World Journal of Agricultural Sciences 8 (6): 568-584, 2012
ISSN 1817-3047

DOI: 10.5829/idosi.wjas.2012.8.6.1688

An Insight in Statistical Techniques and Design in Agricultural and Applied Research

Ajay S. Singh and Micah B. Masuku

Department of Agricultural Economics and Management,
Faculty of Agriculture, University of Swaziland, Swaziland

Abstract: Advance applied science researches have experienced a dramatic change in knowledge and an exponential increase in technology. A lot of these technical developments involve agricultural researches and these researches deal with groups rather than individual cases and usually field and experimental study. The goal of applied research is to provide data to support existing knowledge by filling information gaps or develop new methods. Agricultural research requires proper study design, management, data collection and analysis to obtain statistically sound results. Agricultural researchers and scientists have an important role to play in the agricultural production and development of a nation. In view of the day to day radical changes in agricultural research, the scenario is becoming tough for agricultural scientists and associated scholars. Statistical science is concerned with the aspect of theory of design of experiments and sample investigation and drawing valid inferences from using various statistical methods. The statisticians design the experiments, trials and analyze the data and interpret the facts. Statistical design and technique helps to describe the involvement of complex phenomena and behavior of agricultural growth. The impact of associated factor can be analyzed with the help of simple statistical design, sampling techniques with inferential statistics. The techniques of drawing valid interpretation depend on how the data has been gathered and also depending upon the research objective. This paper describes the basic concept of statistical research design and techniques used for analysis and interpretation of investigations and also discuss the experimental error and biasness in the research investigation.

Key words: Hypothesis Testing · Parametric Test · Statistical Power · Design of Experiment · Sampling Technique

INTRODUCTION

Agriculture also called farming or husbandry for cultivation of animals, plants, fungi and other life forms for food, fiber, bio-fuel and other products used to sustain life [1]. Agriculture was the key development in the rise of sedentary human civilization, whereby farming of domesticated species created food surpluses that nurtured the development of civilization. The study of agriculture is known as agricultural science. Agriculture generally speaking refers to human activities, although it is also observed in certain species of ant and termite [2, 3]. Until the Industrial Revolution, the majority of the human population engaged in agriculture. Pre-industrial agriculture was typically subsistence agriculture in which farmers raised most of their crops for their own consumption instead of trade. A remarkable swift in agricultural practices has occurred over the past century in adoption to new technologies and the development of world markets and also led to technological improvements in agricultural techniques.

Modern agronomy, plant breeding, pesticides and fertilizers and technological improvements have sharply increased yields from cultivation, but at the same time have caused widespread ecological damage and negative human health effects [4]. Selective breeding and modern practices in animal husbandry such as intensive pig farming have similarly increased the output of meat, but have raised concerns about animal cruelty and the health effects of the antibiotics, growth hormones and other chemicals commonly used in industrial meat production [5].

Corresponding Author: Ajay S. Singh, Department of Agricultural Economics and Management, Faculty of Agriculture, University of Swaziland, Swaziland.

In the late 19^{th} century, to find new species and new agricultural practices in different countries of the world. Two early examples of expeditions include Frank N. Meyer's fruit- and nut-collecting trip to China and Japan from 1916-1918 [6] and the Dorsett-Morse Oriental Agricultural Exploration Expedition to China, Japan and Korea from 1929-1931 to collect soybean germplasm to support the rise in soybean agriculture in the United States [7].

The Green Revolution refers to a series of research, development and technology transfer initiatives, occurring between the 1940s and the late 1970s, that increased agriculture production around the world, beginning most markedly in the late 1960s [8]. In the early 20th century the over use of pesticides and synthetic fertilizers damages the long-term fertility of the soil. While this feeling lay dormant for decades, as environmental awareness has increased in the 21st century there has been a movement towards sustainable agriculture by some farmers, consumers and policymakers. In 2007, one third of the world's workers were employed in agriculture. The services sector has overtaken agriculture as the economic sector employing the most people worldwide [9].

Recent Agricultural Development: In recent years there has been a backlash against perceived external environmental effects of mainstream agriculture, particularly regarding water pollution [10], resulting in the organic movement. One of the major forces behind this movement has been the European Union, which first certified organic food in 1991 and began reform of its Common Agricultural Policy (CAP) in 2005 to phase out commodity-linked farm subsidies [11], also known as decoupling. The growth of organic farming has renewed research in alternative technologies such as integrated pest management and selective breeding. Recent mainstream technological developments include genetically modified food.

In late 2007, several factors pushed up the price of grains consumed by humans as well as used to feed poultry and dairy cows and other cattle, causing higher prices of wheat (58%), soybean (32%) and maize (11%) over the year [12, 13]. Food riots took place in several countries across the world [14, 15, 16]. Contributing factors included drought in Australia and elsewhere, increasing demand for grain-fed animal products from the growing middle classes of countries such as China and India, diversion of food grain to bio-fuel production and trade restrictions imposed by several countries. In 2009, the agricultural output of China was the largest in the world, followed by the European Union, India and the United States, according to the International Monetary Fund. Economists measure the total factor productivity of agriculture and by this measure agriculture in the United States is roughly 2.6 times more productive than it was in 1948 [17].

Six countries - the US, Canada, France, Australia, Argentina and Thailand supply 90% of grain exports [18]. Water deficits, which are already spurring heavy grain imports in numerous middle-sized countries, including Algeria, Iran, Egypt and Mexico [19], may soon do the same in larger countries, such as China and India [20]. Many governments have subsidized agriculture for a variety of political and economic reasons. These agricultural subsidies are often linked to the production of certain commodities such as wheat, maize, rice, soybeans and milk [21].

Agricultural Research Service (ARS): The Agricultural Research Service (ARS) is the principal in-house research agency of the United States Department of Agriculture (USDA). ARS has more than 2,200 permanent scientists working on approximately 1,100 research projects at more than 100 locations across the country, with a few locations in other countries. ARS's complex role in conducting scientific research for the American public is reflected in its mission, which is to conduct research to develop and transfer solutions to agricultural problems of high national priority and provide information access and dissemination to:

- Ensure high quality, safe food and other agricultural products,
- Assess the nutritional needs of Americans,
- Sustain a competitive agricultural economy,
- Enhance the natural resource base and the environment and
- To provide economic opportunities to rural citizens, communities and society as a whole.

Statistics is important in the field of social science, agriculture, medical, engineering, etc because it provides tools to analyze collected data. Scientists frequently use statistics to analyze research data. Statistics provides scientific methods for appropriate data collection, analysis and summarization of data and inferential statistical methods for drawing conclusions in the face of uncertainty. Statistical methodologies have wide applicability to almost any branch of science dealing with the study of uncertain phenomena.

Rational for Using Statistics: Statistics can help understand a phenomenon by confirming or rejecting a hypothesis. It is vital to know how we acquire knowledge to most scientific theories. The statistical methods are analysis of data depends upon the objective for collection of the data. This is not only more convenient, but would offer some insight into the appropriate directions for the planning.

In the 17th century Captain John Graunt of London found the origin of vital statistics, known as father of vital statistics. He was the first man to study the statistics of birth and death and calculate life expectancy and also constructed the life table. The theoretical development of modern statistics stated during the mid 17th century with the introduction of probability theory and theory of chance. In Germany, the systematic collection of official statistics originated towards the end of 18th century in order to have a concept of the relative power of different German states, information regarding population and collection of industrial and agricultural output. Sir Ronald A. Fisher (1890-1912) known as the father of statistics, established statistics on a very sound place by applying it to various fields, such as genetics, biometry, education, agriculture etc. He also introduced the concept of point estimation, inference and exact sampling distributions.

Applications and Limitations of Statistics: Statistics has already become a very important and useful subject and the various techniques are being used to analyze and solve the problems in different discipline.

Limitations of Statistics:

- Statistics is not suited to study the qualitative phenomenon. Statistics being a science with a set of numerical data associated with quantitative measurement.
- Statistics does not study individuals. Statistics deals with an aggregate of objects and does not give any special importance to the individual of a series.
- Statistical laws are not exact like as physical or natural law of sciences, statistical analysis is only in terms of probability and chance not an exact.
- Statistics is liable to be misused. The most important limitation of statistics is that it must be used by experts.
- Statistical methods are more dangerous tools in the hand of the inexpert.

However, in agricultural research, statistics finds some of the very interesting applications which often lead to the development of newer statistical techniques. Consequently, the branch of statistics dealing with agricultural sciences has been recognized as agricultural statistics.

Different Types of Data

Data: Data is the collection/set of observations of characteristics. There are three different types of data.

Ordinal Data: Ordinal data are measurements that enable the units of the population sample to be ordered with respect to the variable of interest.

Interval Data: Interval data are measurements that the determination of how much more or less of the characteristics being measured is proposed by one unit of the sample or population than other.

Ratio Data: Ratio data are measurements that enable the determination of how many times as much of the characteristics being measured are proposed by one unit of the sample or population than other.

Research Data: The results of a scientific investigation often contain much more data or information than the researcher needs. This data-material, or information, is called raw data. To be able to analyze the data sensibly, the raw data is processed into "output data". There are many methods to process the data, but basically the scientist organizes and summarizes the raw data into a more sensible chunk of data. Any type of organized information may be called a "data set". The raw data can give you ideas for new hypotheses, since you get a better view of what is going on. You can also control the variables which might influence the conclusion.

This paper therefore discusses the basic concept of statistical research designs, methodology and techniques used for analysis of data and interpretation of results and also discuss the experimental design, error and different types of biasness in the agricultural research investigations.

Agricultural Research and Statistical Techniques: Agricultural research and interpretation is based on a collection of statistical tools used to elucidate the associations with the outcome. A deeper understanding of this science is that of discovering causal relationships. Statistical technique of a research study means, planning the study in scientific manner so that the objectives of the study are fulfilled to facilitate meaningful interpretations of the data collected during the research.

Area and Types of Research: Generally, there are two types of research investigations, experimental and non-experimental/observational study. The experimental study, involves a planned interference with the natural course of events so that it can be observed. In the observational study, the investigator is more passive observer interfering as little as possible with the phenomena and wishes to record. There are different types of investigation in the agricultural research. Agricultural research investigations can be broadly classified in to four sections.

- Planning of research proposals.
- Execution of the investigation.
- Appropriate analysis of data or outputs.
- Meaningful interpretations of the results.

Basic Steps in the Proposals of Research:

- Definition of research problems,
- Formulation of objectives and hypothesis.
- Methodology of research for the particular problems.
- Selection of variables for the research study.
- Coverage of all possible subject matters associated with research objectives.
- Well defined tools and techniques for data analysis.
- Well defined study population, sample, control, sample size and time coverage.
- Formulation of analytical methods for the data and planning for resources.
- Anticipation and estimation of possible errors and evolving appropriate actions to rectify the errors.

Different types of investigations in the agricultural research and basic statistics use described in detail.

Sample Design and Sampling Techniques: How to select the individuals on which information are to be gathered?.

- Investigations may be carried out on an entire group or a representative taken out from the group.
- Whenever a sample is selected it should be a random sample.
- While selecting the samples the heterogeneity within the group should be kept in mind and proper sampling technique should be applied.

Several sampling designs are available depending upon the type and nature of population as well as objectives of the research investigation. Some important sampling designs are discussed below.

Purposive Sampling: In this approach sampling units are selected according to our purpose. Purposive sampling provides biased estimate and it is not statistically recognized and also can not be generalized. This technique can be used only for some specific purposes.

Random Sampling/ Probability Sampling: In this method of sampling each unit included in the sample will have certain pre assigned probability of inclusion in the sample. This sampling method provides better estimate of parameters compared to purposive sampling. Every single individual in the sampling frame has known and non- zero chance of being selected into the sample. Random sampling is also known as probability sampling.

Simple Random Sampling: In the simple random sampling method each unit of the population have equal chance of inclusion in the sample. This technique provides the unbiased and better estimate of the parameters if the population is homogeneous.

Stratified Random Sampling: Stratified random sampling is useful techniques for data collection if the population is heterogeneous. In this technique, the entire heterogeneous population is divided into a number of homogeneous groups, usually known as strata. Each of these groups is homogeneous within itself and then units are sampled at random from each of these stratums. The sample size in each stratum varies according to the relative importance of the stratum in the population. The technique of drawing the stratified sample is known as Stratified Sampling. In other words, stratification is the process by which the population is divided into subgroup/strata. Sampling will then be conducted separately in each group/strata. Strata or subgroup are chosen because evidence is available that they are related to outcome. The selection of strata will vary by area and local conditions. After stratification sampling is conducted separately in each stratum. In stratified sample, the sampling error depends on the population variance within strata, but not between the strata.

Systematic Random Sampling: In this method of sampling the first unit of the sample selected at random and the subsequent units are selected in a systematic way. If there are N units in the population and n units are to be selected. R = N/n (The R is known as the sampling interval). The first number is selected at random out of the remainder of this R (Sampling Interval) to the previous selected number.

Multistage Random Sampling: In Multistage random sampling units are selected at various stages. The sampling designs may be either same or different at each stage. Multistage sampling technique is also referred to as cluster sampling, it involves the use of samples that are to some extent of clustered. The principle advantage of this sampling technique is that it permits the available resources to be concentrated on a limited number of units of the frame, but in this sampling technique the sampling error will be increased.

Sample Size for Investigation and Recording: The sample size should be carefully fixed so that the sample size will be adequate to draw valid and generalized conclusions. The fixation of the adequate sample size requires specific information about the problems under investigation in the population under study. The sub classifications of sample require for analysis, variation, precision, availability and cost of investigations. The information collected during investigation from samples is to be recorded on pre-designed schedule or on questionnaire. The design of questionnaire depends on the objectives and facilities for analysis.

Different Types of Error in the Research Investigation

Sampling Error: There are two types of sampling error, first, faulty sampling design and second due to small sample size.

Non Sampling Error: There are three types of non sampling error, coverage error, observational error and processing error. Coverage errors crop up when all the units in the sample are not covered due to non cooperation or no response. Second, observational errors are due to improper experimental technique or an interaction of the above factors. Processing errors, due to theoretical errors in analysis or clerical/computational error or computational errors.

Random Error: Random error is the result of fluctuations around a true value because of sampling variability. Random error is just that: random. It can occur during data collection, coding, transfer, or analysis. Random error include: poorly worded questions, a misunderstanding in interpreting an individual answer from a particular respondent, or a typographical error during coding. Random error affects measurement in a transient, inconsistent manner and it is impossible to correct for random error. In other word, random error in all sampling procedures is also known as sampling error.

In the agricultural investigation, precision of agricultural variables is a measure of random error. Precision is also inversely related to random error, so that to reduce random error is increase precision. Confidence intervals are computed to demonstrate the precision of relative estimates. The narrower the confidence interval, the more precise the relative risk estimate.

There are two basic ways to reduce random error in a research investigation. The first is to increase the sample size of the study. In other words, add more subjects to the study. The second is to reduce the variability in measurement in the study. This might be accomplished by using a more precise measuring device or by increasing the number of measurements.

Systematic Error: A systematic error or bias occurs when there is a difference between the true value and the observed value from any cause other than sampling variability. A mistake in coding that affects all responses for that particular question is simple example of a systematic error.

Investigational Error: In agricultural investigation generally, these are two types of errors, response error and measurement error.

- Response error due to under coverage of the sample or non cooperation of people or missing observation. These errors can be reduced by efforts of the investigators and also proper planning of the sample size allowing mortalities etc.
- The second type of error is measurement error. These errors can be reduced by standardization of techniques, design and proper training of investigator.

Hypothesis and Statistical Inference: Inferential statistics or statistical inference includes the testing of hypothesis which is essential and important part of research investigations. In traditional statistical hypothesis testing, the statistician starts with a null hypothesis and an alternative hypothesis, performs an experiment and then decides whether to reject the null hypothesis in favor of the alternative. In other words hypothesis is a numerical statement about the parameter [22].

The first step in hypothesis testing is to state the null hypothesis ($H_{o)}$ which follows logically from alternative hypothesis (H_1) [23, 24]. Alternative hypothesis define the research statement in positive terms [23]. Acceptance or rejection of null hypothesis based on our statistical testing parametric or non parametric methodologies [22, 24, 25]. If null hypothesis (H_0) is accepted, then H_1 must be rejected and vice versa due to that hypothesis are mutually exclusive. If H_0 is accepted, this concludes that no statistical differences exist and if any difference in groups or observations are due to only chance or due to sampling fluctuations. On the other hand, if H_0 is rejected or H_1 is accepted this indicates that a significant difference exits and the differences are not only due to chance or sampling fluctuations.

Statistical Error in Hypothesis Testing: There are two types of error or incorrect conclusions possible in hypothesis testing and possibilities in which the statistical test falsely indicates that significant differences exists between the two or more groups and also analogously to a wrong positive results. Rejection of null hypothesis (H_0) when it is true is called as Type I error and acceptance of null hypothesis (H_0) when it is false and it is known as Type II error and Type II error is more harmful then Type I error [23, 24].

The probability of Type I error is known as level of significance (α) and the probability of type II error is known as the power of the test β or (1-α) [23, 24]. By convention, statistical significance is generally accepted if the probability of making type I error is less than 0.05, which is commonly denoted as $p < 0.05$ [25, 26]. The probability of type II error is more difficult to derive than probability of type I error, actually it is not one single probability value. The probability of type II error (β) is often ignored by researcher [27]. The probability of type I error (α) and probability of type II error (β) are inter-related. As α arbitrarily decreased, β is increased. Similarly, α is increased, β is decreased [22, 23].

Statistical Power: Statistically power indicates mathematically the probability of not making a type II error. Statistical Power is defined as (1-β) [24, 26]. β indicates the probability of making II error and if sample size increases, power increases. Power is analogous to sensitivity in hypothesis testing. Sensitivity indicates the probability that the diagnostic test can detect disease when it present. Power indicates the probability that the statistical test can detect significant differences, when in fact such differences truly exist.

P-Value: The p value is the probability to observe effects as big as those seen in the study if there is really no difference between the groups or treatments. The reasoning of hypothesis testing and p values is convoluted. The p values helps to assessing whether this apparent effect is likely to be actual or could just by chance or sampling fluctuation. The p values give the magnitude of difference present between populations. In calculation of p values, first assume that no true difference between the two groups/treatments. The p values allow the assessment of findings that are significantly different or not. If the p value is small, the findings are unlikely to have arisen by chance or sampling fluctuation, reject the null hypothesis. If the p is large, the observed difference is plausibly chance finding, we do not reject the null hypothesis. By convention, p value of less than 5% is considered small or significant. Sometimes p value is less than 1% or 0.01, called as highly significant [24, 28].

Confidence Interval: Confidence interval, like p values, provides a guide to help the interpretation of research findings in the light of probability. Confidence interval describes the different information from that arising in the hypothesis test. Confidence interval provides a range about the observed effect size. The formal definition of confidence interval is a range of values for a variable of interest constructed so that this range has a specified probability is called the confidence level and the end points of confidence interval are called the confidence limits [29]. By conventional, confidence interval at the 95% corresponds to hypothesis testing with p values, with a cut off for p is less than 0.05 [24, 30].

Critical Region: A region in the sample space, which amounts to rejection of H_0 is termed as critical region or region of rejection. In other words the critical region is represented by a portion of the area under the probability curve of the sampling distribution of the test statistic.

One Tailed and Two Tailed Test: A test of any statistical hypothesis where the alternative hypothesis is one tailed (right tailed/ left tailed) is called a one tailed test. For example, A test for testing the mean of a population.

H_0 : $\mu = \mu_0$ against the alter native hypothesis
H_1 : $\mu > \mu_0$ (Right tailed test) or H_1: $\mu < \mu_0$ (Left tailed test)

A test of statistical hypothesis where the alternative hypothesis is two tailed such as

H_0 : $\mu = \mu_0$ against the alter native hypothesis
H_1 : $\mu \neq \mu_0$ (two tailed test) where $\mu < \mu_0$ and $\mu > \mu_0$

Degree of Freedom (dF): The number of independent variates which make up the test statistic is known as degree of freedom. The number of degree of freedom, in general, is the total number of observations less the number of independent constraints imposed on the observations.

Parametric Test and Non-Parametric Test: Parametric statistics is a part of inferential statistics which assumes that the data have come from a type of probability distribution and makes inferences about the parameters of the distribution [31]. Most well-known elementary statistical methods are parametric [32]. Parametric test have more statistical power. Generally speaking parametric methods have more assumptions than non-parametric methods [33]. If the extra assumptions are correct, parametric methods can provide more accurate and precise estimates. However, if the assumptions are incorrect, parametric methods can provide very misleading results. On the other hand, parametric formulas are often simpler to write down and faster to compute. In some cases, but definitely not all cases, their simplicity makes up for their non-robustness, especially if care is taken to examine diagnostic statistics [34].

Non-Parametric Statistics: The non-parametric covers techniques that do not rely on data belonging to any particular distribution. Non parametric statistic is distribution free methods, which do not rely on assumptions that the data are drawn from a given probability distribution. As such it is the opposite of parametric statistics. It includes non-parametric statistical models, inference and statistical tests.

Non-parametric statistics, whose interpretation does not depend on the population fitting of any parametric distributions. Statistics based on the ranks of observations are one example of non parametric statistics and ranks also play a central role in many non-parametric approaches. In these techniques, individual variables are typically assumed to belong to parametric distributions and assumptions about the types of connections among variables are also made. These techniques include, among others; Student's t-test, Z-test, F-test, Chi-square test, Wilcoxon Signed Rank test, Mann Whitney U test.

Student's T- Test: In 1908, 'Student' derived a new distribution and test statistic known as t. The value of t is dependent upon the sample size 'n' and for each value of n-1, (degree of freedom used for estimating the standard deviation of sample). The student's t-test is a statistical method that is used to test if two sets of data differ significantly. In actual working the t-test or t statistics is calculated as a ratio of the difference between the two means to the standard error of the difference. The t-test is applicable for small samples (n < 30) and for quantitative data.

t- test = (Mean of x_1 – Mean of x_2) / s_{md}

s_{md} is the standard error of the difference of two sample means

where: $s_{md} = s_d$ / vn

In the actual research experiment, the observations may be carried out on two independent samples one known as the control group and the other known as the treated group. In such cases the comparisons are defined as unpaired comparison. In some other research experiment to overcome the variability between two groups, the observations may be carried out on a single sample. In such cases the comparisons values of observations are treated as paired comparisons. The estimation of standard error (s_{md}) is slightly different for these cases.

(I) t-test for comparing paired observation- In this case t-statistics is [Mean of d / s_{md}] with (n-1) degree of freedom. Whereas the mean of 'd' is the difference in the values of the variable before and after exposure or treatment and n is the number of observations in the sample.

$S_{md} = s_{d\,/}$ vn where s_d is the standard deviation of the values of d_i. For the calculation of s_d = v [(d_i – Mean of d)^2 / (n-1)].

After the computation of t-statistics compare the value with t distribution Table at α (conventionally, 1% or 5%) level of significance with (n-1) degree of freedom.

In the other situation, for comparing the means of two independent sample t-statistics is equal to (Mean of x_1 - Mean of x_2) / s_{md} with ($n_1 + n_2$ -2) degree of freedom. Here s_{md} is the estimated standard error of the difference between the two sample means.

S_{md} = v[($n_1 + n_2$)/ (n_1. n_2)]*[{(n_1 – 1) s_1^2 + (n_2 – 1) s_2^2}/($n_1 + n_2$ – 2)] where s_1^2 and s_2^2 are the standard deviations of the two samples and n_1 and n_2 are their respective sample sizes.

If in experiment two sample sizes are equal ($n_1 = n_2$). Therefore,

s_{md} = [($s_1^2 + s_2^2$)/ n] and degree of freedom is (2 n -2).

Z-Test: Z-test is a statistical test where normal distribution is applied and is basically used for dealing with problems relating to large samples when $n \geq 30$.

n = sample size. For example suppose a person wants to test if both rice and wheat are equally popular in a particular city. Then he/she can take a sample of size 500 from the town out of which suppose 280 are rice takers. To test the hypothesis, she/he can use Z-test.

Uses of Z-Test's for Different Purposes: There are different types of Z-test each for different purpose. Some of the popular types are outlined below:

- z test for single proportion is used to test a hypothesis on a specific value of the population proportion.

Statistically speaking, we test the null hypothesis H_0: $p = p_0$ against the alternative hypothesis H_1; $p >< p_0$ where p is the population proportion and p_0 is a specific value of the population proportion we would like to test for acceptance.

- z test for difference of proportions is used to test the hypothesis that two populations have the same proportion.
- z -test for single mean is used to test a hypothesis on a specific value of the population mean.

Statistically, to test the null hypothesis H_0: $\mu = \mu_0$ against the alternative hypothesis H_1: $\mu >< \mu_0$ where μ is the population mean and μ_0 is a specific value of the population that we would like to test for acceptance.

Unlike the t-test for single mean, this test is used if $n \geq 30$ and population standard deviation is known.

- z test for single variance is used to test a hypothesis on a specific value of the population variance.

Statistically speaking, we test the null hypothesis H_0: $\sigma = \sigma_0$ against H_1: $\sigma >< \sigma_0$ where σ is the population mean and σ_0 is a specific value of the population variance that we would like to test for acceptance.

In other words, this test enables us to test if the given sample has been drawn from a population with specific variance σ_0. Unlike the chi square test for single variance, this test is used if $n \geq 30$.

- z test for testing equality of variance is used to test the hypothesis of equality of two population variances when the sample size of each sample is 30 or larger.

Assumptions: Irrespective of the type of z-test used, it is assumed that the populations from which the samples are drawn are normal.

F-Test: Any statistical test that uses F-distribution can be called as F-test. It is used when the sample size is small i.e. $n < 30$. However one assumption of t-test is that the variance of the two populations is equal- here two populations are the population of heights of male and female students. Unless this assumption is true, the t-test for difference of means cannot be carried out. The F-test can be used to test the hypothesis that the population variances are equal.

F-Test for Different Purposes: There are different types of tests each for the different purposes. Some of the popular types are outlined below.

- F-test for testing equality of variance is used to test the hypothesis of equality of two population variances.
- F-test for testing equality of several means. Test for equality of several means is carried out by the technique named Analysis of Variance (ANOVA). To test if there are significant differences among the three levels of the drug in terms of efficacy, the ANOVA technique has to be applied. The test used for this purpose is the F-test.
- F-test for testing significance of regression is used to test the significance of the regression model. The appropriateness of the multiple regression models as a whole can be tested by this test. A significant F indicates a linear relationship between Y and at least one of the X's.

Assumptions: Irrespective of the type of F-test used, one assumption has to be met. The populations from which the samples are drawn have to be normal. In the case of F-test for equality of variance, a second assumption has to be satisfied in that the larger the sample variances have to be placed in the numerator of the test statistic.

Like t-test, F-test is also a small sample test and may be considered for use if sample size is < 30.

Testing: In attempting to reach decisions, we always begin by specifying the null hypothesis against a complementary hypothesis called alternative hypothesis. The calculated value of the F-test with its associated p-value is used to infer whether one has to accept or reject a null hypothesis.

If the associated p-value is small i.e. (<0.05) we say that the test is significant at 5% and one may reject the null hypothesis and accept the alternative one.

On the other hand if associated p-value of the test is >0.05, one may accept the null hypothesis and reject the alternative. Evidence against the null hypothesis will be considered very strong if p-value is less than 0.01. In that case the test is significant at 1%.

Uses: The main use of F-distribution is to test whether two independent samples have been drawn for the normal populations with the same variance, or if two independent estimates of the population variance are homogeneous or not, since it is often desirable to compare two variances rather than two averages. For instance, college administrators would prefer two college professors grading exams to have the same variation in their grading. For this, the F-test can be used and after examining the p-value, inference can be drawn on the variation.

Assumptions: In order to perform F-test of two variances, it is important that the populations from which the two samples are drawn are normally distributed. The two populations are independent of each other.

If the two populations have equal variances, then s_1^2 and s_2^2 are close in value and F is close to 1. But if the two population variances are very different, s_1^2 and s_2^2 tend to be very different, too.

Chi-Squared Test: Chi-square test is based on χ^2 distribution. It has large number of application in applied research. Generally it is used to test the goodness of fit, to test the independence of attributes and to test the homogeneity of independent estimates of the population variance. It has to be noted that the Chi square goodness of fit test and test for independence of attributes depend only on the set of observed and expected frequencies and degrees of freedom. These two tests do not need any assumption regarding distribution of the parent population from which the samples are taken. Since these tests do not involve any population parameters or characteristics, they are also termed as non parametric or distribution free tests. A Chi-Squared test gives an estimate of the agreement between a set of observed data and a random set of data that you expected the measurements to fit.

Calculating Chi Squared: The Chi squared calculation involves summing the distances between the observed and random data.

$\chi^2 = \Sigma$ [(Observed – Expected)^2 / Expected]

Calculation of expected frequencies in 2 x 2 Table

			Total
	A O(a)	B O(b)	(a+b)
	C O(c)	D O(d)	(c + d)
Total	(a+c)	(a +d)	N=a+b+c+d

E(a) = (a+b)(a+c) / N E(b) = (a+b)(b+d) / N
E (c) = (a+c)(c+d) / N E(d) = (b+d)(c +d) /N

χ^2 test ={ [O(a) – E(a)]^2/E(a)} + {[O(b)- E(b)]^2/E(b) +{ [O(c) – E(c)]^2 /E(c)}+{ [O(d) – E(d)]^2 / E(d)}

with (2-1)(2-1) degree of freedom with α (Conventionally, 0.05 or 0.01) level of significance.

Similarly, for 'm' rows and 'n' columns to test the independent of attributes.

Wilcoxon Signed Rank Test: The Wilcoxon Signed Rank Test is a non-parametric statistical test for testing hypothesis on median. The test has two versions: "single sample" and "paired samples / two samples".

Single Sample: The first version is the analogue of independent one sample t-test in the non parametric context. It uses a single sample and is recommended for use whenever we desire to test a hypothesis about population median.

m_0 = the specific value of population median

The null hypothesis here is of the form H_0: R = R_0, where m_0 is the specific value of population median that we wish to test against the alternative hypothesis H_1: R ≠ R_0.

Paired Samples: The second version of the test uses paired samples and is the non parametric analogue of dependent t-test for paired samples. This test uses two samples but it is necessary that they are paired. Paired samples imply that each individual observation of one sample has a unique corresponding member in the other sample. Wilcoxon Signed Rank Test. Most of the standard statistical techniques can be used provided certain standard assumptions such as independence, normality etc. are satisfied. These non parametric techniques cannot be used if the normality assumption is not satisfied. Among others, the t-test requires this assumption and it is not advisable to use it if this assumption is violated. Wilcoxon Signed Rank Test is that it neither depends on the form of the parent distribution nor on its parameters. It does not require any assumptions about the shape of the distribution. For this reason, this test is often used as an alternative to t test's whenever the population cannot be assumed to be normally distributed. Even if the normality assumption holds, it has been shown that the efficiency of this test compared to t-test is almost 95%.

Mann-Whitney U-Test: The Mann-Whitney U-test is used to test whether two independent samples of observations are drawn from the same or identical distributions. An advantage with this test is that the two samples under consideration may not necessarily have the same number of observations. This test is based on the idea that the particular pattern exhibited when 'm' number of X random variables and 'n' number of Y random variables are arranged together in increasing order of magnitude provides information about the relationship between their parent populations.

Assumptions: The test has two important assumptions. First the two samples under consideration are random and are independent of each other, as are the observations within each sample. Second the observations are numeric or arranged by ranks.

Calculation: In order to calculate the test statistics, the combined set of data is first arranged in ascending order with tied scores receiving a rank equal to the average position of those scores in the ordered sequence.

Let T denote the sum of ranks for the first sample. The Mann-Whitney test statistic is then calculated using $U = n_1 n_2 + \{n_1 (n_1 + 1)/2\} - T$, where n_1 and n_2 are the sizes of the first and second samples respectively.

Analysis of Variance (ANOVA): Analysis of variance is more useful technique used in agricultural research. If three or more than two groups / means to be tested. However, a comparison of three or more than three or more series observation can be compared through analysis of variance. Analysis of variance is based on t-distribution. In this technique total variation present in the sample data is expressed as the sum of its non negative components where each of these components is measure of variation due to some specific independent source or factor or cause. In other words, amount of variation due to each of the independent factors separately and then comparing these estimates due to assignable factors with the due to chance factor or experimental error.

One Way Analysis of Variance: The one way analysis of variance allows us to compare several groups of observations, all of which are independent but possibly with a different mean for each group. A test of great importance is whether or not all the means are equal. The observations all arise from one of several different groups (or have been exposed to one of several different treatments in an experiment). We are classifying 'one-way' according to the group or treatment.

Two Way Analysis of Variance: Two way analysis of variance is a way of studying the effects of two factors separately (their main effects) and (sometimes) together (their interaction effect).

Assumptions:

- The observations are independent.
- Parent population from which observations are taken is normal.
- Various treatment and environmental effects are additive in nature.

To test the equality of mean of group or treatment effects

Hypothesis:

H_0: $\mu_1 = \mu_2 = \ldots\ldots = \mu_k$
Steps:
$X_{11}, X_{12}, \ldots\ldots\ldots, X_{1j}$
$X_{21}, X_{22}, \ldots\ldots\ldots, X_{2j}$
….., ….., ……….., …..
$X_{i1}, X_{i2}, \ldots\ldots\ldots, X_{ij}$

- Calculate the sum of all observation ΣX_{ij}
- Calculate the sum of squares of all observations ΣX^2_{ij}
- Calculate the sum of observation in each column $(C_i) = \Sigma C_i$
- Calculate the Correction Factor (C. F.) = $(\Sigma X_{ij})^2 / N$ (where n is number of observations).
- Calculate the total sum of squares (TSS) = ΣX^2_{ij} – C.F. = S_t^2
- Calculate the column sum of squares CSS = $\Sigma (C_i^2 / K_i)$ – C.F.

or treatment sum of squares (different treatments in different columns)= C_t

- Total sum of square = Sum of square due to treatments + Sum of square due to error.
- Separation of variation or analysis of variance (ANOVA).

Source of Variation	Sum of Squares (S.S)	Degree of freedom (D.F.)	Mean Sum of Squares (MSS)	Variance Ratio
Column/Treatment	C_t^2	(K – 1)	C_t^2 / (K-1) = MSS due to Treatment	F- test = */** $F_{K-1, N-K}$
Error or Experimental Error	C_E^2			
Sum of square due to Error	(n –K)	C_E^2 / (N-K) = **		
MSS due to Experimental Error				
Total	S_t^2			

Compare the F calculated ($F_{K-1, N-K}$) at α level of significance with the F value from the Table. If F calculated is greater than Table value of F, Null hypothesis is rejected otherwise accepted.

Design of Experimental Techniques Commonly Used in Agricultural Research: Design of experiments deals with the study of methods for comparing the treatment, varieties, factors etc. under different experimental situations faced by agricultural research worker. The main objective of any experimental design is to provide the maximum amount of information relevant to the problem under the investigation. Experimental design provides maximum amount of information at minimum cost.

There are three basic principles of experimental design.

- Replication
- Randomization
- Local Control

Replication means repetition of the basic experiment. It is useful for more precise estimate of the mean effect of any factor and it is also useful for estimation of experimental error and determination of confidence interval.

Randomization is the technique or device for eliminating the bias.

Local Control: The purpose of the local control is to make the experimental design more efficient and reduce the experimental error.

Experimental Design and Design of Experiment: We are concerned with the analysis of data generated from an experiment. It is wise to take time and effort to organize the experiment properly to ensure that the right type of data and enough of it is available to answer the questions of interest as clearly and efficiently as possible. This process is called experimental design. We should also attempt to identify known or expected sources of variability in the experimental units since one of the main aims of a designed experiment is to reduce the effect of these sources of variability on the answers to questions of interest. That is, we design the experiment in order to improve the precision of our answers.

Treatment: In experiments, a treatment is something that researchers administer to experimental units. For example, a rice field is divided into four, each part is 'treated' with different fertilizer to see which produces the most rice; a teacher practices different teaching methods on different groups in the class to see which methods yield the best results; a doctor treats a patient with different treatments to see which is most effective.

Factor: A factor of an experiment is a controlled independent variable; a variable whose levels are set by the experimenter or researcher. A factor is a general type or category of treatments. Different treatments constitute different levels of a factor. For example, three different groups of farmers are subjected to different training methods. The farmers are the experimental units, the training methods, treatments; where the three types of training methods constitute three levels of the factor 'type of training'.

Main Effect: This is the simple effect of a factor on a dependent variable. It is the effect of the factor alone averaged across the levels of other factors.

Interaction: An interaction is the variation among the differences between means for different levels of one factor over different levels of the other factors.

Blocking: This is the procedure by which experimental units are grouped into homogeneous clusters in an attempt to improve the comparison of treatments by randomly allocating the treatments within each cluster or 'block'.

Completely Randomized Design (CRD): The structure of the experiment in a CRD is assumed to be such that the treatments are allocated to the experimental units completely at random. In the design of experiments, CRDs are for studying the effects of one primary factor without the need to take other irrelevant variables into account. The CRDs have one primary factor. The experiment compares the values of a response variable based on different levels of that primary factor. For CRDs, the levels of the primary factor are randomly assigned to the experimental units. It is the simplest design for researcher of agricultural sciences based on principle of randomization and replication. In this design of experiment, treatments are allotted randomly on experimental unit over the entire experimental material.

If v treatment the i^{th} treatment being replicated r_i times (i= 1, 2, …v)

$r_i = r$; I = 1, 2, ……..v

It is similar to one way ANOVA.

Linear Model for a Completely Randomized Design:

$Y_{ij} = \mu + T_i + E_{ij}$

with

- $Y_{i,j}$ being any observation for which $X_1 = i$ (*i* and *j* denote the level of the treatment/factor and the replication within the level of the factor, respectively)
- μ is the general location parameter
- T_i is the effect of having treatment level *i*

Estimating and Testing Model Factor Levels

$\Sigma\, r_i = n$ (Total number of experimental unit)
$\Sigma_{i=1} \Sigma_{j=1} Y_{ij} = G$ = Grand Total
$\Sigma_{j=1} = Y_{ij} = Y_{i*} = T_i$

Total response from the units receiving i^{th} treatment.

Total Sum of Square (TSS) = Sum of Square Treatment (SST) + Sum of Square Error (SSE) = $S_T^2 + S_E^2 = \Sigma\Sigma\,(Y_{ij}$ – Mean of $Y_{**})^2$

SST = $S_T^2 = \Sigma_{i=1} r_i$ (Mean of Y_{i*} - Mean of $Y_{**})^2$
SST = $S_E^2 = \Sigma\Sigma\,(Y_{ij}$ - Mean of $Y_{i*})^2$

Separation of Variation or Analysis of Variance (ANOVA)

Source of Variation	Sum of Squares (S.S)	Degree of freedom (D.F.)	Mean Sum of Squares (MSS)	Variance Ratio
Column/Treatment	S_t^2	(v – 1)	S_t^2 / (v-1) = * MSS due to Treatment	F- test = */** $F_{v-1, N-v}$
Error or Experimental Error	S_E^2			
Sum of square due to Error	(N –v)	S_E^2 / (n-v) = **		
MSS due to Experimental Error				
Total	S_T^2			

Compare the F calculated ($F_{v-1, N-v}$) at α level of significance with the F value from the Table. If F calculated is greater than Table value of F, the null hypothesis is rejected otherwise accepted.

Randomized Complete Block Design (RCBD): The RCB is the standard design for agricultural experiments. The field is divided into units to account for any variation in the field. Treatments are then assigned at random to the subjects in the blocks-once in each block. In other words the RCBD is a design in which the subjects are matched according to a variable which the experimenter wishes to control. The subjects are put into groups (blocks) of the same size as the number of treatments. The members of each block are then randomly assigned to different treatment groups.

Field Marks:

- Treatments are assigned at random within blocks of adjacent subjects, each treatment once per block.
- The number of blocks is the number of replications.
- Any treatment can be adjacent to any other treatment, but not to the same treatment within the block.
- Used to control variation in an experiment by accounting for spatial effects.

Sample Layout: There are 4 blocks (I-IV) and 4 treatments (A-D) in this layout.

Block I A E B D C
Block II E D C B A
Block III C B A E D
Block IV A D E C B

Model for a Randomized Block Design: The model for a randomized block design with one irrelevant variable is

$Y_{ij} = \mu + T_i + B_j$ + Random Error

where

Y_{ij} is any observation for which $X_1 = i$ and $X_2 = j$
X_1 is the primary factor
X_2 is the blocking factor
μ is the general location parameter (i.e., the mean)
T_i is the effect for being in treatment i (of factor X_1)
B_j is the effect for being in block j (of factor X_2)

Estimates for a Randomized Block Design:

Estimate for μ: Y = the average of all the data
Estimate for T_i: Y_i - Y with Y_i = average of all Y for which $X_1 = i$
Estimate for B_j: Y_j - Y with Y_j = average of all Y for which $X_2 = j$

ANOVA Table:

Source of Variation	Sum of Square (SS)	Degree of Freedom (DF)	Mean Sum of Square (MSS)	F
Blocks (B)	SS_b	b-1	MSS_b	MSS_B / MSS_E
Treatments (S_t)	SS_t	t-1	MSS_t	MMS_t / MSS_E
Error (E)	SS_E	(t-1)*(b-1)	MSS_E	
Total	SS_T	(t* b) - 1		

where: t = number of treatments and b = number of blocks or replications.

Compare the calculated values F calculated at α level of significance with the F value from the table. If calculated F is greater than table value of F, null hypothesis is rejected otherwise accepted.

Latin Square Design: In randomized block design (RCBD) whole experiment is divided into homogeneous group and treatments are allocated randomly, but in the field of experimental area are not homogeneous. For example, land fertility varies in strips or high or low level fertility. In the design of experiments, Latin squares are a special case of row-column designs for two blocking factors: Many row-column designs are constructed by concatenating Latin squares.

Layout of Design: In the Lattin Square Design, number of treatments (m) is equal to number of replications (n).

A B D C
B A C D
D C B A
C D A B

Two way elimination of variation as a result of cross grouping often results in small error mean sum of square.

ANOVA Table:

Source of Variation	Sum of Square (SS)	Degree of Freedom (DF)	Mean Sum of Square (MSS)	F
Rows (S_R)	SS_R	m-1	MSS_R	MSS_R / MSS_E
Column (S_C)	SS_c	m-1	MSS_C	MSS_C / MSS_E
Treatment (S_t)	SS_t	m-1	MSS_t	MSS_t /MSS_E
Error (E)	SS_E	(m-1)*(m-2)	MSS_E	
Total	SS_T	m^2 - 1		

Compare the different calculated values F at α level of significance with the F value from the table. If calculated F is greater than table value of F, null hypothesis is rejected otherwise accepted.

Factorial Design: Factorial indicates the effect of several factors at different levels estimate the effects of each factors and also the interaction effect. In other words, a factorial design is used to evaluate two or more factors simultaneously. The treatments are combinations of levels of the factors. The main feature of factorial designs over one-factor at a time experiment is that they are more efficient and they allow interactions to be detected. In the simple example, if two fertilizers potash (K) and nitrogen (N) used and let p different levels of potash and K different levels of nitrogen and interaction NK. General form of factorial design experiment is S^n factorial design with n factors each at s level.

Null Outcome: The null case is a situation where the treatments have no effect.

Main Effects: A main effect is an outcome that is a consistent difference between levels of a factor.

Interaction Effects: An interaction effect exists when differences on one factor depend on the level of another factor. It is important to recognize that an interaction is between factors, not levels. In the simple situation two factors and two level with interaction 2^2 – Factorial Design. 2 factors each at 2 levels.

a_0 b_0 or 1 :Factors A and B both at I^{st} level
a_1 b_0 or a : Factors A at II^{nd} level and B at I^{st} level
a_0 b_1 or b : Factor A at I^{st} level and factor B at II^{nd}
a_1 b_1 or ab : Both factors A and B at II^{nd} level

Let [1], [a], [b] and [ab] denotes the total yield of the r experimental units receiving the treatments 1, a, b and ab and corresponding mean value is divided by r denoted as (1), (a), (b) and (ab)

The main effects A, B and the interaction AB.

Steps for Analysis:

- The effect of A at first level on B at first level = $(a_1\ b_0) - (a_0 b_0) = (a) -1$
- The effect of second level of A at the second level of factor B

$= (a_1\ b_1) - (a_0 b_1) = (ab) - (b)$

These two effects are termed simple effects of factor A

A = ½ [(ab) – (b) + (a) – (1)] = ½ (a-1)(b+1)

Similarly B = ½ (b-1)(a+1)
AB = BA =1/2 [(a-1)(b-1)]
3.
[A] = [ab] – [b] + [a] -1
[B] = [ab] + [b] – [a] – 1
[AB] = [ab] – [a] –[b] +1

Sum of Square due to main effect A with 1 d.f. = $[A]^2 / 4r$
Sum of Square due to main effect B with 1 d.f. = $[B]^2 / 4r$
Sum of Square due to interaction effect AB = $[AB]^2 / 4r$
Total Degree of freedom (4r-1). Degree of freedom of Blocks = r -1 and degree of freedom for error = 3(r-1)

- Calculate the Mean Sum of Square with the help of degree of freedom.
- Calculate the F values with Analysis of Variance.

Split-Plot Designs: The split-plot design is an experimental design that is applicable when a factorial treatment structure has two levels of experimental units. In the case of the split-plot design, two levels of randomization are applied to assign experimental units to treatments. The first level of randomization is applied to the whole plot and is used to assign experimental units to levels of treatment factor A. The whole plot is split into sub plots and the second level of randomization is used to assign the sub plot experimental units to levels of treatment factor B. Since the split-plot design has two levels of experimental units, the whole plot and sub-plot portions have separate experimental errors.

The Strip-Plot Designs: In this design where there are only two factors, Factor A is applied to whole plots like the usual split-plot designs but factor B is also applied to strips which are actually a new set of whole plots orthogonal to the original plots used for factor A. Example of strip-plot design where both of the factors have three levels.

Whole Plots				
	A_3	A_1	A_2	←Strip Plot
B_1	A_3B_1	A_1B_1	A_2B_1	
B_3	A_3B_3	A_1B_3	A_2B_3	
B_2	A_3B_2	A_1B_2	A_2B_2	

It is important to note that the split-block design has three sizes of experimental units where the units for effects of factor A and B are equal to whole plot of each factor and the experimental unit for interaction AB is a sub-plot which is the intersection of the two whole plots.

Biasness in the Research Investigations

Bias: Bias is systematic error in the estimate. In other words, conclusions are systematically different from the truth. Biasness can occur during any stage of research /investigation.

- During the review of the study.
- During the selection of sample.
- During the measurement of exposure and outcome.
- During the analysis and interpretation of data.
- During the publication of the research outputs.

There are mainly three types of bias in epidemiological research.

Selection Bias: Selection bias is one of three types of bias that can threaten the validity of a study. Selection bias occurs when study subjects are selected or become part of the study as a result of a third, unmeasured variable which is associated with both the exposure and outcome of interest [35].

Information Bias: Information bias is bias arising from systematic error in the assessment of a variable [36].

Confounding Bias: When two or more factors go together and the effect of one may be confused with another. In other words confounding has traditionally been defined as bias arising from the co-occurrence or mixing of effects of extraneous factors, referred to as confounders, with the main effect(s) of interest. [37, 38]. A more recent definition of confounding invokes the notion of counterfactual effects [38].

CONCLUSIONS

Agriculture research is the study of the distribution and determinants of the agricultural related events in the specific area and time. Agricultural research is directly associated with, through the collection of data related to agricultural production and development of nation. Agricultural investigation makes a significant contribution to emerging development based management and it has played a key role in the development of statistical methods. The absence of wide homogeneity in the experimental material that is often used in the agricultural research led to the application of statistical methodology and consequently many improvement and newer development in statistics. Modern agricultural research based on better living management is complex, requiring multiple set of skills such as medical, social, technological, mathematical, statistical, etc. Research investigation is the part of wider development of nation, public health and it is associated with better life of human beings. In the advance agricultural research with the help of appropriate statistical tools and research designs provide the unbiased estimates, conclusions and appropriate interpretation. In this paper, the role of statistical research design and applications of basic techniques in agricultural research, have been emphasized scientifically.

REFERENCES

1. Report, International Labour Office, 1999. Safety and health in agriculture. International Labour Organization, pp: 77.
2. Report, 2010. For sustainable architecture, think bug. NewScientist. Archived from the original on 28 February 2010.
3. Hölldobler B. and E.O. Wilson, 1990. The Ants. Cambridge MA: Belknap. ISBN 978-0-674-48525-9.
4. Report, 2006. Human Health Issues | Pesticides | US EPA". Epa.gov. 28 June 2006.
5. Report, "EU Scientists Confirm Health Risks of Growth Hormones in Meat". Organicconsumers.org.
6. Report, USDA NAL Special Collections. Dorsett-Morse Oriental Agricultural Exploration Expedition Collection.
7. Hazell, Peter B.R., 2009. The Asian Green Revolution. Intl Food Policy Res Inst. GGKEY:HS2UT4LADZD.
8. Barrionuevo, Alexei, Bradsher Keith, 2005. Sometimes a Bumper Crop Is Too Much of a Good Thing. The New York Times, 8 Dec. 2005, USA.
9. Luc-Normand Tellier, 2009. Urban world history: an economic and geographical perspective. PUQ. pp: 26. ISBN 2-7605-1588-5.
10. European Commission, 2003. CAP Reform.
11. At Tyson and Kraft, 2007. Grain Costs Limit Profit. The New York Times. Bloomberg. 6 September 2007.
12. McMullen, Alia, 2008. Forget oil, the new global crisis is food. Financial Post (Toronto), & Jan. 2008,
13. Watts, Jonathan, 2007. Riots and hunger feared as demand for grain sends food costs soaring, The Guardian (London), 4 Dec. 2007, UK.
14. Mortished, Carl, 2008. Already we have riots, hoarding, panic: the sign of things to come?, The Times (London), 7 March 2008, UK.
15. Borger, Julian, 2008. Feed the world? We are fighting a losing battle, UN admits. The Guardian (London), 26 Feb. 2008, UK.
16. McKie, Robin, Rice, Xan, 2007. Millions face famine as crop disease rages, The Observer, (London, 22 April 2007, U.K.
17. Report, 2005. The Food Bubble Economy. The Institute of Science in Society.
18. Brown, Lester R., 2010. Global Water Shortages May Lead to Food Shortages-Aquifer Depletion. Archived from the original on 24 July 2010.
19. Report, 2006. India grows a grain crisis, Asia Times (Hong Kong). 21 July 2006.
20. Schneider, Keith, 1989. Science Academy Recommends Resumption of Natural Farming. The New York Times. 8 Sep. 1989, USA.
21. Jowit, J., 2010. Corporate Lobbying Is Blocking Food Reforms, Senior UN Official Warns: Farming Summit Told of Delaying Tactics by Large Agribusiness and Food Producers on Decisions that Would Improve Human Health and the Environment. The Guardian (London)., The Guardian, 22 Sept. 2010, UK.
22. Hopkins, K.D. and G.V. Glass, 1978. Basic statistics for the behavioral sciences, Englewood Cliffs, New Jersey, Prentice Hall, USA.
23. Keppel, G., 1978. Design and analysis. A researcher's handbook. Englewood Cliffs, New Jersey, Prentice Hall. USA.
24. Gupta, S.C. and V.K. Kapoor, 1970. Fundamental of mathematical statistics, SC Publication, New Delhi, India.
25. Elenbaas R.M., J.K. Elenbass and P.G. Cuddy, 1983. Evaluating the medical literature Part II: Statistical Analysis, Ann. Emerg. Med., 12: 610-613.
26. Sokal, R.R and F.I. Rohlf, 1981. Biometry (ed. 2) New York, WH Freeman and Co.
27. Freeman, J.A., T.C. Chalmers, H. Smith, *et al*., 1978. The importance of beta, the type II error and sample size in the design and interpretation of randomized clinical trial. New Engl. Jr. of Med., 299: 690-694.
28. Rao, N.S.N., 1985. Elements of Health Statsitics, First edition, R. Publication, varanasi, India.
29. Last, J.M., 1988. A dictionary of epidemiology, Oxford: International Jr. of Epidemiology.

.30. Gardner, M.J. and D.G. Altman, 1986. Confidence intervals rather than p values: estimation rather than hypothesis testing, BMJ, 292: 746-750.
31. Seymour, G. and Wesley M. Johnson, 2006. Modes of Parametric Statistical Inference, John Wiley and Sons, ISBN 978-0-471-66726-1.
32. Cox, D.R., 2006. Principles of Statistical Inference, Cambridge University Press, ISBN 978-0-521-68567-2.
33. Corder and Foreman, 2009. Nonparametric Statistics for Non-Statisticians: A Step-by-Step Approach, John Wiley & Sons, ISBN 978-0-470-45461-9.
34. David Freedman, 2005. Statistical Models: Theory and Practice, Cambridge University Press.
35. Nutter, Jr., F.W., 1999. Understanding the interrelationships between botanical, human and veterinary epidemiology: the Ys and Rs of it all. Ecosys Health, 5(3): 131-40.
36. Clayton, David and Michael Hills, 1993. Statistical Models in Epidemiology, Oxford University Press, USA.
37. Neil Myburgh, Debra Jackson, 2010. "Measuring Health and Disease I: Introduction to Epidemiology".
38. Carol Buck, Alvaro Llopis, Enrique Nájera, Milton Terris, 1998. The Challenge of Epidemiology: Issues and Selected Readings. Scientific Publication No. 505. Pan American Health Organization. Washington, DC., pp: 3.