APPLICATION OF MULTIVARIATE ANALYSIS TO AGRONOMIC TRIAL

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DECLARATION

I declare that the work in this thesis entitled "Application of Multivariate Analysis to Agronomic Trial" has been performed by me in the department of Mathematics under the supervision of Dr. S.U Gulumbe.

The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this thesis was previously presented for another Degree or Diploma at any University. I accept any omission or error that might be observed.

DANDAURA, Enoch Nehemiah ……. ……

Name of Student Sign Date

CERTIFICATION

This Thesis titled "Application of Multivariate Analysis to Agronomic Trial" by DANDAURA, Enoch Nehemiah meets the regulations governing the award of the degree of Master of Science of Ahmadu Bello University, Zaria and is approved for its contribution to scientific knowledge and literary presentation.

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DEDICATION

This research work is dedicated to my daughter, Jael (late) and to my father, Dandaura N. Ma'aji (late).

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ABSTRACT

Bivariate correlation was carried out on the growth and yield characters of cowpea (*Vigna unguiculata* [L] Walp) and pod yield and number of pods were observed to be positively and significantly correlated with all the components assessed (Number of Branches, Weight of defoliated leaves, Number of Pods, Length of Pods, Shoot Dry Weight, Plant Height, Number of Leaves, Leaf Area Plant, and Crop Growth Rates) except leaf area index and weight of defoliated leaves. The various parameters exhibited significant interrelationship with one another. Of the 10 growth characters considered in the study, the Principal component analysis shows the reduction of the dimension of the variates to 3 components and these three components explain about 95.57% of the variation. All variables considered shows normality with a linear line indicating that the data observed multivariate normal distribution.

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CHAPTER ONE

GENERAL INTRODUCTION

1.0 Introduction

Multivariate analysis refers to any statistical technique used to analyze data that arises from more than one variable. This essentially models reality where each situation, product, or decision involves more than a single variable. Multivariate analysis can be used for both spectral and non-spectral type of data. Spectra data are essentially data derived by the use of spectroscopic instrument. This data specifies variable with its properties and undoubtedly provide a great deal of useful information about organic molecules. Spectral data are used by scientists to: (i). Discover the chemical composition of materials by looking at the high (and other kinds of electromagnetic radiation) and (ii). Identify and monitor the production of products in factories.

The advent of gas chromatograph (GC) machines with non-destructive detectors has made research in flavor more interactive, and some GCs now incorporate sniffing ports to enable trained assessors to smell individual flavor compounds as they are separated by the GC.

A Non-spectral data is essentially data collected from sensory and environment. Any data that is collected from other sources, than spectroscopic and chromatographic instruments is non-spectral data.

The principal component analysis (PCA) and cluster analysis (CA) are the most common multivariate statistical methods in environmental studies. Principal component analysis is widely used to reduce data dimensionality (Salawu, 2008) and to extract a small number of latent factors for analyzing relationships among the observed variables. If large differences exist in the standard deviations of variables, PCA result will vary considerably depending on whether the correlation or covariance matrix is used (Farnham *et al*, 2003).

Factor analysis (FA) is a statistical approach that can be used to analyze interrelationship among a large number of variables and to explain these variables in terms of their common underlying dimension (factors). The statistical approach involving finding a way of condensing the information contained in a number of original variables into a smaller set of dimension (factors) with a minimum loss of information (Everith and Dunn, 2001).

Agronomy is the study of soils and plants, relating to the scientific study of soils management, land cultivation and crop production. It describes plants characteristics that are important during growth and development of a crop e.g height and stem strength. The data on cowpea was collected and used for the analysis.

1.1 Statement of the Problem

Over the years the measurable dimensions of agricultural trial are numerous. This leads to cumbersome and time consuming tasks in the gathering and analysis of data from agricultural experiments.

Efforts were made in this thesis to reduce the dimensionality of the measurement from m to p, ($p < m$) such that maximum information will be retained and large percent variation will be explained with the use of fewer variables.

1.2 Objective of the Study

The specific objectives of the study include:-

- To test the multivariate normality assumption on agronomic trial.
- To study the relationship of the agronomic measured characteristics in both the growth and yield parameter.
- To determine the percent contribution of both direct and indirect correlation in path analysis.
- To reduce the dimensionality of the measured characteristics from m to p; where $p < m$.

1.3 Significance of the Study

The Significance of this study is that the model constructed will provide:

- The agriculturist with useful information on the most prominent characteristics to use in the crop management.
- The agriculturist with information on direct and indirect contributions of the crop characteristics
- Demonstration of the application of Path Analysis and Principal Component Analysis in agricultural experiments to obtain useful information.

1.4 Brief History of Cowpea

Cowpea (vigna Unguiculata (L) walp), common name for any of a genus of leguminous herbs also knows as black-eyed pea. Cowpeas are sprawling or twining herbs with triple leaves and pods 20 to 30 cm long enclosing several kidney-shaped seeds. Cowpeas were cowpea originally native of Asia are now an important forage and cover crops in Southern United State and Africa. Worldwide Cowpea production has increased dramatically in the last 25 years (Adebayo and Tukur, 1999).

Being a drought tolerant and warm weather crops, cowpea is well as adapted to the drier regions of the tropics where other food legumes do not perform well.

It also has the unique ability to fix atmospheric nitrogen through its nodules and it grows well even in the soil with more than 85% sand and with less than 0.2% organic matter and low level of phosphorous, where soil PH is in the range of 5.5 to 6.5 (Tuan and Philips, 1992).

Cowpea is consumed in many forms: young leaves, green pods, green seeds are used as vegetables and dry seed are used in various food preparations. With over 25% protein, in its seeds and tender leaves, cowpea is a major source of protein, minerals and vitamins in the daily diets. Therefore Cowpea seed is valued as a nutritional supplement to cereals and animals. Its seeds is a nutritious component in the human diet as well as livestock feed with nutrient content as follows: Protein, 24.8%, Fat, 1.9% Fiber, 6.3% Carbohydrate, 63.6%, Thiamine, 0.00074%, Riboflavin, 0.00042% and Niacin, 0.00281%, thus its positively impacts on the health of women and children (Van and Gerike, 2000).

1.5 Definition of Terms and Concepts.

Variance (MS): The term MS (mean sum of square) is a short form of mean sum of squares (MSS), which is calculated by dividing the sum of squares with its degrees of freedom. One of the 'S'was dropped in usage and its short form MS is used. It is the most important measure of dispersion. In fact it has a very crucial role in biostatistical analysis of experimental data and in the tests of significance. The MS in the analysis of variance table is the same as variance. Mathematically, it is square of standard deviation.

Coefficient of Variation (C.V): It is defined as the calculated standard deviation expressed as a percentage of the mean.

Completely Randomized Design: The simplest experimental design used where experimental material is uniform e.g. in the laboratory, green house, screen house, growth chamber.

Continuous Variable: They are variables which can have any values between certain limits e.g. yield, weight etc.

Number of Pods: The average number of pods in a stand of cowpea.

Length of Pods: The length of pods from the base to the tips of the pod. Shoot Dry Weigh

Plant Height: It's the measurement of cowpea stand from the ground to the longest leaf tip or panicle.

Number of Leaves: This will be determined by counting the total number of fully expanded leaves on the tagged plants and the average will be computed.

Leaf Area Plant: This will be determined by measuring the length and maximum width of the leaves of five tagged plants and multiplied by a constant coefficient of 0.75 (Montgomery, 1911)

Leaf Area Index: This will be determined by measuring the length and breadth from the widest portion of functional leaves of each leaf from the tagged plant with a ruler. The product of length and breadth will then be multiplied by a factor,

0.75 from which area of individual leaves of the sampled plants will be obtained, added and divided by the land area occupied by the tagged plants.

$$\text{LAI} = \frac{A}{P} = \text{leaf area per plant / Area subtended by plant}$$

Where, A = Leaf area per plant (m^2)

P = Ground area per plant (m^2)

LAI = leaf area index.

Crop Growth Rates: Three plants will be randomly sampled from each sub-plot for destructive sampling these will be oven dry at 70^0c for 24 hours using the formula by Smith and Haddad, (2000). The unit of measurement is g cm^{-2} wk^{-1}.

$$CGR = \frac{W_2 - W_1}{(t_2 - t_1)} \qquad 1.x$$

W_1 = dry matter weight at a sampling period

W_2 = dry matter weight at the next sampling period

t_1 = time at which w_1 was taken

t_2 = time at which w_2 was taken

Path Model: A path model is a diagram relating intermediary, and dependent variables. Single arrows indicate causation between exogenous or intermediary variables and the dependent(s). Arrows also connect the error terms with the respective endogenous variables. Double arrows indicate correlation between pairs of exogenous variables.

Endogenous Variables: These are variables which form an internal part of the system. Endogenous variables are those which do have incoming arrows. Endogenous variables include intervening casual arrows in the path diagram. The dependent variable(s) have only incoming arrows.

Exogenous Variables: These are variables which form an external part of the system. Exogenous variables are those with no explicit causes (no arrows going to them, other than the measurement error term). If exogenous variables are correlated, this is indicated by a double-headed arrow connecting them.

Causal Paths: To a given variable include (1) the direct paths from arrows leading to it, and (2) correlated paths from endogenous variables with others have arrows leading to the given variable.

Path Coefficient: A path coefficient is a standardized regression coefficient (beta) showing the direct effect of an independent variable on a dependent variable in the path model. Thus when the model has two or more causal variables, path coefficients are partial regression coefficients which measure the extent of effect of one variable on another in the path model controlling for other prior variables, using standardized data or a correlation matrix as input.

Effect Decomposition: Path coefficients may be used to decompose correlations in the model into direct and indirect effects. This is based on the rule that in a linear system, the total causal effect of variable i on variable j is the sum of the values of all the paths from i to j.

Disturbance Terms: The residual error terms, reflect unexplained variance (the effect of unmeasured variables) plus measurement error.

1.6 Contribution to Knowledge

This research x-rays the application of Principal Component Analysis and Path Analysis in the reduction and partitioning of agricultural data.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

Agronomy is the science of crop production and the manipulation of cultural practices in a way to improve the productivity of the crop and the soil. The actual practice of agronomic trial include varietals trial, fertilizer trial, planting date, weed management, inter and intra row spacing, crop protection etc. Though few examples of multivariate analysis of agronomic trials exist in the literature, such analysis can provide useful additional information as a supplement to normal univariate analysis.

Multivariate techniques provide the statistical tools that can be used by the researchers to analyze complete set of data. It handles the analysis of problems that involves independent variables and several dependent variables, which may be correlated to one another to varying degrees (Anderson, 1984). This chapter is intended to provide an overview of multivariate concepts and a thorough dimension of path analysis, principal component and factor analysis. This thesis focuses on the reduction of the dimensionality of the agronomic variables and testing the normality assumption of a multivariate normal distribution.

2.1: Normality.

Normality of data can be assessed either by the shape of the curve on the histogram plot or by the linearity of quantile-quantile plot. In Q – Q plots, we

compare the real value of the variables against the standardized values (Kendall *et al.* 2004). Suppose that f(x, θ) is the density distribution of the population, where θ is the unknown parameter. Q– Q plots can be used to test for the normality of the order statistic, $X_{(1)} \leq X_{(2)} \leq X_{(3)} \ldots \leq X_{(n)}$ where $X_{(i)}$, is the $\frac{1}{n}$th quantile of the sample. Thus, if the plot of $(X_{(i)}, Z_{Z(i)})$ or the Q–Q plot is linear, then the variable is assessed as normal. The linearity of the Q-Q plots can also be tested by a sample correlation coefficient, r_Q (Kendall *et al*, 2004).

Let ρ be correlation between $X_{(i)}$ and $Z_{(i)}$. We reject Ho: |ρ| =0, i.e linearity in favour of Hi: $|\rho| \neq 0$, if the sample correlation coefficient is less than our critical value. The correlation coefficient is given by:

$$r_Q = \frac{Cov\left(X_{ii}, Z_{jj}\right)}{\sqrt{Var\left(X_{ii}\right) \times Var\left(Z_{jj}\right)}}$$

$0 \leq r_Q \leq 1$

The Q–Q plot will be considered linear if the value of r_Q is high, i.e close to 1

2 .2 Path Analysis

Path analysis is a statistical technique that differentiates between correlation and causation. It partitions correlations into direct and indirect effects (Afifi and Clark, 1984). The technique features multiple linear regression and generates standardized partial regression coefficients (Path coefficients). Path coefficients are independent of units of measurement; the relative importance between causal relationship may be determined (Loelilin, 1987; Pantone *et al*., 1989). It has been

used rather extensively in agronomic studies to study factors affecting plant yield (Pantone *et al*., 1992). Path coefficient analysis is a method of partitioning simple coefficient of correlation in its linearly correlated variables in to the direct effect between an independent and dependent variables and the indirect effect(s) via its respective coefficient (s) of correlation and the path coefficient. Simple correlation of coefficient is also known by several other names, like linear correlation coefficient, first degree of polynomial response, total correlation coefficient, etc (Dewey and Lu, 1959). It is called linear correlation coefficient to distinguish it from other curvilinear responses. It is known as first degree of polynomial, because higher degrees of polynomials like, quadratic (second degree), cubic (third degree), quartic (fourth degree), etc. can be estimated and their significance is tested in Analysis of Variance (ANOVA) by the significance of response with the deviation from that response. Normally, four to five degrees of polynomials explain all the variances. It is essential that the cause and effect type of relationship must exist between the independent and dependent variables proven beyond doubt with the logic and literature. Otherwise simple coefficient of correlation is the most abused statistic. Generally, it is considered that any two variables can be related. The way case of smoking and lung cancer has lingered on for decades is a good example. The principle of path analysis is explained using a simple example with two independent and a dependent variable, followed by another example with three independent and a dependent variable. It is also possible to work path coefficients with more than one related dependent variables.

The choice of variables and their number is very important. It is not worth selecting variables with negative correlations and path coefficients, because they do not contribute to the dependent factors. Also, higher number of factors may result in a high residual, which cannot be explained

2 .3 Factor analysis

A statistical approach that can be used to analyze interrelationships among a large number of variables and to explain these variables in terms of their common underlying dimensions (factors). The statistical approach involving finding a way of considering the information contained in a number of original variables into a smaller set of dimensions (factors) with a minimum loss of information (Harry., 1976).

There are two main types of factor analysis.

- Principal component analysis
- Common factor Analysis

2 .3. 1 Principal component analysis

This method provides a unique solution, so that the information contained in the original data can be condensed to as few variables as possible. It looks at the total variance among the variables, so the solution generated will include as many factors as there are variables, although it is unlikely that they will all meet the criteria for retention. In principal component analysis, a linear combination of all the original variables is taken so as to reduce the number of variables from p to m,

where the number m of principal components is less than p. The method allows us to take the principal components and use them to gain information about the entire data set via the correlation between the principal components and the original variables (Kendal *et al*., 2004). Matrices of correlations or loadings matrices show which Principal Component each variable is most highly associated with. The first principal Component is determined by the linear combination that has the highest variance. Variance measures the diffusion of the data. After the first principal component is obtained, it must be determined whether a sufficient amount of information is displayed by the data set. If adequate information is not provided, then the linear combination that displays the highest variances accounted for after the first principal component's variation is removed and designated as the second principal component. The process continues until sufficient amount of variance is explained (Richard, 1974). The use of multivariate methods is more common in other disciplines, is seen increasingly in agronomic trials (Smith and Haddad, 2000) presented results of electrophoretic, chromatographic and pedigree analysis of maize inbred lines and hybrids using principal coordinates and cluster analysis to illustrates genetic distances and genetic diversity with the given germplasm base.

2.3.2. Common Factor Analysis

This is generally referred to as "factor analysis". The factor analysis techniques use estimates of common variance among the original variables to

generate the factor solution. This results into a reduction of the factors to less than the number of original variables. It is a tedious task in factor analysis to choose the number of factors to keep than in principal component analysis.

Factor analysis has a common factor model that is attributable to the underlying common factors and to an additional source of variance called specific factors (or sometimes errors). The specific factors are attributable to particular variables in the original data set. The objective of factor analysis is to identify these variables or common factors and explain their relationships to the observed data in terms of a few underlying, but unobservable variance. In other words, our goal is to infer factor structure from the pattern of correlation in the data by letting the observed patterns of association in the data to determine the factor solution.

CHAPTER THREE

METHODOLOGY

3.0 Sources of Data

The data used in this project were obtained from the research station of the Institute for Agricultural Research, ABU, Samaru Zaria, Nigeria. The data are the results of the fertility trial of cowpea rain-fed in the period 2004/05 and 2005/06 rainy seasons. The experiment was conducted in the randomized complete block design using a five fertilizer rates (0, 30, 60, 90 and 120) grams and replicate three times. The observed data were measured on both vegetative and production stages.

3.1 Quartile-Quartile Plot

Prior to the use of any multivariate method, we must test for normality. The multivariate tools PCA, FA and CA cannot be applied unless the variables X_1, X_2,. . . , X_P have a multivariate normal distribution. If each X_i is normally distributed, then it is reasonable to assume that X_1 , X_2,. . . , X_P has a multivariate normal distribution. If not, a reasonable and appropriate transformation can be applied, such as the log transformation, a square root transformation, arcsine transformation or Box-con transformation, in order to obtain an overall multivariate normality.

A one dimensional random variable X is said to be normally distributed if

$$f(x_{i1},x_{i2},\ldots,x_{ip}) = \begin{cases} (2\pi)^{-\frac{p}{2}}|\Sigma| e^{-\frac{1}{2}(x-\mu)'\Sigma^{-1}(x-\mu)} & -\infty \le x \le \infty, -\infty \le \mu \le \infty, \sigma > 0 \\ 0 & otherwise \end{cases} \quad 3.1$$

i = 1, 2, . . . , n.

$X_{ij} = (x_{ij})$ for i = 1, 2, . . . , n

j = 1, 2, . . . , n

$X'_{ij} = (x_{i1}, x_{i2}, \ldots, x_{ip})$

$\mathrm{Var}(X_{i.}) = \sum_i$

Furthermore, a p-dimensional random variable (X_1, X_2,…,X_p) is said to be normally distributed if

$$f(x_1,\ldots,x_p) = \begin{cases} \frac{1}{(2\pi)^{p/2}}|\Sigma|^{1/2} e^{-\frac{1}{2}(x-\mu)\Sigma^{-1}(x-\mu)} & -\infty \le x \le \infty, -\infty \le \mu \le \infty \\ 0 & otherwise \end{cases} \quad 3.2$$

where $\sum$ is the variance-covariance matrix of the data.

3.2 Population Principal Components.

Principal components are particular linear combination of the p random variables x_1, x_2, . .. x_p. These linear combinations represent the selection of a new coordinate system obtained by rotating the original system with x_1, x_2, ..., x_p as the co-ordinate axes.

Principal components depend solely on the covariance matrix $\sum$ (or the correlation matrix ρ) of x_1, x_2, ..., x_p. Their development does not require a multivariate normal assumption.

Let the random vector X' = [x_1, x_2, . . . , x_p]have the covariance matrix $\sum$ with eigen values $\lambda_{i1} \geq \lambda_{i2} \geq \cdots \geq \lambda_{ip} \geq 0$.

Consider the linear combinations

$$\begin{aligned} Y_1 &= \ell_1^1 X = \ell_{11} X_1 + \ell_{21} X_2 + \cdots + \ell_{p1} X_p \\ Y_2 &= \ell_2^1 X = \ell_{12} X_1 + \ell_{22} X_2 + \cdots + \ell_{p2} X_p \\ &\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ Y_p &= \ell_p^1 = \ell_{1p} X_1 + \ell_{2p} X_1 + \cdots + \ell_{pp} X_p \end{aligned} \qquad 3.3$$

Note that

$$\text{Var}(Y_i) = \ell_i^1 \sum \ell_i \qquad i = 1, 2, \ldots . p \qquad 3.4$$

$$\text{Cov}(Y_i, Y_k) = \ell_i^1 \sum \ell_k \qquad i, k = 1, 2, \ldots p. \qquad 3.5$$

Therefore, the principal components are those uncorrelated linear combinations Y_1, Y_2 , . . . , Y_p whose variance in (2) are as large as possible. (Richard and Wichern , 1974)

Then, First Principal Component = Linear Combination of $\ell_1^1 X$ that maximizes Var($\ell_1^1 X$) subject to $\ell_1^1 \ell_1 = 1$

Second Principal Component = Linear Combination $\ell_2^1 X$ that maximizes Var ($\ell_2^1 X$) subject to $\ell_2^1 \ell_{21} = 1$ and Cov ($\ell_1^1 X$, $\ell_2^1 X$) = 0

Principal Component = Linear Combination $\ell_i^1 X$ that maximizes

$$\text{Var}(\ell_i^1 X) \text{ subject to } \ell_i^1 \ell_i = 1 \qquad 3.6$$

and

$$\text{Cov}(\ell_i^1 X, \ell_k^1 X) = 0 \text{ for } k < I \qquad 3.7$$

Basic Assumptions

In principal component analysis the basic equations are

$$X_i = Q_{ir} Z_r ; \qquad (i , r , = 1, 2, \ldots , p) \qquad 3.8$$

Where

Z_r = the r^{th} component, and

Q_{ir} = the weight of the r^{th} component in the i^{th} variates, in matrix notation

$X = QZ$

$X = \{x_1, x_2, \ldots , x_p\}$

$Z = \{z_1, z_2, \ldots , z_p)$ and $Q = \{Q_{ir}\}$

We first transform to new variates

$$Y_1, Y_2, \ldots , , \ldots , Y_p \qquad 3.9$$

Satisfying

$Y = U^1X,$

$X = UY$

Where , $Y = (Y_1 , \ , Y_2 , \ldots , Y_p)$ and U is an orthogonal matrix.

Procedure for obtaining eigen values and Vector.

- Obtain the variance – covariance matrix $\sum$ for the p – variates
- Obtain an identity matrix I , in the order of $\sum$.
- Multiply a scalar λ with the I matrix
- Equates the det $\left|\sum - \lambda I\right| = 0$.
- The value of λ are the eigen value. For any latent root there exist a corresponding latent vectors, obtained by $\sum x = \lambda x$.(Everith and Dunn, 2001)

3.3 Factor Analysis Theory.

Factor analysis is a method that can be used to reduce the dimensionality of multivariate data. However, Factor Analysis is concerned with identifying underlying sources of variance common to two or more variables. These common factors describe, if possible, the covariance relationships among these variables. Factor Analysis has a common factor model that observes the variation in each variable. This model is attributable to the underlying common factors and to an additional source of variation called specific factors (or some errors).

The objective of Factor Analysis is to identify these variables or common factors and explain their relationships to the observed data in terms of a few underlying, but unobservable variable (Harry,1976) In other words, the goal is to infer factor structure from the patterns of correlation in the data by letting the observed patterns of association in the data determine the factor solution.

Factor Analysis can also be applied after the application of principal components. In order for our m-Factors model to be adequate the number m of factors should be less than p, which is the total number of variables as in principal component analysis.

3.4 Path Analysis

Simple correlation coefficients were calculated for each pair of the parameters using the formula by Steel and Torrie (1984).

$$r = \frac{S_{XY}}{\sqrt{S_{XX} S_{YY}}} \qquad 3.10$$

r = Correlation coefficient between X and Y.
SP_X = Sums of pro duct
SS_X = Sums of square
X = Independent variable
Y = Dependent variable

Besides the direct effect of the exogenous (X_1) on the endogenous (Y), there is indirect effect of X on Y via other x's by virtue of its relationship with the X's. A change in a variable, say X_1, will affect its linear correlation r_{12}, with another variable, X_2, which invariably affects Y.

Let P_i be the direct effect of X_i on Y, and change is only partial and proportional to r_{12}. That is, $r_{ij} P_j$ is an indirect effect of X_i via X_j. Hence, the direct and indirect effect could be partitioned as done by (Dewey and Lu 1959) for an 8-independent variable.

$$r_{1y} = P_1 + r_{12} P_2 + r_{13} P_3 + r_{14} P_4 + r_{15} P_5 + r_{16} P_6 + r_{17} P_7 + r_{18} P_8 \quad (1)$$

$$r_{2y} = r_{12} P_1 + P_2 + r_{23} P_3 + r_{24} P_4 + r_{25} P_5 + r_{26} P_6 + r_{27} P_7 + r_{28} P_8 \quad (2)$$

$$r_{3y} = r_{13} P_1 + r_{23} P_2 + P_3 + r_{34} P_4 + r_{35} P_5 + r_{36} P_6 + r_{37} P_7 + r_{38} P_8 \quad (3)$$

$$r_{4y} = r_{14} P_1 + r_{24} P_2 + r_{34} P_3 + P_4 + r_{45} P_5 + r_{46} P_6 + r_{47} P_7 + r_{48} P_8 \quad (4)$$

$$r_{5y} = r_{15} P_1 + r_{25} P_2 + r_{35} P_3 + r_{45} P_4 + P_5 + r_{56} P_6 + r_{57} P_7 + r_{58} P_8 \quad (5)$$

$$r_{6y} = r_{16} P_1 + r_{26} P_2 + r_{36} P_3 + r_{46} P_4 + r_{56} P_6 + P_6 + r_{67} P_7 + r_{68} P_8 \quad (6)$$

$$r_{7y} = r_{17} P_1 + r_{27} P_2 + r_{37} P_3 + r_{47} P_4 + r_{57} P_5 + r_{67} P_6 + P_7 + r_{68} P_8 \quad (7)$$

$$r_{8y} = r_{18} P_1 + r_{28} P_2 + r_{38} P_3 + r_{48} P_4 + r_{58} P_5 + r_{68} P_6 + r_{78} P_7 + P_8 \quad (8)$$

These are converted to percentages to balance the differences in units. The percentage direct contributions, combined contributions of any two variables and the residual effect were worked out as follows.

a). The direct percentage contribution = $(P_i)^2$ x 100

b). The combined contributions of any two variables = $2(P_i P_j r_{ij})$

c).The residual effect $(R_x)= 1– (r_{1y}P_1+ r_{2\ y}P_2+ r_{3\ y}P_3+ r_{4y}P_4+ r_{5\ y}P_5+ r_{6\ y}P_6 +r_{7\ y}P_7+r_{8\ y}P_8)$

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 Introduction

This chapter consists of the results obtained from the analysis conducted in the research work. The data obtained from the Institute for Agricultural Research, Samaru, ABU Zaria was subjected to statistical analysis using the SPSS ver. 15 statistical package. The path analyses was carried out on the variables and correlation coefficient were partitioned into both direct and indirect contributions and observed that shoot dry weight and crop growth rate are contributing more to the yield of cowpea. The Principal component analysis was carried out using a 90 x 10 dimension matrix. This order of the dimension was the runs of the trial and the parameter measured in the crop. The principal component analysis was able to extract three component from the earlier dimension and its explain about 95.6% of the variation in the model. Prior to the analysis, the data was subjected to the normality test using the Q-Q plot and linearity was obtained in the plot which shows that the Multivariate Normal Distribution was observed in the data. If not, transformation can be applied, such as log transformation, a square root transformation, or an exponential transformation, in order to obtain an overall multivariate normality. Since the below Q-Q plot have a linear plot, then the variables are assessed as normal.

4.1 Q-Q Plot to Test for Normality

FIG.1: Q-Q plot of the variable showing Normality with a linear line indicating that the data observed Multivariate Normal Distribution.

Fig. 4.1: Q-Q Plot of Shoot Dry Weight

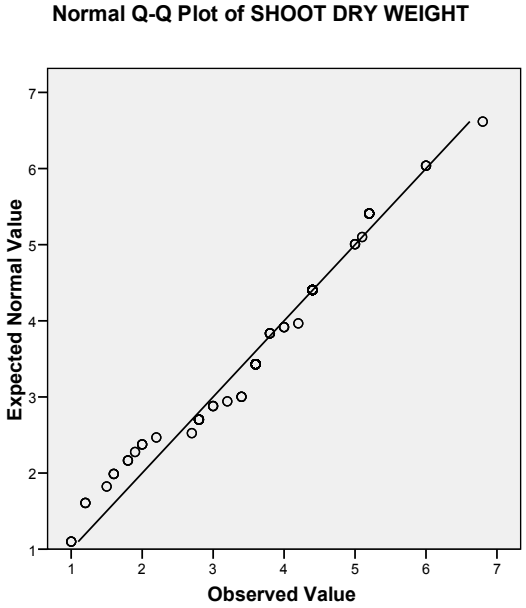
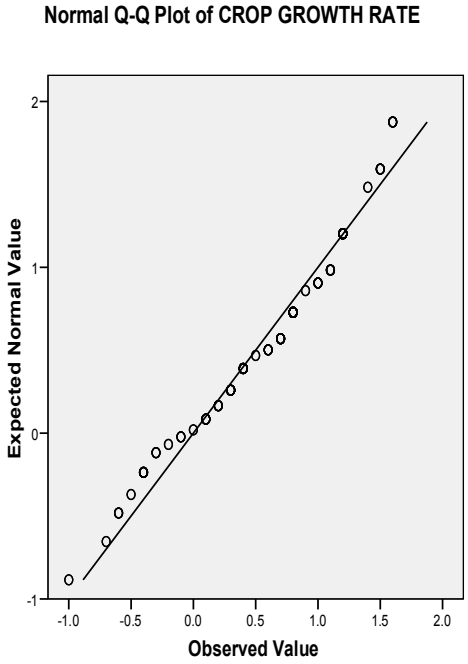


Fig. 4.2: Q-Q Plot of Crop Growth Rate

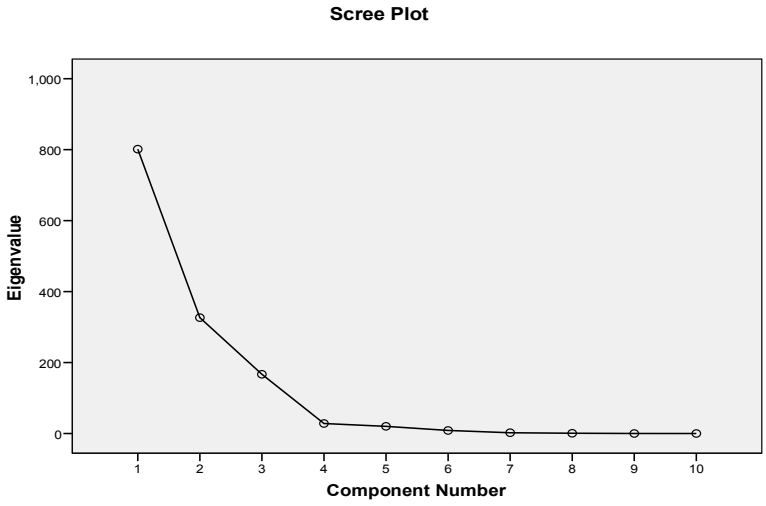


Since the above Q-Q plots have a linear plot, the variables are assessed as normal.

4.2 Principal Component Scree Plot Analysis

SPSS ver. 15 was used to run the principal components Analysis on our ten variables. In cases where such large matrices are being utilized, tools such as SPSS and MINITAB must be used (Kendall *et al*, 2004). The package can efficiently and accurately analyze the data without the possibility of human error. The 90 x 10 dimension raw data matrix was used in determining the principal component and the scree plot for determining the principal component to be kept. The first intuition is to determining the percentage of the information to be covered by the principal components no matter how many component chosen. However, this can defeat the aim of principal components analysis: to sufficiently reduced the dimensionality of the data. As shown below in the scree plot, the "elbow" in the plot appear in the 4th principal component, therefore the first three principal components are kept – a valuable reduction in dimensionality.

FIG. 4.3: Scree Plot for the determination of the Component



4.3 Principal Component Extraction

The first three principal components account for 95.6% of the variance. The eigen values, proportions of the variance, and the cumulative percentage of the variance covered by each principal component shown in Table1.

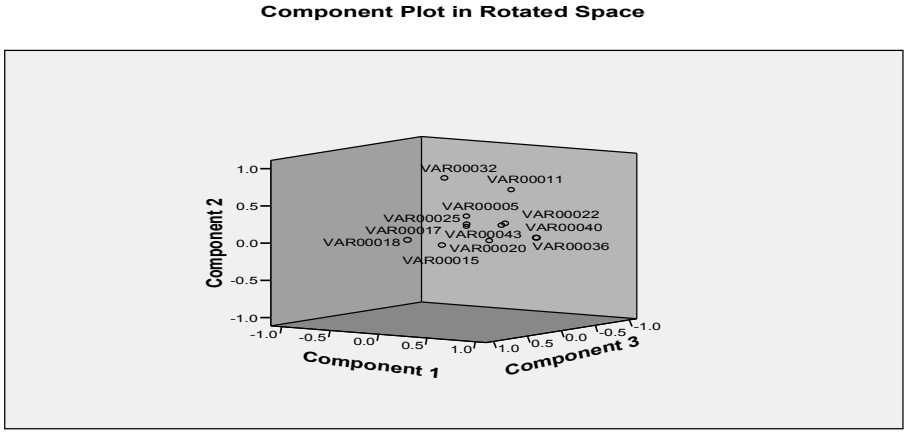
Table 4.1.The Principal Component Extracted.

Principal Components Coefficients			
Variables	PCA 1	PCA 2	PCA 3
Number of Branches	**0.435**	-0.126	**0.644**
Weight of defoliated leaves	**0.481**	**0.477**	0.359
Number of Pods	**0.462**	**-0.543**	-0.215
Length of Pods	**0.558**	-0.267	-0.317
Shoot Dry Weight	**0.827**	0.214	-0.172
Plant Height	0.169	**0.721**	**-0.469**
Number of Leaves	**0.560**	0.169	**0.453**
Leaf Area Plant	**0.868**	-0.151	-0.069
Leaf Area Index	**0.866**	-0.164	-0.064
Crop Growth Rates	**0.815**	0.128	-0.115
% of Variance	59.15	24.10	12.32
% Cumulative	59.15	83.25	95.57

In the above Table, the principal component result were shown with a VARIMAX normalized rotation applied, which can maximized the variances of the factor loadings across variables for each factor. Factor loadings > 0.71 are typically regarded as excellent and < 0.32 very poor (Nowak, 1998; Garcia *et al*., 2004). In this study, all principal factors extracted from the variables were retained with eigen values > 1.0, as suggested by the Kaiser criterion (Kaiser, 1960). Three principal components explain the variation in the model with about 96%. The earlier dimension of the data 90 x 10 had been reduced to a dimension of 90 x 3

with a large variation explained. The principal component technique was applied in the identification of the most influencing factors that contributes to the yield of cowpea. A 3-D plot of the PCA loading as presented in Fig.2, and the relationship among the 10 characters measured in cowpea are readily seen. Three factors were obtained, accounting for 95.57% of the total variance. Factor 1 is dominated by Number of Branches, Weight of defoliated leaves, Number of Pods, Length of Pods, Shoot Dry Weight, Number of Leaves, Leaf Area Plant, Leaf Area Index and Crop Growth Rates, accounting for 59.15% of the total variance. Factor 2 is dominated by Weight of defoliated leaves and Number of Pods accounting for 24.10% of the total variance. Factor 3 is dominated by Number of Branches, Plant Height and Number of Leaves accounting for 12.32% of the total variance.

Fig. 4.4: Three Component Plot in Rotated Space



4.4 Partitioning using Path Analysis

The correlation coefficient of the variables were partitioned into both direct and indirect contributions and observed that shoot dry weight and crop growth rate are contributing mostly to the yield of cowpea. This finding was in agreement with that of Mukhtar (2006). See Table 2

Table 4.2: The direct and indirect contribution of some yield parameters to cowpea yield

	1	2	3	4	5	6	7	8	9	10	P^2
1	**0.209**	-.209	0.284	-0.390	0.105	0.053	-.163	0.021	-.001	0.125	0.044
2	0.033	**-0.13**	0.144	-0.234	0.033	0.029	.123	-0.07	-.001	0.069	0.017
3	0.040	-0.01	**0.473**	-1.33	0.300	0.048	-.197	0.035	0.003	0.378	0.224
4	0.047	-.018	1.122	**0.746**	0.317	0.049	-.158	0.039	.004	0.515	0.557
5	0.026	-.005	0.513	-.641	**0.864**	0.040	-.015	0.045	-.001	-.022	0.746
6	0.038	-.013	0.239	-.295	0.118	**0.294**	-.101	0.029	-.004	0.063	0.086
7	0.069	0.033	0.585	-.556	0.258	0.059	**-0.49**	0.085	0.009	0.271	0.240
8	0.026	0.054	0.301	-.401	0.227	0.050	-.245	**0.171**	0.020	0.0314	0.029
9	-.040	.0023	0.559	-.0891	.0086	-.016	-.059	0.045	**0.074**	0.0511	0.005
10	0.027	-.009	0.567	-0.915	-.019	0.019	-.137	0.006	0.004	**0.983**	0.966

V1= Number of Branches, V2= Weight of defoliated leaves, V3= Number of Pods, V4 = Length of Pods, V5 = Shoot Dry Weight, V6 = Plant Height, V7 = Number of Leaves, V8 = Leaf Area Plant, V9 = Leaf Area Index and V10 = Crop Growth Rates.

The correlation coefficients for the growth and yield parameter of cowpea are shown in Table 3. Pod yield and number of pods were observed to be positively and significantly correlated with all the components assessed (Number of Branches, Length of Pods, Shoot Dry Weight, Plant Height, Number of Leaves, Leaf Area Plant, and Crop Growth Rates) except leaf area index and weight of defoliated leaves. The various parameters exhibited significant interrelationship

with each other. This shows the importance of the parameter to the pod yield of cowpea (Ado *et al*., 1988) reported that as the correlation coefficients between two variables is the sum of the paths connecting them, partitioning the correlation gives the direct and indirect contributions of the different independent parameters (components) on the dependent variable (pod yield).

Table 4.3: Correlation Coefficient matrix for the growth and yield component of cowpea

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V17
V1	1	0.159*	0.193**	.182*	.198**	0.156**	0.328**	0.123	-0.019	0.127	.223**
V2	0.159**	1	0.098	0.098	0.068	0.576**	-.248**	-0.408**	-0.017	0.071	.134
V3	0.193**	0.098	1	.162*	.534**	.353**	.397**	0.204**	0.038	0.385**	.762**
V17	0.223**	0.134	.762**	.169*	.670**	0.368**	0.318**	0.230**	0.051	0.524**	1
V4	0.182*	0.098	0.162*	1	0.118	-0.008	0.203**	0.169*	-0.055	0.064	0.169*
V5	0.198**	0.068	0.534**	0.118	1	0.161*	0.487**	0.226**	0.123	0.847**	.670**
V6	0.156**	0.576**	0.353**	-0.008	0.161*	1	-0.002	0.040	0.003	0.125	.368**
V7	0.328**	-0.248**	0.397**	.203**	.487**	-0.002	1	0.499**	0.120	0.276**	.318**
V8	0.123	-0.408**	0.204**	.169*	.226**	0.040	0.499**	1	.264**	0.032	.230**
V9	-0.019	-0.017	0.038	-0.055	0.123	0.003	0.120	0.264**	1	0.052	0.051
V10	0.127	0.071	0.385**	0.064	.847**	-0.125	0.276**	0.032	0.052	1	.524**

* indicates significance with P<0.05,

** indicates significance with P<0.01

*** indicates significance with P<0.001

Where

V1= Number of Branches, V2= Weight of defoliated leaves, V3= Number of Pods, V4 = Length of Pods, V5 = Shoot Dry Weight, V6 = Plant Height, V7 = Number of Leaves, V8 = Leaf Area Plant, V9 = Leaf Area Index and V10 = Crop Growth Rates, V 17 = Pod Yield

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Summary and Conclusion.

The result of the study shows that the data used in the study observed normality assumption as shown by the plotted Q-Q plot in Fig. 1 and 2. It was observed that a linear plot indicated by the Q-Q plot signifies linearity. The data observed a multivariate normal distribution.

In Table 3 of chapter four, it was observed that Pod yield and number of Pods were observed to be positively and significantly correlated with all the components assessed (Number of Branches, Weight of defoliated leaves, Number of Pods, Length of Pods, Shoot Dry Weight, Plant Height, Number of Leaves, Leaf Area Plant, and Crop Growth Rates) except Leaf Area Index and Weight of Defoliated Leaves. The various parameters exhibited significant interrelationship with each other. This shows the importance of the parameter to the pod yield of cowpea. (Ado *et al*., 1988) reported that the correlation coefficients between two variables is the sum of the paths connecting them, partitioning the correlation gives the direct and indirect contributions of the different independent parameters (components) on the dependent variable (pod yield). In Table 2, Shoot Dry Weight and Crop Growth Rate contribute mostly to the yield of Cowpea. Also, principal component was used in the reduction of the dimensionality of the data collected. The dimension of the variable was reduced to three component with the first

component explaining 59.15%, second component explains 24.10% and the third component explains 12.32% of the variation. Cumulatively, 95.57% of the variation was explained by the three components as shown in both the table of principle component coefficient and the scree plot (Table 1 and Fig. 3).

5.2 Recommendation.

It is observed from this research work that a base line information was gotten that the data generated from field trials of cowpea are of multivariate normal distributions and data reduction techniques can be employed to help in analyzing and understanding of the data.

This would assist the users of this type of data to make use of multivariate statistical methods. Moreso, since often the variables are correlated.

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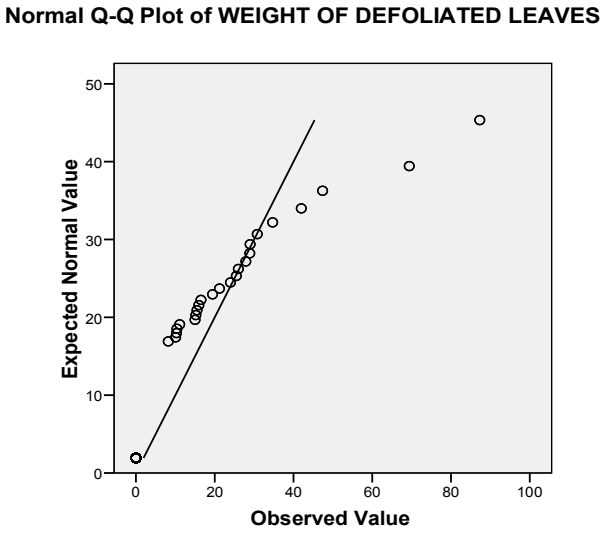
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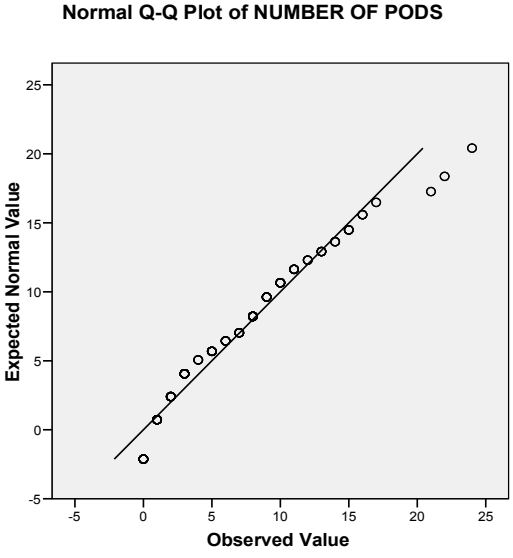
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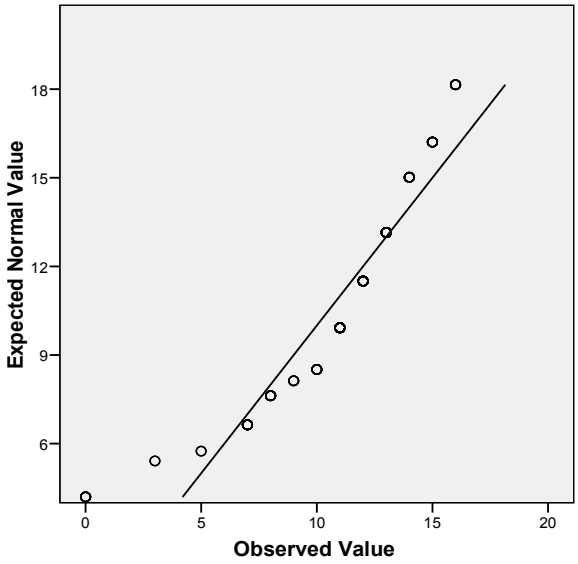
APPENDIXES

Appendix 1: Q-Q Plots of Variables

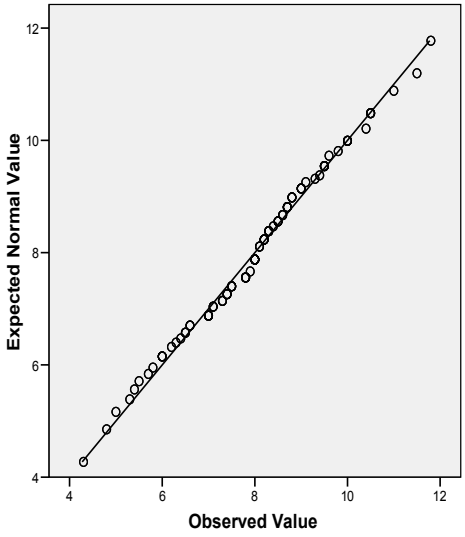




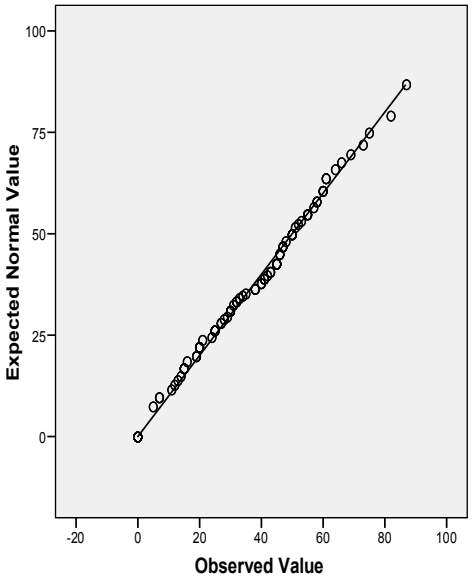
Normal Q-Q Plot of LENGTH OF PODS



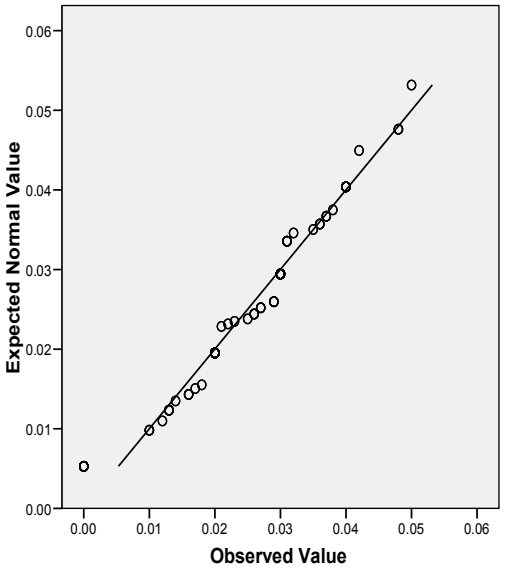
Normal Q-Q Plot of PLANT HEIGHT



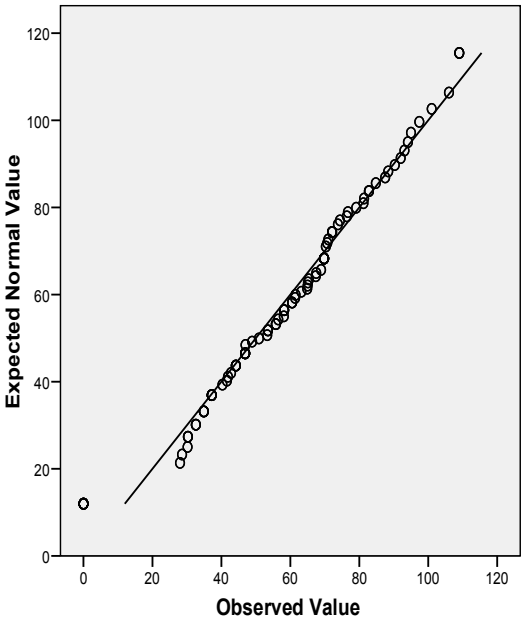
Normal Q-Q Plot of NUMBER OF LEAVES



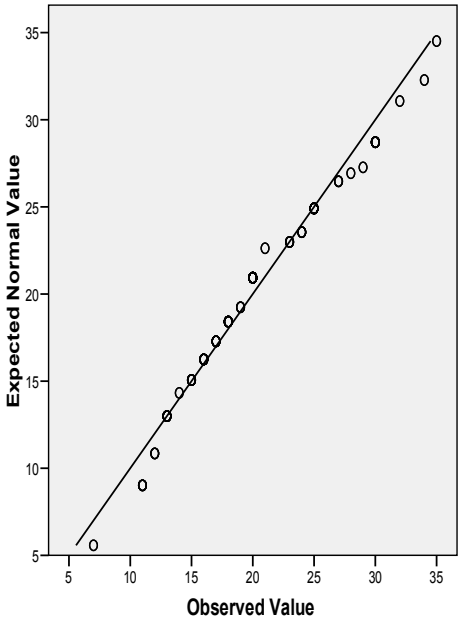
Normal Q-Q Plot of LEAF AREA INDEX



Normal Q-Q Plot of LEAF AREA PLANT



Normal Q-Q Plot of NUMBER OF BRANCHES



Appendix 2: Data of Fertility Trial of Cowpea

Title

S/No	No.of Branches	Weight of Defoliated Leaves	Number of Pods	Pod Yield	Length of Pods	Short Dry Weight	Plant Height	Number of Leaves	Leaf Area Plant	Leaf Area Index	Crop Growth Rate
1	25.00	0.00	10.00	13.57	13.00	2.80	7.80	50.00	82.80	0.04	0.40
2	13.00	0.00	11.00	3.95	13.00	3.00	8.10	25.00	42.80	0.02	0.10
3	13.00	0.00	6.00	20.26	11.00	3.20	8.60	30.00	58.20	0.03	0.10
4	13.00	0.00	3.00	12.30	9.00	1.80	6.50	20.00	40.30	0.02	-0.60
5	12.00	0.00	0.00	0.00	0.00	1.00	6.40	7.00	0.00	0.00	-0.50
6	13.00	0.00	14.00	81.42	12.00	3.60	7.50	42.00	58.20	0.03	0.30
7	13.00	0.00	13.00	26.99	11.00	3.60	6.50	16.00	81.20	0.04	0.80
8	11.00	0.00	8.00	12.70	9.00	3.60	8.60	14.00	79.10	0.04	0.20
9	20.00	0.00	17.00	7.72	11.00	4.40	7.40	21.00	28.00	0.01	1.20
10	20.00	0.00	9.00	0.00	12.00	4.40	7.30	0.00	69.80	0.03	0.20
11	20.00	0.00	3.00	70.32	11.00	3.60	5.40	45.00	82.80	0.04	0.30
12	18.00	10.40	8.00	52.43	12.00	6.80	9.30	40.00	64.90	0.03	1.40
13	18.00	24.00	6.00	58.00	14.00	5.20	8.20	41.00	109.00	0.05	1.10
14	19.00	29.00	2.00	14.00	11.00	4.40	4.80	47.00	90.30	0.04	1.20
15	20.00	47.40	6.00	48.70	11.00	5.20	11.80	52.00	109.00	0.05	1.60
16	30.00	0.00	9.00	23.68	13.00	4.40	8.00	50.00	28.60	0.01	1.20
17	25.00	0.00	8.00	16.99	11.00	3.00	7.50	45.00	47.00	0.02	1.00
18	15.00	0.00	5.00	15.83	13.00	2.20	7.30	19.00	37.20	0.02	0.10
19	20.00	0.00	4.00	0.00	11.00	1.20	7.80	20.00	34.90	0.02	-0.40
20	14.00	0.00	0.00	0.00	0.00	1.00	7.50	5.00	0.00	0.00	-1.00
21	20.00	0.00	9.00	45.00	11.00	3.60	8.70	58.00	60.50	0.03	0.80
22	7.00	0.00	12.00	28.57	13.00	4.40	11.50	27.00	67.50	0.03	1.20
23	16.00	0.00	5.00	13.59	13.00	5.20	8.70	28.00	48.90	0.02	1.60
24	20.00	0.00	8.00	22.80	13.00	4.40	10.00	19.00	81.40	0.04	0.70
25	20.00	0.00	7.00	24.01	13.00	4.40	7.40	0.00	88.40	0.04	1.20
26	25.00	0.00	13.00	74.74	15.00	4.40	8.40	48.00	84.80	0.04	1.20
27	24.00	15.20	12.00	34.59	12.00	4.40	9.10	60.00	70.30	0.03	1.20
28	34.00	30.80	5.00	38.20	13.00	4.40	8.00	60.00	65.00	0.03	1.20
29	18.00	26.00	3.00	36.60	11.00	3.60	8.80	45.00	95.00	0.04	0.80
30	18.00	42.00	5.00	38.31	11.00	4.40	8.00	46.00	92.00	0.04	1.20
31	27.00	0.00	8.00	32.47	11.00	3.60	8.30	38.00	34.90	0.02	0.80
32	28.00	0.00	3.00	15.96	12.00	3.40	5.50	31.00	30.30	0.01	0.70
33	20.00	0.00	5.00	3.97	11.00	2.80	7.10	50.00	32.60	0.01	-0.10
34	20.00	0.00	0.00	3.64	7.00	1.60	8.70	32.00	30.30	0.01	-0.20
35	19.00	0.00	2.00	0.00	13.00	1.20	8.00	11.00	0.00	0.00	-0.40
36	20.00	0.00	15.00	10.32	15.00	5.20	5.80	55.00	65.10	0.03	1.60
37	20.00	0.00	16.00	0.00	13.00	3.60	8.20	13.00	72.10	0.03	0.80
38	16.00	0.00	2.00	5.51	13.00	3.60	8.20	7.00	69.80	0.03	0.80
39	20.00	0.00	8.00	3.91	11.00	4.40	6.60	12.00	58.20	0.03	1.20
40	20.00	0.00	0.00	17.34	11.00	3.60	7.10	0.00	44.20	0.02	0.80
41	35.00	0.00	9.00	65.90	10.00	3.60	6.00	47.00	68.90	0.03	0.80
42	27.00	10.08	4.00	34.20	7.00	3.60	7.00	46.00	65.40	0.03	0.80
43	25.00	15.00	3.00	16.16	12.00	2.00	4.30	43.00	61.40	0.03	0.00
44	32.00	16.50	11.00	24.10	11.00	2.80	8.50	38.00	50.90	0.02	0.40
45	25.00	28.90	8.00	34.30	11.00	3.60	5.70	40.00	56.50	0.03	0.80
46	30.00	0.00	11.00	6.18	14.00	3.60	7.00	61.00	69.80	0.03	0.70
47	29.00	0.00	10.00	13.65	7.00	4.00	6.00	27.00	44.20	0.02	1.00
48	13.00	0.00	7.00	0.00	13.00	2.80	8.00	30.00	46.90	0.02	0.40
49	16.00	0.00	2.00	13.54	11.00	1.60	9.40	33.00	55.80	0.02	-0.70
50	11.00	0.00	0.00	9.12	0.00	1.50	8.30	15.00	0.00	0.00	-0.30
51	20.00	0.00	9.00	85.60	13.00	4.40	11.00	57.00	46.90	0.02	1.20
52	17.00	0.00	8.00	22.90	13.00	4.40	10.00	38.00	37.20	0.02	1.20

53	23.00	0.00	7.00	2.17	12.00	4.40	8.50	30.00	69.80	0.03	1.20
54	18.00	0.00	22.00	26.97	13.00	3.80	6.30	25.00	69.80	0.03	0.40
55	17.00	0.00	3.00	0.00	13.00	4.40	8.50	0.00	72.10	0.03	1.00
56	24.00	0.00	16.00	72.62	15.00	4.40	9.50	45.00	73.80	0.03	0.20
57	18.00	11.10	6.00	5.02	10.00	5.20	10.50	43.00	70.70	0.03	1.10
58	15.00	8.20	7.00	0.00	15.00	2.80	8.80	25.00	41.60	0.02	0.40
59	30.00	21.20	3.00	22.80	15.00	5.20	9.00	61.00	63.20	0.03	0.60
60	20.00	34.70	10.00	26.33	11.00	5.10	8.20	45.00	101.00	0.04	0.90
61	25.00	0.00	2.00	20.24	11.00	5.00	9.00	87.00	67.40	0.03	1.50
62	16.00	0.00	11.00	29.10	7.00	4.00	8.10	46.00	41.90	0.02	1.00
63	13.00	0.00	1.00	18.19	8.00	3.60	8.00	25.00	32.60	0.01	0.50
64	16.00	0.00	2.00	6.02	13.00	1.80	8.00	30.00	46.90	0.02	-0.10
65	11.00	0.00	0.00	0.00	0.00	3.40	8.00	20.00	0.00	0.00	-0.40
66	20.00	0.00	9.00	49.28	12.00	3.60	8.00	66.00	69.80	0.03	0.80
67	17.00	0.00	5.00	14.28	10.00	4.40	10.50	58.00	72.10	0.03	0.60
68	23.00	0.00	1.00	7.66	7.00	4.40	8.70	15.00	60.50	0.03	0.80
69	18.00	0.00	1.00	0.00	12.00	4.40	9.50	15.00	58.10	0.03	1.10
70	17.00	0.00	0.00	0.00	14.00	3.60	10.40	0.00	53.50	0.02	0.80
71	24.00	0.00	15.00	77.63	12.00	2.80	7.00	73.00	93.10	0.04	0.40
72	18.00	10.30	21.00	50.80	16.00	4.40	7.80	47.00	76.40	0.03	1.20
73	15.00	15.50	15.00	49.27	7.00	4.40	7.90	75.00	61.50	0.03	0.70
74	30.00	27.90	10.00	45.00	10.00	5.20	7.00	55.00	106.00	0.05	1.10
75	20.00	87.30	3.00	22.61	11.00	3.60	9.00	50.00	53.30	0.02	0.30
76	21.00	0.00	10.00	10.50	12.00	5.00	8.30	41.00	44.20	0.02	0.40
77	17.00	0.00	10.00	0.00	13.00	3.80	10.00	51.00	37.20	0.02	0.10
78	15.00	0.00	8.00	23.78	5.00	2.70	5.00	34.00	37.20	0.02	-0.30
79	16.00	0.00	1.00	0.00	14.00	1.90	5.30	29.00	34.90	0.02	-0.40
80	12.00	0.00	1.00	0.00	11.00	2.00	9.60	24.00	0.00	0.00	-0.60
81	20.00	0.00	8.00	59.12	14.00	3.60	9.80	55.00	30.20	0.01	0.30
82	30.00	0.00	8.00	49.27	8.00	3.60	9.50	64.00	55.80	0.02	0.30
83	25.00	0.00	8.00	18.32	3.00	4.20	9.50	35.00	46.90	0.02	0.60
84	30.00	0.00	3.00	14.38	8.00	4.40	8.80	20.00	76.70	0.03	0.70
85	25.00	0.00	1.00	3.25	16.00	3.80	6.00	0.00	74.40	0.03	0.40
86	25.00	0.00	13.00	21.06	8.00	3.60	6.20	60.00	71.00	0.03	0.80
87	13.00	15.98	24.00	43.76	13.00	3.60	6.60	32.00	97.40	0.04	0.30
88	23.00	25.50	14.00	20.45	16.00	6.00	7.40	69.00	94.10	0.04	1.50
89	15.00	19.45	3.00	19.65	8.00	4.40	7.80	53.00	53.50	0.02	1.20
90	25.00	69.40	2.00	6.65	13.00	6.00	10.50	82.00	87.50	0.04	1.50