APPLICATION OF RESPONSE SURFACE METHODOLOGY IN MODELLING AND OPTIMIZATION OF THE YIELDS OF COMMON BEAN (*Phaseolus vulgaris L.)* USING ANIMAL ORGANIC MANURES

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DECLARATION AND RECOMMENDATION

Declaration:

This thesis is my original work and has not been presented for award of a diploma or conferment of degree in this or any other institution

Signature ………………………………… Date …11/09/2019….

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Recommendations

This thesis has been examined, passed and submitted with our approval as University supervisors.

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DEDICATION

I dedicate this work to my parents who have stood with me throughout my academic life. I also dedicate this work to my brothers who have always been motivating me.

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ABSTRACT

The objective of design and analysis of experiments is to optimize a response which is influenced by several independent variables. In agriculture, many statistical studies have focused on investigating the effect of application of organic manure on the yield and yield components of crops. With most of these studies showing a clear positive effect of application of organic manures on the yield and yield components of various crops. However, many of these studies do not try to optimize the application of the manures for maximum productivity, but select the best treatment among the treatment range used. This is mainly due to design and analysis of experiments applied. Therefore, there is a need to apply a statistical method that would establish the effect of the application of organic manures on crop production and in addition optimize the levels of application of these manures for maximum productivity. This study aimed at application of response surface methodology for optimization of the yields of common bean (*Phaseolus Vulgaris* L.) using animal organic manure. The study was conducted at Chuka University Horticultural Demonstration Farm. An experiment laid down in a Randomized Complete Block Design was used. The treatments consisted of three organic manure sources (cattle manure, poultry manure and goat manure) each at three levels (0, 3 and 6 tonnes per ha). Data was collected from six weeks after sowing to physiological maturity. Data collected included the number of pods per plant grain yields at harvest. The data collected was subjected to analysis of variance and multiple Regression Analysis using the R-statistical software. The Central Composite Design was used to develop a second order polynomial model, with a goal of optimizing the multiple responses of common beans to animal organic manure. The findings indicated that there was a positive response of the goat and the poultry manure ($p < 0.05$) to common bean performance with the interaction of poultry and goat yielding the best results (p-value=1.51E-07)<0.05. Cattle manure did not significantly increase performance of common beans. This could be attributed to slow realise of nutrients and low N content in cattle manure. It was concluded that more use of poultry and goat would increase the yields of common beans in the area of study. The recommended levels of application of the manures in the area of study were 2.1608 t ha^{-1}, 12.7213 t ha^{-1} and 4.1417 t ha^{-1} cattle manure, poultry manure and goat manure respectively. These are the optimum levels that would lead to maximum yield of common beans without an extra cost of input.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATION AND ACRONYMS

ANOVA	Analysis of Variance
BBD	Box-Behnken Design
CCD	Central Composite Design
DF	Degree of Freedom
FO	First Order
N	Nitrogen
NACOSTI	National Commission for Science, Technology and Innovation
NPK	Nitrogen Phosphorous and Potassium
PDN	Number of Pods per Plant
PNB	Number of Branches per Plant
PQ	Partial Quadratic
RCBD	Randomized Complete Block Design
RSM	Response Surface Methodology
TWI	Two-way with Interaction

CHAPTER ONE
INTRODUCTION

1.1 Background to the Study

Response Surface Methodology is a vital statistical design of experiments subject. The method explores associations amongst numerous descriptive variables and one or more response variables. Response Surface Methodology was first presented by Box and Wilson (1951) who were driven by the need to carry experiments efficiently through a proper choice of design, and to determine operating conditions on a set of controllable variables that give rise to an optimal response. The objective of design and analysis of experiments is to optimize a response (output variable) which is affected by numerous independent variables (input variables).

Statistical methods have been used to examine the relationship between application of organic manure and crop productivity (Faisal *et al*., 2013; Admas *et al*., 2015; Alhrout *et al*., 2016 & Shafeek *et al*., 2017). However, most of these studies have focused on the effect of application of organic manure on the yield and yield components of various crops. For instance, split plot designs and randomized complete block designs had been applied to investigate the effect of organic and inorganic fertilizers on the yield and yield components of maize (Faisal *et al*., 2013). The treatments used were different fertilizer levels assigned to the main plots. Faisal *et al*., (2013), showed that there was a significant effect of the farm yard manure ($p < 0.05$) on the yield and yield components of maize. The farm yard manure application led to increase in the number of leaves and the leaf area (Faisal *et al*., 2013). However, this study did not attempt to optimize levels of farm yard manure or the inorganic fertilizers using the treatment range applied for maximum production of maize.

Admas *et al*. (2015) also applied randomized complete block design to investigate the effect of different levels of sulphur, nitrogen and compost manure on the yield and yield components of maize. The study considered variables such as maize grain yield, total above ground dry biomass, plant height, grain number per cob, cob weight, thousand seed weight, nitrogen and sulphur concentration of leaves and grains. The results revealed a positive effect of the integrated application of organic and inorganic fertilizers to the crop yields (Adams *et al*., 2015). Just like in Faisal *et al*. (2013), the positive effect was established but there was no optimization on the levels of fertilizer and compost manure that would lead to the highest response.

The effect of chicken manure, NPK fertilizers and their combinations on common beans, using a randomized complete block design, demonstrated variable bean crop performance (Alhrout *et al*., 2016). The study considered various yield and yield components i.e., plant height, average of leaves number per plant, average of pods number per plant, grain yield per plant, and pod productivity per hectare. The results showed that the application of NPK and chicken manure significantly increased the production of common bean but chicken manure was recommended since it was cheaper than the NPK (Alhrout *et al*., 2016). However, no optimization was done in this study and thus the levels of the manures that would yield the best production remained unknown.

A study using Randomized Complete Block Design (RCBD) with five replications showed a significant effect of cattle manure on the growth, yield and nutrient content of mung bean. The study revealed a statistically significant variation on different growth parameters and yield for different levels of cattle manure (Mahabub *et al*., 2016). Sanni & Adenubi (2015) carried out the analysis of variance to determine the effect of goat and pig manure on soil chemical properties, growth and yield of okra. The findings showed that application of goat manure resulted in improved okra growth and yield performances (Sanni & Adenubi, 2015). In all these statistical methods applied, it was established that animal manures have a positive effect on crop yields and more specifically the common bean. However, due to limitation of design and analysis of experiments used in this study, the study only established the best treatments among the treatment range applied. The studies did not attempt to optimize the amount of manure or fertilizers that can lead to optimum crop productivity. Optimization of levels of manures and fertilizers is important since it enables the farmers to get the best production without an extra cost in input.

There are various statistical methods that can be used to optimize the dependent variable in an experimental design study. Such methods include the simplex method, central composite designs and the Doehlert design (Lundstedt *et al*., 1998). The central composite designs and the Doehlert design are classified under response surface methodology (RSM). Simplex method normally encircles an optimum only without looking at the entire effects on the dependent variable. However, the response surface methodology can be used to determine the exact optimum. This makes it a superior optimization technique in design and analysis of experiments (Lundstedt *et al*., 1998). Response Surface Methodology is a collection of mathematical and statistical techniques that are useful for empirical modeling and analysis of response that is influenced by several independent variables with an objective of optimizing the response (Myers 2016; Montgomery, 2017). In application, RSM has been widely used in many fields such as industrial, biological sciences, clinical, social, food, engineering, and agricultural sciences (Chelule, 2014).

Response surface methodology is applied in optimization of response surfaces in a situation where y is the response variable of interest and there is a set of predictor variables $x_1, x_2. . . x_k$ (Myers *et al*., 2016). However, in several Response Surface Methodology problems, the form of the relationship between the response and the independent variables is unknown (Montgomery, 2013). For this reason, the starting point in RSM is finding a suitable approximation for the true functional relationship between y and the set of independent variables (Montgomery, 2013). Mostly, a low-order polynomial in some region of the independent variables is employed. If the linear function of the independent variables response models well the response of interest, then the first-order model is the ultimate approximation function (Montgomery, 2013). This first order polynomial is represented as;

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_k x_k + \varepsilon \qquad 1.1$$

If the system contains the curvature, then a higher degree polynomial should therefore be applied, such as the second-order model which is represented as;

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum\sum_{i<j} \beta_i x_i\, x_j + \varepsilon \qquad 1.2$$

The expected value of the response in 1.1 is given by;

$$E\,(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_k x_k \qquad 1.3$$

This expected response can be represented in form of a surface referred to as the response surface (Myers *et al*., 2016). If the response variable of interest is a function of the proportions of the different ingredients used in its formulation, then this type of response surface problem is called a mixture problem (Myers *et al.*, 2016).

The main objective of Response Surface Methodology was to find the operating conditions for the system that are optimum or to find a section of the space factor factor in which operating requirements are satisfied (Montgomery, 2013). The first-order model is expected to be suitable when the experimenter is concerned in approximating the response surface that is true over a moderately small section of the variable space of independent variable in a setting where there is almost no curvature in the response function (Montgomery, 2013). In most of the cases, the curvature in the true response surface is strong enough that the first-order model (even with the interaction term included) is inadequate (Myers *et al*., 2016). A second-order model will likely be required in these situations. Such a response surface could arise in approximating a response such as yield, where we would expect to be operating near a maximum point on the surface (Khuri & Mukhopadhyay, 2010). Thus, this study applied RSM to establish the best levels of the manures that optimized the yields of common beans.

1.2 Statement of the Problem

In Kenya, there has been increasing demand for beans, but bean yields across the country remain low due to low soil fertility, poor soil structure, reduced microbial activates, poor physical, biological and chemical properties of the soil resulting from continuous use of inorganic fertilizers and poor soil management. One possible way of increasing soil nutrients level and improving the above soil properties is application of organic manures. The organic manures (poultry, goat and cow manures) are relatively cheap to acquire since they are locally available. Though many studies have been carried out using organic manure, these studies focus in getting the best applied treatment over the range of treatments used, but not optimising response variable using the range of factors in an experiment. Hence, there is need to carry out a study on how organic manure can be applied in optimisation and modelling of common bean yields using appropriate design called RSM. This is possible since the key objective of RSM is to summarize relationships between several explanatory variables and one or more response variables through a mathematical model and thereafter, optimize the response variable.

1.3 Objectives of the Study

This research was guided by the following general and specific objectives.

1.3.1 General Objective

Application of response surface methodology for optimization and modelling of the yields of common bean (*Phaseolus Vulgaris* L.) using animal organic manures.

1.3.2 Specific Objectives

i. To determine the effects of organic manures on grain yield and yield components of the common bean
ii. To fit statistical models using the collected data
iii. To determine optimal application of organic manure that would optimize common bean production

1.4 Research Hypotheses

$H0_1$: There is no significant effect of organic manure on grain yield and yield components of beans

$H0_2$: There is no statistically significant model fitted from the data

$H0_3$: RSM give optimal application of organic manure that would optimize common bean production

1.5 Significance of the Study

This study is important since it provides suggestions on optimal levels of application of animal manures that will maximise production of common beans. These levels will lead to maximum yield. Moreover, other stake holders can also apply RSM in optimization studies since it has been shown to perform well in optimizing the response under influence of a set of independent variables.

CHAPTER TWO
LITERATURE REVIEW

2.1 Overview of Common Bean Production and Effects of Animal Manures on the Soil

Phaseolus vulgaris (common bean) is one of the most important legumes worldwide (Desiderio *et al*., 2013). It is also an important source of nutrients for more than 300 million people in parts of Latin America and Eastern Africa (Petry *et al*., 2015; Sperotto & Ricachenevsky, 2017). Common bean is also very useful as a vehicle for iron biofortification (Petry *et al*., 2015). Common bean is a major source of micronutrients such as zinc, iron, folic acid and thiamin (Celmeli *et al*., 2018). The annual global bean production is about 12 million metric tons, with 2.5 and 5.5 million metric tons alone in Africa and Latin America, respectively (Belete & Bastas, 2017). The highest world producers are Myanmar, India, Brazil and China with about 3.8, 3.63, 2.94 and 1.4 metric tons per year respectively (FAO, 2017). The best bean producers in Africa are; Kenya, Tanzania and Uganda (FAO, 2017)

Common bean production is mainly carried out by small scale farmers with an average of 0.5-2.0 hectares. Common beans serve as a major element in increasing production in smallholder farmer systems, enhancing food security and nutrition. Common beans are high in protein, dietary fibre, complex carbohydrates, vitamin B components (thiamin, folic acid and niacin) and micro-nutrients, for example iron and zinc (Kotue *et al*., 2018). Besides providing nutrients, common beans comprise rich variety of polyphenolic compounds with prospective health benefits (Imran *et al*., 2014). People who eat beans more have a lower heart disease risk. This is because of the phytochemicals found in beans which are said to protect against the disease (Garden, 2019). Beans also have an extensive range of plant chemicals that has the ability to fight cancer cell spread, in particular, isoflavones and phytosterols which are related with reduction of risk of cancer. Further, beans helps in production to the body with soluble fiber, which plays an important role in controlling blood cholesterol levels (Garden, 2019) Common beans also improves soil fertility through biological nitrogen fixation (Koskey *et al*., 2017).

Despite these benefits, the common beans production is constrained by many factors such as poor varietal selection, drought, heat and cold stress poor agronomic practices such as untimely planting, poor soil fertility, weeds, diseases and pests control, poor postharvest handling and poor marketing strategies (Fageria *et al*., 2010), each of which causes significant reductions in yield and loss of income. Studies have shown that soil fertility is one of the major problems in production of common beans (Langwerden, 2014; Mwaniki, 2002; Lynch *et al*., 2009). Soil fertility as a problem in production of common beans can be solved by applying the organic and the inorganic fertilizers (Langwerden, 2014). The advantage of using the organic fertilizers over the inorganic ones is that they improve the structure of the soil and increase the soil ability to hold water and nutrients. Over time, organic fertilizers make the soil–and plants–healthy and strong (Naguib, 2011). The organic fertilizers are ultimate slow-release fertilizers and it's very difficult to over fertilize or harm the plants. In addition, there is little or no risk of toxic build ups of chemicals and salts that can be deadly to plants. Further, Organic fertilizers are renewable, biodegradable, sustainable, and environmentally friendly and it is cheap since it can be made by composting or finding inexpensive sources such as local dairy farms (Naguib, 2011).

Organic fertilizers, offer useful properties to the soil and also add availability of nutrients, which assists in maintaining the yield and quality of crops and are less expensive than inorganic fertilizers (Thy & Buntha, 2005). Organic fertilizers are not only the source of organic matter and nutrient, but also boost microbial population, physical, biological and chemical properties of the soil (Albiach *et al.* 2000). Among organic fertilizers, compost and animal manures are well known sources of plant nutrients. Compost and animal manures are soil conditioners, which provides nutrients and organic matter within the soil and also ameliorate the water-holding capacity, firmness and structure of soil (Hartl *et al*., 2003). They can improve the physical, chemical and biological properties of degraded or low fertility soil and also be the source of Nitrogen, Phosphorous and Potassium for plants (Baziramakenga & Simard, 2001). It has also been reported that the number of pods per plant, pod dry weight, number of nodules per plant and the plant height of the common beans increased significantly on the application of organic manure (Islam *et al*., 2016). However, the use of organic manure has some negative impacts on crops, like transmission of human pathogens such as *Escherichia coli* in vegetables like lettuce (Johannessen *et al*., 2004). Such effects can be avoided by appropriately treating the manure prior to application.

Composting and pasteurization can be used for treatment though at an additional cost. The benefits animal manure use in crop production outweighs the negative effects while implementing permanent climate change considering that inorganic fertilizer production is associated with externalities like the greenhouse gas production.

Poultry manure has long been used and recognized as the most desirable animal manures because of its high nitrogen content (Eliot, 2005). Further, it supplies other nutrients and serve as soil amendments by adding essential organic matter (Ouda *et al*., 2008). It also improves the soil moisture and nutrient retention and soil physical properties (Lund *et al*., 1980). Poultry manure is often produced in areas where it is needed for pastures and crop fertilization. The increased size and frequent clean out of many poultry operations make poultry manures available in sufficient quantities and on timely basis to supply most fertilizer needs. When properly applied, chicken manures can be valuable resource for common beans, maize and other crop production. The economics of using poultry manures varies considerably. Poultry litter is made out of raw manure and the bedding materials such as sawdust, wood shavings, grass cuttings, banana leaves or rice hulls. The combination provides an excellent source of nitrogen (N), phosphorus (P) and sulphur(S) which is essential for increasing the yields of common beans and its components (Eliot, 2005).

It has also been discovered that 15 t ha^{-1} of poultry manure application is significantly enhanced in all the parameters measured (stem diameter, leaf width and length, mean plant height, leaves per plant, fresh harvest per hectare and branches per plant) of the Amaranthus production. (Mshelia & Degri, 2014). Poultry manure also showed second best effect on growth parameters and yield attributes (Plant height, root length, pod length, number of branches plant, number of leaves plant, plant weight, number of pods plant, number of seeds pod, number of seeds plant and biological yield) than Di-ammonium Phosphate as a nutrient source for yield of bean under the experimental conditions (Rahman *et al*., 2014). Poultry manure increased the vegetable production, yield and quality of lettuce (Masarirambi *et al*., 2012). This therefore means that it is high in essential soil nutrient content.

In addition, poultry manures can be used to reduce the number of toxic compounds such as nitrates produced by long used inorganic fertilizers. Therefore, it improves the quality of leafy vegetables and legumes as well as human health. In addition to this, it is also possible to lessen the escalating effects of ailments such as cancer, HIV and AIDS. Besides this, farm inputs will improve when farmers adopt the use of animal manures rather than inorganic fertilizers (Masarirambi *et al*., 2012).

The application of organic manure such as cattle manure in farming is a common practice in various rural areas. This manure type is not as rich in nitrogen as many other types such as poultry and goat manures; nonetheless, the high levels of ammonia can scorch plants when the fresh manure is directly used. Cow manure that is composted, on the other hand, can deliver plentiful assistances to the garden (Reddy *et al*., 2000). Cattle manure is fundamentally made up of grass and grain that is digested. Cow dung is rich in organic materials and high in nutrients. It comprises of nitrogen of approximately 3 percent, 2 percent phosphorus, and 1 percent potassium (3-2-1 NPK) (Thakur, 2014). Composting cow manure has numerous benefits. Further to eradicating dangerous ammonia gas and pathogens, as well as weed seeds, cow manure that is composted improves large amounts of organic matter to the soil. By incorporating this compost into the soil, you can increase its holding capacity of moisture. This allows less frequent watering, as the plant roots can use the supplementary water and nutrients whenever needed. Furthermore, it will improve aeration, helping to break up compacted soils. Composted cow manure also comprises useful bacteria, which transform nutrients into easily accessible forms so they can be released slowly without tender plant roots burning. Composting cow manure also produces about a third less greenhouse gases, making it environmentally friendly (Weil, 2004).

The highest fertilization rate of cattle manure estimated as 18 m^3 fed^{-1}, gives the tallest plant, the highest number of leaves per plant and the biggest fresh and dry weight of leaves and stems as well as the highest total pods yield per fed. Also, the pod measurements expressed as (pod length, pod diameter, average pod weight) as well as pod nutritional values such as (N, P, K and protein) can be increased with increasing cattle manure rates (Shafeek *et al*., 2017). This manure is also reported to be effective in increasing the yields of cereals (especially maize), legumes, oilseeds, vegetables and pastures, and in increasing plant nutrient concentration, especially N, P and K (Uzoma *et al*., 2011).

Goat manure comprises high nitrogen content as compared to cows, buffaloes and horses manure. In addition, this nitrogen enhances the growth of plants and crops by nitrogen fixation, hence it increases the yield of crops at least by 20%. Garden bed use of goat manure can generate the ideal growing conditions for your plants. The dry pellets that are natural are both easy to collect and then apply, however, they are also less messy than many other types of manure. There are infinite uses for goat manure. Goat droppings can be used in almost all the types of garden, with that of flowering plants, herbs, vegetables, and fruit trees. Goat manure can also be composted and applied as mulch. Many of the fruit gardeners has noticed that after using goat manure, falling of their fruits before maturity due to natural calamities like wind, heavy rainfall, storm and other natural calamities has been decreased by nearly 50% in all the areas where it has been applied. In general, goat manure is used as a fertilizer in most common areas (Gichangi *et al*., 2010). For instance, goat manure fertilizer can provide substantive assistance to gardeners which in turn produce healthier plants and crop yields. Goats not only produce neater pelletized droppings, but their manure doesn't typically attract insects or burn plants as does manure from cows, buffaloes or horses. Goat manure is essentially odourless and is helpful for the soil to sustain its PH. Furthermore, this manure comprises sufficient amounts of the nutrients that plants need for grow optimally, particularly when the goats have bed in stalls. As urine accumulates in goat droppings, the manure holds more nitrogen, thus increasing its fertilizing potency (Botac & Norta, 2016).

2.2 Statistical Analysis of the Effects of Organic Manure on Grain Yields and Yield Components

Analysis of the effects of organic manure on grain yields and yield components of grain crops has been done by applying statistical methods such as randomized complete block design, split plot design and Analysis of Variance (ANOVA) (Faisal *et al*., 2013; Admas *et al*., 2015; Alhrout *et al*., 2016; Shafeek *et al*., 2017). Faisal *et al*. (2013) applied the randomized complete block designs to inestigate how the yield and yield components of maize were affected by application of organic and inorganic fertilizers.

The treatments were fertilizer levels such as (F_1=Control, F_2=HIGO Organic Plus, F_3=Mexicrop Sea-Gold, F_4=FYM, F_5=NP at 120:80 kg ha^{-1}, F_6=NP at 150:100 kg ha ^{1} and F_7=NP at 180:120 kg ha^{-1}). The findings showed a statistically significant effect ($P < 0.05$) of farmyard manure on grain weight and the yield components such as the number of leaves and the area of the leaves.

Randomized complete block design has also been used to investigate the effect of the organic and inorganic manure on the yield and yield components of maize in Ethiopia (Admas *et al*., 2015). The factor combinations were 0, 60 and 120 kg Nitogen ha^{-1}, 0 t ha^{-1}, 5 t ha^{-1} and 10 t ha^{-1} and 0, 15 and 30 kg sulphur ha^{-1} (Admas *et al*., 2015). The yield components under consideration were; yield of maize grain, total above ground dry biomass, plant height, grain number per cob, cob weight, thousand seed weight, nitrogen and sulphur concentration of leaves and grains(Admas *et al*., 2015) . The results showed that integration application of organic and inorganic fertilizers had a positive effect on crop yields (Admas *et al*., 2015). It was then concluded that incorporation of organic compost with inorganic nitrogen and sulphur increased grain yield by adding nutrients. Impact of organic and inorganic fertilizer on yield and yield components of common bean (Phaseolus vulgaris) was investigated using randomized complete block design (RCBD) with four replicates (Alhrout *et al*., 2016). The fertilizers under investigation were chicken manure, chemical fertilizer NPK, and their combinations. The parameters investigated in the study were, plant height (cm), average of leaves number per plant, average of pods number per plant, fruit yield (grams) per plant, and pod productivity t ha^{-1} (Alhrout *et al*., 2016). The pods number per plants was significantly affected by all treatments at $p < 0.01$, and the highest value 21 pods per plant was achieved by the combination of chicken manure with NPK. It was concluded that chicken manure and NPK increase the productivity of common bean, but chicken manure is preferable because it is cheaper than chemical fertilizer (Alhrout *et al*., 2016). Shafeek *et al* (2017) investigated the effect of different rates of cattle manure (6, 12 and 18 m^3 fed^{-1}.) on snap bean cultivars (Bronco or Paulista) and their interaction on improved plant growth, total pods yield and its components as well as nutritional pods values. The statistics method used was a complete randomized block design with three replicates (Shafeek *et al*., 2017). The results showed that the highest fertilization rate of cattle manure (18 m^3 fed^{-1}) gave the tallest plant, the highest number of leaves per plant and the biggest fresh and dry weight of leaves and stems as well as the highest total pods yield per fed (Shafeek *et al*., 2017). Randomized Complete Block Design (RCBD) with five replications was used to study the effect of cowdung on the growth, yield and nutrient content of mungbean (Vigna radiata L.) (Mahabub *et al*., 2016). The factor levels were Cowdung (3 levels); C0: 0 t cowdung ha^{-1} (control), C1: 5 t cowdung ha^{-1} and C2: 10 t cowdung ha^{-1} (Mahabub *et al*., 2016). Results on different growth parameters and yield showed statistically significant variation for different levels of cowdung (Mahabub *et al*., 2016). In determination of the effects of NPK fertilizer and poultry manure on the yield and yield components in cassava/maize/melon systems, the results showed that crop yields were statistically the same under NPK alone and NPK + poultry manure but significantly higher than both poultry manure alone and control in both locations (Ayoola & Adeniyan, 2006). The statistical method applied was the randomized complete block design. Sanni and Adenubi (2015) applied Analysis of Variance (ANOVA) to evaluate the influence of 5 and 10 t ha^{-1} goat and pig manure on soil chemical properties, growth and yield of okra. The result showed that application of 5 t ha^{-1} goat manure resulted in improved okra growth and yield performances, while additional higher level of goat and pig manure at 10 t ha^{-1} did not result in corresponding increase in the growth and yield of okra (Sanni and Adenubi, 2015). The result also showed that addition of goat and pig manures brought about improvement in soil (Sanni and Adenubi, 2015).

2.3 Multiple Regression Analysis

A mathematical model called regression model is used to determine the relationship between a set of independent variables and the dependent variable (response variable Y) (Cohen *et al*., 2014). When there are more than two independent variables, the regression model is called multiple regression model (Cohen *et al*., 2014). In general, a first-order multiple linear regression model with q independent variables and N experimental runs or observations takes the form;

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_q x_q + \varepsilon_i ; i = 1, 2, ..., N \qquad 2.1$$

The equation in 2.1 can be rewritten as;

$$\sum_{i=1}^{N} y_i = \beta_0 + \sum_{i=1}^{q} \beta_i X_i + \varepsilon_i; i = 1, 2, ..., q; i = 1, 2, ..., N \quad 2.2$$

Where the parameter β_j measures the expected change in response *y* per unit increase in X_j *(j=1,2,…q)* when the other independent variables are held constant (Cohen *et al*., 2014).

A multiple-regression model can be written in matrix form as;

$$Y_i(x) = X^{'}\beta + \varepsilon_j \quad 2.3$$

where,

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \; X = \begin{pmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1k} \\ 1 & X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{nk} \end{pmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_q \end{bmatrix} \text{ and } \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \quad 2.4$$

$$n \times 1 \qquad n \times k \qquad k \times 1 \qquad n \times 1$$

where; Y is an ($n \times 1$) vector of observations, X is an ($n \times k$) matrix of levels of independent variables, β is a ($k \times 1$) vector of coefficients of regression, and ε is an ($n \times 1$) vector of random errors. If X is a ($k \times k$) non-singular matrix, then the linear system $Y_i(x) = X^1\beta + \varepsilon_j$ has a unique least squares solution given by $\hat{\beta} = \left(X^1X\right)^{-1} X^1Y$ (Cohen *et al*., 2014).

2.3.1 Parameter Estimation in Multiple Regression Analysis

Consider a multiple linear regression model with q independent predictor variables x_1,...,x_q and one response variable y (Hanson, 2010).

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_q x_q + \varepsilon \quad 2.5$$

Suppose, there are n observations on the q + 1 variables.

$$y_1 = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_q x_{iq} + \varepsilon_i \quad 2.6$$

The observations can be thought as points in (q + 1)-dimensional space. The goal in least-squares regression is to fit a hyper-plane into (q + 1) dimensional space that minimizes the sum of squared residuals (Hanson, 2010).

$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{i=1}^{q} \beta_j x_{ij}\right)^2 \qquad 2.7$$

The derivatives are taken with respect to the model parametersβ_0,..., β_q, and set them equal to zero and derive the least-squares normal equations that our parameter estimates $\hat{\beta}_0$,..., $\hat{\beta}_q$ would have to fulfill (Bremer, 2012).

$$\text{n}\ \hat{\beta}_0 + \hat{\beta}_1 \sum_{i=1}^{n} x_{i1} + \hat{\beta}_2 \sum_{i=1}^{n} x_{i2} + \ldots. + \hat{\beta}_q \sum_{i=1}^{n} x_{iq} = \sum_{i=1}^{n} y_i \qquad 2.8$$

$$\hat{\beta}_0 \sum_{i=1}^{n} x_{i1} + \hat{\beta}_1 \sum_{i=1}^{n} x_{i1}^2 + \hat{\beta}_2 \sum_{i=1}^{n} x_{i1}\, x_{i2} + \ldots. + \hat{\beta}_q \sum_{i=1}^{n} x_{i1}\, x_{iq} = \sum_{i=1}^{n} x_{i1}\, y_i \qquad 2.9$$

$$\vdots$$

$$\hat{\beta}_0 \sum_{i=1}^{n} x_{iq} + \hat{\beta}_1 \sum_{i=1}^{n} x_{i1}\, x_{iq} + \hat{\beta}_2 \sum_{i=1}^{n} x_{iq}\, x_{i2} + \ldots. + \hat{\beta}_q \sum_{i=1}^{n} x_{iq}^2 = \sum_{i=1}^{n} x_{iq}\, y_i \qquad 2.10$$

These equations are much more conveniently formulated with the help of vectors and matrices

Let

$$\underset{n \times 1}{Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}},\ \underset{n \times k}{X = \begin{pmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1k} \\ 1 & X_{21} & X_{22} & \cdots & X_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{nk} \end{pmatrix}},\ \underset{k \times 1}{\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_q \end{bmatrix}} \text{ and } \underset{n \times 1}{\varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}} \qquad 2.11$$

With this compact notation, the linear regression model can be written in the form of 2.3;

The least-squares parameter estimates β are the vectors that minimize;

$$\sum_{i=1}^{n} \varepsilon_i^2 = \varepsilon' \varepsilon = (y - \mathrm{X}\beta)'\,(y - \mathrm{X}\beta) \qquad 2.12$$

The aim is to get the “best” β in the sense that there is minimized sum of squared residuals. The minimum that the sum of squares could be is zero. If all ε_i were zero, then

$$\hat{y} = X\,\hat{\beta} \tag{2.13}$$

Further, suppose that $\hat{\beta}$ fulfils the equation above. Then the residuals $y - \hat{y}$ are orthogonal to the columns of X

$$X'(y - X\,\hat{\beta}) = 0 \tag{2.14}$$

$$X'y - X'X\hat{\beta} = 0 \tag{2.15}$$

$$X'X\hat{\beta} = X'y \tag{2.16}$$

These vector normal equations are the same normal equations that one could obtain from taking derivatives. To solve the normal equations (i.e., to find the parameter estimates $\hat{\beta}$), multiply both sides with the inverse of $X'X$. Thus, the least-squares estimator of β is;

$$\hat{\beta} = (X'X)^{-1}\,X'y \tag{2.17}$$

This works best only and only if the inverse does exists. In the absence of the universe, the usual equations can still be determined, but the resolution may not be unique. The inverse of $X'X$ exists, if the columns of X are linearly independent. That means that no column can be written as a linear combination of the other columns (Hanson, 2010). The vector of fitted values $\hat{y}$ in a linear regression model can be expressed as;

$$\hat{y} = X\hat{\beta} = X\,(X'X)^{-1}\,X'y = H_y \tag{2.18}$$

The n × n matrix H = X $(X'X)^{-1}\,X'$ is usually referred as the hat-matrix. It maps the vector of experiential values y onto the vector of fitted values yˆ that lie on the regression hyper-plane (Bremer, 2012). The regression residuals can be written in different ways as;

$$\varepsilon = \text{y - } \hat{y} = y - \text{X}\hat{\beta} = \text{y - } H_y = (\text{I - } H_y)\text{y} \qquad 2.19$$

2.3.2 Model Diagnostic in Multiple Regression Analysis

There are several ways in which to judge how well a specific model fits the data (Taylor, 2016). To begin with, a smaller residual variance is desirable. Other quantities that describe the "goodness of fit" of the model are R^2 and adjusted R^2. The R^2 is the proportion of variation in the response that is explained through the regression on all the predictors in the model (Taylor, 2016). To weigh the proportion of variation explained with the number of predictors, adjusted R^2 can be used.

$$R^2_{Adj} = 1 - \frac{SS_R/(n-q-1)}{SST/(n-1)} \qquad 2.20$$

k is the number of predictors in the current model and $SS_R/(n-q)$ is actually the estimated residual variance of the model with k predictors. The adjusted R^2 does not automatically increase when more predictors are added to the model and it can be used as one tool in the arsenal of finding the "best" model for a given data set. Higher adjusted R^2 indicates a better fitting model. To test individual regression coefficients, individual hypothesis tests for each slope (or even the intercept) in the model can be formulated (Taylor, 2016). For instance; H_0: β_j = 0 versus H_A: $\beta_j \neq 0$
tests whether the slope associated with the j^{th} predictor is significantly different from zero. The test statistics for this test is;

$$\text{t} = \frac{\hat{\beta}_j}{se(\hat{\beta}_j)} \sim \text{t(df = n – q -1)} \qquad 2.21$$

$se(\hat{\beta}_j)$ is the square root of the j^{th} diagonal entry of the covariance matrix $\hat{\sigma}^2\,(X'X)^{-1}$ of the estimated parameter vector $\hat{\beta}$. If this test's null hypothesis is rejected, we can conclude that the j^{th} predictor has a significant influence on the response, given the other repressors in the model at the same time (Taylor, 2016).

2.3.3 Application of Multiple Regression Analysis

Multiple regression can be applied in problems when there is need to predict the values of a response (dependent) variable from a collection of predictor (independent) variable values (Peter *et al*., 2019). It has been widely used in education (Hsu, 2005). For instance, it has been used in prediction of first-year grade-point average in college from the SAT scores and high school grade-point average (Kobrin *et al*., 2008). In agriculture, multiple regression analysis has been used in prediction of crop yields (Sellam & Poovammal, 2016). It has also been used in identifying associations between soil and production variables (Dahal & Routray, 2011).

2.4 Response Surface Methodology

Response surface methodology, or RSM, is a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response (Montgomery, 2013). For instance, suppose that a researcher wishes to find the levels of variables, say x_1 and x_2, that maximizes the response, say y, then the response variable is a function of the variables x_1 and x_2 and it can be presented as;

$$y = f(x_1, x_2) + \varepsilon \qquad 2.22$$

where ε is the observed error in the response

The expected value of the response is given by,

$$E(y) = f(x_1, x_2). \qquad 2.23$$

If the variables x_1 and x_2 represents temperature and pressure respectively and the variable y represented yields, then, this expected response can be represented in form a surface referred to as the response surface (Figure 1)

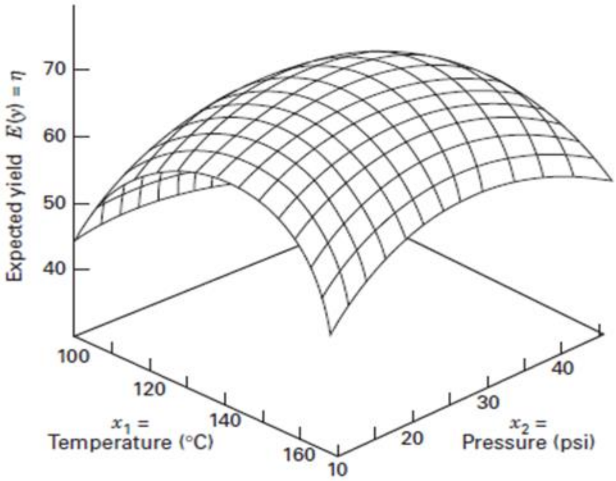

Figure 1: Response surface showing the expected response as a function of x_1 and x_2(Montgomery, 2013)

The key observation in Figure 1 is that the response surface is curved because the model contains quadratic terms that are statistically significant.

Contour plots are used to visualize the shape of the response surface where each contour corresponds to a particular height in the response surface (Figure, 2).

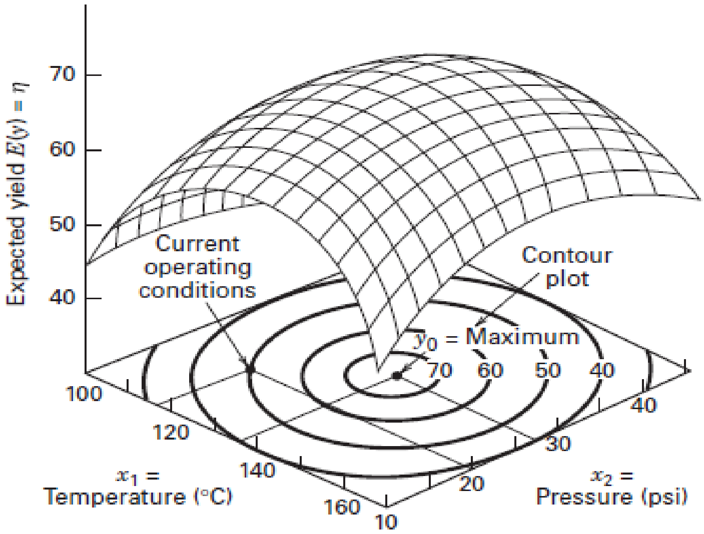

Figure 2: A contour plot of a response surface (Montgomery, 2013).

The key observation in Figure 2 is that each contour corresponds to a particular height of the response surface. In most RSM problems, the form of the relationship between the response and the independent variables is unknown (Montgomery, 2013). For this reason, the starting point in RSM is to find a suitable approximation for the true functional relationship between y and the set of independent variables (Montgomery, 2013). Mostly, a low-order polynomial in some region of the independent variables is employed. If the response is well modeled by a linear function of the independent variables, then the approximating function is the first-order model (Montgomery, 2013).

This first order polynomial is represented as shown in equation 2.5. If there is curvature in the system, then a polynomial of higher degree must be used, such as the second-order model which is represented as shown by equation 1.2. The method of least squares, discussed in 2.3.1, is used to estimate the parameters in the response surface models.

The main aim of RSM is to find the optimum working conditions for the system or to define a region of the factor space in which working necessities are fulfilled (Montgomery, 2013). The first-order model is probable to be suitable when the experimenter is concerned about approximating the true response surface over a relatively small region of the independent variable space in a setting where there is little curvature in *f* that is, the response function (Montgomery, 2013). The response surface and contour plot for a particular first order model is as in Figure 3.

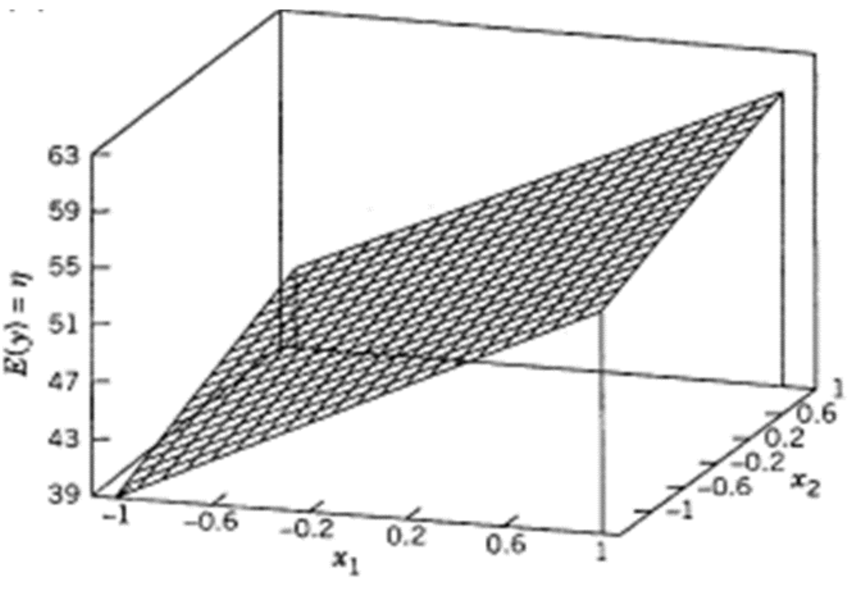

Figure 3: The response surface plot for a particular first order model (Myers *et al.*, 2016).

The key observation in Figure 3 is that the response surface is not curved because the model contains quadratic terms that are statistically insignificant.

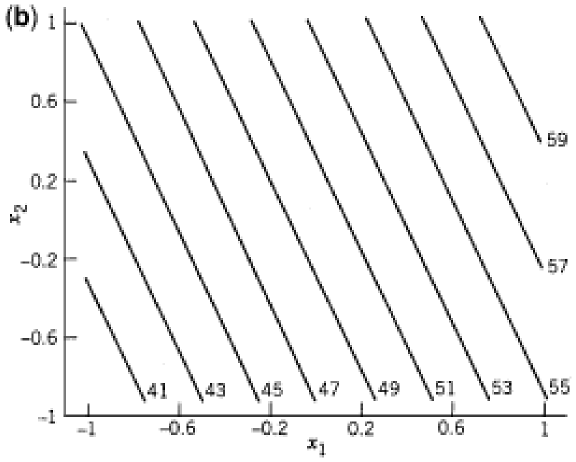

Figure 4: The contour surface plot for a particular first order model (Myers *et al*., 2016)

Figure 5 shows the first-order model with interaction that would yield response surface and the contour plot that is a three-dimensional in nature

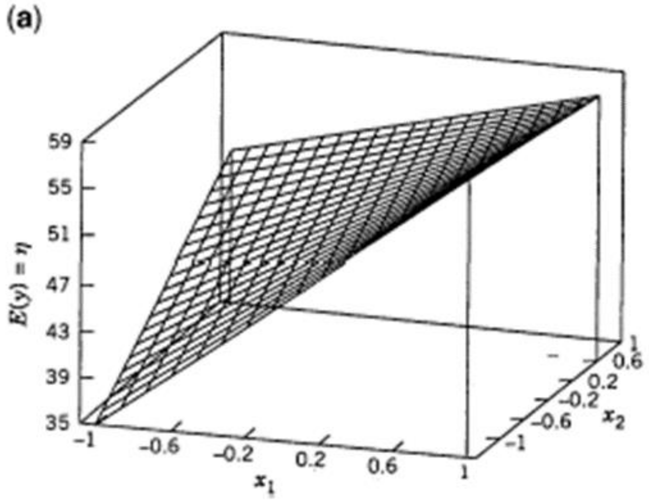

Figure 5: Response surface for the first-order model with interaction (Myers *et al*., 2016)

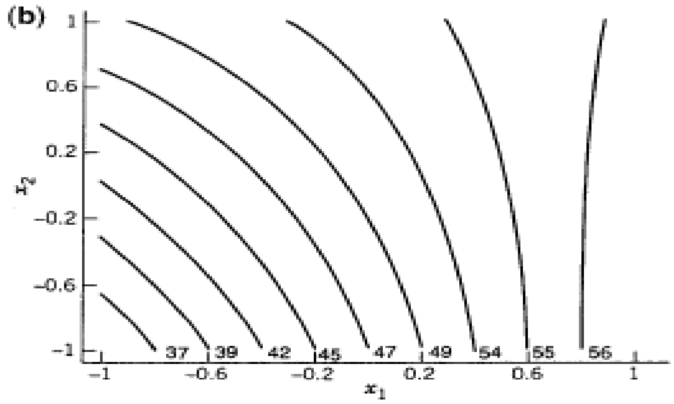

Figure 6: Contour plot for the first-order model with interaction (Myers *et al*., 2016)

Usually the true response surface curvature is strong enough that the first-order model even with inclusive of the interaction function is inadequate (Montgomery, 2013). A second-order model will likely be required in these situations. A second-order model produces a mound-shaped response surface and elliptical contours (Figure 7 and Figure 8). Such like response surface could be experienced as a result of approximating a response such as yield, where we would then expect to be working near a maximum point on the surface.

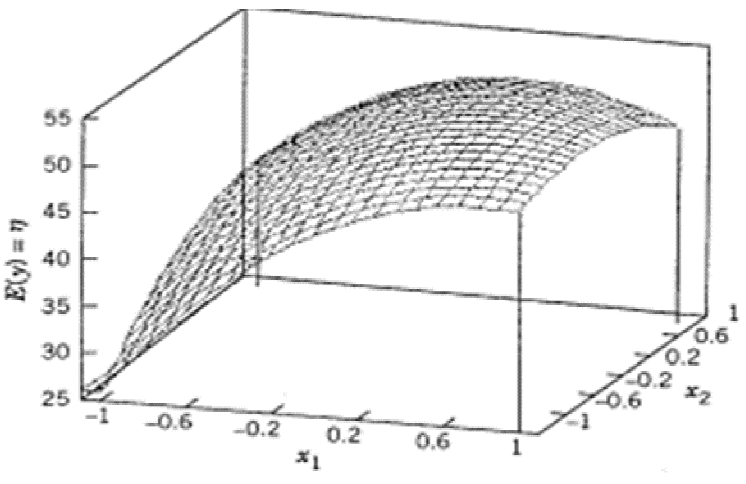

Figure 7: Response surface for the second-order model (Myers *et al.*, 2016)

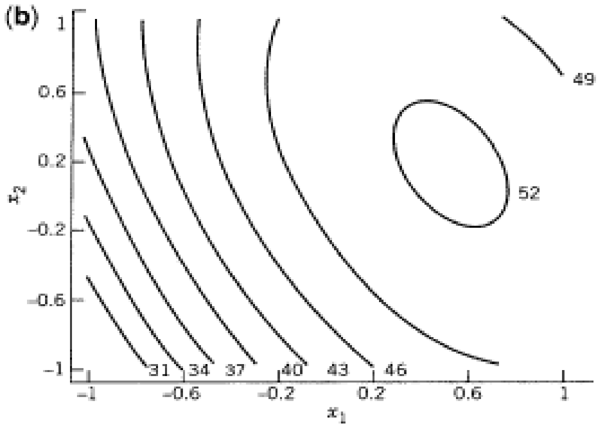

Figure 8: Contour plot for the second-order model (Myers *et al*., 2016).

The second order model is widely used because it is a very flexible model and thus it fit a wide variety of the functional forms of the response.

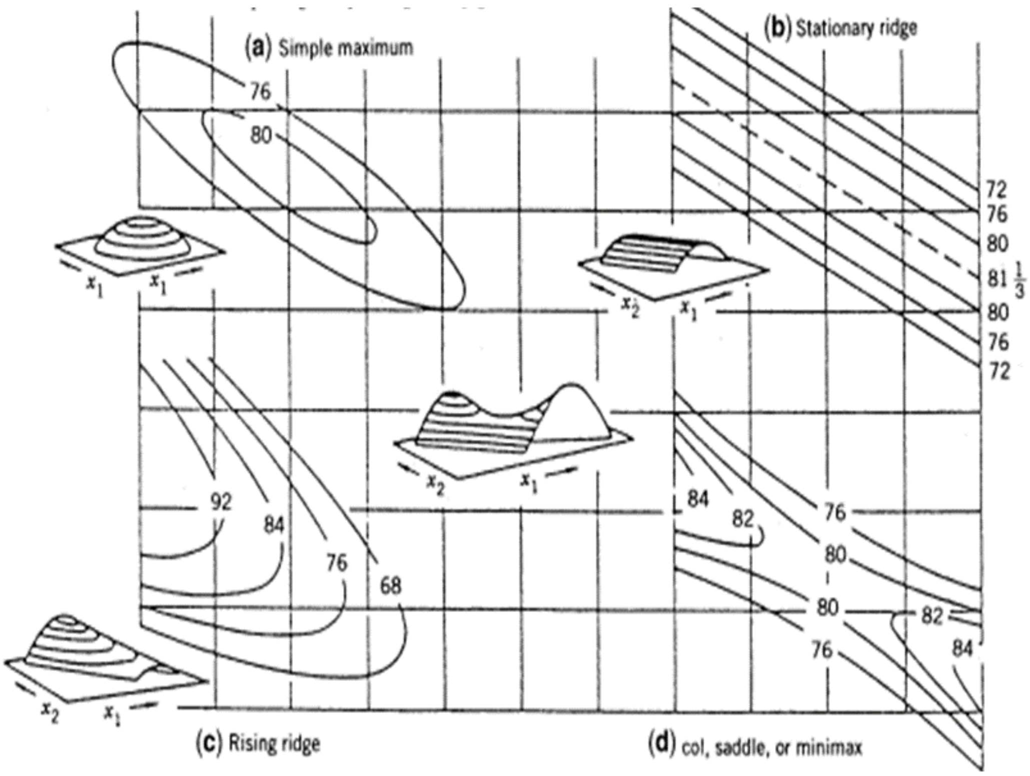

Figure 9: Some examples of types of surfaces defined by the second-order model in two variables x_1 and x_2 (Box & Draper *et al*., 1951)

Its parameters can easily be estimated through the method of least squares. There is considerable practical experience indicating that second-order models work well in solving real response surface problems. The practical application of response surface methodology (RSM) necessitates coming up with an approximating model for the true response surface (Carley *et al*., 2004). The model of approximation is based on observed data from the process or system and is an empirical model. Multiple regression is a collection of statistical techniques useful for building the types of empirical models required in RSM (Carley *et al*., 2004). The method of least squares is typically used to estimate the regression coefficients in a multiple linear regression model (Hanson, 2010).

2.4.1 Model Adequacy in Response Surface Methodology

Checking model adequacy involves examining the fitted model to ensure that it provides an adequate approximation to the true system and verify that none of the least squares regression assumptions are violated (Myers *et al*., 2016). Proceeding with exploration and optimization of a fitted response surface will likely give poor or misleading results unless the model provides an adequate fit. There are several techniques for checking model adequacy; residual analysis, scaling residuals, influence diagnostics and testing for lack of fit (Myers *et al*., 2016).

Residual analysis involves a check of the normality assumption may be made by constructing a normal probability plot of the residuals (Draper & Smith, 2014). If the residuals plot approximately along a straight line, then the normality assumption is satisfied (Draper & Smith, 2014). Residuals from the least squares fit, defined by;

$$e_i = y_i - \hat{y}_i, \text{ i} = 1,2,3, \ldots, \text{n}. \tag{2.24}$$

This is the use of standardized residuals to check the presence of outliers (Santos Nobre & da Motta, 2007). Standardized residual is given by;

$$d_i = \frac{e_i}{\hat{\sigma}}, \tag{2.25}$$

where $\hat{\sigma} = \sqrt{MSE}$

Most of the standardized residuals should lie in the interval -3 $\leq d_i \leq 3$, and any observation with a standardized residual outside of this interval is potentially unusual with respect to its observed response (Santos Nobre & da Motta, 2007).

In RSM, the process mostly involves fitting the regression model to data from a designed experiment (Myers *et al*., 2016). It is frequently useful to obtain two or more observations (replicates) on the response at the same settings of the independent variables. When this has been done, it is important to conduct a formal test for the lack of fit on the regression model (Aerts *et al*., 2000). The lack-of-fit test requires that there were true replicates on the response y for at least one set of levels on the independent variables x_1, x_2, …, x_q. Suppose that we have *ni* observations on the response at the i^{th} level of the regressors x_i, i = 1, 2, …, m. Let y_{ij} denote the j^{th} observation on the response at x_i, i = 1, 2, …, m. And j = 1, 2, …,n_i. There are n = $\sum_{i=1}^{m} n_i$ observations altogether (Aerts *et al*., 2000). The test procedure involves partitioning the residual sum of squares into two components, say

$$SS_E = SS_{PE} + SS_{LOF} \qquad 2.26$$

Where SS_{PE} is the sum of squares due to pure error and SS_{LOF} is the sum of squares due to lack of fit.

To develop this partitioning of SSE, note that the $(i, j)^{th}$ residual is

$$(y_{ij} - \hat{y}_i) = (y_{ij} - \bar{y}_i) + (\bar{y}_i - \hat{y}_i) \qquad 2.27$$

where $\bar{y}_i$ is the average of the n_i observations at x_i. Squaring both sides of Equation 2.27 and summing over *i* and *j* yields;

$$\sum_{i=1}^{m}\sum_{j=1}^{n_i}(y_{ij} - \hat{y}_i)^2 = \sum_{i=1}^{m}\sum_{j=1}^{n_i}(y_{ij} - \bar{y}_i)^2 + \sum_{j=1}^{n_i} n_i(\bar{y}_i - \hat{y}_i)^2 \qquad 2.28$$

The left-hand side of Equation 2.28 is the usual residual sum of squares. The two components on the right-hand side measure pure error and lack of fit. We see that the pure error sum of squares

$$SS_{PE} = \sum_{i=1}^{m}\sum_{j=1}^{n_i}(y_{ij} - \bar{y}_i)^2 \qquad 2.29$$

is obtained by computing the corrected sum of squares of the repeat observations at each level of x and then pooling over the m levels of x. If the assumption of constant variance is satisfied, this is a model-independent measure of pure error, because only the variability of the y's at each x_i level is used to compute SS_{PE} (Myers *et al.*, 2012). Because there are n_i 21 degrees of freedom for pure error at each level x_i, the total number of degrees of freedom associated with the pure error sum of squares is

$$\sum_{i=1}^{m}(n_i - 1) = \mathrm{n} - \mathrm{m} \qquad 2.30$$

The sum of squares for lack of fit,

$$SS_{LOF} = \sum_{j=1}^{n_i} n_i(\bar{y}_i - \hat{y}_i)^2 \qquad 2.31$$

The test statistic for lack of fit is

$$F_0 = \frac{SS_{LOF}/(m-p)}{SS_{PE}/(n-m)} = \frac{MS_{LOF}}{MS_{PE}} \qquad 2.32$$

Therefore, to test for lack of fit, we would compute the test statistic F_0 and conclude that the regression function is not linear if $F_0 > F_{(\alpha,m-p,n-m)}$ (Aerts *et al.*, 2000). This test procedure may be easily introduced into the analysis of variance conducted for significance of regression. If we conclude that the regression function is not linear, then the tentative model must be abandoned and attempts made to find a more appropriate equation (Aerts *et al.*, 2000).

2.4.2 Applications of Response Surface Methodology

As earlier stated, response surface methodology is applied in problems where a response of interest is influenced by several variables and the objective is to optimize this response (Montgomery, 2013). It has been applied in for optimization of leaching parameters for ash reduction from low-grade coal (Behera *et al.*, 2018). Cevheroğlu Çıra *et al*. (2016) applied response surface methodology in modeling and optimization of marble surface quality. It has also been applied in biotechnology in optimization of extracellular glucoamylase production by *candida guilliermondii* (Mohamed *et al.*, 2017). In chemistry, RSM has been applied in optimization of cadmium ion removal from an aqueous solution by eggshell powder (Sabah *et al*., 2018). This shows that RSM is a very important tool in whenever the main objective is to optimize the response.

CHAPTER THREE

METHODOLOGY

3.1 Location of the Study

The study was carried at Chuka University Horticultural farm which is approximately 186 km from Nairobi along the Nairobi-Meru highway, Tharaka Nithi County in Meru South, Kenya. This study was done in August to December 2018. The common soil types found in these regions are Humic Nitisols (Jaetzold and Schmidt 1983), which are deep, well weathered with moderate to high inherent fertility. This area had an altitude of approximately 1560 m above sea level. Its latitude and longitudes are (0.3190° S, 37.6575° E). It receives annual rainfall ranging from 2208 mm in the western part to 544 mm in the eastern part of the region. The climate is warm with annual average temperatures of about 19.5°C. This region is a potential agricultural area where farming is characterized by both rearing of livestock mainly on small land holding and growing of crops. The livestock reared include; cattle, goats, sheep and poultry. Main crops grown include; beans, tea, bananas, coffee, maize, sunflower, tobacco and vegetables.

3.2 Research Design

The study used Randomized Complete Block Design (RCBD), with three treatments (cow manure, poultry manure and goat manure) each at three levels (0, 3 and 6 tonnes per hectare), and replicated three times. Box-Behnken Design consisting of 27 experimental runs determined by 3^3 full factorial designs ($3*3^{3-1}$), which is effective design for fitting second-order model, was used in optimisation of bean yield. A 5-level-3 factor Box Behnken Design (BBD) was employed in bean yield grain and bean component experiment where optimization required 27 experimental runs. Thus, Central Composite Design (CCD) was applied in determining the association between the factors affecting the response and the response or the “surface”.

3.3 Experiment

The study used organic manures (cow manure, goat manure and poultry manure) in optimization of grain yield in beans. This study also used KATX 56 bean variety from KALRO in Embu. This is because KATX 56 variety was certified and recommended for use by KALRO. Spacing of bean plants was 30 cm between each row and 15 cm between plants. The three treatments consisted of cattle manure, goat manure and poultry manure (each at three levels). Three blocks, each measuring 5 metres by 3 metres with each block having nine experimental units. Each experimental unit had 3 rows each consisting of 6 plants.

3.4 Land Preparation, Crop Establishment and Management

Land was prepared to a fine tilth 2-4 week before onset of rains to allow organic materials to fully decompose. Ploughing was done by use of hoes. Timely planting and sowing were then done at the onset of rains after a minimum of 30 mm of rainfall had been received. The manures were also thoroughly mixed with the soil before covering the seed. After two weeks of emergence, first weeding was done and the second weeding was done before flowering. Pesticides such as Diezol at 5 ml lt^{-1} at seven days interval was used to control pests such as Bean fly.

3.5 Data Collection

Data was collected on bean grain yield in terms of weight at harvest and the number of pods per plant. Data on the number of pods per plant in each row was done seven weeks after planting by counting manually the number of pods in six plants with maximum number of pods per experimental unit. The weight of the grain yield was measured by use of the weighing scale. This was done by examining the effect of each treatment on the number of pods at the seventh week after sowing. Also, data on the effect of each treatment on the grain yield weight per plot at harvest were also recorded. The obtained data was converted in terms of kilograms per plot treatment.

3.6 Data Analysis

The collected data was subjected into analysis using R software and Design Expert. Multiple Linear Regression analysis was obtained by employing the use of least squares method to predict quadratic polynomial model for (grain yield, number of branches per plant and number of pods per plant). Analysis of Variance (ANOVA) was used to check the adequacy of the model for the response (grain yield, number of branches per plant and number of pods per plant) of the common bean in the experimentation at 95% confidence level. In developing the regression model, the test factors were coded according to the formulae given as;

$$x_i = \frac{X_i - X_0}{X} \qquad 3.1$$

x_i was a coded variable of the ith variable, X_0, an average of the variable in high and low level, X is (variable at high level- variable at low level)/2 and X_i, an encoded value of the ith test variables.

3.7 Modeling Process

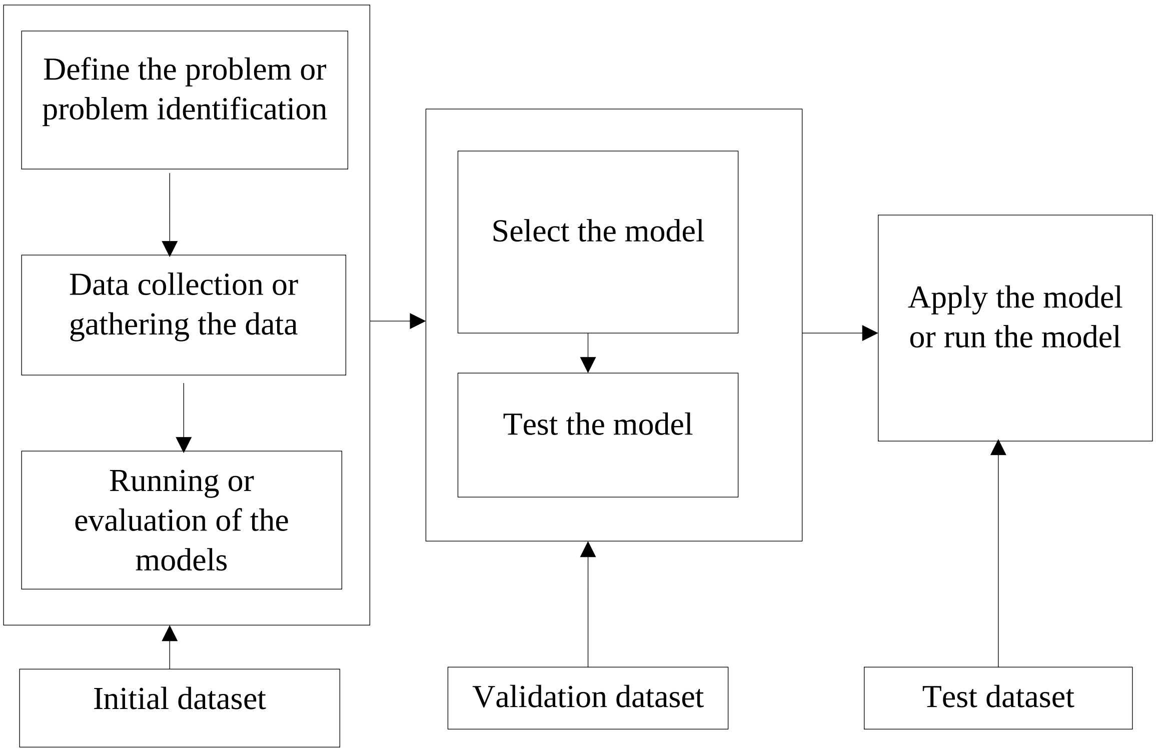

Figure 10: Modeling Process

3.8 Ethical Consideration

The researcher sought for authorization from Chuka University Ethics Review Committee before data collection was done (Appendix VII). A research permit was then obtained from NACOSTI (Appendix VIII & IX). The researcher also ensured that the study was done in an ethical manner, ensuring accuracy of the data and avoiding plagiarism. The data collected and the analysis were done as per the stated procedures. Conclusions and recommendations were published for easy dissemination of information. Should there be need for use of the study results for policy matters, the information would be released to requesting institution in consultation with Chuka University.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Preliminary Analysis

A standard normal distribution of data assists in creating reliable conclusions and accurate conclusion. Goodness of fit test for Skewness and Kurtosis test were used to find the normality of the data. Skewness is used to find if the frequency curve of the distribution is not a symmetric bell-shaped curve making it stretched more to one side than the other thus rendering the data not to be normal. This part shows important descriptive statistics of the time series data comprising of the mean, standard deviation, coefficient of variation, skewness, and kurtosis values of weight of bean yield, branches per plant, and number of pods per plant (Table 1). The result of the study showed that the average weight yield produced was 13.50 grams with a median of 10.3 grams and a standard deviation of 9.8752 (Table 1). The average number of branches per plant was 4.2037 with a median of 4 and a standard deviation of 0.4529. The average number of pods per plant was 4.5802 with a median of 4 and a standard deviation of 3.1657 (Table 1).

Table 1: Summary statistics for the weight of bean yield, number of pods per plant and the number of branches per plant.

Response	Mean	Standard deviation	Median	Skewness	Kurtosis
WBY	13.508	9.8752	10.3	1.3061	1.1803
NPP	4.2037	1.5807	4	0.4529	-0.3893
NBP	4.5802	3.1657	4	1.3371	1.1981

Where, WBY is the weight of grain yield, NPP is the number of pods per plant and NBP is the number of branches per plant.

Regarding the normality test of the data, the data of bean yield, number branches per plant and number of pods per plant indicated that the data was normally distributed since their skewness and kurtosis test values were falling within the range of ±3 and ±1 respectively. For instance, the skewness and kurtosis value for weight of bean yield, number of branches per plant and number of pods per plant were; 1.3061, 0.4529 and 1.3371 respectively for skewness test and 1.1803, -0.3893 and 1.1981 respectively for the kurtosis (Table 1). This information on this study is similar to the findings of Aczel and Sounderpadian (2002) who attributed that for the normality of data and the skewness should be between a range of ±3. The average yield per block shows that the error bars for block overlap at 95% confidence interval. This shows that blocks had no significant effect on bean yield at 0.05 level of significance (Appendix 1). After the preliminary statistics, the analysis based on each objective was carried out as discussed under the subheadings below.

4.2 Effects of Organic Manures on Grain Yield and Yield Components of the common beans

Descriptive and normality test statistics of the grain yield and yield components of common beans were carried out and results presented in the subsequent tables. The results indicated that the treatment C6P6G6 had an average yield of 35.38 grams with a median of 36.50 grams and standard deviation of 0.98 (Table 2). Treatment C0P0G0 had an average bean yield of 4.58 grams with a median of 7.50 and a standard deviation of 0.57 (Table 2).

Table 2: Effects of Organic Manure per Treatment on the Grain Yields (Weight in grams per plant)

Treatment	Mean	Standard Deviation	Median	Skewness	Kurtosis	Maximum	Minimum
C0P0G0	4.586	0.57	7.50	0.55	1.55	4.32	5.52
C0P0G3	16.43	1.55	11.5	0.43	1.46	12.05	19.36
C0P0G6	5.259	0.75	8.10	0.22	1.92	4.12	6.24
C0P3G0	24.63	1.22	15.36	0.55	1.63	14.56	36.51
C0P3G3	6.043	1.71	9.25	0.77	0.92	5.25	8.90
C0P3G6	13.34	1.25	15.28	-0.64	0.91	10.35	17.76
C0P6G0	19.51	1.66	18.32	0.52	1.25	15.68	26.81
C0P6G3	12.88	0.75	12.50	0.21	1.96	8.50	15.19
C0P6G6	17.26	0.75	16.33	0.18	1.56	14.86	18.15
C3P0G0	12.07	1.14	11.25	0.23	1.83	9.75	13.52
C3P0G3	7.13	0.97	7.75	-0.26	2.08	6.34	9.90
C3P0G6	8.34	1.14	10.50	0.05	1.93	7.50	12.55
C3P3G0	7.34	0.15	7.31	0.007	0.83	6.87	11.92
C3P3G3	17.66	0.37	16.23	0.18	1.52	12.62	25.53
C3P3G6	14.54	0.75	12.42	0.71	1.48	11.64	16.52
C3P6G0	8.84	0.82	8.80	0.473	1.58	6.49	10.24
C3P6G3	29.51	1.41	27.50	0.004	1.58	26.51	34.10
C3P6G6	16.99	1.52	15.55	0.431	1.44	12.32	20.36
C6P0G0	5.40	1.21	6.52	1.09	0.65	5.20	7.58
C6P0G3	7.47	1.17	8.21	-0.37	1.52	6.55	9.25
C6P0G6	11.67	0.84	13.35	0.46	1.28	9.64	15.72
C6P3G0	9.63	1.83	10.22	-0.029	2.01	7.15	12.79
C6P3G3	9.80	1.51	10.20	0.715	1.15	7.12	12.05
C6P3G6	19.01	1.03	23.25	0.39	1.37	15.42	26.91
C6P6G0	16.27	1.52	18.15	-0.14	1.52	12.68	19.26
C6P6G3	16.44	1.86	14.50	0.515	1.18	12.50	20.35
C6P6G6	35.38	0.98	36.50	0.325	2.22	24.35	46.58

The findings showed that a combination of the highest level of cattle, poultry and goat manures (C6P6G6) had the highest average yield of 35.38 grams. This means that it is the most effective treatment while treatment C0P0G0 had the lowest average yield of 4.586 grams. Treatment with no manure had the lowest average yields. Regarding the normality test of the data, the data of treatments and the yields (weight) indicated that the data was normally distributed since their skewness and kurtosis test values were falling within the range of ±3 and ±1 respectively. This information on this study is similar to the findings of Aczel and Sounderpadian (2002) who attributed that the normality of data, the skewness should be between a range of ±3.

After carrying out the summary analysis for the treatments and the yields, the study sought to carry out the summary statistics for the average yield by grouped factors and the findings were presented in Table 3. The average yield grouped by factors for cattle manure at level 0 was 13.11 grams, at level 3 the average yield was 13.43 and at level 6 the average yield was 13.99 (Table 3). For poultry, the average yield at level 0 was 12.45 grams, at level 3, it was 13.56 grams and 18.51 grams at level 6 (Table 3). For goat manure at level 0, yields were 11.80 grams, at level 3 it was 13.43 grams and at level 6, the yield was 15.30 grams (Table 3). The skewness value for all levels of cattle, goat and poultry were 1.2472, 1.541, 1.0731, 1.7405, 1.2217, 1.0218, 1.5731, 1.3005, and 0.6443 respectively (Table 3). Kurtosis values were found to be; 1.1717, 1.7147, 0.45, 1.4614, 1.7085, -0.6542, 1.0542, 0.7514 and 0.3351 respectively (Table 3).

Table 3: Effects of Organic Manure Factor Levels on Grain Yield (Weight in grams per plant)

Factor	Mean	Standard Deviation	Median	Skewness	Kurtosis	Maximum	Minimum
C0	13.11	9.74	8.60	1.2472	1.1717	26.9	1.5
C3	13.43	9.84	10.30	1.541	1.7147	30.8	2.3
C6	13.99	10.20	12.20	1.0731	0.45	40.5	1.8
P0	12.45	5.28	6.55	1.5731	1.4614	28.5	1.9
P3	13.56	9.13	10.85	1.3005	1.7085	41.7	3.3
P6	18.51	11.55	15.75	0.6443	-0.6542	46.9	2.8
G0	11.80	9.14	8.70	1.7405	1.0542	28.6	1.5
G3	13.43	10.36	9.30	1.2217	0.7514	36.8	1.8
G6	15.29	9.96	12.65	1.0218	0.3351	42.5	3.1

The findings showed that there was an increasing tread of yield with increase in poultry manure and goat manure. This shows that poultry manure and goat manure have a positive effect on bean grain yield. However, there was an insignificant effect of cattle manure. Therefore, there would be an increase in yields with increase in the levels of goat manure and poultry manure (Muriithi *et al*., 2017). Regarding the normality test, the results indicated that all the variables were normally distributed since their skewness test values lied within the range of ±3. Also, the Kurtosis test values were within the threshold range of either ±1 and, or ±2.

The study also sought to determine the summary statistics for the treatments and average number of branches per plant. The findings were presented in Table 4. The average mean of the number of branches per plant was in the range of 2.667 to 6.833. Treatment C6P6G6 had the highest mean of 6.833 and treatment C0P0G0 had the lowest mean of 2.667(Table 4)

Table 4: Effects of Organic Manures per Treatment on the Number of Branches per Plant

Treatment	Mean	Standard Deviation	Median	Skewness	Kurtosis	Maximum	Minimum
C0P0G0	2.667	0.5477	3.50	0.000	-2.3056	4	3
C0P0G3	3.50	1.5166	3.50	0.430	-1.4444	6	2
C0P0G6	3.00	0.8944	3.00	0.000	-1.9583	4	2
C0P3G0	5.00	1.4142	5.00	0.000	-1.5833	7	3
C0P3G3	3.00	1.0954	3.00	0.7607	-0.9167	5	2
C0P3G6	4.50	1.3784	5.00	-0.767	-0.9513	6	2
C0P6G0	3.667	1.5055	3.00	0.4667	-1.6664	6	2
C0P6G3	4.00	0.8944	4.00	0.000	-1.9583	5	3
C0P6G6	5.167	0.7528	5.00	-0.1736	-1.5366	6	4
C3P0G0	4.167	1.472	4.50	-0.2323	-1.7165	6	2
C3P0G3	2.833	0.9832	2.50	0.2533	-2.081	4	2
C3P0G6	3.333	1.2111	3.50	0.0417	-1.8809	5	2
C3P3G0	3.00	0.6325	3.00	0.000	-0.9167	4	2
C3P3G3	4.833	0.7528	5.00	0.1736	-1.5366	6	4
C3P3G6	6.00	0.8944	6.00	0.000	-1.9583	7	5
C3P6G0	3.667	0.8165	3.50	0.4763	-1.5833	5	3
C3P6G3	7.00	1.4142	7.00	0.000	-1.5833	9	5
C3P6G6	4.50	1.5166	4.50	0.430	-1.4444	7	3
C6P0G0	3.50	1.2111	2.00	1.0843	-0.6412	5	2
C6P0G3	3.833	1.169	4.00	-0.3709	-1.6181	5	2
C6P0G6	3.50	0.8367	3.00	0.8537	-1.1718	5	3
C6P3G0	4.167	1.8348	4.50	-0.2009	-2.0126	6	2
C6P3G3	4.333	1.5055	4.00	0.7055	-1.1473	7	3
C6P3G6	5.333	1.0328	5.00	0.3698	-1.3724	7	4
C6P6G0	4.50	1.5166	4.5	-0.430	-1.4444	6	2
C6P6G3	3.667	1.8619	3.5	0.7115	-1.0708	7	2
C6P6G6	6.833	0.9832	6.5	0.2533	-2.081	8	6

The results indicated that treatment C3P6G3 and C6P6G6 had the highest average number of branches per plant with an average of 7.000 and 6.833 respectively. Treatments C0P0G0 had 2.667 and treatment C0P3G3 and C0P0G6 had low average number of branches per plant of 3 respectively. This shows that highest level of poultry, cattle and goat manure combination was the best and treatment C0P0G0 was insignificant treatment in this study. The data of treatments and average number of branches per plant indicated that the data was normally distributed since their skewness and kurtosis test values were falling within the range of ±3 and ±1 respectively.

The summary statistics for the average number of branches per plant by factors were also carried out and findings presented in Table 5. The results showed that for cattle manure at level 0 the average number of branches per plant was 3.931 at level 3 the average number of branches per plant was 4.3704 and at level 6 the average number of branches per plant was 4.3148 (Table 5). For poultry, the average number of branches per plant at level 0 was 3.3704, at level 3 it was 4.463 and 4.7778 at level 6 (Table 5). For goat manure, at level 0 it gave an average of 3.8148, at level 3 it increased to 4.1111 and at level 6, it shifted to 4.6852 (Table 5).

Table 5: Effects of Organic Manure Factor Levels on the Number of Branches per Plant

Factor	Mean	Standard Deviation	Median	Skewness	Kurtosis	Maximum	Minimum
C0	3.931	3.394	2.500	1.395	1.8153	7.00	1.00
C3	4.370	3.055	3.500	1.455	1.2163	8.00	1.00
C6	4.315	3.621	3.550	1.107	0.3458	4.00	1.00
P0	3.370	1.554	2.500	1.870	4.0048	600	1.00
P3	4.463	2.714	4.500	1.210	1.2349	5.00	1.00
P6	4.778	3.215	5.000	0.695	-0.6285	7.00	1.00
G0	3.815	2.751	3.500	1.680	4.1124	5.00	1.00
G3	4.111	3.531	3.500	1.692	0.1186	4.00	1.00
G6	4.685	3.463	4.000	1.521	0.3059	3.00	1.00

The findings showed that cow manure have a non-significant effect on bean yield. The increasing trend of number of branches per plant with increase in poultry manure showed that poultry manure has a positive effect on number of branches per plant. Regarding the normality test of the data, the data of treatments and average number of branches per plant by factors indicated that the data was normally distributed since their skewness and kurtosis test values were falling within the range of ±3 and ±1 respectively.

The findings of the summary statistics for treatments and average number of pods per plant were presented in Table 6. Treatment C0P0G0 had 1.8333 mean number of pods per plant and treatment C6P6G6 had mean number of pods per plant of 11.333 (Table 6).

Table 6: Effects of Organic Manure per Treatment on the Number of Pods per Plant

Treatment	Mean	Standard deviation	Median	Skewness	Kurtosis	Maximum	Minimum
C0P0G0	1.8333	0.7528	2	0.1736	-1.5366	3	1
C0P0G3	5.333	3.2042	4.5	0.2961	-1.8809	10	2
C0P0G6	2.00	0.6325	2	0	-0.9167	3	1
C0P3G0	8.3333	2.2509	8.5	0.3572	-1.4389	12	6
C0P3G3	2.1667	0.9832	2	0.7989	-0.6541	4	1
C0P3G6	4.1667	1.9408	3.5	0.3546	-1.8078	7	2
C0P6G0	6.8333	5.7417	4	0.6106	-1.6714	16	2
C0P6G3	4.6667	1.633	4.5	0.2126	-1.8646	7	3
C0P6G6	5.1667	1.9408	4.5	0.3546	-1.8078	8	3
C3P0G0	3.6667	1.2111	3.5	-0.0417	-1.8809	5	2
C3P0G3	2.6667	0.8165	2.5	0.4763	-1.5833	4	2
C3P0G6	2.8333	0.9832	2.5	0.2533	-2.081	4	2
C3P3G0	3.1667	0.9832	3.5	-0.2533	-2.081	4	2
C3P3G3	5.3333	5.1251	3	0.6716	-1.4479	14	1
C3P3G6	4.50	1.6432	4	0.4508	-1.7569	7	3
C3P6G0	3.00	0.6325	3	0	-0.9167	4	2
C3P6G3	10.167	1.7224	10	0.3769	-1.318	13	8
C3P6G6	5.1667	3.3714	5	0.5852	-1.2433	11	2
C6P0G0	2.1667	0.7528	2	-0.1736	-1.5366	3	1
C6P0G3	2.8333	1.169	2.5	0.8809	-0.9043	5	2
C6P0G6	3.6667	2.1602	3.5	0.2572	-1.5833	7	1
C6P3G0	3.50	2.0736	2.5	0.6729	-1.4643	7	2
C6P3G3	3.3333	1.5055	3	0.7055	-1.1473	6	2
C6P3G6	6.3333	1.9664	5.5	0.9304	-0.877	10	5
C6P6G0	4.50	1.6432	4.5	0	-1.2082	7	2
C6P6G3	5.00	3.9497	4.5	0.3084	-1.7056	11	1
C6P6G6	11.333	2.0656	12	-0.4833	-1.6287	13	8

The results indicated that the number of pods per plant are affected in the same way with treatment P0C0G0 having the lowest average number of yields per plant (1.8333) and P6C6G6 had the highest average number of pods per plant of 11.33. The data of treatments and average number of pods per plant by factors indicated that the data was normally distributed since their skewness and kurtosis test values were falling within the range of ±3 and ±1 respectively.

Also, the summary statistics for the number of pods per plant factor were carried out and the results presented in Table 7. For cattle manure at level 0 the average number of pods per plant was 3.15 at level 3 the average number of branches per plant was 4.50 and at level 6 the average number of branches per plant was 4.74 (Table 7). For poultry manure, the average number of branches per plant at level 0 was 3.00, at level 3 it was 4.54 and 6.20 at level 6 (Table 7). For goat manure at level 0, the average number of pods per plant was 3.11, at level 3 it was 4.61 and at level 6, it shifted to 5.02 (Table 7). The skewness for cattle manure levels, poultry manure levels and goat manure levels were 1.40, 1.46, 1.10, 1.85, 1.21, 0.70, 1.96, 1.09 and 1.05 respectively. Corresponding kurtosis values were 1.82, 1.22, 0.35, 2.00, 1.23, -0.63, 1.11, 0.12 and 0.31 respectively (Table 7).

Table 7: Effects of Organic Manure per Factor Levels on the Number of Pods per Plant

Treatment	Mean	Standard deviation	Median	Skewness	Kurtosis	Max	Min
C0	3.15	3.20	3.00	1.40	1.82	16.00	1.00
C3	4.50	3.08	3.50	1.46	1.22	14.00	1.00
C6	4.74	3.26	4.00	1.10	0.35	13.00	1.00
P0	3.00	1.75	2.50	1.85	2.00	10.00	1.00
P3	4.54	2.82	4.00	1.21	1.23	14.00	1.00
P6	6.20	3.77	5.00	0.70	-0.63	16.00	1.00
G0	3.11	2.97	3.00	1.96	1.11	16.00	1.00
G3	4.61	3.35	3.00	1.09	0.12	14.00	1.00
G6	5.02	3.16	4.00	1.05	0.31	13.00	1.00

This increasing trend of number of pods per plant with increase in poultry manure and goat manure showed that poultry manure and goat manure had a positive effect on number of pods per plant. However, the result indicated that cattle manure had almost insignificant effect on the number of pods per plant as well shown by the insignificant increase with increase in the cattle manure levels. The data for treatments and average number of pods per plant by factors indicated that the data was normally distributed since their skewness and kurtosis test values were falling within the range of ±3 and ±1 respectively well attributed by the findings of Aczel and Sounderpadian (2002).

The analysis findings were found to be consistent with several similar studies. For instance, in a study that was carried out to determine the effects of chicken manure on growth, yield and quality of Lettuce (Lactuca sativa L.) ‘Taina’ under a lath house in a Semi-Arid Sub-Tropical environment, the researcher applied 60, 40 and 20 t/ha levels of chicken manure. Inorganic fertilizer control of 2:3:2 (22) + 0.5% Zn was applied at a rate of 955 kg ha^{-1} basal covering and limestone ammonium nitrate (LAN 28%) at a rate of 100 kg/ha as side dressing. The findings displayed that the levels of chicken manure significantly ($P < 0.05$) influenced nutritional quality, yield and growth of lettuce. A consistency of dominance of the different chicken manure level application was seen as lettuce provided with 60 t ha^{-1} showed the values in number of leaves were significantly higher, marketable yield, plant height and mean of dry mass of leafs (Masarirambi *et al*., 2012).

The results of this research were in line with the findings of a field study that intended at shaping the effect of organic fertilizer on the yield components and growth components as well, winged bean and yard long bean, it showed that plants grown with Vemicompost manure (20%) formed the fresh biomass that was significantly high for bush bean (527.55 g m^{-2}), winged bean (1168.61 g m^{-2}) and yard long bean (409.84 g m^{-2}). In all the legumes tested the maximum pod number, pod weight, pod length and pod dry weight were established in the Vemicompost (20%) treatment. Photosynthetic rates in the three legumes peaked at pod formation stage in all treatments, with the highest photosynthetic rate observed in winged bean (56.17 µmol m^{-2} s^{-1}) grown with Vemicompost (20%). The highest yield for bush bean (2.98 t ha^{-1}), winged bean (7.28 t ha-1) and yard long bean (2.22 t ha^{-1}) were also found in Vemicompost (20%) treatment. A study conducted on the influence of cow manure biochar on maize output under sandy soil condition showed that cow manure biochar contained some vital plant nutrients which suggestively affected the maize crop growth. Maize nutrient uptake and yield production were significantly enhanced with increasing the biochar mixing rate. Application of biochar at 15 and 20 t ha^{-1} mixing rates significantly increased maize grain yield by 150 and 98% (Uzoma *et al*., 2011).

The results of this research were also in agreement with the results of a field study conducted by Ojeniyi *et al* (2007) to determine the influence of amended animal manures disbursed grain and cocoa husk on nutrient status, yield and growth of tomato, the results showed that field experimentations were carried out at two regions in Akure, Southwest Nigeria to compare effect of NPK (15-5-15) fertilizer (200 kg ha^{-1}) and each of Spent Grain (SG) and ground 1 Cocoa Husk (CH) amended with Cattle Dung (CD), Poultry Manure (PM) and Goat Manure (GM) at equal rates (12.5 t ha^{-1} :12.5 t ha^{-1}). The effects of treatments on leaf N, P and K concentrations, growth and fruit yield 11 of tomato were studied. Compared with control, NPKF and animal manure amended SG and CH increased leaf N and K, plant height, number of branches, leaf area, number and weight of fruits significantly ($p>0.05$). Fruit yields given by CD, PM and GM amended CH and PM and GM amended SG were similar. Among eight treatments compared, CH and SG amended with PM gave highest fruit yields. Compared with control, NPKF, amended SG and CH increased fruit yield by 268,342 and 397%, respectively. In a research that was conducted to examine the discrepancy responses in yield of pumpkin (Cucurbita maxima L.) and nightshade (Solanum retroflexum Dun.) to the use of three animal manures (chicken, cow and kraal manures), the findings indicated that the biomass yield of crops improved linearly with rise in application rates of kraal and chicken manures, but steeper in the latter. Results showed that significant decline in biomass yield in chicken manure at rates above 8.5 t ha^{-1} were not due to salinity. The crops' response to cattle and goat kraal manures was linear but polynomial (cubic) in layer chicken manure (Azeez *et al*., 2010).

A randomized complete design analysis was carried out to investigate if the means of different blocks were significant in reducing the variability at $\alpha = 0.05$. The results of the randomized complete design were presented in the Table 8. The F-values for blocks, treatments and the interaction of block and treatments were 6.8094, 6.5154 and 0.9542 respectively (Table 8). Their corresponding P-values were 0.1035, 1.16E-12 and 0.5346 respectively (Table 8).

Table 8: Analysis of Variance of Randomize Complete Design

	df	SS	MS	F value	p-value
Block	1	345.9712	345.9712	6.809376	0.103543
Treatments	26	8606.941	331.0362	6.515426	1.16E-12
Block: Treatment	26	1260.616	48.48524	0.954282	0.534599

Residuals	108	5487.271	50.80806

The hypotheses were;

$$H_0 : \mu_1 = \mu_2 \dots = \mu_{27}$$
$$H_1 : \mu_1 \neq \mu_2 \dots . \neq \mu_{27}$$

$$H_0 : \beta_1 = \beta_2 = \beta_3$$
$$H_1 : \beta_1 \neq \beta_2 \neq \beta_3$$

The results showed that p value = 0.104 for the blocks which was greater than the level of significance (0.05). Thus, the rejection of the null hypothesis and concluding that blocks were not significant in reducing variability. However, the treatments had a significant effect on bean yield $F (26, 108) = 6.51$, p value= < 0.001 which is less than 0.05.

4.3 Fitted Models for Bean Yield and Yield Components

A linear regression model with 3 factors as the predictors for weight of bean yield that is cattle manure, poultry manure and goat manure with their level interactions was carried out and results presented (Table 9). The p-values for the interaction of manures with levels for C3P3, P3G3, C6P3G6, C6P3G6, C3P3G6 and C6P6G6 were 0.000122, 9.01E-07, 7.38E-07, 0.000872, 2.75E-06 and 0.014955 respectively which were less than 0.05 (Table 9). The p-values for insignificant manure interaction levels for C3, C6, P6G6, C6P6 and C6P6G3 were 0.141, 0.8053, 0.3099, 0.448 and 0.0779 respectively which were greater than the significant level (0.05) (Table 9).

Table 9: Regression linear model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.583333	2.959366	1.548755	0.123782
cattleC3	6.2	4.185176	1.481419	0.140825
cattleC6	1.033333	4.185176	0.246903	0.805358

poultryP3	20.76667	4.185176	4.961958	2.06E-06
poultryP6	14.66667	4.185176	3.504432	0.000621
goatG3	10.7	4.185176	2.556643	0.011675
goatG6	0.816667	4.185176	0.195133	0.845582
cattleC3:poultryP3	-13.4167	5.918733	-3.95636	0.000122
cattleC6:poultryP3	-16.8667	5.918733	-2.84971	0.005063
cattleC3:poultryP6	-16.7167	5.918733	-2.82437	0.005456
cattleC6:poultryP6	-6.03333	5.918733	-1.01936	0.309854
cattleC3:goatG3	-18.1167	5.918733	-2.38508	0.018465
cattleC6:goatG3	-8.58333	5.918733	-1.4502	0.149323
cattleC3:goatG6	-2.96667	5.918733	-0.50123	0.617023
cattleC6:goatG6	4.183333	5.918733	0.706795	0.480912
poultryP3:goatG3	3.4833	5.918733	-5.15031	9.01E-07
poultryP6:goatG3	1.625	5.918733	-2.8131	0.00564
poultryP3:goatG6	1.115	5.918733	-2.11194	0.036534
poultryP6:goatG6	4.5	5.918733	-0.7603	0.448402
cattleC3:poultryP3:goatG3	13.48333	8.370352	5.194923	7.38E-07
cattleC6:poultryP3:goatG3	18.5	8.370352	3.404875	0.000872
cattleC3:poultryP6:goatG3	10.98333	8.370352	4.896249	2.75E-06
cattleC6:poultryP6:goatG3	14.86667	8.370352	1.77611	0.077967
cattleC3:poultryP3:goatG6	20.43333	8.370352	2.441156	0.015935
cattleC6:poultryP3:goatG6	16.55	8.370352	1.977217	0.050054
cattleC3:poultryP6:goatG6	13.81667	8.370352	1.650667	0.101131
cattleC6:poultryP6:goatG6	24.63333	8.370352	2.46505	0.014955

The model was simplistically presented as;

$$Y = 4.58 + 6.2C3 + 1.03C6 \ldots + 0.82G6 - 13.41C3P3 - 16.87C3P3 + \cdots$$
$$+ 4.5P6G6 + 13C3P3G3 + \cdots + 24.633C6P6G6$$

The results showed that when level 3 of cattle manure was compared to level 0 the result was not significant this is the same case when level 6 of cow manure was compared to level 0 of cattle manure. On average when all the other factors are held constant when poultry manure level 3 is compared to poultry manure level 0 the yield increases by 20.76 grams, moving from poultry level 0 to poultry level 6 the yield increases by 14.667 grams. Moving from level 0 to level 3 in goat manure, bean yield increases by 10.7 on average (Table 10). Further, the findings indicated that, a unit increase in treatment P6G6G6 leads to a corresponding increase in grain yield of common beans by 24.63 grams hence the most effective treatment. However, a unit increase in treatment C3G3 leads to a corresponding decrease in yields by 18.12 grams which showed that this treatment was not significant. Cattle manure did not have a significant effect in bean yield production F (2, 135) = 0.2066, p value = 0.814366 which is greater than 0.05. Poultry manure was significant F (2, 135) = 26.03741, p value < 0 .001. The interaction between poultry and cattle manure was also not significant (Table 9).

The findings were in agreement with the findings of Enujeke (2014) who argued that poultry manure is the richest known animal manure and it is essential for establishing and maintaining the optimum soil physical condition for plant growth and production. In a research done on response surface methodology for optimization of multiple responses of watermelon using organic manure, the researcher found that the response surface corresponding to the second order model indicates that moderately low cattle manure and high poultry manure increase yields of watermelon. This was because poultry manure has been reported to be rich in nutrient concentration especially nitrogen which enhance growth and production of watermelon (Muriithi, 2018).

Factorial ANOVA on the three factors was also carried out and the findings were presented in Table 10. The p-values for cattle manure, poultry, goat, interaction of cattle and poultry, cattle and goat, poultry and goat, and finally the interaction for cattle, poultry and goat were 0.8144,2.73E-10, 0.046512, 0.228636, 1.28E-07, 1.51E-07 and 2.83E-06 respectively (Table 10).

Table 10: Analysis of Variance of a 3^3 Factorial Design for Organic Manures

	df	SS	MS	F value	p-value
Cattle	2	21.61346	10.80673	0.205658	0.814366
Poultry	2	2736.381	1368.191	26.03741	2.73E-10
Goat	2	329.8731	164.9365	3.138833	0.046512
cattle: poultry	4	299.7799	74.94497	1.426244	0.228636
cattle:goat	4	2243.815	560.9537	10.67525	1.28E-07
poultry: goat	4	568.4514	142.1128	2.704485	1.51E-07
cattle:poultry:goat	8	2407.028	300.8784	5.725881	2.83E-06
Residuals	135	7093.858	52.5471		

The results showed that factor cattle manure was not significant F (2, 135) = 0.205, p value = 0.814 (Table 10). Also, from the factorial ANOVA, poultry manure was significant F (2, 135) = 26.04, p value < 0.001 (Table 10). From Table 10 on factorial ANOVA, goat manure was significant F (2, 135) = 3.13, p value = 0.0465. The results also indicated that interaction between poultry and cattle manure was not significant, while the interaction between poultry and goat, cattle and goat were significant. Interaction plot further confirms that the interaction between poultry and cattle manure was insignificant (Appendix V). There was also slight interaction between goat and poultry manure and significant interaction between goat and cattle manure (Appendix V). Poultry manure is the richest known animal manure (Mangila *et al*., 2007), and it is essential for establishing and maintaining the optimum soil physical condition for plant growth and production. A combination of cattle manure, poultry manure and goat manure were superior compared to a combination of goat and cattle manure, goat and poultry and also a combination of cattle and poultry manure.

The RSM first order ANOVA for the grain yield was carried out and the findings were presented. The intercept and coefficients for cattle manure, poultry and goat manures were 13.508, 0.44167, 5.033 and 1.7463 respectively. The t values for cattle, poultry and goat manures were 0.5137, 5.8554 and 2.0311 respectively. Their corresponding p-values were <0.001, 0.6082, <0.001 and 0.04392 respectively (Table 11).

Table 11: Analysis of Variance of the First Order Response Surface Methodology for Grain Yield (Weight in grams per plant)

	Estimate	Std. Error	t-value	p-value
Intercept	13.50802	0.70201	19.2419	<0.001
Cattle	0.44167	0.85979	0.5137	0.60818
Poultry	5.0333	0.85979	5.85542	<0.001
Goat	1.74630	0.85979	2.0311	0.04392

The model in Table 11 can be summarized in a mathematical equation as;

$$Y = 13.50802 + 0.44167X_1 + 5.0333X_2 + 1.7463X_3 .$$

Where *Y* is grain yield; X_1 = cattle manure; X_2 = poultry manure; X_3 = goat manure

This model showed that unit increase in cattle manure, poultry manure and goat manure lead to a corresponding increase of 0.4417, 5.0333 and 1.7463 respectively in the grain yield of common beans. The p-values for poultry (<0.001) and goat (0.04392) manures were found to be less than 0.05 hence significant. However, cow manure was not significant (p-value=0.60818>0.05).

First order RSM was then performed and results presented. The p-value for first order RSM was <0.001 and for the lack of fit was also <0.001. Their corresponding F statistics values were 12.8868 and 4.5677 respectively (Table 12).

Table 12: Analysis of Variance of the First Order Response Surface Methodology for Grain Yield (Weight in grams per plant)

	df	SS	MS	F Value	p-value
FO($x1, x2, x3$)	3	3086.5	1028.85	12.8868	<0.001
Residuals	158	12614.3	79.84		
Lack of Fit	23	5520.4	240.02	4.5677	<0.001
Pure Error	135	7093.9	52.55		

The findings indicated that the Adjusted R-squared for the first order response surface model was 0.1813 with F-statistic: 12.89 on 3 and 158 DF, p-value = < 0.001. This model echoes what was found by the linear model and the factorial ANOVA model. Cow manure did not have a significant effect on bean yield t value (158) = 0.1537, p value < 0.608. Poultry manure was significant t value (158) = 5.855, p value < 0.001. Goat manure also had a positive effect on bean yield t (158) = 2.03 p value = 0.0439 (Table 11). However, the ANOVA model showed that the model lacked fit F (23, 135) = 4.5677, p value < 0.001 (Table 12).

Since the first order RSM fit was insignificant, a second order response surface model was fitted to see if the fit would be improved. The coefficients for the second order model for cattle, poultry, goat, their interaction and the quadratic of cattle, poultry and goat manures on grain yields were 0.4417, 5.033, 1.7463, 1.45, 4.1444, 1.7458, 0.1231, -0.0852 and 0.1204 respectively (Table 13). Their corresponding p-values were 0.59039, <0.001, 0.0346, 0.1503, <0.001, 0.03871, 0.9309, 0.9522 and 0.9325 respectively (Table 13).

Table 13: Second Order Response Surface Methodology Model for Grain Yield (Weight in grams per plant)

	Estimate	Std Error	t- value	p-value
Intercept	13.4025	1.7688	7.5773	<0.001
Cattle	0.4417	0.8188	0.5394	0.59039
Poultry	5.033	0.8188	6.1473	<0.001
Goat	1.7463	0.8188	2.1328	0.0346
Cattle:poultry	1.45	1.0028	1.4459	<0.001

Cattle:goat	4.1444	1.0028	4.1329	0.1503
Poultry: goat	1.7458	1.0028	1.7410	0.03871
Cattle^2	0.1231	1.4182	0.0868	0.9309
Poultry ^2	-0.0852	1.4182	-0.0601	0.9522
Goat^2	0.1204	1.4182	0.0849	0.9325

The model was simplistically presented as;

$$Y_1 = 13.40 + 0.4412X_1 + 5.033\ X_2 + 1.7463\ X_3 + 1.45\ X_1X_2 + 4.1444\ X_1X_3 \\ + 1.7458X_2X_3 + 0.1231X_1^2 - 0.0852\ X_2^2 + 0.1204\ X_3^2$$

Where Y_1 = weight of the grain yield; X_1 = cattle manure; X_2 = poultry manure; X_3 = goat manure.

The regression coefficient estimates show that for a unit change in cattle manure, poultry manure and goat manure, grain yield of common beans would increase by unit factors of 0.411, 5.033 and 1.7463 respectively. This implies that poultry manure is slightly more effective than goat manure. In addition, it was found that combined application of poultry and goat manure had a regression coefficient value of 1.7458 and a P-value of 0.03871<0.05, hence statistically significant at 5% significance level. This implies that for one unit change in combined poultry and goat manure, grain yield for common beans would increase by a factor of 1.7458. Similarly, combined application of poultry and cattle manure had a regression coefficient value 4.144 and a P-value of <0.0001<0.05, hence statistically significant at 5% significance level. This implies that for one unit change in combined application of cattle and poultry manure, grain yield of common beans would increase by a factor of 4.144. This shows that combined poultry and cattle manure is much more effective than combined poultry and goat manure and also cattle and goat manure. However, it was observed that the quadratic terms were not significant.

Since the quadratic terms were not significant, a first order with interaction terms only was performed. Since the two interaction terms were significant too, it was found necessary to fit a first order response surface model with two-way interactions. The p-values for first order RSM, two-way interaction, lack of fit and the partial quadratic terms were <0.001, 0.0001, <0.001 and 0.9993 respectively (Table 14).

Table 14: Analysis of Variance for First Order with Two-Way Interaction Response Surface Methodology Model for Grain Yield (Weight in grams per plant)

	df	SS.	MS.	F value	p-value
FO($x1,x2, x3$)	3	3086.5	1028.85	14.2098	<0.001
TWI($x1,x2,x3$)	3	1607.5	535.84	7.4008	0.0001
PQ($x1, x2, x3$)	3	1.3	0.44	0.0061	0.9993
Residuals	152	11005.4	72.40		
Lack of fit	17	3911.5	230.09	4.3787	<0.001
Pure Error	135	7093.9	52.55		

The findings showed that the p-values (<0.001) for first order and second order models were less than 0.05 hence significant. Lack of fit (p-value=<0.001<0.05) was also significant.

The comparison of first order model, first order with two-way interactions and second order model was also done to determine the best model. The Akaike information criterion for first order model, first order with two-way interactions and the second order model were 1175.224, 1159.16 and 1165.14 respectively (Table 15).

Table 15: The Akaike Information Criterion for Response Surface Methodology Models

	df	AIC
First order model	5	1175.244
First order with two-way interactions	8	1159.16
Second order model	11	1165.14

The findings revealed that the first order model with two-way interactions was found to be the best model since it had the lowest AIC of 1159.16. First order with two-way interactions response surface model for grain yield was also done to determine the significant interactions. The p-values for cattle, poultry, goat manures and their interaction were 0.5868, <0.001, 0.0328, 0.0407, 0.1463 and <0.001 respectively (Table 16).

Table 16: First Order with Two-Way Interactions Response Surface Methodology Model for the Grain Yield (Weight in grams per plant)

	Estimate	Std Error	t-value	p-value
Intercept	13.508	0.6621	20.4026	<0.001
Cattle	0.4417	0.8109	0.5447	0.5868

Poultry	5.0333	0.8109	6.2073	<0.001
Goat	1.7463	0.8109	2.153	0.0328
Cattle: poultry	1.45	0.9931	1.4601	0.0407
Cattle:goat	4.1444	0.9931	4.173	0.1463
Poultry: goat	1.7458	0.9931	1.7579	<0.001

The findings showed that poultry manure (p-value=<0.001), goat manure (p-value=0.0328) and the interaction between cattle and poultry (p-value=0.0407), interaction between poultry and goat (p-value<0.001) were significant with p-values <0.05.

First order with two-way interactions ANOVA table for grain yield was also done and the results showed that the F statistics values for first order RSM and two-way interaction were 11.384 and 5.93 respectively with corresponding p-values as <0.001 (Table 17). The F statistic and p-values for the lack of fit were 0.8855 and 0.6055 respectively (Table 17).

Table 17: Analysis of Variance of First Order with Two-Way Interactions Response Surface Methodology Model for Grain Yield (Weight in grams per plant)

	df	SS	MS	F value	p-value
FO (x_1, x_2, x_3)	3	3086.5	1028.85	11.384	<0.001
TWI(x_1, x_2, x_3)	3	1607.5	535.84	5.93	<0.001
Residuals	155	14007.6	90.372		
Lack of fit	20	912.9	45.65	0.8855	0.6055
Pure Error	135	7093.9	52.54		

The ANOVA test results showed that the lack of fit test was insignificant, F (20, 912.9) = 0.8855 with a p-value = 0.6055 and the first order and two-way interaction (p-value<0.001) were significant with their p-values less than 0.05. Therefore the study found that there is no significant lack of fit in the model and so the study concludes that the reduced model is adequate and thus, model satisfies the adequacy conditions in non-linear form.

Since the first order RSM fit for the number of branches per plant was insignificant, a second order response surface model was fitted to see if the fit would be improved. The t-values for the second order model for cattle, poultry, goat, their interaction and the quadratic of cattle, poultry and goat manures on number of branches per plant were

0.461493, 6.141404, 1.739473, 1.217377, 4.391254, 1.695633, 0.077218, -0.05215 and 0.094483 respectively (Table 18). Their corresponding p-values were 0.645092, 6.59E-09, 0.083937, 0.225311, 2.08E-05, 0.019632, 0.014512, 0.004511 and 0.006435 respectively (Table 18).

Table 18: Second Order Response Surface Methodology Model for Number of Branches per Plant

	Estimate	Std Error	t-value	p-value
Intercept	4.580247	0.212965	21.507	2.20E-48
Cattle	0.12037	0.260828	0.461493	0.645092
Poultry	1.601852	0.260828	6.141404	6.59E-09
Goat	0.453704	0.260828	1.739473	0.083937
Cattle:poultry	1.388889	0.319448	1.217377	0.225311
Cattle:goat	1.402778	0.319448	4.391254	2.08E-05
Poultry: goat	1.541667	0.319448	1.695633	0.019632
Cattle^2	0.423871	1.211642	0.077218	0.014512
Poultry ^2	-0.187555	1.211642	-0.05215	0.004511
Goat^2	0.257942	1.211642	0.094483	0.006435

The model was simplistically written as;

$$Y_2 = 4.5805 + 0.12037X_1 + 1.601852\,X_2 + 0.453704X_3 + 1.388889\,X_1X_2 + 1.40277X_1X_3 + 1.541667X_2X_3 + 0.423871X_1^2 - 0.187555X_2^2 + 0.257942X_3^2$$

Where Y_2 = number of branches per plant; X_1 = cattle manure; X_2 = poultry manure; X_3 = goat manure

The model indicated that the interaction between poultry and goat manures was highly significant (p-value=0.019632<0.05). The quadratic functions for cattle (p-value=0.014511), poultry (p-value=0.004511) and goat manures (p-value=0.006435) were also significant with their p-values less than 0.05.

Since the first order and the second order lack of fit were significant, a first order with two-way interactions ANOVA for the number of branches per plant was done. The F statistics values for first order RSM and two-way interaction were 13.6519 and 7.8801 respectively with corresponding p-values as <0.001 (Table 19). The F statistic and p-values for the lack of fit were 0.6518 and 0.8661 respectively (Table 19). The findings in this study were also in agreement with the findings of study in response surface modeling and optimizing conditions for anthocyanins extraction from purple sweet potato, all model terms were statistically significant as indicated by low p-values. Lack of fit that was not significant showed that the model fitted well with the data, thus no further specification of the model was required (Kokkaew *et al.*, 2015). Therefore, it is true to say that the results obtained in this study were similar to the results produced in studies available in the literature.

Table 19: Analysis of Variance of First Order with Two-Way Interaction Response Surface Methodology Models for Number of Branches per Plant

	df	SS	MS	F value	p-value
FO($x1, x2, x3$)	3	300.92	100.306	13.6519	<0.001
TWI($x1, x2, x3$)	3	173.69	57.898	7.8801	<0.001
Residuals	155	1138.85	7.347		
Lack of fit	20	99.85	4.9925	0.6518	0.8661164
Pure Error	135	1035	7.66		

The results showed that the first order (p-value=<0.001) and first order with two-way interaction (p-value=<0.001) were significant since their p-values were less than 0.05. However, lack of fit (p-value=0.8661>0.05) was insignificant thus making the model significant.

The effect of the manures on the number of pods per plant was examined by performing a second order RSM model. The findings showed that the t-values for the second order model for cattle, poultry, goat, their interaction and the quadratic of cattle, poultry and goat manures on the number of pods per plant were 1.44955, 5.245989, 3.24423, 1.099013, 1.944407, 2.620723, 0.114599, 0.200411 and 0.189227respectively (Table 20). Their corresponding p-values were 0.149204, 5.03E-07, 0.001443, 0.273467, 0.053657, 0.009648, 0.061174, 0.015443 and 0.043227 respectively (Table 20).

Table 20: Second Order Response Surface Methodology Model for Number of Pods per Plant

Term	Estimate	Std.error	Statistic	p-value
Intercept	4.203704	0.109526	38.38091	4.71E-81
Cattle	0.194262	0.134141	1.44955	0.149204
Poultry	0.703704	0.134141	5.245989	5.03E-07
Goat	0.435185	0.134141	3.24423	0.001443
Cattle:poultry	1.180556	0.164289	1.099013	0.273467
Cattle:goat	0.319341	0.164289	1.944407	0.053657

Poultry: goat	1.430286	0.164289	2.620723	0.009648
Cattle^2	0.332525	1.662507	0.114599	0.061174
Poultry ^2	-0.251653	1.662507	0.200411	0.015443
Goat^2	0.493751	1.662507	0.189227	0.043227

The findings were presented in a mathematical equation as;

$$Y_3 = 4.2037 + 0.1943X_1 + 0.7037\,X_2 + 0.4352X_3 + 1.1806X_2 + 0.3193X_1X_3 + 1.4304X_2X_3 + 0.3325X_1^2 - 0.2517X_2^2 + 0.4938X_3^2$$

Where Y_3= number of pods per plant; X_1 = cattle manure; X_2 = poultry manure; X_3 = goat manure**.** The model indicated that the interaction between poultry and goat manures was highly significant (p-value=0.0097<0.05). The quadratic functions for poultry (p-value=0.015443) and goat manures (p-value=0.043227) were also significant with their p-values less than 0.05.

Since the first order and the second order lack of fit were significant, a first order with two-way interactions ANOVA for the number of pods per plant was done and results showed that the F statistic for the first order RSM, two-way interaction and lack of fit were 13.3822, 3.95522 and 1.312996 respectively. Their corresponding p-values were <0.001, <0.001 and 0.1811626 respectively (Table 21).

Table 21: Analysis of Variance of First Order with Two-Way Interactions Response Surface Methodology Model of Number of Pods per Plant

	df	SS	MS	F value	p-value
FO($_{x1, x2, x3}$)	3	78.019	26.0062	13.3822	<0.001
TWI($_{x1, x2,x3}$)	3	23.042	7.6806	3.95522	<0.001
Residuals	155	301.218	1.9433		
Lack of fit	20	49.051	2.45255	1.312996	0.1811626
Pure Error	135	252.167	1.867904		

The results showed that the first order (p-value=<0.001) and first order with two-way interaction (p-value=<0.001) were significant since their p-values were less than 0.05. However, lack of fit (p-value=0.1812>0.05) was insignificant thus the first order with two-way interaction model becomes significant model for optimization.

4.4 Optimal application different levels of organic manure that maximizes yields and yield

The study of the response surface is well demonstrated by use of contours. They describe the topography or shape of the surface and locate the optimal points with ease. Graphical visualization helps in understanding the second-order response surface. Three dimensional plots for different combination of variables (poultry, cattle and goat manure) which display the tendency of variation of responses within the selected range of input variables. Response Surface Methodology can be illustrated with three-dimensional plots by presenting the response in function of two factors and keeping the other constant. The findings were presented in Figures 11, 12 and 13.

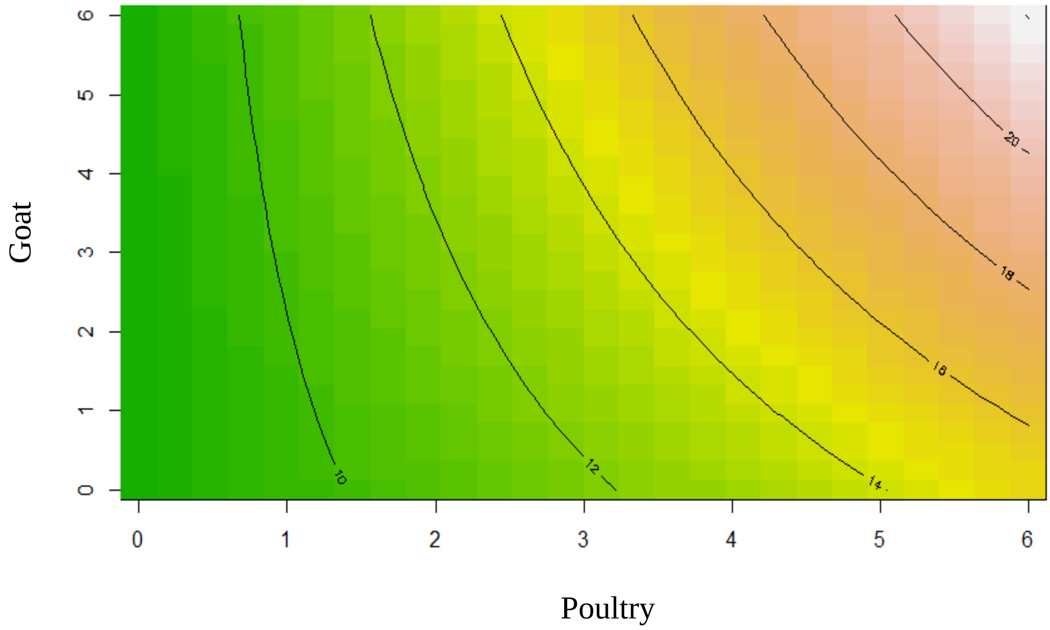

Figure 11: Response surface contour plot for grain yield as a function of goat manure and poultry manure at constant level of cattle manure

The findings of this study showed that poultry manure and goat manure have a direct effect on the grain yield to a certain level and then with more increase, led to decrease in poultry manure and goat manure. The optimal rate of application of cattle manure, poultry manure, and goat manure was 2.1608 t ha^{-1}, 12.7213 t ha^{-1} and 4.1417 t ha^{-1} respectively.

This result finding were in agreement with a research experiment which was conducted to examine the effect of combined use of application of Cattle Manure with mineral Nitrogen Phosphate on growth, yield components, yield, the economics of potato, and on selected soil physio-chemical characteristics (Boateng *et al*., 2006). It was concluded that, the use of combined application of Cattle Manure (7.5 t ha^{-1}) together with 75% of recommended rates of mineral Nitrogen Phosphate (123.75 kg N ha^{-1} and 103.05 kg P2O5 ha^{-1}) can significantly increase potato yield, gave a high economic return and improve soil health (Boateng *et al*., 2006). Almost similar study was carried out to determine the effect of inorganic manure and farmyard manure on soil physical properties, root distribution, and water-use efficiency of soybean in Vertisols of central India. The results showed that a combination of farmyard manure and inorganic manure has significant effect on the root distribution and high-water retention efficiency by 78% resulting to increase in yields of soybeans. Another field experiment was conducted to assess the effect of the combined use of farmyard manure and inorganic fertilizer on the growth and yield of sorghum and on soil chemical properties. The results posted a significant improvement in the yield and general growth of sorghum due to the main and interaction effects of farmyard manure and inorganic fertilizer application (Makinde *et al*., 2001). These findings are similar to the results obtained in this study.

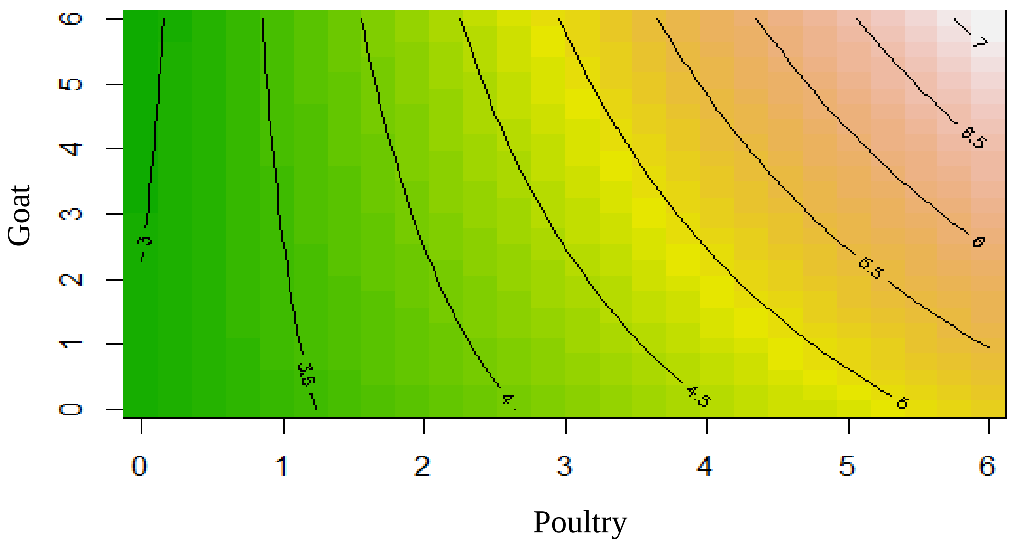

Figure 12: Response surface contour plot for number of branches per plant as a function of goat manure and poultry manure at constant level of cattle manure

The result showed that poultry manure and goat manure have a direct effect on the number of branches up to a certain level and then branch number decreased with continuous increase poultry manure and goat.

This result findings were in agreement with several studies. For instance, according to a study by Muriithi *et al.,* (2017), the response surface corresponding to the second order model indicated a moderately low goat manure and high poultry manure increased yields of watermelon. This was accredited that poultry manure were rich in nutrient concentration particularly nitrogen which facilitated production and general growth of watermelon (Enujeke, 2013). In investigation of the effects of organic and inorganic fertilizers on yield and yield components of maize, it was inferred that integrated application of organic and inorganic fertilizers increased crop yields (Admas *et al*., 2015). When investigating the effectiveness of farmyard manure and fertilizer-NPK on the Growth parameters of french bean (Phaseolus vulgaris) in Shimoga, Karntaka. The field experiment was conducted to investigate the effect of poultry manure, chemical fertilizer NPK, and their combination on the productivity and yield components of French bean (Arjumandbanu *et al*., 2013). It was resolved that Chicken manure and NPK increase the productivity of French bean, but chicken manure was preferable because it was cheaper than chemical fertilizer and it was readily available in Jordan throughout the year (Arjumandbanu *et al*., 2013).

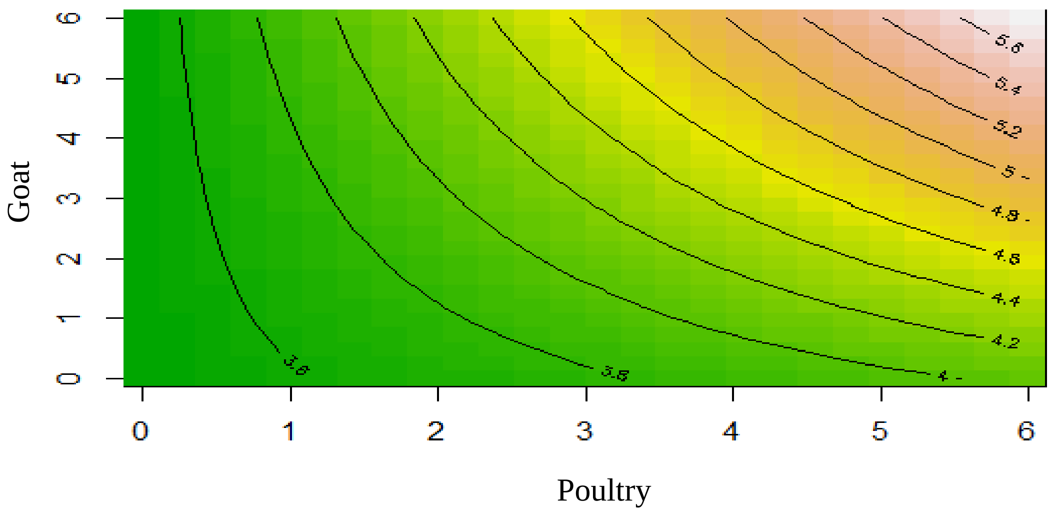

Figure 13: Response surface contour plot for number of pods per plant as a function of goat manure and poultry manure at constant level of cattle manure

The results of this study showed that poultry manure had relatively higher effect on the number of pods per plant than goat manure. However, both poultry and goat manure had a direct effect on the number of pods per plant up to a certain level and then pod number decreased with continuous increase poultry manure and goat manure.

Several studies conducted almost similar studies and were in agreement with the findings obtained in this study. For instance, a field trial was conducted to investigate the effect of different organic materials and chemical fertilizer on yield and quality of bitter gourd (Momordica charantia L.), the researcher concluded that poultry manure and goat/sheep manure at 6 t ha^{-1} or at 8 t ha^{-1} replacing 25% or 50% recommended dose of NPK fertilizers, respectively showed more promising results as compared to buffalo manure, while combined application of poultry, goat/sheep and cattle manure could not surpass the effectiveness of poultry and goat/sheep manure (Arfan-ul-Haq *et al*., 2015). A field experiment was conducted in order to study the effect of phosphorus and manure application on agronomic performance and seed yield of groundnut (Melese, 2011). The results showed that the integrated use of manure (10 t ha^{-1}) and inorganic phosphorus (180 kg ha^{-1} fertilizer resulted in highest seed yield of groundnut compared to the application of either fertilizer alone (Dechassa and Melese, 2011).

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

The study aimed at applying response surface methodology in modelling and optimization of the yields of common bean using animal organic manures. It was guided by the following specific objectives; to determine the effects of organic manures on grain yield and yield components of the common bean, to fit a statistical model using the collected data and finally to determine the optimal application of organic manure that would optimize common bean production. In applying RSM, the main objective was to find the operating conditions for the system that are optimum or to find a section of the space factor factor in which operating requirements are satisfied. Therefore, in this research, first order with two-way interaction model was found to be the most suitable model and it was obtained by employing a least squares technique for prediction of grain yield and components of common beans.

The first objective of the study was to determine the effects of organic manures on grain yield and yield components of the common bean. It was found that poultry manure and goat manure were the most significant variables for the yields and yield components, followed by their interaction poultry and goat manure, as well as cow manure and goat manure. However, cow manure and the interaction of cow and goat manure had negative effect and were insignificant at 95% confidence level. Plant that received adequate amount of poultry or goat manure had higher grain yield and the bean components (number of branches per plant and the number of pods per plant) possibly because higher rate of manure not only improve the soil conditions for crop establishment, but also released adequate nutrient element for grain yield and bean components enhancement.

The second objective of the study was to develop statistical models using the collected data. A first order with two-way interaction model was found to be the most suitable model for prediction. First order with two-way interaction model was obtained by employing a least squares technique for prediction of grain yield and components of common beans. The study found that there was no significant lack of fit in the model for all the responses (grain yield, number of pods per plant and the number of branches per plant) and so the study concluded that the reduced model was adequate.

The third objective of the study was to determine the optimal application of organic manure that would optimize common bean production. The optimal levels of cattle manure, poultry manure and goat manure as obtained from the stationary points of the response surface were 2.1608 t ha^{-1}, 12.7213 t ha^{-1} and 4.1417 t ha^{-1} respectively. Therefore, this study concluded that if these levels are applied in the production of common beans, there would be optimal yields without an extra cost in the inputs.

5.2 Conclusion

The goal of this study was to apply RSM in modelling and optimization of the yields of common bean using animal organic manures. The optimal conditions for the production of common beans were done using the graphical contour response surfaces. The process of optimization also involved use fitting the first order RSM, first order with two-way interaction RSM and second order RSM. It can be concluded that from this study that goat and poultry manure had a positive impact on the yield and the yield components of common beans. This is because increase in the levels of the poultry manure and goat manure led to increase in the yield. The parameter that was used to measure yield was the weight of the bean grains in grams which was observed to increase with increase in the levels of poultry manure and goat manure. However, cattle manure was found to have very minimal impact on the yields and yield components of common beans. Though, in some cases it showed that positive effect. Similarly, the parameters of interest for the yield components in this study were the grain yield at harvest, number of pods per plant and the number of branches per plant. These parameters increased with increase in the levels of poultry manures and the levels of goat manures. However, poultry manure had superior impact compared to goat and cow manures on the yields and yield components of the beans. This result agreed with findings from other studies that showed poultry manure having superior effect on yield and components of yield. This is due to its high nutritional contents.

5.3 Recommendation

i. Based on the findings of the study, the following recommendations were made;Poultry manure was found to be the most effective manure in the grain yield and yield components of common beans followed by goat manure. Interaction of poultry and goat and the interaction of poultry and cow had also positive effect. However, cow manure and the interaction of cow manure and goat manure were insignificant.

ii. The optimal levels of cattle manure, poultry manure and goat manure as obtained from the stationary points of the response surface as obtained using R software were 2.1608 t ha^{-1}, 12.7213 t ha^{-1} and 4.1417 t ha^{-1} respectively. These are the levels that this research can recommend to the farmers in the area of study to apply so as to obtain optimal yields without an extra cost in the inputs. More use of poultry manure is also recommended for use in the area of study to increase the yields of common beans.

iii. First order with two-way interaction RSM model showed good performance in modeling and optimization of yield and yield components of common beans and it can be recommended for future research in different regions.

5.4 Further Research

i. RSM can be applied in regions where common beans are grown in large scale to determine the optimal application of poultry and goat manures and their interactions that produces maximum yields.

ii. The study showed that poultry, cattle and goat manure influenced the yields and yield components of common beans in the study area. However, the study focused only on organic manure among all other sources of important nutrients. Thus, there is need to do further research by incorporating the use of inorganic manure in presence of animal organic manure and examine the effects on yields and yield components of the beans by applying RSM designs.

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APPENDICES

Appendix I: R Codes

```
library(pacman)
p_load(data.table, stringr, magrittr, foreach, ggplot2, zoo, knitr, plyr,
    dplyr, ggthemes, readxl, stringi, Hmisc, tidyr, rockchalk, stargazer, rsm)
```

```
setwd("E:/leornard/kimtai")
load("kimtai data 2018-09-16.rda")
weight_sum <- df %>% summarise(mean = mean(weight), sdparity =sd(weight), md = median(weight),
                              skew = skewness(weight), kurt = kurtosis(weight),
                              max = max(weight), min = min(weight))
mynames <- c("Mean", "Standard Deviation", "Median", "Skweness", "Kurtosis",
             "Maximum", "Minimum")
names(weight_sum) <- c("Mean", "Standard Deviation", "Median", "Skweness", "Kurtosis",
                  "Maximum", "Minimum")
weight_sum[, 1:7] <- apply(weight_sum[, 1:7], 2, round, 4)
write.csv(weight_sum, file = "weight sum.csv", row.names = F)
summaryTrt <- df %>% group_by(treatments) %>%
  summarise(mean = mean(weight), sdparity =sd(weight), md = median(weight),
            skew = skewness(weight), kurt = kurtosis(weight),
            max = max(weight), min = min(weight))
write.csv(summaryTrt, file = "summary stats treatments.csv", row.names = F)

ggplot(summaryTrt, aes(x=treatments, y=mean)) +
  geom_bar(stat = "identity")+
  theme_economist()+
  geom_errorbar(aes(ymin=mean - 1.96 *sdparity/sqrt(27), ymax=mean + 1.96*sdparity/sqrt(27)), width=.1)+
  theme(axis.text.x = element_text(hjust = 1, vjust = 1, angle = 45, face = "bold"),
        axis.title = element_text(face = "bold", size = 12),
        axis.text.y = element_text(face = "bold")) +
  ylim(c(0, 40))+
  labs(list(x = "Treatments", y = "mean", title = "Error bars for treatment means"))

ggplot(df, aes(weight))+
  geom_histogram()
```

```
hist(log(df$weight))
nms <- c("cattle", "poultry", "goat")
mylist <- list()
for(i in 1:3){

  this <- df %>% group_by_(nms[i]) %>%
    summarise(mean = mean(weight), sdparity =sd(weight), md = median(weight),
              skew = skewness(weight), kurt = kurtosis(weight),
              max = max(weight), min = min(weight))

  mylist[[i]] <- this

}

factor_summary <- rbindlist(mylist)

names(factor_summary)[2:8] <- mynames
factor_summary[, 2:8] <- lapply(factor_summary[, 2:8], round,4)
write.csv(factor_summary, file = "factor summary.csv", row.names = F)

summaryBlock <- df %>% group_by(block) %>%
  summarise(mean = mean(weight), sdparity =sd(weight), md = median(weight),
            skew = skewness(weight), kurt = kurtosis(weight),
            max = max(weight), min = min(weight), freq = n())

write.csv(summaryBlock, file = "block.csv", row.names = F)

ggplot(summaryBlock, aes(x=block, y=mean)) +
  geom_bar(stat = "identity")+
  theme_economist()+
  geom_errorbar(aes(ymin=mean - 1.96 *sdparity/sqrt(54), ymax=mean +
1.96*sdparity/sqrt(54)), width=.1)+
  theme(axis.text = element_text(hjust = 1, vjust = 1, face = "bold"),
```

```
        axis.title = element_text(face = "bold", size = 12),
        axis.text.y = element_text(face = "bold")) +
  ylim(c(0, 20))+
  labs(list(x = "Block", y = "mean", title = "Error bars for block means"))

fit <- aov(weight~block*treatments, data = df)

summary(fit) %>% xtable::xtable() %>% as.data.frame() %>% write.csv(file = "aov.csv")
fit_lm <- lm(weight~cattle*poultry*goat, data =df)
summary(fit_lm) %>% xtable::xtable() %>% as.data.frame() %>% write.csv(file = "lm model.csv")
anova(fit_lm) %>% xtable::xtable() %>% as.data.frame() %>% write.csv(file = "lm model aov.csv")
plot(fit_lm)
df2 <- df
df2[, 6:8] <- lapply(df2[, 6:8], function(x) gsub("[[:alpha:]]", "", x))
df2[, 6:8] <- lapply(df2[, 6:8], as.numeric)
df2.coded <-coded.data(df2,x1~(cow-3)/3, x2~(poultry-3)/3, x3~(goat-3)/3)
p_load(rsm)
#df3 <- df2[df2$cattle != 0 & df2$goat != 0 &df2$poultry != 0,]
rsm.model <- rsm(weight~ SO(x1, x2, x3), data = df2.coded)
summary(rsm.model)
rsm.model.FO <- rsm(log(weight)~ FO(x1, x2, x3), data = df2.coded)
rsm.model.SO <- rsm(weight~ SO(x1, x2, x3), data = df2.coded)
rsm.model.FO.TWI <- rsm(weight~ FO(x1, x2, x3)+TWI(x1, x2, x3), data = df2.coded)
summary(rsm.model.FO)
summary(rsm.model.SO)
summary(rsm.model.FO.TWI)
anova(rsm.model.FO, rsm.model.)
AIC(rsm.model.FO, rsm.model.FO.TWI, rsm.model.SO) %>% write.csv(file = "aic.csv")
```

```
contour(rsm.model.FO, ~ x1 + x2+x3, image = TRUE,
       main="first-order model")



contour(rsm.model.SO, ~ x1 + x2+x3, image = TRUE,
        main="second-order model")
contour(rsm.model.FO.TWI, ~ x1 + x2+x3,
        main="First-order with two way interactions model", image =T)
rsm.model.SO <- rsm(weight~ FO(cow, poultry, goat), data = df2)
summary(rsm.model.SO)
par(mfrow = c(2, 2))
attach(df)
interaction.plot(cattle, poultry, weight)
interaction.plot(goat, poultry, weight)
interaction.plot(cattle, goat, weight)
detach(df)

par(mfrow = c(1, 1))
df2[, 6:8] <- lapply(df2[, 6:8], as.numeric)
df2.coded <-coded.data(df2,x1~(cattle-3)/3, x2~(poultry-3)/3, x3~(goat-3)/3)
rsm.model.FO.TWI <- rsm(pdn~ FO(x1, x2, x3)+TWI(x1, x2, x3), data = df2.coded)
contour(rsm.model.FO.TWI, ~ x1 + x2+x3,
        main="First-order with two way interactions model", image =T)
summary(rsm.model.FO.TWI) %>% broom::tidy() %>% write.csv(file = "model
pdn.csv")
tx <- summary(rsm.model.FO.TWI)
tx
rsm.model.FO.TWI <- rsm(pnb~ FO(x1, x2, x3)+TWI(x1, x2, x3), data = df2.coded)
contour(rsm.model.FO.TWI, ~ x1 + x2+x3,
        main="First-order with two way interactions model", image =T)
summary(rsm.model.FO.TWI) %>% broom::tidy() %>% write.csv(file = "model
pnb.csv")
tx <- summary(rsm.model.FO.TWI)
```

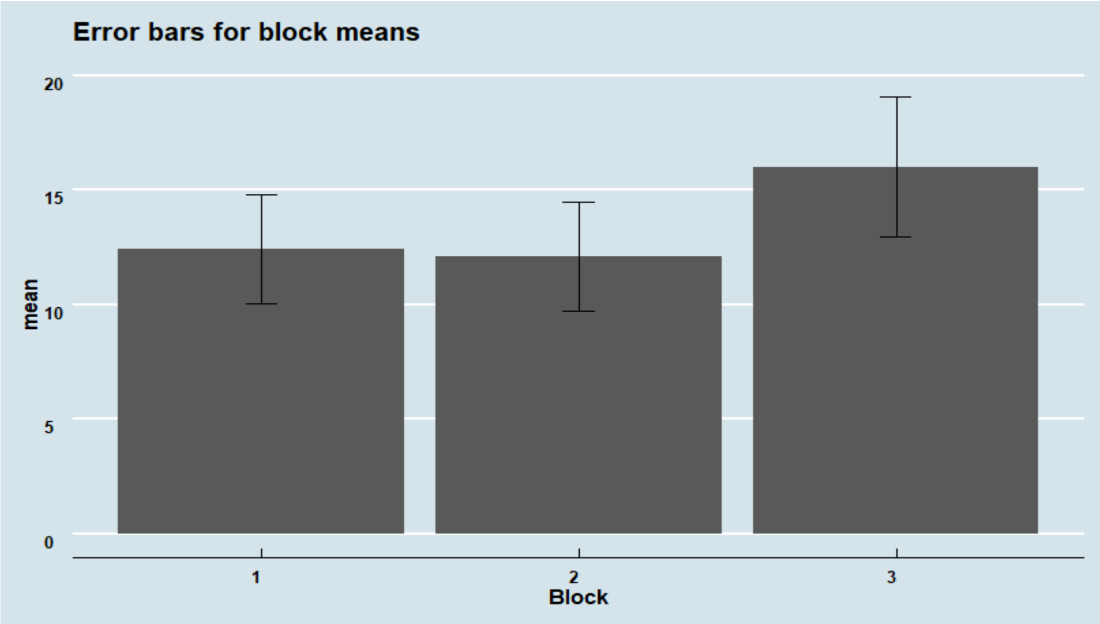
```
tx
######
weight_sum_pnb <- df %>% summarise(mean = mean(pnb), sdparity =sd(pnb), md =
median(pnb),
                               skew = skewness(pnb), kurt = kurtosis(pnb),
                               max = max(pnb), min = min(pnb))
mynames <- c("Mean", "Standard Deviation", "Median", "Skweness", "Kurtosis",
             "Maximum", "Minimum")
names(weight_sum_pnb) <- c("Mean", "Standard Deviation", "Median", "Skweness",
"Kurtosis",
                       "Maximum", "Minimum")
weight_sum_pnb[, 1:7] <- apply(weight_sum_pnb[, 1:7], 2, round, 4)
write.csv(weight_sum_pnb, file = "weight sum pnb.csv", row.names = F)
summaryTrt_pnb <- df %>% group_by(treatments) %>%
  summarise(mean = mean(pnb), sdparity =sd(pnb), md = median(pnb),
            skew = skewness(pnb), kurt = kurtosis(pnb),
            max = max(pnb), min = min(pnb))
names(summaryTrt_pnb) <- c("Treatment","Mean", "Standard Deviation", "Median",
"Skweness", "Kurtosis",
                           "Maximum", "Minimum")
summaryTrt_pnb[, 2:8] <- apply(summaryTrt_pnb[, 2:8], 2, round, 4)
write.csv(summaryTrt_pnb, file = "summary stats treatments pnb.csv", row.names = F)
avg <- sd(summaryTrt_pnb$Mean)
ggplot(summaryTrt_pnb, aes(x=treatments, y=mean)) +
  geom_bar(stat = "identity")+
  theme_economist()+
  geom_errorbar(aes(ymin=mean - 1.96 *sdparity/sqrt(27),
                    ymax=mean + 1.96*sdparity/sqrt(27)), width=.1)+
  theme(axis.text.x = element_text(hjust = 1, vjust = 1, angle = 45, face = "bold"),
        axis.title = element_text(face = "bold", size = 12),
        axis.text.y = element_text(face = "bold")) +
  ylim(c(0, 8))+
```

```
   labs(list(x = "Treatments", y = "mean", title = "Error bars for treatment means PNB"))
nms <- c("cattle", "poultry", "goat")
mylist <- list()
for(i in 1:3){
      this <- df %>% group_by_(nms[i]) %>%
      summarise(mean = mean(pnb), sdparity =sd(pnb), md = median(pnb),
             skew = skewness(pnb), kurt = kurtosis(pnb),
             max = max(pnb), min = min(pnb))

   mylist[[i]] <- this

}

factor_summary_pnb <- rbindlist(mylist)

names(factor_summary_pnb)[2:8] <- mynames
factor_summary_pnb[, 2:8] <- lapply(factor_summary_pnb[, 2:8], round,4)



write.csv(factor_summary_pnb, file = "factor pnb.csv", row.names = F)
weight_sum_pdn <- df %>% summarise(mean = mean(pdn), sdparity =sd(pdn), md = median(pdn),
                          skew = skewness(pdn), kurt = kurtosis(pdn),
                          max = max(pdn), min = min(pdn))
mynames <- c("Mean", "Standard Deviation", "Median", "Skweness", "Kurtosis",
          "Maximum", "Minimum")
names(weight_sum_pdn) <- c("Mean", "Standard Deviation", "Median", "Skweness", "Kurtosis",
                    "Maximum", "Minimum")
weight_sum_pdn[, 1:7] <- apply(weight_sum_pdn[, 1:7], 2, round, 4)
write.csv(weight_sum_pdn, file = "weight sum pdn.csv", row.names = F)
```

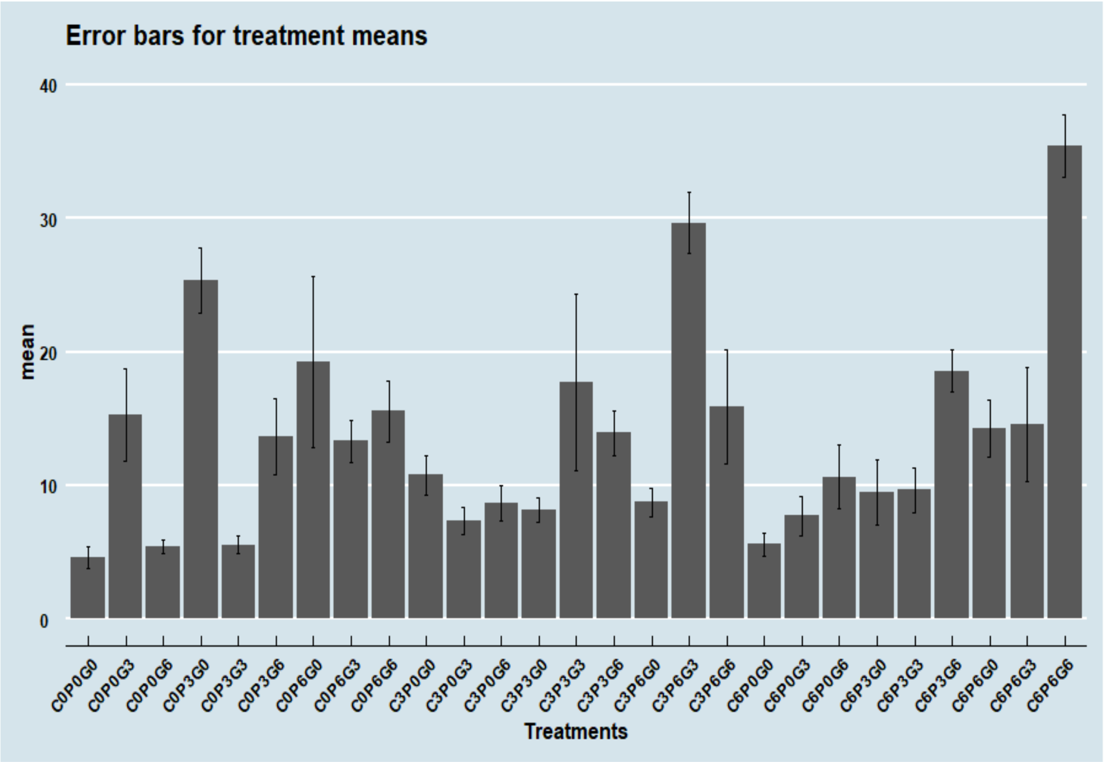
```
summaryTrt_pdn <- df %>% group_by(treatments) %>%
  summarise(mean = mean(pdn), sdparity =sd(pdn), md = median(pdn),
            skew = skewness(pdn), kurt = kurtosis(pdn),
            max = max(pdn), min = min(pdn))

names(summaryTrt_pdn) <- c("Treatment","Mean", "Standard Deviation", "Median",
"Skweness", "Kurtosis",
                   "Maximum", "Minimum")

summaryTrt_pdn[, 2:8] <- apply(summaryTrt_pdn[, 2:8], 2, round, 4)




write.csv(summaryTrt_pdn, file = "summary stats treatments pdn.csv", row.names = F)

avg <- sd(summaryTrt_pdn$Mean)
ggplot(summaryTrt_pdn, aes(x=treatments, y=mean)) +
  geom_bar(stat = "identity")+
  theme_economist()+
  geom_errorbar(aes(ymin=mean - 1.96 *sdparity/sqrt(27),
                ymax=mean + 1.96*sdparity/sqrt(27)), width=.1)+
  theme(axis.text.x = element_text(hjust = 1, vjust = 1, angle = 45, face = "bold"),
      axis.title = element_text(face = "bold", size = 12),
      axis.text.y = element_text(face = "bold")) +
  ylim(c(0, 12.5))+
  labs(list(x = "Treatments", y = "mean", title = "Error bars for treatment means
PDN"))
nms <- c("cow", "poultry", "goat")
mylist <- list()
for(i in 1:3){

  this <- df %>% group_by_(nms[i]) %>%
    summarise(mean = mean(pdn), sdparity =sd(pdn), md = median(pdn),
```

```
              skew = skewness(pdn), kurt = kurtosis(pdn),
              max = max(pdn), min = min(pdn))


   mylist[[i]] <- this

}

factor_summary_pdn <- rbindlist(mylist)

names(factor_summary_pdn)[2:8] <- mynames
factor_summary_pdn[, 2:8] <- lapply(factor_summary_pdn[, 2:8], round,4)

write.csv(factor_summary_pdn, file = "factor pdn.csv", row.names = F)
```

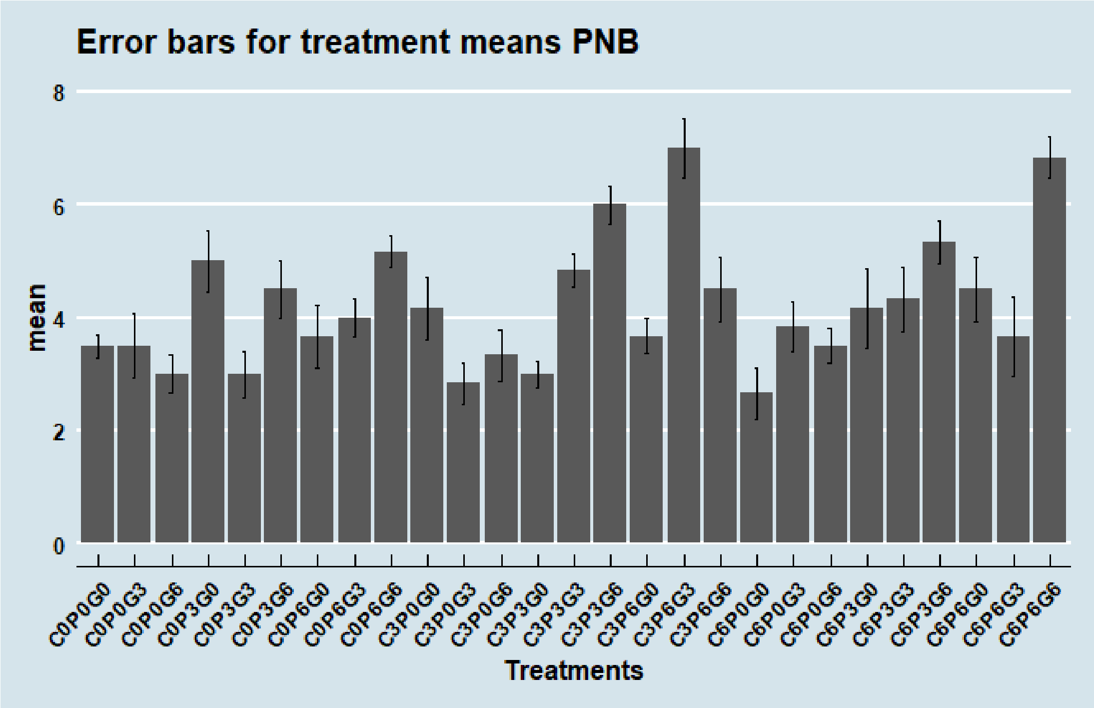
Appendix II: Error bars for block means


Error bars for block means
20
15
10
5
0
mean
1
2
3
Block

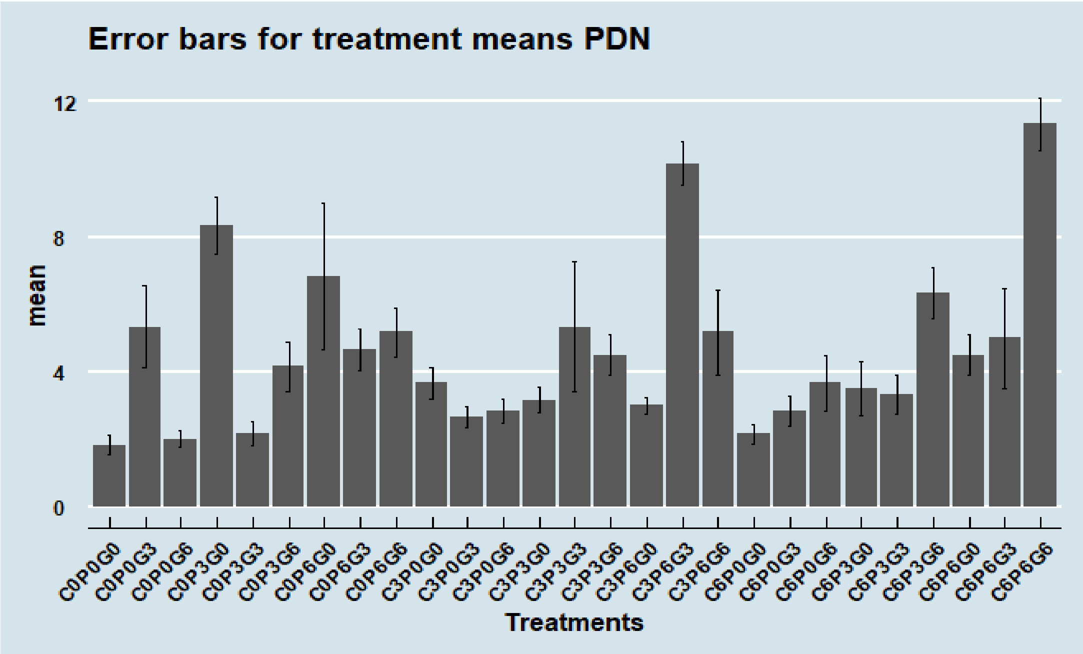
Appendix III: Error bars for treatment means



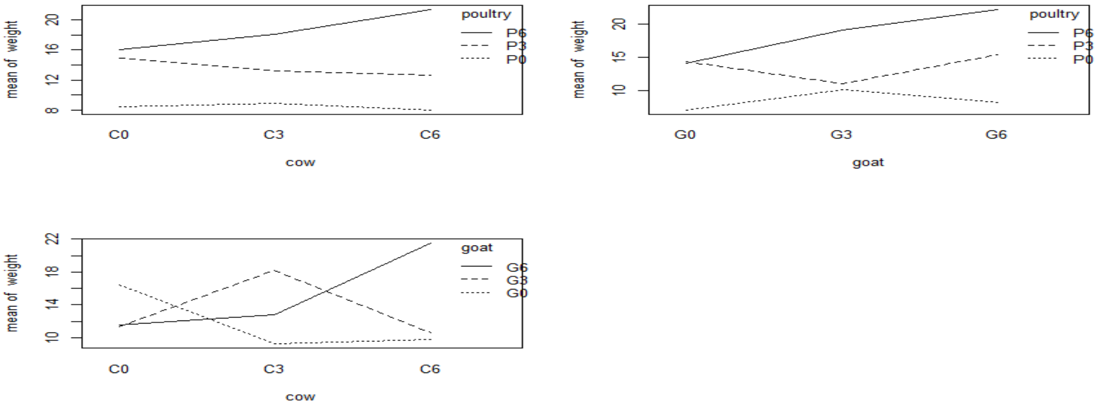
Appendix IV: Error bars for treatment means PNB



Appendix V: Error bars for treatment means PDN



Appendix VI: Interaction plot for ANOVA



Appendix VII: Chuka University Ethics review Authorization

CHUKA **UNIVERSITY**

Telephones: 020 2310512
020 2310518

P.O. Box 109
Chuka

CHUKA UNIVERSITY

OFFICE OF THE CHAIRMAN
INSTITUTIONAL ETHICS REVIEW COMMITTEE

Our Ref: CU/IERC/NCST/18/22 14th March, 2018

THE CHIEF EXECUTIVE OFFICER
NATIONAL COMMISION FOR SCIENCE, TECHNOLOGY AND INNOVATION
P.O. BOX 30623-00100
NAIROBI

Dear Sir/Madam,

RE: RESEARCH CLEARANCE AND AUTHORIZATION FOR KIMTAI LEONARD MASAI REG NO SM18/29047/16

The above matter refers:

The Institutional Ethics Review Committee of Chuka University met and reviewed the above MSC Research Proposal titled Modeling and Application of the response surface Methodology in Optimization of the Yields of Common Bean (*Phaseolus vulgaris L*) using animal Organic Manure. The Supervisor is Dr. Moses Muraya

The committee recommended that after candidate amends the issues highlighted in the Attached research clearance and authorization check list, the permit be issued.

Attached please find copies of the minutes, research clearance and authorization check list for your perusal. Kindly assist the student get the research permit.

Yours faithfully,

Prof. Adiel Magana
CHAIR
INSTITUTIONAL ETHICS REVIEW COMMITTEE
cc: BPGS

Appendix VIII: NACOSTI Authorization Letter

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY AND INNOVATION

Telephone:+254-20-2213471,
2241349,3310571,2219420
Fax:+254-20-318245,318249
Email: dg@nacosti.go.ke
Website : www.nacosti.go.ke
When replying please quote

NACOSTI, Upper Kabete
Off Waiyaki Way
P.O. Box 30623-00100
NAIROBI-KENYA

Ref: No. **NACOSTI/P/19/44245/29023**

Date: **24th April, 2019**

Leonard Masai Kimtai
Chuka University,
P.O. Box 109-60400,
CHUKA.

RE: RESEARCH AUTHORIZATION

Following your application for authority to carry out research on ***"Modelling and application of the response surface methodology in optimisation of the yields of common bean (Phaseolus Vulgaris L.) using animal organic manure"*** I am pleased to inform you that you have been authorized to undertake research in **Tharaka Nithi County** for the period ending **23rd April, 2020.**

You are advised to report to **the County Commissioner and the County Director of Education, Tharaka Nithi County** before embarking on the research project.

Kindly note that, as an applicant who has been licensed under the Science, Technology and Innovation Act, 2013 to conduct research in Kenya, you shall deposit **a copy** of the final research report to the Commission within **one year** of completion. The soft copy of the same should be submitted through the Online Research Information System.

GODFREY P. KALERWA MSc., MBA, MKIM
FOR: DIRECTOR-GENERAL/CEO

Copy to:

The County Commissioner
Tharaka Nithi County.

The County Director of Education
Tharaka Nithi County.

National Commission for Science, Technology and Innovation is ISO9001:2008 Certified

Appendix IX: NACOSTI Permit

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013

The Grant of Research Licenses is guided by the Science, Technology and Innovation (Research Licensing) Regulations, 2014.

CONDITIONS

1. The License is valid for the proposed research, location and specified period.
2. The License and any rights thereunder are non-transferable.
3. The Licensee shall inform the County Governor before commencement of the research.
4. Excavation, filming and collection of specimens are subject to further necessary clearance from relevant Government Agencies.
5. The License does not give authority to transfer research materials.
6. NACOSTI may monitor and evaluate the licensed research project.
7. The Licensee shall submit one hard copy and upload a soft copy of their final report within one year of completion of the research.
8. NACOSTI reserves the right to modify the conditions of the License including cancellation without prior notice.

National Commission for Science, Technology and innovation
P.O. Box 30623 - 00100, Nairobi, Kenya
TEL: 020 400 7000, 0713 788787, 0735 404245
Email: dg@nacosti.go.ke, registry@nacosti.go.ke
Website: www.nacosti.go.ke

REPUBLIC OF KENYA

NACOSTI

National Commission for Science, Technology and Innovation

RESEARCH LICENSE

Serial No.A 24201

CONDITIONS: see back page

THIS IS TO CERTIFY THAT:
MR. LEONARD MASAI KIMTAI
of CHUKA UNIVERSITY, 109-60400
CHUKA,has been permitted to conduct
research in *Tharaka-Nithi County*

on the topic: *MODELLING AND APPLICATION OF THE RESPONSE SURFACE METHODOLOGY IN OPTIMISATION OF THE YIELDS OF COMMON BEAN (PHASEOLUS VULGARIS L.) USING ANIMAL ORGANIC MANURE*

for the period ending:
23rd April,2020

Permit No : NACOSTI/P/19/44245/29023
Date Of Issue : 24th April,2019
Fee Recieved :Ksh 1000

....
Applicant's Signature

....
Director General
National Commission for Science, Technology & Innovation