STATISTICAL MODELS FOR THE ASSESSMENT OF YIELD LOSS DUE TO WEEDS

By

PRIYALAKSHMI. M

THESIS

Submitted in partial fulfilment of the requirement for the degree

Master of Science in Agricultural Statistics

Faculty of Agriculture
Kerala Agricultural University

DEPARTMENT OF AGRICULTURAL STATISTICS
COLLEGE OF HORTICULTURE
VELLANIKKARA, THRISSUR
KERALA, INDIA

2002

DECLARATION

I do hereby declare that this thesis entitled **"Statistical models for the assessment of yield loss due to weeds"** is a bonafide record of research work done by me during the course of research and that this thesis has not previously formed the basis for the award to me of any degree, diploma, associateship, fellowship or other similar title of any other university or society.

College of Horticulture

Vellanikkara

Date: 09.01.02

PRIYALAKSHMI.M

(97-19-01)

Dr. P.V. Prabhakaran
Associate Dean(Retd.)

'Abhilash' TC 11/1719
Nettissery.P.O.
Thrissur

CERTIFICATE

Certified that this thesis entitled **"STATISTICAL MODELS FOR THE ASSESSMENT OF YIELD LOSS DUE TO WEEDS"** is a record of research work done independently by Mrs. Priyalakshmi.M under my guidance and supervision that it has not previously formed the basis for the award of any degree, diploma, fellowship or associateship to her.

Place : Nettissery
Date : 09-01-02

Dr. P.V. Prabhakaran
(Chairman, Advisory Committee)

CERTIFICATE

We, the undersigned members of the advisory committee of Mrs. Priyalakshmi.M, a candidate for the degree of the Master of science in Agricultural Statistics, agree that this thesis entitled **"STATISTICAL MODELS FOR THE ASSESSMENT OF YIELD LOSS DUE TO WEEDS"** may be submitted by Mrs. Priyalakshmi.M in partial fulfillment of the requirement for the degree.

Dr. P.V. Prabhakaran
(Chairman, Advisory Committee)
Associate Dean(i/c) (Retd.)
'Abhilash' TC 11 / 1719
Nettissery. P.O.
Thrissur.

Dr. C.T. Abraham
Associate Professor
AICRP on Weeds
College of Horticulture
Kerala Agricultural University
Vellanikkara.

Dr. V.K.G. Unnithan
Associate Professor
Department of Agrl. Statistics
College of Horticulture
Kerala Agricultural University
Vellanikkara

S. Krishnan

Sri. S. Krishnan
Assisstant Professor
Department of Agrl. Statistics
Colloge of Horticulture
Kerala Agricultural University
Vellanikkara

Jacob Mathew
EXTERNAL EXAMINER
Jacob Mathew
Principal Scientist (Retd)
(Statistics)
CPCRI (ICAR)
Kayamkulam

ACKNOWLDGEMENT

It is with immense pleasure that I express my deep sense of gratitude and indebtedness to Dr. P.V. Prabhakaran, Associate Dean (Retd.), College of Horticulture, Vellanikkara and chairman of my advisory committee for his meticulous guidance, keen interest, constant encouragement, ever willing help, constructive criticisms and painstaking scrutiny of the manuscript during the course of my study, without which it would have been difficult on my part to prepare this thesis. I consider myself fortunate in having the privilege of being guided by him.

I owe my debt of gratitude to Dr. V.K.G. Unnithan, Associate Professor & Head, Department of Agricultural statistics, College of Horticulture, Vellanikkara for his valuable suggestions, critical scrutiny of the manuscript and inbound support at all stages of the endeavor.

I express my sincere thanks to Dr. C.T. Abraham, Associate Professor, Department of Agronomy, College of Horticulture, Vellanikkara for his encouragement, cooperation and help rendered.

I extent my profound sense of gratitude to Sri. S. Krishnan., Assistant Professor ,Department of Agricultural statistics, College of Horticulture , Vellanikkara for his valuable suggestions and help during my periods of study.

I take this opportunity to place on record my sincere thanks to smt. T.K. Indira Bai , Smt. Graceamma Kurian, Smt. Laly John. C., Smt. P. Soudamini, Smt. T.K. Ajitha, Department of Agricultural Statistics, Dr. Mareen Abraham, Department of Plant breeding & Genetics and Dr C. George Thomas, Department of Agronomy , College of Horticulture, Vellanikkara for their suggestions and encouragement in the course of my study.

I am grateful to my classmates Sunilkumar and Sajitha for their encouragement and good wishes.

I thankfully acknowledge the cooperation, encouragement and help rendered by my colleagues in the Directorate of Research, Sobha, Rajalakshmi, Malathi, Anju, Sathiaseelan, Radhakrishnan, Fathima & Babay, Jayapradeep in the Disc, Viswanathan Nair and Sebastian in the CCF.

I express my deep respect and gratitude to the Director of Research, Dr.R.Vikraman Nair, Dr. C. Sundareswaran Nair , ADR (AR&T), Sri. P.M. Balakrishnan, Admistrative Officer, Sri Ramachandran Nair, Sri. K.F. Mathew and Sri. Sulaiman section officers in the Directorate of Research.

I am forever indebted to my husband Unnikrishnan for his constant prayers , personal sacrifices, boundless patience and unceasing encouragement which had always been my source of solace.

I duly acknowledge with full heart, incessant encouragement, moral support and timely passion by my Father, my brother Dr. Praveen and my sister Preetha.

I am Grateful to Kerala Agricultural University for the award of Research Fellowship.

Above all , I bow my head before the Lord Krishna for the success of this endeavor.

PRIYALAKSHMI. M.

Dedicated to my

beloved mother

Smt. M. Baby (Late) Section Officer, KAU

CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS

A.I.C.R.P	- All India co-ordinated research project.
A.R.S	- Agronomic research station.
Adj.	- Adjusted.
AL	- Avoidable loss.
ANOVA	- Analysis of variance.
C.O.H.	- College of Horticulture.
DAS	- Days after sowing.
Est.	- Estimated.
Expt.	- Experiment.
MLRA	- Multiple linear regression analysis.
No.	- Number.
Obsn.	- Observation.
P.C.	- Principal component.
P.C.A	- Principal component analysis.
PAL	- Percentage avoidable loss.
PTC	- Productive tiller count.
r	- Linear correlation coefficient.
R.B.D.	- Randomised block design.
S.E.	- Standard error.
T.W.P	- Total weed population.
TTC	- Total tiller count.
WDM	- Weed dry matter.

INTRODUCTION

1. INTRODUCTION

Agriculture is the major means of livelihood security for the rural population of Kerala. It continues to be the most important and single largest sector of the economy , which accounts for one-third of the state's income. However, due to various reasons agricultural production in Kerala has been almost stagnant or declining in recent years. Agricultural production depends on various factors and any setback in these factors severely affects the yield of crops. Among the various factors affecting crop production, the unwanted and undesirable plants called 'weeds' occupy a prominent position. They have been there, since we started to cultivate crops about 10,000 BC. Weeds cause considerable loss to crop yields {Dawson and Holstun (1971)}. They are plants with no economic value and are well adapted for multiplication. The dominance of weeds depends on the season, the soil, the cultural practices, the duration and the genetic architecture of the crop species.

Cultivators adopt various weed control measures to reduce weed infestation and enhance crop yield. But, the problem is to decide whether such methods are economically viable or not. For this, one basic requirement is to have an approximate idea on the degree by which a given weed infestation is likely to reduce crop yield if left uncontrolled. Models of weed-crop competition are therefore an essential part of any short or long-term economic analysis. Though several simple models to express weed-crop competition using weed density as the independent variable are available in plenty (Zimdahl, 1980), no effort has so far been made to test the adequacy of such models or to evaluate their relative efficiency under Kerala conditions. In the absence of a 'global model' to describe weed-crop competition the utility of known models has to be revalidated under specific micro environments for their applicability and adaptability. It is also desirable to develop alternative models of better adaptability for specific environments.

The simple crop yield - weed density models takes into account the interplay of none of the weeds except the one whose effect is to be investigated and hence are not useful to estimate the expected over all loss through weed infestation. Further, fitting of such models, in the strict sense, requires the generation of data from specifically designed experiments with known, prefixed densities of weed population which is beyond the purview of an ordinary experimenter and is not strictly cost effective.

As several weeds affect the crop at different stages of growth, it would be more realistic to assess crop loss by developing composite prediction models involving all major weeds simultaneously rather than restricting the study to a single weed variable at a time. Indices of weed infestation based on data at different crop growth stages are also useful for increasing the predictability of such models. The models so developed could be used for estimating the extent of yield loss due to each of the weeds and the total loss. They are also helpful in fixing priorities for weed control research and for commercial weed control operations in future years.

Although weeds affect almost every crop the loss incurred by them is not independent of the crop species. Annual crops are worsely affected by weed infestation than perennial crops. As far as the state of Kerala is concerned, rice , the staple food crop, assumes prime importance due to its role in the cultural and elusive history of Kerala. However the productivity loss of rice in Kerala is very low. Among the many factors contributing to this low productivity , weeds also have their due share by their abundance at critical stages of crop-growth.

As such it would be desirable to know how much percentage of production of rice in Kerala is lost annually by weed infestation and what are the major weeds contributing to such a loss and their relative share in total loss. The problem shall be approached either by generating data through designed experiments or by utilizing the available data from completed or ongoing trials on weed control. The present investigation utilizes the second approach, i.e. estimation of crop loss based on available data gathered from weed control trials.

Among the food crops of Kerala tapioca occupies the second position just below paddy. The acreage and production of tapioca in our state is also declining day by day. It is well known that lack of weed control measures contributes to considerable yield loss in tapioca. Hence it would be worthwhile to examine how much tuber yield of tapioca would be lost solely by weed infestation with a view to know the economic viability and adaptiveness of weed control measures on the crop. Another annual crop requiring special attention is sesamum, which is mainly cultivated in the Onattukara tract of South Kerala.

As far as the state of Kerala is concerned no systematic study involving multivariate approach on crop loss has so far been conducted to estimate yield loss in any of the agricultural crops. It would be highly rewarding to identify the major weed variables affecting the major crops of Kerala so as to assess the relative contribution of each of them towards the total loss with a view to evolve a suitable weed control strategy. It would also be desirable to get advance estimates of crop production based on observations on weed density or weed growth at critical stages of plant growth. A comparative evaluation of the existing models will be useful for the future researcher in weed control research in describing the response pattern of various kinds of weeds in relation to crop yield. A reliable estimate of the economic loss and avoidable loss due to weed infestation is also essential to know whether weed control methods are economically viable or not.

Hence the present study aims at the following objectives: -

1. Identification of suitable statistical models for assessing the effect of weeds on the yield of three important crops of Kerala *viz.*, rice, tapioca and sesamum.
2. Estimation of the overall yield loss in these three crops due to weed infestations and the assessment of the relative share of each of the different species of weeds in the overall crop loss of each crop.
3. Estimation of the avoidable loss in crop yield due to the application of herbicides or weed control measures.
4. Comparative evaluation of a set of available univariate models of crop-weed competition

   based on empirical data to know their relative efficiency and adaptability.

LIMITATIONS:

This study gives only some preliminary information on the extent of yield loss in certain specific crops by weeds. The estimates so obtained are not general but strictly specific to the crop and data generated. Extrapolation from the models could be erroneous and undesirable. The study indicates only the general trends and provides some empirical information, though scanty, on the effect of weeds on crops for which no information is presently available. Further as a preliminary work no attempt has been made in this study to furnish estimates of standard errors of crop loss and to build up non linear multiple regression models for estimating loss.

REVIEW OF LITERATURE

2. REVIEW OF LITERATURE

A lot of information has been accumulated over the years in various surveys, which demonstrates the ability of the weeds to reduce crop yields. A short review of the studies conducted by various workers is cited below:

Dew (1972) derived an index of competition which could be used to estimate crop loss due to weeds when weed and crop species, density of weed stand and expected 'weed- free yield' are known using experimental data in wheat, barley and flax. According to him, yield loss due to weeds is given by

$$L = a \times b_1 x$$

Where 'L' = Yield loss in g/m^2

'a' = expected weed free yield (g/m^2)

'x' = number of weeds per m^2

'b_1' = index of competition

The study conducted in U.S by Abernathy (1979) revealed that the losses in yield due to weeds in the absence of herbicides for corn, cotton, peanuts, sorghum, soybeans, rice and small grain including wheat were 25,40,90,35,24,70 and 20 percent respectively.

Diether *et al.* (1983) conducted field studies in 1979 and 1980 to determine yield losses caused by perennial sowthistle (*Sonchus arvensis* L.) in rapeseed (*Brassica napus* L., *B. campestris* L.) fields in Saskatchewan and Manitoba. They found that the relationship between percentage yield loss and density of perennial sowthistle could be expressed by a linear square root function.

Marra and Carlson (1983) presented a model for determination of economic thresholds or minimum weed population densities for justifying the use of post emergence herbicide treatment, in five weed species in soybeans (*Glycine max* L. Merr.) Sensitivity analysis was performed with the model utilizing economic, statistical and agronomic variables. The model was later refined to include a parameter, which represented the number of field days lost during the spraying period. Predictions from both the simple and refined models were consistent with economic theory.

Spitters (1983) introduced a simple model to estimate the degree of intra and inter specific competition and niche differentiation from final biomass data of a set of populations varying in species composition and total density. According to him biomass production was approximately linear to the uptake of that resource which limited growth, so that the distribution of the limiting resource among the plants reflected itself in their biomasses. Interplant competition was better measured by biomass than by the yield of any plant part, because dry-matter distribution within the plant varied with the competitive stress. He also used the ordinary hyperbolic equation to represent the proposed relationship.

Kropff *et al.* (1984) conducted a field experiment to study the extent of competition between a maize crop and a naturally established weed population, dominated by *Echinochloa crus-galli* (L.) P.B. (barn-yard grass). At the average *Echinochloa* density of 100 plants/m^2, the yield of maize was reduced to only 18 % of that of the weed-free control. This yield reduction strongly varied with years and the observed variation was probably related to differences between density of the crop and weed at the time of emergence. Experimental results were compared with the results of a simulation study for competition for light and water in crop-weed associations.

O'Sullivan *et al.* (1985) collected data from nine farm fields over two years to determine the relationship between percentage loss in yield of rapeseed and density of Canada thistle. Regression analyses of the data for percentage yield loss of rapeseed and numbers of thistle shoots per square metre, using two representations of the data (untransformed and square root transformed), yielded the following equations:

$$\hat{y} = -3.83 + 1.48x$$

$$\hat{y} = -18.63 + 10.42\sqrt{x}$$

where y = estimated percent loss in yield of rapeseed,

x = the number of Canada thistle shoots per square metre. The coefficients1.48 and 10.42 are the indices of competition for the above two equations respectively. The first equation provided a more accurate estimate of percent yield loss at all levels of thistle infestation.

Cousens *et al.* (1984) and Cousens (1985) showed that the loss in crop yield caused by a single species of weed could be well described by the rectangular hyperbola

$$Y_L = \frac{iD}{1 + (iD / a)}$$

Where, 'Y_L' is percentage loss in yield,

'D' is weed density,

'i' is the percentage yield loss per weed plant per unit area as weed density approaches zero

'a' is the percentage yield loss as weed density approaches infinity.

When expressed in terms of yield per unit area this equation becomes

$$Y = Y_{wf}\left[1 - \frac{iD}{100\,(1 + iD\,/\,a)}\right]$$

where Y_{wf} is weed-free yield. It is assumed in the derivation of this equation that weeds are distributed at random and that all other factors, including crop density, are held constant. It was found that this model was, on an average, a better descriptor of data than several other equations with as many parameters.

Cousens (1985) extended the hyperbolic model relating crop yield to weed density by including crop density as a further variable. The models were fitted to the data using the method of maximum likelihood estimation. Comparisons of residual sum of squares showed that the biomass yield and marketable yield could be satisfactorily described by a three-parameter model in the case of wheat and barely field experiment. If Y be the yield, a,b and f be the arbitrary parameters, C the crop density and D the weed density the model is given by

$$Y = \frac{aC}{1 + bC + fD}$$

Weaver *et al.* (1987) estimated the extent of reduction in yield of transplanted and seeded tomatoes at two locations in Southern Ontario, caused by interference from castern black nightshade and hairy nightshade . The per plant observation on dry weight and rate of seed production of nightshades decreased with increasing density. A hyperbolic model in which yield loss was expressed as a function of nightshade density provided an excellent fit to the data .

Spitters *et al.* (1989) studied yield reduction of maize in relation to the size of naturally occurring populations of *Echinochloa crus-galli* and *Chenopodium album* by conducting field experiments over two years. The competitive relations were described accurately by a model based on a hyperbolic relation between yield and plant density. The model was linearised by considering the reciprocals of the average weight per plant. The precision of estimation was improved by using logarithmic transformation of the original data.

Kropff and Spitters (1991) introduced a new simple empirical model, utilizing some additional information on weed characters for early prediction of crop loss due to weed competition. This was derived from the conventional hyperbolic yield density relationship after incorporating the necessary parameters .The model described a single relationship between crop yield loss and relative leaf area of the weeds over a wide range of weed densities and relative times of weed emergence.

Kwon *et al.* (1991) conducted an experiment to study the interference durations of red rice (*Oryza sativa*) in rice. Red rice interference for 120 days after rice emergence reduced straw dry weights of Lemont and Newbonnet (rice cultivars) by 58 and 34 % respectively. Grain yield of Lemont and Newbonnet was reduced by 86 and 52 %, respectively, by red rice interference for 120 days after emergence. Regression analyses indicated that red rice interference reduced straw dry weights of Newbonnet and Lemont 25 and 50 kg/ha/day, respectively, for interference durations of 40 to 120 days after emergence. Grain yield of

Newbonnet and Lemont was reduced by 60 and 93 kg/ha/day, respectively, for interference durations of 60 to 120 days. Negative linear relationships occurred between interference durations of red rice and plant height, panicles/m^2, spikelets/ panicle, filled grains/panicle, or panicle dry weight at harvest on yield of length of both cultivars. However, all parameters were reduced more for Lemontthan for Newbonnet as interference duration increased. Head rice (whole kernels) and total milled rice yields of both cultivars were reduced by season-long red rice interference. Red rice straw dry weight and number of culms/m^2 were greater when red rice was grown with Lemont than when grown with Newbonnet.

Donovan (1991) conducted experiments in four fields near Vegreville, Alberta in 1986 and 1988 to determine the effects of quackgrass shoot populations shortly after emergence. Hyperbolic model was successful in describing the data adequately. A pooled hyperbolic equation, based on shoot density, predicted that an intermediate quackgrass infestation of 50 to 100 shoots /m^2 would reduce canola yield by 18 to 32 %. An economic threshold model based on the hyperbolic function provided a means of estimating yield loss when control of quackgrass with herbicides was economical.

Wilson (1993) attempted to predict yield reduction in dry bean caused by wild proso millet, using rectangular hyperbola regression model. Interference of wild proso millet with dry beans was found to be curvilinear with an increase in weed density from 50 to 110 plants / m^2. He parameterized the rectangular hyperbola described by Cousens to develop a better crop loss prediction equation to estimate economic threshold.

Bahuguna *et al.* (1995) proposed a methodology based on multiple linear regression analysis for estimating crop loss due to weeds. Regression models of crop yield are then fitted on weed characters using step-wise regression technique. Indices of each weed character recorded at different periods were constructed, using the correlation coefficient of crop yield with weed characters as weights and these indices were also used as regressors in the model. Crop loss was estimated on the basis of the fitted models. Avoidable loss of crop yield through the adoption of suitable herbicidal treatments was also obtained on the basis of the differences between treated plot yield and control plot yield. The results of the study revealed that appropriate crop loss estimates could be obtained using dry matter weight of weeds recorded at 60 days after sowing. These models explained 63% variation and 57% variation in crop yield with crop loss estimates as 23.73% (SE-3.90) and 15.13% (SE-1.90) during 1984-1985 and 1985-1986 respectively. The avoidable loss was estimated as 1031kg/ ha with SE of 3.53% and 474kg /ha with SE of 8.65% for 1984-85 and 1985-86 respectively.

Prasad and Suryanarayana (1995) applied single models related to rectangular hyperbola to estimate yield loss in sprouted rice under puddled condition by weed competition They found out the best description of data during initial stages of crop growth, was provided by the model $Y_L = [A/(1+BD)]D$, $Y_L = [A/(1+B_1F_P)]$ in case of weed competition during the later stages, where D indicated the duration of weed competition in the initial stages and duration of weed free condition by F_P.

Dieleman *et al.* (1995) estimated yield loss of soybeans due to pigweed, incorporating pigweed density and time of emergence in the model, which gave the best description of yield loss, in comparison to the two relative leaf area models. Relationship between relative leaf area and soybean yield loss was best described by the one-parameter model estimating a relative damage coefficient 'q' than the two- parameter model that estimated maximum expected yield loss.

Chikoye *et al.* (1995) estimated white bean yield loss due to common ragweed using regression technique. Yield loss parameter estimates i.e., the predicted weed-free crop yield (YWF) and the maximum yield loss, varied among locations and with the time of ragweed emergence, whereas the parameter for yield loss at low weed density was more consistent across all locations and times of weed emergence.

Prabhakaran (1997) developed a modified procedure based on the multiple linear regression technique for the estimation of yield loss in black pepper in the Kannur district of Kerala. The multivariate approach provided a comprehensive estimate of yield loss due to multiple sources and was found to be more efficient and reliable than the traditional univariate procedure. Estimates of avoidable loss due to protective measures were also provided.

A slightly modified approach based on the regression of principal components was applied by Prabhakaran (1998) for estimating the losses due to pests, diseases and drought in black pepper . Stepwise regression analysis was done with the principal components as extrogeneous variables with a view to identifying the best subset of predictor components. The prediction equation consisting of three-selected components was successful in explaining 56% of variations in yield loss.

MATERIALS AND METHODS

3. MATERIALS AND METHODS

A brief account of the materials and methods used in the present investigation is given below under two major heads. 1. Method of data collection 2. Method of data analysis.

3.1 Method of data collection

3.1.a. Source of data

As is already mentioned in Chapter 1, the study is based on secondary data collected from completed field experiments conducted at College of Horticulture, Vellanikkara. The details of the experimental data utilised for the study are appended below under different subheadings. Altogether 9 sets of data pertaining to 3 crops were used for the study. The data utilised for the present investigation were collected from available records of the All India Co-ordinated Research Project (AICRP) on weed control, KAU centre at Vellanikkara, Thrissur

3.1.b Data collection

Altogether 9 sets of secondary data were utilised for the present investigation. Of these 4 sets of data pertain to rice crop, 2 sets to sesame and the remaining 3 sets to tapioca. All the sets of data were collected from the results of AICRP trials on weed control except one set which related to a PG research programme. The details of the experiments from which the above mentioned data were generated are given in Table 3.1

Table – 3.1. The details of the nine experiments

Experimental details	RICE				SESAME		TAPIOCA		
	Expt-1	Expt-2	Expt-3	Expt-4	Expt-5	Expt-6	Expt-7	Expt-8	Expt-9
Variety	Jyothi	Jyothi	Jyothi	Kanchana	Thilothama	Thilothama	Arumasakappa	Arumasakappa	Arumasakappa
Design	RBD	RBD	RBD	RBD	RBD	RBD	RBD	RBD	RBD
No.of replication	3	3	3	3	3	3	3	3	3
No. of treatments	14	16	18	8	12	12	13	13	13
Location	ARS, Chalakudy	ARS, Chalakudy	ARS, Chalakudy	COH, Vellanikkara	ARS, Chalakudy	ARS, Chalakudy	ARS, Chalakudy	ARS, Chalakudy	ARS,Chalakudy
Plot size (Net)	4.5X4.5 sq.m.	4 X4 sq.m.	4 X 4 sq.m.	3.5X3.5sq.m.	3.5X4.5sq.m.	3.5X4.5sq.m.	4.5X 3sq.m.	4.5X 3sq.m.	4.5X 3sq.m.
Year & Season	1999 Mundakan	1994 Mundakan	1985 Mundakan	1985 Mundakan	1996 Feb -May	1997 Feb –May	1992 April –May	1993 April –May	1995 April -May
Period of taking obsn.	30 DAS	60 DAS	30 ,60,90 DAS & at harvest	60 DAS	30 DAS	30 DAS	60 DAS	60 DAS	60 DAS

3. 1.c. Observation on weeds

Observations on counts of individual weeds and their dry matter production were gathered for all the experiments. In the case of experiment-4 observation on certain specific weed characters such as total number of tillers, number of productive tillers and height of the plants were also available and hence they were also utilised for the study.

3. 1.d. Recording of observation

The above observations were recorded in the following ways.

A small quadrat of size 0.5 X 0.5 m^2 was randomly selected in the experimental plot. Then the observation on population of rice plants, population of weeds, total tiller count, etc. seen in the quadrant were taken.

For getting an estimate of the dry matter production of the weeds the roots were removed from the uprooted plants and dried in the sun and then in an oven at 50^0C for 2-3 days after which dry weight was recorded and expressed in g/m^2.

The grain yield was estimated by expressing threshed, cleaned and harvested produce in kg/m^2. The straw yield was estimated by subtracting observed grain yield from the biological yield.

3.2. Analysis of data

Statistical tools used for the estimation of yield loss in this study can be broadly grouped into two categories:

i. Univariate modelling techniques

ii. Multivariate analysis

Both univariate and multivariate models were fitted for prediction of yield loss. The adequacy of the fitted models were assessed in terms of the estimated value of Coefficient of the Determination (R^2) given by,

$R^2 = \{\Sigma y^2 - \Sigma e^2\} / \Sigma y^2$,when

Σe^2 = Error Sum of Squares = $\Sigma(y - y\hat{})^2$

Σy^2 = Total Sum of Squares = $\Sigma(y - \bar{y})^2$

y = observed value ; y^ = estimated value.

3.2.1. Univariate modelling techniques

Univariate analysis of counts describing the relationship between yield loss and weed density for each specific weed was used for getting estimates of crop production in terms of the degree of weed infestation. A wide variety of models has been proposed to describe the relationship between yield loss and weed density by several research workers. The selected statistical models tried in this study are given below.

Equations	Name
1. Y= A+BX	Straight line
2. Y=BX	Straight line through origin
3. Y= 1/ (A+BX)	Reciprocal straight line
4. Y= A+BX+C/X	Linear and reciprocal
5. Y=A+B/X	Hyperbola
6. Y=X/(AX+B)	Reciprocal hyperbola
7. $Y=A+B/X+C/X^2$	Second order hyperbola
8. $Y=A+BX+CX^2$	Parabola

9. $Y=AX+BX^2$	Parabola at origin
10. $Y=AX^B$	Power function
11. $Y=AB^X$	Modified power function
12. $Y=B^{(1/X)}$	Root
13. $Y= AX^{BX}$	Super geometric
14. $Y=AX^{(B/X)}$	Modified geometric
15. $Y=Ae^{BX}$	Exponential
16. $Y=A.\ e^{(B/X)}$	Modified exponential
17. $Y=A+B\log X$	Logarithmic
18. $Y=1/(A+B\log X)$	Reciprocal logarithmic
19. $Y= AB^X X^C$	Hoerl function
20. $Y=AB^{(1/X)}X^C$	Modified Hoerl. function
21. $Y=A.e^{\{(X-B)/2\}}$	Normal
22. $Y=Ae^{\{(\ln(X)-B)^2/C\}}$	Log normal
23. $Y= AX^B(1-X)^C$	Beta
24. $Y= A(X/B)^C e^{(X/B)}$	Gamma
25. $Y=1/[A(X+B)^2+C]$	Cauchy

In this study, simple regression models, both linear and non linear, were fitted using the observations on specific weed counts, weed dry matter production, total weed population etc., as independent variables, and observations on crop yield as the dependent variable. The analysis was done using the computer software ' curve fit '.

In the case of Sacciolepis (a single-weed experiment), an attempt was also made to estimate the amount of yield loss due to the infestation of specific weeds. The observations on rice yield, height of sacciolepis, total tiller count , productive tiller count ,weed count, dry weight and wet weight of sacciolepis, etc. gathered from the relevant experiment were used for the calculation of regression coefficients. The relation between the yield of a given crop and the population density of the competing weed sacciolepis expressed in the form of a simple linear regression equation is given by, $\hat{y} = a + bx$, where ' $\hat{y}$ ' is the yield, ' x ' is a measure of the intensity of weed population, ' a ' is the predicted weed free yield and ' b ' is the regression coefficient of ' y 'on x. Using the transformed values for the independent variable, the equation becomes $y = a + b\sqrt{x}$.

Assuming a simple linear model with the obvious restriction that yield can not be less than zero, it is clear from the basic equation that as 'a' approaches zero, the value of b must also approach zero provided that 'x' remain unchanged.

An index of competition for sacciolepis in rice is useful for the estimation of crop loss when the number of sacciolepis plants per unit area is known. The index of competition , b_1 is defined as - b/a.

The predicted yield loss may be calculated using the equation,

$$L = a - \hat{y}$$

where, L = loss; a = weed free yield; $\hat{y}$ = predicted yield .

For the transformed model ,

$$\hat{y} = a + b\sqrt{x}$$

$$= a - ab_1\sqrt{x}$$

[Since $b_1 = -b/a$, $b = -ab_1$]

Therefore,

$$a - \hat{y} = \hat{L} = ab_1\sqrt{x}$$

Estimate of loss $= \hat{a}\hat{b}_1\sqrt{x}$

where b_1 is the estimate of the index of competition and 'x ' is the number of sacciolepis / m^2.

Expression of the loss in % terms is usually more convenient . The expression becomes ,

Estimate of Percentage loss = $100\, b_1\sqrt{x}$.

3.2.2. Multivariate analysis

The statistical methodology adopted for multiple linear regression analysis is described below.

Let there are 'p' variables in the multiple linear regression model to predict yield, the model is given by

$$Y_u = \beta_0 + \sum \beta_i X_{iu} + e_u$$

Where Y_u is the observed crop yield from the u^{th} plot

X_{iu} the observation on the i^{th} weed variable from the u^{th} plot.

β_0 the intercept

β_i the partial regression coefficient of Y on X_i

and e_u is the random error component which follows $N(0,\sigma^2)$

The model fitted on the sample data is represented as

$$\hat{Y}_u = b_0 + \sum b_{i1} x_{iu}$$

Where b_0 and b_i are estimators of β_0 and β_i.

The analysis of variance of multiple linear regression based on 'n' sets of observations and 'p' experimental variables is given in Table-3.2.

Table-3.2. ANOVA based on 'n' sets of observation

Source of Variation	Degrees of Freedom	Sum of Squares	Mean Squares
Due to Regression	p	$\sum_{i=1}^{p} b_i S_{xi\,y}$	$\{\Sigma\, b_i S_{xi\,y}\}/p$
Deviation from regression	n-p-1	$S_{yy} - \Sigma\, b_i S_{xi\,y}$	$\{S_{yy} - \Sigma\, b_i S_{xi\,y}\}/n\text{-}p\text{-}1 = S^2$
Total	n-1	S_{yy}	

Where S_{yy} and $S_{xi\,y}$ are corrected sum of squares and sum of products. Variation in Y explained by the regressors is obtained as

$R^2 = \Sigma\, b_i S_{xi\,y} / S_{yy}$

Multiplying equation(2) by 100 / b_0, we get

$Y' = 100 + \Sigma b_i' X_i$,

where $Y' = (Y/b_o)\,100$ and $b_i' = (b_i/b_o)100$

The estimate of crop loss in terms of percentage due to the ith regressor is obtained

$$\hat{\alpha}_i = \overline{X}_i b_i'$$

as

Where $\overline{X}_i$ is the mean of the i^{th} regressor variable.

An unbiased estimator of variance of α_i was suggested by Goodman (1960) and is given by,

$$\hat{V}(\hat{\alpha}_i) = \overline{X}_i \hat{V}(b_i') + b_i'^2 \hat{V}(\overline{X}_i) - \hat{V}(b_i')\hat{V}(\overline{X}_i)$$

where,

$$\hat{V}(b_i') = b_i'^2 \left[\frac{c_{ii} s^2}{b_i^2} + \frac{\hat{V}(b_0)}{b_0^2} - \frac{2\,\hat{cov}(b_i, b_0)}{b_i b_0} \right]$$

where c_{ij} is the (i,i)th element in the inverse of the variance-covariance matrix and s^2 is the estimated error mean squared deviation.

Estimated variance of b_0 and b_i are given by

$$\hat{V}(b_0) = \left(\frac{1}{n} + \sum_{i=1}^{p} c_{ii} \overline{X}_i^2 + \sum_{i<j} c_{ij} \overline{X}_i \overline{X}_j \right) s^2$$

$$\hat{V}(b_i) = c_{ii} s^2$$

Covariance of b_0 and b_i and b_i and b_j are given by

$$\hat{cov}(b_i, b_0) = -\left[\sum_{j=1}^{p} \overline{X}_j c_{ij} \right] s^2$$

$$\hat{cov}(b_i, b_j) = c_{ij} s^2$$

The overall percentage loss due to all weed variables is given by

$$\hat{\alpha} = \sum \hat{\alpha}_i = \sum \overline{X}_i b_i'$$

And its estimated variance is given by Khosla (1977) as

$$\hat{V}(\hat{\alpha}) = \sum \overline{X}_i^2 \hat{V}(b_i') + \sum b_i'^2 \hat{V}(\overline{X}_i) - \sum \hat{V}(b_i')\hat{V}(\overline{X}_i)$$

From this model the estimated yield loss for the control treatment (weedy check) due to the i^{th} regressor variable is obtained as

$$\hat{\alpha}_{ic} = b_i' X_{ic}$$

Where X_{ic} is the value of the control treatment.

3.2.2.1.Principal component analysis (PCA)

In the case of inter-correlated variables, in multivariate analysis, it is always profitable to concentrate on those linear combinations of variables, which are mainly responsible for the total divergence. Principal component analysis attempts in transforming a set of original variables in to a fewer number of uncorrelated latent structures which are linear combination of the original variables . The advantage of this technique lies in reducing the dimensionality of the data and the effect of multicollinearity from Muliple Linear Regression Analaysis (MLRA).

Let $X' = [x_1, x_2, \ldots\ldots x_p]$ is a p-dimensional random variable with mean vector μ and covariance matrix Σ. An estimate of Σ will be the usual sample variance-covariance matrix S. Transforming these random variables to a new set of derived variables $Z = [z_1, z_2, \ldots\ldots z_p]$ which are uncorrelated and each Z_j is taken to be a linear combination of the x_i's , so that

$$Z_j = a_{ij}\, x_1 + a_{2j}\, x_2 + \ldots\ldots\ldots + a_{pj} x_p = \sum_{i=1}^{p} a_{ij} X_i \qquad \text{or}$$

$Z = AX$, where A is the p x p matrix of weighting coefficients.

The problem is to find the linear combination which makes $V(Z_j)$ maximum subject to the condition that, $a_j' \, a_j = \Sigma a_{ij}^2 = 1$, the normalization procedure which ensures that the overall transformation is orthogonal.

The first principal component is that linear combination of the several original variables which accounts for the maximum amount of total variation and is given by, $Z_1 = a_{11}\, x_1 + a_{21}\, x_2 + \ldots\ldots\ldots + a_{p1} x_p = a_i' \, x$

So that $a_1' a_1 = 1$ and variance of Z_1 must be maximum.

The variance associated with a principal component is the characteristic root λ_i. The components are generated in decreasing order of variance.

As the principal components are linear composites of original variables, they can be used as regressors in regression analysis with a view to reduce the effect of multicollinearity. The major components contributing to predictability can be identified through step-wise regression analysis.

The yield loss due to each of the different components or factors of PCA could be estimated by using the same procedure as in the case of MLRA as described in section 3.2.2 and the total overall loss can be estimated by aggregation.

3.2.2.2. Step wise regression

It may happen in the case of multiple linear regression analysis that some of the independent variables contribute little or nothing to accuracy of prediction.

In such situations the experimenter finds it difficult to determine the order of importance of the independent variables with the available information. The solution to get a simpler prediction model with maximum degree of precision, is to regress Y on all possible subsets of independent variables and then to select that subset with maximum predictability. This can be done more effectively using SPSS statistical package. The only limitation is that when the number of independent variables is large the procedure becomes impractical . Step wise regression analysis is the most popular procedure in such circumstances which is commonly applied for model fitting. In this technique the variable first obtained with maximum R^2 and minimum error sum of squares best predicts Y and given as first variable and so on in the order of their importance , till no further variable improve the prediction of Y.

3.2.2. Estimation of avoidable loss

The avoidable loss in crop yield (AL) is estimated as $AL = y_t - y_c$, where y_t is the average yield of the treated plots and y_c is the average yield of the weedy check. The percentage avoidable loss (PAL) is calculated as per the expression suggested by Khosla (1977) given by

$$PAL = [\{y_t - y_c\}/ y_t] \times 100.$$

Adjusted coefficient of determination :

Coefficient of determination , R^2 is often informally used as goodness of fit statistic and to compare the validity of regression results under alternative specifications of the independent variables in the model . There are several problems with the use of R^2. The most important problem involved in the use of R^2 is the fact that it is sensitive to the number of independent variables included in the regression model. The addition of each independent variable automatically raise R^2 . Thus one would simply add more variables to an equation if one wished only to maximise R^2. One difficulty with R^2 is that it does not take in to account the degrees of freedom in the problem . A natural solution to this problem is to concern oneself with variances, not variations ,thus eliminating the dependence of goodness of fit on the number of independent variables in the model. Thus we define adjusted coefficeient of determination $\bar{R}^2$ as

$$\bar{R}^2 = 1 - \frac{\text{var}(\bar{e})}{\text{var}(y)}$$

where var(e) is the residual variance and var(y) is the total variance. It can be shown that

$$\bar{R}^2 = 1 - (1 - R^2)\frac{N-1}{N-K}$$

RESULTS

4. RESULTS

The data were analyzed using the methods described in chapter-3 entitled 'Materials and Methods' and the results are presented below under different subheadings.

As a first step a preliminary selection of variables was attempted on the basis of the magnitude and direction of correlation coefficient.

4.1. Experiment 1 (Crop – Rice)

4.1.1. Univariate case

Among the different weed variables counts of *Monochoria* and *Echinochola* showed relatively high negative correlation with grain yield. Weed Dry Matter (WDM) also showed high significant negative correlation (r = -0.956) with grain yield. Hence these variables were selected to serve as independent variables. in building up univariate prediction models. All the functional models described under 3.2.1. were fitted to the experimental data by using yield as the dependent variable (Y) and the relevant weed character as independent variable (X). The relative efficiencies of the models were evaluated in terms of adjusted coefficient of determination. The estimated regression equations of the selected models along with the values of coefficient of determination are given in Table 4.1.1.

In the case of *Monochoria*, none of the functional models turned out to be statistically significant.

Cauchy curve exhibited maximum predictability with regard to the other two independent variables viz., *Echinochola* and WDM with very high R^2 values. In the case of *Echinochola* the best fitted model was given by, Y=1/(0.00067{X-

$0.5208\}^2+0.3485)$ where Y = grain yield of rice per plot and X = No. of *Echinochola* per sample quadrat.

The suitable model for WDM was described by

$Y=1/(0.0001517\{X+8.037\}^2+0.3342)$

Where Y = grain yield per plot and X= Total weed dry matter production per plot.

Table-4.1.1 Selected functional model for estimating yield loss in Experiment-1

Type of weed variable	Equation	Name of Equation	R^2	R^2 (adj.)	Linear correlation coefficient (r)
Counts of Monochoria	Y= 2.974-0.0345X	Straight line	0.426	0.378	-0.65**
Counts of Echinochola	$Y=1/(0.00067\{X-0.5208\}^2+0.3485)$	Cauchy	0.872	0.861	-0.93**
WDM	$Y=1/(0.0001517\{X+8.037\}^2+0.3342)$	Cauchy	0.966	0.959	-0.95**

4.1.2. Multivariate case

Counts on two major weeds, namely , *Monochoria* (X_1), *Echinochola* (X_2) along with WDM (X_3) were used as the independent variables for multiple linear regression analysis. The estimated multiple linear regression equation was given by $Y= 2.95^* - 0.00018X_1 - 0.00493X_2 - 0.03468^*X_3$ (R^2 = 0.915**).

Where X_1= *Monochoria*, X_2 = *Echinochola* and X_3 = WDM

The relation was found to be statistically significant. It could be seen that the three independent variables contributed as much as 92% variation in grain yield .Among the three independent variables effect of WDM alone was found to be significant .. The details of estimation of loss for each of the independent variables and the total loss are given in Table-4.1.2.

Table - 4.1.2 Results of multiple linear regression analysis of Experiment 1

Independent variables	Estimate of Loss	Multiple Linear regression Equation	R^2	R^2(Adj.)
1. Monochoria(X_1)	-0.0325			
2. Echinochola(X_2)	-0.889	$Y=2.95-0.0002X_1-0.00493X_2-0.03468^*X_3$	0.915**	0.889
3. WDM (X_3)	-5.7035			
Total Est. loss	*-6.361*			

It was found that an overall loss of 6.36 % was contributed by the major weed variables in the grain yield of rice in experiment -1.

4.1.2.1. Stepwise Regression Analysis

Step wise regression analysis was attempted to isolate the best subset of predictor variables. The results of step wise regression analysis are given in table - 4.1.3.

Table 4.1.3 - Results of step wise regression analysis of Experiment 1.

Variable/s select ed	Regression estimate(b_i)	Estimate of loss	constant	S.E.(b_i)	R^2
WDM	-0.038**	6.19%	2.945	0.003	0.915**

The selected regression equation for prediction is given by

$Y = 2.945 - 0.038^{**}WDM$

The equation was successful in explaining as much as 92% variation in the grain yield of rice of experiment-1. The estimated yield loss from the above functional model was found to be 6.19%.

4.1.2.2. Principal Component Analysis (PCA)

Principal Component Analysis was attempted on the above set of three independent variables and the component loadings were extracted. The first principal component showed maximum variation (85.707) towards total variability in the data. The first two components together contributed as much as 99% of variability. The results of PCA are given in table -4.1.4.

Table-4.1.4 Results of principal component analysis of Experiment 1 The latent roots, percentage variance and cumulative variance of each component

Principal Components(PC)	Latent roots (λ_i)	% Variance	Cumulative Variance
P_1	2.571	85.707	85.707
P_2	0.401	13.371	99.078
P_3	0.028	0.922	100.00

The multiple linear regression equation fitted with the above principal components as regressors along with their standard errors (S.E.) are given in the table – 4.1.5

Table-4.1.5 Results of multiple linear regression analysis using component vectors as

regressors– Regression models and their predictability of Experiment 1

No.of PC's	R^2	R^2 (adj.)	F	Standard Error	Multiple Linear regression equation
3	0.915	0.888	35.48**	0.100	$Y=2.95-0.0239*P_1+0.0151*P_2-0.021*P_3$
2	0.890	0.864	55.62**	0.097	$Y=2.967-0.0286**P_1+0.0181*P_2$
1	0.862	0.839	73.95**	0.116	$Y=2.99-0.0293**P_1$ (SE of est. 0.116)

It could be seen that the first principal component alone was sufficient to describe the data as it explained as much as 86% variability in the data. The estimated loss using the first principal component (P_1) as the regressor was found to be 7.805%. PCA provided relatively higher estimate of loss than conventional regression technique possibly through the reduction of the effect of multicollinearity.

4.2. Experiment-2 (Crop – Rice)

4.2.1. Univariate case

Counts on *Monochoria, Schoenoplectus* and *Nymphaea* in addition to total weed population (TWP) were used as independent variables in building up univariate prediction equations. The selected regression functions for predicting yield in experiment-2 are tabulated in table - 4.2.1. None of the models tried in the study gave a satisfactorily fit to the experimental data. The fitted curves for each weed with maximum R^2 are given in the table 4.2.1.

Table –4.2.1 Selected functional models for estimating yield of rice in Experiment-2

Weed variables(X)	Equation	Name of equation	R^2	R^2 (adj)	r
Total weed population	$Y=8.37-0.9265E-02X+0.19E-04X^2$	Parabola	0.064	0.022	0.10
Counts of Schoenoplectus	Y=X/{0.1365X+0.1679E-04}	Reciprocal Hyperbola	0.106	0.086	0.18
Counts of Monochoria	$Y=0.9961.e^{\{(X-17.5)/2\}}$	Normal	0.098	0.058	0.12
Counts of Nymphaea	Y=X/{.0.1241X+0.1799E-05)	Reciprocal Hyperbola	0.085	0.065	0.19

4.2.2. Multivariate case

Counts of *Schoenoplectus* (X_1), *Sphenociea* (X_2) and *Lindernia* (X_3) together with weed dry matter (X_4) were taken as the independent variables for multiple linear regression analysis. The estimated regression equation is given by

$$Y = 2839.311^{**} + 13.7^{*} X_1 - 6.15 X_2 - 8.8 X_3 - 8.144^{**} X_4 \quad (R^2 = 0.703^{*})$$

This equation was successful in predicting grain yield of rice in experiment-2 with 70.3% accuracy. Among the four independent variables only two variables namely X_1 and X_4 alone were found to be significant. The overall loss in yield caused by the four independent variables was worked out to be 11.26%.

Table- 4.2.2 Results of multiple linear regression analysis of Experiment 2

Independent variables	Estimated loss	Multiple linear regression equation	R^2	R^2 (adj.)
1.schoenoplectus	7.279			
(X_1)	-3.242	$Y=2839.311^{**}+13.7^{*}X_1-6.15X_2$	0.703*	0.595*
2.sphenoclea (X_2)	-2.325	$- 8.8X_3 - 8.144^{**}X_4$		
3.Lindernia (X_3))	-12.995			
4.WDM (X_4)	*-11.287*			
Total Est. Loss				

4.2.2.1. Stepwise regression Analysis

Results of step-wise regression analysis is presented in table-4.2.3. Among the four predictor variables two variables viz., *Schoenoplectus* and WDM alone were turned out to be significant.

Table –4.2.3 Results of Step-wise regression analysis of Experiment 2

Variable/s Selected	Regression Estimate(b_i)	S.E(b_i)	Computed t- value	Loss(%)
1.Schoenoplectus	-8.498	3.26	-2.599*	-4.474
2.WDM	-0.484	1.23	-3.619**	-0.770

Total loss = - 5.244

Constant, a = 2849.251 Standard Error = 204.4

R^2=0.560 Adj. R^2=0.496

The selected variables are used for fitting an equation in the form,

$$Y= 2849.251 - 8.498^{*}X_1 - 0.484^{**}X_2$$

Where Y= grain yield of rice, X_1 = counts of *Schoenoplectus* and X_2 = WDM.

Results of the analysis showed that significant reduction in yield could be attributed to changes in population density of *Schoenoplectus* in different plots and total weed dry matter content. These two variables alone have contributed 56% of total variations in grain yield. It was found that population counts of *Schoenoplectus* alone was responsible for a reduction of 4.47% of the total loss in grain yield. The total loss caused by these two weed variables was estimated to be 5.3%. The analysis clearly indicated the devastating effect of *Schoenoplectus* which is a major weed causing great havoc to rice cultivars.

4.2.2.2. Principal Component Analysis

The data on the four variables used for the multiple linear regression analysis were subjected to PCA. Among the extracted principal components the first component explained 37.8% of total variability in the data. The details of the latent roots, % variance explained by each component and the cumulative variance are given in the table - 4.2.4.

Table-4.2.4 Results of principal component analysis of Experiment 2

The latent root, percentage variance and cumulative variance of each component

PC	Latent roots(α_i)	%Variance	Cumulative Variance
P_1	1.514	37.844	37.844
P_2	1.221	30.521	68.366
P_3	0.746	18.644	87.009
P_4	0.520	12.992	100.001

Multiple linear regressions analysis was conducted with the estimated principal components as exogenous variables . The results are shown in Table 4.2.5.

Table- 4.2.5. Results of multiple linear regression analysis using component vectors as regressors. – Regression models and their predictability of Experiment 2.

No.of PC's	R^2 (adj.)	R^2	F	Standard Error	Multiple linear regression equation
4	0.624	0.703	2.95	243.35	$Y=2727.43-0.616P_1+2.9*P_2-3.14*P_3-1.68P_4$
3	0.583	0.687	3.58*	233.98	$Y=2708.20+0.955*P_1+2.7*P_2-2.90*P_3$
2	0.570	0.615	1.01	287.9	$Y=2500.1021+0.526P_1+3.265P_2$
1	0.556	0.603	2.17	277.58	$Y=2502.346+0.51412P_1$

The estimated loss due to the first three principal components was found to be 17.09%.

(R^2 =0.473*).

4.3. Experiment – 3 (Crop – Rice)

4.3.1. Univariate case

Among the different weeds of rice observed in this study, *Sacciolepis* and *Isachne* are considered to be more disastrous. These weeds have also yielded significant negative correlation with yield at different stages of plant growth. The effects of other weeds were not found to be substantial. Hence these two weeds alone were considered as important in building up univariate Prediction models.

Population counts of each of the two weeds at the four stages of plant growth viz., 30 DAS, 60DAS , 90DAS and at harvest were regressed with crop yield so as to get the functional form at each stage. The adequacy of each of the functional forms was evaluated in terms of the estimated values of the coefficient of determination.

4.3.1.1. Sacciolepis count as an independent variable.

The study showed that rice yield in general depended significantly on the density of the weeds at different stages of crop growth and in most of the cases the relationship was non-linear.

The promising yield-weed density models for *Sacciolepis* at different stages of crop growth are given in Table-4.3.1

In general the predictability of the model was found to increase with the stage or duration of the crop. The coefficient of determination of the different models varied from 78.09% at 30 DAS to 85.06% at harvest.

At 30 DAS, the linear correlation coefficient was found to be -0.374 and the reciprocal straight line [Y=1/(0.804E-03+0.276E-04X)] gave the maximum predictability (R^2=78.09%). This curve was followed by the Cauchy curve.

At 60 DAS, the correlation was found to be -0.540 and the Cauchy curve [$Y=1/\{0.3464E\text{-}07(X+109.1)^2+0.6066E\text{-}03\}$] showed the maximum predictability with an R^2 value of 79.11% which was followed by the reciprocal straight line with an R^2 value of 76.60%.

At 90 DAS, the correlation was found to be -0.637 while maximum R^2(79.30%) was for Cauchy curve [$Y=1/\{0.4676E\text{-}07(X+40.81)^2+0.8118E\text{-}03\}$]. This was followed by the second order hyperbola with an R^2 value of 75.41%. However, at harvest, the correlation (-0.693) was considerably reduced and the Cauchy curve [$Y=1/\{0.1686E\text{-}06(X-63.28)^2+0.6717E\text{-}03\}$] with an R^2 value of 85.06% was adjudged to be the best fit.

Table –4.3.1. Yield loss – weed (*Sacciolepis*) density models for rice — Experiment 3

Stages of crop growth	Equation	Name of the equation	R^2	R^2 (adj.)	r
30 DAS	$Y=1/(0.804E\text{-}03+0.276E\text{-}04X)$	Reciprocal Straight line	0.781	0.767	-0.374
	$Y=1/\{-0.4617E\text{-}09(X-.3022E+05)^2+0.4223\}$	Cauchy	0.781	0.752	
60 DAS	$Y=1/\{.3464E\text{-}07(X+109.1)^2+0.6066E\text{-}03\}$	Cauchy	0.791	0.763	-0.540*
	$Y=1/(-.7756E\text{-}03+.2875E\text{-}04X)$	Reciprocal st.line	0.766	0.751	
90 DAS	$Y=1/\{.4676E\text{-}07(X+40.81)^2+0.8118E\text{-}03\}$	Cauchy	0.793	0.777	-0.637**
	$Y=-131.7+100900/X-97270/X^2$	Second order hyperbola	0.754	0.741	
Harvest	$Y=1/\{0.1686E\text{-}06(x-63.28)^2+0.6717E\text{-}03\}$	Cauchy	0.850	0.833	-0.693**

Y = Grain yield per plot, X = counts of *Sacciolepis* per sample quadrat per plot.

The results of the analysis showed that grain yield of rice could be predicted with sufficiently high degree of accuracy as early as in 30DAS on the basis of observations on counts of *Sacciolepis* in each of the different plots. The reciprocal straight line and cauchy curve were found to be useful in making early forecasts of grain yield with sufficient degree of precision.

4.3.1.2. Isachne count as an independent variable

The relations between grain yield of rice and density of *Isachne* weed at different stages of crop growth are given in table-4.3.2. The correlation between weed count and grain yield was found to be increasing up to 90 DAS and thereafter it declined. All the correlation coefficients were negative and significant.

At 30 DAS, the correlation was found to be -0.596 and Cauchy curve [$Y=1/\{0.4542E\text{-}08(X-365.6)^2-0.00192\}$] yielded maximum R^2 (51.58%). Thus it would be inferred that early estimates of crop production could be obtained from the cauchy model as early as in 30 DAS by relating rice yield with *Isachne* count.

At 60 DAS three models viz., logarithmic linear and reciprocal and second order hyperbola were found to be promising. The predictability of all these models was very high (> 80%).

The logarithmic straight line [$Y= 3699-490 \log X$] with an R^2 value of 84.17% was adjudged to be the best fit. This was followed by the linear and reciprocal model (R^2 =83.64%) and the second order hyperbola (R^2 =82.33%).

At 90 DAS, the parabola and second order hyperbola excelled all other models in describing the response pattern. The linear correlation between *Isachne* count and grain yield was found to be high and negative. The second degree parabola ($Y= 2505 - 4.495X+ 0.002261X^2$) showed the maximum predictability (R^2 = 0.843%) which was closely followed by the second order hyperbola.

At harvest, the correlation was found to be relatively low (-0.439) and was non-significant. None of the tested models succeeded in explaining the true functional relationship satisfactorily. Hence no attempt could be made for yield prediction at harvest based on isachne count.

Table – 4.3.2. Yield loss – weed*(Isachne)* density models for rice— Experiment 3

Stages	Equation	Name of equation	R^2	R^2 (adj.)	r
30 DAS	$Y=1/\{.4542E\text{-}08(X-365.6)^2-.00192\}$	Cauchy	0.573	0.516	-0.596**
60 DAS	$Y=3699-490\log X$	Logarithmic	0.856	0.842	
	$Y=664.5-.3559X+.5346E+05/X$	Linear & reciprocal	0.851	0.836	-0.780**
	$Y=181.1+1510E+06/X-.3123E+07/x^2$	Second order hyperbola	0.844	0.823	
90 DAS	$Y=2505-4.495X+.002261X^2$	Parabola	0.868	0.843	
	$Y=101.6+0.3067E+06/X-0.2296E+07/X^2$	Second order hyperbola	0.854	0.832	-0.832**
Harvest	$Y=307.6+0.1342E+06/X-0.1381E+07/X^2$	Second order hyperbola	0.490	0.480	-0.439
	$Y=2276-6.610X+0.005423X^2$	Parabola	0.447	0.420	

Where Y= Grain yield of rice, X = counts of *Isachne*

Thus, in general, the prediction equations exhibited relatively high degree of accuracy in describing the yield-weed density relationships especially, at 60 DAS and 90 DAS. But unlike in the case of *Sacciolepis*, count of *Isachne* showed a relatively feeble relationship with the yield at the time of harvest.

Hyperbolic, logarithmic and Cauchy functions were found to be promising in describing the proposed relationship between density of the specific weed (*Isachne*) and rice yield.

4.3.1.3. Total weed population (TWP) as the independent variable.

The details of the promising functional models in relating rice yield with total weed density at different stages of crop growth are given in Table – 4.3.3. The correlations between rice yield and the total weed count at different stages of crop growth except that at harvest were found to be negative and highly significant. Further these values were higher than those of the individual weed count. It shows that total weed count is a better explanatory variable than counts of specific weeds from different plots in describing the yield –weed competition in rice.

At 30 DAS, the correlation was found to be -0.562 and the Cauchy curve [$Y=1/\{0.1050E\text{-}08(X+578.03)^{2+}0.5054E\text{-}03\}$] and the reciprocal straight line yielded relatively higher R^2 values (76.85% and 73.13% respectively) when compared to other models. Hence they can be recommended for making early predictions.

At 60 DAS, the correlation was found to be -0.798 and the second order hyperbola gave the highest Adj.R^2 value (88.50%). However, the conventional hyperbolic model and the linear reciprocal models constitute other functional models with almost identical predictability.

At 90 DAS, the correlation coefficient was found to be -0.888 and the second order hyperbola ($Y=-442+1159E+03/X-7924E+04/X^2$) with an R^2 value of 84.17 % turned out to be the best choice . The parabolic model with an R^2 value of 83.51% and the linear reciprocal model with an R^2 value of 80.74% were also other useful choices.

At harvest the correlation coefficient was drastically declined to a non significant value (-0.439) which indicated that none of the tested models were successful in describing the proposed relationship. However , no effort was made to identify alternative prediction models because crop forecast at harvest would not serve any useful purpose.

Table -4.3.3. Yield loss – weed density(TWP) models for rice—Experiment 3

Stages of crop growth	Equation	Name of the equation	R^2	R^2 (adj.)	r
30 DAS	$Y=1/\{.1050E\text{-}08(X+578.03)^2 +.5054E\text{-}03\}$	Cauchy	0.796	0.769	-0.562**
	$Y=1/\{-.1253E\text{-}02+.5054E\text{-}05X\}$	Reciprocal straight line	0.747	0.731	
60 DAS	$Y=-152+657300/X-3246E+04/X^2$	Second order hyperbola	0.899	0.885	-0.798**
	$Y=197-.1305X+4353E+02/X$	Linear & reciprocal	0.895	0.881	
	$Y=-23.69+4855E+02/X$	Hyperbola	0.890	0.883	
90 DAS	$Y=-442+1159E+03/X-7924E+04/X^2$	Second order hyperbola	0.860	0.842	-0.888**
	$Y=2846-3.082X+.9157E\text{-}03X^2$	Parabola	0.855	0.835	
	$Y=1769-1.049X+8218E+05/X$	Linear & reciprocal	0.830	0.807	
Harvest	$Y=-224.3+.7842E+06/X$	Hyperbola	0.238	0.191	-0.439

Where Y=grain yield of rice , X= Weed density

4.3.1.4. Weed dry matter (WDM) as the independent variable

The relations between grain yield of rice and weed dry matter at different stages of crop growth are given in table – 4.3.4. The correlation between weed dry matter and grain yield of rice was found to be increasing up to 90 DAS and thereafter it declined.

At 30 DAS, the correlation was found to be –0.640and second order hyperbola yielded maximum R^2 (76.8%). Thus it would be inferred that early estimates of crop production could be obtained from the second order hyperbola as early as in 30 DAS by relating rice yield with WDM. At 60 DAS the same model was found to be promising.

At 90 DAS and at harvest , the parabola with an R^2 value of 87% and 46.7% respectively was adjudged to be the best fit.

Table -4.3.4. Yield loss – weed density(WDM) models for rice—Experiment 3 .

Stages of crop growth	Equation	Name of the equation	R^2	R^2 (adj.)	r
30 DAS	Y=-100.9+(0.1536E+05)/X-(0.2251E+05)/X^2	Second order hyperbola	0.795	0.768	-0.640**
60 DAS	Y=-0.1783E+02+(0.8601E+05)/X-(0.6681E+06)/X^2	Second order hyperbola	0.889	0.874	-0.741**
90 DAS	Y=0.2414E+04-5.932X+0.003986 X^2	parabloa	0.885	0.870	-0.924**
Harvest	Y=-0.3434E+04- 11.36X+0.1074E-01 X^2	Parabola	0.529	0.467	-0.560**

Where Y=grain yield of rice , X= Weed Dry Matter

4.3.2. Multivariate case

Multiple regression analysis was used to estimate the over all yield loss in rice by weed infestation when all the major weeds were taken in to consideration with or without the other related components. In addition to the counts of three major weeds viz., *Sacciolepis, Echinochola and Isachne,* two other weed variables Viz. total grass weed population and weed dry matter were also included as explanatory variables for multiple linear regression Analysis. Prediction equations were built up during the four stages of crop growth viz., 30 DAS, 60 DAS, 90 DAS and at harvest. The multiple linear regression equation and their predictability at different stages of crop growth are tabulated as in Table – 4.3.5.

At 30 DAS the four independent variables together contributed 56% variation in grain yield but the relation was not statistically significant. However a reduced model involving only two variables WDM and TWP turned out to be statistically significant. The total loss estimated from the above equation was found to be 44.24%

At 60 DAS, the multiple linear regression equation was given by, $Y = 1860.885 + 5.10\, X_1 + 16.076\, X_2 - 7.58\, X_3 + 0.862\, X_4 + 6.339\, X_5$ with an R^2 value of 0.773 which was highly significant. A reduced model with only two experimental variables viz., $Y = 1195.42 - 0.50X_1 - 0.294X_2$ estimated 22.26% loss.

At 90 DAS, the multiple linear regression equation was given by $Y = 2224.837 + 4.318^{**}X_1 + 21.13X_2 - 4.99\, X_3 + 4.44X_4 - 1.853X_5$, with an R^2 value of 0.902 which was highly significant. These variables caused 68.40% yield loss. The reduced model with only two variable is $Y = 2142.159^{**} - 0.403\, X_1 - 2.003^{**}\, X_2$ estimated 67.01% yield loss.

Table–4.3.5. Results of multiple linear regression analysis of Experiment 3 .

Stages	Independent Variables	Est. loss	Multiple linear regression equation	R^2	R^2 (adj.)
30DAS	1.Saccolepis (X_1) 2.Echinochola(X_2) 3.TGWP (X_3) 4.WDM (X_4) 5.Isachne (X_5) Total Est.loss	44.83 45.37 -317.78 -86.48 259.18 -54.87	$Y = 1525.08 + 5.938X_1 + 10.39X_2 - 5.225X_3 - 42.22X_4 + 5.51X_5$	0.560	0.377
	1. TWP (X_1) 2. WDM (X_2) Total Est.loss	43.145 -87.38 -44.24	$Y = 1259.549^{**} + 0.52X_1 - 35.2509X_2$	0.444*	0.369
60DAS	1.Saccolepis (X_1) 2.Echinochola(X_2) 3.TGWP (X_3)) 4.WDM X_4) 5.Isachne (X_5) Total Est.loss	45.30 34.12 -371.91 9.22 260.01 -23.25	$Y = 1860.885 + 5.10X_1 + 16.076X_2 - 7.58^{*}X_3 + 0.862X_4 + 6.339^{*}X_5$	0.773**	0.679
	1.TWP (X_1) 2.WDM (X_2) Total Est.loss	-8.11 -14.15 22.26	$Y = 1195.42 - 0.50X_1 - 0.294X_2$	0.476*	0.406
90DAS	1.Saccolepis (X_1) 2.Echinochola(X_2) 3.TGWP (X_3)) 4.WDM (X_4) 5.Isachne (X_5) Total Est.loss	35.44 7.46 -242.09 -40.70 171.49 -68.40	$Y = 2224.837 + 4.318^{**}X_1 + 21.13X_2 - 4.99X_3 + 4.44X_4 - 1.853X_5$	0.902**	0.862
	1.TWP (X_1) 2.WDM (X_2) Total Est.loss	-21.53 -45.69 -67.01	$Y = 2142.159^{**} - 0.403X_1 - 2.003^{*}X_2$	0.866**	0.848

4.3.2.1. Step wise regression Analysis

Reduced models with lesser number of predictor variables were developed through step wise regression analysis. The results of the stepwise regression analysis are given in Table 4.3.6. The estimated value of a regression coefficient for the relevant variables along with their standard error and computed t-values at different stages of crop growth are presented in the same table.

Table –4.3.6. Results of Step-wise regression analysis of Experiment 3 .

Crop stage	Variable/s select ed	Regression coefficient (b_i)	S.E (b_i)	Computed t- value	R^2	R^2 (adj.)	Loss(%)
30DAS	WDM	-17.94*	5.38	-3.336**	0.41	0.37	-44.2%
60DAS	Isachne	-0.968*	0.20	-4.95**	0.60	0.58	-50.95%
90DAS	WDM	-2.70*	0.28	-9.69**	0.85	0.84	-64.75%

At 30DAS, the only variable retained in the analysis was WDM whose effect was highly significant. The final form of the model developed through stepwise regression procedure is given by,

Y= 1264.39-17.94**WDM

This model explained WDM alone around as 41% variation in yield. The extent of yield loss contributed by the variable was estimated to be 44.2%.

At 60DAS, the only variable retained in the process was *Isachne* and its estimate was significant at 1% level. The empirical model generated through step wise regression analysis is given by

Y= 1440.07-0.968** ISACHNE

The above relationship described 60% of total variability in the yield. The estimated loss contributed by density of *Isachne* was 50.95%.

At 90DAS, the proposed relationship was found to be statistically significant. The estimated model is given by

Y= 2026.9-2.70**WDM

This equation explained 85% of variation in total grain yield. This shows that around 85% of variation in grain yield of rice in the above experiment could be attributed to the weed infestation at 90DAS in different plots. The estimated loss caused by the effect of WDM in different plots was obtained as 64.75%.

4.3.2.2. Principal Component Analysis

The principal component analysis was done using the five variables *viz.*, Counts of *Sacciolopis, Echinochola* and *Isachne* along with TGWP, WDM for 30DAS, 60DAS and 90DAS. The results showed (table - 4.3.7.) the shear dominance of the first principal component over others . The first principal component contributed 90.63% of total variability in the data.

Table –4.3.7 Results of principal component analysis of Experiment-3 at 30 DAS - The latent roots, percentage variance and cumulative variance of each component.

PC	Latent roots(λ_i)	% Variance of Z_i	Cumulative Variance
P_1	4.523	90.463	90.463
P_2	0.383	7.666	98.129
P_3	0.061	1.219	99.348
P_4	0.031	0.630	99.978
P_5	0.001	0.023	100.00

Multiple linear regression analysis was attempted using these PC's as independent variables. The best subset of predictor variables was identified through stepwise regression analysis. The results are presented in table-4.3.8.

Table-4.3.8 . Results of multiple linear regression analysis using component vectors as regressors– Regression models and their Predictability of Experiment 3 at 30DAS .

No.of PC's	R^2	R^2 (adj.)	F	Standard Error	Multiple linear regression equation
5	0.560	0.377	3.06	552.019	$Y=1499.53-17.799\ P_1+15.68\ P_2+11.24\ P_3-40.87\ P_4-1.82\ P_5$
4	0.497	0.342	3.21.	567.351	$Y = 1410.8138 -16.933P_1+14.974\ P_2+14.99\ P_3-35.312\ P_4$
3	0.369	0.234	2.73	612.147	$Y = 1235.61 -.055851P_1+1.1047\ P_2+10.76107P_3$
2	0..368	0.284	4.37*	591.651	$Y = 1240.30167 -0.0118P_1+1.0046P_2$
1	0.333	0.291	7.99*	588.704	$Y = 1176.2592 -0.05533P_1$*

The estimated loss due to the 1st principal component was 39.69%.

At 60 DAS , Principal Component Analysis showed (table-4.3.9.) that 1st PC contributed (82.745 %) variation towards the total variation. The estimated yield loss due to the first principal component was obtained as 48.22%.

The multiple linear regressions analysis was done using these PC's as explanatory variables and the equations obtained are shown in table – 4.3.10.

Table – 4.3.9. Results of Principal Component Analysis of Experiment 3 at 60DAS - The latent root, percentage variance and cumulative variance of each component.

PC	Latent roots	% Variance	Cumulative Variance
1	4.137	82.745	82.745
2	0.622	12.441	95.185
3	0.414	2.825	98.010
4	0.098	1.958	99.968
5	0.002	0.032	100.00

Table-4.3.10. Results of multiple linear regression analysis using component vectors as regressors – Regression models and their predictability of Experiment 3 at 60 DAS.

No.of PC's	R^2	R^2 (adj.)	F	Standard Error	Multiple linear regression equation
5	0773	0.680	3.00	420.00	$Y = 1151.+1.0143 P_1+0.8647 P_2+0.5653 P_3+1.9886 P_4+3.52 P_5$
4	0.758	0.667	3.73*	413.208	$Y = 1052.544 -1.734P_1-1.4595P_2-0.0219 P_3+4.3824 P_4$
3	0.740	0.649	4.84*	408.832	$Y = 1104.0483 - 0.267P_1+0.0179P_2+0.4514P_3$
2	0.709	0.615	7.67**	396.348	$Y = 1116.031-0.0464P_1+0.14725P_2$
1	0.683	0.591	16.27**	384.263	$Y = 1116.2879 -0.0537P_1$**

At 90 DAS, principal components analysis showed that the 1st PC contributed as much as 75.668% variation towards total variability in yield (table - 4.3.11.). Estimate of loss from linear regression analysis using the first principal component as explanatory variable is 4.822%. (R^2= 0.504**)

Table – 4.3.11 Results of Principal Component Analysis of Experiment-3 at 90DAS - The latent root, percentage variance and cumulative variance of each component.

PC	Latent roots	% Variance	Cumulative Variance
1	3.783	75.668	75.668
2	0.685	13.703	89.372
3	0.455	9.102	98.474
4	0.075	1.509	99.983
5	0.001	0.018	100.00

The multiple linear regression analysis was done using these PC's as predictor variables. The step down regression analysis indicated that the simple linear model $Y= 2059.33 - 1.088^{**} P_1$ explained 88% of variation in the data (table - 4.3.12.)

Table - 4.3.12. Results of multiple linear regression analysis using component vectors as regressors of Experiment 3 at 90 DAS.

No.of PC's	R^2	R^2 (adj.)	F	Standard Error	Multiple linear Regression Equation
5	0.902	0.862	22.16**	260.176	$Y= 2224.395+8.6587 P_1+8.6685 P_2+16.304 P_3+6.3271^* P_4+7.4278 P_5$
4	0.890	0.848	24.75**	272.43	$Y=2116.85+5.8861P_1+5.7041P_2+15.846P_3+5.2146P_4$
3	0.855	0.822	26.94**	296.10	$Y = 2054.913-3.01P_1-1.607P_2-3.5763P_3$
2	0.851	0.821	40.34**	294.77	$Y = 2062.755-1.39P_1^{**}-0.6.4P_2$
1	0.832	0.807	76.96**	299.036	$Y = 2059.38-1.088P_1^{**}$

The correlation of the 1st PC with grain yield was found to be -0.910. The estimated loss obtained from the equation $Y = 2059.38-1.088P_1^{**}$ was 65.713%.

4.4. Experiment – 4 (Crop – Rice)

4.4.1. Univariate case

In this experiment, density of *Sacciolepis* varied from 0 to 320/m^2. In addition to weed count, biometric traits of the weed *Sacciolepis* were used as independent variables in regression analysis. Univariate prediction models were developed by using each of the biometric traits viz. productive tiller counts, height of *Sacciolepis,* weed count and WDM as independent variable and their relative efficiencies compared. In the case of productive tiller counts the linear correlation was found to be relatively low but significant. A hyperbolic function given by Y = 224+0.04227/X (Where Y= Grain yield of rice, X= productive tiller count) with an estimated predictability of 53% was observed to be the best choice.

Height of *Sacciolepis* was also found to have high negative correlation (-0.787) with the grain yield. Among the different curves fitted a second degree parabola given by, $Y = 646.7+5.042X-0.05289X^2$, (Y= Grain yield of rice, X = Height of *Sacciolepis*) showed relatively better predictability.

In the case of total weed count of *Sacciolepis*, the Cauchy model gave the best result. The estimated equation was given by, $Y = 1/\{0.1292E\text{-}06(X+102.6)^2+0.001203\}$ which explained as much as 98.44% variation in grain yield.

When WDM was taken to be the independent variate, the best fitted curve was of the form $Y = 26.14\ e^{[(X-8.681)/2]}$ and this equation was successful in describing the relationship with 91% accuracy.

Table –4.4.1. Yield loss – weed density models for rice— Experiment 4 .

Weed characters	**Equation**	**Name of Equation**	**R^2 (adj.)**	**r**
Productive tiller count	$Y = 224+0.04227/X$	Hyperbola	0.526	-0.5574
Height of saccolepis	$Y = 646.7+5.042X-0.05289X^2$	Parabola	0.812	-0.787**
Weed count	$Y = 1/\{0.1292D\text{-}06(X+102.6)^2+0.001203\}$	Cauchy	0.984	-0.747*
WDM	$Y = 26.14\ e^{[(X-8.681)/2]}$	Normal	0.878	-0.811**

A simple linear regression equation was also fitted using square root of weed count as the independent variable. This equation is given by, $Y = 480.192 - 29.2169^{**} X_1$ with an R^2 value of 0.802^{**} where Y= grain yield ; X_1= square root of weed count. The equation gave better predictability than the conventional linear regression equation. The loss due to the incidence of *Sacciolepis* weed was evaluated by the method described in section 3.2.2. The loss in yield caused by weed density of *Sacciolepis* was found to be 42.314%

4.4.2. Multivariate case.

Multiple linear regression analysis was performed with grain yield as dependent variable and weed characters as independent variables. The following independent variables were included in the functional equation. 1.Total tiller count, 2. Productive tiller count , 3. Height of sacciolepis, 4. Dry matter weight of *Sacciolepis*. The results of multiple linear regression analysis is given in table 4.4.2. The estimated regression equation explained 82% of variation in the grain yield of rice. The total yield loss by weed infestation using multiple linear regression analysis was found to be 56.54%.

Table – 4.4.2 Results of Multiple linear regression analysis of Experiment 4.

Independent Variables.	Estimated Loss	Multiple Linear Regression Equation	R^2	R^2(adj.)
1.TTC (X_1) 2.PTC (X_2) 3.Height(X_3) 4.WDM(X_4) *Total Est. loss*	6.348 12.23 -54.75 -20.36 ***-56.54***	$Y = 637.30 + 2.66 X_1 + 7.76X2 - 2.685^{*}X_3 - 67.27^{*}X_4$	0.819**	0.78
1.Height(X_1) 2.WDM (X_2) *Total Est. loss*	-36.41 -20.27 ***-56.68***	$Y = 642.275 - 1.81^{**}X_1 - 67.4568^{**}X_2$.	0.79**	0.77

The multiple linear regression analysis was also done, using the two variables, Height of *Sacciolepis* and WDM, which are highly correlated with grain yield. The multiple linear regression equation thus obtained is given by, $Y = 642.275 - 1.81^{**}X_1 - 67.4568^{**}X_2$. This equation was successful in explaining 79% variability in yield. The total loss estimated from the reduced model was 56.68%.

4.4.2.1. Stepwise Regression Analysis

Stepwise regression analysis was attempted with four independent variables. A regression equation involving single independent variable was found to be sufficient to describe the proposed relationship. The results are given in table - 4.4.3.

Table – 4.4.3. Results of Step-wise regression analysis of Experiment-4

Variable/s select ed	Regression estimate	S.E	Computed t- value	Loss(%)
WDM	-103.821	15.98	-6.497	-41.8024

Constant, a =477.375; Standard Error = 120.336; R^2=0.65**

The selected prediction equation of the form, $Y= 477.375-103.821^{**}X_1$, where Y is yield and X_1 = weed dry matter. The estimated loss from this equation was found to be 41.8%.

4.4.2.2. Principal Component Analysis

All the variables used for the multiple linear regression analysis along with an additional variable viz., productive tiller count were used for PCA. Among the five PC's the first component showed maximum variation. The latent roots, percentage variance and cumulative variance are given in table-4.4.4.

Table – 4.4.4 Results of Principal Component Analysis of Experiment 4
The latent root, percentage variance and cumulative variance of each component.

PC	Latent roots	% Variance	Cumulative Variance
1	3.109	62.174	62.174
2	0.967	19.350	81.524
3	0.765	15.292	96.816
4	0.149	2.984	99.800
5	0.010	0.200	100.000

Table-4.4.5 Results of multiple linear regression analysis using component vectors as regressors - Regression models and their predictability of Experiment 4.

No.of PC's	R^2	R^2 (adj.)	F	Standard Error(Est.)	Multiple Linear regression equation
5	0.983	0.939	22.72**	4.746	$Y = 647.38+11.29P_1+0.605 P_2-3.93 P_3+20.05 P_4-40.505 P_5$
4	0.965	0.919	20.75**	55.345	$Y=642.34+6.3071P_1+0.406P_2-6.33P_3+9.82P_4$
3	0.889	0.805	10.64**	85.65	$Y=640.905-3.64P_1+23.18P_2-0.12P_3$
2	0.888	0.843	19.82**	76.83	$Y=647.37-3.71P_1+0.189P_2$
1	0.884	0.865	15.90**	74.852	$Y=639.86-3.485^{**}P_1$

The regression equation using the first principal component as explanatory variable explained as much as 88.4% variation in the yield of rice. Percentage loss as estimated from the equation $Y=639.86-3.485^{**}P_1$ was found to be 56.74.

4.5. Experiment – 5 (crop – sesame)

4.5..1. Univariate case

Six weed variables were used as exogenous variables in univariate functional analysis. They were TWP, WDM, rice, *Echinochola, Sacciolepis* and "other weeds". The selected univariate prediction models on the basis of the above six weed variables are given in table – 4.5.1. In the case of TWP a second degree parabola was adjudged to be the most fitting functional form which is given by,

$Y=1.64 - 0.01776X + 0.6428E\text{-}04X^2$ (Y= Grain yield of sesame, X= TWP) with an Adj. R^2 value of 0.3222.

Using WDM as the independent variable, Hoerl curve given by $Y=0.4559(0.9947)^X . X^{(0.3719)}$ with an Adj. R^2 value of 0.3891 was found to be the most promising.

Rice is considered to be a major weed in the sesamum plots and hence a prediction equation to predict its influence is highly necessary. Univariate analysis gave a linear equation, $Y= 1.473 - 0.3996E\text{-}02\ X$ (Y= Grain yield of sesame, X = number of rice plants) showed maximum predictability ($R^2 = 0.3476$).

For *Sacciolepis* the power function $Y=0.8782. X^{(-0.0437)}$ (Y= Grain yield of sesame, X = counts of *Echinochola*) was found to be the best fitting model.

In the case of *Echinochola* no significant functional relationship could be established between grain yield and weed density. The other weeds taken together as a single variate also failed to conform to the tested models.

Table –4.5.1. Yield loss – weed density models for sesame — Experiment 5.

Weed variables(X)	Equation	Name of equation	R^2	R^2 (adj.)	r
Total weed population	$Y=1.64-0.01776X+0.6428E-04X^2$	Parabola	0.3609	0.3222	-0.75**
Weed dry matter	$Y=0.4559(0.9947)^X . X^{(0.3719)}$	Hoerl. Function	0.424	0.3891	-0.75**
	$Y=1427.e^{(X+39.37)/2}$	Normal	0.4113	0.3757	
	Y=1.657-0.2424E-02X-4.099/X	Linear & reciprocal.	0.4016	0.3653	
Rice	Y= 1.473-0.3996E-02X	Straight line	0.3476	0.2824	-0.59*
Echinochola	Y=1/{0.9715+0.860E-02X)	Reciprocal straight line	0.2132	0.1345	-0.36
Sacciolepis	$Y=0.8782. X^{(-0.0437)}$	Power function	0.5026	0.4528	
Others	$Y=1.041. e^{(-0.159)X}$	Exponential	0.0759	0.0487	-0.025

4.5.2. Multivariate case.

Based on correlation analysis four independent variables viz., Rice, *Echinochola*, sedge and WDM were included for multivariate analysis. The multiple linear regression equation (table-4.5.2.) obtained is given by, $Y = 1.487 + 0.0024X_1 + 0.0055X_2 - 0.033X_3 - 0.00288X_4$. The equation explained 68.6% variability in yield. However the relation was not statistically significant and hence no attempt was made to estimate the yield loss from the above model.

4.5.2.1.Stepwise regression Analysis

The results of stepwise regression analysis is given in table-4.5.2.

Table -4.5.2 Results of Step-wise regression analysis of Experiment 5.

Variable/s select ed	Regression estimate	S.E	Computed t- value	Loss(%)
WDM	-0.751	0.001	-3.61**	-11.701

Constant, a =1.51 ; Standard Error = 0.145 : SE(est)=0.2443; R^2=0.565

The selected variables were used for fitting an equation of the form,

$$Y= 1.510-0.751^{**}WDM .$$

This equation explained 56.5% variability in yield. The estimated loss from the model was 31.37% .

4.5.2.2. Principal Component Analysis

The variables used for the multivariate analysis were also used for calculating PCA. The results are shown in the table given below.

Table -4.5.4 Results of Principal Component Analysis of Experiment 5
The latent root, percentage variance and cumulative variance of each component.

PC	Latent roots	% Variance	Cumulative Variance
1	2.545	63.621	63.621
2	1.022	25.543	89.164
3	0.368	9.199	98.363
4	0.065	1.636	99.999

The multiple linear regression analysis was done using the above principal components as explanatory variables. The results are tabulated below.

Table-4.5.5 Results of Multiple linear regression equation using component vectors as regressors - Regression Models and their predictability of Experiment 5.

No. of PC's	R^2	R^2 (adj.)	F	Standard Error(Est.)	Multiple Linear regression equation
4	0.686	0.506	3.82	0.248	$Y=1.487-0.0148P_1+0.0097P_2-0.028P_3+0.00728P_4$
3	0.579	0.421	3.67	0.269	$Y=1.54-0.0109P_1+0.0051P_2-0.014P_3$
2	0.547	0.447	5.44	0.263	$Y=1.533-0.00213P_1-0.00058P_2$
1	0.544	0.498	11.92**	0.250	$Y=1.515-0.00239^{**}P_1$

It could be seen that the linear function of the first principal component viz., $Y=1.515-0.00239^{**}P_1$ explained as much as 55% variation in yield. The loss was estimated from the component was found to be around 23%.

4.6. Experiment-6 (Crop – Sesame)

4.6.1. Univariate case

The major weed, *Echinochola* had a high negative correlation with Grain Yield

(-0.8516). Among the fitted models the super geometric function given by,

$$Y=374.2.X^{(-0.01805X)}$$

where Y = Grain yield of sesame , X= counts of *Echinochola*, exhibited maximum predictability (R^2 =0.599). The normal curve was another promising model with relative high precision.

When TWP was used as the independent variate, no promising models could be extracted to represent the proposed relationship. Similarly in the case of 'other weeds' the effect was statistically non significant.

Table–4.6.1. Yield loss – weed density models for Cassava — Experiment 6.

Type of weed characters	Equation	Name of Equation	R^2	R^2 (adj.)	r
Total weed population	$Y=86.91.e^{\{(X-294.3)/2\}}$	Normal	0.203	0.155	-0.323
Others	Y=257.7-8.79logX	Logarithmic	0.098	0.072	-0.180
Echinechola	$Y=374.2.X^{(-0.01805X)}$ $Y=402.2.\cdot e^{\{(X+11.61)/2\}}$	Super geometric Normal	0.610 0.610	0.599 0.586	-0.852**

4.6.2. Multivariate case

The major weed, *Echinochola* and WDM were taken as the independent variables for conducting MLRA (table- 4.6.2.)

The multiple linear regression equation obtained is given by,

$$Y= 441.295^{**}-7.89^{**}X_1 -0.466187X_2$$

The two variables together caused 78.5% variation in yield.

Table –4.6.2. Results of Multiple linear regression analysis of Experiment 6.

Independent variables	Est. loss	Multiple linear regression equation	R^2	R^2(adj.)	r
1.Echinochola(X_1)	-21.43				-0.81**
2.WDM(X_2)	-24.82	$Y= 441.295^{**}-7.89^{**}X_1$ -	0.785**	0.737**	-0.63*
Total Est. loss	*46.27*	$0.466187X_2$			

The estimated loss from the two components was found to be 46.27% .

4.6.2.1. Stepwise regression analysis.

The results of stepwise regression analysis is given in Table-4.6.3.

Table – 4.6.3. Results of Step-wise regression analysis of Experiment 6.

Variable/s select ed	Regression estimate	S.E	Computed t- value	Loss(%)
Echinochola	-9.4138	1.832	-5.139**	-28.54

Constant, a =394.93 ; Standard Error = 1.8319; R^2=0.725

The selected prediction equation is of the form, Y= 394.93-9.4138**X_1 , where Y is yield and X_1 =Counts of *Echinochola*. The estimated loss from this equation was found to be 28.54%. The results showed the importance of *Echinochola* as the major weed effecting the yield of sesame.

4.6.2.2.Principal Component Analysis

PCA was done using the three independent variables viz., *Echinochola*, WDM and TWP and the first PC dominated the other components. Results of PCA and the MLRA using the latent vectors are given in tables-4.6.4. and 4.6.5.

Table-4.6.4 Results of Principal Component Analysis of Experiment 6.
The latent root ,percentage variance and cumulative variance of each component.

PC	Latent roots	% Variance	Cumulative Variance
1	1.489	49.646	49.646
2	1.124	37.463	87.109
3	0.387	12.889	99.998

Table-4.6.5. Results of multiple linear regression analysis using component vectors as regressors – Regression models and their predictability of Experiment 6.

No.of PC's	R^2	Adj. R^2	F	Standard Error(Est.)	Multiple Linear regression equation
3	0.789	0.710	9.98**	63.893	$Y=453.25-6.0688^{**}P_1+1.6216P_2-5.2819^*P_3$
2	0.599	0.509	6.71*	83.125	$Y=395.69-2.656^*P_1-3.1261P_2$
1	0.492	0.441	9.67**	88.744	$Y=443.968-1.5159^*P_1$

The estimated loss as obtained from the first principal component was found to be 36.463%.

4.7. Experiment – 7 (Crop – Tapioca)

4.7.1. Univariate case

In this experiment one independent variable alone was available for model building and forecasting. Among the fitted models $Y=1/\{-0.3818E\text{-}05(X-186.9)^2+0.2049\}$ (Y = Tuber yield of Cassava, X = WDM) gave maximum predictability (R^2 = 0.397). This was followed by the normal curve (R^2 = 0.366) given by $Y= 4.734.e^{\{(X-177.8)/2\}}$

Table –4.7.1. Yield loss – weed density models for cassava — Experiment 7.

Variable	Equation	Name of equation	R^2	r
Weed dry matter	$Y=1/\{-0.3818E\text{-}05(X-186.9)^2+0.2049\}$	Cauchy	0.397	-0.596*
	$Y= 4.734.e^{\{(X-177.8)/2\}}$	Normal	0.366	

The yield loss estimated from the linear function Y=10.66 – 0.0296*X was found to be 12.77%

4.8. Experiment – 8 (Crop – Tapioca)

4.8.1. Univariate case

In this experiment counts of weeds namely *Digitaria, Scorparia* were used as independent variables along with WDM and TWP for the functional analysis. In the case of WDM the Cauchy curve given by, $Y=1/\{0.1996E\text{-}04(X-25.23)^2+0.07397\}$ turned out to be the best choice. This was followed by the reciprocal straight line Y=1/{0.08178+0.5377E+03X} (Y = Tuber yield of Cassava, X = WDM) with R^2 value of 0.4019.

When TWP was used as the independent variable a second order hyperbola given by, $Y=14.28-387.4/X+3058/x^2$ where X =TWP, was found to be the most promising (R^2 =0.6939). This was followed by linear reciprocal model given by and is given by,

Y= -55.25+1.945X+421.5/X with a predictability of 67.8%.

Using the weed *Digitaria* as the independent variable, Reciprocal Straight line given by, Y=1/(0.08113+0.1618E+02X) (Y=Tuber yield of cassava , X = counts of *Digitaria* (weed) excelled all other models with satisfactory precision.

The best prediction model for the weed *Scorparia* is given by, $Y=X/\{-0.3818E\text{-}05(X-186.9)^2+0.2049\}$, where Y= tuber yield of cassava and X= counts of *Scorparia* weed which is a reciprocal hyperbola with an R^2value of 0.417.

Table – 4.8.1. Yield loss – weed density models for Cassava— Experiment 8 .

Type of weed characters	Equation	Name of equation	R^2	R^2 (adj.)	r
Weed dry matter	$Y=1/\{0.1996E-04 (X-25.23)^2+0.07397\}$ $Y=1/\{0.08178+0.5377E+03X\}$	Cauchy Reciprocal st.line	0.464 0.452	0.402 0.356	-0.35
Total weed population	$Y=14.28-387.4/X+3058/X^2$ $Y= -55.25+1.945X+421.5/X$	Second order hyperbola Linear reciprocal	0.695 0.678	0.634 0.614	0.63
Digitaria (Weed)	$Y=1/(0.08113+0.1618E+02X)$ $Y= 1/\{0.1347E-03 (X-6.653)^2+0.07996\}$	Reciprocal Straight line Cauchy	0.429 0.465	0.377 0.359	-0.52
Scorparia (Weed)	$Y=X/\{-0.3818E-05 (X-186.9)2+0.2049\}$	Reciprocal Hyperbola	0.462	0.417	-0.42

4.8.2. Multivariate case.

Multivariate analysis was done using WDM and TWP as the independent variables. The multiple linear regression equation obtained is given by

$Y=13.89^{**}+0.012X_1-0.483^*X_2$ where Y=tuber yield of cassava, X_1 = WDM and X_2=TWP This equation explained 47% variation in yield. The estimated loss was found to be 40. 62 %.

Table –4.8.2. Results of multiple linear regression analysis of Experiment 8 .

Independent Variables	Est. Loss	Multiple Regression Equation	R^2	R^2(adj.)
1.WDM(X_1) 2.TWP(X_2) Total Est. loss	0.7336 -41.3589 *-40. 62*	$Y=13.89^{**}+0.012X_1-0.483^*X_2$	0.56*	0.472*

4.8.2.1. Stepwise regression analysis

The results of stepwise regression analysis is given in table-4.8.3.

Table-4.8.3. Results of stepwise regression analysis of Experiment 8.

Variable/s selected	Regression estimate	S.E.	Computed t-value	Loss(%)
TWP	1.437	0.1192	-3.620**	13.63

Constant, a = 13.772 ; SE (est) = 1.437 ; R^2=0.544**

The selected variable is used for fitting an equation of the form,

$$Y = 13.772 - 0.4314^{**}TWP$$

This equation explained 54.4% variability in yield. The estimated loss from the model

was13.63%.

4.9. Experiment – 9 (Crop – Tapioca)

4.9.1. Univariate case

The weed variables WDM, TWP and individual weed count on *Cynotis* and *Scorparia* were taken as the independent variables for curve fitting in the univariate case.

The best fitting model by using WDM as the independent variable is reciprocal straight line whose equation is given by, $Y=1/\{0.1119+0.004023X\}$ with an R^2 value of 0.5376 .

When TWP was used as the independent variable Cauchy curve turned out to be the best choice whose equation is given by, $Y=1/\{0.004096(X-5.974)^2+0.09972\}$ with an R^2 value of 0.4114.

For the other variables none of the functional models were found to be suitable for representing proposed relationship though cauchy curve and second degree parabola indicated relatively high R^2 values.

Table –4 9.1. Yield loss – weed density models for cassava—Experiment -9

Type of weed characters	Equation	Name	R^2	R^2 (adj.)	r
Weed dry matter	$Y=1/\{0.1119+0.004023X\}$	Reciprocal straight line	0.576	0.538	-0.505
Total weed population	$Y=1/\{0.004096 (X-5.974)^2+0.09972\}$	Cauchy	0.510	0.411	-0.351
Cynotis (weed)	$Y=1/\{0.09196 (X-1.577)^2+0.1024\}$	Cauchy	0.298	0.157	0.140
***Scorparia* (Weed)**	$Y=1/\{0.09196 (X-1.577)^2+0.1024\}$	Cauchy	0.298	0.157	-0.356
Others	$Y=13.25-3.463X+0.4396X^2$	Parabola	0.231	0.077	-0.219

4.9.2. Multivariate case

The observations on the five variables used in the univariate case were taken as the independent variables for MLRA. As the regression equation was not statistically significant no effort was made to estimate the yield loss from the experiment.

4.10. Estimation of Avoidable Loss

The estimates of avoidable loss for the different experiments mentioned above are given in table- 4.10.1.

Table – 4.10.1. The estimates of avoidable loss for different Experiments.

Expt.	Crop	Mean Yield of treated plots(Yt)	Unit of crop- yield	Mean yield of control plot (Yc)	PAL (%)
1	Rice	2.84	t / ha	1.76	36.97
2	Rice	2527.33	Kg / ha	2393	5.31
3	Rice	744.82	Kg / ha	497.22	33.24
4	Rice	310.57	g / plant	40.83	86.85
5	Sesamum	1.09	Kg / plot	0.61	44.19
6	Sesamum	305.88	Kg / ha	20.33	93.35
7	Tapioca	8.42	t./ha	3.57	57.6
8	Tapioca	12.20	t./ha	8.19	32.89
9	Tapioca	9.66	t./ha	4.98	48.44

The estimates ranged from 5.31% to 93.35%. In general tapioca and sesame afforded more control of pests by insecticidal application when compared to rice.

DISCUSSION

5. DISCUSSION

Estimation of yield loss is very important in formulating suitable strategies for weed control research. Determination of yield loss due to weeds is also useful for crop forecasting. Several statistical tools are available for the estimation of loss due to weeds. An investigation was conducted to estimate the loss due to weeds based on empirical data gathered from nine experiments conducted in Kerala Agricultural University. The important findings of the study are discussed herewith.

In experiment-I WDM had shown the highest significant negative correlation with yield ($r = -0.956$) indicating the supremacy of weed dry matter in building up prediction models. The effects of *Echinochloa* in suppressing rice yield was also significant. The estimated cauchy prediction model involving counts of *Echinochloa* or WDM were successful in explaining substantial amounts of variation in the grain yield of Rice. The prediction model based on WDM could predict rice yield with a precision as high as 97%. WDM was found to be the most contributing weed variable in making univariate yield loss prediction model on rice.

Multiple linear regression analysis resulted in a considerable improvement of prediction in comparison with linear regression analysis. The estimated MLR function explained 92% variation in rice yield. The percentage yield loss estimated from this function was found to be 6.36%.

Step wise regression analysis also revealed the importance of WDM in building up prediction models. The linear function based on WDM was successful in explaining 92% variation in rice yield. The estimated loss caused by variations in WDM was moderate (6.19%).

Principal Component Analysis indicated the sheer dominance of the first component over others. The estimate of loss calculated on the basis of the component vector of the first principal component was higher than the one estimated through the conventional regression estimator which indicated the interplay of multicollinearity in vitiating the results.

In experiment-2 multiple linear regression equation involving four weed variables could explain more than 70% variation in rice yield. A substantially high amount of loss (11.28%) was observed to be caused by the incidence of weeds.

Step wise regression analysis revealed the importance of *Scheonoplectus* and WDM as the major causal factors for yield reduction. However, the expected yield loss due to the effect of *Scheonoplectus* was not very high (4.474%).

Population counts of weed at four stages of crop growth were available in experiment-3 and hence the results were more informative and comparatively of greater adaptability and utility. Among the univariate models tried for describing the response pattern of *Sacciolepis* weed the cauchy curve consistently showed maximum predictability. In majority of the cases the reciprocal straight line and second order hyperbola showed consistently better performance than most of the other functional models.

As far as *Isachne* count was concerned second order hyperbola and the conventional parabola showed better predictability than the other models. It was interesting to note that in the case of these two weeds the probable yield of rice could be predicted with sufficient degree of accuracy as early as in the 30th day after sowing on the basis of weed counts from the respective plots. It is possible to take a decision to control weed at this stage. Prediction equation developed on the basis of total weed population (TWP) showed slightly higher predictability than those based on specific weed counts. However, weed population at the harvest stage did not seem to affect the crop yield and as such resulting equations showed relatively low predictability in various experiments. At the harvest stage TWP failed as a suitable calibrating variable for yield prediction possibly due to the above reasons. In the case of sacciolepis, prediction equations based on the observations gathered on 30 DAS was successful in explaining about 78% variation in rice yield. The prediction equations relating to the later stages of crop growth had not shown much improvement in predictability. Among all the functional models, the hyperbolic models at 60 DAS showed the maximum predictability. The result was in conformity with the earlier findings of Bahuguna *etal.*(1995) on wheat.

The multivariate analysis of data uniformly brought about a considerable improvement of predictability over the conventional linear regression analysis. The estimate of loss obtained in the experiment generally increased with the duration of the crop. The crop loss estimates varied between 56% at 30 DAS to 90.2% at 90 DAS. Stepwise regression analysis undoubtedly indicated the prominence of WDM as the major yield-limiting variable in rice-weed competition studies. It was found that about 65% loss in yield could be accounted by this single predictor variable. At 60 DAS counts of *Isachne* weed exerted a highly significant effect on yield, the estimated loss being as high as 50.95%. The regression of principal components also showed considerable loss due to weeds at different stages of crop growth.

Experiment- 4 was concerned with the effect of sacciolepis at varying densities on the yield of rice crop. Observations were also available on certain morphological characters of the weed. Among the morphological traits height of the weed showed maximum negative correlation with yield. It could be inferred that height of sacciolepis also could be used as a concomitant variable for predicting yield of rice in weedicidal trials along with WDM and TWP. A parabola fitted with height of sacciolepis as the independent variable explained as much as 81.2% variations in rice yield, However, the cauchy model with WDM as the explanatory variable turned out to be the best fit contributing to 98.88% of total variability in yield. A square root function also showed satisfactorily high predictability(R^2 =80.2%). However, the estimate of loss(42.314%) obtained from the function was very low when compared to that from multivariate techniques. The study showed the importance of nonlinear models in response studies. In general non linear models were superior to linear models in predicting the nature of response irrespective of the type of the independent variable. The study also indirectly indicated the inadequacy of the square root model in estimating yield loss. Step wise regression analysis disclosed the importance of WDM as the single best predictor of yield loss in rice contributing to about 65% of total variability. According to multiple linear regression analysis the total yield loss due to the incidence of weeds was 51%. At the same time stepwise regression analysis indicated that 42% loss in yield could be attributed to a single causal factor viz., WDM.

Most of the models failed miserably to get a good fit to the data in sesame experiments. This may be due to the poor quality of the empirical data. Among the weed variables WDM was found to be the most important component in describing the relation between weed incidence and yield. Among the various weeds with specific effect sacciolepis was found to be the most contributing. The estimate of yield loss based on the multiple linear regression analysis involving four weed variables was found to be 29.3%. Stepwise regression analysis also indicated the utility of WDM as the predictor variable. The linear regression equation based on WDM explained 56.5% of total variations in sesame yield and the percentage loss estimated based on the equation was also relatively high(31.5%). The analysis of data of the other experiment on sesame showed the devastating effect of *Echinochloa*. But this may be due to the effect of seasonal factors or the use of inefficient treatments. The super geometric model was found to be suitable in representing the effect of *Echinochloa* on sesame yield. A multiple linear regression equation involving two variables viz.,WDM and *Echinochloa* succeeded in explaining about 79% variability in yield. The estimated loss from this experiment was 46.2%. The multiple linear regression analysis of principal components resulted in a loss estimate of 36.46% based on a single component.

In the case of tapioca also WDM turned out to be a significant yield predictor and the cauchy model as the most promising (Expt-8 and Expt-9) In certain specific experiments total weed population outweighed even WDM to get better functional relationship (Expt-8 and Expt-9). As mentioned before reciprocal straight line was also found to be a suitable choice in building up yield prediction models based on weed variables. In experiment-8 the estimated percentage loss based on regression of WDM on yield was found to be 13.63%.

In the case of Expt-9 multivariate regression analysis failed to produce a significant result and hence no effort was made to find out the expected loss. Among the univariate models reciprocal straight line and cauchy curve showed relatively better performance.

The avoidable loss in rice in all the experiments was relatively less compared to the expected loss. But the result was not in conformity with the findings in other two crops. However, a large portion of the expected loss could have been avoided by taking precautionary measures at the right time by using appropriate technological interventions.

The results of the study consistently showed the importance of WDM as a predictor variable in crop-weed competition studies. Another variable useful for comprehensive functional analysis is TWP and it is also advantageous to record observation on TWP in addition to WDM for data analysis and meaningful interpretations. Although there is hardly any functional model with universal adaptability in response studies, certain models have shown definite superiority over others in specific situations. In this study non-linear models undoubtedly excelled their linear counterparts in representing the response pattern. Among the fitted models the cauchy curve, the hyperbolic function, the reciprocal straight line and the normal curve were found to be the most promising. Most of the functional models developed empirically from the experimental data exhibited high degree of predictability. The predictability of multivariate linear models included in the study was higher than those reported by Bahuguna *etal.* (1995) on wheat. *Echinochloa* was found to be one of the major weeds causing great damage to rice crop. Effect of other weeds such as *Schoenoplectus* was also found to be significant in one of the trails. The intensity of damage by weeds depended on the crop, season and the type of control measures used .The effect of weeds varied considerably between seasons due to climatological factors or environmental changes. Thus it is hardly possible to develop a robust prediction model on the basis of short-range data .

Multiple linear regression functions showed better predictability than simple linear functions. Most of the prediction equations based on multiple linear regression analysis showed significant contributions of the weed variables in suppressing the potential yield. The estimates of crop loss obtained through the technique of PCA, though somewhat smaller,in most cases seemed to be more realistic than those through multiple linear regression analysis . PCA estimates are free from multicollinearity and hence are expected to be statistically more dependable and consistent.

Considerable extent of variation in the estimates of crop loss has been observed in various experiments in the study. The estimate of loss ranged from 5.3% to 90.2% in rice,31.37% to 46.27% in sesame and 12.77% to 40.62% in tapioca. Maximum loss due to weeds was observed in Expt-3. The estimated loss was so high as to presume it to be quite unrealistic. However, the reliability of the result can not be questioned in the light of the finding by Abernothy (1979) who recorded 70% average annual loss due to weeds for rice crop in USA. In most of the other reported cases the estimate of loss ranged from 10% to 40% with an average annual loss around 25%. According to Rao (1989) weeds cause 30% to 50% loss annually to winter cereals. Bhahuguna *etal.*(1995) have found that in wheat the estimate of crop loss varied from 21% to 27% with different regressor variables. Thus the present finding is in conformity with the findings of the earlier workers.

The percentage avoidable loss varied from 5.31% to 86.85%. Tapioca and sesame had shown greater percentage of avoidable loss when compared to rice indicating that there was greater scope for the adoption of plant protection measures in these two crops for enhancing production. Bhahuguna (1995) found that the adoption of suitable weedicidal treatments resulted in an average avoidable loss of 22.5% in 1984-85 wheat crop while that in the succeeding year was 9.42%.

The estimates obtained in the study are in conformity with the findings of a number of other workers on different crops. Effect of weeds in lowering crop yield depends on the nature of the crop, the season, treatments and cultural practices. However, weed control measures often result in considerable saving of yield. A reliable estimate of yield loss is essential to know whether weed control measures are economically viable or not. The study showed that the application of weed control measures are generally effective in enhancing crop production. The functional models developed in the study are useful in getting advance estimates of crop production under specific micro environments.

SUMMARY

6. SUMMARY

The study entitled " STATISTICAL MODELS FOR THE ASSESMENT OF YEILD LOSS DUE TO WEEDS" was developed with a view to identify suitable functional models for assessing the effect of weeds on the yields of three major crops of Kerala, viz., rice ,sesame and tapioca and to estimate the overall loss and avoidable loss in the yields of these crops caused by weed infestation. Several univariate functional models were developed and their efficiencies compared on the basis of empirical data Multivariate technique such as multiple linear regression analysis, stepwise regression analysis and principal component analysis were also used for the prediction of crop yield and estimate yield loss. The study was based on secondary data collected from completed field experiments of AICRP on weed control, College of Horticulture, Vellanikkara. Altogether nine sets of data pertaining to the three crops were available for the study. Of these four sets of data (Expt-1, Expt-2, Expt-3, Expt-4) related to experiments on rice, two sets of data were on sesame and the remaining three sets were on tapioca. The observations on weed characters like counts of individual weeds, weed dry matter production, total number of tillers, number of productive tillers and crop yield were collected for the above nine experiments .

In the first experiment cauchy curve exhibited the maximum predictability with weed dry matter as the independent variable. In the case of multivariate analysis using stepwise regression technique weed dry matter (WDM) was adjudged to be the major component for the yield prediction. The estimated loss due to WDM was 6.19 % which was comparable to the estimates of loss through multiple linear regression analysis (MLRA) (6.36%) and principal component analysis (7.81%).

In the second experiment on rice none of the tested univariate models gave a satisfactory fit to the experimental data . This may be due to the poor quality of the data generated in the experiment. When MLRA was attempted density of *Schoenoplectus* was found to exert significant effect on grain yield. Weed dry matter also exhibited significant effect on yield loss. Results of stepwise regression analysis indicated that the two variables together had contributed to an estimated loss of 5.244% in annual yield, the major contributor being the density of *Schoenoplectus* (4.474%).

In the third experiment on rice the weeds *Sacciolepis* and *Isachne* were found to be relatively more disastrous than other weeds at different stages of plant growth . The reciprocal straight line and cauchy curve were found to be useful in making early reliable forecasts of grain yield based on counts of *Schoenoplectus*. Prediction equations from univariate modeling exhibited relatively high degree of accuracy ($R^2 > 0.83$) in describing the yield-weed density relationship especially at 60 days after sawing (DAS) and 90 DAS . The counts of *Isachne* showed relatively feeble relationship with grain yield at the time of harvest. Prediction equations involving total weed population (TWP) as the independent variable showed higher predictability than those based on specific weed counts.

In multiple linear regression analysis the estimated loss due to weeds at 30 DAS was found to be 54.87 %, but the estimate declined to 23.25 % at 60 DAS and it incrased to a maximum of 68.4 % at 90 DAS. The step wise regression analysis clearly indicated the supremacy of WDM as the major predictor variable . The estimated loss increased steadily from 30 DAS to 90 DAS in both stepwise regression technique and in MLRA using first principal component as the regressor. The estimated maximum loss, through stepwise regression technique was recorded as 64.75% at 90 DAS while that through PCA at the same period was recorded to be 75.67%

In the fourth experiment on rice (Single weed experiment) certain morphological characters were also taken into consideration along with other variables. Attempts on univariate modeling indicated the utility of cauchy curve in describing the proposed relationship. Using MLRA the total yield loss by weed infestation was found to be 56.54 % . The percentage loss estimated from the regression equation involving the first principal component was also similar to that through MLRA with original independent variables.

In the fifth experiment effect of weeds on sesame crop was studied. It was necessary to examine the influence of rice plants in sesame field since it was a major weed in sesame. When number of rice plants per plot was taken as an independent variable a straight line fit was obtained with satisfactory predictability. The multivariate estimate of loss was using MLRA with rice , *Echinochloa* and *Sedge* as independent variable was found to be 29.3 % . However stepwise regression analysis with WDM as the independent variable showed that the loss was still higher (31.37%). The estimate of loss through MLR using first principal component as regressor (23%) was also comparable.

The analysis of data on the second experiment on sesame showed the shear dominance of *Echinochloa* as the major weed causing great havoc to crop growth. Using counts of *Echinocloa* as the independent variable the super geometric model was successful in explaining as much as 60% variation in the yield of sesame. The estimated loss due to this weed through stepwise regression analysis was found to be 28.54%. However the estimated loss through PCA was slightly higher (36.46%).

In the seventh experiment i.e. the first experiment on tapioca, observations on WDM alone were available for model building. Among the fitted models cauchy curve gave maximum predictability. The loss estimated from linear function (12.77%) was not comparatively high.

The second experiment on tapioca showed the utility of TWP as a better predictor variable than WDM or specific weed counts in building up regression models. The second order hyperbola and the linear reciprocal model were found to be suitable in describing the yield loss – weed density relations in tapioca with TWP as the explanatory variable. The stepwise regression analysis showed that the expected loss in tapioca caused by variation in the level of TWP was 13.63%.

In the ninth experiment the weed variables ,WDM,TWP and individual weed count on *Cynotis* and *Scorparia* were taken as independent variables for building up univariate and multivariate models. Reciprocal straight line with WDM as the independent variable turned out to be the best fitting model. Multivariate analysis did not produce statistically significant results and hence loss estimation was not attempted.

In conclusion, the study revealed the importance of weeds in suppressing the potential yield of plants. Weeds cause considerable damage to almost all crops. The effect of weeds on crops depends on the type of management, crop and season. Crop loss estimates showed wide variation between seasons and locations. *Echinocloa* was found to be one of the major weeds causing considerable havoc to rice crop. Several functional models were developed for predicting crop yield based on weed count and related parameters. In general non linear models were more efficient than linear model in predicting crop yield. Weed dry matter (WDM) was found to be the major predictor variable in building up prediction models. This was followed by Total Weed Population (TWP). Multivariate regression models were more powerful in predicting crop yield than univariate models. WDM was found to be the most important variable in estimating crop loss. In most of the cases the estimated functional models described the proposed relationship with satisfactory precision.

REFERENCES

REFERENCES

Abernathy, J.R. 1979. Effects of weed on crop yield. *Abstr. of weed Sci. Soc. of Am.* 30:14-15

Bhahuguna, G.N., Singh, B.H., and Mohan, M. 1995. Models for assessing the effect of weeds on wheat yield. *J. Indian Soc. of agric. Statistics* 47 (1) : 101-102

Chikoye, D., Weise, S.E. and Swanton, C.J. 1995. Influence of common ragweed (*Ambrosia artemisiifolia*) Time of emergence and density on whitebean (*Phaseolus vulgaris*). *Weed Sci.* 43: 375-380

Cousens, R. 1985a. A simple model relating yield loss to weed density and a comparison with other models. *Ann. appl. Biol.* 107: 230-252

Cousens, R. 1985b. An empirical model relating crop yield to weed and crop density and a statistical comparison with other models. *J. agric. Sci. Camb.* 105: 513-521

Cousens, R., Peters, N.C.B.and Marshall, C.J. 1984. Models of yield loss-weed density relationships. *Proceedings 7th Ecology and Systematics, Column EWRS, Paris.* 367-374

Dawson, J.H. and Holstun, J.T. Jr. 1971. Estimating losses from weeds in crops – Crop loss assessment methods. *F.A.O. Manual* 3 (2): 1-4

Dew, D.A. 1972. An index of competition for estimating crop loss due to weeds. *Can. J. Pl. Sci.* 52: 921-927

Dieleman, A., Hanill, A.S., Weise, S.E. and Swanton, C.J. 1995. Empirical model of pigweed (*Ameranthus Spp.*) interference in Soybean (*Glycine max*). *Weed Sci.* 43: 612-618

Diether, P., Peschken, A., Gordon Thomas and Robin F.Wise.1983. Loss in yield of rapeseed(*Brassicanapus, B.Campestris*) caused by perennial sowthistle(*Soncbus arvensis*) in Saskatcheivan and Manitoba. *Weed Sci.* 31: 740-744

Donovan, J.T. 1991. Quackgrass (*Elytrigia repens*) interference in Canola (*Brassica campestris*). *Weed Sci.* 39: 397-401

Goodman, L.A. 1960. On the exact variable of products. *J. Am. Statistical Ass.* 55: 708-713

Khosla, R.K. 1977. Techniques for assessment of loss due to pests and diseases of rice. *Indian J. agric. Sci.* 47(4): 171-174

Kropff, M.J. and Spitters, C.J.T. 1991. A simple model of crop loss by weed competition from early observations on relative leaf area of the weeds. *Weed Res.* 31: 97-105

Kropff, M.J., Vossen, F.J.H. and Spitters, C.J.T. 1984. Competition between a maize crop and a natural population of Echinocloa Crus-galli (L.) P.B. *Neth. J. agric. Sci.* 32: 324-327

Kwon, S.L., Smith, R.J. and Talbert, R.E. 1991. Interference durations of Red rice(*Oryza sativa)* in rice(*O.sativa*). *Weed Sci.* 39: 363-368

Marra,M.C. and Carlson,G.A. 1983. An economic threshold model for weeds in soyabeans. *Weed Sci.* 31: 604-609

O'Sullivan, P.A., Weiss, G.M. and Kossatz, V.C. 1985. Indices of competition for estimating rapeseed yield loss due to canada thistle. *Can .J. Pl. Sci.* 65: 145-149

Prabhakaran, P.V. 1997. Quantitative determination of loss in yield of black pepper (*Piper nigrum* L.) in Kannur District. (Kerala , India), *J. spices and aromatic crops*. 6(1): 31-36

Prabhakaran, P.V.1998. A statistical model for assessing the loss due to pests, diseases and drought due to black pepper (*Piper nigrum* L.). *Developments in plantation crops Res.* (eds. Mathew, N.M. and Kuruvila Jacob, C.). Allied Publications, New Delhi, pp. 333-336

Prasad, B.N.R.V and Suryanarayana, G.1995. Simple models to predict yield loss due to weed competition in sprouted Rice(Oryza Sativa L.) under puddled condition. *Mysore J.agric. Sci.* 29: 230-236

Rao, V.S. 1989. *Principles of Weed Science.*3rd ed., Oxford and I.B.H. Publishing Co. New Delhi, p.540

Spitters, C.J.T.1983. An alternative approach to the analysis of mixed cropping experiments. 1.Estimation of competition effects. *Neth.J.agric. Sci*.31: 1-11

Spitters, C.J.T., Kropff, M.J. and Groot, W.D. 1989. Competition between maize and Echinocloa crus-galli analysed by a hyperbolic regression model. *Ann. Appl. Biol.*110: 541-550

Weaver, S. E., Nancy, S. and Chin,S.T. 1987. Estimating yield loss of Tomatos (*Lycopersicon esculentum)* caused by nightshade (*Solanum spp.)* interference. *Weed Sci.* 35: 163-168

Wilson,G. Robert. 1993. Wild proso millet (*Panicum miliaceum)* interference in dry beens (*Phasedus vulgaris) Weed Sci.* 41: 607-610

Zimdahl,R.L. 1980. *Weed Crop Competition - A Review.* International Plant Protection Center, USA, p.196

APPENDICES

Name of the Experiments

Experiment -1	Evaluation of Butanil (MON 12396) in direct seeded rice
Experiment -2	Effectiveness and crop selectivity of pre-emergence herbicides under different method of application in puddled rice.
Experiment -3	Time of application of pre-emergence herbicides in dry-sown rice.
Experiment -4	Crop-weed competition study of Sacciolepis interrupta on rice.
Experiment -5	Integrated weed management in sesame.
Experiment -6	Integrated weed management in sesame.
Experiment -7	Integrated weed management in cassava.
Experiment -8	Integrated weed management in cassava.
Experiment -9	Integrated weed management in cassava.

Name of treatments in trails of Rice.

Sl. No	Name of treatments	Method
1	Oxyflorfen 0.1kg/ha	Spray
2	Oxyflorfen 0.1kg/ha	Sandmix
3	Thiobencarb 1kg/ha	Spray
4	Thiobencarb 1kg/ha	Sandmix
5	Butachlor 1.25kg/ha	Spray
6	Butachlor 1.25kg/ha	Sandmix
7	Anilophos 0.4kg/ha	Spray
8	Anilophos 0.4kg/ha	Sandmix
9	Pendimethalin 1kg/ha	Spray
10	Pendimethalin 1kg/ha	Sandmix
11	Pretilachlor + safener 0.75kg/ha	Spray
12	Pretilachlor + safener 0.75kg/ha	Sandmix
13	X.D.E. 100gm/ha	Spray
14	X.D.E. 100gm/ha	Sandmix
15	Handweeding	
16	Unweeded control	

Name of treatments in trails of Sesame.

Sl. No	Name of treatments	Method
1	Alachlor	PPI
2	Pendimethalin	PPI
3	Fluchloralin	PPI
4	Oxyflourfen	PPI
5	Metolachlor	PPI
6	Alachlor	Pre-em
7	Pendimethalin	Pre-em
8	Fluchloralin	Pre-em
9	Oxyflourfen	Pre-em
10	Metolachlor	Pre-em
11	Handweeding (Inter cultivation at 15 & 35 DAS)	
12	Unweeded control	

Name of treatments in trails of Tapioca.

Sl. No	Name of treatments
1	Oxyfluorfen 0.125 kg/ha (pre-em) + Spade weeding at 60 & 90 DAP
2	Oxyfluorfen 0.125 kg/ha (pre-em) + Spade weeding at 90 DAP
3	Pendimethalin 1.5kg/ha (pre-em) + Spade weeding at 60 & 90 DAP
4	Pendimethalin 1.5kg/ha (pre-em) + Spade weeding at 90 DAP
5	Oxadiazon 0.75kg/ha (pre-em) + Spade weeding at 60 & 90 DAP
6	Oxadiazon 0.75kg/ha (pre-em) + Spade weeding at 90 DAP
7	Fluchloralin 1.0 kg/ha (pre-em) + Spade weeding at 60 & 90 DAP
8	Fluchloralin 1.0 kg/ha (pre-em) + Spade weeding at 90 DAP
9	Diuron 1.5kg/ha (pre-em) + Spade weeding at 60 & 90 DAP
10	Diuron 1.5kg/ha (pre-em) + Spade weeding at 90 DAP
11	Paraquat 0.4kf/ha (3 sprays at 30,60 & 90 DAP as protective spray)
12	Spade weeding
13	Unweeded control

STATISTICAL MODELS FOR THE ASSESSMENT OF YIELD LOSS DUE TO WEEDS

By

PRIYALAKSHMI. M

ABSTRACT OF THE THESIS

Submitted in partial fulfilment of the requirement for the degree

Master of Science in Agricultural Statistics

Faculty of Agriculture
Kerala Agricultural University

DEPARTMENT OF AGRICULTURAL STATISTICS
COLLEGE OF HORTICULTURE
VELLANIKKARA, THRISSUR
KERALA, INDIA

2002

ABSTRACT

A study was undertaken to identify suitable functional models for assessing the effect of weeds on the yields of three major crops of Kerala Viz. Rice, Tapioca and Sesame and to estimate the loss in yield in these crops caused by the major weeds . The data required for the study were gathered from the available records of A.I.C.R.P on weed control . Multivariate techniques such as multiple linear regression analysis, step wise regression analysis and principal component analysis were used along with univariate techniques for the prediction of yield and yield loss. The study undoubtedly revealed the importance of weed in suppressing the potential yield of plants. The effect of weeds on crops depended on the type of management , crop and season . Crop loss estimates showed wide variation between seasons and locations. The estimate of loss ranged from 5.3% to 68.4% in rice , 31.4% to 46.3% in sesame and 12.8% to 40.6% in tapioca. The percentage of avoidable loss in different crops varied from 5.3% to 93.4%. Weed dry matter (W.D.M.) was found to be the most important weed character in predicting crop yield and yield loss. Echinocloa was found to be one of the major weeds causing considerable havoc to rice crop . In general non linear models were more efficient than linear model in predicting crop yield . The cauchy function, reciprocal hyperbola, second order hyperbola and reciprocal straight line were adjudged to be the most

promising univariate functional models in describing the yield-weed relation ship. Multivariate regression models were found to be more powerful in predicting crop yield than univariate models. In most of the cases the fitted statistical models described the proposed relation ship with satisfactorily high degree of precision.