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Proceedings of the Symposium on "Statistical Models for Optimizing Nutrients Recommendations for Cropping Systems"

The symposium on Statistical Models for Optimizing Nutrients Recommendations for Cropping Systems was held during the 55th Annual Conference of the Indian Society of Agricultural Statistics at Central Institute of Agricultural Engineering and Indian Institute of Soil Science (ICAR), Nabi Bagh, Berasia Road, Bhopal-462 038 (M.P.) from January 15 to 17, 2002. The symposium was held on January 16, 2002 under the Chairmanship of Prof. Aloke Dey, Head, Indian Statistical Institute, Delhi Centre, New Delhi. Dr. V.K. Gupta, Principal Scientist & Head, Division of Design of Experiments, IASRI, New Delhi and Dr. K.N. Singh, Senior Scientist, Indian Institute of Soil Science, Bhopal were Convenors. Five papers were presented by the officers from the concerned organizations as follows

1. Soil testing programme - New perspective (A. Subba Rao, S. Srivastava and K.N. Singh)
2. Soil test nitrogen calibration for rice on Irugur series (Typic ustropept) using modified Mitscherlich's and response plateau models, a comparison (K. Alivelu, S. Srivastava, A. Subba Rao, K.N. Singh, G. Selvakumari and N.S. Raju)
3. Statistical techniques for optimizing input requirements for cropping systems (Rajender Parsad and V.K. Gupta)
4. Statistical models for optimizing nutrients recommendations for cropping systems (G. Nageswara Rao)
5. Statistical modelling of spatial variability in intercrop experiments (V.K. Bhatia and Rajender Parsad)

The presentations highlighted the problems and issues related to development of methodology, its implementation and users of statistics so generated. After detailed discussions, the following recommendations were made.

(i) To conduct studies on designing of experiments and analysis of spatial and temporal data related to soil test crop response correlations.

(ii) To develop efficient designs and analytical techniques for cropping systems research.

(iii) To develop optimization methods for obtaining optimum input requirements for cropping systems.

(iv) To strengthen interactions with the subject matter specialists.

(v) To identify data needs to support the theoretical research related to designing, modelling and optimization.

Soil Testing Programme - New Perspective

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Soil Testing helps to assess (i) nutrient supplying power of soils (ii) predict crop responses to applied plant nutrients (iii) correct soil problems like acidity, salinity and sodicity (iv) monitor the soil fertility against depletion and (v) accumulation of certain elements in toxic amounts. As fertilizer is one of the costliest inputs in agriculture, it is desired to advocate the most precise and profitable rates to farmers. The most appropriate and economic doses of fertilizers can be evolved on the basis of soil tests and crop response studies. More profitable responses to applied nutrients can be obtained by applying fertilizers where they are needed the most.

During 1956-57 the semi quantitative soil test calibrations were evolved and advocated for use. The quantitative refinements in the fertilizer recommendations based on the soil and plant analysis were made subsequently (1967-68) through the All India Coordinated Research Project for Investigations on Soil Test Crop Response Correlation (STCR). The ICAR project on soil test crop response correlation has used the targeted yield approach to develop relationship between crop yield on the one hand, and soil test estimates and fertiliser inputs, on the other. In order to tide over the management problem of conducting a field experiment at different sites, which differ from each other in the extent of uncontrolled variables, the project seeks to create artificial fertility gradients in 4 adjoining plots by applying different amounts of fertilisers to a preceding non-experimental crop. Each of the four large plots is subdivided into subplots of which 6 are control plots, and 21 receive different quantities and combinations of fertiliser nitrogen, phosphorus and potassium, in a fractional factorial design (Ramamoorthy and Velayutham [2]).

Ramamoorthy *et al.* [1] established the theoretical basis and experimental proof for the fact that Liebig's law of the minimum operates equally well for N, P and K. Among the various methods of fertiliser recommendation, the one based on yield targeting is unique in the sense that this method not only indicates soil test based fertiliser dose but also the level of yield the farmer can hope to achieve if good agronomic practices are followed in raising the crop. The essential basic data required for formulating fertiliser recommendation for targeted yield are (i) nutrient requirement in kg/q of produce, grain or other economic produce (ii) the per cent contribution from the soil available nutrients (iii) the per cent contribution from the applied fertiliser nutrients (Ramamoorthy *et al.* [1]). The above-mentioned three parameters are calculated as follows:

Nutrient Requirement of N, P and K for Grain Production

$$\text{kg of nutrient/q of grain} = \frac{\text{Total uptake of nutrient (kg)}}{\text{Grain yield (q)}}$$

Contribution of Nutrient from Soil

% Contribution from soil (CS)

$$= \frac{\text{Total uptake in control plots (kg ha}^{-1}) \times 100}{\text{Soil test values of nutrient in control plots (kg ha}^{-1})}$$

Contribution of Nutrient from Fertiliser

Contribution from Fertiliser (CF) = Total uptake of nutrients in treated plots

− (Soil test values of nutrients in fertiliser treated plots × CS)

$$\text{\% Contribution from Fertiliser} = \frac{\text{CF}}{\text{Fertiliser dose (kg ha}^{-1})} \times 100$$

Calculation of Fertiliser Dose

The above basic data are transformed into workable adjustment equation as follows

Fertiliser dose

$$= \frac{\text{Nutrient requirement in kg / q of grain}}{\text{\% CF}} \times 100\,\text{T} - \frac{\text{\%CS}}{\text{\%CF}} \times \text{Soil test value}$$

$$= \text{a constant} \times \text{yield target (q ha}^{-1}) - \text{b constant} \times \text{soil test value (kg ha}^{-1})$$

Ramamoorthy *et al.* [1] have refined the procedure of fertiliser prescription as given by Truog [5] and later extended to different crops in different soils (Randhawa and Velayutham [3]). The procedure provides a scientific basis for balanced fertilisation and balance between applied nutrients and soil available nutrients. In the targeted yield approach, it is assumed that there is a linear relationship between grain yield and nutrient uptake by the crop, as for obtaining a particular yield, a definite amount of nutrients are taken up by the plant. Once this requirement is known for a given yield level, the fertiliser needed can be estimated taking into consideration the contribution from soil available nutrients. The basic data and the targeted yield equation generated by Delhi centre for wheat crops are given in Table 1.

Table 1. The basic data and targeted yield equation for wheat crop by Delhi centre

	NR(kg q^{-1})			CS%			CF%		
	N	P_2O_5	K_2O	N	P_2O_5	K_2O	N	P_2O_5	K_2O
Basic Data	2.21	0.90	3.35	25.3	48.3	41.00	57.20	27.10	126.7
Targeted Yield Equation	$FN = 3.864T - 0.442SN$ $FP_2O_5 = 3.32T - 4.081\ SP$ $FK_2O = 2.644T - 0.388SK$								

Nutrient availability in soil after the harvest of a crop is much influenced by the initial soil nutrient status, the amount of fertilizer nutrients added and the nature of the crop raised. For soil test based fertilizer recommendations the soils are to be tested after each crop that is not practicable. Hence it has become necessary to predict the soil test values after the harvest of a crop. It is done by developing post-harvest soil test value prediction equations making use of the initial soil test values, applied fertilizer doses and the yields obtained or uptake of nutrients. Precise fertilizer schedules for pigeonpea-wheat, rice-rice-pulse and okra-sunflower crop sequences have been worked out by Delhi and Coimbatore centres. The prediction equations developed by Coimbatore centre for rice crop are given in Table 2. It is seen that the prediction equations are highly significant for all the three major nutrients for both kharif and rabi rice at Coimbatore. The fertilizer recommendations based on the prediction equations are given in Table 3.

Table 2. Prediction equations for post-harvest soil test values for kharif rice

Nutrient	R^2	Multiple regression equation
Kharif rice		
N	0.98^{**}	$PHN = -27.83 + 1.09^{**}\ SN + 0.145^{**}\ FN + 0.002RY$
P	0.95^{**}	$PHP = -0.66 + 0.975^{*}SP + 0.17^{**}FP + 0.002RY$
K	0.98^{**}	$PHK = -14.84 + 1.05^{**}SK + 0.16^{**}FK + 0.0006RY$

Table 3. Fertiliser recommendations for yield targets of rice-rice-residual pulse cropping sequence based on initial soil test values

	First crop (kharif season)						Yield target ($q\ ha^{-1}$)	Second crop (rabi season)					
	Fertiliser dose ($kg\ ha^{-1}$)			PHSTV ($kg\ ha^{-1}$)				Fertiliser dose ($q\ ha^{-1}$)			PHSTV ($kg\ ha^{-1}$)		
	N	P_2O_5	K_2O	N	P_2O_5	K_2O		N	P_2O_5	K_2O	N	P_2O_5	K_2O
40(L)	57	34	46	261	20.6	205	40	70	30	59	257	21.2	204
50(M)	106	52	81	271	23.9	211	50	114	42	95	279	26.1	212
60(H)	155	71	116	280	27.3	217	60	158	54	131	300	31.1	219

ISTV : Initial soil test value; PHSTV: Post harvest soil test value; (L): Low target; (M):Medium target and (H): High target

ISTV: $KMnO_4$ – N = 250 kg ha^{-1}; Olsen – P = 15 kg ha^{-1} and NH_4OAc – K = 200 kg ha^{-1}

In addition to the contribution of soil and fertilizer nutrients the contribution of organic manures, compost, bioculture etc., as nutrient suppliers for computing the fertilizer requirement under integrated nutrient management systems were worked out for different crops. An example is for sugarcane crop is shown in Table 4. Some of these systems tested and farmers' field conditions showed the saving in cost of fertilizer. It is observed that more than 60 kg of N + P_2O_5 + K_2O can be saved for a yield target of 40 to 60 q ha^{-1} of rice and maize under IPNS system. Different types of organic manures are tested and used at different centres depending upon their local availability and accessibility to farmers. The fertilizer recommendations emanating from these trials are published elsewhere (Subba Rao and Srivastava [4]).

Table 4. Basic data, fertiliser adjustment equations and calibrations

Centre : Coimbatore; Year : 1997; Soil : Entisol/Inceptions				
	Basic data			Fertiliser adjustment equations
	N	P_2O_5	K_2O	
NR	1.63	0.52	2.00	FN = 4.17 T – 1.09 SN – 1.11 ON
Cs	29.51	34.77	40.15	FP_2O_5 = 1.01 T – 2.56 SP –1.01 OP
Cf	34.77	52.13	74.80	FK_2O = 3.44 T – 1.08 SK – 1.03 OK
Co	30.97	35.40	50.00	

Many statistical models were evaluated at project coordinating unit, IISS, Bhopal and also at different centres of STCR to arrive at more precise and profitable rates of fertilizer application. These were linear response plateau (LRP), quadratic response plateau (QRP) and quantitative evaluation of fertility of tropical soils (QUEFTS) models.

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Soil Test Nitrogen Calibration for Rice on Irugur Series (Typic Ustropept) Using Modified Mitscherlich's and Response Plateau Models, a Comparison

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Use of right amount of nitrogenous fertilizer is fundamental for farm profitability and environmental protection. For efficient fertilizer use, it is necessary to have information on the optimum doses for a crop under different soil climatic conditions. Curve fitting techniques are often used to estimate optimal fertilizer rates, but significant problem exists in selecting a proper model for a particular soil-cropping situation. The objective of the work reported here was to compare and evaluate linear and quadratic response models with yield plateau specification (LRP and QRP) and modified Mitscherlich equation for

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rice on Irugur series (Typic Ustropept). The three models gave better fit to the data, when evaluated by R^2 statistic. Even though all the three models predicted nearly same maximum yields, the fertilization recommendations estimated by linear response plateau and quadratic response plateau models were considerably lower than that given by modified Mitcherlich's equation. Due to systematic bias the Mitscherlich model predicted larger optimal N feartilizer rate than LRP and QRP. It is suggested that the yield plateau considerations should be given a serious attention in response analysis to avoid the excess use of nitrogenous fertilizers than the actually needed. Between the plateau models the QRP based recommendations were less than those of LRP.

Introduction

Selection of the most appropriate rate of nitrogenous fertilizer is a major decision affecting the profitability of rice production and also the impact of agriculture on the environment. Fertilizer recommendations are embodied in response models, which prescribe a nitrogen dose as a function of site year chracteristics present at the time when the fertilizer recommendation decision is made. Numerous response models have been used to arrive at the optimal rate of nitrogenous fertilizer and the choice of the model will affect the predicted fertilizer rate (Cerrato and Blackmer [2], Paris [4]). Anderson and Nelson (1990) used R^2 values for choosing between different models. The objective of the work reported here was to compare and evaluate response models (Modified Mitscherlich's model, Linear-plus-plateau and Quadratic-plus-plateau) commonly used for describing crop response of rice raised on red noncalcareous (Typic Ustropept) soils to nitrogen fertilizer based on R^2 values and based on behaviour of residuals.

Material and Methods

The data was used from the field experiments at Agricultural Research Station, Bhavanisagar, Periyar district (western zone, Tamilnadu) in 1993-1994 during kharif (June-October) and rabi (November-March). The experimental field represents red noncalcarious soil of Irugur series. Modified Mitcherlichs model by Mombiela *et al.* (1981) and also used by Payton *et al.* (1989) was adopted for relating crop yields to soil and fertilizer N. This modified equation was

$$Y = A(1 - \mathrm{Exp}(-c(f(T) + x)))$$

where Y is predicted yield obtained by application of x units of N fertilizer to a soil with a N soil test value, T. The parameter A is defined as the maximum yield and c is a proportionality constant related to the efficiency of soil and fertilizer N. f (T) is a total effective nitrogen which is a linear function of T.

Linear response plateau model is defined by

$$Y = \text{Min}\ (aFN + dSN, Y_{max})$$

where Y is the yield of grain (kg/ha) and FN is the rate of N application (kg/ha), a and d are parameters of the model and SN is soil test N. Parameters are estimated by nonlinear procedure of SPSS.

Quadratic response model is defined by

$$Y = \text{Min}\ (a(FN + bSN) + d(FN + bSN)^2, Y_{max})$$

where Y is yield of grain (kg/ha), FN is the rate of N application (kg/ha), a, b and d are parameters of the model and SN is soil test value. Parameters of the model are estimated using nonlinear procedure of SPSS.

Results and Discussion

Grain yield was significantly affected by the fertilizer N in both kharif and rabi rice. The crop response pattern depicted shows that the response to fertilizer N is linear in first two fertility gradients and quadratic in third and fourth gradients. When evaluated by R^2 statistic, the three models seem to fit the yield data about equally well (Figure 1). Data show considerable disagreement among the models when they are used to identify economic optimum rates of fertilization (Table 1). The magnitude of these differences indicates a need to justify selection of one model over the other models. Models predicted maximum rice grain yield in each season, although the exponential model tended to predict slightly higher maximum yields than did the other models. The validity of this model for predicting maximum yields is because of higher predicted optimum rate. Analyses of residuals show that quadratic response plateau model fit the response data with less systematic bias than others and suggest that exponential model fit least well. Due to systematic bias, the Mitscherlich model predicted a larger optimal N fertilizer rate than did the LRP and QRP. The QRP based recommendations were lower than LRP. Soil and fertilizer nutrient efficiencies of QRP seem more logical than LRP (Patil *et al.* [5]).

Table 1. Mean predicted economic optimum rates of fertilization (kg/ha) by 3 models

Season-year	Modified Mitscherlich's	LRP	QRP
Kharif	285	180	140
Rabi	212	137	118

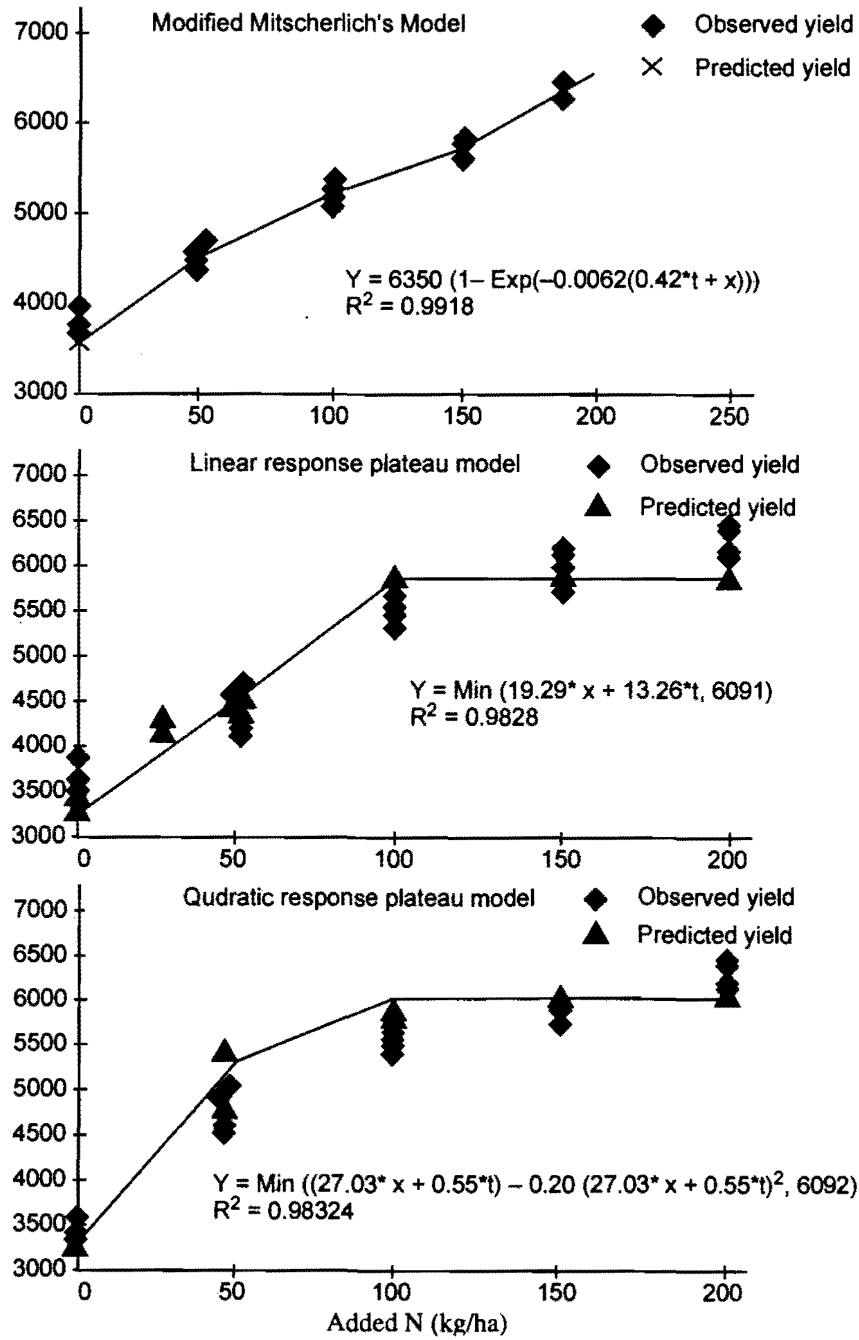

Figure 1. Example of how each of the three models fit the response data for Kharif Rice

Conclusion

These models analyses indicated that the plateau models are preferable to the Mitscherlich's model for predicting N fertilizer requirements of rice for this data set. Among Plateau models Quadratic response plateau model is preferable because of its less systematic bias and its less optimal rate for the same maximum yield. QRP predicted nearly 90 kg less than Mitscherlich's model and 40 kg less than LRP. QRP based recommendations are economical than other two models.

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Statistical Techniques for Optimizing Input Requirements for Cropping Systems

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In agriculture, there is no dearth of statistical considerations for single response variable. Broadly there are two approaches, viz., (i) designing an experiment and (ii) analytical techniques. Optimization problem is central to these researches. However, when one talks of several response variables, then both the designing problem and the analytical techniques become complicated. The optimization problem is also not easy. Of course, simplifications may be introduced by converting the several response variables into a single one in terms of total gross returns or total calories, etc. The purpose of the present talk is to address to these and related issues.

In very simple terms, growing of two or more crops on the same field in one year is multiple cropping. Intercropping is also a form of multiple cropping. Cropping patterns used on a farm and their interactions with farm are called the cropping systems. In a cropping systems research the response variable is a vector comprising of productivity of several crops of the system. The basic requirement is to maximize the vector of response variable. It is, therefore, desirable to undertake basic and applied research for developing strategies that contribute to enhance efficient cropping systems appropriate for different farming situations and agro-ecological zones.

There are two problems associated with the cropping system. The first problem is to identify the best cropping system among the class of various cropping systems and to determine the optimum nutrient requirements for that system. The other one is to develop statistical models to obtain optimum nutrient recommendations for maximizing the total production for a given cropping system. Of course, these investigations have to be region specific and would also have to be specific to the farm sizes (marginal, small, medium, large farmers).

There may be broadly two different approaches to any investigation of this kind, viz., (i) the standard method of designing experiments, (ii) the exploratory approach of identification of relevant factors vis-a-vis response surface methodology. This includes the estimation of parameters from the general linear multi-response models, the design and analysis of multi-response experiments, the testing of lack of fit, and more importantly, the simultaneous optimization of several response functions.

When designing experiments for cropping systems research one has to bear in mind that there is direct effects of treatments given to both the kharif and rabi crops. There is also the residual effect of the treatments given to kharif crop and also the interaction between the residual effect of the treatments of the kharif crop and the direct effect of the treatments of the rabi crop. Block designs with factorial structure, Kronecker product designs, etc. are very useful for these types of experimentations. Balanced confounded factorial designs for asymmetrical factorials are also useful for these experimental settings. In fact, an extended group divisible design has been recommended to a Ph.D. student of Division of Agronomy, IARI, New Delhi. There were 5 herbicidal treatments to be applied to the kharif crop and 4 herbicidal treatments to the rabi crop. The interest was to compare the direct effects of kharif and rabi treatments, residual effects of kharif treatments and interaction between the residual effects of kharif treatments and direct effects of rabi treatments. If we denote the kharif treatments as 1, 2, 3, 4, 5 and rabi treatments as a, b, c, d, then the layout of the design is given as

Block 1	1a	2a	3a	4a	5a	1b	2b	3b	4b	5b
Block 2	1a	2a	3a	4a	5a	1c	2c	3c	4c	5c
Block 3	1a	2a	3a	4a	5a	1d	2d	3d	4d	5d
Block 4	1b	2b	3b	4b	5b	1c	2c	3c	4c	5c
Block 5	1b	2b	3b	4b	5b	1d	2d	3d	4d	5d
Block 6	1c	2c	3c	4c	5c	1d	2d	3d	4d	5d

This is an extended group divisible design with 20 treatments with association scheme as

1a	1b	1c	1d
2a	2b	2c	2d
3a	3b	3c	3d
4a	4b	4c	4d
5a	5b	5c	5d

The two treatments are $(01)^{th}$ associates if first factor is at same levels i.e. in the same row, $(10)^{th}$ associates if the second factor is at same levels i.e. in the same column and rest are $(11)^{th}$ associates. As a result the parameters of the design are $v = 5 \times 4$ $(= 20)$, $b = 6$, $r = 3$, $k = 10$, $\lambda_{01} = 1$, $\lambda_{10} = 3$, $\lambda_{11} = 1$, and the efficiencies of different factorial effects as compared to the randomized complete block design are $\in(10) = 1$, $\in(01) = 2/3$, $\in(11) = 1$, respectively. Here $\in(10)$, $\in(01)$, $\in(11)$ denote respectively the efficiencies of main effect of first factor, main effect of second factor and interaction of first and second factors respectively. The extended group divisible designs are also useful for the experimental situations in which the treatments in both or any one crop have factorial structure.

Some experiments are also conducted to develop suitable integrated nutrient supply system of a crop sequence. In these experiments, the treatments do not comprise of a complete factorial structure and the experimenter is interested in estimating the residual and direct effect of the treatments along with their cumulative effects. The structurally incomplete row-column designs can give efficient block designs for such experimental situations.

There is always a temptation to analyze the data of such experimental settings as multivariate. However, if one strictly looks at the data then it does not fit into a multivariate setting. Firstly, there is incompleteness in the data. Secondly, the design matrices are not the same for all the responses. Thus, multivariate data analysis is not possible.

The optimization problem has been solved by making use of the linear programming approach. However, there is a scope to explore the possibility of using quadratic programming and dynamic programming. The linear programming approach has been illustrated for obtaining the optimum levels of various inputs that maximize the returns per hectare for given crop sequence. The experiments with mixtures methodology has also been used for analysis of data, particularly, the data generated from replacement series intercropping experiments consisting of different row ratios as treatments. The sole crop treatments have been considered as pure blends and different proportions of the two crops are treated as mixtures. The second order canonical polynomial has been fitted between the response (monetary returns) and proportions of crops. The optimum proportion of area allocated to component crops for maximizing of returns has also been obtained.

In this talk some methodological investigations have been made. This is only a partial solution. Developing statistical models using Artificial Neural Networks may be one possibility in future. Basic research needs to be carried out and the data requirements to support the basic research also need to be examined. There is a strong need to create information system to cater to the data requirements of the scientists engaged in cropping system research.

Statistical Models for Optimizing Nutrients Recommendations for Cropping Systems

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The All India Coordinated Agronomic Research Project (AICRP) has been in operation in Andhra Pradesh from 1968-69 with headquarters at Acharya N.G. Ranga Agricultural University, Rajendra Nagar, Hyderabad. This scheme operates on two types of experimentation, one conducted at research stations of the Agricultural University and the other conducted on cultivators fields in different districts. The experiments are conducted to study the production potential of intensive cropping sequences under optimum availability of inputs as well as under resource constraints. The crop sequences used are rice-wheat (Rudrur) and rice-rice sequence (Rajendra Nagar and Maruteru). For the present study, response surfaces have been fitted to establish relationship between nitrogen, phosphorus fertilizers and yield. Pooled analysis of the experiments conducted over the years at several locations has also been carried out by taking N, P & K at different levels to know the overall response of these fertilizers.

Experiments conducted to study the response pattern of crop yield to the application of fertilizer help in predicting crop yield for varying levels of fertilizer and to optimize fertilizer dose for attaining either maximum yield or maximum profit from a given unit area. It is therefore, necessary to have an efficient model, which is suitable for both prediction of yield and also optimization of chemical fertilizer. In the present study, the response pattern of different varieties of rice and sorghum to the application of nitrogen has been studied. Different statistical models such as linear, quadratic, exponential and inverse polynomials have been considered to the response of rice and sorghum yield to nitrogen fertilizer and also to find out efficient model(s) among them to obtain optimum and maximum dose.

The data for the study has been collected from All India Coordinated Research Project located at Rajendra Nagar, Hyderabad for the experiments conducted at 3 centres namely Rudrur, Maruteru and Rajendra Nagar in Andhra Pradesh. In Rudrur (kharif) N and P were found significant with respect to yield in all the 13 years. However, the response to K was found significant only in 6 years. NP, NK and PK were found to be significant in 6, 2 and 4 years respectively. NPK was found not significant in all the years. For wheat crop, N and P only were found significant in all the years. K was significant in 6 years out of 12 years. NP was significant in only 4 years. At Maruteru (kharif) center, N and P were found significant in 6 out of 12 experiments, NP was found significant in 7 out of 12 experiments. In rabi season, N was found significant in all the 13 years whereas P in 10 years and K was in 6 years. NP was significant in 8 out of 13 years. At Rajendra Nagar (kharif), N and P were found significant in all the years whereas K in 4 out of 12 years. NP, NK and PK were found significant in the last six years. In rabi season, N and P were significant in 10 out of 12 years. However, NPK was found significant in all the 12 years.

In kharif 1983-1984, 1984-1985, 1985-1986, 1986-1987, 1988-1989, and 1989-1990, the linear effects of N and P were positive indicating the increase in yield with the increase in the dose of fertilizers. NP was positive in 1985-1986, 1986-1987, 1988-1989, and 1989-1990 years whereas it was negative in 1983-1984 and 1984-1985. N^2 and P^2 were positive in 1988-89 only in rice crop. In rabi, there was positive linear effects of N and P in the years 1978-1979, 1980-1981, 1984-1985 and 1987-1988 in wheat crop.

This study was undertaken with the main objective to compare the performance of various models to explain adequately the response of rice and sorghum grain yield to nitrogen. There were 20 experiments for rice and 20 experiments for sorghum conducted by All India Coordinated Research Project on Rice and Sorghum, Hyderabad at different locations, 3 types of quadratic equations commonly used (a) Ordinary polynomials (b) Exponential polynomials and (c) Inverse polynomials were fitted. Further, the adequacy of the models were examined by residual plots. These investigations suggested ordinary polynomials were better for majority of sorghum experiments and exponential polynomials for rice experiments. However, the ordinary polynomials were over estimating optimum nitrogen levels compared to other inverse polynomials may perform better when the observations are negatively skewed.

Statistical Modelling of Spatial Variability in Intercrop Experiments

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The main objective of any agricultural field experiment is to obtain precise estimates of variety or treatments means and their contrasts. Soil fertility, soil water-holding capacity, soil physical characteristics and other environmental factors often vary across an experimental site. Good experimental design can reduce the impact of some of these factors but unless they are appropriately included in the statistical model when they occur, they will result in poor precision in estimates of variety effects and variety contrasts. The term spatial (or nearest neighbour) analysis is to refer to an analysis where one can incorporate the effect of relationship among adjacent observations into the model and investigate the variance structure of each trial for precise estimates of treatment effects. This approach does not obviate the need for good experimental design but rather increases it because once a treatment effect is confounded with an environmental effect, the two cannot be disentangled.

Spatial variability can be partly controlled by using an appropriate experimental design. Most variety trials use complete or incomplete block designs and are analyzed using the traditional analysis of variance. Block designs attempt an *a priori* reduction of the experimental error considering spatial heterogeneity among blocks. This approach does not consider the presence of spatial variability within blocks, and researchers face the problem of having to find blocks in the field that are homogeneous without knowing their most appropriate shape, dimension and orientation. When field variety trials are laid out in a rectangular array of r rows and c columns with replicates allocated contiguously, then spatial analysis can be performed with the aim of improving precision of estimates of variety effects and variety contrasts.

This appealing idea was presented as early as 1937 by Papadakis and developed by many research workers to adjust a plot for spatial variability by using information from the immediate neighbours. One useful measure for examining the heterogeneity patterns of the soil is the spatial autocorrelation of neighbouring plots within rows or within columns. That is, form the correlation between residuals at various distances apart. If there is no spatial pattern, all the correlations will be low. If there is pattern in the residuals, neighbouring residuals will be more similar and so have higher correlation. Gleeson and Cullis [2] proposed to sequentially fit a class of autoregressive-integrated-moving average models (ARIMA) to the plot errors in one direction (rows or columns). This was in the context of randomised complete block experiments. They found that differencing along the block and then fitting a moving average (MA) correlation structure to the residuals in that direction resulted in big gains in efficiency of the trial. Cullis and Gleeson [1] extended the previous model to two directions (rows and columns) assuming that, in the field, rows and columns are regularly spaced. Gilmour *et al.* [3] distinguished between global, natural and extraneous variation. For natural variation arising from unevenness of soil moisture, soil depth or other natural variation, they proposed using a separable autoregressive (AR) correlation structure, without differencing. Thus, they model the natural variation as the direct product of an AR correlation structure for columns and an AR correlation structure for rows, denoted by AR1 × AR1. Extraneous variation includes effects introduced by the experimental operations. These operations are usually aligned with rows or columns and are usually modelled with random row and column effects. Global effects include any major (non-stationary) trends across the field. These are fitted as linear trends, cubic smoothing splines, row and column contrasts and covariates.

The variogram is used by Gilmour *et al.* [3] as a major diagnostic tool for checking for the presence of extraneous variation, along with trellis plots of residuals and plots of other random effects. It is essentially the complement of the spatial autocorrelation matrix but is easier to view and interpret. If there is no pattern to the residual, the variogram is essentially flat. Pattern shows itself in that the variance of differences between residuals that are near to each other will tend to be lower than for those that are far apart from plots. In other words, strong patterns in the variogram indicate that extraneous variation is present.

Keeping these aspects of spatial patterns in mind the present study is confined to the analysis of one of the intercrop experiment to illustrate the effect of relationship among neighboring observations on the comparison of the treatments. The analysis of the data is being carried out by using ASREML software package. This package is based on the techniques of REML. The REML (Residual Maximum Likelihood) estimation method is used to estimate variance components in the context of mixed linear models. It is a useful tool for analyzing field variety trials as it allows for the fitting of spatial variability within field trials in a variety of ways. It allows for various experimental designs, multiple covariables and performs across site analysis. Under this experiment the effect of intercrop has been studied by considering two crops grown as Rabi crop Arhar of 270 days and the other Kharif crop Urad of 90 days along with continued Arhar crop. Both these crops are grown as solo crops and as well as mixture among themselves. In all 15 different combinations are formed. The experiment has been conducted in RBD with four replications and the lay out is taken as the rectangular array of 5 columns and 12 rows. For the Arhar crop the fertilizer dose of Kg per hectare is $N_{18}\ P_{46}\ K_0$ and for the Urad it is $N_{18}\ P_{46}\ K_0$, $N_9\ P_{23} K_0$, and $N_0 P_0\ K_0$. For incorporating the spatial effect, the variogram, a fundamental tool that guides us in improving the basic $AR1 \times AR1$ spatial model needs to be obtained and examined thoroughly. However, there are no formal tests or procedures associated with these displays. We formally test terms suggested by these figures using likelihood ratio tests (for random effects) and approximate F tests (for fixed effects) and limit ourselves to terms for which there is a plausible biological basis. Common terms are strong (non-stationary) trends across the experiment, edge effects and row/column effects probably induced by agronomic processes associated with conducting the trial (serpentine sowing or harvesting, unequal plot sizes, machinery effects). Second, we note that the variogram is quite smooth with strong effects, which do not have the typical $AR1 \times AR1$ appearance. In particular residuals in the same row have much less variation than residuals in the same column. i.e. there are strong row effects. This suggests there are non-stationary trends present.

There are two approaches for fitting such curvature. The traditional approach is to fit polynomials. Another approach is to use cubic smoothing splines. We prefer the latter because it is a non-parametric curve. Both models fit the same linear component. They only differ in the way the curvature component is fitted. An advantage of the spline model is that it allows for recovery of treatment information from the curvature component because it is fitted as a random effect. The quadratic model does not provide such recovery because it is fitted as a fixed effect.

The F ratio for pol(col, –2) is 5.01 ($P < 0.05$). So, after adding a quadratic trend for both rows and columns the log-likelihood is –189.61. Note that the addition of fixed effects is tested by F-ratios and not for the comparison of log-likelihood values. A cubic smoothing spline is fitted in ASREML by including the terms lin(row) !r spl(row). The lin(row) term is an alternative to pol(row, –1) which does not centre or rescale the variable fitted. The spl(row) term fits the curvature. Replacing the quadratic terms with cubic spline effects makes very little difference in this example. The cubic model may fit slightly better on the basis of the average SED (278.4 for quadratic model, 274.6 for the cubic spline model). In general, the modeling approach for spatial analysis of variety trials should be done trying, as much as possible, to include terms in the model that are related to an identifiable source of variation. Results of the different models, their Log-likelihood values, error variances and SED are given in Table 1.

Table 1. Results for various models. In the linear model random terms are bold

Linear model μ + entry	Error variance Model	Log-likelihood	Error variance	Standard error of difference
	Id × ID	−232.13	424504	532.0
+ **rep**	Id × ID	−223.48	206588	371.1
+ **rep** + **blk**	Id × ID	−221.42	133293	326.5
	AR(1) × AR(1)	−221.47	413035	296.1
+ **row**	AR(1) × AR(1)	−220.07	171003	299.5
+ pol (row, −2)	AR(1) × AR(1)	−203.69	171946	292.3
+ lin(row) + **spl(row)**	AR(1) × AR(1)	−212.51	233964	293.6
+ lin (row) + **spl(row)**	Id × ID	−213.91	148251	322.2
+ pol(row, −2) + pol(col, −2)	AR(1) × AR(1)	−189.61	126013	278.4
+ lin(row) + lin(col)	AR (1) × AR(1)	−211.56	405426	298.8
+ lin(row) + lin (col) + **spl(row)**	AR(1) × AR(1)	−208.90	172706	299.1
+ lin(row) + lin(col) + **spl(row)** + **spl(col)**	AR(1) × AR(1)	−206.84	110718	274.6
+ lin(row) + lin(col) + **spl(row)**+ **spl(col)**	Id × ID	−207.52	110699	290.1

The greatest differences are between the adjusted means of the RBD and the other models. Notice that adding the extraneous model terms to the basic AR1 × AR1 model has not greatly altered the adjusted means and that in the example the two-way spline model gives very similar adjusted means to the two-way quadratic polynomial model.

We conclude that there are highly significant row effects which are adequately fitted by including lin(row) !r spl(row) or possibly pol (row, 2) in the model. Furthermore, there is a suggestion of column effects such that similar terms fitted to columns are significant ($P < 0.05$) and so probably should be included but will have little effect on the adjusted means.

Once the row effects are in the model, the AR error correlations become non-significant and could be dropped. However, the estimated correlations are small and generally there is no loss in efficiency from leaving them in.

From the results so obtained, it has been observed that there is a need to incorporate the effect of row in the model for true comparison of treatment effects. The different ways of incorporating this effect has been illustrated. The effect of intercrop has also been studied analyzing both the crops together.

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