(0,0) = 1$ to $\hat{\rho}^-(1,0)$. In general spatial correlation decays at a faster rate along columns than along rows. For reference, the correlation attenuation curves predicted from Smith's model with $b_1 \cong 0.9$ and $b_2 \cong 0.6$ are included in Fig. 4 as $\rho_s(0.9)$ and $\rho_s(0.6)$, respectively. These correlation patterns reflect a pattern of 'fertility' ridges running the length of the field with more or less constant performance within any one column.

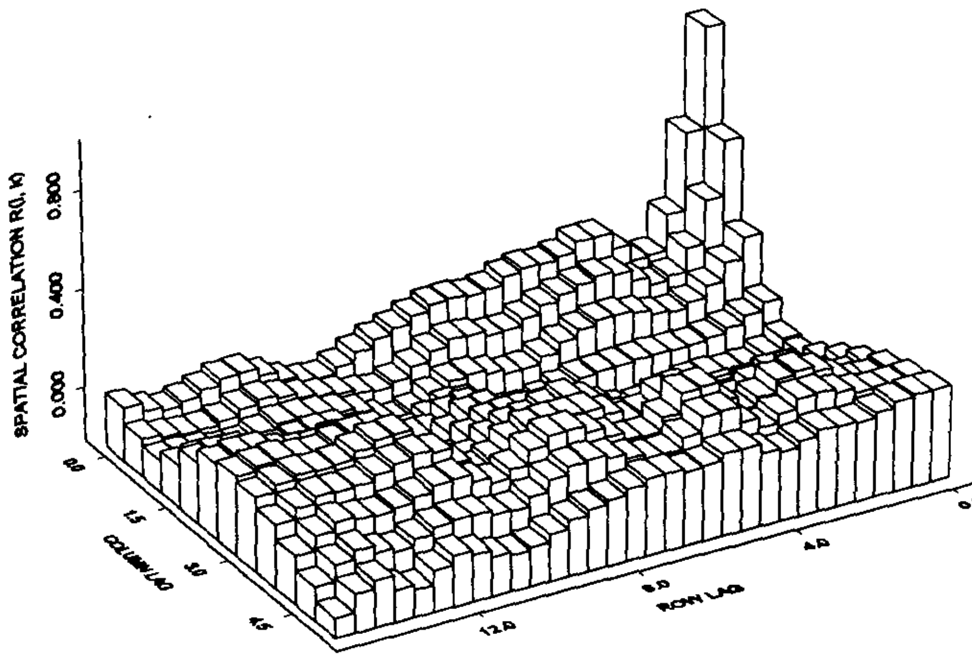


Fig. 3.4.2. (Jute data) Spatial correlation surface R+(l, k) for different row and column lags.

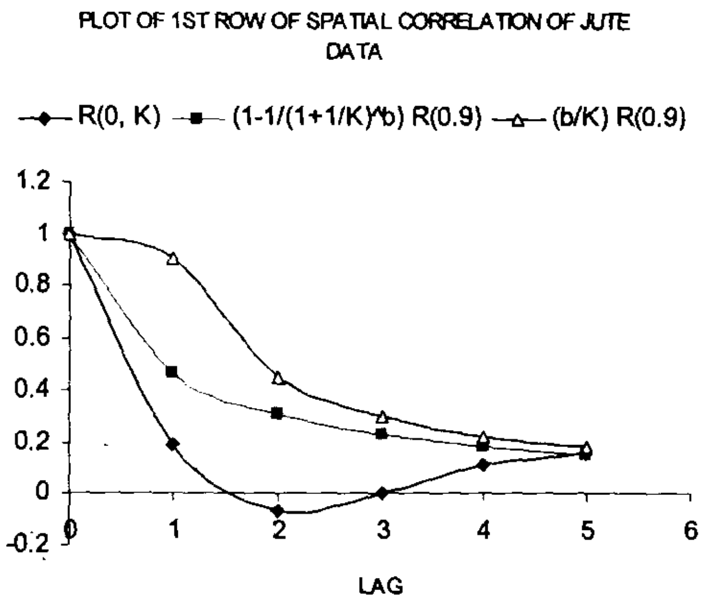


Fig. 3.4.3. (Jute data) plot of first row of spatial correlation matrix.

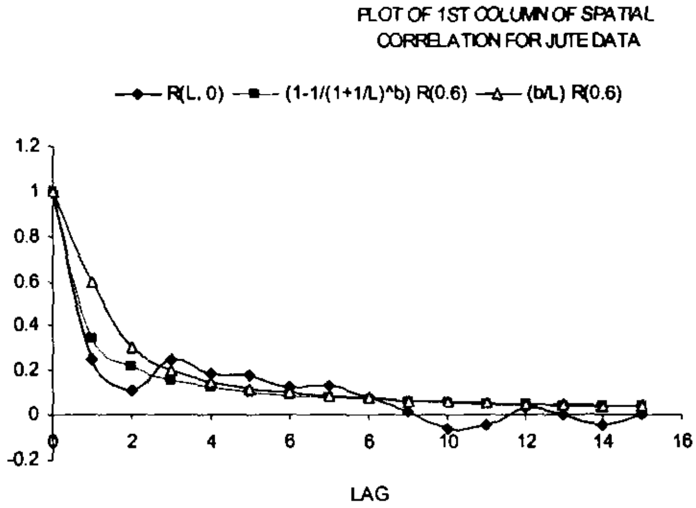


Fig. 3.4.4. (Jute data) plot of first column of spatial correlation matrix.

TABLE 3.4.2:Average Spatial correlation R(l, k)

l	K					
	0	1	2	3	4	5
0	1.000	0.192	-0.068	0.005	0.111	0.156
1	0.245	0.069	-0.173	-0.055	0.045	0.079
2	0.109	0.077	-0.114	-0.011	0.180	0.129
3	0.245	0.078	-0.121	-0.081	0.149	0.140
4	0.186	0.071	-0.119	-0.094	0.037	0.085
5	0.182	0.014	-0.068	0.011	0.124	0.114
6	0.123	-0.040	-0.129	-0.026	-0.008	0.056
7	0.133	0.005	-0.075	0.037	0.070	0.087
8	0.078	0.012	0.009	0.060	0.101	0.040
9	0.019	-0.052	-0.041	0.034	0.052	0.012
10	-0.061	-0.063	-0.069	-0.050	0.044	-0.040
11	-0.049	0.026	0.044	0.096	0.059	-0.034
12	0.030	-0.021	-0.006	0.091	-0.009	-0.057
13	0.003	-0.058	0.016	0.060	0.022	-0.067
14	-0.047	0.023	0.090	0.118	0.050	-0.051
15	0.003	-0.025	0.050	0.062	-0.064	-0.148

The matrix of STMSE(ac/AC), shown in Table 3.4.4, revealed a faster increase in variance along rows than along columns. For example, a 1 X 4 plot was better than either a 2 X 2 or a 4 X 1. The advantage of orienting plot length with columns became even greater as plot length increased. A 1 X 6 plot is 28 % more efficient than a 3 X 2 plot and 46 % more efficient than a 6 X 1 plot. In this field, very little penalty would be paid, in STMSE by doubling plot size from R X 3 to R X 6. This is because the negative correlations of lags greater than about three offset the impact of the earlier positive correlations.The overall behavior of STMSE was shown by graphing ln {STMSE(ac/AC)/ac} versus ln (ac) using only the border rows and columns of STMSE for simplicity. Independent units would give a line with slope – 1.0. If Smith's model holds, all points would fall about a line with slope – *b*. If the two-dimensional model holds the graph would be a parallelogram with the slopes for all columns being – b_1 and those for all rows being – b_2. For the Jute data (Fig.3.4.6), the graphs of rows were reasonably linear but showed a gradual change in slope from – 0.578 for Column 1 to – 0.661 for Column 6. The graphs of rows showed a distinct downward curvature, reflecting the impact of the negative lag correlations, with the average slope changing from – 0.85 for Row 1 to – 1.06 for Row16. Analyses of the four quarters of the Jute field data demonstrated the sensitivity of uniformity trial data to the specific location of the trial. The northeast quarter gave a Smith's b ≅ 0.95. That for the southwest quarter also gave concordant regression but with a distinct upward curvature and b ≅ 0.739. The northwest and southeast quarters gave the b values as 0.60 and 0.87. The spatial correlation matrices for the four quarters were also different. It is evident that results from uniformity trials, for both correlation and variance, are specific to the particular field being studied.

TABLE 3.4.3: MSE for plots a x c units

	Number of unit plots, c					
a	1	2	3	4	5	6
1	1610.48	1921.48	1951.94	1970.69	2051.66	2189.29
2	2002.92	2424.12	2305.87	2208.12	2247.77	2400.08
3	2251.37	2792.27	2570.00	2400.64	2482.57	2723.45
4	2575.75	3240.66	2921.85	2662.98	2781.23	3114.83
5	2892.36	3678.13	3264.96	2904.88	3025.66	3420.58
6	3201.47	4075.41	3577.33	3141.45	3285.01	3755.20
7	3478.46	4397.40	3793.07	3274.60	3416.06	3936.20
8	3740.20	4695.19	3991.63	3408.66	3558.01	4133.54
9	3971.69	4959.22	4182.19	3560.87	3737.41	4374.73
10	4162.91	5160.01	4309.82	3655.74	3859.12	4550.58
11	4301.85	5288.72	4359.64	3662.42	3882.84	4611.56
12	4404.63	5390.26	4405.87	3689.71	3940.43	4708.12
13	4498.61	5478.44	4444.62	3720.67	4000.66	4799.12
14	4579.73	5542.19	4464.30	3738.64	4048.42	4871.84
15	4640.28	5592.65	4491.02	3782.66	4133.50	4985.16
16	4693.81	5632.61	4515.18	3830.04	4216.72	5083.60

TABLE 3.4.4: Standardised Mean Square Error for plots of a x c units

a	Number of unit plots, c: 1	2	3	4	5	6
1	1.000	1.193	1.212	1.224	1.274	1.359
2	1.244	1.505	1.432	1.371	1.396	1.490
3	1.398	1.734	1.596	1.491	1.542	1.691
4	1.599	2.012	1.814	1.654	1.727	1.934
5	1.796	2.284	2.027	1.804	1.879	2.124
6	1.988	2.531	2.221	1.951	2.040	2.332
7	2.160	2.730	2.355	2.033	2.121	2.444
8	2.322	2.915	2.479	2.117	2.209	2.567
9	2.466	3.079	2.597	2.211	2.321	2.716
10	2.585	3.204	2.676	2.270	2.396	2.826
11	2.671	3.284	2.707	2.274	2.411	2.863
12	2.735	3.347	2.736	2.291	2.447	2.923
13	2.793	3.402	2.760	2.310	2.484	2.980
14	2.844	3.441	2.772	2.321	2.514	3.025
15	2.881	3.473	2.789	2.349	2.567	3.095
16	2.915	3.497	2.804	2.378	2.618	3.157

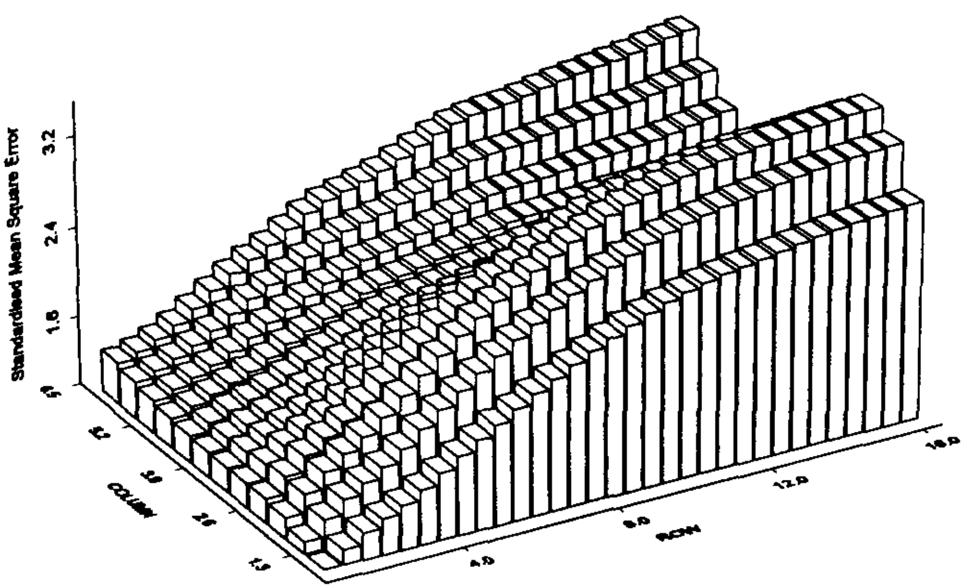


Fig.3.4.5: Three dimensional plot of Standardised Mean Square Error for plots of a x c units

TABLE 3.4.5: Cost per unit of information for plots a x c units

a	Number of unit plots, c: 1	2	3	4	5	6
1	3308.57	2305.49	1786.02	1522.51	1409.74	1379.58
2	2403.21	1872.81	1453.04	1234.20	1160.32	1170.58
3	2060.00	1759.55	1375.46	1170.85	**1140.10**	1199.00
4	1989.96	1811.33	1425.06	1203.98	1198.03	1297.37
5	1987.40	1898.69	1499.40	1251.29	1251.61	1376.00
6	2017.41	1987.68	1574.92	1308.45	1321.46	1474.95
7	2050.40	2055.25	1618.45	1330.60	1346.38	1519.35
8	2090.54	2122.78	1662.56	1359.06	1380.60	1574.49
9	2125.65	2183.30	1708.84	1398.62	1432.47	1649.06
10	2148.94	2222.70	1733.71	1418.53	1464.47	1700.94
11	2153.82	2237.06	1731.18	1406.89	1461.40	1711.79
12	2148.25	2245.11	1730.52	1405.43	1472.87	1737.47
13	2144.80	2251.83	1729.50	1407.04	1486.62	1762.29
14	2140.47	2252.01	1723.19	1405.05	1496.76	1781.37
15	2131.00	2249.75	1721.32	1413.90	1521.49	1816.04
16	2122.16	2245.77	1719.86	1424.79	1546.12	1845.87

TABLE 3.4.6 JUTE DATA

PLOT SIZE	ln(p)	STMSE	STMSE/p	ln(STMSE/p)
(row1) 1	0	1	1	0
2	0.693147	1.193	0.5965	-0.51667604
3	1.098612	1.212	0.404	-0.90634041
4	1.386294	1.224	0.306	-1.18417019
5	1.609438	1.274	0.2548	-1.36727637
6	1.791759	1.359	0.2265	-1.48501035
(row 16) 16	2.772589	2.915	0.182188	-1.70271892
32	3.465736	3.497	0.109281	-2.21383047
48	3.871201	2.804	0.058417	-2.84015407
64	4.158883	2.378	0.037156	-3.29262332
80	4.382027	2.618	0.032725	-3.419616
96	4.564348	3.157	0.032885	-3.41472602
(Column 1) 1	0	1	1	0
2	0.693147	1.244	0.622	-0.47481519

3	1.098612	1.398	0.466	-0.76356965
4	1.386294	1.599	0.39975	-0.91691594
5	1.609438	1.796	0.3592	-1.02387595
6	1.791759	1.988	0.331333	-1.10463037
7	1.94591	2.16	0.308571	-1.17580194
8	2.079442	2.322	0.29025	-1.23701267
9	2.197225	2.466	0.274	-1.29462719
10	2.302585	2.585	0.2585	-1.3528596
11	2.397895	2.671	0.242818	-1.41544235
12	2.484907	2.735	0.227917	-1.47877523
13	2.564949	2.793	0.214846	-1.53783309
14	2.639057	2.844	0.203143	-1.59384583
15	2.70805	2.881	0.192067	-1.64991276
16	2.772589	2.915	0.182188	-1.70271892
(Column 6) 6	1.791759	1.359	0.2265	-1.48501035
12	2.484907	1.49	0.124167	-2.08613055
18	2.890372	1.691	0.093944	-2.36505171
24	3.178054	1.934	0.080583	-2.51846346
30	3.401197	2.124	0.0708	-2.64789631
36	3.583519	2.332	0.064778	-2.7367927
42	3.73767	2.444	0.05819	-2.84403361
48	3.871201	2.567	0.053479	-2.92846314
54	3.988984	2.716	0.050296	-2.98982387
60	4.094345	2.826	0.0471	-3.05548231
66	4.189655	2.863	0.043379	-3.13778475
72	4.276666	2.923	0.040597	-3.20405567
78	4.356709	2.98	0.038205	-3.26478556
84	4.430817	3.025	0.036012	-3.32390574
90	4.49981	3.095	0.034389	-3.3700218
96	4.564348	3.157	0.032885	-3.41472602

	b		b
row1->	-0.85186	row2->	-0.9379631
row16->	-1.06021	row15->	-1.0655809
col1->	-0.57843	col2->	-0.5786431
col6->	-0.6612	col5->	-0.7132134

JUTE DATA

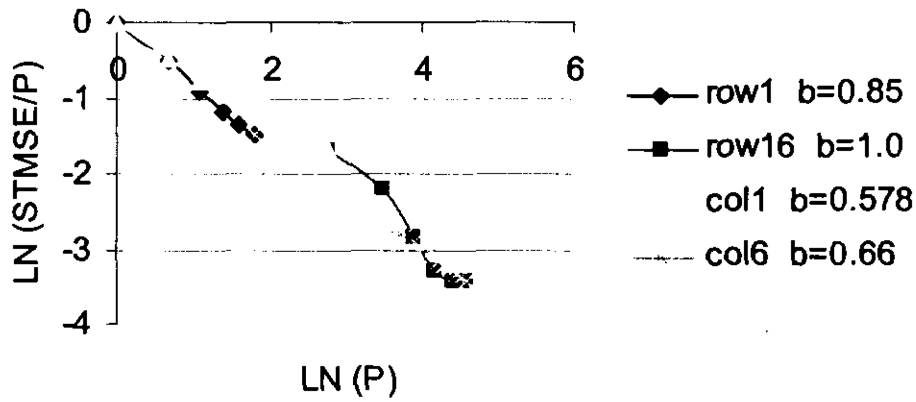


Fig. 3.4.6 Plot of ln(STMSE/p) versus ln(p) using the first and last rows and columns of the STMSE matrix from the Jute data.

The changing slopes over rows and columns and the distinct curvature of the graphs (Fig.7) for the rows are clear indications that in this case even two-dimensional version of Smith's model may be inadequate to find the optimum plot size. However we can use the table 12 containing the cost aspect. It is observed that the cost per unit of information is minimum for 3m. x 5m. plot for the Jute data.

One end of the Rice field was dominated by very high yields, the middle region by low yield, and the other end by a mixture of high and intermediate yields. Yield was not constant within any of these regions and appeared to change along both row and column. The only obvious patter was a cycling across rows, but because the pattern lacked regularity no cycle length could be ascertained from a visual inspection of the field response surface.

The spatial correlations started at relatively low values and remained fairly constant within the rows of Table 3.4.7. Within the columns of Table 3.4.7, correlations decreased to a negative correlation at about lag 5 to lag 7. This suggested that there was a minor micro-environmental cycle in the field with a half-cycle length of about 6 units, and that conditions with a row remained relatively constant. There is some indication that diagonal lag correlations decreased faster in $\hat{\rho}^-$ than in $\hat{\rho}^+$, suggesting slight skewness of the fertility pattern relative to the sides of the field.

The matrix of STMSE(ac/AC), shown in Table 3.4.11, revealed a faster increase in variance along columns than along rows. For example, a 4 X 1 plot was better than either a 2 X 2 or a 1 X 4. The advantage of orienting plot length with columns became even greater as plot length increased. A 8 X 1 plot is 47 % more efficient than a 4 X 2 plot, 90.6 % more efficient than a 2 X 4 plot and 132 % more efficient than a 1 X 8 plot. In this field, very little penalty would be paid, in STMSE by doubling plot size from 5 X C to 10 X C. This is because the negative correlations of lags greater than about three offset the impact of the earlier positive correlations.

The overall behavior of STMSE was shown by graphing ln {STMSE(ac/AC)/ac} versus ln (ac) using only the border rows and columns of STMSE for simplicity. Independent units would give a line with slope – 1.0. If Smith's model holds, all points would fall about a line with slope – b. If the two-dimensional model holds the graph would be a parallelogram with the slopes for all columns being $-b_1$ and those for all rows being $-b_2$. For the Rice data (Fig.3.4.12), the graphs of rows were reasonably linear but showed a gradual change in slope from – 0.625 for row 1 to – 0.57 for row 11. The graphs of columns showed a upward curvature, reflecting the impact of the negative lag correlations, with the average slope changing from – 1.04 for column 1 to – 0.99 for column 9. The patterns of change in $\hat{\rho}^+$ and $\hat{\rho}^-$ differed appreciably, there were sizeable negative correlations, was a clear tendency for the correlations to cycle back to positive values, some nearly as large as the lag-one correlations. The first row of $\hat{\rho}^-$ showed a slow decay relative to the decay from $\hat{\rho}(0,0) = 1$ to $\hat{\rho}^-(1,0)$ and the first column of $\hat{\rho}^-$ showed a very strong cycle from positive values at l = 1 to negative at l = 4,5 and 7 and back to positive at l = 8, 9 and 10 [see $\hat{\rho}^-(1,0)$ and $\hat{\rho}^-(0,k)$, respectively in Fig. 3.4.10 & 3.4.9]. For reference, the correlation attenuation curves predicted from Smith's model with $b_1 \cong 0.9$ and $b_2 \cong 0.6$ are included in Fig.3.4.10 as $\rho_s(0.9)$ and $\rho_s(0.6)$, respectively. These correlation patterns reflect a pattern of 'fertility' ridges running the length of the field with more or less constant performance within any one column.

TABLE 3.4.7: Rice data: Spatial correlation R-(l, k)

l \ k	-8	-7	-6	-5	-4	-3	-2	-1	0
0	0.101	0.065	0.054	0.139	0.056	0.214	0.206	0.195	1.000
1	0.012	0.028	-0.081	-0.097	0.067	0.037	0.04	0.07	-0.039
2	-0.052	-0.102	-0.018	-0.013	-0.097	-0.059	-0.021	0.063	0.035
3	0.037	-0.018	-0.06	-0.016	0.021	-0.062	-0.015	-0.029	0.029
4	-0.056	-0.05	0.119	-0.094	-0.069	-0.002	-0.17	-0.074	-0.041
5	0.017	0.055	-0.057	0.008	-0.021	-0.077	-0.035	-0.043	-0.107
6	-0.036	0.073	0.075	0.061	-0.012	-0.056	0.076	0.014	0.063
7	-0.02	-0.007	0.119	0.032	0	-0.064	-0.004	-0.131	-0.093
8	-0.059	-0.026	-0.124	-0.15	-0.013	0.107	0.074	0.17	0.08
9	0.057	0.048	-0.092	0.112	0.183	-0.022	0.134	0.126	0.005
10	-0.037	0.029	0.004	0.048	0.01	0.005	0.005	-0.013	0.113

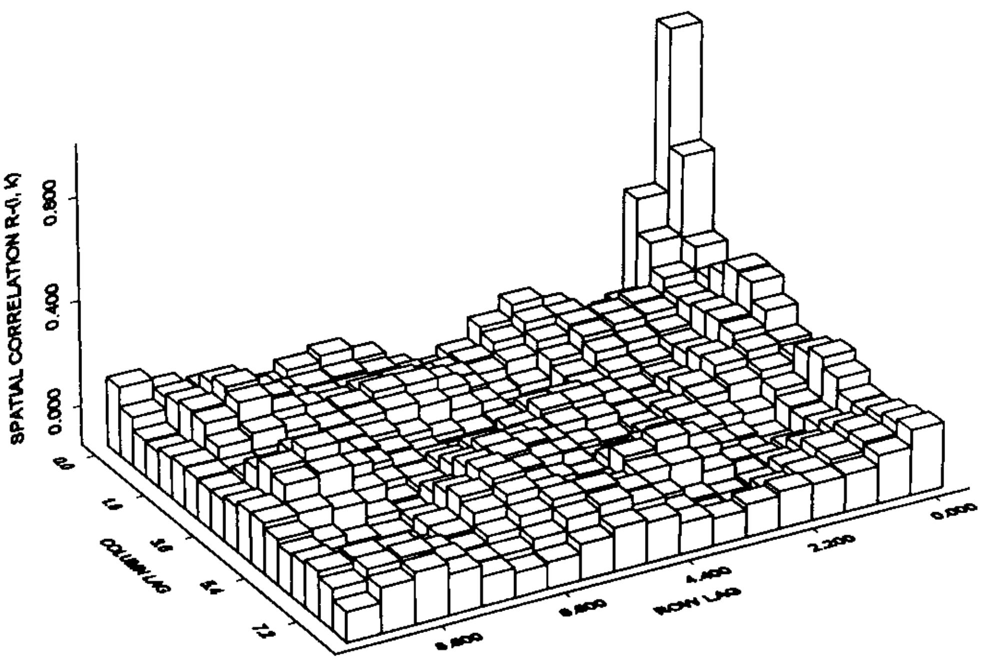


Fig. 3.4.7 (Rice data) Spatial correlation surface R-(l, k) for different row and column lags.

TABLE 3.4.8: Rice data: Spatial correlation R+(l, k)

l	0	1	2	3	4	5	6	7	8
0	1	0.195	0.206	0.214	0.056	0.139	0.054	0.065	0.101
1	-0.039	0.084	0.031	0.052	0.037	0.081	0.094	0.096	-0.018
2	0.035	-0.016	0.062	0.029	0.057	0.009	0.049	0.064	0.07
3	0.029	0.065	-0.002	0.034	0.191	0.087	0.068	0.126	0.042
4	-0.041	-0.075	0.056	-0.041	-0.024	0.005	-0.049	0.065	0.02
5	-0.107	-0.064	-0.013	-0.102	-0.046	0.004	0.03	0.117	0.117
6	0.063	0.031	-0.025	-0.004	-0.105	-0.031	0.067	0.06	0.046
7	-0.093	-0.043	-0.147	-0.17	-0.028	-0.085	-0.064	-0.052	0.011
8	0.08	0.032	-0.065	0.006	-0.089	0.01	0.031	-0.037	-0.222
9	0.005	0.069	0.125	-0.01	0.205	0.005	0.088	0.035	-0.033
10	0.113	0.071	0.014	0.077	-0.076	0.043	-0.091	-0.008	0.097

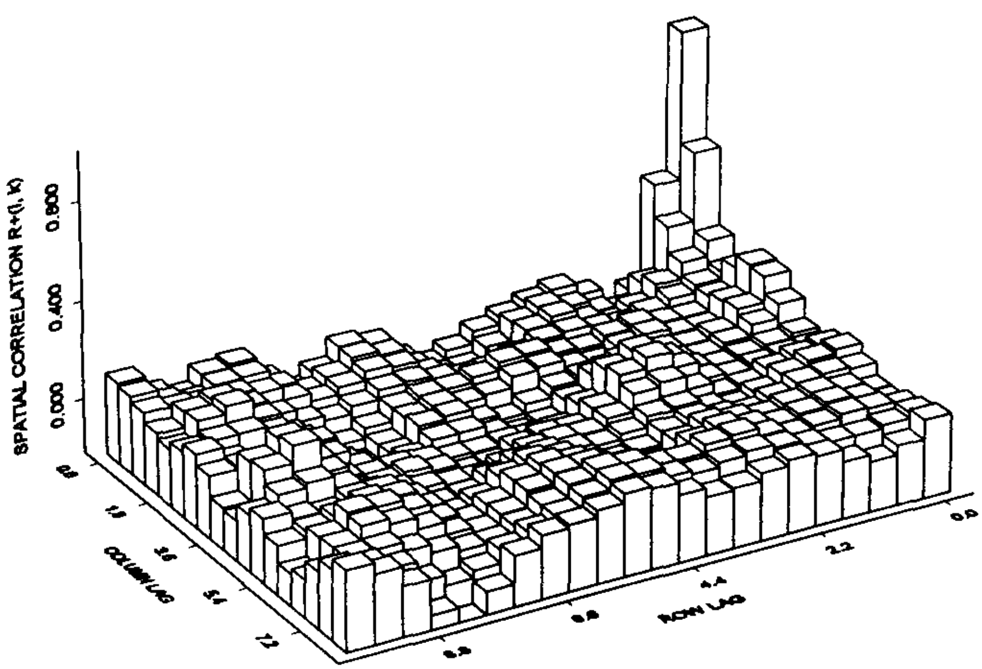


Fig.3.4.8 (Rice data) Spatial correlation surface R+(l, k) for different row and column lags.

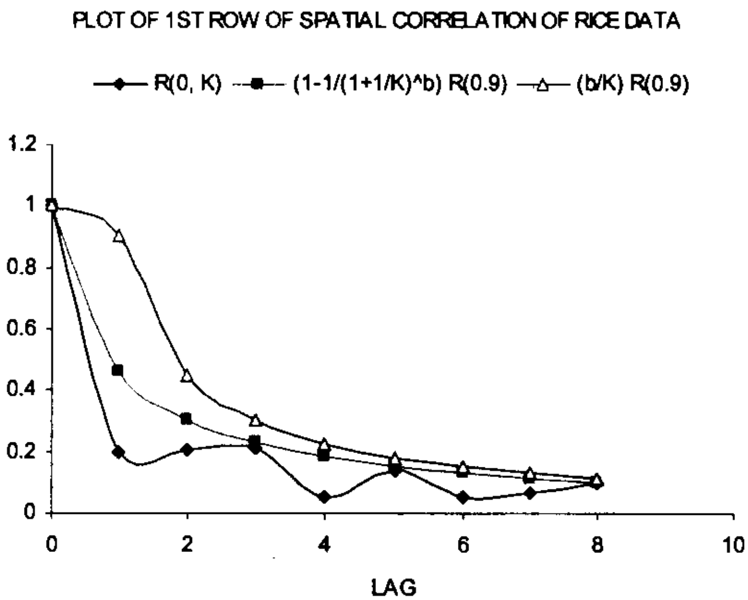


Fig. 3.4.9: Plot of first row of spatial correlation matrix.

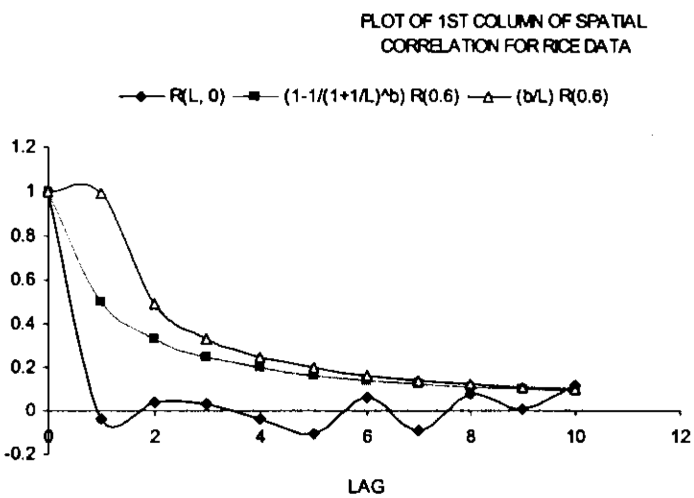


Fig. 3.4.10: Plot of the correlation attenuation curve for rows and columns for rice data.

TABLE 3.4.9: Average Spatial correlation R(l,k)

l \ K	0	1	2	3	4	5	6	7	8
0	1.000	0.195	0.206	0.214	0.056	0.139	0.054	0.065	0.101
1	-0.039	0.077	0.035	0.045	0.052	-0.008	0.006	0.062	-0.003
2	0.035	0.024	0.021	-0.015	-0.020	-0.002	0.015	-0.019	0.009
3	0.029	0.018	-0.009	-0.014	0.106	0.036	0.004	0.054	0.039
4	-0.041	-0.074	-0.057	-0.021	-0.046	-0.045	0.035	0.008	-0.018
5	-0.107	-0.054	-0.024	-0.090	-0.034	0.006	-0.013	0.086	0.067
6	0.063	0.023	0.025	-0.030	-0.058	0.015	0.071	0.066	0.005
7	-0.093	-0.087	-0.076	-0.117	-0.014	-0.027	0.027	-0.029	-0.005
8	0.080	0.101	0.004	0.057	-0.051	-0.070	-0.047	-0.032	-0.140
9	0.005	0.097	0.129	-0.016	0.194	0.058	-0.002	0.041	0.012
10	0.113	0.029	0.009	0.041	-0.033	0.046	-0.043	0.010	0.030

TABLE 3.4.10: MSE for plots a x c units

a \ Number of unit plots, c	1	2	3	4	5	6	7	8	9
1	13988.34	16722.78	19522.36	22372.56	24391.87	26379.21	28013.28	29463.74	30904.72
2	13445.82	17250.38	20725.50	24210.71	26893.61	29288.35	31239.74	33141.07	34922.14
3	13586.70	17961.08	21855.03	25586.01	28443.99	30939.59	33012.97	35038.39	36934.46
4	13857.45	18644.59	22751.74	26563.37	29776.52	32583.97	34916.32	37248.09	39453.29
5	13794.68	18420.95	22313.25	25944.88	29133.66	31889.61	34259.91	36698.39	39008.27
6	13259.72	17535.93	21132.53	24369.45	27316.52	29896.49	32174.40	34693.39	37151.17
7	13110.08	17219.14	20691.57	23637.26	26319.83	28729.58	30984.20	33652.75	36293.78
8	12695.06	16400.25	19524.84	21938.88	24216.63	26330.63	28470.33	31153.96	33854.22
9	12608.98	16295.03	19254.94	21387.84	23370.78	25201.99	27176.63	29792.23	32381.74
10	12553.95	16477.66	19610.71	21651.05	23675.52	25515.64	27523.52	30235.20	32859.86
11	12775.23	16961.51	20273.23	22303.64	24370.54	26259.07	28294.28	31090.66	33765.93

TABLE 3.4.11: Standardised MSE for plots a x c units

a	Number of unit plots, c								
	1	2	3	4	5	6	7	8	9
1	1.000	1.195	1.396	1.599	1.744	1.886	2.003	2.106	2.209
2	0.961	1.233	1.482	1.731	1.923	2.094	2.233	2.369	2.497
3	0.971	1.284	1.562	1.829	2.033	2.212	2.360	2.505	2.640
4	0.991	1.333	1.626	1.899	2.129	2.329	2.496	2.663	2.820
5	0.986	1.317	1.595	1.855	2.083	2.280	2.449	2.623	2.789
6	0.948	1.254	1.511	1.742	1.953	2.137	2.300	2.480	2.656
7	0.937	1.231	1.479	1.690	1.882	2.054	2.215	2.406	2.595
8	0.908	1.172	1.396	1.568	1.731	1.882	2.035	2.227	2.420
9	0.901	1.165	1.376	1.529	1.671	1.802	1.943	2.130	2.315
10	0.897	1.178	1.402	1.548	1.693	1.824	1.968	2.161	2.349
11	0.913	1.213	1.449	1.594	1.742	1.877	2.023	2.223	2.414

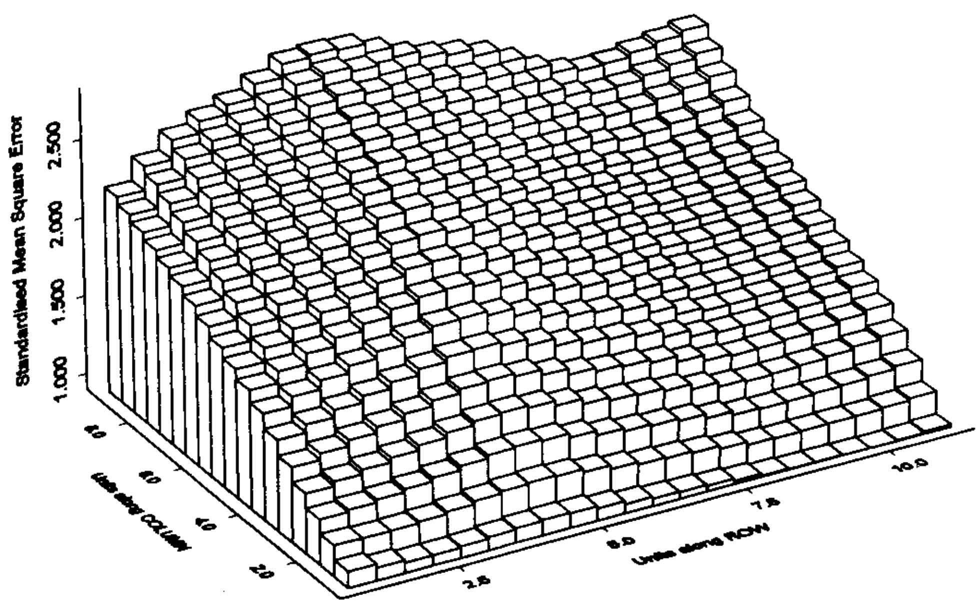


Fig.3.4.11 Three dimensional plot of Standardised Mean Square Error for plots of a x c units

TABLE 3.4.12: Cost per unit of information for plots a x c units for Rice data.

a	Number of unit plots, c: 1	2	3	4	5	6	7	8	9
1	21069.79	14808.69	13248.65	12868.48	12515.96	12444.13	12386.99	12375.21	12447.60
2	11906.81	9922.24	9777.05	10168.86	10461.08	10786.61	11043.60	11348.42	11657.24
3	9220.48	8472.96	8802.62	9423.07	9887.13	10327.84	10694.69	11091.93	11479.89
4	7970.67	7831.01	8379.24	9096.03	9734.24	10314.94	10795.28	11309.78	11809.29
5	7078.33	7165.38	7756.09	8481.64	9162.42	9765.24	10288.54	10858.14	11407.06
6	6255.14	6458.31	7054.18	7714.51	8364.86	8948.72	9472.05	10085.46	10693.18
7	5797.05	6087.16	6703.12	7308.07	7904.07	8457.91	8990.83	9658.60	10327.20
8	5332.12	5615.90	6180.88	6661.38	7165.10	7654.38	8171.21	8855.10	9549.65
9	5078.56	5439.39	5984.78	6401.88	6834.24	7253.86	7732.97	8403.84	9072.26
10	4883.24	5386.71	6005.19	6406.01	6858.04	7285.48	7777.44	8476.67	9155.85
11	**4825.13**	5449.18	6131.80	6536.16	7004.36	7448.36	7949.62	8672.64	9365.97

TABLE 3.4.13: RICE DATA

PLOT SIZE	ln(p)	STMSE	STMSE/p	ln(STMSE/p)
(Row 1)				
2	0.693147	1.195	0.5975	-0.515
3	1.098612	1.396	0.465333	-0.765
4	1.386294	1.599	0.39975	-0.91692
5	1.609438	1.744	0.3488	-1.05326
6	1.791759	1.886	0.314333	-1.1573
7	1.94591	2.003	0.286143	-1.25126
8	2.079442	2.106	0.26325	-1.33465
9	2.197225	2.209	0.245444	-1.40468
(Row 11)				
22	3.091042	1.213	0.055136	-2.89795
33	3.496508	1.449	0.043909	-3.12563
44	3.78419	1.594	0.036227	-3.31794
55	4.007333	1.742	0.031673	-3.4523
66	4.189655	1.877	0.028439	-3.55998
77	4.343805	2.023	0.026273	-3.63922
88	4.477337	2.223	0.025261	-3.67848
99	4.59512	2.414	0.024384	-3.71383
(Column 1)				
2	0.693147	0.961	0.4805	-0.73293
3	1.098612	0.971	0.323667	-1.12804
4	1.386294	0.991	0.24775	-1.39534
5	1.609438	0.986	0.1972	-1.62354
6	1.791759	0.948	0.158	-1.84516
7	1.94591	0.937	0.133857	-2.01098
8	2.079442	0.908	0.1135	-2.17595
9	2.197225	0.901	0.100111	-2.30147

9	2.197225	0.901	0.100111	-2.30147
10	2.302585	0.897	0.0897	-2.41128
11	2.397895	0.913	0.083	-2.48891
(Column 9) 9	2.197225	2.209	0.245444	-1.40468
18	2.890372	2.497	0.138722	-1.97528
27	3.295837	2.64	0.097778	-2.32506
36	3.583519	2.82	0.078333	-2.54678
45	3.806663	2.789	0.061978	-2.78098
54	3.988984	2.656	0.049185	-3.01216
63	4.143135	2.595	0.04119	-3.18955
72	4.276666	2.42	0.033611	-3.3929
81	4.394449	2.315	0.02858	-3.55504
90	4.49981	2.349	0.0261	-3.64582
99	4.59512	2.414	0.024384	-3.71383

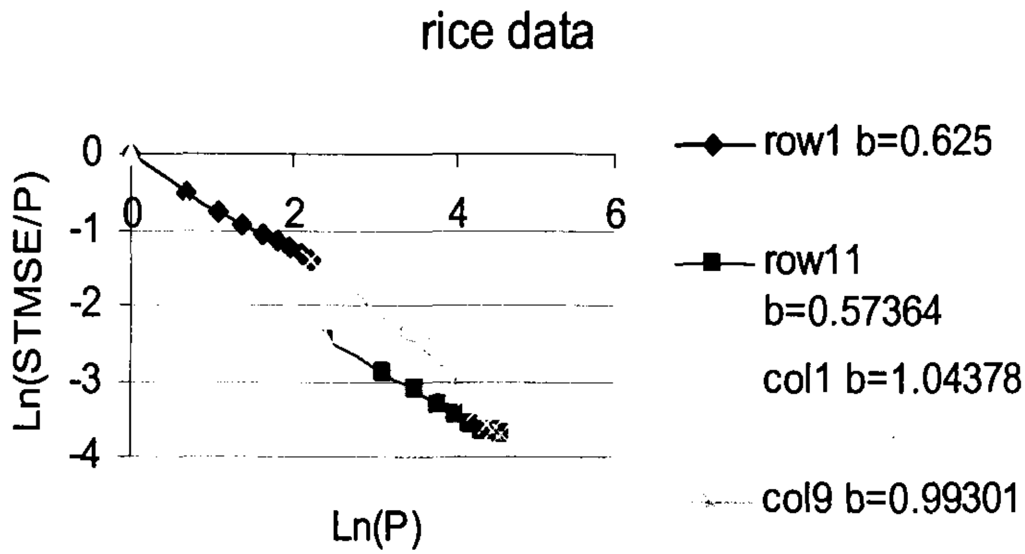


Fig. 3.4.12 Plot of ln(STMSE/p) versus ln(p) using the first and last rows and columns of the STMSE matrix from the Rice data.

The changing slopes over rows and columns and the distinct curvature of the graphs (Fig.7) for the rows are clear indications that in this case even two-dimensional version of Smith's model may be inadequate to find the optimum plot size. However we can use the table 3.4.12 containing the cost aspect. It is observed that the cost per unit of information is minimum for 11m. x 1m. plot for the Rice data. However, using M.S.E. matrix we can find C.V. for each plot size and shape. Now using method of maximum curvature optimum plot size for Jute field is 4.02 sq.m. with b_1=0.83, b_2=1.0 and X_{opt}=1.28m. X 3.13m. & optimum plot size for Rice field is 3.73 sq.m. with b_1=1.0, b_2=0.77 and X_{opt}=3.205m. X 1.165m.

Chapter 4

MODELING SPATIAL VARIABILITY

4.1 INTRODUCTION: Since the beginning of the application of statistics, observations are assumed to have been taken under identical conditions and they are independent of each other. Here independence is a convenient assumption that makes the analysis / algebra tractable. However, the assumption of independence in real life data is often unrealistic. R.A.Fisher was aware of the spatial dependence of agricultural field experiments. He established the principles of randomizations, blocking and replication. Randomization controls unwanted bias and neutralizes (but does not remove) the effect of spatial correlation. Randomization does not neutralize the spatial correlation at spatial scales larger or smaller than the plot dimensions.

To measure the spatial dependence in a data set we have to see the similarity among data values separated and situated at a particular distance or lag. One quick way to express the similarity or dissimilarity between the paired values is to plot them in a $Z(s)$ vs $Z(s+h)$ scattergram. The plot is known as h scattergram. If the difference between all the $Z(s)$ and $Z(s+h)$ values is small, then all the points (scatter of points) will be close to the 45E line and the variable is described as autocorrelated. Alternatively, the larger the difference between the pairs, the more diffuse will be the scatter of points around the 45E or $Z(s)$ vs $Z(s+h)$ line. When h is small the scatter of points will, on average, be tighter; when h is large, the scatter is typically more diffuse. The tightness or diffuseness of the cloud of points about the 45E line may be thought of as their moment of inertia about the line. If s_i and s_j are the co-ordinates for all i = 1 to N points in an h-scattergram then the moment of inertia for all points is defined as moment of inertia = $\frac{1}{2N}\sum_{i=1}^{N}(s_i - s_j)$. In other words, the moment of inertia summarizes the spread of the cloud in an h-scattergram. The h-scattergram can be useful models of the degree of similarity or dissimilarity between samples separated by a common distance but they are not practical because too many h-scattergrams would be required to adequately characterize the spatial similarity for all samples and for all h values. Therefore a meaningful summary of these h-scattergrams is moment of inertia. Intimately, related to the moment of inertia is one of the most familiar tools in geostatistics: the semivariogram or simply the variogram.

4.2. Spatial model: Suppose that the data {Z(s_1), Z(s_2),............. Z(s_n)}, observed at known spatial locations {s_1, s_2,............s_n} are modeled as a realization of a partially samples random process {Z(s): s 0 D $\subset$ R^d}. Here the spatial index set D could have positive Lebesgue measure, be a countable set of points of R^d, or be a finite subset of R^d. Here let Z(s) = μ(s) + δ(s), s 0 D where δ(.) is a zero mean error process that is not generally white noise. We call a random variable to be white noise when it is distributed normally, independently, identically with a zero mean and constant variance. The mean process μ(.) = E(Z(.)) is assumed to be made up of spatial trend, exogenous variables and treatment effects α (should different treatments be applied at different locations throughout D) and will be called large scale variation. The error process is assumed to contain no treatment component, and as such is only of consequence in how it affects efficient estimation of τ, the treatment contrasts. We can assume and decompose δ(.) as δ(s) = W(s) + η(s) + ε(s) , s 0 D. W(.) is a zero mean L_2 continuous [i.e. $E(W(s+h) - W(s))^2 \rightarrow 0$ as $\|h\| \rightarrow 0$.] intrinsically stationary process whose variogram range is larger than $\min\{\|s_i - s_j\| : 1 \le i < j \le n\}$. Here W(.) is called the smooth scale variation. η(.) is a zero mean, intrinsically stationary process, independent of W whose variogram range exists and is smaller than $\min\{\|s_i - s_j\| : 1 \le i < j \le n\}$. Here η(.) is called the micro scale variation and its variance is called C_{MS}. ε(.) is a zero mean white noise process independent of W(.) and η(.). η(.) is also called the measurement error and its variance is called C_{ME}. Here we assume that the error process δ(.) is intrinsically stationary. The intrinsic stationarity can be defined through first differences as E(Z(s+h) – Z(s)) = 0 and Var(Z((s+h) – Z(s)) = 2.γ(h) where {Z(s): s 0 D} and h = (s_i – s_j). The quantity 2.γ(h) is known as variogram and γ(h) is called the semivariogram. Alternatively this means that $E(\delta(s_1) - \delta(s_2))^2 = 2.\gamma(s_1 - s_2)$ where s_1, s_2 0 D. The classical estimator of variogram 2.γ(h) is a crucial parameter. The classical estimator of the variogram as proposed by Matheron (1963) is $2.\hat{\gamma}(h) \equiv \frac{1}{|N(h)|}\sum_{N(h)}(Z(s_i) - Z(s_j))^2$ where sum is over $N(h) \equiv \{(i,j) : s_i - s_j = h\}$ and $|N(h)|$ is the number of distinct elements of $N(h)$. Cressie and

Hawkins(1980) present a more robust approach to the estimation of variogram :

$$2.\bar{\gamma}(h) \equiv \left\{ \frac{1}{|N(h)|} \sum_{N(h)} |Z(s_i) - Z(s_j)|^{1/2} \right\}^4 \Bigg/ \left(0.457 + \frac{0.494}{|N(h)|} \right)$$

Here the word "robust" is used to describe inference procedures that are stable when model assumptions depart from those of a central model. In case of above robust estimator Cressie and Hawkins (1980) use the available knowledge of robust *location* estimation and take fourth roots of squared differences. Thus the estimator is robust to contamination by outliers (Hawkins and Cressie, 1984). Another robust estimator is $2.\tilde{\gamma}(h) \equiv \left[med\left\{ |Z(s_i) - Z(s_j)|^{1/2} : (s_i - s_j) \in N(h) \right\} \right]^4 \big/ B(h)$ where med(.) denotes the median of the sequence {.} and B(h) corrects for bias [asymptotically, B(h) = 0.457]. The variogram must satisfy a property called conditional negative definiteness i.e. $\sum_{i=1}^{m}\sum_{j=1}^{m} a_i a_j .2\gamma(s_i - s_j) \leq 0$ for any finite number of spatial locations (s_i: i = 1,2,.....,m) and real numbers (a_i: i = 1, 2,.....,m) satisfying $\sum_{i=1}^{m} a_i = 0$. The function C(.) = C(s_i – s_j) = Cov(Z(s_i), Z(s_j)) is called a covariogram.

Now,

$2.\gamma(h) = \text{var}\ (Z(s_i) - Z(s_j))$

$$\text{or, } 2.\gamma(h) = \text{var}\ (Z(s_i)) + \text{var}\ (Z(s_j)) - 2.\text{cov}(Z(s_i), Z(s_j))$$

$$\text{or, } 2.\gamma(h) = 2.C(0) - 2.C(h) = 2.(C(0) - C(h))$$

where C(0) = var (Z(s)). Here the semivariogram is very simply related to covariogram. If C(h) → 0 as $\|h\| \to 4$ [e.g. when Z(.) is a stationary ergodic Gaussian process], then 2.γ(h)→ 2.(C(0)) i.e. .γ(h)→ C(0); the quantity C(0) is called the *sill* of the semivariogram. Moreover any vector $\mathbf{r_0}$ for which $\gamma(\mathbf{r_0}(1+\varepsilon))$ = C(0) for any ε > 0 is called the range of the variogram in the direction $r_0 / \|r_0\|$. This means the correlation between Z(s) and Z(s + (h.r_0 / $\|r_0\|$)) is zero for all $h \geq \|r_0\|$.

Here if 2. γ(s_i – s_j) is a function of only of $\|s_i - s_j\|$, it is called *isotropic*. Clearly γ(-h) = γ(h) and γ(0) = 0. If γ(h) → C_o >0 as h → 0, then C_o was called the nugget effect by Matheron(1962). This component of the semivariogram is often used to model micro scale variation (small nuggets) and causes a discontinuity at the origin. More generally the nugget effect is made up of two components $C_o = C_{MS} + C_{ME}$ where C_{MS} represents the variance of a white noise process used to model the noncontinuous micro scale variation of the physical process and C_{ME} represents the variance of a white noise process used to model measurement error i.e. error resulting from doing the measurement several times and not being able to obtain exactly the same result.

4.3. Spatial modeling of uniformity data: Let the model be $Z(s) = \mu(s) + \delta(s)$. The most common problems in statistical analysis involve inference on the large scale variation $\mu(.)$. Usually $\delta(.)$ is assumed to be white noise. Modelling and fitting spatial dependence parameters from the data allows for efficient estimation of the parameters in $\mu(.)$. Besag(1977) illustrated use of modeling spatial or temporal correlation in error process $\delta(.)$ for the efficient estimation of $\mu(.)$. To illustrate and to obtain a true model for spatial variation responses from the uniformity trials shall be used. By treating the uniformity data as a spatial data we can write the data as {Z(i (1.0), j (1.0)): i = 1,2,.......,R; j = 1,2,........,C }. Here each unit plot is a square plot of area 1mt. X 1mt. We denote Z(i,j), the (i,j)-th data where i = 1 corresponds to the most Easterly row and j =1 corresponds to the most Northerly column. Considering the two way layout of the plots we can propose the stochastic model $Z(i,j) = a + r_i + c_j + \delta(i,j)$. Now we can estimate the mean process i.e. $\mu(s) = a + r_i + c_j$ (where $s = (i,j)$) by *median polish.* Assuming one observation per grid node o.l.s. estimators of a, r_i, c_j can be obtained. However its disadvantage is that the residuals $(Z(s_i) - \hat{\mu}(s_i) : i = 1,2,........n)$ give biased estimators of the unknown spatial dependence in the error process $\delta(.)$. But median polish technique is a sensible one. When the distribution of error process is symmetric, $E(ave\{Z(s_i) : i \in A\}) = E(med\{Z(s_i) : i \in A\})$. Further, $med\{Z(s_i) : i \in A\}$ has attractive outlier resistance properties.

MEDIAN POLISH ALGORITHM: The median polish algorithm (Emerson and Hoaglin, 1983) that produces the all effect ã, the row effects { $\subseteq_k$: k = 1,2,........R} and the column effects { $\check{c}_l$: l = 1,2,.........,C} from a p X q array of numbers {Z(i,j): i = 1,2,.....R; j = 1,2,......C} also gives less biased residuals.

For i= 1,3,5,.........., define

$Z_{k,l}^{(i)} \equiv Z_{k,l}^{(i-1)} - \text{med}\{ Z_{k,l}^{(i-1)}: l = 1,........,C \}$, k = 1,......, R+1; l = 1,......,C

$Z_{k,C+1}^{(i)} \equiv Z_{k,C+1}^{(i-1)} - \text{med}\{ Z_{kl}^{(i-1)}: l = 1,\ldots\ldots,C \}, k = 1,\ldots\ldots, R+1;$

------------------------- (i)

and for i = 2,4,6,........., define

$Z_{k,l}^{(i)} \equiv Z_{k,l}^{(i-1)} - \text{med}\{ Z_{k,l}^{(i-1)}: k = 1,\ldots\ldots,R \}, k = 1,\ldots\ldots, R; l=1,\ldots\ldots,C+1$

$Z_{p+1,l}^{(i)} \equiv Z_{p+1,l}^{(i-1)} + \text{med}\{ Z_{k,l}^{(i-1)}: k = 1,\ldots\ldots,R \}, l = 1,\ldots\ldots, C+1;$

To start the algorithm, assume $Z_{k,l}^{(0)} = \begin{cases} Z_{k,l} & k = 1,\ldots\ldots,R;\; l = 1,\ldots\ldots,C \\ 0, & \text{elsewhere} \end{cases}$

In words start with R x C data and create R+C+1 extra cells with zero in them. Use equations at (i) to remove row medians from the data and accumulate the amounts removed in the p extra row cells. Do the same to the columns of the table, removing column medians from not only the data but also the column of accumulated row removals. This last amount removed goes into the extra (R+1, C+1)-th cell. Repeat the process until convergence. Assuming convergence, the estimated effects are

$\tilde{a} \equiv Z^{\infty}_{R+1,C+1}$

$$\subseteq_k \equiv Z^{\infty}_{k,C+1}\ ;\ k = 1,\ldots\ldots,R$$

$$\check{c}_l \equiv Z^{\infty}_{R+1,C+1}\ ;\ l = 1,\ldots\ldots,C$$

with the property that

$$Z_{k,l} = \tilde{a} + \subseteq_k + \check{c}_l + Z^{\infty}_{k,l}\ ;\ k = 1,\ldots\ldots,R \qquad l = 1,\ldots\ldots,C$$

Thus, the original R x C table is replaced with a R x C table of residuals. $\{ Z^{\infty}_{k,l}\ ; k = 1,\ldots\ldots,R; l = 1,\ldots\ldots,C\}$ and the R + C + 1 extra cells contain the row effect $\subseteq_k$, the column effect $\check{c}_l$ and the all effect $\tilde{a}$. Now observing the row and column effects we can detrend the data as $R(i,j) = Z(i,j) - \tilde{a} - \subseteq_k - \check{c}_l$. Now we have to analyse the median-polish residuals R(i,j) as if they are a sampling from an intrinsically stationary random process. Now these residuals will be used to estimate $2.\gamma(h) = \text{var}(\delta(s+h) - \delta(s))$. The common variogram models (γ_u) in terms of a Dimensionless Length h/a are given in the following table:

Table 4.3.1:

Name	Function	Effective range
Exponential	$1-\exp(-h/a)$	3.0 a

Spherical	1.5 (h/a) – 0.5 $(h/a)^3$, $h < a$ 1 , $h \geq a$	0.82 a
Gaussian	1 – exp $[-(h/a)^2]$	1.7 a
Michaelis-Menton	$(h/a) / [1 + (h/a)]$	19.0 a
Linear	h/a	None

As sample support size increases, variance is expected to decrease. With respect to a variogram this would correspond to a decrease in sill. Some other models considered are rational quadratic model, wave model and power model.Various parametric variogram models are presented by Journel and Huijbregts(1978). Here we consider the following basic models:

(i) *Linear model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots h = 0 \\ c_o + b_l \|h\|, \ldots\ldots\ldots h \neq 0 \end{cases}$

$\theta = (c_o, b_l)'$, where $c_o \geq 0$, and $b_l \geq 0$.

(ii) *Spherical model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots h = 0, \\ c_o + c_s\{(3/2)(\|h\|/a_s) - (1/2)(\|h\|/a_s)^3\}, \ldots 0 < \|h\| \leq a_s, \\ c_o + c_s, \ldots\ldots\ldots \|h\| \geq a_s, \end{cases}$

$\theta = (c_o, c_s, a_s)'$, where $c_o \geq 0, c_s \geq 0, a_s \geq 0$.

(iii) *Exponential model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots h = 0 \\ c_o + c_e\{1 - \exp(\|h\|/a_e)\}, \ldots\ldots\ldots h \neq 0 \end{cases}$

$\theta = (c_o, c_e, a_e)'$, where $c_o \geq 0, c_e \geq 0, a_e \geq 0$.

(iv) *Rational quadratic model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots h = 0 \\ c_o + c_r\|h\|^2/(1 + \|h\|^2/a_r), \ldots\ldots\ldots h \neq 0 \end{cases}$

$\theta = (c_o, c_r, a_r)'$, where $c_o \geq 0, c_r \geq 0, a_r \geq 0$.

(v) *Wave model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots h = 0 \\ c_o + c_w\{1 - a_w Sin(\|h\|/a_w)/\|h\|\}, \ldots\ldots\ldots h \neq 0 \end{cases}$

$\theta = (c_o, c_w, a_w)'$, where $c_o \geq 0, c_w \geq 0, a_w \geq 0$.

(vi) *Power model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots\ldots\ldots h = 0 \\ c_o + b_p \|h\|^{\lambda}, \ldots\ldots\ldots h \neq 0 \end{cases}$

$\theta = (c_o, b_p, \lambda)'$, where $c_o \geq 0, b_p \geq 0, 0 \leq \lambda < 2$.

(vii) *Gaussian model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots\ldots\ldots h = 0 \\ c_o + c_g \{1 - \exp[-(\|h\|/a_g)^2]\}, \ldots\ldots\ldots h \neq 0 \end{cases}$

$\theta = (c_o, c_g, a_g)'$, where $c_o \geq 0, c_g \geq 0, a_g \geq 0$.

(viii) *Michaelis-Menton model*: $\gamma(h;\theta) = \begin{cases} 0, \ldots\ldots\ldots\ldots\ldots\ldots h = 0 \\ c_o + c_m (\|h\|/a_m)/(1 + \|h\|/a_m), \ldots\ldots\ldots h \neq 0 \end{cases}$

$\theta = (c_o, c_m, a_m)'$, where $c_o \geq 0, c_m \geq 0, a_m \geq 0$.

4.4 RESULTS OF VARIGRAM MODEL FITTINGS: The following is the result of different variogram model fittings through nonlinear regression techniques. The asymptotic standard errors of the parameters is displayed (StdErr.) in column three. The standard errors and coefficients of variation can be used as a gauge of the fitted curve's accuracy. The parameter coefficients of variation, expressed as a percentage, are displayed [CV(%)] in column four. This is the normalized version of the standard errors i.e. CV% = standard error * (100/ parameter value).The coefficient of variation values and standard errors (see above) can be used as a gauge of the accuracy of the fitted curve. The last column shows the parameter dependencies. Parameters with dependencies near 1 are strongly dependent on one another. This may indicate that the equation(s) used are too complicated and "over-parameterized"—too many parameters are being used, and a model with fewer parameters may be better. Dependencies are used to determine when the data has been "over-parameterized." Too many parameters result in dependencies very near 1.0. If a mathematical model contains too many parameters, a less complex model may be found that adequately describes the data. Dependencies near 1.0 (0.999 for example) indicate that the equation uses too many parameters. If two parameters are dependent on one another, one can probably use an equation with one less parameter. 'Converged, tolerance satisfied' message appears when the convergence criterion, which compares the relative change in the norm to the specified tolerance, is satisfied. This is to be noted that result may still be a false or local minimum. Hence choice of the initial parameter value is important in fitting of nonlinear regression. By observing the actual data, fitting a linear equation and from experience we are able to find a suitable guess for initial parameter values of our data.

JUTE DATA

Plot size (1X1) Average variogram (Spherical model) Rsquare =0.75008

Parameter	Value	StdErr	CV(%)	Dependencies
a	-6.669e-1	2.045e+2	3.067e+4	0.9850332
b	2.825e+3	2.060e+2	7.291e+0	0.9849500
c	1.569e+0	1.888e-1	1.204e+1	0.0437719

EXPONENTIAL MODEL FITTING $y = a - b.\exp(-x/c)$

1X1plot Rsq.= 0.747920763

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.828e+3	2.603e+1	9.204e-1	0.0677606
b	2.832e+3	2.071e+2	7.314e+0	0.0368422
c	5.157e-1	1.126e-1	2.182e+1	0.0678951

JUTE DATA GAUSSIAN MODEL $y = a - b.\exp[-(x/c)^2]$

1 X 1 plot Rsq.= 0.749893722

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.825e+3	2.554e+1	9.039e-1	0.0392436
b	2.826e+3	2.063e+2	7.300e+0	0.0426184
c	7.514e-1	8.753e-2	1.165e+1	0.0465566

MICHAELIS-MENTON MODEL FITTING $y = a - b / (1+x/c)$

1X1plot Rsq.= 0.741325044

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.869e+3	4.001e+1	1.395e+0	0.5951695
b	2.870e+3	2.119e+2	7.384e+0	0.0700972
c	1.153e-1	6.949e-2	6.027e+1	0.5811760

VB (1X1) MODEL FITTING $y = li*(1-\exp(-k*(t-t0)))$ Rsquare =0.748515357

Parameter	Value	StdErr	CV(%)	Dependencies
li	2.826e+3	2.640e+1	9.343e-1	0.0488314
k	1.948e+0	4.151e-1	2.131e+1	0.0708874

t0	7.606e-4	3.807e-2	5.005e+3	0.0240221

Plot size (3X4) Average variogram (Spherical model) Rsquare =0.997048

Parameter	Value	StdErr	CV(%)	Dependencies
a	-3.972e+0	3.655e+1	9.202e+2	0.7261903
b	1.430e+5	3.377e+8	2.362e+5	1.0000000
c	6.821e+2	1.611e+6	2.362e+5	1.0000000

Plot size (1X9) Average variogram (Spherical model) Rsquare =0.144939

Parameter	Value	StdErr	CV(%)	Dependencies
a	3.201e+2	9.930e+1	3.102e+1	0.8311002
b	1.993e+2	1.343e+2	6.738e+1	0.8262073
c	9.644e+0	1.683e+0	1.745e+1	0.0906206

1 X 5 plot Exponential model Rsq.= 0.80138329

Parameter	Value	StdErr	CV(%)	Dependencies
a	8.573e+2	3.767e+1	4.394e+0	0.3417261
b	8.120e+2	1.201e+2	1.479e+1	0.2152217
c	1.228e+0	3.983e-1	3.244e+1	0.3341955

1 X 9 plot Exponential model Rsq.= 0.520408977

Parameter	Value	StdErr	CV(%)	Dependencies
a	4.775e+2	3.207e+1	6.717e+0	0.1250416
b	4.651e+2	1.242e+2	2.670e+1	0.0666696
c	6.579e-2	2.121e+1	3.224e+4	0.0666904

3 X 4 plot Exponential model Rsq.= 0.997047272

Parameter	Value	StdErr	CV(%)	Dependencies
a	5.410e+6	2.706e+3	5.002e-2	0.9999500
b	5.410e+6	2.706e+3	5.002e-2	0.9999500
c	1.720e+4	6.892e+2	4.006e+0	0.6428947

2 X 4 plot Gaussian model Rsq.= 0.926215626

Parameter	Value	StdErr	CV(%)	Dependencies
a	3.772e+2	2.527e+1	6.698e+0	0.4560605
b	3.577e+2	5.147e+1	1.439e+1	0.3479337

c	1.453e+0	3.032e-1	2.087e+1	0.3678394

7 X 1 plot Gaussian model Rsq.= 0.765057035

Parameter	Value	StdErr	CV(%)	Dependencies
a	5.351e+3	5.627e+2	1.052e+1	0.4462170
b	5.133e+3	1.278e+3	2.491e+1	0.2716941
c	1.037e+0	3.099e-1	2.989e+1	0.3492266

1 X 5 plot Michaelis-menton model Rsq.= 0.835191808

Parameter	Value	StdErr	CV(%)	Dependencies
a	9.197e+2	5.445e+1	5.920e+0	0.7384739
b	9.122e+2	1.170e+2	1.283e+1	0.3543180
c	6.338e-1	3.305e-1	5.215e+1	0.6895369

2 X 9 plot Michaelis-menton model Rsq.= 0.831729125

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.058e+2	4.820e+1	2.343e+1	0.9534801
b	2.022e+2	5.060e+1	2.503e+1	0.8259530
c	1.650e+0	1.419e+0	8.602e+1	0.9050725

3 X 4 plot Michaelis-menton model Rsq.= 0.997047527

Parameter	Value	StdErr	CV(%)	Dependencies
a	1.289e+7	2.706e+3	2.099e-2	0.9999500
b	1.289e+7	2.706e+3	2.099e-2	0.9999500
c	4.099e+4	1.625e+3	3.964e+0	0.6428697

JUTE DATA (Plot size: 1 X 1)

VB Model fit y = li*(1-exp(-k*(t-t0)))

PLOT SIZE 1 X 5 Rsq.= 0.801400488

Parameter	Value	StdErr	CV(%)	Dependencies
li	8.584e+2	3.803e+1	4.430e+0	0.2353937
k	7.976e-1	2.582e-1	3.237e+1	0.4146764
t0	-7.252e-2	1.917e-1	2.643e+2	0.2624308

PLOT SIZE 2 X 9 Rsq.= 0.828658671

Parameter	Value	StdErr	CV(%)	Dependencies
li	1.707e+2	2.741e+1	1.606e+1	0.7497911
k	5.070e-1	2.849e-1	5.620e+1	0.8093811
t0	-9.577e-2	3.748e-1	3.913e+2	0.4015472

PLOT SIZE 3 X 5

Rsq.= 0.982025531

Parameter	Value	StdErr	CV(%)	Dependencies
li	1.731e+4	2.821e+5	1.629e+3	0.9999781
k	1.530e-2	3.009e-1	1.967e+3	0.9999782
t0	6.471e-2	2.669e-1	4.124e+2	0.6824447

Rice data

RICE DATA(22 x 18) SPHERICAL MODEL

****

Plot size= 1X1 considering value of variogram zero at lag distance zero.

(Average) Rsquare= 0.7393

Parameter	Value	StdErr	CV(%)	Dependencies
a	5.304e+0	1.924e+3	3.627e+4	0.9824561
b	2.400e+4	1.941e+3	8.087e+0	0.9824286
c	1.251e+0	2.375e-1	1.899e+1	0.0188417

Plot size (4X1) (specify zero value at lag distance zero)

Variogram Rsquare=0.2539 (deleting some outliers)

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.350e+4	1.100e+4	4.679e+1	0.8652831
b	2.389e+4	1.403e+4	5.870e+1	0.8454202
c	4.652e+0	5.340e-1	1.148e+1	0.3405543

Plot size (7X1) (specify zero value at lag distance zero)

Variogram(+ve) Rsquare=0.60456

Parameter	Value	StdErr	CV(%)	Dependencies
a	5.733e+4	3.955e+4	6.899e+1	0.7767580
b	1.444e+5	5.870e+4	4.064e+1	0.7765686
c	4.641e+0	5.156e-1	1.111e+1	0.1322368

RICE DATA

EXPONENTIAL MODEL FITTING $y = a - b.\exp(-x/c)$

1X1plot Rsq.= 0.743520975

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.406e+4	2.620e+2	1.089e+0	0.0689071
b	2.401e+4	1.925e+3	8.019e+0	0.0294025
c	4.466e-1	1.313e-1	2.940e+1	0.0579423

3 X 4 plot Rsq.= 0.969082944

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.680e+4	2.863e+3	1.068e+1	0.5008269
b	2.611e+4	4.956e+3	1.898e+1	0.3337013
c	3.449e-2	8.631e+3	2.503e+7	0.3344359

5 X 3 plot Rsq.= 0.838761915

Parameter	Value	StdErr	CV(%)	Dependencies
a	5.742e+4	5.358e+4	9.331e+1	0.9765797
b	5.682e+4	5.425e+4	9.546e+1	0.9255816
c	1.050e+0	2.234e+0	2.127e+2	0.9460384

RICE DATA GAUSSIAN MODEL

1 X 1 plot Rsq.= 0.739834638

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.401e+4	2.598e+2	1.082e+0	0.0399447
b	2.401e+4	1.939e+3	8.079e+0	0.0228372
c	6.092e-1	1.307e-1	2.146e+1	0.0251401

3 X 4 plot Rsq.= 0.62834579

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.019e+4	9.522e+3	4.717e+1	0.5000022
b	1.936e+4	1.649e+4	8.518e+1	0.3333343
c	1.326e-1	4.099e+3	3.090e+6	0.3333353

RICE DATA: The nonlinear fit for each model for different plot sizes and shapes for Rice field.

MICHAELIS-MENTON MODEL FITTING $y = a - b / (1+x/c)$

1X1plot Rsq.= 0.74668923

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.443e+4	4.147e+2	1.698e+0	0.6330444
b	2.443e+4	1.939e+3	7.939e+0	0.0731899
c	1.017e-1	7.696e-2	7.566e+1	0.6174203

3 X 3 plot Rsq.= 0.741799083

Parameter	Value	StdErr	CV(%)	Dependencies
a	4.400e+4	3.459e+4	7.863e+1	0.9728021
b	4.387e+4	3.645e+4	8.309e+1	0.8995999
c	4.641e-1	1.607e+0	3.463e+2	0.9444143

3 X 4 plot Rsq.= 0.799663134

Parameter	Value	StdErr	CV(%)	Dependencies
a	1.530e+4	1.103e+4	7.209e+1	0.7667423
b	1.506e+4	1.440e+4	9.560e+1	0.7377259
c	-4.682e-1	5.186e-1	1.108e+2	0.8803511

RICE DATA **VB model**

PLOT SIZE 1 x 1 Rsq.=0.743524413

Parameter	Value	StdErr	CV(%)	Dependencies
li	2.406e+4	2.623e+2	1.090e+0	0.0490000
k	2.212e+0	6.106e-1	2.760e+1	0.0646307
t0	-1.112e-3	3.657e-2	3.290e+3	0.0169929

PLOT SIZE 3 x 1 Rsq.=0.425702768

Parameter	Value	StdErr	CV(%)	Dependencies
li	1.054e+4	6.550e+3	6.211e+1	0.0991765
k	4.818e+0	3.357e+9	6.968e+10	0.9999985
t0	-2.240e+0	1.559e+9	6.961e+10	0.9999985

PLOT SIZE 5 x 3 Rsq.=0.838750937

Parameter	Value	StdErr	CV(%)	Dependencies
li	5.749e+4	5.392e+4	9.378e+1	0.9450076
k	9.492e-1	2.101e+0	2.213e+2	0.9473917
t0	-1.105e-2	3.043e-1	2.755e+3	0.2073947

4.5 Relating variogram parameters to plot and block size and shape: Soil heterogeneity complicates the design and analysis of field experiments. A variety of complicated block designs are developed to tackle such heterogeneity in the experimental materials. Generally analysis of experimental results supposes that residuals are spatially independent. But in field experiments strong spatial autocorrelation of soil properties is observed. To overcome the effect of spatial dependence of soil properties, plots are randomized within blocks. Randomisation of plots within blocks is expected to equalize error over all treatment differences thus allowing the use of usual statistical methods of analysis. However, the underlying hypothesis is that spatial variability is random; i.e., spatially unstructured within blocks. But, in the presence of a significant spatial correlation over small distances, the assumption of independence between plots is violated. In such a situation, a field researcher may be faced with contradictory results: clear difference in crop yields between experimental plots but no significant treatment effect. One way to tackle such spatial correlation is to study and analyse the structure of spatial variability of crop yield data obtained from uniformity trials. Using variogram parameters like nugget, sill and range we can investigate the optimal experimental plot size and shape and the configuration of blocks. Here it is understood that the range is the separation distance beyond which two observations are independent of each other. The sill is the variogram value corresponding to the range. The discontinuity at the origin is called the nugget effect and arises from a combination of random errors and sources of variation at distances smaller than the shortest sampling interval (Goovaerts, 1998). The nugget/sill ratio (**NSR**) can be used as a criterion indicating the extent to which the experimental errors between plots were randomly distributed in space (Bhatti *et al.*, 1991; Ersboll, 1996). We find **NSR** for every plot configuration studied. The determination criteria is that the smaller the **NSR**, the less random errors remain between plots; thus the less the plot configuration meets the condition that experimental errors can be considered to be random. Conversely, the largest **NSR** represents the configuration which best meets the underlying hypothesis of classical ANOVA techniques (Fagroud *et al.*, 2002). Similarly we can also study for block configuration. So far parameters of the variogram model of plot observations are summarized in the **NSR** ratio. Since the ranges of the variogram models greatly differ, this **NSR** ratio is standardized as **NSR/Range** by Fagroud *et al*(2002) for studying the best block configuration. From the plot of **NSR/Range** vs. number of plots per block the ratio **NSR/Range** indicates that the optimal number of plots per block should be neither too high (i.e. **NSR** small) nor too small (i.e. significant spatial correlation) since it represents a compromise between two parameter requirements indicating a weak spatial dependence of the residual errors: a large **NSR** and a short range.

Using the variogram parameters found after fitting we compute the nugget to sill ratios for different plot sizes and shapes and also for different models. The values of NSR and NSR/range are shown in the following tables:

TABLE : 4.5.1

JUTE	SPFERICAL				
plot	nugget		NSR	range	NSR/range
1X1	-0.6669	2825	-0.00024	1.569	-0.00015
2X1	6.209	1662	0.003722	1.607	0.002316
3X1	66.01	2628	0.024503	2.186	0.011209
4X1	170.6	1002	0.145489	2.912	0.049962
5X1	1109	4255	0.206749	3.304	0.062575
6X1	1147	6314	0.153733	2.991	0.051398
7X1	348.2	5598	0.058558	2.824	0.020736
8X1	116.8	779	0.130386	2.489	0.052385
9X1	679.9	8621	0.0731	2.173	0.03364
1X2	-10.36	1599	-0.00652	1.584	-0.00412
2X2	3.789	1009	0.003741	1.469	0.002547
3X2	291.6	1559	0.157571	2.725	0.057824
4X2	55.04	737.4	0.069456	2.587	0.026848
5X2	198	6302	0.030462	3.224	0.009448
1X3	0.00005994	1119	5.36E-08	1.336	4.01E-08
2X3	46.36	743.6	0.058687	4.589	0.012789
3X3	45.33	951.6	0.04547	3.141	0.014476
4X3	-18.96	564.6	-0.03475	3.604	-0.00964
1X4	0.001341	884.2	1.52E-06	1.295	1.17E-06
2X4	34.85	383.6	0.083284	4.652	0.017903
3X4	-3.972	143000	-2.8E-05	682.1	-4.1E-08
4X4	-8.883	208	-0.04461	2.209	-0.0202
1X5	167.3	693.7	0.194309	4.408	0.044081
2X5	28.99	428.4	0.063381	3.95	0.016046
3X5	-15.69	79690	-0.0002	457.9	-4.3E-07
4X5	-1.922	228.1	-0.0085	2.514	-0.00338
1X6	0.004263	951.2	4.48E-06	1.764	2.54E-06
2X6	27.2	606.5	0.042923	4.733	0.009069
3X6	-15.59	943.2	-0.01681	3.917	-0.00429

plot	nugget		NSR	range	NSR/range
4X6	-4.965	335.4	-0.01503	2.734	-0.0055
1X7	5.494	748.1	0.00729	1.059	0.006884
2X7	35.09	462.5	0.07052	5.078	0.013887
3X7	13.17	650.3	0.01985	3.952	0.005023
4X7	2.701	21870	0.000123	335.1	3.69E-07
1X8	0.006294	511.9	1.23E-05	0.5686	2.16E-05
2X8	-14.03	341.7	-0.04282	4.972	-0.00861
3X8	-22.83	444.3	-0.05417	3.606	-0.01502
4X8	-12.17	193	-0.0673	2.607	-0.02582
1X9	320.1	199.3	0.616288	9.644	**0.063904**
2X9	19.02	153.4	0.110312	5.381	0.0205
3X9	3.383	273.7	0.012209	3.011	0.004055
4X9	-9.274	116.9	-0.08617	2.691	-0.03202

TABLE: 4.5.2

JUTE EXPONENTIAL

plot	sill	b	NSR	c	NSR/range
1X1	2828	2832	-0.00141	0.5157	-0.00274
1X2	1594	1596	-0.00125	0.5527	-0.00227
1X3	1121	1120	0.000892	0.4265	0.002092
1X4	885.7	885.1	0.000677	0.4118	0.001645
1X5	857.3	812	**0.05284**	1.228	0.04303
1X6	963.4	952.1	0.011729	0.8488	0.013819
1X7	753.9	753.9	0	0.1824	0
1X8	512.2	512.1	0.000195	0.06504	0.003002
1X9	477.5	465.1	0.025969	0.06579	**0.394719**
2X1	1668	1673	-0.003	0.4637	-0.00646
2X2	1012	1013	-0.00099	0.3885	-0.00254
2X3	766.6	778.8	-0.01591	1.57	-0.01014
2X4	405	405.7	-0.00173	1.522	-0.00114
2X5	383.8	394.1	-0.02684	0.9367	-0.02865
2X6	555.6	588	-0.05832	1.289	-0.04524
2X7	462	475.9	-0.03009	1.502	-0.02003
2X8	313.9	331	-0.05448	2.003	-0.0272
2X9	170.6	162.6	0.046893	1.97	0.023804
3X1	2731	2737	-0.0022	0.7756	-0.00283
3X2	1610	1611	-0.00062	0.3414	-0.00182
3X3	1147	1136	0.00959	1.587	0.006043
3X4	5410000	5410000	0	17200	0
3X5	2583000	2583000	0	9892	0
3X6	1329	1342	-0.00978	3.094	-0.00316
3X7	820	824	-0.00488	2.347	-0.00208
3X8	555.4	575.2	-0.03565	2.527	-0.01411
3X9	263	267.6	-0.01749	1.067	-0.01639
4X1	994.9	1004	-0.00915	0.5014	-0.01824
4X2	783.5	778.1	0.006892	0.8425	0.008181
4X3	1159	1172	-0.01122	4.773	-0.00235
4X4	186	189.3	-0.01774	0.9018	-0.01967
4X5	244.9	247.1	-0.00898	1.242	-0.00723
4X6	409	413.2	-0.01027	1.728	-0.00594
4X7	350600	350600	0	3580	0

plot	sill	b	NSR	c	NSR/range
4X8	239.7	246.3	-0.02753	1.969	-0.01398
4X9	161.1	166.4	-0.0329	2.438	-0.01349
5X1	5018	4992	0.005181	0.6152	0.008422
5X2	8154	8067	0.01067	2.022	0.005277
6X1	6655	6609	0.006912	0.4848	0.014258
7X1	5447	5451	-0.00073	0.7885	-0.00093
8X1	745.9	747.5	-0.00215	0.3773	-0.00569
9X1	7668	7656	0.001565	0.06809	0.022983

TABLE 4.5.3

JUTE		Gaussian			
plot	sill	b	NSR	c	NSR/range
1X1	2825	2826	-0.00035	0.7514	-0.00047
1X2	1589	1595	-0.00378	0.7681	-0.00492
1X3	1119	1119	0	0.6396	0
1X4	884.2	884.2	0	0.6165	0
1X5	826.7	825.7	0.00121	0.7963	0.001519
1X6	951.7	950.9	0.000841	0.8445	0.000995
1X7	756.5	754.8	0.002247	0.5664	0.003967
1X8	513.8	514.4	-0.00117	0.5682	-0.00206
1X9	535.1	581.3	-0.08634	0.5637	-0.15316
2X1	1668	1667	0.0006	0.7547	0.000794
2X2	1014	1017	-0.00296	0.6893	-0.00429
2X3	715.9	689.1	0.037435	1.53	0.024468
2X4	377.2	357.7	0.051697	1.453	0.035579
2X5	382.2	378.7	0.009158	1.19	0.007695
2X6	545.9	557.1	-0.02052	1.48	-0.01386
2X7	436.9	436.1	0.001831	1.438	0.001273
2X8	300.8	287.5	0.044215	2.268	0.019495
2X9	144.4	141.5	0.020083	0.9651	0.020809
3X1	2683	2638	0.016772	0.9616	0.017442
3X2	1607	1607	0	0.5893	0
3X3	897.1	889.3	0.008695	1	0.008695
3X4	1112	1067	0.040468	2.211	0.018303
3X5	1156	1110	0.039792	2.824	0.014091
3X6	940.1	902.5	0.039996	1.877	0.021308
3X7	624.1	610	0.022593	1.495	0.015112
3X8	415.1	428.5	-0.03228	1.584	-0.02038
3X9	250.8	252.5	-0.00678	1.111	-0.0061
4X1	1002	1002	0	0.8606	0
4X2	713.7	710.3	0.004764	0.7991	0.005962
4X3	533.2	539.2	-0.01125	1.563	-0.0072
4X4	181.1	183.7	-0.01436	1.03	-0.01394
4X5	217.1	217.8	-0.00322	1.083	-0.00298
4X6	325.9	326.5	-0.00184	1.216	-0.00151
4X7	342.2	324.7	0.05114	2.155	0.023731
4X8	184.1	190.5	-0.03476	1.3	-0.02674
4X9	111.7	117.5	-0.05192	1.367	-0.03798
5X1	4908	4878	0.006112	0.7294	0.00838

plot	sill	b	NSR	c	NSR/range
5X2	5061	4900	0.031812	1.024	0.031066
6X1	6365	6365	0	-0.1521	0
7X1	5351	5133	0.04074	1.037	0.039286
8X1	755.5	758.2	-0.00357	0.7338	-0.00487
9X1	7696	7695	0.00013	0.1859	0.000699

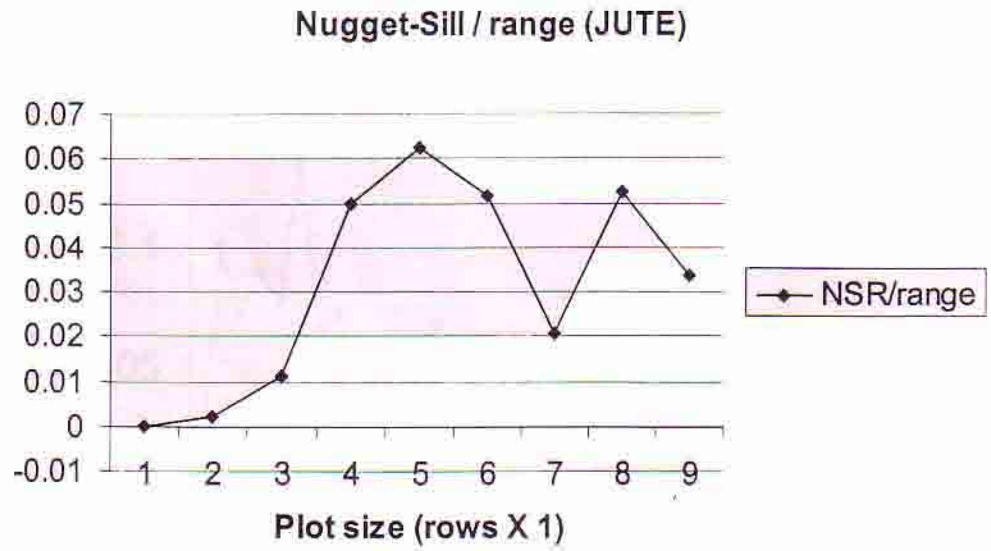
TABLE:4.5.4

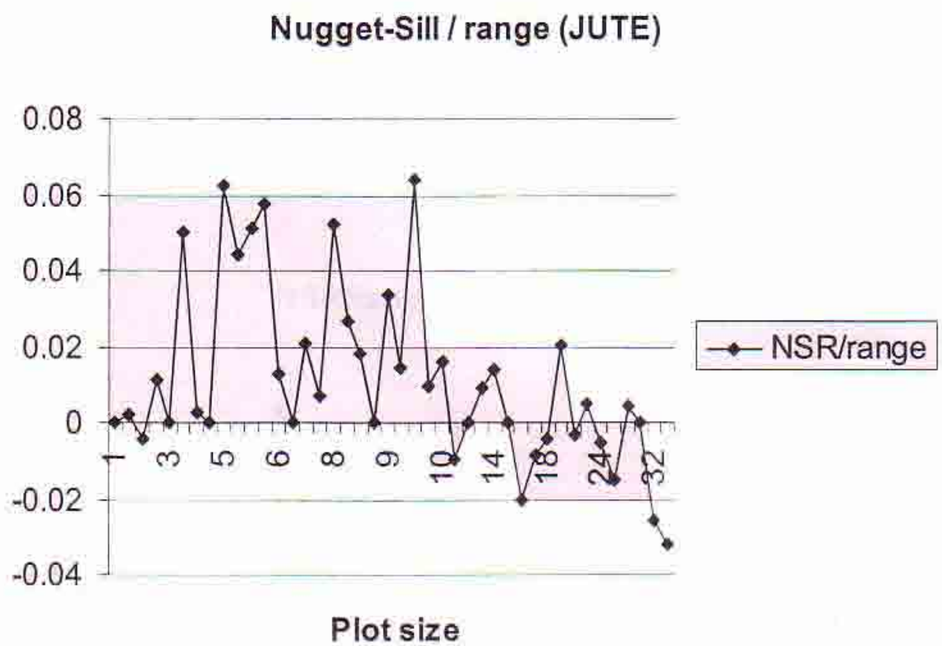
JUTE Michaelis-menton

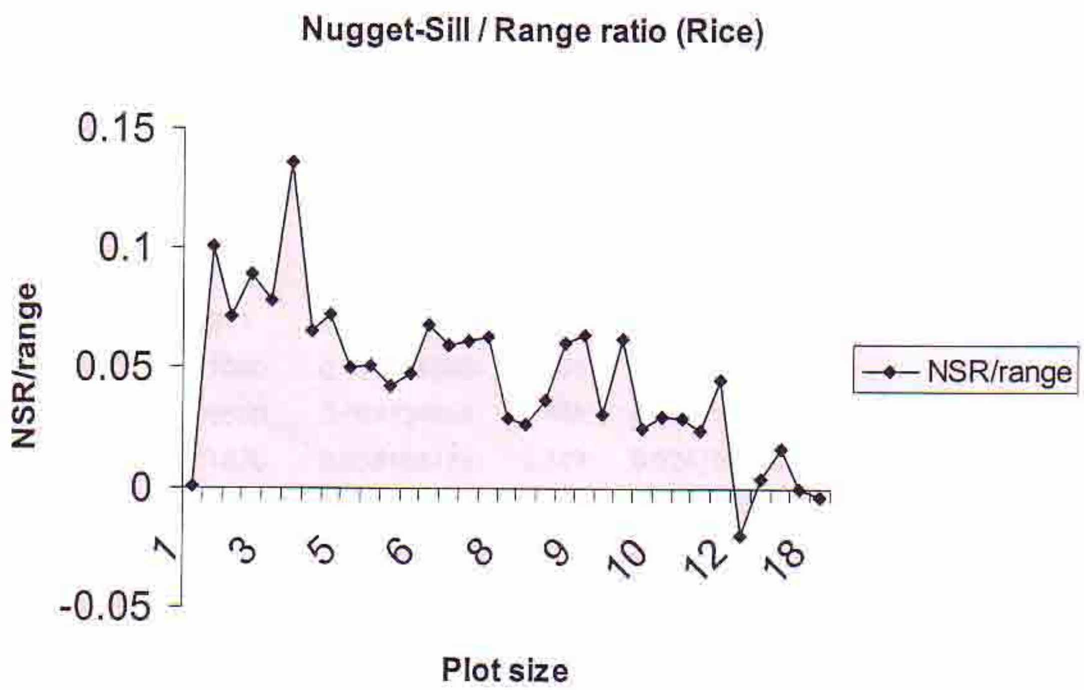
plot	sill	b	NSR	range	NSR/range
1X1	2869	2870	-0.00035	0.1153	-0.003023
1X2	1638	1639	-0.00061	0.1868	-0.0032682
1X3	1177	1174	0.002549	0.2657	0.009593
1X4	909.6	909.3	0.00033	0.1516	0.0021756
1X5	919.7	912.2	0.008155	0.6338	0.0128666
1X6	1018	1018	0	0.4347	0
1X7	751	751	0	-0.01598	0
1X8	525.3	525.2	0.00019	0.1182	0.0016106
1X9	470	469.9	0.000213	-0.1168	-0.0018216
2X1	1631	1631	0	0.08459	0
2X2	1031	1031	0	0.07935	0
2X3	973.7	984.1	-0.01068	1.583	-0.0067473
2X4	504.7	506.9	-0.00436	1.449	-0.0030083
2X5	431.8	436.4	-0.01065	0.6315	-0.0168695
2X6	664.6	684.1	-0.02934	1.127	-0.0260346
2X7	568.6	579.3	-0.01882	1.408	-0.0133652
2X8	418.6	430.7	-0.02891	2.289	-0.0126282
2X9	205.8	202.2	0.017493	1.65	0.0106016
3X1	3033	3039	-0.00198	0.454	-0.0043574
3X2	1615	1615	0	0.02729	0
3X3	1578	1572	0.003802	1.866	0.0020377
3X4	12890000	12890000	0	40990	0
3X5	6087000	6087000	0	23310	0
3X6	2147	2158	-0.00512	4.833	-0.0010601
3X7	1224	1228	-0.00327	3.235	-0.0010102
3X8	897.1	913.7	-0.0185	3.963	-0.0046692
3X9	330.6	333.4	-0.00847	1.048	-0.0080815
4X1	1002	1002	0	0.0691	0
4X2	949.2	947.6	0.001686	0.7014	0.0024032
4X3	2151	2163	-0.00558	8.855	-0.00063
4X4	236.8	238.5	-0.00718	0.9104	-0.0078856
4X5	337.6	339.1	-0.00444	1.494	-0.002974
4X6	616.1	619.2	-0.00503	2.435	-0.0020664
4X7	609000	609000	0	6218	0
4X8	389.4	394.6	-0.01335	3.132	-0.0042637
4X9	279.3	283.7	-0.01575	4.218	-0.0037349
5X1	5529	5524	0.000904	0.3414	0.0026489
5X2	11500	11440	0.005217	2.532	0.0020606
6X1	7183	7175	0.001114	0.2254	0.0049412
7X1	6187	6194	-0.00113	0.5116	-0.0022115
8X1	707.4	707.8	-0.00057	-0.07468	0.0075717
9X1	7500	7500	0	-0.05585	0

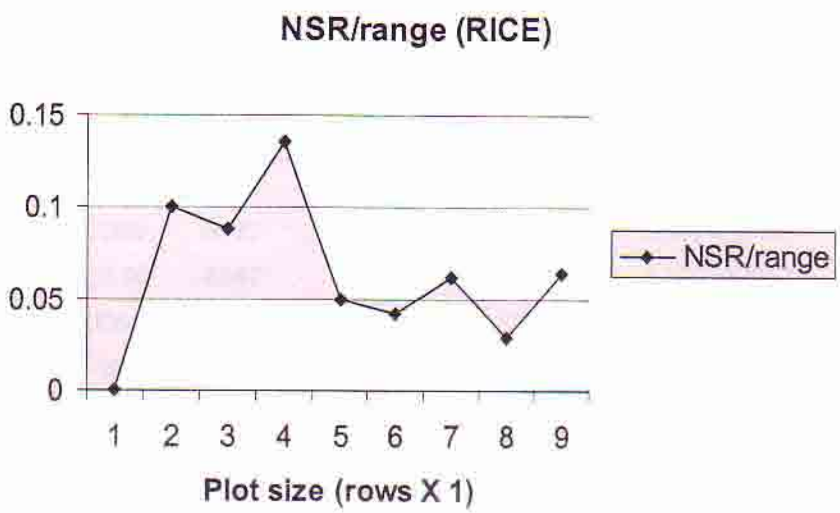
TABLE 4.5.5

JUTE			**VB**			
plot	Li	K	t0	nugget	NSR	NSR/range
1X1	2826	1.948	0.000761	-4.19024	-0.00148	-0.00076
1X2	1594	1.809	0.000721	-2.07982	-0.0013	-0.00072
1X3	1121	2.341	-0.00023	0.612073	0.000546	0.000233
1X4	885.7	2.43	-0.00029	0.618126	0.000698	0.000287
1X5	858.4	0.7976	-0.07252	48.24285	0.056201	0.070463
1X6	963.5	1.177	-0.01008	11.36358	0.011794	0.01002
1X7	753.9	5.31	-3.1E-05	0.124009	0.000164	3.1E-05
1X8	512	8.055	2.16E-06	-0.00889	-1.7E-05	-2.2E-06
1X9	482	10.13	0.001123	-5.51453	-0.01144	-0.00113
2X1	1668	2.145	0.001389	-4.97706	-0.00298	-0.00139
2X2	1012	2.556	0.000694	-1.797	-0.00178	-0.00069
2X3	766.6	0.637	0.02475	-12.1818	-0.01589	-0.02495
2X4	405	0.6572	0.002639	-0.70302	-0.00174	-0.00264
2X5	383.9	1.066	0.02459	-10.1962	-0.02656	-0.02492
2X6	555.5	0.7759	0.07317	-32.4496	-0.05842	-0.07529
2X7	461.9	0.6658	0.04463	-13.9312	-0.03016	-0.0453
2X8	314.8	0.4938	0.1039	-16.5726	-0.05264	-0.10661
2X9	170.7	0.507	-0.09577	8.090399	0.047395	0.093482
3X1	2731	1.29	0.001811	-6.38759	-0.00234	-0.00181
3X2	1610	2.931	4.16E-05	-0.19627	-0.00012	-4.2E-05
3X3	1148	0.6297	-0.01619	11.64422	0.010143	0.016108
3X4	9168	0.03584	0.02734	-8.98781	-0.00098	-0.02735
3X5	17310	0.0153	0.06471	-17.1465	-0.00099	-0.06474
3X6	1329	0.3232	0.03119	-13.4649	-0.01013	-0.03135
3X7	820	0.4261	0.01128	-3.95074	-0.00482	-0.01131
3X8	555.2	0.3958	0.08862	-19.8196	-0.0357	-0.09019
3X9	263	0.9372	0.0184	-4.57463	-0.01739	-0.01856
4X1	994.6	2.008	0.004607	-9.24359	-0.00929	-0.00463
4X2	783.6	1.187	-0.00588	5.44737	0.006952	0.005857
4X3	1159	0.2096	0.05408	-13.2122	-0.0114	-0.05439
4X4	186.1	1.105	0.01586	-3.29021	-0.01768	-0.016
4X5	244.8	0.8059	0.0113	-2.23949	-0.00915	-0.01135
4X6	409	0.5789	0.01749	-4.16214	-0.01018	-0.01758
4X7	5887	0.01702	-0.01889	1.892412	0.000321	0.018887
4X8	238.9	0.5109	0.05359	-6.63124	-0.02776	-0.05433
4X9	161.1	0.4103	0.07797	-5.23709	-0.03251	-0.07923
5X1	5017	1.627	-0.00309	25.11871	0.005007	0.003077
5X2	8155	0.4943	-0.02162	86.68655	0.01063	0.021505
6X1	6652	2.073	-0.00324	44.50119	0.00669	0.003227
7X1	5448	1.267	0.000576	-3.97529	-0.00073	-0.00058
8X1	745.6	2.748	0.001286	-2.63956	-0.00354	-0.00129
9X1	7767	15.74	4.83E-06	-0.59075	-7.6E-05	-4.8E-06


Nugget-Sill / range (JUTE)
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
-0.01
1 2 3 4 5 6 7 8 9
Plot size (rows X 1)
NSR/range


Nugget-Sill / range (JUTE)
0.08
0.06
0.04
0.02
0
-0.02
-0.04
1 3 5 6 8 9 10 14 18 24 32
Plot size
NSR/range





RICE	SPHERICAL				
plot	nugget		NSR	range	NSR/range
1X1	3.542	24170	0.000146524	1.268	0.000115555
2X1	6616	5565	0.543140957	5.431	0.100007541
3X1	18200	25230	0.419065162	4.742	0.088373084

plot	nugget		NSR	range	NSR/range
4X1	25860	13550	0.656178635	4.825	0.135995572
5X1	21560	53520	0.287160362	5.78	0.049681724
6X1	10040	41130	0.196208716	4.629	0.042386847
7X1	57330	144400	0.284191741	4.641	0.061235023
8X1	18240	46320	0.282527881	9.784	0.028876521
9X1	54570	112400	0.326825178	5.129	0.063721033
1X2	8770	9158	0.489178938	6.893	0.070967494
2X2	1929	7671	0.2009375	3.081	0.065218273
3X2	3785	31080	0.108561595	2.301	0.04718018
4X2	2642	38550	0.064138668	2.401	0.026713314
5X2	3817	61820	0.058153176	2.349	0.024756567
6X2	2373	37210	0.059949979	2.066	0.029017415
1X3	7014	7702	0.476624083	6.155	0.077436894
2X3	1446	5806	0.199393271	2.947	0.067659746
3X3	2987	36640	0.075377899	2.445	0.030829407
4X3	2027	38970	0.049442642	2.053	0.024083118
5X3	2214	51710	0.041057785	2.454	0.016730964
1X4	5592	7461	0.428407263	5.973	0.071723968
2X4	798.9	7416	0.097250119	2.638	0.036865094
3X4	1887	23710	0.073719577	1.642	0.04489621
1X5	3259	8599	0.274835554	5.363	0.051246607
2X5	528.8	7211	0.068322179	2.263	0.030190976
1X6	3397	7458	0.312943344	5.301	0.059034775
2X6	-310.3	8229	-0.03918572	2.012	-.019476006
1X7	3009	6072	0.331351173	5.305	0.062460165
2X7	58.95	6987	0.008366508	2.114	0.003957667
1X8	3060	6146	0.332391918	5.52	0.060215927
2X8	-10.33	6163	-0.00167895	2.222	-.000755601
1X9	2649	5263	0.334807887	5.445	0.061489052
2X9	-41.82	5190	-0.00812326	2.044	-.003974197

RICE EXPONENTIAL

plot	sill	b	NSR	range	NSR/range
1X1	24060	24010	0.002078138	0.4466	0.004653242
1X2	16630	16590	0.002405292	0.6933	0.003469337
1X3	13200	13270	-0.00530303	0.7179	-0.0073868
1X4	11460	11480	-0.0017452	0.6949	-0.0025114
1X5	9560	9573	-0.00135983	0.5216	-0.0026070
					-
1X6	8966	9083	-0.0130493	0.6304	0.020700028
1X7	7424	7436	-0.00161638	0.3932	-0.0041108

plot	sill	b	NSR	range	NSR/range
1X8	7786	7807	-0.00269715	0.5127	-0.0052606
1X9	6715	6801	-0.01280715	0.6068	-0.0211060
2X1	11880	11920	-0.003367	0.4901	-0.0068700
2X2	8911	8942	-0.00347885	0.4325	-0.0080435
2X3	6565	6577	-0.00182788	0.4564	-0.0040049
2X4	7013	7058	-0.00641665	0.5025	-0.0127694
2X5	5959	5925	0.005705655	0.03167	0.180159625
2X6	6197	6248	-0.00822979	0.5394	-0.0152573
2X7	5879	5896	-0.00289165	0.5071	-0.0057023
2X8	5550	5586	-0.00648649	0.715	-0.0090720
2X9	4110	4124	-0.00340633	0.4758	-0.0071591
3X1	38450	38400	0.00130039	0.1029	0.012637416
3X2	27370	26800	0.020825722	0.08392	0.248161601
3X3	38470	37930	0.014036912	0.7206	0.019479478
3X4	26800	26110	0.025746269	0.03449	0.746485029
4X1	39680	39670	0.000252016	0.076	0.003316002
4X2	39040	38670	0.009477459	0.6663	0.014224012
4X3	35200	35190	0.000284091	0.04587	0.006193392
5X1	61130	61010	0.00196303	0.4427	0.004434221
5X2	61610	61250	0.005843207	0.6296	0.009280825
5X3	57420	56820	0.010449321	1.05	0.009951734
6X1	41820	41890	-0.00167384	0.6105	-0.0027417
6X2	31700	31750	-0.00157729	0.07332	-0.0215123
7X1	168200	168200	0	0.3188	0
8X1	54760	54720	0.00073046	0.4232	0.00172604
9X1	142400	139800	0.018258427	0.05253	0.347580944

RICE	Gaussian				
plot	sill	b	NSR	range	NSR/range
1X1	24010	24010	0	0.6092	0
1X2	16520	16490	0.001815981	0.8364	0.002171187
1X3	13120	12970	0.011432927	0.9326	0.012259197
1X4	11390	11220	0.014925373	0.9091	0.016417746
1X5	9550	9551	-0.00010471	0.7441	-0.0001407
1X6	9002	9015	-0.00144412	0.9097	-0.0015874
1X7	7450	7451	-0.00013423	0.6833	-0.0001964
1X8	7800	7804	-0.00051282	0.7666	-0.0006689
1X9	6754	6783	-0.00429375	0.9008	-0.0047665
2X1	11880	11870	0.000841751	0.7602	0.0011072
2X2	8933	8962	-0.00324639	0.7362	-0.004409657
2X3	6558	6552	0.000914913	0.7281	0.001256576
2X4	7168	7164	0.000558036	0.8532	0.00065405
2X5	6638	6638	0	0.5739	0
2X6	6373	6402	-0.00455045	0.8645	-0.005263675
2X7	5929	5933	-0.00067465	0.7721	-0.000873786
2X8	5478	5491	-0.00237313	0.8944	-0.002653319
2X9	4182	4187	-0.0011956	0.7752	-0.001542312
3X1	42210	44430	-0.05259417	0.3133	-0.167871599
3X2	29980	29980	0	0.1592	0
3X3	33140	33070	0.002112251	0.09366	0.022552328

plot	sill	b	NSR	range	NSR/range
3X4	20190	19360	0.04110946	0.1326	0.310026094
4X1	39620	39500	0.003028773	0.3208	0.009441313
4X2	35220	35250	-0.00085179	0.2236	-0.003809431
4X3	44000	43640	0.008181818	1.031	0.007935808
5X1	60350	60340	0.0001657	0.347	0.000477522
5X2	56760	56760	0	0.3152	0
5X3	42090	42090	0	0.2045	0
6X1	41570	41570	0	0.7935	0
6X2	31220	31210	0.000320307	0.2031	0.001577093
7X1	168300	168300	0	0.5753	0
8X1	54420	54420	0	0.6164	0
9X1	143100	141800	0.009084556	0.2978	0.030505562

RICE **VB**

plot	sill	b	NSR	range	NSR/range
1X1	24060	24010	0.002078138	0.4466	0.004653242
1X2	16630	16590	0.002405292	0.6933	0.003469337
1X3	13200	13270	-0.00530303	0.7179	-0.0073868
1X4	11460	11480	-0.0017452	0.6949	-0.0025114
1X5	9560	9573	-0.00135983	0.5216	-0.0026070
1X6	8966	9083	-0.0130493	0.6304	-0.0207000
1X7	7424	7436	-0.00161638	0.3932	-0.0041108
1X8	7786	7807	-0.00269715	0.5127	-0.0052606
1X9	6715	6801	-0.01280715	0.6068	-0.0211060
2X1	11880	11920	-0.003367	0.4901	-0.0068700
2X2	8911	8942	-0.00347885	0.4325	-0.0080435
2X3	6565	6577	-0.00182788	0.4564	-0.0040049
2X4	7013	7058	-0.00641665	0.5025	-0.0127694
2X5	5959	5925	0.005705655	0.03167	0.180159625
2X6	6197	6248	-0.00822979	0.5394	-0.0152573
2X7	5879	5896	-0.00289165	0.5071	-0.0057023
2X8	5550	5586	-0.00648649	0.715	-0.0090720
2X9	4110	4124	-0.00340633	0.4758	-0.0071591
3X1	38450	38400	0.00130039	0.1029	0.012637416
3X2	27370	26800	0.020825722	0.08392	0.248161601
3X3	38470	37930	0.014036912	0.7206	0.019479478
3X4	26800	26110	0.025746269	0.03449	0.746485029
4X1	39680	39670	0.000252016	0.076	0.003316002
4X2	39040	38670	0.009477459	0.6663	0.014224012
4X3	35200	35190	0.000284091	0.04587	0.006193392
5X1	61130	61010	0.00196303	0.4427	0.004434221
5X2	61610	61250	0.005843207	0.6296	0.009280825
5X3	57420	56820	0.010449321	1.05	0.009951734
6X1	41820	41890	-0.00167384	0.6105	-0.0027417
6X2	31700	31750	-0.00157729	0.07332	-0.0215123
7X1	168200	168200	0	0.3188	0
8X1	54760	54720	0.00073046	0.4232	0.00172604
9X1	142400	139800	0.018258427	0.05253	0.347580944

RICE Michaelis-menton

plot	sill	b	NSR	range	NSR/range
1X1	24430	24430	0	0.1017	0
1X2	17140	17170	-0.00175029	0.2052	-0.008529687
1X3	13460	13500	-0.00297177	0.1671	-0.01778437
1X4	11700	11730	-0.0025641	0.1758	-0.014585339
1X5	9558	9559	-0.00010462	0.06292	-0.001662816
1X6	8978	8988	-0.00111383	0.1059	-0.010517789
1X7	7259	7260	-0.00013776	-0.04027	0.003420909
1X8	7803	7806	-0.00038447	0.06873	-0.005593882
1X9	6764	6774	-0.00147842	0.1186	-0.012465558
2X1	12010	12010	0	0.07236	0
2X2	8966	8967	-0.00011153	0.04856	-0.002296797
2X3	6763	6765	-0.00029573	0.1133	-0.002610121
2X4	7352	7359	-0.00095212	0.1498	-0.006355954
2X5	6910	6910	0	0.09604	0
2X6	6624	6633	-0.0013587	0.2394	-0.00567542
2X7	6260	6264	-0.00063898	0.2118	-0.003016892
2X8	6523	6538	-0.00229956	0.5501	-0.00418025
2X9	4256	4258	-0.00046992	0.1446	-0.003249826
3X1	38490	38490	0	-0.00371	0
3X2	30130	30130	0	-0.02913	0
3X3	44000	43870	0.002954545	0.4641	0.006366183
3X4	15300	15060	0.015686275	-0.4682	-0.033503363
4X1	39400	39400	0	-0.02508	0
4X2	44060	43990	0.001588743	0.4038	0.003934479
4X3	42510	42480	0.000705716	0.2621	0.002692546
5X1	61720	61720	0	0.06429	0
5X2	69440	69370	0.001008065	0.3795	0.002656296
5X3	72660	72390	0.003715937	1.005	0.00369745
6X1	43760	43800	-0.00091408	0.2414	-0.003786565
6X2	28940	28940	0	-0.1479	0
7X1	167600	167600	0	0.01082	0
8X1	57320	57310	0.000174459	0.1703	0.001024423
9X1	144400	144400	0	-0.01447	0

Chapter 5

A NEW METHOD FOR DETERMINATION OF PLOT SIZE.

5.1 Introduction: It is well known that the application of classical analysis of variance technique to data from designed experiments assumes that the observations are independent. In real life situation, it is not an usual phenomenon that the observed data are random. The data from field experiments are often found to be spatially correlated. This chapter is devoted to the development of a new method for obtaining optimum plot size using the well known variogram technique which is used to discover the spatial heterogeneity structure in a set of data. This method calls for determination of particular (optimum) plot size for (and higher) the data become random. The particular plot size is identified by invoking the theory of minimization of curvature(maximization of radius of curvature). The fundamental basis of the method lies in studying the nature of the curvature of variogram curve for each possible plot size and shape. Decrease in range implies that with a slight increase in the lag distance between pairs of sample observations the variogram immediately attains its sill value. Attaining sill value again indicates that pairs of observations are no longer dependent on the separation distance between them. In other words, at this point pairs of observations become independent of each other.

5.2 Material and method: Here we determine the point at which the radius of curvature becomes maximum. To find this we use the method of determination of maximum curvature as described in section 2.3. We have deduced the values of h_{opt} for each of the spherical, exponential, Michaelis-Menton and VB models. The following table summarizes the solutions corresponding to h_{opt} for different models:

TABLE 5.2.1 : Point of maximum curvature for different models.

Model	h_{opt}
Spherical: $y=a+b.(1.5\,.(x/c)-0.5\,.(x/c)^3)$	$c.\sqrt{\dfrac{6.b+\sqrt{81.b^2+20.c^2}}{15.b}}$
Exponential: $y = a - b.\,\exp(-\,x/c)$	$c.\log_e\left(\dfrac{\sqrt{2}.b}{c}\right)$
Michaelis-Menton: $y = a - b.\,\exp[-(x/c)^2]$	$-c+\sqrt{b.c}$
VB : $y = L_\infty\,.\,[1-\exp\{-\,k.\,(t-t_0)\}]$	$\dfrac{1}{\sqrt{2}.L_\infty.k}$

Finally we compute the amount of curvature at the h_{opt} value for each of different plot sizes and shapes. We choose that plot size and shape which gives the maximum amount of radius of curvature at h_{opt}. As the centre of curvature of the variogram curve is on the negative side of the normal, the curvature values will be –ve. The following tables present the maximum curvature values for different plot sizes and shapes.

5.3. Results:

TABLE 5.3.1 : Amount of curvature of spherical curve for Jute data.

plot	b	c		h_{opt}	y1	y2	curvature
1X1	2825	1.569	25425	4432.425	-2.2E+10	-9725508	-1.03E+24
1X2	1599	1.584	14391	2532.816	-3.9E+09	-3057087	-1.898E+22
1X3	1119	1.336	10071	1494.984	-1.6E+09	-2104595	-1.85E+21
1X4	884.2	1.295	7957.802	1145.039	-8E+08	-1398565	-3.671E+20
1X5	693.7	4.408	6243.331	3057.834	-1.1E+08	-74298.9	-1.973E+19
1X6	951.2	1.764	8560.804	1677.917	-7.3E+08	-872304	-4.493E+20
1X7	748.1	1.059	6732.902	792.238	-5.9E+08	-1497093	-1.393E+20
1X8	511.9	0.5686	4607.101	291.0664	-3.5E+08	-2431520	-1.822E+19
1X9	199.3	9.644	1794.218	1922.216	-1231460	-1281.32	-1.457E+15
2X1	1662	1.607	14958	2670.834	-4.3E+09	-3208866	-2.452E+22
2X2	1009	1.469	9081.002	1482.221	-1E+09	-1415338	-8.154E+20
2X3	743.6	4.589	6692.431	3412.385	-1.3E+08	-78770.7	-3.082E+19
2X4	383.6	4.652	3452.463	1784.517	-1.8E+07	-20398.6	-2.956E+17
2X5	428.4	3.95	3855.64	1692.185	-3E+07	-35288	-7.542E+17
2X6	606.5	4.733	5458.541	2870.571	-7.1E+07	-49261.9	-7.175E+18
2X7	462.5	5.078	4162.562	2348.585	-2.9E+07	-24886.4	-1.003E+18
2X8	341.7	4.972	3075.38	1698.946	-1.2E+07	-14169.4	-1.231E+17
2X9	153.4	5.381	1380.81	825.483	-1006295	-2438.18	-4.179E+14
3X1	2628	2.186	23652	5744.808	-1.2E+10	-4335824	-4.455E+23
3X2	1559	2.725	14031.01	4248.275	-2.1E+09	-981930	-9.241E+21
3X3	951.6	3.141	8564.412	2988.977	-4.1E+08	-275356	-2.531E+20
3X4	143000	682.1	1287004	97540382	-6.4E+12	-131855	**-2.017E+33**
3X5	79690	457.9	717212.9	36490096	-1.7E+12	-90863.2	-5.014E+31
3X6	943.2	3.917	8488.818	3694.517	-3.2E+08	-173949	-1.907E+20
3X7	650.3	3.952	5852.727	2569.989	-1E+08	-81229.8	-1.4E+19
3X8	444.3	3.606	3998.733	1602.15	-3.6E+07	-45543.2	-1.066E+18
3X9	273.7	3.011	2463.337	824.1144	-1E+07	-24788.6	-4.299E+16
4X1	1002	2.912	9018.009	2917.825	-5.2E+08	-355201	-3.918E+20
4X2	737.4	2.587	6636.61	1907.655	-2.3E+08	-243745	-5.156E+19
4X3	564.6	3.604	5081.426	2034.821	-7.5E+07	-73626.5	-5.709E+18
4X4	208	2.209	1872.026	459.4739	-6110534	-26598.6	-8.578E+15
4X5	228.1	2.514	2052.931	573.446	-7081046	-24696.9	-1.438E+16
4X6	335.4	2.734	3018.625	916.9859	-2.1E+07	-45149.3	-1.965E+17
4X7	21870	335.1	196835.7	7328701	-4.7E+10	-12778.3	-8.034E+27
4X8	193	2.607	1737.039	503.1544	-4136341	-16442.1	-4.304E+15
4X9	116.9	2.691	1052.169	314.5841	-890443	-5661.5	-1.247E+14
5X1	4255	3.304	38295	14058.52	-3.5E+10	-4975541	-8.598E+24
5X2	6302	3.224	56718	20317.65	-1.2E+11	-1.1E+07	-1.378E+26

plot	b	c		h_{opt}	y1	y2	curvature
6X1	6314	2.991	56826	18885.17	-1.3E+11	-1.3E+07	-1.505E+26
7X1	5598	2.824	50382	15808.75	-9.3E+10	-1.2E+07	-6.863E+25
8X1	779	2.489	7011.009	1938.932	-2.8E+08	-293864	-7.868E+19
9X1	8621	2.173	77589	18733.43	-4.4E+11	-4.7E+07	-1.832E+27

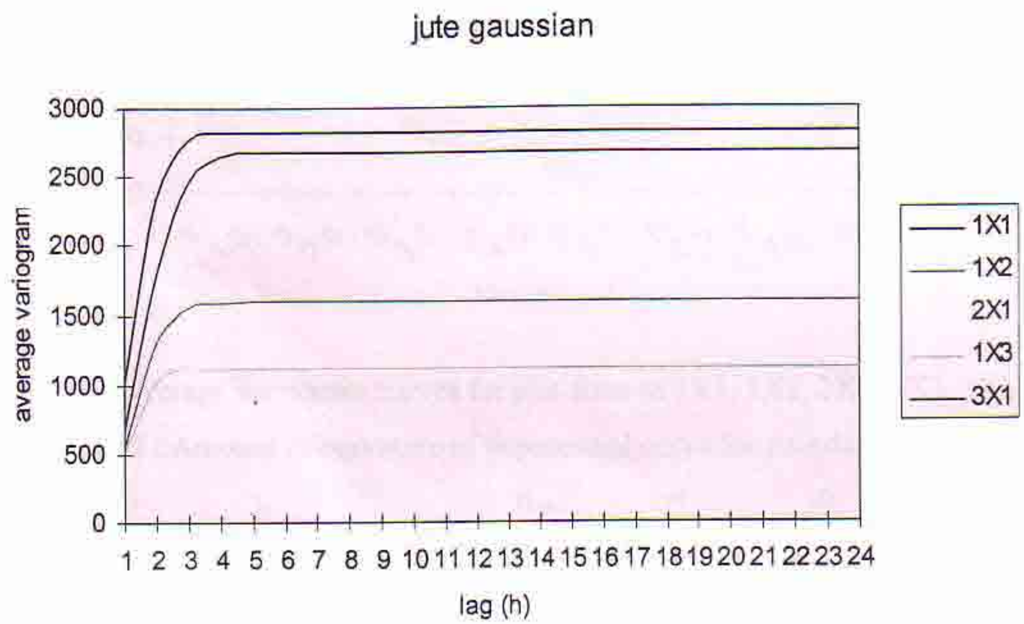


Fig. 5.3.1 : Average variogram curves for plot sizes of 1X1, 1X2, 2X1, 1X3, 3X1.

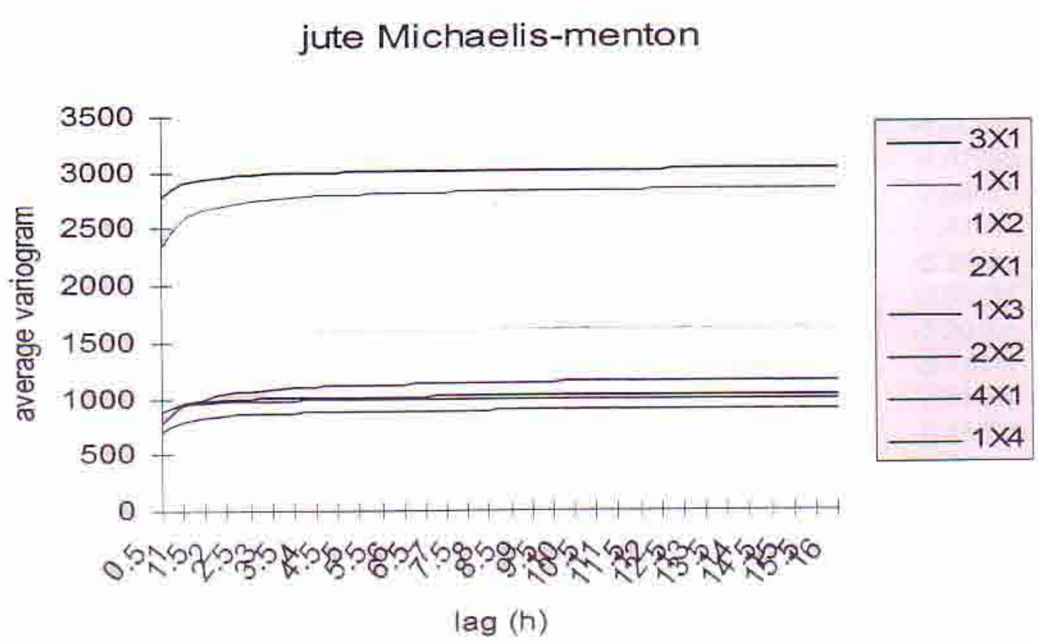


Fig. 5.3.2 :Average variogram curves for plot sizes of 1X1, 1X2, 2X1, 1X3, 3X1, 2X2, 1X4, 4X1.

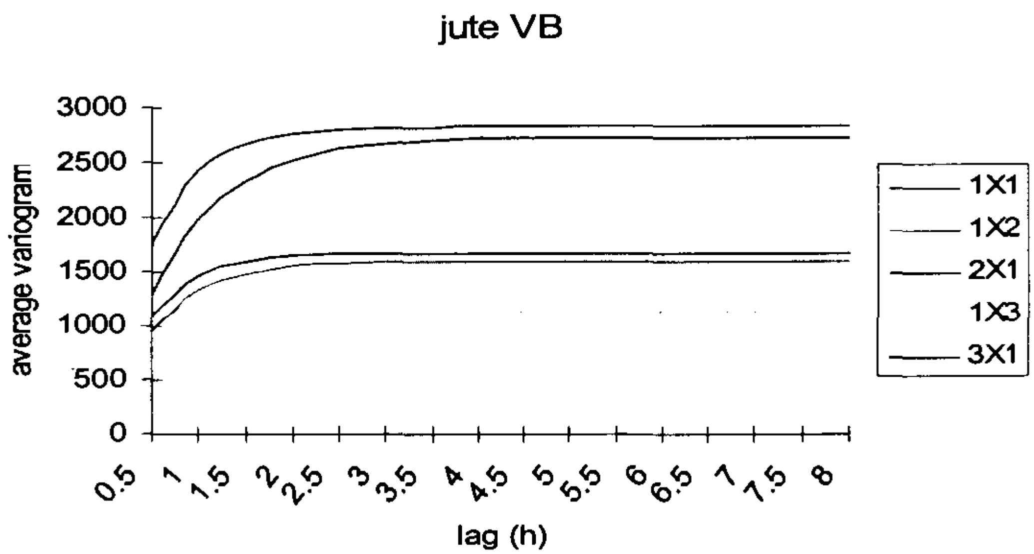


Fig. 5.3.3 : Average variogram curves for plot sizes of 1X1, 1X2, 2X1, 1X3, 3X1.

TABLE 5.3.2 : Amount of curvature of exponential curve for Jute data.

plot	b	c		h_{opt}	y1	y2	**curvature**
1X1	2832	0.5157	7766.246	4.619405	0.707107	-1.37116	-1.33983
1X2	1596	0.5527	4083.743	4.595573	0.707107	-1.27937	-1.43596
1X3	1120	0.4265	3713.761	3.505745	0.707107	-1.65793	-1.10808
1X4	885.1	0.4118	3039.632	3.302427	0.707107	-1.71711	-1.06989
1X5	812	1.228	935.1314	8.400364	0.707107	-0.57582	-3.19044
1X6	952.1	0.8488	1586.325	6.254956	0.707107	-0.83307	-2.20525
1X7	753.9	0.1824	5845.261	1.582026	0.707107	-3.87668	-0.47389
1X8	512.1	0.06504	11134.97	0.606033	0.707107	-10.8719	-0.16898
1X9	465.1	0.06579	9997.731	0.605933	0.707107	-10.7479	-0.17093
2X1	1673	0.4637	5102.392	3.958822	0.707107	-1.52492	-1.20473
2X2	1013	0.3885	3687.512	3.190637	0.707107	-1.82009	-1.00935
2X3	778.8	1.57	701.522	10.28861	0.707107	-0.45039	-4.07898
2X4	405.7	1.522	376.9688	9.028751	0.707107	-0.46459	-3.95427
2X5	394.1	0.9367	595.0054	5.984174	0.707107	-0.75489	-2.43362
2X6	588	1.289	645.1184	8.3391	0.707107	-0.54857	-3.34892
2X7	475.9	1.502	448.0854	9.169686	0.707107	-0.47078	-3.90231
2X8	331	2.003	233.7018	10.92445	0.707107	-0.35302	-5.20395
2X9	162.6	1.97	116.7265	9.376872	0.707107	-0.35894	-5.11821
3X1	2737	0.7756	4990.591	6.604474	0.707107	-0.91169	-2.01507
3X2	1611	0.3414	6673.398	3.006329	0.707107	-2.0712	-0.88698
3X3	1136	1.587	1012.317	10.98203	0.707107	-0.44556	-4.12315
3X4	5410000	17200	444.8195	104879.9	0.707107	-4.1E-05	**-44686.9**
3X5	2583000	9892	369.2796	58477.09	0.707107	-7.1E-05	-25700.2
3X6	1342	3.094	613.4048	19.86046	0.707107	-0.22854	-8.03845
3X7	824	2.347	496.5113	14.56925	0.707107	-0.30128	-6.09768
3X8	575.2	2.527	321.9057	14.59155	0.707107	-0.27982	-6.56534
3X9	267.6	1.067	354.68	6.264587	0.707107	-0.66271	-2.77215
4X1	1004	0.5014	2831.812	3.985464	0.707107	-1.41026	-1.30268

plot	b	c		h_{opt}	y1	y2	curvature
4X2	778.1	0.8425	1306.112	6.044778	0.707107	-0.8393	-2.18888
4X3	1172	4.773	347.2571	27.92236	0.707107	-0.14815	-12.4006
4X4	189.3	0.9018	296.8625	5.13419	0.707107	-0.78411	-2.34295
4X5	247.1	1.242	281.3625	7.004438	0.707107	-0.56933	-3.22681
4X6	413.2	1.728	338.1673	10.06308	0.707107	-0.40921	-4.48948
4X7	350600	3580	138.4981	17652.47	0.707107	-0.0002	-9301.11
4X8	246.3	1.969	176.9024	10.19075	0.707107	-0.35912	-5.11561
4X9	166.4	2.438	96.52385	11.14115	0.707107	-0.29004	-6.33411
5X1	4992	0.6152	11475.54	5.750873	0.707107	-1.14939	-1.59834
5X2	8067	2.022	5642.167	17.46608	0.707107	-0.34971	-5.25331
6X1	6609	0.4848	19279.16	4.783415	0.707107	-1.45855	-1.25955
7X1	5451	0.7885	9776.637	7.244542	0.707107	-0.89677	-2.04858
8X1	747.5	0.3773	2801.815	2.995016	0.707107	-1.87412	-0.98025
9X1	7656	0.06809	159013.4	0.815496	0.707107	-10.3849	-0.1769

TABLE 5.3.3 : Amount of curvature of VB curve for Jute data.

plot	Li	K	t0		h_{opt}	y1	y2	curvature
1X1	2826	1.948	0.0007606	7785.314	4.600347	0.707107	-1.37744	-1.33371
1X2	1594	1.809	0.0007208	4077.95	4.596271	0.707107	-1.27916	-1.43619
1X3	1121	2.341	-0.0002333	3711.265	3.510714	0.707107	-1.65534	-1.10981
1X4	885.7	2.43	-0.0002873	3043.743	3.300471	0.707107	-1.71827	-1.06917
1X5	858.4	0.7976	-0.07252	968.2552	8.54771	0.707107	-0.56399	-3.25737
1X6	963.5	1.177	-0.01008	1603.774	6.260196	0.707107	-0.83226	-2.20737
1X7	753.9	5.31	-3.098E-05	5661.392	1.627356	0.707107	-3.75474	-0.48928
1X8	512	8.055	2.155E-06	5832.443	1.0765	0.707107	-5.69574	-0.32254
1X9	482	10.13	0.001123	6905.124	0.87378	0.707107	-7.16299	-0.25647
2X1	1668	2.145	0.001389	5059.858	3.977657	0.707107	-1.51674	-1.21122
2X2	1012	2.556	0.0006941	3658.107	3.210671	0.707107	-1.80736	-1.01646
2X3	766.6	0.637	0.02475	690.5947	10.28778	0.707107	-0.45043	-4.07861
2X4	405	0.6572	0.002639	376.4156	9.026823	0.707107	-0.46471	-3.95325
2X5	383.9	1.066	0.02459	578.7491	5.991634	0.707107	-0.75378	-2.43722
2X6	555.5	0.7759	0.07317	609.5437	8.338037	0.707107	-0.54864	-3.34847
2X7	461.9	0.6658	0.04463	434.9174	9.169226	0.707107	-0.47079	-3.90219
2X8	314.8	0.4938	0.1039	219.837	11.0251	0.707107	-0.34917	-5.26139
2X9	170.7	0.507	-0.09577	122.393	9.38596	0.707107	-0.3585	-5.12441
3X1	2731	1.29	0.001811	4982.26	6.601531	0.707107	-0.91217	-2.01401
3X2	1610	2.931	0.00004159	6673.547	3.004445	0.707107	-2.07253	-0.88641
3X3	1148	0.6297	-0.01619	1022.329	10.98879	0.707107	-0.44527	-4.1259
3X4	9168	0.03584	0.02734	464.6839	171.3822	0.707107	-0.02534	-72.491
3X5	17310	0.0153	0.06471	374.5446	387.3661	0.707107	-0.01082	**-169.809**
3X6	1329	0.3232	0.03119	607.4511	19.86186	0.707107	-0.22854	-8.0386
3X7	820	0.4261	0.01128	494.129	14.56842	0.707107	-0.3013	-6.09734
3X8	555.2	0.3958	0.08862	310.7708	14.58851	0.707107	-0.27987	-6.56411
3X9	263	0.9372	0.0184	348.5805	6.264526	0.707107	-0.6627	-2.77217
4X1	994.6	2.008	0.004607	2824.406	3.961805	0.707107	-1.41987	-1.29386
4X2	783.6	1.187	-0.005877	1315.407	6.044588	0.707107	-0.83934	-2.18878
4X3	1159	0.2096	0.05408	343.5498	27.91349	0.707107	-0.14821	-12.3954
4X4	186.1	1.105	0.01586	290.8196	5.149528	0.707107	-0.78135	-2.3512
4X5	244.8	0.8059	0.0113	279.0022	6.998792	0.707107	-0.56986	-3.22382

plot	b	c		h_{opt}	y1	y2	curvature	plot
4X6	409	0.5789	0.01749	334.8435	10.06009	0.707107	-0.40934	-4.48795
4X7	5887	0.01702	-0.01889	141.6996	291.0334	0.707107	-0.01203	-152.648
4X8	238.9	0.5109	0.05359	172.6104	10.13587	0.707107	-0.36126	-5.08529
4X9	161.1	0.4103	0.07797	93.47857	11.13752	0.707107	-0.29013	-6.33214
5X1	5017	1.627	-0.003085	11543.74	5.746085	0.707107	-1.15046	-1.59685
5X2	8155	0.4943	-0.02162	5700.718	17.47453	0.707107	-0.34952	-5.25607
6X1	6652	2.073	-0.003238	19501.43	4.761954	0.707107	-1.46583	-1.25329
7X1	5448	1.267	0.0005757	9761.773	7.250954	0.707107	-0.8959	-2.05057
8X1	745.6	2.748	0.001286	2897.595	2.902173	0.707107	-1.94313	-0.94544
9X1	7767	15.74	4.832E-06	172891.3	0.766232	0.707107	-11.1299	-0.16506

TABLE 5.3.4 : Amount of curvature of Michaelis-menton curve for Jute data.

plot	b	c	h_{opt}	y1	y2	curvature
1X1	2870	0.1153	18.07566	1	-0.10994	-25.725901
1X2	1693	0.1868	17.59669	1	-0.11246	-25.149648
1X3	1174	0.2657	17.39589	1	-0.11324	-24.977262
1X4	909.3	0.1516	11.58935	1	-0.17034	-16.604209
1X5	912.2	0.6338	23.411	1	-0.08318	-34.004481
1X6	1018	0.4347	20.60157	1	-0.09507	-29.749776
1X8	525.2	0.1182	7.7608	1	-0.25384	-11.142589
2X1	1631	0.08459	11.66132	1	-0.17027	-16.611218
2X2	1031	0.07935	8.96553	1	-0.22112	-12.791392
2X3	984.1	1.583	37.88636	1	-0.05067	-55.818103
2X4	506.9	1.449	25.65263	1	-0.0738	-38.327486
2X5	436.4	0.6315	15.9693	1	-0.12048	-23.477078
2X6	684.1	1.127	26.63954	1	-0.07203	-39.267816
2X7	579.3	1.408	27.15166	1	-0.07003	-40.389464
2X8	430.7	2.289	29.1096	1	-0.0637	-44.404331
2X9	202.2	1.65	16.61554	1	-0.1095	-25.831376
3X1	3039	0.454	36.69039	1	-0.05384	-52.530106
3X2	1615	0.02729	6.611486	1	-0.30126	-9.3886474
3X3	1572	1.866	52.29443	1	-0.03693	-76.594412
3X4	12890000	40990	685894.5	1	-2.8E-06	**-1027969.9**
3X5	6087000	23310	353370.2	1	-5.3E-06	-532706.24
3X6	2158	4.833	97.29248	1	-0.01958	-144.42724
3X7	1228	3.235	59.79341	1	-0.03173	-89.135627
3X8	913.7	3.963	56.21169	1	-0.03324	-85.09986
3X9	333.4	1.048	17.64433	1	-0.107	-26.434947
4X1	1002	0.0691	8.251849	1	-0.24036	-11.7676
4X2	947.6	0.7014	25.07934	1	-0.07758	-36.459474
4X3	2163	8.855	129.5407	1	-0.01445	-195.72105
4X4	238.5	0.9104	13.82495	1	-0.13573	-20.838925
4X5	339.1	1.494	21.01412	1	-0.08886	-31.831286
4X6	619.2	2.435	36.39478	1	-0.05151	-54.913605
4X7	609000	6218	55318.67	1	-3.3E-05	-87025.996
4X8	394.6	3.132	32.02319	1	-0.05689	-49.716943
4X9	283.7	4.218	30.37458	1	-0.05782	-48.921296
5X1	5524	0.3414	43.08548	1	-0.04605	-61.414878
5X2	11440	2.532	167.6622	1	-0.01175	-240.69101

plot	b	c	h_{opt}	y1	y2	curvature
6X1	7175	0.2254	39.98958	1	-0.04973	-56.872577
7X1	6194	0.5116	55.78094	1	-0.03553	-79.609678

TABLE 5.3.5 : Amount of curvature of spherical curve for Rice data.

plot	b	c		h_{opt}	y1	y2	curvature
1X1	24170	1.268	217530	30647.56	-1.7E+13	-1.1E+09	-4.275E+30
1X2	9158	6.893	82422.01	63126.1	-1.7E+11	-5295488	-8.818E+26
1X3	7702	6.155	69318.01	47405.81	-1.1E+11	-4697558	-2.939E+26
1X4	7461	5.973	67149.01	44564.55	-1E+11	-4680910	-2.424E+26
1X5	8599	5.363	77391	46116.44	-1.8E+11	-7712613	-7.293E+26
1X6	7458	5.301	67122	39534.86	-1.2E+11	-5938140	-2.724E+26
1X7	6072	5.305	54648.01	32211.96	-6.3E+10	-3930194	-6.453E+25
1X8	6146	5.52	55314.01	33925.92	-6.3E+10	-3719018	-6.751E+25
1X9	5263	5.445	47367.01	28657.04	-4E+10	-2802801	-2.311E+25
2X1	5565	5.431	50085.01	30223.52	-4.8E+10	-3149865	-3.424E+25
2X2	7671	3.081	69039	23634.35	-2.2E+11	-1.9E+07	-5.707E+26
2X3	5806	2.947	52254	17110.28	-1E+11	-1.2E+07	-8.49E+25
2X4	7416	2.638	66744	19563.41	-2.3E+11	-2.4E+07	-5.261E+26
2X5	7211	2.263	64899	16318.49	-2.5E+11	-3E+07	-5.04E+26
2X6	8229	2.012	74061	16556.75	-4.2E+11	-5E+07	-1.429E+27
2X7	6987	2.114	62883	14770.52	-2.4E+11	-3.3E+07	-4.326E+26
2X8	6163	2.222	55467	13694.19	-1.6E+11	-2.3E+07	-1.71E+26
2X9	5190	2.044	46710	10608.36	-1E+11	-1.9E+07	-5.583E+25
3X1	36110	5.127	324990	185136	-1.4E+13	-1.5E+08	-1.757E+31
3X2	31080	2.301	279720	71515.08	-2E+13	-5.5E+08	-1.37E+31
3X3	36640	2.445	329760	89584.8	-3E+13	-6.7E+08	-4.079E+31
3X4	23710	1.642	213390	38931.82	-1.2E+13	-6.3E+08	-2.886E+30
4X1	23890	4.652	215010	111136.3	-4.4E+12	-7.9E+07	-1.074E+30
4X2	38550	2.401	346950	92558.55	-3.6E+13	-7.7E+08	-5.928E+31
4X3	38970	2.053	350730	80005.41	-4.3E+13	-1.1E+09	-7.48E+31
5X1	53520	5.78	481680	309345.6	-4E+13	-2.6E+08	-2.448E+32
5X2	61820	2.349	556380	145215.2	-1.5E+14	-2.1E+09	-1.653E+33
5X3	51710	2.454	465390	126896.3	-8.5E+13	-1.3E+09	-4.532E+32
6X1	41130	4.629	370170	190390.8	-2.3E+13	-2.4E+08	-4.839E+31
6X2	37210	2.066	334890	76875.86	-3.7E+13	-9.7E+08	-5.378E+31
7X1	144400	4.641	1299600	670160.4	-9.7E+14	-2.9E+09	**-3.173E+35**
8X1	46320	9.784	416880	453194.9	-1.5E+13	-6.7E+07	-5.26E+31
9X1	112400	5.129	1011600	576499.6	-4.2E+14	-1.4E+09	-4.971E+34

TABLE 5.3.6 : Amount of curvature of exponential curve for Rice data.

plot	b	c		h_{opt}	y1	y2	curvature
1X1	24010	0.4466	76030.6	5.019289	0.707107	-1.58331	-1.16030084
1X2	16590	0.6933	33840.77	7.230718	0.707107	-1.01991	-1.80124624
1X3	13270	0.7179	26140.99	7.301947	0.707107	-0.98497	-1.86515891
1X4	11480	0.6949	23363.32	6.989945	0.707107	-1.01757	-1.80540316
1X5	9573	0.5216	25955.27	5.30161	0.707107	-1.35565	-1.35515655
1X6	9083	0.6304	20376.43	6.254913	0.707107	-1.12168	-1.63782724
1X7	7436	0.3932	26744.89	4.00832	0.707107	-1.79834	-1.02156357
1X8	7807	0.5127	21534.55	5.11542	0.707107	-1.37918	-1.33203367
1X9	6801	0.6068	15850.47	5.868335	0.707107	-1.1653	-1.57651265

plot	b	c		h_{opt}	y1	y2	curvature
2X1	11920	0.4901	34395.89	5.119434	0.707107	-1.44278	-1.27331715
2X2	8942	0.4325	29239.07	4.44751	0.707107	-1.63493	-1.12366796
2X3	6577	0.4564	20379.67	4.528535	0.707107	-1.54931	-1.18576198
2X4	7058	0.5025	19863.72	4.973067	0.707107	-1.40718	-1.3055333
2X5	5925	0.03167	264579	0.395428	0.707107	-22.3273	-0.08228107
2X6	6248	0.5394	16381.18	5.234277	0.707107	-1.31091	-1.40140231
2X7	5896	0.5071	16442.92	4.922749	0.707107	-1.39441	-1.31748445
2X8	5586	0.715	11048.67	6.656697	0.707107	-0.98896	-1.85762449
2X9	4124	0.4758	12257.71	4.479138	0.707107	-1.48614	-1.23616466
3X1	38400	0.1029	527753.2	1.35585	0.707107	-6.87179	-0.26734204
3X2	26800	0.08392	451631.6	1.092691	0.707107	-8.42596	-0.21803056
3X3	37930	0.7206	74439.52	8.083505	0.707107	-0.98127	-1.87217372
3X4	26110	0.03449	1070604	0.47885	0.707107	-20.5018	-0.08960765
4X1	39670	0.076	738182.3	1.026908	0.707107	-9.30404	-0.19745379
4X2	38670	0.6663	82076.6	7.539457	0.707107	-1.06124	-1.73109818
4X3	35190	0.04587	1084940	0.637457	0.707107	-15.4154	-0.11917376
5X1	61010	0.4427	194897.6	5.392188	0.707107	-1.59726	-1.15016834
5X2	61250	0.6296	137580.3	7.449404	0.707107	-1.1231	-1.63574878
5X3	56820	1.05	76529.16	11.8077	0.707107	-0.67343	**-2.72798002**
6X1	41890	0.6105	97037.52	7.010282	0.707107	-1.15824	-1.58612553
6X2	31750	0.07332	612401.5	0.977	0.707107	-9.64412	-0.19049095
7X1	168200	0.3188	746144	4.311029	0.707107	-2.21803	-0.8282667
8X1	54720	0.4232	182858.6	5.12769	0.707107	-1.67086	-1.09950585
9X1	139800	0.05253	3763698	0.795352	0.707107	-13.461	-0.13647694

TABLE 5.3.7 : Amount of curvature of VB curve for Rice data.

plot	Li	K	t0		h_{opt}	y1	y2	curvature
1X1	24060	2.212	-0.001112	75265.46	5.075189	0.707107	-1.56412	-1.1745372
1X2	16630	1.442	-0.001668	33913.49	7.232429	0.707107	-1.01965	-1.8017172
1X3	13200	1.384	0.003369	25835.98	7.344065	0.707107	-0.97864	-1.8772227
1X4	885.8	2.423	-0.0003071	3035.317	3.308843	0.707107	-1.71332	-1.072256
1X5	9560	1.914	0.000713	25877.05	5.309549	0.707107	-1.3534	-1.3574066
1X6	8990	1.502	0.006646	19096.1	6.569389	0.707107	-1.06207	-1.7297445
1X7	7425	2.531	0.0005997	26576.86	4.025806	0.707107	-1.78969	-1.0265019
1X8	7786	1.952	0.001384	21493.6	5.111789	0.707107	-1.38027	-1.3309817
1X9	6729	1.578	0.006585	15016.63	6.100954	0.707107	-1.11581	-1.6464361
2X1	11880	2.023	0.001398	33988.13	5.158969	0.707107	-1.43048	-1.284269
2X2	8907	2.343	0.001646	29513.37	4.39456	0.707107	-1.65675	-1.1088674
2X3	6563	2.2	0.0008845	20419.26	4.5119	0.707107	-1.55563	-1.1809437
2X4	7119	1.876	0.003532	18887.17	5.25206	0.707107	-1.32653	-1.384902
2X5	6651	2.971	-1.113E-05	27945.03	3.445965	0.707107	-2.10081	-0.8744787
2X6	6216	1.809	0.004201	15902.47	5.352034	0.707107	-1.27916	-1.4361947
2X7	5883	1.961	0.00143	16315.16	4.94781	0.707107	-1.38664	-1.3248731
2X8	5554	1.393	0.00456	10941.38	6.681019	0.707107	-0.985	-1.8650942
2X9	4120	2.054	0.001529	11967.75	4.573083	0.707107	-1.4524	-1.2648862
3X1	10540	4.818	-2.24	71816.2	0.080852	0.707107	-3.40684	-0.5392437
3X2	30570	19.16	-2.534E-05	828334.9	0.711205	0.707107	-13.5482	-0.135599
3X3	38420	1.395	-0.01006	75796.05	8.044278	0.707107	-0.98641	-1.8624202
3X4	23750	20.69	-0.0003726	694926.9	0.649775	0.707107	-14.63	-0.1255716

plot	Li	K	t0		h_{opt}	y1	y2	curvature
4X1	37310	20.1	0.0003959	1060563	0.69066	0.707107	-14.2128	-0.1292575
4X2	39040	1.501	-0.006317	82871.56	7.538685	0.707107	-1.06137	-1.7308969
4X3	35370	204.1	-3.383E-06	10209232	0.07907	0.707107	-144.32	-0.0127294
5X1	61130	2.259	-0.0009194	195292.5	5.391845	0.707107	-1.59735	-1.1501001
5X2	61640	1.585	-0.003738	138167.8	7.463911	0.707107	-1.12076	-1.6391648
5X3	57490	0.9492	-0.01105	77172.94	11.84504	0.707107	-0.67119	**-2.737122**
6X1	35120	3.138	0.0001175	155855.6	3.810406	0.707107	-2.2189	-0.8279402
6X2	31870	45.95	-2.275E-05	2071012	0.316485	0.707107	-32.4916	-0.0565414
7X1	168200	3.137	0.00003353	746200.5	4.31076	0.707107	-2.21819	-0.8282041
8X1	44950	10.58	0.0004692	672559	1.268791	0.707107	-7.48119	-0.2455649
9X1	145200	44.45	-1.175E-05	9127532	0.360546	0.707107	-31.4309	-0.0584494

TABLE 5.3.8 : Amount of curvature of Michaelis-menton curve for Rice data.

plot	b	c	h_{opt}	y1	y2	curvature
1X1	24430	0.1017	49.74337	1	-0.04012	-70.4916
1X2	17170	0.2052	59.15206	1	-0.03369	-83.9438
1X3	13500	0.1671	47.32869	1	-0.04211	-67.1692
1X4	11730	0.1758	45.23493	1	-0.04404	-64.2205
1X5	9559	0.06292	24.4616	1	-0.08155	-34.6829
1X6	8988	0.1059	30.74583	1	-0.06483	-43.6309
1X7	7260	-0.04027	-----	-----	-----	-----
1X8	7806	0.06873	23.09388	1	-0.08635	-32.7569
1X9	6774	0.1186	28.22565	1	-0.07056	-40.0848
2X1	12010	0.07236	29.40719	1	-0.06784	-41.6904
2X2	8967	0.04856	20.81858	1	-0.09584	-29.5106
2X3	6765	0.1133	27.57198	1	-0.07224	-39.1529
2X4	7359	0.1498	33.05228	1	-0.06024	-46.9548
2X5	6910	0.09604	25.6651	1	-0.07764	-36.4318
2X6	6633	0.2394	39.60957	1	-0.05019	-56.355
2X7	6264	0.2118	36.2123	1	-0.05491	-51.5115
2X8	6538	0.5501	59.42117	1	-0.03335	-84.8122
2X9	4258	0.1446	24.66884	1	-0.0806	-35.0915
3X1	38490	-0.00371	-----	-----	-----	-----
3X2	30130	-0.02913	-----	-----	-----	-----
3X3	43870	0.4641	142.2246	1	-0.01402	**-201.792**
3X4	15060	-0.4682	-----	-----	-----	-----
4X1	39400	-0.02508	-----	-----	-----	-----
4X2	43990	0.4038	132.8747	1	-0.01501	-188.484
4X3	42480	0.2621	105.2557	1	-0.01895	-149.225
5X1	61720	0.06429	62.9276	1	-0.03175	-89.084
5X2	69370	0.3795	161.8731	1	-0.01233	-229.46
5X3	72390	1.005	268.7207	1	-0.00741	-381.45
6X1	43800	0.2414	102.5853	1	-0.01945	-145.419
6X2	28940	-0.1479	-----	-----	-----	-----
7X1	167600	0.01082	42.57359	1	-0.04697	-60.2235
8X1	57310	0.1703	98.62187	1	-0.02024	-139.713
9X1	144400	-0.01447	-----	-----	-----	-----

Thus using the three criteria i.e. Nugget to sill ratio (NSR), NSR/Range, maximum curvature value of the variogram models we have found optimum plot size and shapes for rice and jute data. These are summarized in the following table:

TABLE 5.3.9: Optimum plot sizes of Jute data for five different models:

Model	NSR	NSR/Range	Curvature
Michaelis-menton	2 X 9	1 X 5	3 X 4
Gaussian	2 X 4	7 X 1	-----
VB	1 X 5	2 X 9	3 X 5
Exponential	1 X 5	1 X 9	3 X 4
Spherical	1 X 9	1 X 9	3 X 4

TABLE 5.3.10 : Optimum plot sizes of Rice data for five different models:

Model	NSR	NSR/Range	Curvature
Michaelis-menton	3 X 4	3 X 3	3 X 3
Gaussian	3 X 4	3 X 4	-----
VB	3 X 1	3 X 1	5 X 3
Exponential	3 X 4	3 X 4	5 X 3
Spherical	4 X 1	4 X 1	7 X 1

Chapter 6

A CASE STUDY OF MERCER & HALL WHEAT GRAIN YIELD DATA.

6.1 INTRODUCTION: By now we have introduced a new concept of finding optimum plot size and shape using variogram analysis of the uniformity data. Here the average variogram curves are studied for different plot sizes and shapes. Fagroud *et al*(2002) studied the plot size and shape using the concept of nugget to sill ratio of variogram data. However their method is crude compared to our new suggested method as it takes care of the specific amount of curvature of the variogram curves fitted under different models.

6.2 MATERIAL AND METHOD: Mercer and Hall carried out uniformity trial on wheat yield at Rothamsted Experimental Station in 1910. A uniform area of one acre was harvested in separate plots each 1/500 acre in area. The dimension of each plot was 3.3m. (East-West) X 2.51 m. (North-South) i.e. 8.283 sq.m. The data given by Mercer and Hall (1911) consist of 20 X 25 lattice of plots with 20 rows of plots running East to West and 25 columns of plots running North to South. He studied both grain and straw yield. Here we consider only the wheat grain yield data as published in Cressie(1993). The object of their study was to determine the plot size that would "reduce the inevitable error within working limits". As a matter of interest they concluded that 1/40 acre i.e. 103.54 sq.m., should give adequate precision.

6.3 RESULTS AND DISCUSSIONS: Data is first analysed using the Smith's model of relating variance per unit area to the plot sizes. The fitted model shows that the heterogeneity coefficient b = 0.4570399. The analysis of the first row and first column indicates that the index of heterogeneity is more pronounced along the column than along the row direction. This is also reported by the Zhang *et al*(1994). For different plot sizes and shapes the following table shows how the variance per unit area and C.V. decreases with increase in plot size.

TABLE 6.3.1: Mercer & Hall wheat grain yield data.

Plot size	Width	Length	No.of plots	Plot mean	Variance	Variance per unit area	C.V.
1	1	1	500	393.982	2262.349	2262.349	12.07267
2	2	1	250	787.964	6549.59	1637.398	10.27072
2	1	2	240	790.2125	5511.632	1377.908	9.394987
3	3	1	150	1178.58	11629.64	1292.182	9.150063
3	1	3	160	1185.319	9914.214	1101.579	8.400285
4	4	1	125	1575.928	19526.45	1220.403	8.866971

Plot size	Width	Length	No.of plots	Plot mean	Variance	Variance per unit area	C.V.
4	2	2	120	1580.425	17110.05	1069.378	8.276596
4	1	4	120	1580.425	15088.13	943.0084	7.772198
5	5	1	100	1969.91	29524.04	1180.962	8.72251
5	1	5	100	1969.91	18497.62	739.9046	6.90417
6	6	1	75	2357.16	36887.79	1024.661	8.148023
6	3	2	72	2364.5	29131.83	809.2175	7.21846
6	2	3	80	2370.637	32581.06	905.0295	7.614081
6	1	6	80	2370.637	23734.89	659.3024	6.498729
7	7	1	50	2773.64	39645.47	809.0912	7.178715
7	1	7	60	2782.15	34488.61	703.8492	6.675093
8	8	1	50	3144.96	48033.3	750.5204	6.96877
8	4	2	60	3160.85	54769.9	855.7797	7.404011
8	2	4	60	3160.85	49942.78	780.356	7.070212
8	1	8	60	3160.85	36256.54	566.5085	6.02406
9	9	1	50	3535.74	64239.02	793.0743	7.168349
9	3	3	48	3546.75	53549.19	661.1011	6.52448
9	1	9	40	3594.3	27916.72	344.6508	4.648554
10	5	2	48	3951.063	78191.32	781.9132	7.077264
10	2	5	50	3939.82	61609.8	616.098	6.300115
12	6	2	36	4729	102277.9	710.2635	6.762724
12	4	3	40	4741.275	108584.2	754.0569	6.950054
12	3	4	36	4729	85859.2	596.2444	6.196181
12	2	6	40	4741.275	83059.7	576.8035	6.07855
14	7	2	24	5567.208	101764.5	519.2067	5.730081
14	2	7	30	5564.3	118021.2	602.1492	6.174042
15	5	3	32	5926.594	151451.1	673.116	6.566456
15	3	5	30	5892.9	92654.34	411.7971	5.165399
16	8	2	24	6310.708	128812.5	503.1739	5.687232
16	4	4	30	6321.7	168823.2	659.4655	6.499533
16	2	8	30	6321.7	122619.6	478.9828	5.539187
18	9	2	24	7093.5	183263.7	565.6285	6.035005
18	6	3	24	7093.5	192991.7	595.6533	6.193109
18	3	6	24	7093.5	147996.9	456.7805	5.423326
18	2	9	20	7188.6	88890.95	274.3548	4.147481
20	5	4	24	7902.125	238813.2	597.033	6.184225
20	4	5	25	7879.64	207941.3	519.8533	5.78714
21	7	3	16	8350.813	172776.3	391.7829	4.977523
21	3	7	18	8323.5	196994.4	446.6992	5.332378
24	8	3	16	9466.063	236309.3	410.2592	5.135362
24	6	4	18	9458	311433.4	540.683	5.900425
24	4	6	20	9482.55	276948.2	480.8129	5.549759
24	3	8	18	9458	178162.8	309.3105	4.462819
25	5	5	20	9849.55	283828.2	454.1252	5.408931
27	9	3	16	10640.25	345077.6	473.3575	5.520858
27	3	9	12	10737.92	165860.4	227.5176	3.792724
28	7	4	12	11134.42	271122.9	345.82	4.676443

Plot size	Width	Length	No.of plots	Plot mean	Variance	Variance per unit area	C.V.
28	4	7	15	11128.6	426216	543.6429	5.866436
30	6	5	15	11785.8	341403.4	379.3372	4.957639
30	5	6	16	11853.19	397731.2	441.9236	5.320589
32	8	4	12	12621.42	390365.1	381.2159	4.950253
32	4	8	15	12643.4	403748.6	394.2857	5.025642
35	7	5	10	13868.2	178292	145.5445	3.044709
35	5	7	12	13910.75	587522.6	479.6103	5.510128
36	9	4	12	14187	575818.2	444.3042	5.348748
36	6	6	12	14187	564647.3	435.6846	5.29661
36	4	9	10	14377.2	305756.4	235.9232	3.846037
40	8	5	10	15724.8	352451.6	220.2822	3.775414
40	5	8	12	15804.25	560494.6	350.3091	4.737092
42	7	6	8	16701.63	482860.6	273.7305	4.160563
42	6	7	9	16647	787818	446.6089	5.331838
45	9	5	10	17678.7	626602.7	309.4334	4.477605
45	5	9	8	17971.5	409680	202.3111	3.561542
48	8	6	8	18932.13	792484.6	343.9603	4.702145
48	6	8	9	18916	660584	286.7118	4.296697
49	7	7	6	19602.67	298393.6	124.2789	2.786632
54	9	6	8	21280.5	1168376	400.6776	5.079366
54	6	9	6	21475.83	623596.8	213.8535	3.67707
56	8	7	6	22220.67	750009.6	239.1612	3.897412
56	7	8	6	22268.83	387718.4	123.6347	2.796152
63	9	7	6	24970.5	1487230	374.7116	4.883845
63	7	9	4	25193.25	393270.7	99.08558	2.48921
64	8	8	6	25242.83	710451.2	173.45	3.339097
72	9	8	6	28374	1127955	217.584	3.743048
72	8	9	4	28629.75	875573.3	168.8992	3.268351
81	9	9	4	32213.75	1303589	198.6876	3.544289

TABLE 6.3.1A: Average values for same plot sizes but different shapes.

Plot size	No.of plots	Plot mean	Variance	Variance per sq.m.	C.V.
1	500	393.982	2262.349	2262.349	12.07267
2	245	789.0883	6030.611	1507.653	9.832854
3	155	1181.95	10771.93	1196.881	8.775174
4	122	1578.926	17241.54	1077.596	8.305255
5	100	1969.91	24010.83	960.4333	7.81334
6	76.8	2365.734	30583.89	849.5526	7.369823
7	55	2777.895	37067.04	756.4702	6.926904
8	57.5	3156.878	47250.63	738.2912	6.866763
9	46	3558.93	48568.31	599.6087	6.113794
10	49	3945.442	69900.56	699.0056	6.68869
12	38	4735.138	94945.25	659.3421	6.496877
14	27	5565.754	109892.9	560.678	5.952062
15	31	5909.747	122052.7	542.4566	5.865928

Plot size	No.of plots	Plot mean	Variance	Variance per sq.m.	C.V.
16	28	6318.036	140085.1	547.2074	5.908651
18	23	7117.275	153285.8	473.1043	5.44973
20	24.5	7890.883	223377.3	558.4432	5.985683
21	17	8337.157	184885.4	419.2411	5.154951
24	18	9466.153	250713.4	435.2664	5.262091
25	20	9849.55	283828.2	454.1252	5.408931
27	14	10689.09	255469	350.4376	4.656791
28	13.5	11131.51	348669.5	444.7315	5.27144
30	15.5	11819.5	369567.3	410.6304	5.139114
32	13.5	12632.41	397056.9	387.7508	4.987948
35	11	13889.48	382907.3	312.5774	4.277419
36	11.3	14250.4	482074	371.9707	4.830465
40	11	15764.53	456473.1	285.2957	4.256253
42	8.5	16674.32	635339.3	360.1697	4.746201
45	9	17825.1	518141.4	255.8723	4.019574
48	8.5	18924.07	726534.3	315.3361	4.499421
49	6	19602.67	298393.6	124.2789	2.786632
54	7	21378.17	895986.4	307.2656	4.378218
56	6	22244.75	568864	181.398	3.346782
63	5	25081.88	940250.4	236.8986	3.686528
64	6	25242.83	710451.2	173.45	3.339097
72	5	28501.88	1001764	193.2416	3.5057
81	4	32213.75	1303589	198.6876	3.544289

The relation $y = a\,x^{-b}$ in estimated form was $y = 12.41195\ x^{-0.2852526}$ with $\phi = 0.976363$, thus indicating a good fit. It is found that $x_{opt} = 2.311197$ units when units plots were 3.3 m. x 2.51 m. Model 3 i.e. $y = a'.x_1^{b_1}.x_2^{b_2}$ applied to C. V. data resulted in $y = 12.41203\ x_1^{-0.227}.x_2^{-0.3434}$, which too was a good fit since $\phi = 0.982$. The relative magnitude of b_1 and b_2 again indicate the C.V values to expectedly fall at a higher rate as the plot size was increased along length than along width of the wheat field. For attaining $x_2 > x_1$ with $x_1x_2 = 2.311197$ it is sufficient to evaluate conditional maxima of x_2 at different x_1,s which be possibly due to $b_2 > b_1$. The equation $x_{02} = 2.603391\ x_1^{-0.169}$ gave an excellent fit to the underlying relationship between x_{02} & x_1. its solution provided $x_{1opt} = .403109$ unit $x_{2opt} = 5.733429$ units. Accordingly optimum plot size is 19.14sq. mt. with 1.33026 m. along the width and 14.391 m. along the length of the wheat field.

The above mentioned data is again analysed for finding different variogram values for different lags and also for different plot sizes and shapes. Here in the following table we present only the robust variogram values for the basic plot size.

TABLE 6.3.2: Robust variogram values for basic plot size average over same lag distance.

LAG	AV-ve	AV+ve	Average	LAG	AV-ve	AV+ve	Average
1	2632.37	2632.37	2632.37	8.602	5300.65	4442.58	4871.61
1.414	3638.12	3349.26	3493.69	8.944	5212.14	4558.18	4885.16
2	3111.44	3111.44	3111.44	9	4206.07	4206.07	4206.07
2.236	4033.18	3518.14	3775.66	9.055	4479.2	4331.42	4405.31
2.828	4304.04	3919.42	4111.73	9.22	4435.49	4469.49	4452.49
3	3106.62	3106.62	3106.62	9.434	4762.81	5041.57	4902.19
3.162	3853.99	3754.68	3804.33	9.487	4360.61	4270.95	4315.78
3.606	3891.22	3596.62	3743.92	9.849	4740.63	4209.41	4475.02
4	3538.74	3538.74	3538.74	9.899	4459.5	4418.51	4439.01
4.123	4130.9	4074.23	4102.56	10	4324.84	5058.19	4691.51
4.243	3472.8	3399.89	3436.34	10.05	4689.96	5012.51	4851.23
4.472	4679.13	3888.93	4284.03	10.2	4295.23	4866.86	4581.05
5	3999.37	3842.75	3921.06	10.3	4034.9	4886.85	4460.88
5.099	4477.63	3994.64	4236.13	10.44	4548.38	4916.96	4732.67
5.385	4762.64	4122.37	4442.5	10.63	3748.48	4722.54	4235.51
5.657	4772.83	4010.12	4391.47	10.77	4612.23	5024.61	4818.42
5.831	4339.92	3991.92	4165.92	10.82	3834.33	5160.09	4497.21
6	3824.31	3824.31	3824.31	11	5214.65	5214.65	5214.65
6.083	4303.86	3887.66	4095.76	11.05	5080.37	5252.22	5166.29
6.325	4852.01	3762	4307.01	11.18	4695.72	4991.2	4843.46
6.403	5019.91	4239.83	4629.87	11.31	3807.52	4530.09	4168.81
6.708	4262.33	3661.54	3961.94	11.4	4174.64	4703.79	4439.21
7	4283.22	4283.22	4283.22	11.66	3840.39	5602.72	4721.55
7.071	4939.01	4387.29	4663.15	11.71	5352.14	4956.73	5154.43
7.211	4851.03	3694.34	4272.69	12.04	3351.17	5035.98	4193.58
7.28	4779.85	4217.33	4498.59	12.08	4728.49	5747.08	5237.79
7.616	4637.96	3915.67	4276.82	12.21	3859.29	5644.99	4752.14
7.81	5075.93	4600.5	4838.21	12.53	4027.06	5648.92	4837.99
8	4360.08	4360.08	4360.08	12.73	3401.14	4713.59	4057.36
8.062	5019.8	4267.12	4643.46	12.81	4672.86	5649.8	5161.33
8.246	4872.12	4906.9	4889.51	13.04	3864.88	5896.47	4880.67
8.485	4796.28	3914.4	4355.34	13.45	4353.07	5247.73	4800.4
8.544	4613.43	4601.32	4607.37	13.6	4607.16	5475.81	5041.49

Now different number of units along row and column directions are used to construct larger plots with different plot shapes. For each size and shape we find the variogram values and fit a number of models like spherical, exponential, Gaussian, Michaelis-menton and VB.From the fit for each model we find the variogram parameters like range, nugget and sill. The fit for each model are given in the following:

Mercer and Hall (1 X 1) Spherical model y=a+b*(1.5*(x/c)-0.5*(x/c)^3) Rsq.= 0.645465

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.347e+3	2.071e+2	8.823e+0	0.9286223
b	2.443e+3	2.364e+2	9.674e+0	0.9229586
c	1.085e+1	6.093e-1	5.618e+0	0.2312960

(1 X 1) Exponential model y = a - b.exp(-x/c) Rsq.= 0.781267

Parameter	Value	StdErr	CV(%)	Dependencies
a	4.646e+3	6.283e+1	1.352e+0	0.5217601
b	3.992e+3	3.072e+2	7.696e+0	0.4043345
c	2.118e+0	2.428e-1	1.146e+1	0.6447663

(1 X 1) Gaussian model y = a - b / exp(x/c)^2 Rsq.= 0.781271

Parameter	Value	StdErr	CV(%)	Dependencies
a	4.647e+3	6.295e+1	1.355e+0	0.5234602
b	3.990e+3	3.070e+2	7.692e+0	0.4050133
c	4.241e+0	4.872e-1	1.149e+1	0.6460648

(1 X 1) Michaelis-menton model y = a - b / (1+x/c) Rsq.= 0.826949

Parameter	Value	StdErr	CV(%)	Dependencies
a	5.136e+3	1.066e+2	2.075e+0	0.8685361
b	5.019e+3	3.061e+2	6.100e+0	0.6475390
c	1.156e+0	2.062e-1	1.784e+1	0.8829620

(1 X 1) VB model y = li . (1-exp(-k . (t-t0))) Rsq.= 0.78129

Parameter	Value	StdErr	CV(%)	Dependencies
li	4.646e+3	6.260e+1	1.348e+0	0.4557491
k	4.730e-1	5.507e-2	1.164e+1	0.7125638
t0	-3.192e-1	1.873e-1	5.869e+1	0.5612791

(3 X 1) Spherical model y=a+b*(1.5*(x/c)-0.5*(x/c)^3) Rsq.= 0.163940

Parameter	Value	StdErr	CV(%)	Dependencies
a	4.057e+3	7.760e+2	1.913e+1	0.8943563
b	2.223e+3	1.545e+3	6.951e+1	0.9377237
c	1.322e+1	1.680e+1	1.270e+2	0.9614503

(6 X 1) Exponential model y = a - b.exp(-x/c) Rsq.= 0.877393

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.713e+4	1.298e+3	4.784e+0	0.2222222
b	2.339e+4	3.671e+3	1.569e+1	0.1250000
c	2.087e-2	4.948e+5	2.371e+9	0.1250000

(7 X 2) Spherical model y=a+b*(1.5*(x/c)-0.5*(x/c)^3) Rsq.= 0.245716

Parameter	Value	StdErr	CV(%)	Dependencies
a	7.796e+2	1.515e+3	1.943e+2	0.7575758
b	1.718e+3	2.141e+3	1.246e+2	0.7372188
c	2.591e+0	8.182e-1	3.158e+1	0.1574018

(7 X 2) Gaussian model y = a - b / exp(x/c)^2 Rsq.= 0.578916

Parameter	Value	StdErr	CV(%)	Dependencies
a	2.361e+3	7.625e+2	3.230e+1	0.4000145
b	2.437e+3	1.525e+3	6.256e+1	0.2500045
c	8.253e-2	5.776e+2	6.998e+5	0.2500114

(7 X 2) Michaelis-menton model y = a - b / (1+x/c) Rsq.= 0.637873

Parameter	Value	StdErr	CV(%)	Dependencies
a	1.696e+3	7.971e+2	4.699e+1	0.5796912
b	1.716e+3	1.347e+3	7.848e+1	0.5401640
c	-4.147e-1	4.254e-1	1.026e+2	0.7335319

(4 X 3) Spherical model y=a+b*(1.5*(x/c)-0.5*(x/c)^3) Rsq.= 0.9622942

Parameter	Value	StdErr	CV(%)	Dependencies
a	-6.036e+1	1.760e+2	2.916e+2	0.8122625
b	9.063e+5	3.263e+10	3.601e+6	1.0000000
c	1.947e+3	7.014e+7	3.603e+6	1.0000000

(4 X 3) Exponential model y = a - b*exp(-x/c) Rsq.= 0.962307

Parameter	Value	StdErr	CV(%)	Dependencies
a	5.366e+6	1.079e+4	2.011e-1	0.9999500
b	5.366e+6	1.079e+4	2.011e-1	0.9999500
c	7.680e+3	8.784e+2	1.144e+1	0.7391650

(4 X 3) Michaelis-menton model y = a - b / (1+x/c) Rsq.= 0.962301

Parameter	Value	StdErr	CV(%)	Dependencies
a	9.177e+6	1.079e+4	1.176e-1	0.9999500
b	9.177e+6	1.079e+4	1.176e-1	0.9999500
c	1.313e+4	1.106e+3	8.423e+0	0.7391696

(3 X 6) Gaussian model y = a - b / exp(x/c)^2 Rsq.= 0.93373

Parameter	Value	StdErr	CV(%)	Dependencies
a	1.561e+3	2.468e+2	1.581e+1	0.5018041
b	1.510e+3	4.270e+2	2.827e+1	0.3341371
c	1.356e-2	4.998e+3	3.686e+7	0.3357385

(1 X 7) Exponential model y = a - b*exp(-x/c) Rsq.= 0.757976

Parameter	Value	StdErr	CV(%)	Dependencies
a	1.083e+3	2.974e+2	2.747e+1	0.9519928
b	9.719e+2	2.850e+2	2.933e+1	0.7865196
c	3.397e+0	2.667e+0	7.850e+1	0.9134872

(1 X 7) VB model y = li * (1-exp(-k * (t-t0))) Rsq.= 0.757993

Parameter	Value	StdErr	CV(%)	Dependencies
li	1.086e+3	3.035e+2	2.796e+1	0.9030766
k	2.919e-1	2.398e-1	8.215e+1	0.9334464
t0	-3.718e-1	7.581e-1	2.039e+2	0.6389446

(3 X 5) VB model y = li * (1-exp(-k * (t-t0))) Rsq.= 0.85441

Parameter	Value	StdErr	CV(%)	Dependencies
li	7.380e+4	4.778e+6	6.474e+3	0.9999869
k	1.965e-2	1.321e+0	6.723e+3	0.9999869
t0	6.277e-2	5.427e-1	8.646e+2	0.6894852

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Using the variogram parameters found after fitting we compute the nugget to sill ratios for different plot sizes and shapes and also for different models. The values of NSR and NSR/range are shown in the following tables:

Table 6.3.3: Nugget to Sill ratios under spherical model.

M&Hall	a	b	NSR	c	NSR/range
1X1	2347	2443	0.489979123	10.85	0.045159366
2X1	1505	2195	0.406756757	9.259	0.04393096
3X1	4057	2223	**0.646019108**	13.22	0.048866801
4X1	1054	1843	0.363824646	9.662	0.037655211

M&Hall	a	b	NSR	c	NSR/range
5X1	1117	1727	0.392756681	10.62	0.036982738
6X1	14190	18960	0.428054299	6.874	0.062271501
7X1	1619	1342	0.546774738	6.932	0.07887691
8X1	13440	20220	0.399286988	6.993	0.057098096
9X1	31440	44130	0.41603811	7.125	0.058391314
1X2	1505	2194	0.406866721	9.259	0.043942836
2X2	455.8	1871	0.195891353	5.092	0.038470415
3X2	1182	4071	0.225014278	5.401	0.041661596
4X2	295.7	1758	0.143984029	4.916	0.029288859
5X2	292.6	1850	0.136563054	5.512	0.02477559
6X2	2908	26300	0.099561764	2.107	0.047252854
7X2	779.6	1718	0.312139654	2.591	**0.120470727**
8X2	2952	34200	0.079457364	2.85	0.027879777
9X2	7777	75360	0.093544391	2.92	0.03203575
1X3	914.5	1210	0.430454225	6.348	0.067809424
2X3	47.19	1757	0.026155782	3.332	0.007849874
3X3	201.9	3225	0.058916222	2.536	0.023231949
4X3	-60.4	906300	-6.6605E-05	1947	-3.4209E-08
5X3	-6.44	559600	-1.1508E-05	1351	-8.5184E-09
1X4	967.7	821.3	0.540916713	5.904	0.091618684
2X4	167.6	1383	0.108087192	3.011	0.03589744
3X4	188.8	3193	0.055828257	2.02	0.027637751
4X4	-33.5	1499	-0.02288003	2.462	-0.00929327
5X4	-10.5	1931	-0.00548303	3.544	-0.001547131
1X5	471.9	558.9	0.457799767	7.787	0.058790262
2X5	109.8	615.6	0.151364764	2.972	0.050930271
3X5	-88.7	401100	-0.00022112	421.6	-5.24469E-07
1X6	502.7	748.9	0.401645893	7.802	0.051479863
2X6	120.1	882.9	0.119740778	2.64	0.045356355
3X6	67.29	1675	0.038621584	1.523	0.025358887
1X7	245.7	1272	0.161889702	16.46	0.00983534
2X7	29.25	519.5	0.053302961	2.037	0.026167384
1X8	233.2	801	0.2254883	11.29	0.019972392
2X8	18.07	610.3	0.028756943	1.905	0.015095508
1X9	127.7	436.5	0.226338178	5.297	0.042729503
2X9	27.77	439.9	0.059379477	2.128	0.02790389

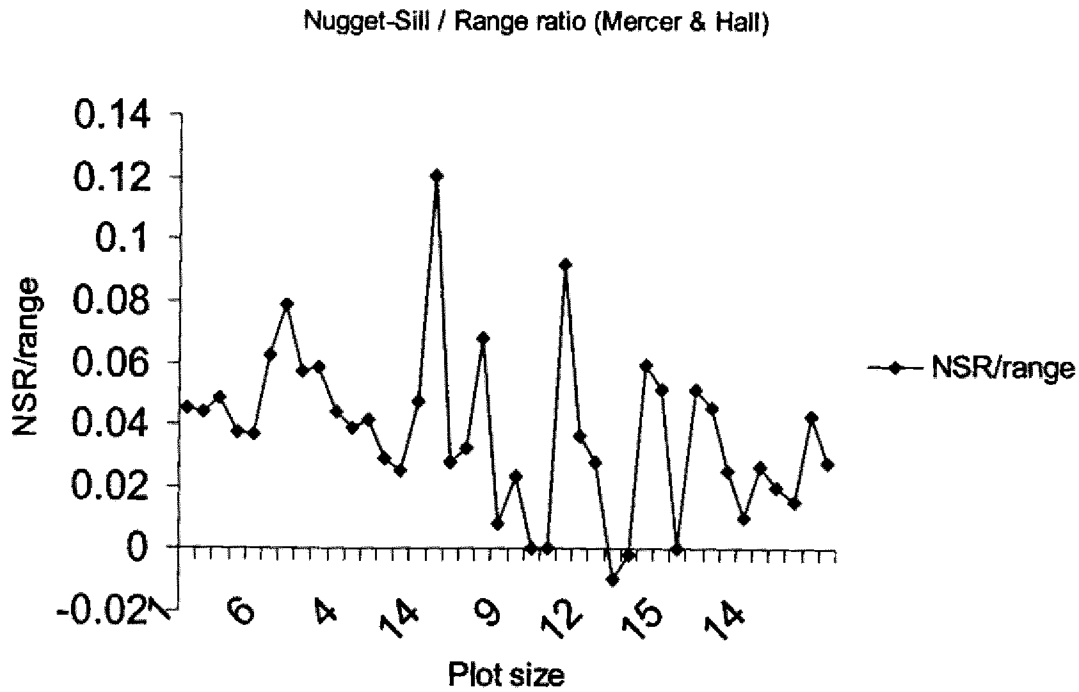

Table 6.3.4: Nugget to Sill ratios under exponential model.

M&Hall	a	b	NSR	c	NSR/range
1X1	4646	3992	0.140766251	2.118	0.066461875
2X1	3586	3280	0.085331846	2.036	0.041911516
3X1	5626	5584	0.007465339	0.6303	0.011844105
4X1	2741	2500	0.087924115	2.006	0.043830566
5X1	2618	2408	0.080213904	1.831	0.043808795
6X1	27130	23390	0.137854773	0.02087	**6.605403609**
7X1	2888	2882	0.002077562	0.104	0.019976561
8X1	29110	28520	0.020267949	0.03766	0.538182399
9X1	65910	64490	0.02154453	0.07356	0.292883774
1X2	3585	3281	0.084797768	2.033	0.041710658
2X2	2369	2279	0.037990713	1.689	0.022493022
3X2	5190	4853	0.064932563	1.658	0.039163186
4X2	2089	2072	0.008137865	1.719	0.004734069
5X2	2249	2189	0.026678524	2.197	0.012143161
6X2	23830	23790	0.001678556	0.03955	0.042441377
7X2	2331	2317	0.006006006	0.005829	1.030366445
8X2	28480	28490	-0.00035112	0.3381	-0.00103852
9X2	64530	64530	0	0.285	0
1X3	1972	1994	-0.01115619	0.9062	-0.012310954
2X3	1758	1792	-0.01934016	1.178	-0.016417792
3X3	3347	3338	0.002688975	0.8092	0.003323004
4X3	5E+06	5E+06	0	7680	0
5X3	8E+05	810100	0	1302	0
1X4	1665	1682	-0.01021021	0.5812	-0.017567464

M&Hall	a	b	NSR	c	NSR/range
2X4	1432	1448	-0.01117318	0.7296	-0.015314123
3X4	3225	3215	0.003100775	0.482	0.006433144
4X4	2989	3009	-0.0066912	3.079	-0.002173173
5X4	5396	5403	-0.00129726	6.326	-0.000205068
1X5	925.2	916	0.009943796	0.6453	0.015409571
2X5	655.6	655.3	0.000457596	0.5558	0.000823311
3X5	2E+06	2E+06	0	1348	0
1X6	1087	1076	0.010119595	0.8031	0.012600666
2X6	862.4	865.5	-0.00359462	0.4324	-0.008313181
3X6	1529	1510	0.012426422	0.05845	0.212599187
1X7	1083	971.9	0.102585411	3.397	0.030198826
2X7	422.7	422.9	-0.00047315	0.08611	-0.005494702
1X8	819.8	771.4	0.05903879	1.815	0.032528259
2X8	437.9	443	-0.01164649	0.004273	-2.725601365
1X9	494.9	506.9	-0.02424732	0.9047	-0.026801506
2X9	382.7	382.7	0	0.07044	0

Table 6.3.5: Nugget to Sill ratios under Gaussian model.

M&Hall	a	b	NSR	c	NSR/range
1X1	4647	3990	0.141381536	4.241	0.03333684
2X1	3586	3280	0.085331846	4.071	0.020960905
3X1	5626	5583	0.007643086	1.263	0.006051533
4X1	2740	2501	0.087226277	4.002	0.021795672
5X1	2618	2407	0.080595875	3.667	0.021978695
6X1	29050	28950	0.003442341	0.05731	0.060065273
7X1	2824	2651	0.061260623	0.1818	0.336967124
8X1	29500	29490	0.000338983	0.03955	0.008571
9X1	66790	66640	0.002245845	0.08566	0.026218132
1X2	3586	3280	0.085331846	4.07	0.020966056
2X2	2369	2280	0.037568594	3.382	0.011108396
3X2	5188	4852	0.064764842	3.31	0.019566418
4X2	2090	2072	0.00861244	3.442	0.002502162
5X2	2251	2190	0.027099067	4.4	0.006158879
6X2	25140	25500	-0.01431981	0.0918	-0.155989206
7X2	2361	2437	-0.03218975	0.08253	-0.390036958
8X2	28480	28490	-0.00035112	0.6763	-0.000519183
9X2	64530	64530	0	0.5699	0
1X3	1972	1994	-0.01115619	1.812	-0.006156836
2X3	1759	1792	-0.01876066	2.366	-0.007929273
3X3	3348	3340	0.002389486	1.621	0.001474082
4X3	5E+06	5367000	0	15360	0
5X3	8E+05	810100	0	2605	0
1X4	1665	1682	-0.01021021	1.16	-0.008801905
2X4	1433	1448	-0.01046755	1.463	-0.007154853
3X4	3235	3224	0.003400309	0.9864	0.003447191
4X4	2990	3009	-0.00635452	6.158	-0.001031912
M&Hall	a	b	NSR	c	NSR/range

M&Hall	a	b	NSR	c	NSR/range
5X4	5396	5403	-0.00129726	12.65	-0.00010255
1X5	924.2	916.7	0.008115127	1.262	0.00643037
2X5	655.6	655.3	0.000457596	1.112	0.000411507
3X5	2E+06	1925000	0	2696	0
1X6	1088	1075	0.011948529	1.627	0.007343903
2X6	864.1	866.7	-0.00300891	0.8948	-0.003362663
3X6	1561	1510	0.032671365	0.01356	**2.409392663**
1X7	1084	972.5	0.102859779	6.811	0.015102008
2X7	404.7	405.9	-0.00296516	0.09755	-0.030396303
1X8	819.7	771.4	0.058923997	3.628	0.016241454
2X8	470.5	481.4	-0.02316684	0.1267	-0.182848017
1X9	494.1	507.1	-0.02631046	1.777	-0.014806113
2X9	373.4	373.4	0	0.09996	0

Table 6.3.6: Nugget to Sill ratios under Michaelis-menton model.

M&Hall	a	b	NSR	c	NSR/range
1X1	5136	5019	**0.022780374**	1.156	0.019706206
2X1	4079	4034	0.011032116	1.323	0.008338712
3X1	5869	5865	0.000681547	0.2511	0.002714246
4X1	3158	3104	0.01709943	1.403	0.012187762
5X1	3009	2950	0.019607843	1.299	0.015094567
6X1	29160	29160	0	-0.01141	0
7X1	2578	2577	0.000387898	-0.2224	-0.001744144
8X1	29610	29610	0	-0.00075	0
9X1	67080	67080	0	-0.0027	0
1X2	4080	4034	0.01127451	1.324	0.008515491
2X2	2919	2894	0.008564577	1.49	0.005748038
3X2	6269	6150	0.018982294	1.349	0.014071382
4X2	2763	2763	0	1.86	0
5X2	3026	3002	0.007931262	2.45	0.00323725
6X2	20520	20520	0	-0.2527	0
7X2	1696	1716	-0.01179245	-0.4147	**0.028436105**
8X2	29050	29050	0	0.06748	0
9X2	66690	66680	0.000149948	0.07648	0.001960611
1X3	2107	2123	-0.00759374	0.4308	-0.017627055
2X3	2176	2197	-0.00965074	1.085	-0.008894687
3X3	3979	3977	0.000502639	0.6354	0.000791059
4X3	9E+06	9E+06	0	13130	0
5X3	2E+06	2E+06	0	3018	0
1X4	1692	1694	-0.00118203	0.1195	-0.00989149
2X4	1617	1623	-0.00371058	0.4675	-0.007937059
3X4	3681	3678	0.000814996	0.31	0.002629019
4X4	5420	5437	-0.00313653	5.558	-0.000564327
5X4	10200	10210	-0.00098039	11.94	-8.21099E-05
1X5	1010	1004	0.005940594	0.4176	0.01422556
2X5	716.7	716.8	-0.00013953	0.2873	-0.000485654
M&Hall	a	b	NSR	c	NSR/range

M&Hall	a	b	NSR	c	NSR/range
3X5	4E+06	4E+06	0	3126	0
1X6	1220	1215	0.004098361	0.5597	0.007322424
2X6	870.8	871.1	-0.00034451	0.0655	-0.005259707
3X6	1187	1185	0.00168492	-0.3312	-0.005087319
1X7	1245	1203	0.03373494	2.39	0.014115038
2X7	390.1	390.3	-0.00051269	-0.1657	0.00309408
1X8	975.6	959.1	0.016912669	1.449	0.011671959
2X8	367.8	369.4	-0.00435019	-0.3002	0.014490974
1X9	534.2	539.6	-0.01010857	0.4878	-0.020722783
2X9	371.3	371.3	0	-0.05098	0

Table 6.3.7: Nugget to Sill ratios under VB model.

M&HALL	VB					
plot	sill(Li)	K	t0	nugget	NSR	NSR/range
1X1	4646	0.473	-0.3192	651.0741	**0.14013648**	0.296271628
2X1	3586	0.4915	-0.1807	304.7537	0.084984295	0.172908027
3X1	5626	1.58	-0.004993	44.20857	0.007857904	0.004973357
4X1	2742	0.4975	-0.1862	242.5941	0.088473398	0.177835975
5X1	2617	0.5467	-0.1522	208.9413	0.079840027	0.146039924
6X1	29260	12.24	0.0002228	-79.903	-0.00273079	-0.000223104
7X1	2770	12.74	0.0006481	-22.966	-0.00829098	-0.000650783
8X1	29620	17.42	0.0001094	-56.5021	-0.00190757	-0.000109504
9X1	67140	18.91	0.00006441	-81.8259	-0.00121874	-6.44492E-05
1X2	3585	0.4924	-0.1789	302.2939	0.084321868	0.171246685
2X2	2370	0.5907	-0.06583	90.39046	0.038139434	0.064566505
3X2	5191	0.6028	-0.1115	337.4317	0.065003226	0.107835478
4X2	2090	0.5811	-0.0149	18.01792	0.008621014	0.014835681
5X2	2250	0.4546	-0.05967	60.2131	0.026761377	0.058867965
6X2	24450	28.51	0.00001444	-10.0678	-0.00041177	-1.4443E-05
7X2	2224	9.869	-0.0002238	4.906689	0.002206245	0.000223553
8X2	28480	2.957	0.00001332	-1.12177	-3.9388E-05	-1.33203E-05
9X2	64530	3.51	-9.968E-06	2.257715	3.49871E-05	9.96783E-06
1X3	1972	1.104	0.01043	-22.8383	-0.01158127	-0.01049028
2X3	1759	0.8439	0.02192	-32.8413	-0.01867044	-0.022123997
3X3	3348	1.234	-0.002086	8.607085	0.002570814	0.002083317
4X3	26750	0.02672	0.09494	-67.9455	-0.00254002	-0.095060524
5X3	29850	0.02146	0.02236	-14.3268	-0.00047996	-0.022365366
1X4	1666	1.695	0.005441	-15.4357	-0.00926515	-0.005466167
2X4	1433	1.364	0.007807	-15.3412	-0.01070565	-0.007848715
3X4	3235	2.031	-0.001727	11.32701	0.003501393	0.001723975
4X4	2990	0.3248	0.01957	-19.066	-0.00637658	-0.019632329
5X4	5402	0.1579	0.008253	-7.0442	-0.001304	-0.00825838
1X5	925.1	1.554	-0.006247	8.93727	0.009660869	0.006216775
2X5	655.6	1.799	-0.0002148	0.253291	0.000386351	0.000214759
3X5	73800	0.01965	0.06277	-91.0833	-0.00123419	-0.062808727
1X6	1088	1.233	-0.009343	12.46175	0.011453819	0.009289391
M&HALL	VB					

M&HALL	VB					
plot	sill(Li)	K	t0	nugget	NSR	NSR/range
2X6	863.6	2.251	0.001388	-2.70244	-0.00312927	-0.001390171
3X6	1581	37.58	0.00005162	-3.06993	-0.00194176	-5.16701E-05
1X7	1086	0.2919	-0.3718	111.6914	0.102846603	**0.352335055**
2X7	434.9	88.74	0.00001443	-0.55725	-0.00128134	-1.44392E-05
1X8	820.6	0.5478	-0.1126	49.08702	0.059818446	0.109197602
2X8	454	22.14	0.00004002	-0.40244	-0.00088644	-4.00377E-05
1X9	494.8	1.106	0.02183	-12.0918	-0.02443781	-0.022095665
2X9	383.2	80.11	4.591E-06	-0.14096	-0.00036785	-4.59184E-06

The following tables present the maximum curvature values for different plot sizes and shapes and also for different models.

TABLE 6.3.8:

M&H	SPHERICAL						
plot	b	c		h	y1	y2	curvature
1X1	2443	10.85	21987.05	26506.57	-2E+09	-152093	-5.385E+22
2X1	2195	9.259	19755.04	20323.52	-1.7E+09	-168602	-2.983E+22
3X1	2223	13.22	20007.09	29388.1	-1.2E+09	-84827.7	-2.283E+22
4X1	1843	9.662	16587.06	17807.08	-9.7E+08	-109154	-8.409E+21
5X1	1727	10.62	15543.07	18340.77	-7.3E+08	-79333.7	-4.854E+21
6X1	18960	6.874	170640	130331	-1.5E+12	-2.3E+07	-1.441E+29
7X1	1342	6.932	12078.04	9302.753	-5.2E+08	-112437	-1.272E+21
8X1	20220	6.993	181980	141398.5	-1.8E+12	-2.5E+07	-2.223E+29
9X1	44130	7.125	397170	314426.3	-1.8E+13	-1.2E+08	-5.146E+31
1X2	2194	9.259	19746.04	20314.26	-1.7E+09	-168448	-2.973E+22
2X2	1871	5.092	16839.02	9527.135	-1.9E+09	-405035	-1.773E+22
3X2	4071	5.401	36639.01	21987.47	-1.9E+10	-1704414	-3.86E+24
4X2	1758	4.916	15822.02	8642.331	-1.7E+09	-383650	-1.188E+22
5X2	1850	5.512	16650.02	10197.2	-1.7E+09	-337945	-1.514E+22
6X2	26300	2.107	236700	55414.1	-1.3E+13	-4.7E+08	-4.647E+30
7X2	1718	2.591	15462	4451.338	-2.9E+09	-1318964	-1.918E+22
8X2	34200	2.85	307800	97470	-2.1E+13	-4.3E+08	-2.16E+31
9X2	75360	2.92	678240	220051.2	-2.2E+14	-2E+09	-5.318E+33
1X3	1210	6.348	10890.04	7681.088	-4.2E+08	-108998	-6.73E+20
2X3	1757	3.332	15813.01	5854.325	-2.4E+09	-834171	-1.745E+22
3X3	3225	2.536	29025	8178.6	-2E+10	-4851569	-1.61E+24
4X3	906300	1947	8156705	1.76E+09	-5.7E+14	-650030	**-2.902E+38**
5X3	559600	1351	5036404	7.56E+08	-1.9E+14	-514714	-1.431E+37
1X4	821.3	5.904	7391.747	4848.964	-1.4E+08	-58054.1	-4.803E+19
2X4	1383	3.011	12447.01	4164.214	-1.3E+09	-632913	-3.616E+21
3X4	3193	2.02	28737	6449.86	-2.4E+10	-7495772	-1.884E+24
4X4	1499	2.462	13491	3690.538	-2.1E+09	-1112112	-7.771E+21
5X4	1931	3.544	17379.01	6843.465	-3E+09	-890632	-3.178E+22
1X5	558.9	7.787	5030.221	4352.186	-3.4E+07	-15454.4	-2.461E+18
2X5	615.6	2.972	5540.416	1829.565	-1.2E+08	-128713	-1.268E+19
3X5	401100	421.6	3609900	1.69E+08	-2.3E+14	-2715347	-4.457E+36
1X6	748.9	7.802	6740.19	5842.941	-8.1E+07	-27641.3	-1.905E+19
2X6	882.9	2.64	7946.109	2330.857	-3.9E+08	-335534	-1.782E+20
3X6	1675	1.523	15075	2551.025	-4.6E+09	-3628700	-2.732E+22
1X7	1272	16.46	11448.24	20937.25	-1.9E+08	-17915.9	-3.683E+20

M&H SPHERICAL

M&H	SPHERICAL						
plot	b	c		h	y1	y2	curvature
1X8	801	11.29	7209.177	9043.357	-6.8E+07	-15100.9	-2.108E+19
2X8	610.3	1.905	5492.707	1162.622	-1.8E+08	-307906	-1.862E+19
1X9	436.5	5.297	3928.571	2312.153	-2.4E+07	-20371.9	-6.412E+17
2X9	439.9	2.128	3959.111	936.108	-6E+07	-128199	-1.685E+18

TABLE 6.3.9

M&H	EXPONENTIAL						
plot	b	c		h	y1	y2	curvature
1X1	3992	2.118	2665.505	16.7071	0.707107	-0.33386	-5.50273
2X1	3280	2.036	2278.301	15.74069	0.707107	-0.3473	-5.28968
3X1	5584	0.6303	12528.9	5.947381	0.707107	-1.12186	-1.63757
4X1	2500	2.006	1762.48	14.9938	0.707107	-0.3525	-5.21174
5X1	2408	1.831	1859.872	13.78425	0.707107	-0.38619	-4.75708
6X1	23390	0.02087	1584976	0.297942	0.707107	-33.8815	-0.05422
7X1	2882	0.104	39190.03	1.099922	0.707107	-6.7991	-0.2702
8X1	28520	0.03766	1070987	0.522875	0.707107	-18.7761	-0.09784
9X1	64490	0.07356	1239840	1.032083	0.707107	-9.61265	-0.19111
1X2	3281	2.033	2282.358	15.72112	0.707107	-0.34781	-5.28189
2X2	2279	1.689	1908.225	12.75859	0.707107	-0.41865	-4.38815
3X2	4853	1.658	4139.432	13.80834	0.707107	-0.42648	-4.30761
4X2	2072	1.719	1704.625	12.79125	0.707107	-0.41135	-4.46609
5X2	2189	2.197	1409.064	15.92975	0.707107	-0.32185	-5.70797
6X2	23790	0.03955	850673.6	0.540007	0.707107	-17.8788	-0.10275
7X2	2317	0.005829	562143.2	0.077173	0.707107	-121.308	-0.01514
8X2	28490	0.3381	119168.7	3.951813	0.707107	-2.09141	-0.87841
9X2	64530	0.285	320207.7	3.612867	0.707107	-2.48108	-0.74045
1X3	1994	0.9062	3111.832	7.288537	0.707107	-0.7803	-2.35438
2X3	1792	1.178	2151.333	9.039787	0.707107	-0.60026	-3.06053
3X3	3338	0.8092	5833.718	7.016905	0.707107	-0.87383	-2.10236
4X3	5E+06	7680	988.1081	52959.68	0.707107	-9.2E-05	**-19953.2**
5X3	810100	1302	879.9189	8827.338	0.707107	-0.00054	-3382.7
1X4	1682	0.5812	4092.752	4.833825	0.707107	-1.21663	-1.51
2X4	1448	0.7296	2806.718	5.792857	0.707107	-0.96917	-1.89556
3X4	3215	0.482	9432.981	4.411248	0.707107	-1.46703	-1.25227
4X4	3009	3.079	1382.062	22.26527	0.707107	-0.22965	-7.99948
5X4	5403	6.326	1207.872	44.89319	0.707107	-0.11178	-16.4354
1X5	916	0.6453	2007.469	4.907268	0.707107	-1.09578	-1.67654
2X5	655.3	0.5558	1667.388	4.123488	0.707107	-1.27223	-1.44401
3X5	2E+06	1348	2019.556	10259.13	0.707107	-0.00052	-3502.21
1X6	1076	0.8031	1894.775	6.06088	0.707107	-0.88047	-2.08652
2X6	865.5	0.4324	2830.717	3.436839	0.707107	-1.63531	-1.12341
3X6	1510	0.05845	36534.86	0.614077	0.707107	-12.0976	-0.15186
1X7	971.9	3.397	404.6141	20.39197	0.707107	-0.20816	-8.82566
2X7	422.9	0.08611	6945.429	0.761715	0.707107	-8.21167	-0.22372
1X8	771.4	1.815	601.0602	11.61363	0.707107	-0.38959	-4.71551
2X8	443	0.004273	146617.5	0.05083	0.707107	-165.482	-0.0111
1X9	506.9	0.9047	792.3785	6.038908	0.707107	-0.78159	-2.35048

2X9	382.7	0.07044	7683.412	0.630214	0.707107	-10.0384	-0.18301

TABLE 6.3.10

M&H	Michaelis-menton					
plot	b	c	h+ve	y1	y2	curvature
1X1	5019	1.156	75.01462	1	-0.02626	-107.72153
2X1	4034	1.323	71.73165	1	-0.02738	-103.31488
3X1	5865	0.2511	38.12469	1	-0.05212	-54.271567
4X1	3104	1.403	64.58876	1	-0.03031	-93.326438
5X1	2950	1.299	60.60455	1	-0.03231	-87.544846
6X1	29160	-0.01141	____	____	____	____
7X1	2577	-0.2224	____	____	____	____
8X1	29610	-0.00075	____	____	____	____
9X1	67080	-0.0027	____	____	____	____
1X2	4034	1.324	71.75826	1	-0.02737	-103.35392
2X2	2894	1.49	64.17628	1	-0.03046	-92.86614
3X2	6150	1.349	89.7353	1	-0.02196	-128.81265
4X2	2763	1.86	69.82807	1	-0.0279	-101.38225
5X2	3002	2.45	83.31071	1	-0.02332	-121.28396
6X2	20520	-0.2527	____	____	____	____
7X2	1716	-0.4147	____	____	____	____
8X2	29050	0.06748	44.20773	1	-0.04517	-62.614599
9X2	66680	0.07648	71.33561	1	-0.02801	-100.99194
1X3	2123	0.4308	29.81136	1	-0.06613	-42.768877
2X3	2197	1.085	47.73861	1	-0.04096	-69.047013
3X3	3977	0.6354	49.63373	1	-0.03979	-71.091291
4X3	9177000	13130	333992.5	1	-5.8E-06	**-490905.31**
5X3	1877000	3018	72246.77	1	-2.7E-05	-106440.46
1X4	1694	0.1195	14.1084	1	-0.14057	-20.121282
2X4	1623	0.4675	27.07796	1	-0.07261	-38.955167
3X4	3678	0.31	33.45655	1	-0.05923	-47.753115
4X4	5437	5.558	168.2777	1	-0.01151	-245.84079
5X4	10210	11.94	337.2124	1	-0.00573	-493.77606
1X5	1004	0.4176	20.05849	1	-0.09767	-28.957569
2X5	716.8	0.2873	14.06319	1	-0.13937	-20.294661
3X5	4465000	3126	115016.2	1	-1.7E-05	-167078.36
1X6	1215	0.5597	25.51779	1	-0.07669	-36.87914
2X6	871.1	0.0655	7.488112	1	-0.26477	-10.68242
3X6	1185	-0.3312	____	____	____	____
1X7	1203	2.39	51.23061	1	-0.0373	-75.830996
2X7	390.3	-0.1657	____	____	____	____
1X8	959.1	1.449	35.83016	1	-0.05365	-52.720696
2X8	369.4	-0.3002	____	____	____	____
1X9	539.6	0.4878	15.73616	1	-0.12327	-22.944144
2X9	371.3	-0.05098	____	____	____	____

TABLE 6.3.11

M&H	VB model						
plot	Li	K	t0	h	y1	y2	curvature
1X1	4646	0.473	-0.3192	16.68223	0.707107	-0.33446	-5.492762
2X1	3586	0.4915	-0.1807	15.73196	0.707107	-0.34754	-5.286015
3X1	5626	1.58	-0.004993	5.969154	0.707107	-1.11723	-1.644352
4X1	2742	0.4975	-0.1862	15.01954	0.707107	-0.35179	-5.222264
5X1	2617	0.5467	-0.1522	13.77226	0.707107	-0.38658	-4.752289
6X1	29260	12.24	0.0002228	1.073365	0.707107	-8.65499	-0.212261
7X1	2770	12.74	0.0006481	0.849779	0.707107	-9.00854	-0.203931
8X1	29620	17.42	0.0001094	0.775104	0.707107	-12.3178	-0.149143
9X1	67140	18.91	0.00006441	0.761609	0.707107	-13.3714	-0.137392
1X2	3585	0.4924	-0.1789	15.70783	0.707107	-0.34818	-5.276353
2X2	2370	0.5907	-0.06583	12.78464	0.707107	-0.41769	-4.398301
3X2	5191	0.6028	-0.1115	13.81532	0.707107	-0.42624	-4.310014
4X2	2090	0.5811	-0.0149	12.80331	0.707107	-0.4109	-4.470962
5X2	2250	0.4546	-0.05967	15.94764	0.707107	-0.32145	-5.715082
6X2	24450	28.51	0.00001444	0.484098	0.707107	-20.1596	-0.091129
7X2	2224	9.869	-0.0002238	1.047809	0.707107	-6.97844	-0.263256
8X2	28480	2.957	0.00001332	3.952569	0.707107	-2.09091	-0.878619
9X2	64530	3.51	-9.968E-06	3.611692	0.707107	-2.48194	-0.740193
1X3	1972	1.104	0.01043	7.28608	0.707107	-0.78065	-2.35333
2X3	1759	0.8439	0.02192	9.086209	0.707107	-0.59673	-3.078654
3X3	3348	1.234	-0.002086	7.026239	0.707107	-0.87257	-2.10541
4X3	26750	0.02672	0.09494	259.0216	0.707107	-0.01889	-97.23339
5X3	29850	0.02146	0.02236	317.308	0.707107	-0.01517	-121.066
1X4	1666	1.695	0.005441	4.897734	0.707107	-1.19855	-1.532788
2X4	1433	1.364	0.007807	5.817573	0.707107	-0.96449	-1.904748
3X4	3235	2.031	-0.001727	4.496986	0.707107	-1.43613	-1.27921
4X4	2990	0.3248	0.01957	22.2642	0.707107	-0.22967	-7.999003
5X4	5402	0.1579	0.008253	44.94369	0.707107	-0.11165	-16.45393
1X5	925.1	1.554	-0.006247	4.895495	0.707107	-1.09884	-1.671864
2X5	655.6	1.799	-0.0002148	4.123941	0.707107	-1.27209	-1.444178
3X5	73800	0.01965	0.06277	388.1549	0.707107	-0.01389	**-132.2176**
1X6	1088	1.233	-0.009343	6.112409	0.707107	-0.87186	-2.107118
2X6	863.6	2.251	0.001388	3.519406	0.707107	-1.5917	-1.154188
3X6	1581	37.58	0.00005162	0.301777	0.707107	-26.5731	-0.069135
1X7	1086	0.2919	-0.3718	20.54456	0.707107	-0.2064	-8.900569
2X7	434.9	88.74	0.00001443	0.122929	0.707107	-62.7486	-0.029277
1X8	820.6	0.5478	-0.1126	11.67047	0.707107	-0.38735	-4.742746
2X8	454	22.14	0.00004002	0.431931	0.707107	-15.6553	-0.117348
1X9	494.8	1.106	0.02183	6.035824	0.707107	-0.78206	-2.349074
2X9	383.2	80.11	4.591E-06	0.133303	0.707107	-56.6463	-0.032431
8X1	745.6	2.748	0.001286	2.902173	0.707107	-1.94313	-0.945443
9X1	7767	15.74	4.832E-06	0.766232	0.707107	-11.1299	-0.165062

Thus using the three criteria i.e. Nugget to sill ratio (NSR), NSR/Range, maximum curvature value of the variogram models we have found optimum plot size and shapes (i.e. number of units to be taken along row and column directions) for Mercer and Hall wheat grain yield data. These are summarized in the following table:

TABLE 6.3.12: Plot sizes found using the method of NSR and curvature.

Model	NSR	NSR/Range	Curvature
Michaelis-menton	1 X 1	7 X 2	4 X 3
Gaussian	1 X 1	3 X 6	-----
VB	1 X 1	1 X 7	4 X 3
Exponential	1 X 1	6 X 1	4 X 3
Spherical	3 X 1	7 X 2	3 X 5

Chapter 7

SUMMARY AND CONCLUSION

The study reveals the existence of structural heterogeneity due to which the observations vary among themselves even if other factors are controlled so that they do not cause any variability in the observations. The presence of structured heterogeneity of soil induces error in the treatment comparisons. It is known that the classical experimental design is based on the three concepts of randomization, replication and local control. Randomisation endeavors to neutralize the effects of spatial correlation and yields valid tests for the hypothesis of equal treatment effects. Here we have tried to identify and estimate the covariance and spatial correlation structure. If the correlation is present the analysis based on appropriate correlation structure is more efficient than one based on independence. The works on spatial modeling proves the need of obtaining the *a priori* information on structured heterogeneity of soil before conducting the field experiment and, also, it emphasizes the need of obtaining *a posteriori* information before analysis of the field experiment observations for inferring on the treatment comparisons more precisely. Again the distribution of several soil properties may be spatially structured. It indicates that not only on the basis of plot yield but also on the basis of soil properties heterogeneity structure and thereby the optimum plot size and shape can be studied more precisely. Hence there is further scope of studying the nature of spatial dependence on the basis of various soil properties viz. soil P^H, amount of macro and micro nutrients present in the soil, which ultimately play an important role in determining the crop yield from each plot.

The Smith's (1938) method of determining optimum plot size is based on minimizing the cost per unit of information. Following the method cost aspect has been given importance along with the average estimate of heterogeneity of the field as another determining criteria. The value of $X_{opt} = \frac{b.k_1}{(1-b).k_2}$ indicates that as the heterogeneity of the field increases, optimum plot size also increases. Again with the increase in the fixed cost (k_1) (in proportion to the variable cost (k_2)) the optimum plot size also increases accordingly. However, if the data related to the cost aspect are not available and there exist a random fertility structure in the field, still we can search for optimum plot size by observing the graph of C.V. vs. plot size using the general equation of $y = a.x^{-b}$. Here C.V. values are used to compare the nature of relative variation in two or more different types of situations. Optimum plot size is found by maximizing the radius of curvature i.e. the point when there is no further appreciable decrease in C.V. value with the increase in plot size. But the associated cost for experimentation goes up with the increase in plot size. Hence it can be said that if an experimenter primarily faces with the cost constraint Smith's optimum plot size can take care of his problem. Otherwise, it is better to go for other methods (described as above and also as below) in order to determine optimum plot size. However if there are bidirectional heterogeneity operating in the field the above mentioned general equation is modified as $y = a' x_1^{-b_1} x_2^{-b_2}$. The bidirectional fertility coefficients namely, b_1 and b_2 are then found by using least squares technique and finally optimum plot dimensions have been determined. Optimum block size has been studied by searching for minimum value of within block C.V. and highest blocking efficiency individually when blocks run along row and column directions. Thus we can also find the optimum plot and block dimensions. In the foregoing discussion the assumption of independence of the plot observations holds true. But as mentioned earlier that observations from field plots are often found to be spatially correlated. If the analysis of field plot observations show presence of spatial dependence the above mentioned methods become limited in terms of their validity. Here determination of optimum plot size by using the spatial correlation structure appears to be a better choice. It is well known that spatial dependence can be studied using the variogram analysis based on plot observations. Here optimum plot size and shape is determined by using the criteria of independence of the observations. Using the estimated values (obtained by using nonlinear estimation) of the variogram parameters, the nugget/sill ratio (**NSR**) is used as a criterion indicating the extent to which the experimental errors between plots were randomly distributed in space. The smaller the **NSR**, the less the plot configuration meets the condition that experimental errors can be considered to be random. So the largest **NSR** represents the configuration which best meets the underlying hypothesis of classical ANOVA techniques. We have also given a new approach to determine optimum plot size whereby we find the point h_{opt}. The plot size which shows maximum radius of curvature at h_{opt} is the optimum one.

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APPENDIX

```
REM Program to find v(x), vx, c.v. and heterogeneity for all
REM plot sizes and shapes
DIM Y(36, 30), V(200), PD(200), VV(200), S(200)
CLS
INPUT "GIVE NAME OF DATA FILE  : ", DF$
INPUT "GIVE NAME OF OUTPUT FILE  : ", OF$
OPEN "I", #1, DF$
OPEN "O", #2, OF$
INPUT "GIVE NO. OF ROWS & COLUMNS", R, C
P = R * C: G = 0: SS = 0
FOR I = 1 TO R
FOR J = 1 TO C
INPUT #1, Y(I, J)
```

```
G = G + Y(I, J): SS = SS + Y(I, J) ^ 2
NEXT J
NEXT I
N = 1: CF = G ^ 2 / P: VV(N) = (SS - CF) / (P - 1)
M = G / P: S(N) = 1: W = 1: L = 1
V(N) = VV(N): PD(N) = P
VV1 = SQR(VV(N))
CV = (VV1 / M) * 100
PRINT #2, "PLOT            No.of PLOT        VARIANCE"
PRINT #2, "SIZE WIDTH LENGTH PLOTS MEAN VARIANCE /SQ.MT. C.V."
PRINT #2, S(N), W, L, PD(N), M, VV(N), V(N), CV
FOR L = 1 TO 9
REM IF C / L <> C \ L GOTO 10
FOR W = 1 TO 9
IF (L = 1 AND W = 1) THEN GOTO 8
REM IF R / W <> R \ W GOTO 8
REM IF L * W > 36 THEN GOTO 8
CN = 1: YM = 0: TT = 0: N = N + 1: SM = 0: GT = 0
S(N) = L * W: PD(N) = (R \ W) * (C \ L): PJ = 1: PK = 1
FOR I = 1 TO PD(N)
T = 0
FOR J = PJ TO PJ + W - 1
FOR K = PK TO PK + L - 1
PRINT "I J K : ", I; J; K
T = T + Y(J, K)
NEXT K
NEXT J
YM = YM + (T / S(N)) ^ 2: TT = TT + T ^ 2: PJ = PJ + W: SM = SM + T / S(N)
GT = GT + T
IF I = (R \ W) * CN THEN
CN = CN + 1: PK = PK + L: PJ = 1: PRINT "PJ,PK,W : ", PJ; PK; W
END IF
NEXT I
SM = SM / PD(N): VR = YM / PD(N) - SM ^ 2: CF = GT ^ 2 / (PD(N) * S(N))
VV(N) = S(N) * (TT / S(N) - CF) / (PD(N) - 1): V(N) = VV(N) / (S(N) ^ 2)
GT = GT / PD(N): CVT = (SQR(VV(N)) / GT) * 100
5 PRINT #2, S(N), W, L, PD(N), GT, VV(N), V(N), CVT
8 NEXT W
10 NEXT L
FOR I = 1 TO N
FOR J = I + 1 TO N
IF S(I) > S(J) THEN
TEMP = S(I): TEM = VV(I): T = V(I)
S(I) = S(J): VV(I) = VV(J): V(I) = V(J)
S(J) = TEMP: VV(J) = TEM: V(J) = T
END IF
```

```
NEXT J
NEXT I
FOR I = 1 TO N
PRINT S(I); VV(I); V(I)
NEXT I
INPUT BB
K = 0: CO = LOG(V(1)): NS = 0: DS = 0: S(0) = 0: VX = VV(1)
PRINT #2, "Plot size    Var/unit area"
FOR I = 1 TO N
IF S(I) = S(I - 1) GOTO 20
T = VV(I): CT = 1: LS = LOG(VV(I)): TOT = V(I): MIN = V(I): VX = V(I)
FOR J = I + 1 TO N
IF S(I) = S(J) THEN
CT = CT + 1: T = T + VV(J): TOT = TOT + V(J): LS = LS + LOG(VV(J))
IF V(J) < MIN THEN
MIN = V(J)
END IF
END IF
NEXT J
IF VV(I) > VV(I + 1) THEN
KAM = VV(I + 1): JADA = VV(I)
ELSE
KAM = VV(I): JADA = VV(I + 1)
END IF
IF CT = 2 THEN
F = JADA / KAM: PRINT "F"; PD(N); "d.f. calc."; F: INPUT A$
IF A$ = "Y" OR A$ = "y" THEN
PRINT #2, "For plot size"; S(I); "calculated F "; PD(N); ","; PD(N); "d.f. is "; F
YV = LOG(MIN) - CO: VX = MIN
ELSE
VX = TOT / CT: YV = LOG(VX) - CO
END IF
END IF
IF CT > 2 THEN
X2 = 2.3026 * PD(N) * (CT * LOG(T / CT) - LS) / (1 + ((CT + 1) / (3 * CT * PD(N))))
DF = CT - 1
PRINT "X^2"; DF; "d.f. calc.="; X2: INPUT A$
IF A$ = "Y" OR A$ = "y" THEN
PRINT #2, "For plot size"; S(I); "calculated X2"; DF; "d.f. is "; X2
YV = LOG(MIN) - CO: VX = MIN
ELSE
VX = TOT / CT: YV = LOG(VX) - CO
END IF
END IF
PRINT #2, S(I), VX
SZ = LOG(S(I))
```

```
NS = NS + CT * SZ * YV: DS = DS + CT * SZ ^ 2
20 NEXT I
PRINT "NS = "; NS
B = -NS / DS
PRINT "Smith's index of soil heterogeneity= "; B
PRINT #2, "Smith's index of soil heterogeneity= "; B
CLOSE #1, #2
END
```

```
REM Program to find optimum plot size and shape by the method of maximum curvature.
DIM Y(36, 30), V(100), PD(100), VV(100), S(100), RW(100), CL(100), CV(100)
CLS
INPUT "GIVE NAME OF DATA FILE  : ", DF$
INPUT "GIVE NAME OF OUTPUT FILE  : ", OF$
OPEN "I", #1, DF$
OPEN "O", #2, OF$
INPUT "GIVE NO. OF DATA", N
FOR I = 1 TO N
INPUT #1, S(I), RW(I), CL(I), CV(I)
PRINT #2, S(I), RW(I), CL(I), CV(I)
NEXT I
SX = 0: SY = 0: SSX = 0: SXY = 0: ACV = 0: SX1 = 0: SX2 = 0: S1Y = 0: S2Y = 0
S12 = 0: SS1 = 0: SS2 = 0
FOR I = 1 TO N
LS = LOG(S(I)): LCV = LOG(CV(I)): LR = LOG(RW(I)): LC = LOG(CL(I))
SX = SX + LS: SY = SY + LCV: SX1 = SX1 + LR: SX2 = SX2 + LC: S1Y = S1Y + LR * LCV
S2Y = S2Y + LC * LCV: S12 = S12 + LR * LC: SSX = SSX + LS ^ 2: SXY = SXY + LS *
LCV
ACV = ACV + LCV: SS1 = SS1 + LR ^ 2: SS2 = SS2 + LC ^ 2
NEXT I
ACV = ACV / N: SX = SX / N: SY = SY / N: SX1 = SX1 / N: SX2 = SX2 / N
COV1Y = (S1Y / N - SX1 * SY): COV2Y = (S2Y / N - SX2 * SY): COV12 = S12 / N - SX1 *
SX2
V1 = SS1 / N - SX1 ^ 2: V2 = SS2 / N - SX2 ^ 2: B = -(SXY / N - SX * SY) / (SSX / N - SX ^ 2)
A = EXP(SY + B * SX): XO = ((A * B) ^ 2 * (1 + 2 * B) / (2 + B)) ^ (1 / (2 + 2 * B))
B2 = (COV1Y * COV12 - V1 * COV2Y) / (V1 * V2 - COV12 ^ 2)
B1 = -(COV1Y + B2 * COV12) / V1: A1 = EXP(SY + B1 * SX1 + B2 * SX2)
RSS = 0: RSS1 = 0: VCV = 0
FOR I = 1 TO N
RSS = RSS + (CV(I) - A / S(I) ^ B) ^ 2: RSS1 = RSS1 + (CV(I) - A1 / ((RW(I) ^ B1) * (CL(I) ^
B2))) ^ 2
VCV = VCV + (CV(I) - ACV) ^ 2
NEXT I
FIT = 1 - RSS / VCV: FIT1 = 1 - RSS1 / VCV
PRINT #2, "A,B,Xopt,FIT= ", A; B; XO; FIT
PRINT #2, "A,B1,B2,FIT= ", A1; B1; B2; FIT1
```

```
PRINT #2, "Fixed x1  conditional maxima x02  Fixed x2  Conditional maxima x01"
SR = 0: SX2 = 0: SSR = 0: SSX2 = 0: SRX2 = 0
FOR I = 1 TO N
X20 = ((B2 * A1 / (RW(I)) ^ (B1)) ^ 2 * (1 + 2 * B2) / (2 + B2)) ^ (1 / (2 + 2 * B2))
X10 = ((B1 * A1 / (CL(I)) ^ (B2)) ^ 2 * (1 + 2 * B1) / (2 + B1)) ^ (1 / (2 + 2 * B1))
LR = LOG(RW(I)): LX2 = LOG(X20): LX1 = LOG(X10)
SR = SR + LR: SX2 = SX2 + LX2: SSR = SSR + LR ^ 2: SSX2 = SSX2 + LX2 ^ 2: SRX2 =
SRX2 + LR * LX2
PRINT #2, RW(I); X20; CL(I); X10
NEXT I
SR = SR / N: SX2 = SX2 / N: B = -(SRX2 / N - SR * SX2) / (SSR / N - SR ^ 2)
A = EXP(SX2 + B * SR)
X10 = ((A * B) ^ 2 * (1 + 2 * B) / (2 + B)) ^ (1 / (2 + 2 * B)): X20 = XO / X10
PRINT #2, "A,B,X10,X20= ", A; B; X10; X20
CLOSE #1, #2
END

REM Program to find within block C.V., R.E., B.E. for different plot sizes and shapes
REM and block size when blocks run row direction.
DIM Y(36, 22), TY(36, 22)
CLS
INPUT "GIVE NAME OF DATA FILE  : ", DF$
INPUT "GIVE NAME OF OUTPUT FILES FOR CV, RE, BE : ", OF1$, OF2$, OF3$
OPEN "I", #1, DF$
OPEN "O", #2, OF1$
OPEN "O", #3, OF2$
OPEN "O", #4, OF3$
INPUT "GIVE NO. OF ROWS & COLUMNS", R, C
P = R * C: G = 0: SS = 0
FOR I = 1 TO R
FOR J = 1 TO C
INPUT #1, Y(I, J)
G = G + Y(I, J): SS = SS + Y(I, J) ^ 2
NEXT J
NEXT I
N = 1: CF = G ^ 2 / P: VV = (SS - CF) / (P - 1)
M = G / P: S = 1: W = 1: L = 1
V = VV: PD = P
VV1 = SQR(VV)
CV = (VV1 / M) * 100
PRINT #2, "TABLE: C.V. for different plots when blocks run row(E->W) direction"
PRINT #2, " "
PRINT #3, "TABLE: Relative Efficiencies for different plots when blocks run row(E->W)
direction"
PRINT #3, " "
```

```
PRINT #4, "TABLE: Blocking Efficiencies for different plots when blocks run row(E->W) direction"
PRINT #4, " "
FOR LG = 3 TO 12
PRINT #2, " "
PRINT #3, " "
PRINT #4, " "
PRINT #2, LG; "plot blocks: "
PRINT #2, "row        no. of units along column(N->S) direction"
PRINT #2, "E->W  1          2          3          4          5          6          7          8          9"
PRINT #3, LG; "plot blocks: "
PRINT #3, "row        no. of units along column(N->S) direction"
PRINT #3, "E->W  1          2          3          4          5          6          7          8          9"
PRINT #4, LG; "plot blocks: "
PRINT #4, "row        no. of units along column(N->S) direction"
PRINT #4, "E->W  1          2          3          4          5          6          7          8          9"
FOR W = 1 TO 9
PRINT #2, W;
PRINT #3, W;
PRINT #4, W;
FOR L = 1 TO 9
IF (L = 1 AND W = 1) THEN
FOR I = 1 TO R
FOR J = 1 TO C
TY(I, J) = Y(I, J)
NEXT J
NEXT I
GOTO 5
END IF
CN = 1: MT = 0: TT = 0: N = N + 1: RN = 1
S = L * W: PD = (R \ W) * (C \ L): PJ = 1: PK = 1
FOR I = 1 TO PD
T = 0
FOR J = PJ TO PJ + W - 1
FOR K = PK TO PK + L - 1
PRINT "I J K : ", I; J; K
T = T + Y(J, K)
NEXT K
NEXT J
T = T / S: PJ = PJ + W: TY(RN, CN) = T
RN = RN + 1
IF I = (R \ W) * CN THEN
RN = 1: CN = CN + 1: PK = PK + L: PJ = 1: PRINT "PJ,PK,W : ", PJ; PK; W
```

```
END IF
NEXT I
5 REM **PRINT #2, S(N); W; L; PD(N); VV(N); V(N); CV
REM Block sum of squares(blocks run in row direction)
RT = R \ W: CT = C \ L
IF LG > RT THEN
GOTO 8
END IF
PJ = 1: NR = 0: BB = 0: T = 0: SS = 0
FOR K = 1 TO CT
7 IF (PJ + LG - 1) > RT THEN
PJ = 1
GOTO 20
END IF
B = 0
FOR J = PJ TO PJ + LG - 1
B = B + TY(J, K): SS = SS + TY(J, K) ^ 2
NEXT J
B = B / LG: BB = BB + B ^ 2: T = T + B: NR = NR + 1
PJ = PJ + LG
GOTO 7
20 NEXT K
IF NR = 1 THEN
GOTO 8
END IF
T = T / NR: VB = BB / NR - T ^ 2: V = SS / (NR * LG) - T ^ 2
VAR = V - VB
PRINT "L,W,T,NR,BB, VAR= ", L, W, T, NR, BB, VAR
CV = (SQR(VAR) / T) * 100
PRINT #2, " ";
PRINT #2, USING "########.##"; CV;
IF L = 1 AND W = 1 THEN
V1 = VAR: R1 = NR
END IF
RE = (V1 / R1) / (VAR / NR)
PRINT #3, " ";
PRINT #3, USING "########.##"; RE;
BE = V / VAR
PRINT #4, " ";
PRINT #4, USING "########.##"; BE;
8 NEXT L
PRINT #2, " "
PRINT #3, " "
PRINT #4, " "
10 NEXT W
PRINT #2, " "
```

```
PRINT #2, " "
PRINT #3, " "
PRINT #3, " "
PRINT #4, " "
PRINT #4, " "
25 NEXT LG
CLOSE #1, #2, #3, #4
END

REM Program to find diagonal and off diagonal spatial correlation, M.S.E., S.T.M.S.E.
REM and Cost per unit of information matrix for uniformity data.
DIM Y(36, 18), K1(20, 20), K2(20, 20), KM(20, 20), COVP(18, 9), COVN(18, 9), COV(18, 9)
DIM ROP(18, 9), RON(18, 9), MC(18, 9), MSE(18, 9), STMSE(18, 9)
CLS
INPUT "GIVE NAME OF DATA FILE  : ", DF$
INPUT "GIVE NAME OF OUTPUT FILE  : ", OF$
OPEN "I", #1, DF$
OPEN "O", #2, OF$
INPUT "GIVE NO. OF ROWS & COLUMNS:- ", R, C
FOR I = 1 TO R
FOR J = 1 TO C
INPUT #1, Y(I, J)
NEXT J
NEXT I
M = R / 2 - 1: N = C / 2 - 1
REM Module to compute KM
FOR I = 0 TO M
FOR J = 0 TO M
K1(I, J) = 0: K2(I, J) = I + 1
NEXT J
NEXT I
FOR I = 0 TO M
K1(I, 0) = I + 1
NEXT I
FOR I = 1 TO M
FOR J = 1 TO I
K1(I, J) = 2 * (I - J + 1)
NEXT J
NEXT I
FOR I = 0 TO M
FOR J = 0 TO M
KM(I, J) = K1(I, J) / K2(I, J)
NEXT J
NEXT I
FOR I = 0 TO M
FOR J = 0 TO M
```

```
PRINT USING "##.##"; KM(I, J);
NEXT J
PRINT " "
INPUT A$
NEXT I
REM Module for computing Cov+, Cov-, R+, R-
FOR L = 0 TO M
FOR K = 0 TO N
SPP = 0: SPN = 0: SP1 = 0: SN1 = 0: SP2 = 0: SN2 = 0: SSP1 = 0
SSP2 = 0: SSN1 = 0: SSN2 = 0
FOR I = 1 TO (R - L)
FOR J = 1 TO (C - K)
SPP = SPP + Y(I, J) * Y(I + L, J + K): SPN = SPN + Y(I, J + K) * Y(I + L, J)
SP1 = SP1 + Y(I, J): SN1 = SN1 + Y(I, J + K)
SP2 = SP2 + Y(I + L, J + K): SN2 = SN2 + Y(I + L, J)
SSP1 = SSP1 + Y(I, J) ^ 2: SSN1 = SSN1 + Y(I, J + K) ^ 2
SSP2 = SSP2 + Y(I + L, J + K) ^ 2: SSN2 = SSN2 + Y(I + L, J) ^ 2
NEXT J
NEXT I
COVP(L, K) = (SPP - SP1 * SP2 / ((R - L) * (C - K))) / ((R - L) * (C - K) - 1)
COVN(L, K) = (SPN - SN1 * SN2 / ((R - L) * (C - K))) / ((R - L) * (C - K) - 1)
COV(L, K) = (COVP(L, K) + COVN(L, K)) / 2
VP1 = (SSP1 - SP1 ^ 2 / ((R - L) * (C - K))) / ((R - L) * (C - K) - 1)
VP2 = (SSP2 - SP2 ^ 2 / ((R - L) * (C - K))) / ((R - L) * (C - K) - 1)
VN1 = (SSN1 - SN1 ^ 2 / ((R - L) * (C - K))) / ((R - L) * (C - K) - 1)
VN2 = (SSN2 - SN2 ^ 2 / ((R - L) * (C - K))) / ((R - L) * (C - K) - 1)
VP = (VP1 * VP2) ^ .5: VN = (VN1 * VN2) ^ .5
ROP(L, K) = COVP(L, K) / VP: RON(L, K) = COVN(L, K) / VN
PRINT "****"
PRINT "OOOO"
NEXT K
NEXT L
PRINT #2, "Spatial correlation left=>R-(l,k)  right=>R+(l,k)"
PRINT #2, "----------------------------------------------------------------"
PRINT #2, "                              K                    "
PRINT #2, " l    ----------------------------------------------------------"
PRINT #2, "    ";
FOR K = -(C / 2) + 1 TO C / 2 - 1
PRINT #2, K;
NEXT K
PRINT #2, " "
PRINT #2, "----------------------------------------------------------------"
FOR L = 0 TO (R / 2 - 1)
PRINT #2, L;
FOR K = (C / 2 - 1) TO 0 STEP -1
PRINT #2, USING "#####.###"; RON(L, K);
```

```
NEXT K
FOR K = 1 TO (C / 2 - 1)
PRINT #2, USING "#####.###"; ROP(L, K);
NEXT K
PRINT #2, " "
NEXT L
PRINT #2, "Average Spatial correlation R(l,k)"
PRINT #2, "-----------------------------------------------------------------"
PRINT #2, "                              K                    "
PRINT #2, " l    -------------------------------------------------------"
PRINT #2, "    ";
FOR K = 0 TO C / 2 - 1
PRINT #2, K;
NEXT K
PRINT #2, " "
PRINT #2, "-----------------------------------------------------------------"
FOR L = 0 TO (R / 2 - 1)
PRINT #2, L;
PRINT #2, USING "#####.###"; RON(L, 0);
FOR K = 1 TO (C / 2 - 1)
ROA = (RON(L, K) + ROP(L, K)) / 2
PRINT #2, USING "#####.###"; ROA;
NEXT K
PRINT #2, " "
NEXT L
REM Module to find product KM*COV
FOR L = 0 TO (R / 2 - 1)
FOR K = 0 TO (C / 2 - 1)
S = 0
FOR I = 0 TO (R / 2 - 1)
S = S + KM(L, I) * COV(I, K)
NEXT I
MC(L, K) = S
NEXT K
NEXT L
REM Module to compute KN
FOR I = 0 TO N
FOR J = 0 TO N
K1(I, J) = 0: K2(I, J) = I + 1
NEXT J
NEXT I
FOR I = 0 TO N
K1(I, 0) = I + 1
NEXT I
FOR I = 1 TO N
FOR J = 1 TO I
```

```
K1(I, J) = 2 * (I - J + 1)
NEXT J
NEXT I
FOR I = 0 TO N
FOR J = 0 TO N
KM(I, J) = K1(I, J) / K2(I, J)
NEXT J
NEXT I
FOR I = 0 TO N
FOR J = I TO N
T = KM(I, J): KM(I, J) = KM(J, I): KM(J, I) = T
PRINT USING "##.##"; KM(I, J);
NEXT J
PRINT " "
INPUT A$
NEXT I
REM Module to compute MSE & STMSE
FOR L = 0 TO (R / 2 - 1)
FOR K = 0 TO (C / 2 - 1)
S = 0
FOR I = 0 TO (C / 2 - I)
S = S + MC(L, I) * KM(I, K)
NEXT I
MSE(L, K) = S: STMSE(L, K) = S / MSE(0, 0)
NEXT K
NEXT L
PRINT #2, "      MSE for plots a x c units"
PRINT #2, "---------------------------------------"
PRINT #2, "      Number of unit plots, c         "
PRINT #2, " a     -------------------------------"
PRINT #2, "      ";
FOR K = 1 TO C / 2
PRINT #2, K;
NEXT K
PRINT #2, " "
PRINT #2, "----------------------------------------------------------------"
FOR L = 0 TO R / 2 - 1
PRINT #2, L + I;
FOR K = 0 TO (C / 2 - 1)
PRINT #2, USING "#######.##"; MSE(L, K);
NEXT K
PRINT #2, " "
NEXT L
PRINT #2, "Standardised MSE for plots a x c units"
PRINT #2, "---------------------------------------"
PRINT #2, "      Number of unit plots, c         "
```

```
PRINT #2, " a     --------------------------------"
PRINT #2, "     ";
FOR K = 1 TO C / 2
PRINT #2, K;
NEXT K
PRINT #2, " "
PRINT #2, "----------------------------------------------------------------"
FOR L = 0 TO R / 2 - 1
PRINT #2, L + 1;
FOR K = 0 TO (C / 2 - 1)
PRINT #2, USING "##.###"; STMSE(L, K);
NEXT K
PRINT #2, " "
NEXT L
INPUT "GIVE COSTS K1, K2: ", C1, C2
PRINT #2, "Cost per unit of information for plots a x c units"
PRINT #2, "----------------------------------------"
PRINT #2, "      Number of unit plots, c        "
PRINT #2, " a     --------------------------------"
PRINT #2, "     ";
FOR K = 1 TO C / 2
PRINT #2, K;
NEXT K
PRINT #2, " "
PRINT #2, "----------------------------------------------------------------"
FOR L = 0 TO R / 2 - 1
PRINT #2, L + 1;
FOR K = 0 TO (C / 2 - 1)
COSTPI = (C1 + C2 * (L + 1) * (K + 1)) * MSE(L, K) / ((L + 1) * (K + 1))
PRINT #2, USING "#######.##"; COSTPI;
NEXT K
PRINT #2, " "
NEXT L
END
```