RESPONSE SURFACE METHODOLOGY FOR OPTIMIZATION OF MULTIPLE RESPONSES OF WATERMELON USING ORGANIC MANURE

BY

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DECLARATION

Declaration by the Student

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

This thesis is dedicated to my family, particularly my late mother, Faithcate Muriithi

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ABSTRACT

Response Surface Methodology (RSM) is a critical technique in developing new processes, optimizing their performance and improving the design. Field experiment was conducted at horticultural research and teaching farm of Chuka University to evaluate the responses of watermelon to organic manure. The study investigated the use of Central Composite Design (CCD) in formulation of optimal use of organic manure in order to obtain maximum growth and yield of watermelon. The main objective of this study was to optimize the multiple responses of watermelon to organic manure using CCD and RSM. The study was guided by the following specific objectives; to establish the effect of organic manure on growth and yield of watermelon using CCD, determine a three-factor second-order model that best fits the data and find optimal settings on the control variables (poultry manure, cow manure and goat manure) that produce maximum response values on watermelon crop. The parameters assessed to achieve the objective of the study were vine length, number of branches/plant and fruit weight of watermelon. A statistical model of the second-order that best fits the data was used to achieve the objectives. The predicted values were found to be in good agreement with the experimental values which define the propriety of the models and the achievement of CCD in the optimization of multiple responses of watermelon. The results of the study showed that high rate of goat and poultry manure had significance influence on growth and yield of watermelon (fruit weight of 93.73 tonnes per hectare, 9 branches per watermelon plant and vine length of 225.4 cm) at 5% significance level. Based on the finding of this study, it was recommended that farmers in the study area apply 17.64 tons/ha of poultry manure, 11.2 tons/ha of cow manure and 18.1 tons/ha of goat manure for growth and yield of watermelon. Furthermore, in order to create much awareness of RSM on Agricultural settings the study recommends joint development by statisticians and Agriculturalists to reasonably model practical Agricultural research problems using CCD and RSM. Finally, further research may be commissioned with CCD, Box–Behnken and Doehlert design approach to plan the experiments for growth and yield of watermelon with an overall objective of optimizing the responses (such as number of fruits/plant and number of leaves per plant) of watermelon to organic manure (poultry manure, goat manure, rabbit manure and donkey manure). It is anticipated that the findings of the current study will provide necessary information useful to the policy makers, Agriculturalist and stakeholders to enhance growth and yield of watermelon in Kenya.

ABBREVIATIONS AND ACRONYMS

ANOVA	Analysis of Variance
ASTM	American Society for Testing and Materials
CCD	Central Composite Design
CCRD	Central Composite Rotatable Design
DEA	Data Envelopment Analysis
DF	Degree of Freedom
DOE	Design of Experiment
DRC	Dual Route Cascaded
EXPV	Experimental Values
FD	Factorial Design
IITA	International Institute of Tropical Agriculture
KSC	Kenya Seed Company
MSS	Mean Sum of Squares
OM	Organic Manure
PREDV	Predicted Values
RSM	Response Surface Methodology
SPV	Scaled Prediction Variance
SS	Sum of Squares

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CHAPTER ONE

INTRODUCTION

1.1 Introduction

This chapter presents the background to the study and the key construct under investigation, namely application of Response surface methodology on yields and growth of Watermelon. It also presents research problem, objectives of the study, research hypothesis and scope of the study as well as the significance of this study.

1.2 Background to Study

Watermelon *(Citrullus lanatus thumb)* is a member of the cucurbitaceous family. According to Jarret (1996), it originated from the Kalahari and Sahara deserts in Africa. In Kenya, the crop is mainly grown in lower and dry Semi-arid areas of the Country, namely Nyanza, Central, Coast and Rift Valley. Watermelon is a crop with huge economic importance to man as well as highly nutritious, sweet and thirst quenching (Mangila et al., 2007). It is mostly used to make a variety of salads, juice and food flavor. It is a cash crop for farmers due to its high returns on investment. Watermelon contains Vitamin C and A in a form of disease-fighting beta-carotene. Also, it contains potassium which helps in the control of blood pressure and possibly prevent stroke as suggested by IITA (2013).

In spite of the increasing relevance of watermelon in Kenya, yields across the country are decreasing and not encouraging because of rapid reduction in soil fertility caused by both continuous cropping and use of inappropriate soil amendment materials. One of the ways of increasing the soil fertility is by application of organic material such as poultry manure, cow manure, and goat manure which are available in most parts of the country. Animal waste is essential for establishing and maintaining the optimum soil physical, chemical and biological condition that are appropriate for plant growth and development. Although readily available, utilization of these organic manures in watermelons has not been optimized for increased plant growth and fruit production.

Response surface methodology (RSM) is an important subject in the statistical design of experiment. RSM is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes (Myers et al., 2004). It also has important applications in the design, development and formulation of new products, as well as in the improvement of existing product designs. For instance, the growth of a plant is affected by a certain amount of water x_1 and sunshine x_2. The plant can grow under any combination of treatment x_1 and x_2. Therefore, water and sunshine can vary continuously and obtain an optimal combination. When treatments are from a continuous range of values, then a response surface methodology is useful for developing, improving and optimizing the response variable. In this case, the growth of a plant is the response variable, y and it is a function of water and sunshine holding other factors constant.

$$y = f(x_1, x_2) + e \tag{1}$$

The variable x_1, and x_2 are predictor variables upon which the response y depends on. The dependent variable y is a function of x_1, x_2 and the experimental error term is denoted by e. The error term represents any measurement error on the response, as well as other type of variations not counted in the function. It is a statistical error that is assumed to be distributed normally with zero mean and variance of one. In most RSM problems, the true response function f is unknown. In order to develop a proper approximation for function the experimentation usually starts with a lower order polynomial in some small region. If the response can be defined by a linear function of an independent variable, then the approximation function is a first order model. This model can be expressed as follows

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + e \tag{2}$$

If there is a curvature in the response surface, then a higher degree polynomial should be used. In this case, an approximating function with two variables is known as second order model given as follows.

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_{11} x^2_1 + \alpha_{22} x^2_2 + \alpha_{12} x_1 x_2 + e \tag{3}$$

In order to get the most efficient result in the approximation of empirical model the proper experimental design must be used to collect data. The data is then used to develop an empirical model that relates the process response to the factors. The Method of Least Squares is used to estimate the parameters in the empirical model, (Box & Hunter, 1987). The response surface analysis is performed by using the fitted surface. The response surface designs are types of designs for fitting response surface. These methods are exclusively used to examine the “surface” or the relationship between the response and the factors affecting the response. Regression models are used for the analysis of the response as well as the nature of the relationship between the response and the factors. Details of experimental designs for fitting response surfaces are found in Montgomery (2005) and Khuri (2010).

In this study, Central Composite Design was used for experimental design model with 5-level- 3 factors experiment. A 5-level-3-factor central composite design was employed in watermelon crop experiment where optimization required 20 experimental runs. Poultry manure, cow manure, and goat manure were the independent variables to optimize the responses of interest that include; fruit weight at maturity, number of branches and vine length per plant. Also, the study optimized several of responses at the same time. Multi-response problem is often difficult due to different factors taken into account during problem-solving. Optimizing multiple responses is of main concern among decision makers. Derringer et al. (1980) proposed desirability function approach for simultaneous optimization of several response variables. The proposed procedure optimizes multiple responses simultaneously and overcomes the limitations of RSM when dealing with a large number of responses. Desirability function was used to consider several responses as efficiency response surface.

1.2 Statement of Problem

In many fields such as Biological and Clinical Science, Agricultural sciences and the process industries, a response of interest is usually influenced by several variables and the objective is to optimize the value of the response. Response surface methodology has been applied in such fields, but not much application of the same has been done on Agriculture. In Kenya, watermelon cultivation is gradually gaining ground. It is a crop with huge economic importance to man as well as being highly nutritious, sweet and thirst- quenching. In order to increase crop production, there is need to increase soil nutrient content with organic manure such as poultry manure, cow manure or other animal wastes. At present, there are no optimization standards with respect to the application rate of poultry manure, cow manure and goat manure for enhancement of yield of watermelon in Kenya. The challenge is to determine the optimal level that will guarantee optimal returns on investment on watermelon crop using RSM to identify the most appropriate rates of application of animal manure for increased growth and yield in Kenya. The purpose of the experiment was to investigate the use of Central Composite Design and RSM in formulation of optimal use of organic manure in order to obtain maximum growth and yield of watermelon

1.3 Objectives of Study

1.3.1 Broad Objective

The main objective of the study was to optimize the multiple responses of watermelon to organic manure using Central Composite Design and Response Surface Methodology.

1.3.2 Specific Objectives

The study was guided by the following specific objectives;

i. To establish the effect of organic manure on growth and yield of watermelon using Central Composite Design
ii. To determine appropriate second-order polynomial model that best fits the data
iii. To find an optimal settings on the control variables that produce maximum response values on watermelon crop

1.4 Research Hypothesis

The null hypothesis states that there is no quantifiable effect of poultry, cow and goat manure on the overall responses (fruit weight at maturity, number of branches and vine length per plant) of watermelon production. If this is true then:

$$H_{O\alpha} : \alpha_1 = \alpha_{11} = 0; \ \alpha_2 = \alpha_{22} = 0; \ \alpha_3 = \alpha_{33} = 0; \ \alpha_{12} = \alpha_{13} = \alpha_{23} = 0$$

$$H_{O\beta} : \beta_1 = \beta_{11} = 0; \ \beta_2 = \beta_{22} = 0; \ \beta_3 = \beta_{33} = 0; \ \beta_{12} = \beta_{13} = \beta_{23} = 0$$

$$H_{O\delta} : \delta_1 = \delta_{11} = 0; \ \delta_2 = \delta_{22} = 0; \ \delta_3 = \delta_{33} = 0; \ \delta_{12} = \delta_{13} = \delta_{23} = 0$$

Where α_1, β_1 and δ_1 the linear coefficient,α_{ii}, β_{ii} and δ_{ii} are the quadratic coefficient and α_{ij}, β_{ij} and δ_{ij} the cross-product coefficient (For *i=123; j=2,3 and i<j* representing the three independent variables in the study)

The alternative hypothesis postulated that at least one of the coefficients is not zero.

Then;

$H_{1\alpha}$; At least one *α≠0*

$H_{1\beta}$; At least one *β≠0*

$H_{1\delta}$; At least one *δ ≠0*

1.5 Significance of the Study

It is expected that the findings of this study will contribute to the knowledge gap and add value to the current literature on response surface methodology. Moreover, scholars and academicians wishing to carry out research in this area may use the finding of this study for further research. Also, the use of scientific model will go a long way in maximizing the crop yield and saving the small scale farmer the extra cost of buying input. Increased production of food crops can improve the livelihood of the smallholder farmer in Kenya thus a huge economic importance to man.

The findings of this study will be of importance to the government and private sector stakeholders in policy formulation and implementation since the agriculture industry has been identified as one of the key sectors in the economic pillar of the Kenya Vision 2030 whose aim is to transform the country into a modern, globally competitive middle-income country by the 2030. The finding of this study will be disseminated through a conference presentation.

The findings of this study will provide insights on the consideration to put in mind when developing a Watermelon production policy in Kenya which is currently lacking. Such a policy will provide an improvement evaluation framework to assess the production of watermelon. The finding of this study will be disseminated through a conference presentation and journal publications.

Finally, the findings of this study will add to the documented evidence on the optimization of watermelon production in Kenya. Such evidence will be available for use by donors, government agencies and other institutions to improve production of the crop.

1.6 Scope of the study

The study covered randomized incomplete block design. The process design was a 2^3 Factorial and central composite design. An experiment was carried out at Chuka University teaching and research farm where watermelon was planted in a rain shelter using different rates of poultry, cow and goat manure.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents a review of the literature relevant to this study. Presented also is a summary of an empirical study on the study variables and identifying some gaps therein.

2.2 Response Surface Methodology

In many fields such as Biological and Clinical Science, food science and the process industries, a response of interest is usually influenced by several variables and the objective is to optimize the value of the response. The optimal value of the response may either be a maximum or minimum value, depending upon the product or process in question. For instance, if the response in an experiment is the yields, from a chemical process, then the objective might be to find a setting of the factors affecting the yield so that the yields are maximized. Alternatively, if the response in an experiment is the number of defects, then the goal would be to find the factors setting that minimize the number of defects.

Montgomery (1997) defines an experiment as a series of tests, called *runs*, in which changes are made in the input variables in order to identify the reasons for changes in the output response. Response Surface Methodology (RSM) is a technique for designing experiment, help researchers to build models, evaluate the effects of several factors and achieve the optimal conditions for desirable responses. In addition, it reduces the number of the experiments in a study (Shahin et. al., 2009).

RSM has an extensive application in the real-world and according to Hill and Hunter, RSM method was introduced by Box and Wilson in 1951 who suggested using a first-degree polynomial model to approximate the response variable. They acknowledged that this model is only an approximation, not accurate, but such a model is easy to estimate and apply, even when little is known about the process (Wikipedia, 2015).

2.3 Optimal Experimental Design

Optimal Experimental Design plays an important role in scientific research. The basic idea underlying the optimal design is that statistical inferences about quantities of interest can be improved by optimally selecting levels of the control variables. These values should be chosen to minimize the variability of the parameter estimation. In experimental designs, efficient use of the available resource for experimental design is critical because costs are usually high and resources are usually limited. Therefore many criteria have been developed to measure the performance of an experimental design based on the optimal design theory (Kiefer and Wolfowitz., 1959). A design optimality criterion can be characterized as an estimation criterion or a prediction criterion. The commonly used and employed for this study was D-optimality criterion. It is an estimation criterion which maximizes parameter information by minimizing variability of the parameter estimates.

2.4 Overview of Response Surface Methodology

Silva et al. (2011) applied the RSM for optimization of biodiesel production by transesterification of soybean oil with ethanol. In the study, the transesterification process can be affected by differing parameters. The combined effects of temperature, catalyst concentration, reaction time and molar ratio of ethanol in relation to oil were investigated and optimized using Central Composite Rotatable Design and Response Surface

Methodology. The CCRD has an advantage of predicting response based on a few sets of experimental data in which all parameters vary within a chosen range. It was found that RSM was a suitable method to optimize the operations condition in order to maximize the ethyl esters production and minimize the glycerol production.

Mansourpoor and Shariati (2012) also applied response surface methodology for optimization of biodiesel production from sunflower oil using response surface methodology. The study found that biodiesel produced by transesterification of triglycerides with alcohol is the newest form of energy that has attracted the attention of many researchers due to various advantages associated with its usages. The study revealed that RSM was successfully applied for transesterification of methanol and that the optimal reaction condition within the experimental range would be the molar ratio of 6.825:1, a temperature of 48ºC and concentration of KOH equal to 0.679wt% to reach an optimal yield of 98.18%.

Design of experiment was applied to investigate the influence of operating factors including the reaction temperature, catalyst concentration and methanol to oil molar ratio on the product yield, biodiesel yield and biodiesel purity to obtain optimum conditions, (Shadkam et al., 2013). Here Response Surface Methodology coupled with Central Composite Design (CCD) was utilized as a tool for optimization. RSM is a powerful method which applies a collection of mathematical and statistical techniques to study the effect of independent variables on the value of dependent variables. The CCD is a standard RSM design tool to achieve appropriate data without performing a lot of experiments, (Leduc et al., 2009; Liu et al., 2010 and Vicente et al., 1998).

Atapour & Kariminia (2013) found that RSM was a suitable method to optimize the operating conditions. At optimal operating conditions, the fuel properties of BaO biodiesel produced were comparable with those of other studies and confirmed to EN 14214 and ASTM 6751 standards.

Response Surface Methodology is a useful statistical technique which has been applied in research into complex variation process (Tanarkorn and Vittaya, 2013). It was applied for the determination of optimum conditions on both esterification and transesterification steps. Optimum conditions for biodiesel production were determined with the aid of CCD. Both RSM and CCD show their applicability in a scientific research with a view of making evidence-based conclusion and recommendations.

Aghdeab and Laith (2014) used RSM to demonstrate the optimization process of hole diameter production using Electrical Discharge Machining (EDM). In their study, an attempt was made to estimate the optimum machining condition to produce the best possible response within the experimental constraints. The study was useful to researchers and industries for developing a robust, reliable knowledge based and early prediction of response without experimenting with EDM process for copper alloy. RSM method was used to design the experiment using second-order response surface.

Mead and Pike (1975) reviewed the role of RSM in agriculture but, in so doing, emphasized the use of nonlinear models to accommodate biological data rather than of the empirical models traditionally used in RSM. Khuri and Cornell (1987) analyzed an experiment on snap bean yield conducted using a central composite design. However such papers are rare and there is surprisingly little interest in RSM in agricultural applications within the mainstream statistical literature. On balance it is clear that while certain approaches within RSM are not appropriate for an agricultural setting, there is nevertheless a wealth of knowledge embedded within the broad field of RSM which can be drawn upon with advantage by agriculturalists.

Mapham (1975) modeled empirically the dependence of the yield of sugar cane on varying amounts of the nutrients namely; nitrogen, phosphorus and potassium using a second-order polynomial model and in addition presented some valuable insights into the use of RSM with an agricultural as opposed to an industrial settings.

Edmondson (1991) provides an interesting application of RSM to greenhouse experiments and, in addition, presents some valuable insights into the use of RSM within an agricultural as opposed to an industrial setting. Designs taken from the RSM paradigm can be used to good effect in a traditional agricultural setting and this point is further underscored by the work of Khuri and Cornell, (1987).

RSM has received attention for modeling the performance of Agricultural experiments. For instance, Salawu et al. (2007) used inverse polynomials and ordinary polynomial to model the yield of maize against the levels of nitrogen, phosphorous, and potassium as control factors. The study revealed that inverse polynomial model provided a better fit than the traditional second-degree model. The latter model may produce negative estimates of the yield response, which, of course, must be positive.

Muriithi (2015) investigated the operating conditions required for optimal production of potato tuber yield in Kenya. The potato production process was optimized by the application of two level three factors design and RSM. The combined effect of water, nitrogen and phosphorous mineral nutrient were investigated and optimized using RSM. It was found that optimal production condition for the potato tuber yield was 70.04% irrigation water, 124.75 Kg/Ha of nitrogen supplied as urea and 191.04 Kg/Ha phosphorus supplied as triple super phosphate. In his conclusion, increased productivity of potatoes can improve the livelihood of smallholder potato farmers in Kenya and save the farmers extra cost of input.

However, there exists some study where optimization was achieved using traditional method. For instance, Enujeke (2013b) studied the effect of five different rates of poultry manure on response of watermelon. It was found that plants that received highest rate of poultry manure (20 tonnes per hectare) were superior in the parameters tested with vine length of 177.5 cm at 8 weeks, mean number of leaves of 3.71 mm, number of branches/plant of 5.77, and mean fruit weight of 1309.43 tonnes per hectare). Based on the findings of the study, it was recommended that farmers in the study area apply 20 tonnes per hectare of poultry manure for increased growth and yield of watermelon.

In a view of above studies, it is evident that Response Surface Methodology coupled with Central Composite Design is a suitable statistical approach to a scientific research. In this study, the researchers employed CCD and RSM in crop production with a view of determining the operating conditions and optimizing the value of crop yield.

The orthogonal design was motivated by Box and Wilson (1951) in the case of the first order model, Myers, Khuri and Carter (1989). For the second order model, many subject-matter scientists and engineers have a working knowledge of the CCD and 3-level designs by Box and Behnken, (1960). There exists much information about the response surface models. Myers et al. (1989) suggested important development of optimal design theory in the field of experimental design emerged follows World War II. Some of the various authors who have published their work on optimality include, Chernoff (1953) and Kiefer (1959)

Multi-response problem is often difficult due to different factors taken into account during problem- solving. Optimizing multiple responses is of main concern among decision makers. Allen and Yu (2002) extended response surface methodology with novel low-cost response surface methods. Candiotti et al. (2014) presented methods and application of RSM when several responses have to be simultaneously optimized and classified method to two category, graphical optimization and desirability functions.

Tsai et al. (2010) presented a novel optimization procedure for multiple responses by using Data Envelopment Analysis (DEA) which can efficiently analyze data with multiple inputs and multiple outputs and response surface methodology. The proposed procedure optimizes multiple responses simultaneously and overcomes the limitations of RSM when dealing with a large number of responses. Analytical results indicated that the parameter-setting obtained using the proposed procedure satisfied the quality requirement of each response. Similarly, Sahu et al. (2013) proposed a data environment approach for optimization of multiple responses in electrical discharge machining of AISI D2 Steel and presented an equivalent single response capable of representing all individual responses.

Shadkam et al. (2015) proposed DRC model in solving a multi-objective problem. DRC model is a combination of data envelopment analysis, Response surface methodology and Cuckoo algorithm and response surface methodology used for optimization purpose. DEA was used to consider several response surfaces as efficiency response surface. Then the efficiency response was solved by Cuckoo algorithm. The study found that DRC approach decreases the response surface from three to one. Basically instead of making various response surfaces for each response, just one response surface was used for efficiency.

Enujeke (2013) evaluated the response of watermelon to the different rate of poultry manure and reported that the plant that received the highest rate of poultry manure were superior in the parameter tested. It was recommended that farmers in the study area should apply twenty tons of poultry manure per hectare for increased growth and yield of watermelon.

Response surface methodology is a powerful method which applies a collection of mathematical and statistical techniques to study the effect of independent variables on the value of dependent variables. The CCD is a standard RSM design tool to achieve appropriate data without performing a lot of experiments (Leduc et al., 2009; Liu et al., 2010 and Vicente et al., 1998).

Derringer et al. (1980) proposed desirability function approach for simultaneous optimization of several response variables. The Desirability method is very effective in optimizing processes that have multiple answers, which should be optimized simultaneously. As a result of the geometric mean, the Desirability value (D) evaluates, in general, the levels of the combined set of responses. It is an index which also belongs to the interval [0,1] and is maximized when all the answers get close as possible to your specifications. The closer one is to D, the closer to the original answers will be their respective specification limits.

The good general point of the system is the great point achieved by maximizing the geometric mean, calculated from the individual desirability functions. The advantage of using the geometric mean is to have the comprehensive settlement in a balanced manner, allowing all answers meet the expected values and forcing the algorithm to approximate the specifications imposed (Wu, 2005). Desirability function was used to consider several responses as efficiency response surface. The desirability method is a method of bonding, used for the determination of the best conditions for process adjustments, making possible the simultaneous optimization of multiple responses. With that, the best conditions of the responses will be obtained simultaneously minimizing, maximizing, or seeking nominal values, depending on the situation more convenient for the process (Wang and Wan, 2009).

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter describes how the study was planned and executed. Specifically, the chapter discusses the research design employed in the study, the effect of organic manure on growth and yield of watermelon as well as determining appropriate second-order models that best fits the data. The original design was developed using CCD and full Factorial designs. The chapter ends with a discussion of optimal settings on the control variables that produce maximum response values.

3.2 Establishing the effect of OM on Growth and Yield of Watermelon

3.2.1 Design of Experiment for RSM

In experiments, different factors are considered while selecting designs so as to suit particular objectives. For example, a design with a small number of runs but gives enough information on the coefficients of the model developed would be preferred as far as cost is concerned. Another factor considered in the selection of a design is the prediction capability of the design. Scaled prediction variance (SPV) has been suggested as a measure of prediction variance. SPV considers the total sample size to penalize large designs. In experiments where the cost is not a major issue, unscaled prediction variance, which compares variances without penalizing the sample size, is recommended (Cho, 2010).

Response Surface Methodology design allows estimation of interaction and even quadratic effect and therefore, gives an idea of the shape of the response surface under investigation. Box-Behnken design and central composite design (CCD) are an effective design for fitting second-order model to response surface because they use a relatively small number of observations to estimate the parameters. Rotatability is a reasonable basis for the selection of a response surface design. The purpose of RSM is optimization and the location of optimum is unknown prior to running the experiment. It makes sense to use a design that provides an equal precision of estimation in all directions. The CCD and RSM is a mathematical tool for evaluating the responses necessary to optimize watermelon growth process. In this study, CCD was used for experimental design model with 5-level- 3 factors experiment. A 5-level-3-factor Central Composite Design was employed in watermelon growth process, optimization requiring 20 experimental runs. Poultry manure (X_1), cow manure (X_2) and goat manure (X_3) were the independent variables to optimize the response value of interest (fruit weight of watermelon at maturity, number of branches and vine length per plant). In developing the regression model, the test factors were coded according to the formulae given as $x_i = \frac{X_i - X_0}{X}$ where x_i is a coded variable of the i^{th} variable, X_0 is an average of the variable in high and low level, X is (variable at high level- variable at low level)/2 and X_i is an encoded value of the i^{th} test variables.

Table 3.1: Three Factors at Five Levels Estimated Values

Symbols	Predictor Variable	Code Levels				
		-1.682	-1	0	+1	+1.682
X_1	Poultry manure (Tons/Ha)	1.6	5	10	15	19.4
X_2	Cow manure (Tons/Ha)	1.6	5	10	15	19.4
X_3	Goat manure (Tons/Ha)	1.6	5	10	15	19.4

The experiment was carried out in a Randomized complete Block Design (RCBD) with four replicates. Rates of poultry manure, cow manure and goat manure in tons per hectare were as shown in Table 3.1. The manure was incorporated into the soil two weeks before planting.

3.2.2 Central Composite Design

There are many designs available for fitting a second-order model. The most popular one is central composite design. This design was introduced by Box and Wilson (1951). It consists of factorial design, a set of central points and axial points equidistant to the center point. The experiment was carried out as a CCD consisting of 20 experiments determined by the $\mathbf{2^3}$ full factorial designs with six axial points and six center points as shown in Figure 3.1. The CCD was adopted for this study because it requires few points and that information on quantitative variables is used effectively.

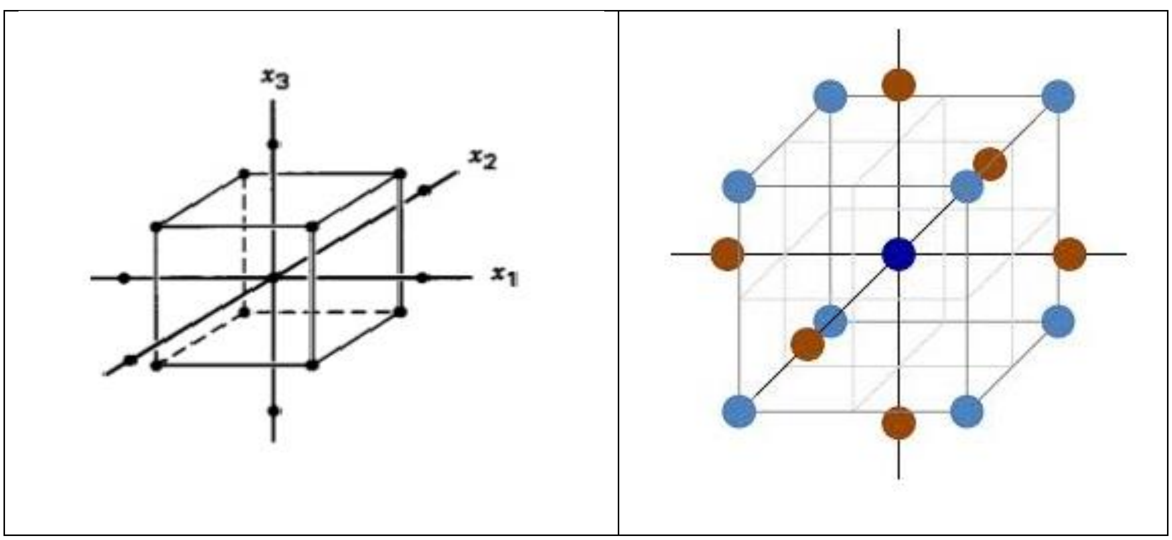

Figure 3.1: Layout of the Central Composite Design for 3 variables at 5 levels

The center runs contain information about the curvature of the surface, if the curvature is significant, the additional axial points allow for the experimenter to obtain an efficient estimation of the quadratic terms. CCD can run in incomplete blocks. A block is a set of relatively homogeneous experimental conditions so that an experimenter divides the observations into groups that are run in each block. An incomplete block design may be conducted when all treatment combinations cannot be run in each block. In order to protect the shape of the response surface, the block effects need to be orthogonal to treatment effects. This can be done by choosing the correct distance of the axial ($a=2^{3/4}$) and a number of center points in factorial and axial blocks (Montgomery, 1997). Response surface design is said to be rotatable if the precision of the estimated response surface at some point to the origin and not on the direction (Oehlert, 2000). When the rotatable design is rotated about the center, the variance of response will remain the same. Table 3.2 shows the Design Matrix Adopted for this study generated using Central Composite Design.

Table 3.2: Full Factorial Central Composite Design Matrix

	Coded values			Organic Manure (ton/Ha)		
Runs	X_1	X_2	X_3	Poultry	Cow	Goat
1	-1.682	0	0	1.92	12	12
2	-1	1	1	6	18	18
3	-1	-1	1	6	6	18
4	-1	-1	-1	6	6	6
5	-1	1	-1	6	18	6
6	0	0	0	12	12	12
7	0	0	-1.682	12	12	1.92
8	0	0	0	12	12	12
9	0	1.682	0	12	24	12
10	0	0	0	12	12	12
11	0	0	1.682	12	12	24
12	0	0	0	12	12	12
13	0	0	0	12	12	12
14	0	-1.682	0	12	1.92	12
15	0	0	0	12	12	12
16	1	1	-1	18	18	6
17	1	-1	1	18	6	18
18	1	1	1	18	18	18
19	1	-1	-1	18	6	6
20	1.682	0	0	24	12	12

3.2.3 Data Source

Data was obtained from an experiment carried out at horticultural research and teaching farm of Chuka University, Kenya. A land measuring 448 meters squared (28 M by16 M) was selected for the study and prepared for planting. It was marked according to the experimental layout (see Appendix III). Twenty plots of 400 cm by 300 cm each were made and composite soil samples collected from the plots at 0-15 cm depth in order to assess the initial soil physical-chemical properties. The composite soil samples collected from individual plots was analyzed in the laboratory to determine initial physical-chemical properties of soils for the study. Similarly, the chemical analysis of poultry, goat and cow manure used for the experiment was evaluated using appropriate method.

Each plot had 3 seeds per stand at a depth of 3cm, using a spacing of 200cm by 100cm, with 100cm alley pathways. Data collected includes; watermelon fruit weight at maturity, measured using a weighting scale after harvest 75-85 days from planting, number of branches determined by direct counting and vine length measured with tape measure from the base to the growing tip of the plant. Sukari F1 watermelon a newly developed variety from East Africa Seed Company was used in the study.

3.2.4 Result Presentation and Conclusion

The results of the study were presented in form of graphs. The appropriate conclusions were made and recommendations stated accordingly

3.3 Determining an appropriate Second-Order Model that best fits the Data

3.3.1 Response Surface Methodology

Response surface methodology (RSM) is a collection of statistical and mathematical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several (three) variables and the objective is to optimize this response (Montgomery, 1997). The RSM makes it possible to evaluate operation variable that may or may not have a significant effect in the main response. The design procedure of RSM is as follows;

i. Develop an original design of experiment for adequate and reliable measure of the response of interest (Fruit weight of watermelon at maturity, number of branches and vine length per plant)
ii. Develop statistical model of the second-order model with best fit

iii. Find the optimal set of experimental parameters, that produce a maximum value of response

iv. Present the direct and interactive effect of process parameter through two and three-dimensional plots

In this study, the main objective was to determine a region of the factor space in which operating requirements are satisfied. In most RSM problems, the form of the relationship between the response and the independent variable is unknown. It is therefore, important to find a suitable approximation for the true relationship between the controllable input parameters and the obtained response surfaces.

3.3.2 Mathematical Models

The second- order model representing the watermelon fruit weight at maturity, number of branches and vine length per plant each were expressed as a function of poultry manure, cow manure and goat manure being in the input variable of watermelon response.

To define the response equation, X_1, X_2 and X_3 are assigned to poultry manure, cow manure and goat manure respectively. Appropriate polynomial (second-order) models were expressed as;

$$Y_1 = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_{11} X_1^2 + \alpha_{22} X_2^2 + \alpha_{33} X_3^2 + \alpha_{12} X_1 X_2 + \alpha_{13} X_1 X_3 + \alpha_{23} X_2 X_3 + e \quad (8)$$

$$Y_2 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{23} X_2 X_3 + e \quad (9)$$

$$Y_3 = \delta_0 + \delta_1 X_1 + \delta_2 X_2 + \delta_3 X_3 + \delta_{11} X_1^2 + \delta_{22} X_2^2 + \delta_{33} X_3^2 + \delta_{12} X_1 X_2 + \delta_{13} X_1 X_3 + \delta_{23} X_2 X_3 + e \quad (10)$$

Where Y_i ; (i=1,2,3) is the i^{th} predicted response (1= for Fruit weight of watermelon at maturity, 2= for Number of branches per plant and 3= for Vine length at 8 weeks), X_i represent the control factors in the experimental data, α_0, β_0 and δ_0 the constant, α_i, β_i and δ_i the linear coefficient, α_{ii}, β_{ii} and δ_{ii} are the quadratic coefficient and α_{ij}, β_{ij} and δ_{ij} the cross-product coefficient (For *i=1,2,3; j=2,3 and i<j).*

The equation can be rewritten in matrix form as follows

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{e} \quad (11)$$

Where $\boldsymbol{Y}$ is the response vector, $\boldsymbol{X}$ is a matrix of the chosen experimental design, $\boldsymbol{\beta}$ is the vector constituted by parameters of the model and $\boldsymbol{e}$ is the residual. Assuming that $E(\boldsymbol{e})=0$ and $var(\boldsymbol{e}) = \delta^2 I_{20}$ the least squares estimates of parameter (solution) to equation (6) can be obtained by minimizing the error sum of squares as follows

$$L = \sum_{i=1}^{20} \boldsymbol{e}_i^2 = \boldsymbol{e}^T\boldsymbol{e} = (\boldsymbol{Y} - \boldsymbol{X\beta})^T\,(\boldsymbol{Y} - \boldsymbol{X\beta})$$

L is minimized by taking derivatives with respect to the model parameters and equating to zero

$$\frac{\partial L}{\partial \boldsymbol{\beta}} = -2\boldsymbol{X}^T\boldsymbol{Y} + \boldsymbol{2}\boldsymbol{X}^T\boldsymbol{X}\widehat{\boldsymbol{\beta}} = \boldsymbol{0}$$

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X^T X})^{-1}\boldsymbol{X^T Y} \quad (12)$$

The analysis of a second-order model was done by computer softwares (R- Program and Design Expert).

R is a language and environment for statistical computing and graphics. It is a GNU project which was developed at Bell Laboratories (formerly AT&T, now Lucent Technologies) by John Chambers and colleagues. R provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering among others) and graphical techniques, and is highly extensible.

Design–Expert is a statistical software package from Stat-Ease Inc. that is specifically dedicated to performing design of experiments (DOE). Design–Expert offers comparative tests, screening, characterization, optimization, robust parameter design, mixture designs and combined designs. Design–Expert provides test matrices for screening up to 50 factors. Statistical significance of these factors is established with analysis of variance (ANOVA). Graphical tools help identify the impact of each factor on the desired outcomes and reveal abnormalities in the data. The software determines the main effects of each factor as well as the interactions between factors by varying the values of all factors in parallel.

3.3.3 Analysis of Variance

ANOVA is a statistical decision-making tool used for detecting any differences in average performance of tested parameters (Muriithi, 2015). It employs the sum of squares and F-statistic to find out the relative importance of the analyzing process parameter, measurement errors and uncontrolled parameters. The analysis of variance for fitting the data to the second-order and contour plots helped characterize the response surface. It was adopted to check the adequacy of the model for the response in the experimentation

3.3.4 Validation of the Models

In addition to verification through ANOVA technique, the models were validated by conducting experiment with a new set of parameters and the multiple response values were measured compared with the predicted values using the models discussed in section 3.3.2. Deviation of the predicted values from the experimental values was computed to get the percentage (%) error for the validation data.

3.3.5 Result Presentation and Conclusion

The results of the study were presented in form of tables. The appropriate conclusions were made and recommendations stated accordingly

3.4 Finding optimal settings on the control variables that produce maximum response values

3.4.1 Determining the Optimal Parameter-Setting

The stationary point was found by use of matrix algebra. The second-order model in matrix form is as shown below.

$$\hat{Y} = \widehat{\alpha_0} + X^T\boldsymbol{b} + X^T\boldsymbol{BX} \tag{13}$$

The derivatives of $\hat{Y}$ with respect to the elements of the vector X are

$$\frac{\partial \hat{Y}}{\partial X} = \boldsymbol{b} + 2\boldsymbol{BX} = 0$$

Therefore the solution to stationary point is

$$X_s = -\frac{1}{2}\boldsymbol{B}^{-1}\boldsymbol{b} \tag{14}$$

where $\boldsymbol{b} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix}$ and $\boldsymbol{B} = \begin{bmatrix} \alpha_{11} & \frac{\alpha_{12}}{2} & \frac{\alpha_{13}}{2} \\ \frac{\alpha_{21}}{2} & \alpha_{22} & \frac{\alpha_{23}}{2} \\ \frac{\alpha_{31}}{2} & \frac{\alpha_{32}}{2} & \alpha_{33} \end{bmatrix}$

$\boldsymbol{b}$ is a (3x1) vector of the first-order regression coefficient and $\boldsymbol{B}$ is a (3x3) symmetric matrix whose main diagonal element are the quadratic coefficient (α_{ii} or β_{ii} or δ_{ii}) and whose off-diagonal elements are mixed interaction coefficient (α_{ij} or β_{ij} or δ_{ij}) $_{i \neq j}$. In results, the estimated response value of the stationary points can be calculated as

$$\widehat{y_s} = \widehat{\alpha_0} + \frac{1}{2}x_s^T\boldsymbol{b} \tag{15}$$

Analysis of data was done using R- Program version 3.5.0 and Design Expert version 10.

3.4.2 Multiple Responses Optimization Using Desirability Function

In this study, the experimenter optimized a number of responses at the same time. The problem in dealing with multiple responses is that the three might be conflicting objectives because of the difference requirement of each of the responses (Candioti, 2014). In such a case experimenter opts to involve the use of desirability function. The Desirability method is very effective in optimizing processes that have multiple answers, which should be optimized simultaneously. Under this study this approach, was adopted each i^{th} response was assigned a desirability function, d_i where the value of d_i varies between 0 and 1. The function d_i is defined differently based on the objective of the response. The objective of the responses is to maximize the fruit Weight of watermelon at maturity, Number of branches and vine length per plant. Then d_i is defined as follows

$$d_i = \begin{cases} 0 & y_i < L \\ (\frac{y_i - L}{T - L})^w & L \leq y_i \leq T \\ 1 & y_i > T \end{cases} \qquad (16)$$

Where T is the target value of the i^{th} response y_i, L is acceptable lower limit value for this response and w the weight. When $w=1$, the function is linear, $w>1$, more weight is assigned to achieving the target for the response and $w<1$ less weight is assigned the target for the response.

Once a desirable function is defined for each of the responses, an overall desirability function is defined as the weighted geometric average of the individual desirability (d_i) according to the following equation. r_1

$$D = (d_1^{r_1}.d_2^{r_2}.d_3^{r_3})^{\frac{1}{(r1+r2+r3)}} = f(y_1, y_2, y_3) \qquad (17)$$

Where r_1, r_2 and r_3 is the weight assigned to importance of each response. The greater *ri* the more important the response with respect to the other responses (Myers et al., 2009). The objective is to find the setting that returns the maximum value of D (global index) that is maximum response surface of efficiency in the feasible region (Wang and Wan, 2009).

3.4.3 Result Presentation and Conclusion

The results of the study were presented in form of tables, relevant graph as well as response surfaces and contour surface plots. The appropriate conclusions were made and recommendations stated accordingly.

CHAPTER FOUR

RESULTS AND DISCUSION

4.1 Introduction

This chapter presents the outcome of the data analysis in respect to the key objectives of the study. The overall objective of the study was to optimize the multiple responses of watermelon to organic manure using Central Composite Design and Response Surface Methodology. The study was guided by the following specific objectives; to establish the effect of organic manure on growth and yield of watermelon using Central Composite Design, to determine appropriate second-order polynomial model that best fits the data and to find an optimal settings on the control variables that produce maximum response values on watermelon crop. The data used for this research was obtained from an experiment carried out at horticultural research and teaching farm of Chuka University in the year 2016 rainy seasons.

4.2 Establishing the Effect of OM on Growth and Yield of Watermelon

The study sought to establish the effect of organic manure on increased growth and yield of watermelon and the results are presented in the sub-sections 4.21 to 4.24.

4.2.1 Full Factorial Central Composite Design Matrix and Experimental Results

This section presents the experimental and predicted data for the increased growth and production of watermelon. Table 4.1 shows all results expressed as mean ± standard deviation for four watermelon plants in each plot. To determine the effect of treatment, data was analyzed using one way analysis of variance repeated measures. P-values of less than 5% were regarded as significant. Data was analyzed using the statistical package (R-Gui and Design Expert version 10). Experimental values were analyzed to get regression model. The predicted values of fruit weight, number of branches and vine length of watermelon plant were calculated using the regression models and compared with the experimental values.

Table 4.1: Full Factorial Central Composite Design Matrix and Experimental Results

	Coded values			Fruit Weight (Tons/Ha)		Number of Branches		Vine Length (cm)	
Runs	X_1	X_2	X_3	EXPV	PREDV	EXPV	PREDV	EXPV	PREDV
1	-1.682	0	0	51.6	50.2	5	5	170.5	168.1
2	-1	1	1	54.0	56.7	6	7	176.0	180.6
3	-1	-1	1	46.0	49.2	3	4	169.2	167.2
4	-1	-1	-1	50.0	52.7	5	5	169.0	167.9
5	-1	1	-1	46.0	45.2	4	5	165.4	165.6
6	0	0	0	60.8	60.6	6	6	180.2	181.2
7	0	0	-1.682	50.0	50.0	5	5	168.6	167.1
8	0	0	0	68.0	60.6	7	6	190.6	181.2
9	0	1.682	0	58.0	50.8	6	5	178.9	177.2
10	0	0	0	56.0	60.6	6	6	174.9	181.2
11	0	0	1.682	76.0	71.2	7	7	200.9	195.3
12	0	0	0	56.0	60.6	6	6	175.8	181.2
13	0	0	0	58.0	60.6	6	6	179.6	181.2
14	0	-1.682	0	48.0	50.8	5	5	169.2	167.8
15	0	0	0	64.0	60.6	6	6	185.7	181.2
16	1	1	-1	48.0	49.0	4	4	172.9	171.6
17	1	-1	1	66.0	70.1	7	7	188.4	192.5
18	1	1	1	76.0	77.6	7	8	208.1	205.9
19	1	-1	-1	56.0	56.5	6	7	174.1	173.8
20	1.682	0	0	72.0	71.0	7	7	195.9	194.4

4.2.2 Effect Estimates of Organic Manure on Fruit Weight of Watermelon

The study sought to establish and understand the effect of main and interactive effect of organic manure on fruit weight of watermelon crop and the effect estimates are as shown in Figure 4.1.

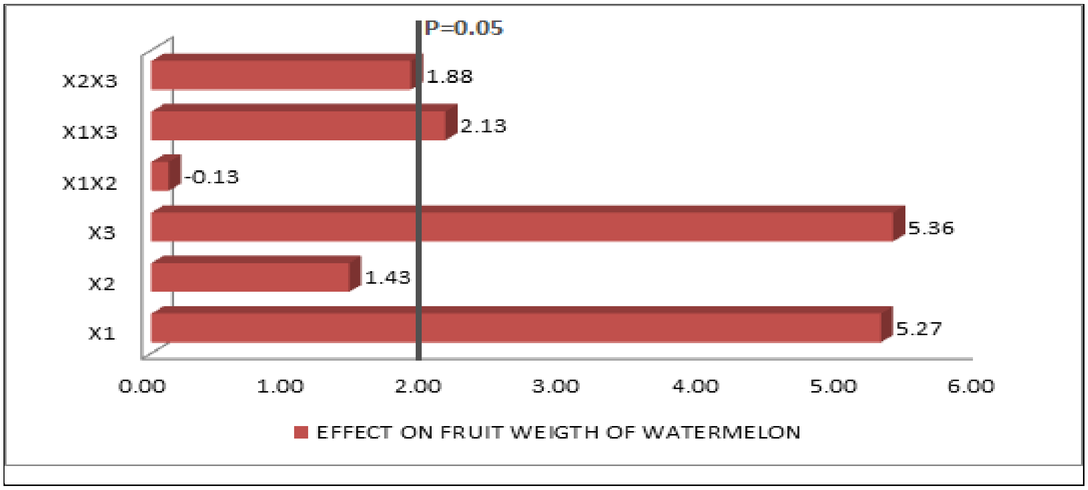

Figure 4.1: Standardized Effect of Organic Manure on Fruit Weight of Watermelon

As indicated in Figure 4.1, goat manure (X_3) and poultry manure (X_1) were the most significant variables for fruit weight of watermelon (effect of X_3=5.36 and effect of X_1=5.27, followed by their interaction poultry and goat manure (effect of X_1 X_3=2.13) , as well as cow manure (X_2) and goat manure (X_3**)** (effect of X_2 X_3=1.88). In the presence of an interactive effect, the variable cannot be analyzed separately, therefore the application of statistical method reveals the interactions (X_1 X_3 and X_2 X_3) were significant at 5% significance level. However, interaction of poultry and cow manure (X_1 X_2) had negative effect (effect of X_1 X_2=-0.13) and was insignificant at 95% confidence level. In general it was observed that main effects (where poultry, cow or goat manure were applied alone) were more influential on fruit weight of watermelon crop. Plant that received adequate amount of poultry or goat manure had higher fruit weight possibly because higher rate of manure not only improve the soil conditions for crop establishment, but also released adequate nutrient element for yield enhancement. This is in harmony with reports of Enujeke (2013) and Mangila et al. (2008) who found that 20 tonnes per hectare of poultry manure account for an average of 1300 tonnes of watermelon fruit per hectare.

4.2.3 Effect Estimates of Organic Manure on Number of Branches per Plant

The study sought to establish the significance of linear and interactive effect of independent variables on number of branches of watermelon plant and result are provided in Figure 4.2.

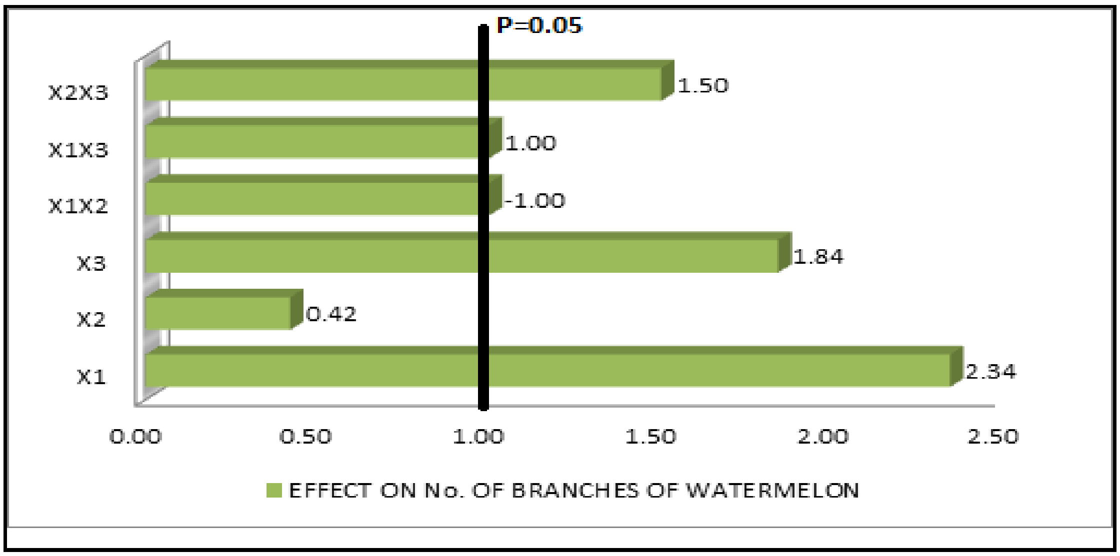

Figure 4.2: Standardized Effect of Organic Manure on No. of Branches of Watermelon

As shown in Figure 4.2, it was observed that poultry manure (X_1) significantly affected the growth of watermelon plants (effect of X_1=2.34), followed by goat manure (X_3) (effect of X_3 =1.84), as well as interaction of cow and goat manure (effect of X_2 X_3=1.50). In the presence of an interactive effect, the variable cannot be analyzed separately, therefore the application of statistical method reveals the interactions (X_1 X_3 and X_2 X_3) are significant at 5% significance Level.

In general, it was observed that main effects especially for poultry and goat manure were more influential on growth of watermelon plant (number of branches). Plants that received adequate poultry manure were superior with respect to higher number of branches of watermelon plant over their counterparts possibly because higher rates of manure supplied nutrients required for vigorous growth. This is similar to the finding of Dauda, et al. (2008) who attributed the vigorous growth of watermelon to increased supply of nutrient from higher rates of poultry manure. The findings are also similar to those of Enujeke (2003) who indicated that higher rates of poultry manure increased growth parameters of maize in Nigeria.

4.2.4 Effect Estimates of Organic Manure on Vine Length of Watermelon Plant

The study sought to establish the significance of linear and interactive effect of independent variables on vine length of watermelon plant and result are as shown in Figure 4.3.

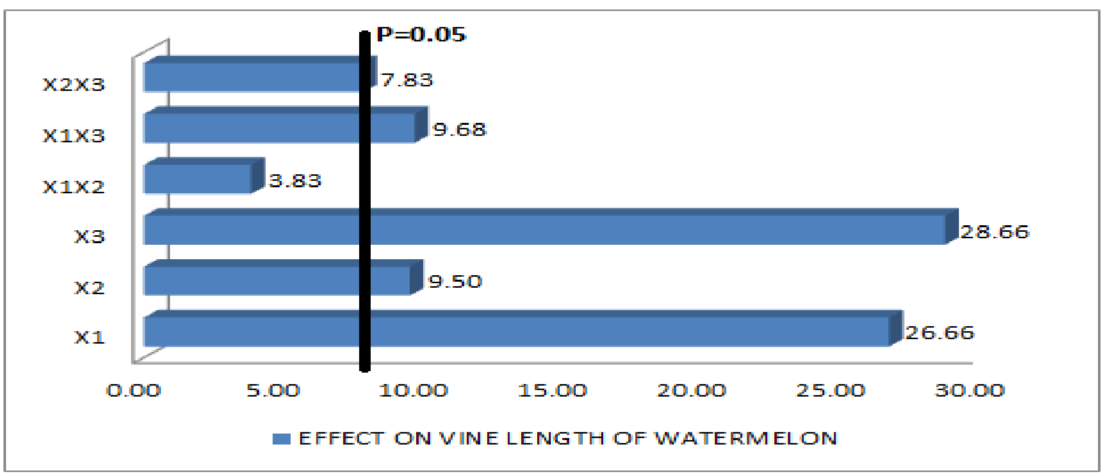

Figure 4.3: Standardized Effect of Organic Manure on Watermelon Vine Length

Figure 4.3, indicates the effect estimates of linear and quadratic terms and their significance in enhancing growth of watermelon plant. Goat manure (X_3) significantly affected growth of watermelon plant (effect of X_3=28.66, followed by poultry manure (X_1) (effect of X_1 =26.66), as well as interaction poultry and goat manure (effect of $X_1 X_3$=9.68). In the presence of an interactive effect, the variable cannot be analyzed separately, therefore the application of statistical method reveals the interactions of ($X_1 X_3$ and $X_2 X_3$) were significant at 5% significance level. Meanwhile, cow manure is deemed statistically significant at 5% significance level, perhaps if applied in large quantities. In general, it was observed that main effects especially where poultry and goat manure were applied were more influential on vine growth. Plant that received adequate amount of poultry or goat manure had higher vine length than other plants possibly because higher rate of manure improved nutrient availability which enhanced increased vine growth. This is consistent with the finding of John et al. (2004) who reported that poultry manure released essential elements associated with high photosynthetic activities which promoted growth and yield of watermelon.

4.3 Determining an appropriate Second-Order Model that best fits the Data

This section presents the relationship between organic manure (poultry, cow and goat manure) and response variables (fruit weight, number of branches and vine length of watermelon) using second-order models.

4.3.1 Model Fitting on Fruit Weight of Watermelon using Organic Manure

The current study was based on the premise that organic manure influences the fruit weight of watermelon and the researcher had set the following hypothesis.

H_o: There is no quantifiable effect of poultry, cow and goat manure on Fruit weight of watermelon.

4.3.1.1 Model Summary Statistics

The researcher sought to evaluate the component of the second order model in order to assess its suitability and the results are portrayed in Table 4.2.

Table 4.2: Model Summary Statistics

Source	Std. Dev.	R^2	Adjusted R^2	PRESS	
Linear	1.61	0.6618	0.5893	75.02	
2FI	1.33	0.819	0.7203	66.96	
Quadratic	0.94	0.9337	0.8591	48.34	Suggested
Cubic	0.94	0.9668	0.8587	266.81	Aliased

Model summary statistics focus on the model maximizing the Adjusted R-Squared and the Predicted R-Squared. R-Squared refer to a measure of proportion of the variation in the dependent variable that is explained by the independent variable for a regression model. Adjusted R-Squared is used to adjust the statistic based on the number of independent variables in the model. It compares the explanatory power of regression model that contains different independent predictors. In this case since the multiple regression models have more than one variable, adjusted R-Squared is the most preferred. The study found that quadratic model was suggested for the data fitting with an adjusted R-Squared value of 85.91%. Model explains about 85.9% of the variability in the response variable. The adjusted R-squared is often used to summarize the fit as it takes into account the number of variables in the model. In addition, quadratic model had the highest adjusted R-Squared and predicted R-Squared thus most suitable for this study.

4.3.1.2 Fitting a Second order Model for the Fruit Weight of Watermelon

The data obtained from the experiment were analyzed to develop a mathematical model. The multiple regression was obtained by employing a least squares technique to predict quadratic polynomial model for the fruit weight of watermelon and pertinent results are presented in Table 4.3. Organic manure (especially poultry manure) is most important parameter affecting growth and production of watermelon (Enujeke and Canakci, 2010). In order to study the interaction factors (combined effect of poultry, cow and goat manure) experiment were conducted varying physical parameter using CCD. A multiple regression data analysis was carried out with "R-Gui" statistical package. The study found that poultry and goat manure had positive significant effect on fruit weight of watermelon at P-value=0.00052<0.05 and 0.00046<0.05 respectively). In addition, it was observed that goat manure was slightly superior in terms of its effect on fruit weight of watermelon. In the findings, one unit change of goat or poultry manure influenced the fruit weight by a factor of 1.57 and 1.54 respectively. However, cow manure had insignificant effect on the fruit weight of watermelon at 5% level (P-value=0.204>0.05).

Table 4.3: Regression Coefficients Estimates on Fruit Weight

Variable	Estimate	Std. Error	t-Value	P-value
Constant	15.14838	0. 46321	32.703	1.69e-11 ***
X_1	1.54326	0.30731	5.022	0.00052 ***
X_2	0.41770	0.30731	1.359	0.20395
X_3	1.56923	0.30731	5.106	0.00046 ***
X_1^2	-0.09017	0.29912	-0.301	0.76924
X_2^2	-0.86780	0.29912	-2.901	0.01580 *
X_3^2	0.01587	0.29912	0.053	0.95874
X_1X_2	-0.06250	0.40154	-0.156	0.87941
X_1X_3	1.06250	0.40154	2.646	0.02448 *
X_2X_3	0.93750	0.40154	2.335	0.04171 *

The study found that combined poultry and goat manure had a significant effect on the fruit weight of watermelon at P-value less than 0.05. Poultry manure is the richest known animal manure (Enujeke et al., 2013 and Mangila et al., 2007), and it is essential for establishing and maintaining the optimum soil physical condition for plant growth and production. In this study, combining cow and goat manure had a significant effect on watermelon production. The results indicate that a one unit change in combined poultry and goat manure, led to change in watermelon fruit weight by a factor of 1.0625 whereas combining cow and goat manure changed the same by a factor of 0.9375. This implies that combined poultry and cow manure would be more superior compared to combined cow and goat manure in influencing the fruit weight of watermelon. The adjusted model obtained for watermelon production as a function of the significant variables is indicated in Equation (19);

$$Y_1 = 15.148 + 1.543X_1 + 0.418X_2 + 1.569X_3 - 0.868X_2^2 + 1.063X_1X_3 + 0.938X_2X_3 \tag{19}$$

Where Y_1 represents the fruit weight (yields) of watermelon

X_1, is the poultry manure

X_2, is the cow manure

X_3 is the goat manure

This is a coded equation, useful for identifying the relative impact of the factors by comparing the factor coefficients.

4.3.1.3 Analysis of Variance

Analysis of variance (ANOVA) was used to check the adequacy of the model for the response (fruit weight of watermelon) in the experimentation at 95% confidence level and the results are as shown in Table 4.4.

Table 4.4: ANOVA for Effect of Organic Manure on Fruit Weight

Source	DF	SS	MSS	F	F-critical	Pr(>F)
Model	9	95.647	10.627	8.239	3.0204	0.00141
X_1	1	32.529	32.529	25.2182	4.9646	0.00052
X_2	1	2.383	2.383	1.8474	4.9646	0.20395
X_3	1	33.633	33.633	26.0743	4.9646	0.00046
X_1^2	1	0.003	0.003	0.0020	4.9646	0.96551
X_2^2	1	11.005	11.005	8.5317	4.9646	0.01528
X_3^2	1	0.004	0.004	0.0028	4.9646	0.95874
X_1X_2	1	0.031	0.031	0.0242	4.9646	0.87941
X_1X_3	1	9.031	9.031	7.0015	4.9646	0.02448
X_2X_3	1	7.031	7.031	5.451	4.9646	0.04171
Residuals	10	12.899	1.290			
Lack of fit	7	7.910	1.13	0.679	8.867	0.5623
Pure Error	3	4.989	1.663			

This study indicates that the model can be considered statistically significant according to the F-test with 95% confidence, as the F-value of 8.24 is higher than $F_{(9,10)}$=3.0204. This shows that the model is highly statistically significant at 95% confidence level. The probability P-value is low 0.001408, indicating the significance of the model. Therefore, the hypothesis that there is no quantifiable effect of poultry, cow and goat manure on the fruit weight of watermelon is not supported by the current study. 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. From Table 4.4, it is observed that the model satisfies the adequacy conditions in non-linear form.

4.3.1.4 Test for Normality

A linearity test was conducted to test for linearity among the residues (normal percentage probability and studentized residual plot) as shown in the Figure 4.4

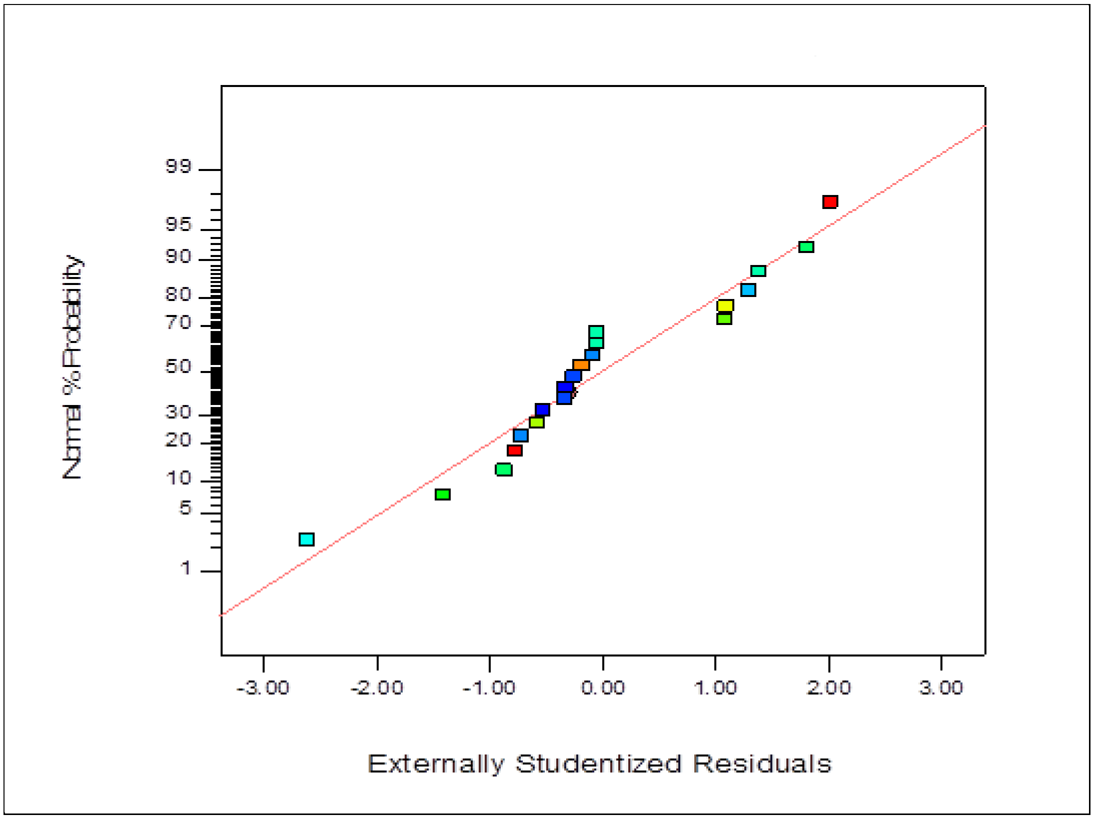

Figure 4.4: Normal Plot of Residuals

Normal probability plot is a graphical technique for assessing whether or not a data set is approximately normally distributed. Departures from this straight line indicate departure from normality. In this case the points are fairly normally distributed as indicated in Figure 4.4.

4.3.1.5 Validation of the Model

The study sought to assess the validity of the model and for easy understanding and clarity, graphical representation of predicted values using the model together with the corresponding measured values of all the responses has been made in Figures 4.5.

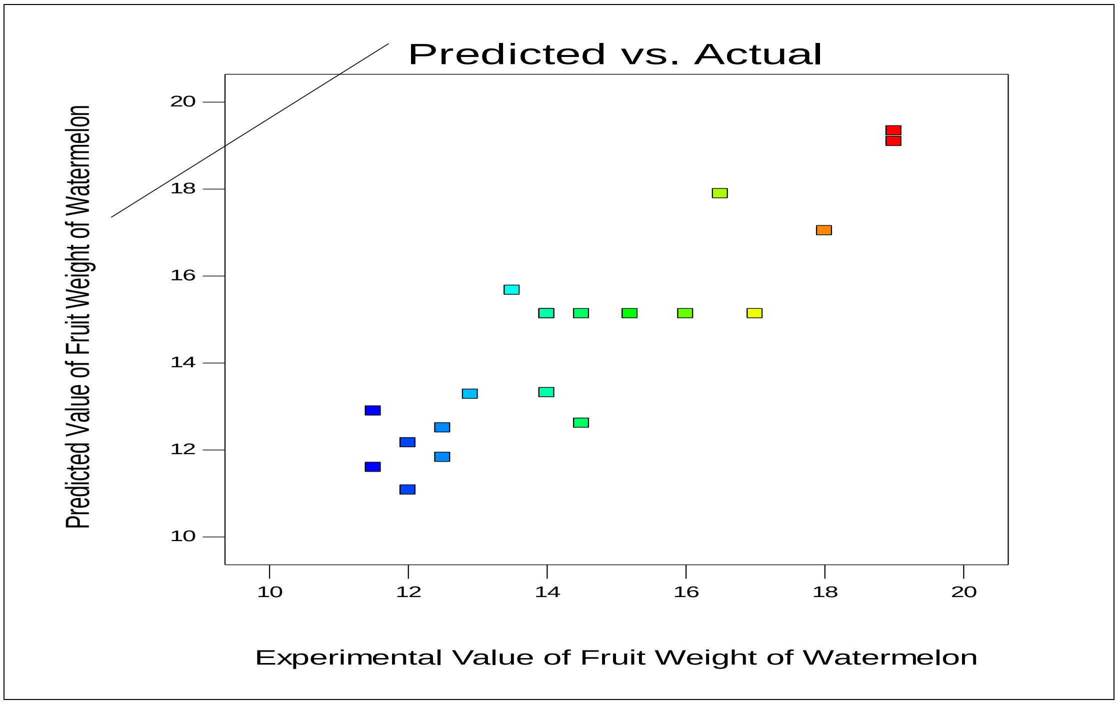

Figure 4.5: Predicted Value versus Experimental Value of Watermelon Fruit Weight

Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the line of the best fit. In the current study, the fitted and observed values are not equal but are close to the line of the best fit. This shows that there was fairly strong correlation between the fitted and observed values as demonstrated in Figure 4.5.

4.3.2 Model Fitting on Number of Branches using Organic Manure

The current study was based on the premise that organic manure influences the number of branches of watermelon plant and the following hypothesis was set.

H_o: There is no quantifiable effect of poultry, cow and goat manure on number of branches of watermelon.

4.3.2.1 Model Summary Statistics

The study sought to assess the suitability of the model fitted and the results are displayed in Table 4.5

Table 4.5: Model Summary Statistics

Source	Std. Dev.	R^2	Adjusted R^2	PRESS	
Linear	0.931222	0.473512	0.360694	24.87216	
2FI	0.559217	0.850821	0.769451	12.26882	
Quadratic	0.343629	0.959034	0.912947	5.419584	Suggested
Cubic	0.387034	0.974016	0.889566	22.9988	Aliased

Model summary statistics focus on the model maximizing the adjusted R-Squared and the predicted R-Squared. Adjusted R-Squared is used to adjust the statistic based on the number of independent variables in the model. It compares the explanatory power of regression model that contain different independent predictors. In this case, since the multiple regression models have more than one variable, adjusted R-Squared was preferred. The study found that quadratic model was suggested for the data fitting with an Adjusted R-Squared value of 0.913. Model explains about 91.3% of the variability in the response variable. The adjusted R-squared is often used to summarize the fit as it takes into account the number of variables in the model. In addition, quadratic model had the highest adjusted R-Squared and predicted R-Squared thus most suitable for this study.

4.3.2.2 Fitting a Second order Model for the Number of Branches of Watermelon Plant

The data obtained from the experiment were analyzed to develop a mathematical model. The multiple regression was obtained by employing a least squares technique to predict quadratic polynomial model for the number of branches of watermelon plant and pertinent results are presented in Table 4.6.

Table 4.6: Regression Coefficients Estimates on Number of Branches

Variable	Estimate	Std. Error	t-Value	P-value
Constant	6.1848	0.2139	28.921	5.69e-11 ***
X_1	0.6856	0.1419	4.832	0.000689 ***
X_2	0.1231	0.1419	0.868	0.405743
X_3	0.5392	0.1419	3.800	0.003485 **
X_1^2	-0.1777	0.1381	-1.287	0.227124
X_2^2	-0.3544	0.1381	-2.567	0.028050 *
X_3^2	-0.1777	0.1381	-1.287	0.227124
X_1X_2	-0.5000	0.1854	-2.697	0.022423 *
X_1X_3	0.5000	0.1854	2.697	0.022423 *
X_2X_3	0.7500	0.1854	4.046	0.002340 **

It was observed that poultry and goat manure were statistically significant at 5% significance level with a P-value of $0.0007<0.05$ and $0.0035<0.05$ respectively (Table 4.6). The regression coefficient estimates show that for one unit change in poultry manure and goat manure, number of branches of watermelon would increase by a factor of 0.6856 and 0.5392 respectively. This implies that poultry manure is slightly more effective than goat manure on growth (number) of branches of watermelon plant. In addition, it was found that combined application of poultry and goat manure had a regression coefficient value of 0.5 and a P-value of $0.022423<0.05$, hence statistically significant at 5% significance level. This implies that for one unit change in combined poultry and goat manure (X_1X_3), growth of branches (in number) of watermelon plant would increase by a factor of 0.5.

Similarly, combined application of poultry and goat manure had a regression coefficient value of 0.75 and a P-value of $0.00234<0.05$, hence statistically significant at 5% significance level. This implies that for one unit change in combined application of cow and goat manure (X_2X_3), growth of branches (in number) of watermelon plant would increase by a factor of 0.75. This shows that combined cow and goat manure is much more effective on growth (number) of branches of watermelon plant than combined poultry and goat manure. However, combined poultry and cow manure was observed to be statistically significant (P-value=$0.022423<0.05$) with regression coefficient value of -0.50. This suggests that for a one unit increase of combined poultry and cow manure, growth of watermelon branches would decrease by a factor of 0.50. This was because cow manure was found to be statistically insignificant in enhancing growth of watermelon plant. Moreover, it was observed that quadratic terms were not statistically significant except for goat manure where the parameter estimate was -0.3544 with a P-value of $0.028<0.05$. The results indicate that for one unit increase of goat manure (quadratic term), growth of watermelon would be negatively affected by a factor of

0.3544. The predicted model for number of branches of watermelon plant in terms of coded factors is as shown in Equation (20);

$$Y_2 = 6.1848 + 0.6856X_1 + 0.1231X_2 + 0.5392X_3 - 0.3544{X_2}^2 - 0.500X_1X_2 + 0.500X_1X_3 + 0.75X_2X_3 \quad (20)$$

Where Y_2 represents the number of branches of watermelon plant

X_1, is the poultry manure

X_2, is the cow manure

X_3 is the goat manure

4.3.2.3 Analysis of Variance

Analysis of variance was used to check the adequacy of the model for the response (number of branches) in the experimentation. The regression model was tested using Analysis of variance for residuals minimization (Table 4.7).

Table 4.7: ANOVA for Effect of Organic Manure on Number of Branches

Source	DF	SS	MSS	F-Value	F-critical	Pr(>F)
Model	9	21.4480	2.3831	8.6690	3.0204	0.00114
X_1	1	6.4199	6.4199	23.3513	4.9646	0.00052
X_2	1	0.2071	0.2071	0.7534	4.9646	0.20395
X_3	1	3.9704	3.9704	14.4416	4.9646	0.00046
X_1^2	1	0.2466	0.2466	0.8968	4.9646	0.96551
X_2^2	1	1.6515	1.6515	6.0069	4.9646	0.01528
X_3^2	1	0.4553	0.4553	1.6561	4.9646	0.95874
X_1X_2	1	2.0000	2.0000	7.2747	4.9646	0.87941
X_1X_3	1	2.0000	2.0000	7.2747	4.9646	0.02448
X_2X_3	1	4.5000	4.5000	16.3680	4.9646	0.04171
Residuals	10	2.7493	0.2749			
Lack of fit	7	1.196	0.171	0.332	8.8867	0.6865
Pure Error	3	1.547	0.516			

ANOVA results revealed that the predicted response model was statistically significant since F-Value is=8.669> 3.02038 (critical value) and Pr(>F)=0.001143<0.05. This implies the hypothesis that there is no quantifiable effect of poultry, cow and goat manure on the number of branches of watermelon plant is not supported by the current study. Therefore, the suggested regression model is statistically significant in the prediction of number of branches of watermelon as a measure of growth of watermelon plant. The study found that lack of fit was insignificant in the model and so the study concludes that the reduced model is adequate. In general, the overall model is adequate for prediction purpose in this study.

4.3.2.4 Test for Normality

The study data were tested for the major assumptions of parametric data analysis as shown in Figure 4.6

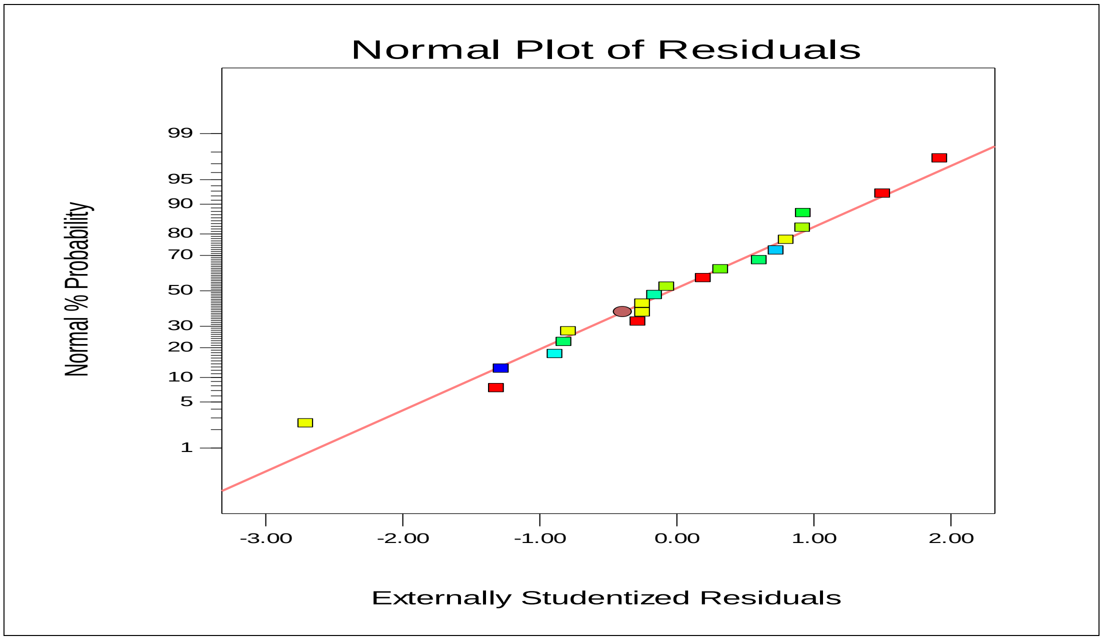

Figure 4.6: Normal Plot of Residuals

Normal probability plot is a graphical technique for assessing whether or not a data set is approximately normally distributed. Departures from this straight line indicate departure from normality. In this case the points are fairly normally distributed (Figure 4.6). This implies that the residuals depict a normal trend.

4.3.2.5 Validation of the Model

The graphical representation of predicted values using the Model together with the corresponding measured values of the response is as shown in Figure 4.7

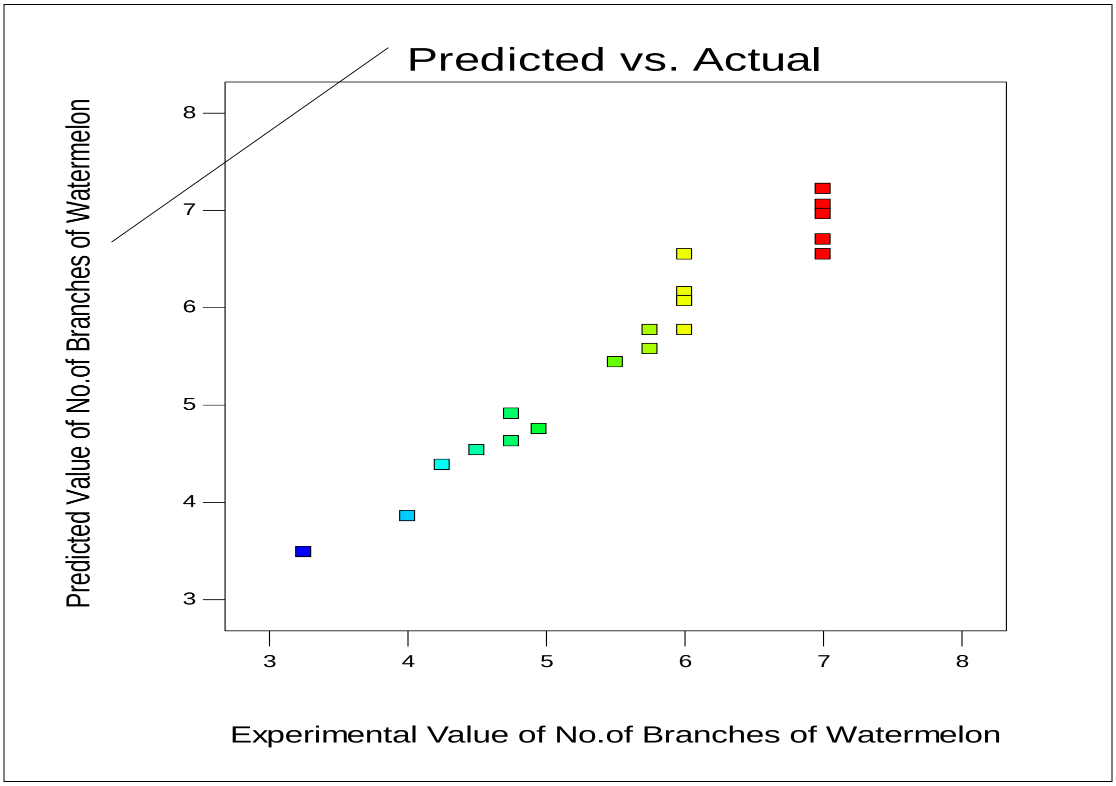

Figure 4.7: Predicted Value versus Experimental Value of Number of Watermelon Branches

In the Figure 4.7, the line of the best fit was plotted taking the predicted value same as the measured value and was considered as a reference line. Measured values of each response are plotted and their closeness to the line of the best fit depicts the accuracy (fitness) of the model. The model developed for the response is considered accurate, where all the measured-values are closer with the line of the best fit. The comparison of both values was fairly good correspondence between them, indicating that empirical model derived from RSM can be used to describe the relationship between the factors and response in growth of watermelon plant in the study area.

4.3.3 Model Fitting on Vine Length of Watermelon Plant using Organic Manure

The study sought to assess the effect of organic manure on the vine length of watermelon plant and the following hypothesis was set.

H_o: There is no quantifiable effect of poultry, cow and goat manure on the vine length of watermelon per plant.

4.3.3.1 Model Summary Statistics

The study sought to assess the suitability of the model fitted and the results are displayed in Table 4.8

Table 4.8: Model Summary Statistics

Source	Std. Dev.	R-Squared	Adjusted R-Squared	PRESS	
Linear	6.504539	0.772725	0.724023	1284.263	
2FI	5.50261	0.872203	0.802496	969.8756	
<u>Quadratic</u>	<u>3.755949</u>	<u>0.956697</u>	<u>0.907981</u>	<u>545.2224</u>	<u>Suggested</u>
Cubic	4.398092	0.970312	0.873827	1569.357	Aliased

Model summary statistics focus on the model maximizing the adjusted R-Squared and the predicted R-Squared. Adjusted R-Squared is used to adjust the statistic based on the number of independent variables in the model. It compares the explanatory power of regression model that contains different independent predictors. In this case, since the multiple regression models have more than one variable, Adjusted R-Squared is the most preferred. The study found that quadratic model was suggested for the data fitting with an adjusted R-Squared value of 0.91. Model explains about 91% of the variability in the response variable. The adjusted R-squared is often used to summarize the fit as it takes into account the number of variables in the model. Similarly, the model with the lowest standard deviation is always regarded as the most suitable for consideration in analysis. In this study, quadratic model had the highest adjusted R-Squared and predicted R-

Squared thus considered fit for prediction of the vine length of watermelon plant using organic manure.

4.3.3.2 Fitting a Second order Model for the Vine Length of Watermelon Plant

The multiple regression was obtained by employing a least squares technique to predict quadratic polynomial model for the vine length of watermelon plant and pertinent results are presented in Table 4.9. The effect of the variable as linear, quadratic or interaction coefficient on the response was tested for significance. The study found that goat and poultry manure were statistically significant at 5% significance level with a P-value of $0.00008<0.05$ and $0.00014<0.05$ respectively. The regression coefficient estimates show that for one unit change in goat manure and poultry manure, vine length of watermelon would increase by a factor of 8.3926 and 7.8065 respectively. This implies that goat manure is slightly more effective than poultry manure on growth of watermelon plant. In addition, it was found that combined application of poultry and goat manure had a regression coefficient value of 4.8375 and a P-value of $0.018<0.05$, hence statistically significant at 5% significance level. This implies that for one unit change in combined poultry and goat manure (X_1X_3), growth of watermelon plant (vine length) would increase by a factor of 4.84.

Table 4.9: Regression Coefficients Estimates on Vine Length

Variable	Estimate	Std. Error	t-Value	P-value
Constant	181.2218	1.9721	91.893	5.70e-16 ***
X_1	7.8065	1.3084	5.967	0.000138 ***
X_2	2.7833	1.3084	2.127	0.059286
X_3	8.3926	1.3084	6.415	7.69e-05 ***
X_1^2	0.1502	1.2735	0.118	0.908443
X_2^2	-3.0840	1.2735	-2.422	0.035956 *
X_3^2	0.6981	1.2735	0.548	0.595603
X_1X_2	1.9125	1.7095	1.119	0.289412
X_1X_3	4.8375	1.7095	2.830	0.017861 *
X_2X_3	3.9125	1.7095	2.289	0.045119 *

Similarly, combined application of cow and goat manure had a regression coefficient value of 3.9125 and a P-value of 0.045119 <0.05, hence statistically significant at 5% significance level. This implies that for one unit change in combined cow and goat manure (X_2X_3), growth of watermelon plant would increase by a factor of 3.9125. This shows that combination of poultry and goat manure is much more effective on growth of watermelon plant than combination cow and goat manure. However, combined poultry and cow manure was found to be statistically insignificant (P-value=0.289412>0.05) with regression coefficient value of 1.9125. This could be attributed to the fact that cow manure was found to be statistically insignificant in enhancing growth of watermelon plant.

Moreover, it was noted that quadratic terms were not statistically significant except goat manure where the parameter estimate was -3.0840 with a P-value of 0.035956 <0.05. The results indicate that for one unit increase of quadratic term of goat manure, growth of watermelon would be negatively affected by a factor of 3.0840. The adjusted model obtained for watermelon growth (vine length) as a function of the significant variables is given in Equation (21).

$$Y_3 = 181.2218 + 7.8065X_1 + 2.7833X_2 + 8.3926X_3 - 3.084X_2^2 + 4.8375X_1X_3 + 3.9125X_2X_3 \quad (21)$$

Where Y_3 represents the vine length of watermelon plant

X_1, is the poultry manure

X_2, is the cow manure

X_3 is the goat manure

4.3.3.3 Analysis of Variance

ANOVA was used to check the adequacy of the model for the response (Vine length) in the experimentation as shown in Table 4.10. This study found that the model can be considered statistically significant according to the F-test with 95% of confidence, as the F-value of 11.37 is higher than F (9,10)=3.0204. The probability P-value is low at 0.00036, indicating the significance of the model. Therefore, the hypothesis that there is no quantifiable effect of poultry, cow and goat manure on the vine length of watermelon plant is not supported by the current study. The study found that lack of fit was insignificant in the model and so the study concludes that the reduced model is adequate. In general, the overall model is adequate for prediction purpose in this study.

Table 4.10: ANOVA for Effect of Organic Manure on Watermelon Vine Length

Source	**DF**	**SS**	**MSS**	**F-Value**	**F-critical**	**Pr(>F)**
Model	9	2392.47	265.83	11.37	3.0204	0.00036
X_1	1	832.35	832.35	35.60	4.9646	0.00014
X_2	1	105.81	105.81	4.53	4.9646	0.05929
X_3	1	962.04	962.04	41.15	4.9646	0.00008
X_1^2	1	1.97	1.97	0.08	4.9646	0.77776
X_2^2	1	144.79	144.79	6.19	4.9646	0.03207
X_3^2	1	7.03	7.03	0.30	4.9646	0.59560
X_1X_2	1	29.26	29.26	1.25	4.9646	0.28941
X_1X_3	1	187.21	187.21	8.01	4.9646	0.01786
X_2X_3	1	122.46	122.46	5.24	4.9646	0.04512
Residuals	10	233.80	23.38			
Lack of fit	7	82.387	11.770	0.233	8.8867	0.7730
Pure Error	3	151.413	50.471			

4.3.3.4 Test for Normality

The study data were tested for the major assumptions of parametric data analysis as shown in Figure 4.8. Normal probability plot is a graphical technique for assessing whether or not a data set is approximately normally distributed. Departures from this straight line indicate departure from normality. In this case the points are fairly normally distributed.

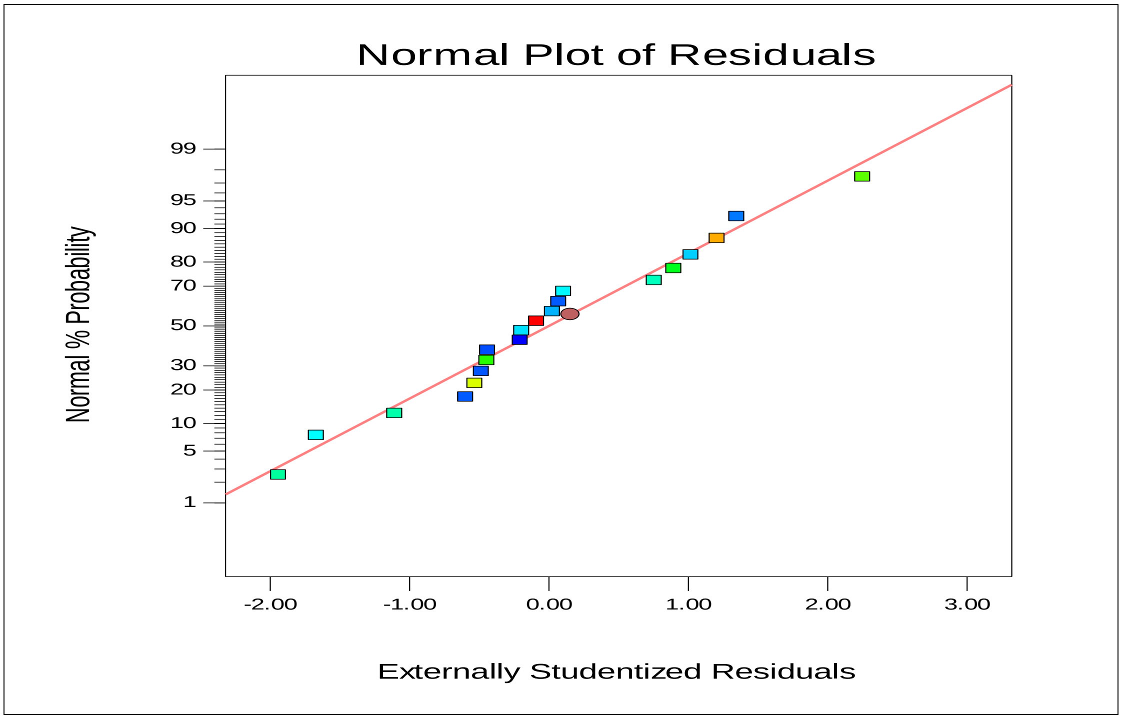

Figure 4.8: Normal Plot of Residuals

4.3.3.5 Validation of the Model

The graphical representation of predicted values using the Model together with the corresponding measured values of the response is as shown in Figure 4.9. The line of the best fit is plotted taking the predicted value on y-axis and experimental value on x-axis and is considered as a reference line. Experimental values of each response are plotted and their closeness to the line of the best fit depicts the accuracy (fitness) of the model. The model developed for the response is considered accurate, where all the measured-values are aligning or closer with the line of the best fit. In this study, the comparison of both values was fairly good correspondence between them, indicating that empirical model derived from RSM can be used to describe the relationship between the factors and response in the growth of watermelon plant (vine length) in the study area.

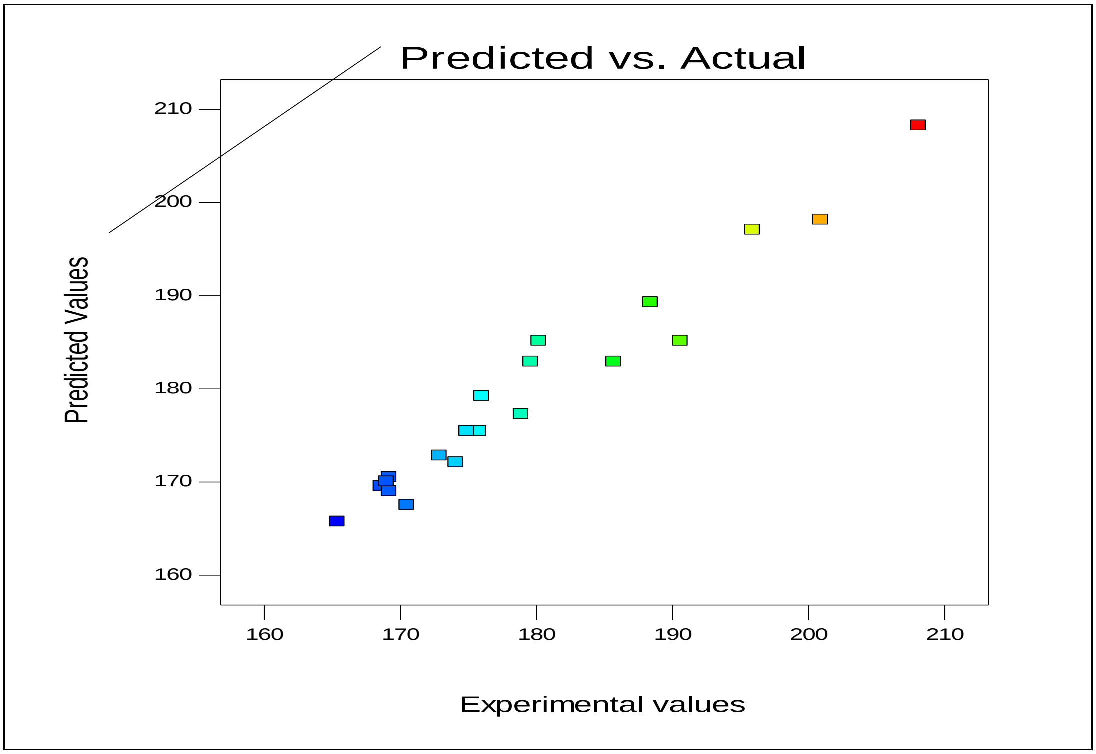

Figure 4.9: Predicted Value versus Experimental Value of Vine Length of Watermelon

4.4 Finding Optimal Settings on the Control Variables that produce Maximum Response Values

One of the main objectives of RSM is the determination of the optimum settings of the control variables that result in a maximum (or a minimum) response over a certain region of interest. This requires having a 'good' fitting model that provides an adequate representation of the mean response because such a model is to be utilized to determine the value of the optimum.

4.4.1 Determining Optimal Conditions for Maximum Watermelon Fruit Weight

The aim of the study was to find the optimal set of experimental parameters that produces a maximum value of response (fruit weight of watermelon). The best solution satisfying the above criteria was obtained using “Design Expert” software version 10 as portrayed in Table 4.11.

Table 4.11: Optimal Conditions for Maximum Fruit Weight

Variables	**Description**	**Optimal Value**	
		Coded Value	**Actual Value**
X_1	Poultry Manure	1.425	17.125tons/Ha
X_2	Cow Manure	0.654	13.27tons/Ha
X_3	Goat Manure	1.615	18.075tons/Ha
Y_1	Fruit Weight	23.287	93.148tons/Ha

The optimum values of selected variables were obtained by solving the regression model and also analyzing the response surface contour plots. It was found that for maximum (optimal) production of water melon fruit weight,17.125 tons/Ha of poultry manure, 13.27 tons/Ha of cow manure and 18.08 tons/Ha of goat manure are required to produce 93.148 ton/Ha of fruit weight of watermelon in study area. This translates to 37.26 tons per acre piece of land of watermelon fruit weight for a period of 75 -85 days after sowing. This study indicates that, a peasant farmer can generate about 745,184 Kenya shillings within a period of 85 day in one acre piece of land. The price of watermelon ranges from 20 to 40 Kenya shillings per kilogram of watermelon

4.4.1.1 Response Surface and Contour Plots

Contour plots play a very important role in the study of the response surface. By generating contour plots using R-software for response analysis, the experimenter can usually characterize the shape of the surface and locate the optimum with reasonable precision. The graphical visualization is very helpful in understanding the second-order response surface. Figures 4.10, 4.11 and 4.12 display plots of 3 dimension (3D) for different combination of variables (poultry, cow and goat manure) which exhibit the trend of variation of response (fruit weight) within the selected range of input variables and also influence of each variable over the other variable.

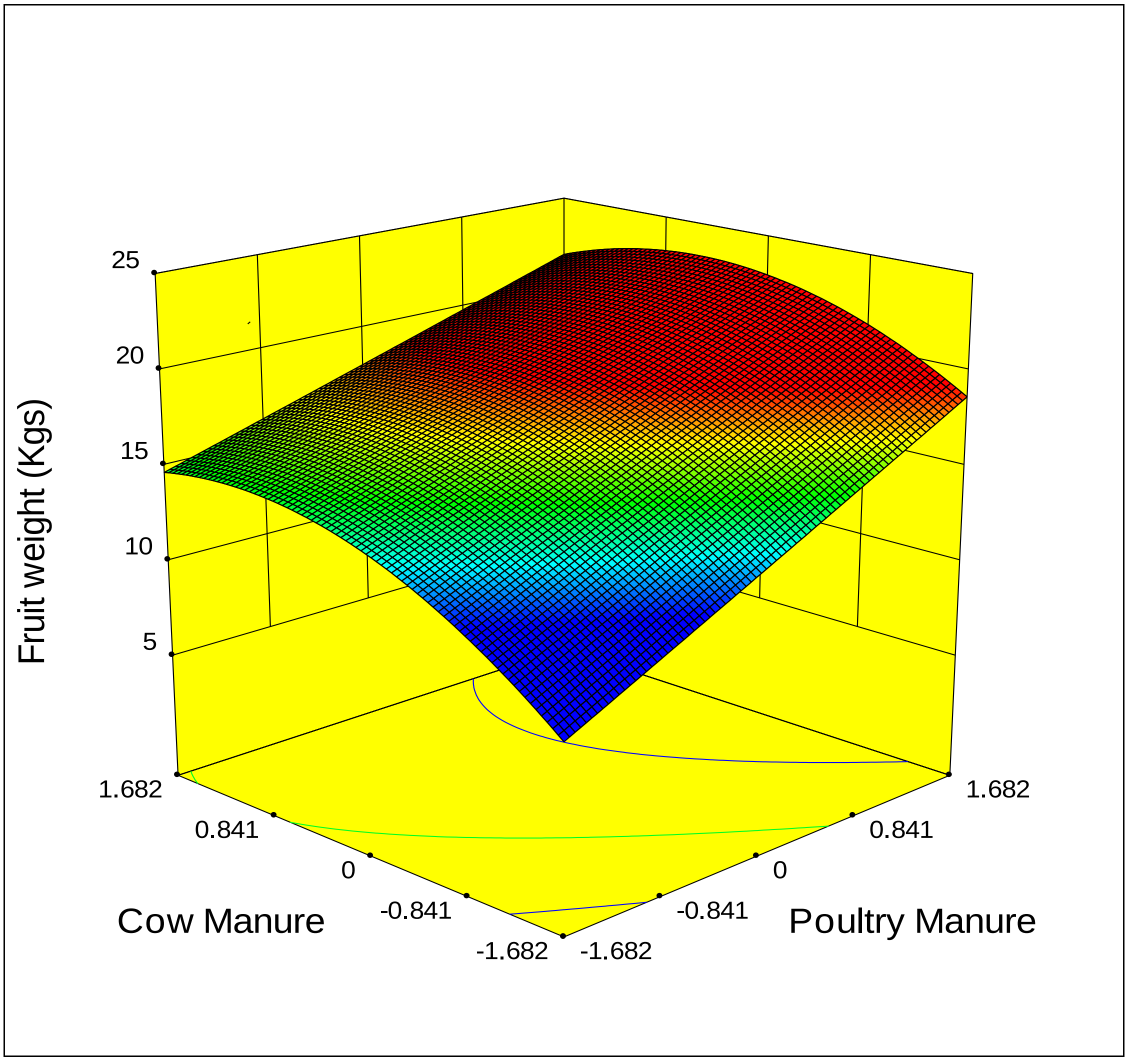

Figure 4.10: Watermelon Fruit Weight as a Function of Poultry and Cow Manure at fixed Goat Manure of 18.075 ton/ha

In Figure 4.10 the fruit weight of watermelon is shown as a function of poultry manure and cow manure. It was found that poultry (X_1) and cow manure (X_2) had positive effect on watermelon production. This suggests that increasing X_1X_2 from low to high will increase the fruit weight of watermelon up to a certain level. The response surface corresponding to the second order model indicates that moderately low cow manure and high poultry manure increase yields of watermelon. This is because poultry manure has been reported to be rich in nutrient concentration especially nitrogen which enhance growth and production of watermelon (Enujeke, 2010).

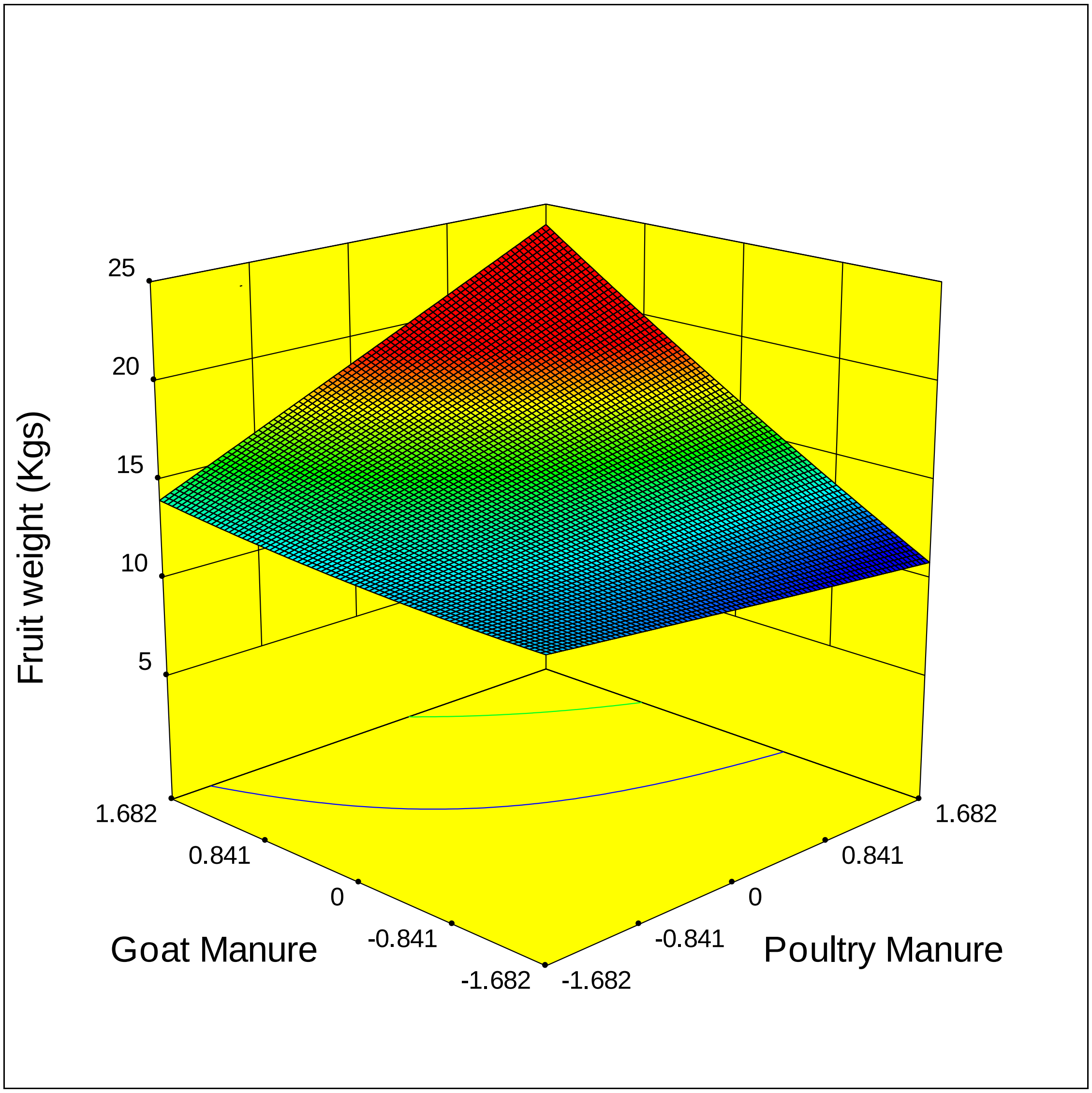

Figure 4.11: Watermelon Fruit Weight as a Function of Poultry and Goat Manure at fixed Cow Manure of 13.27 ton/ha

Figure 4.11 shows fruit weight of watermelon as a function of poultry manure and goat manure. It was noted that lowering the amount of goat manure and high amount of poultry manure levels can attain maximum fruit weight. In this study, poultry manure clearly influenced the production of watermelon yield.

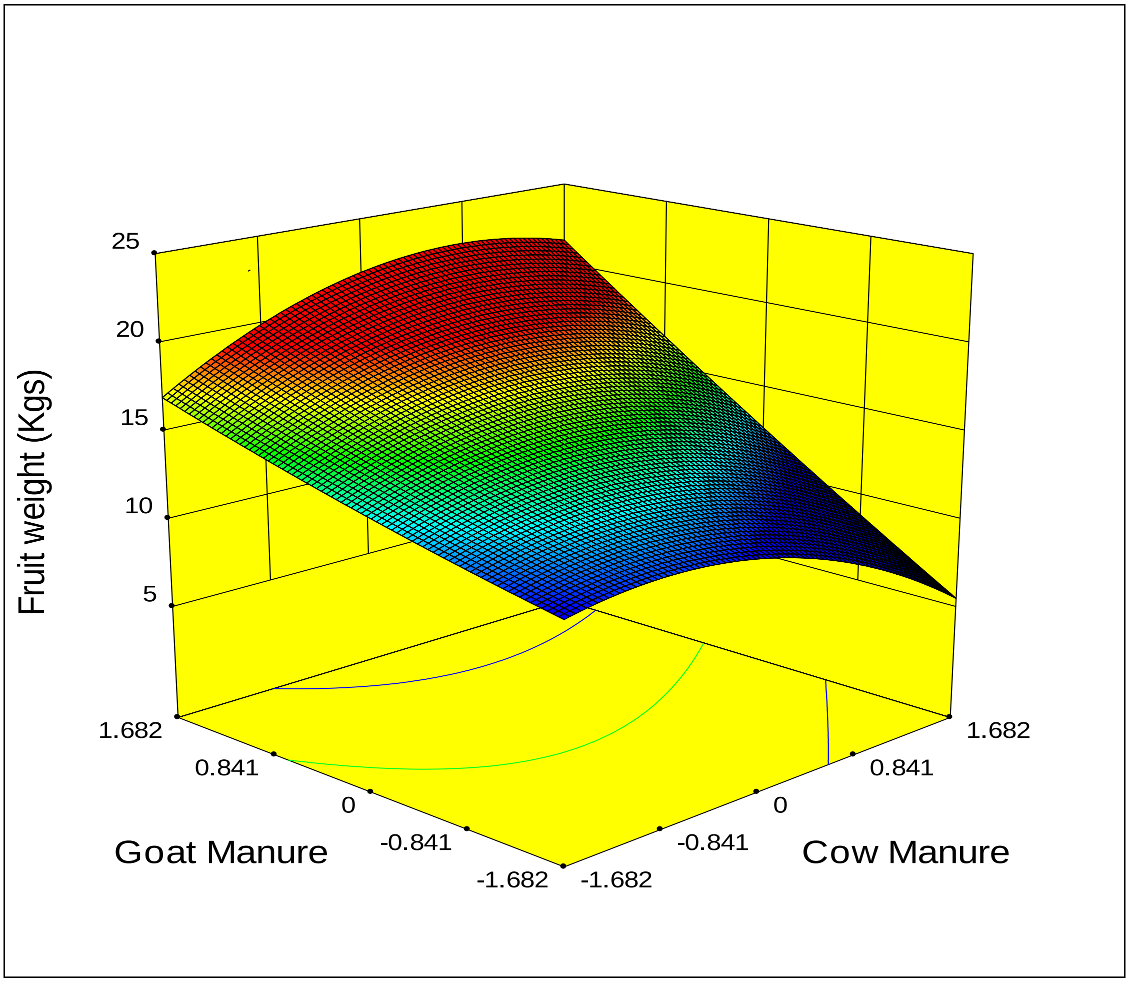

Figure 4.12: Watermelon Fruit Weight as a Function of Cow and Goat Manure at fixed Poultry Manure of 17.13 ton/ha

Figure 4.12 denotes the surface plot of the fruit weight (yields) as a function of cow and goat manure at constant/fixed poultry manure. The results indicated show that cow and goat manure have direct effect on the fruit weight (yields) up to a certain level and then yield decreases with increase of cow manure. It was observed that watermelon production is favoured when fruit weight is maximized (apply little amount of cow manure, high poultry manure and high goat manure levels)

4.4.2 Determining Optimal Conditions for Maximum Number of Branches

The aim of the study was to find the optimal settings on the control variable that produce maximum value of response (number of branches of watermelon plant). The best solution satisfying the above criteria was obtained using "Design Expert" software version 10 as shown in Table 4.12

Table 4.12: Optimum Conditions for Maximum Number of Branches

Variables	Description	Optimum Value	
		Coded Value	Actual Value
X_1	Poultry Manure	0.935	14.675 tons/Ha
X_2	Cow Manure	0.700	13.5 tons/Ha
X_3	Goat Manure	1.553	17.765tons/Ha
Y_2	No. of Branches/plant	**8.407**	**8 Branches/Plant**

In this study, the number of branches of watermelon plant was predicted to be 8.407≈8.This suggests that to achieve maximum value of response (8 branches of watermelon plant), about 14.7 tons/Ha, 13.5 tons/Ha and 17.8 tons/Ha of poultry, cow and goat manure respectively are required. This is optimal condition for maximum number of branches of watermelon plant.

4.4.2.1 Response Surface and Contour Plots

Using design Expert software version 10, three dimensional plots were generated for the RSM evolved. Such plot explicitly gives an ideal of the dominating control variable over others and the order of dominance. The results are as provided in Figure 4.13, 4.14 and 4.15.

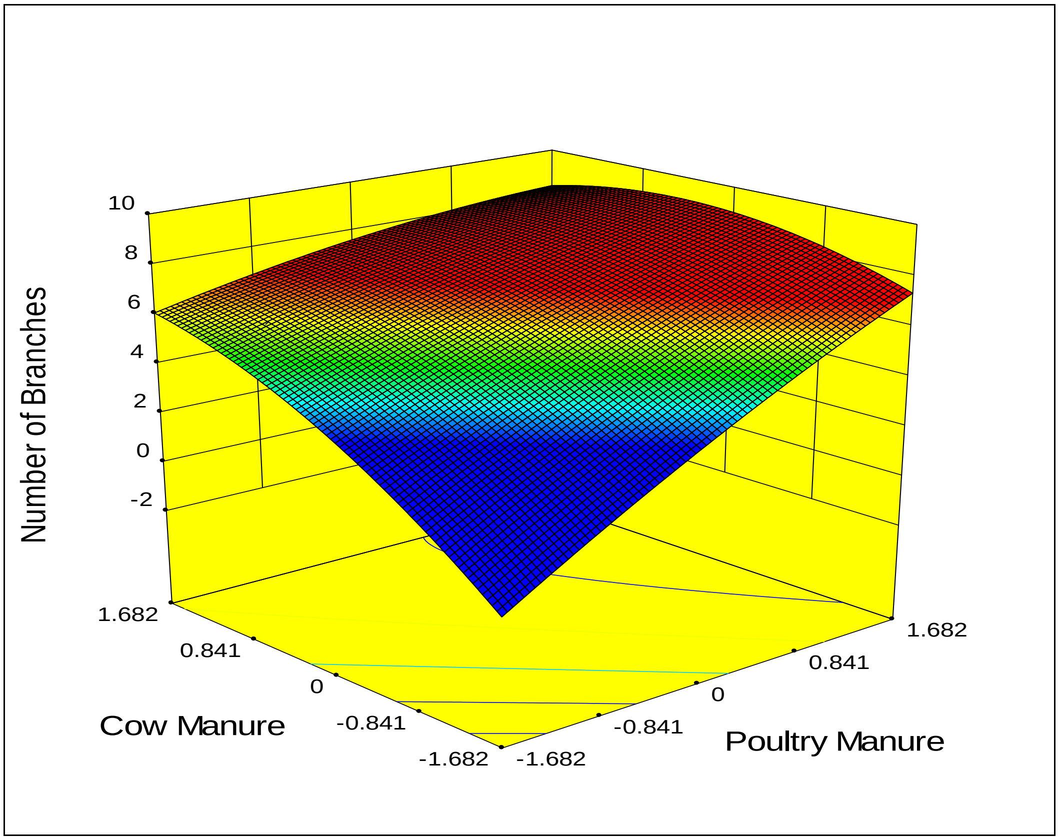

Figure 4.13: Number of Branches as a Function of Poultry and Cow Manure at fixed Goat Manure of 17.77 ton/ha

Figure 4.13 shows growth of watermelon in terms of number of branches as being a function of poultry and cow manure. It was observed that, increasing cow manure and poultry manure resulted to high number of branches of watermelon plant. Poultry manure clearly influenced the growth of watermelon plant. The response surface corresponding to the second order model indicates that moderately high cow manure and high poultry manure increase number of branches of watermelon. As indicated earlier, poultry manure has been reported to be rich of nutrient especially nitrogen which enhances growth of watermelon plant (Enujeke, 2010).

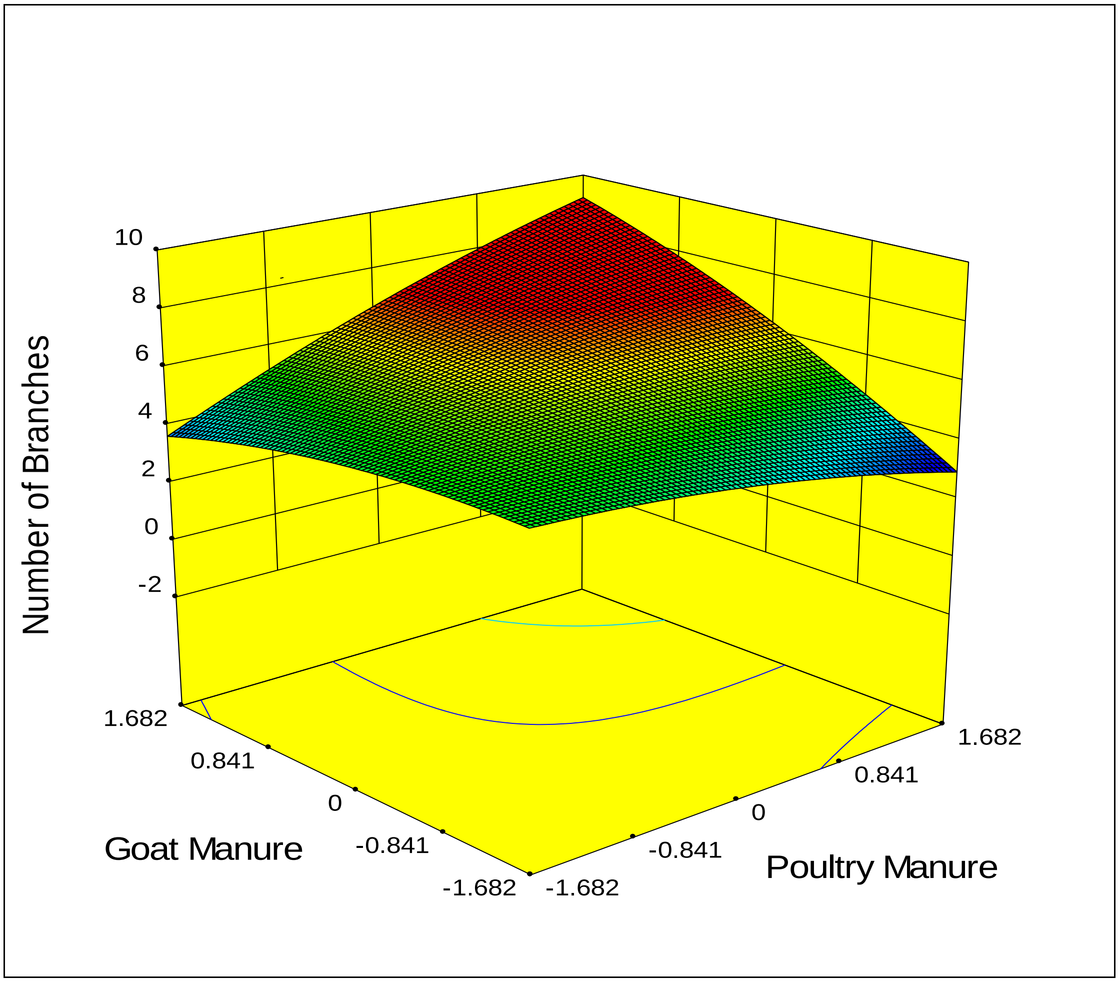

Figure 4.14: Number of Branches as a Function of Poultry and Goat Manure at fixed Cow Manure of 13.5 ton/ha

Figure 4.14 shows growth of watermelon in terms of number of branches as being a function of poultry and goat manure. It was observed that poultry and goat manure affected the number of branches of watermelon plant. At a higher rate of poultry manure and goat manure, one can observe that number of branches increase to reach maximum level.

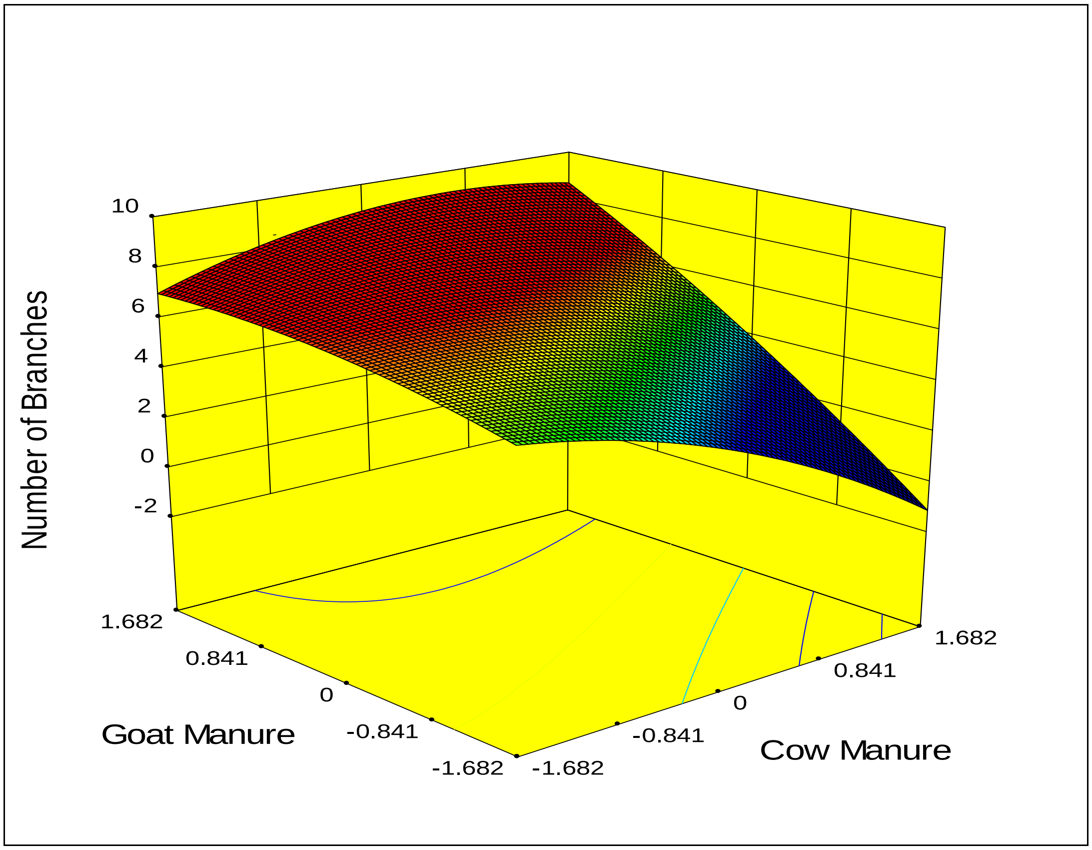

Figure 4.15: Number of Branches as a Function of Goat and Cow Manure at fixed Poultry Manure of 14.68 ton/ha

Figure 4.15 shows the surface plot of the number of branches as a function of cow and goat manure at constant/fixed poultry manure. It was observed that cow and goat manure have direct effect on the number of branches. The number of branches decreases with increasing cow manure and increase of goat manure.

4.4.3 Determining Optimal Conditions for Maximum Vine Length of watermelon

The aim of the study was to find the optimal set of experimental parameters that produces a maximum value of response (vine length of watermelon plant). The best solution satisfying the above criteria was obtained using 'Design expert' software version 10 as show in Table 4.13.

Table 4.13: Optimal Conditions for Maximum Watermelon Vine Length

Variables	Description	Optimal Value	
		Coded Value	**Actual Value**
X_1	Poultry Manure	1.510	17.55 tons/Ha
X_2	Cow Manure	0.704	13.52 tons/Ha
X_3	Goat Manure	1.673	18.37 tons/Ha
Y_3	**Vine Length (cm)**	**223.743**	**223.743cm**

The optimum values of selected variables were obtained by solving the regression model and also analyzing the response surface contour plots. It was found that for a maximum (optimal) growth of vine length of watermelon plant, about 17.6 tons/Ha of poultry manure, 13.5 tons/Ha of cow manure and 18.4 tons/Ha of goat manure are required to produce vine length of 224 cm.

4.4.3.1 Response Surface and Contour Plots

Response surface methodology can be illustrated with 3 dimensional plots by presenting the response in function of two factors and keeping the other constant. This is indicated by the vine length of watermelon in relation to the poultry, cow and goat manure in Figure 4.16, 4.17 and 4.18.

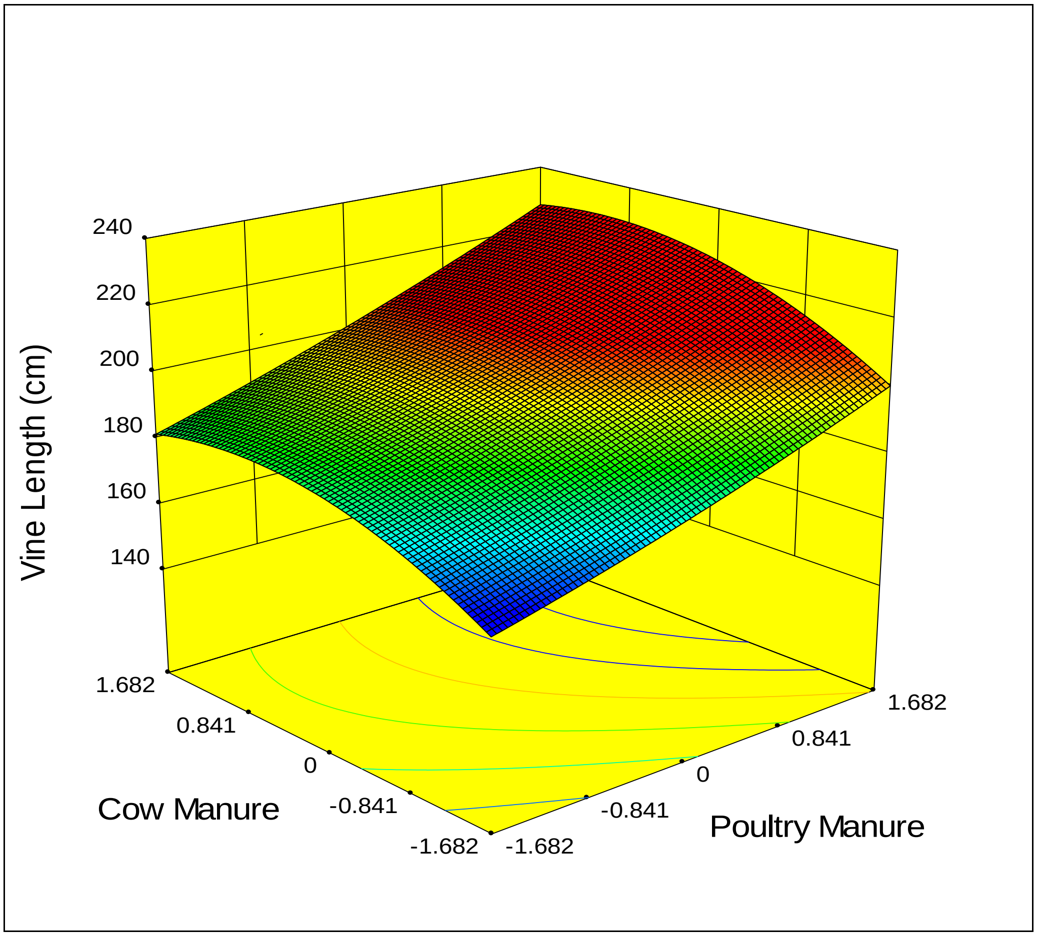

Figure 4.16: Vine Length as a Function of Poultry and Cow Manure at fixed Goat Manure of 18.37 ton/ha

Figure 4.16 shows a plot of 3D for combination of variables (poultry and cow manure) which exhibit the trend of variation of response (vine length) within the selected range of input variables and also influence of each variable over the other variable. The response surface corresponding to the second order model indicates that moderately high cow manure and high poultry manure level influenced the vine length of watermelon plant. An earlier study found that poultry manure is rich in nutrients especially nitrogen which enhances growth of watermelon plant (Enujeke, 2010).

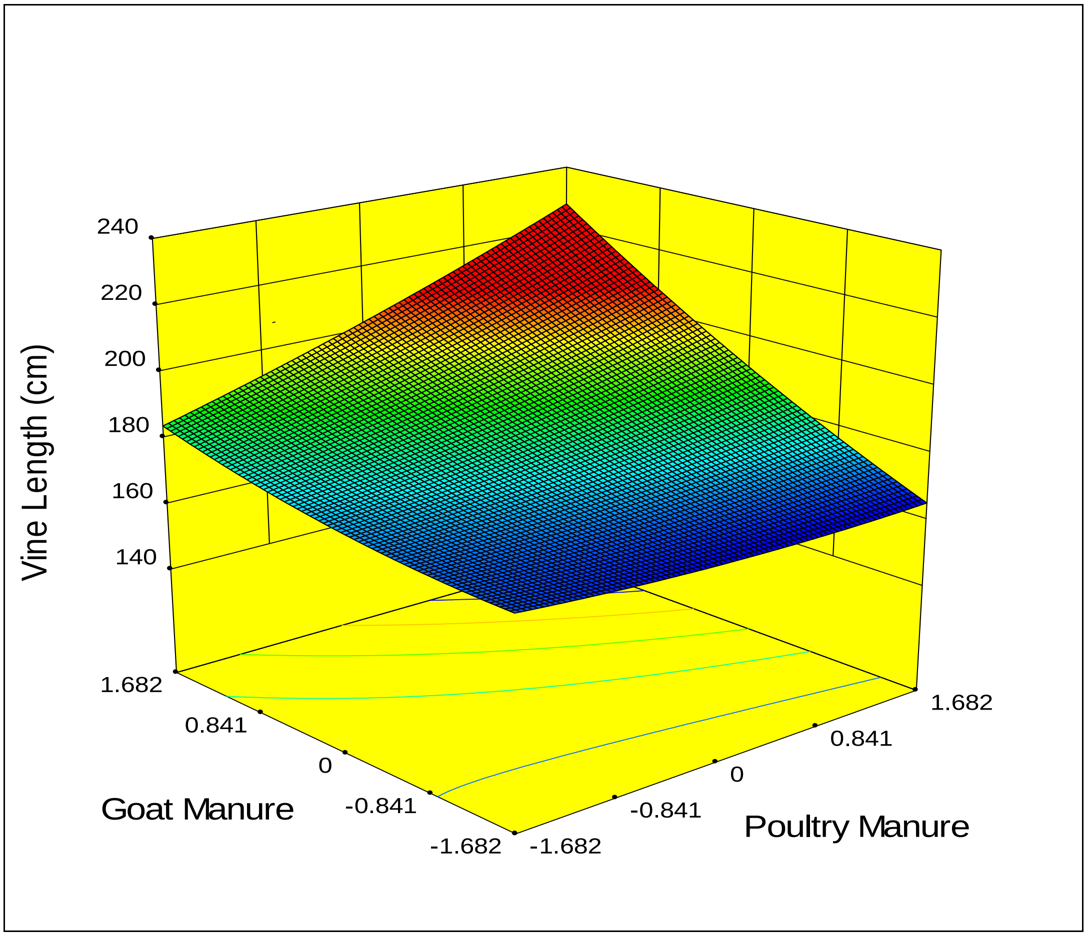

Figure 4.17: Vine Length as a Function of Poultry and Goat Manure at fixed Cow Manure of 13.52 ton/ha

Figure 4.17 shows vine length of watermelon as a function of poultry manure and goat manure. It was observed that increasing the amount of poultry manure and high amount of goat manure enhances attainment of maximum vine length of watermelon plant. Therefore, poultry and goat manure clearly enhance the growth of watermelon plant.

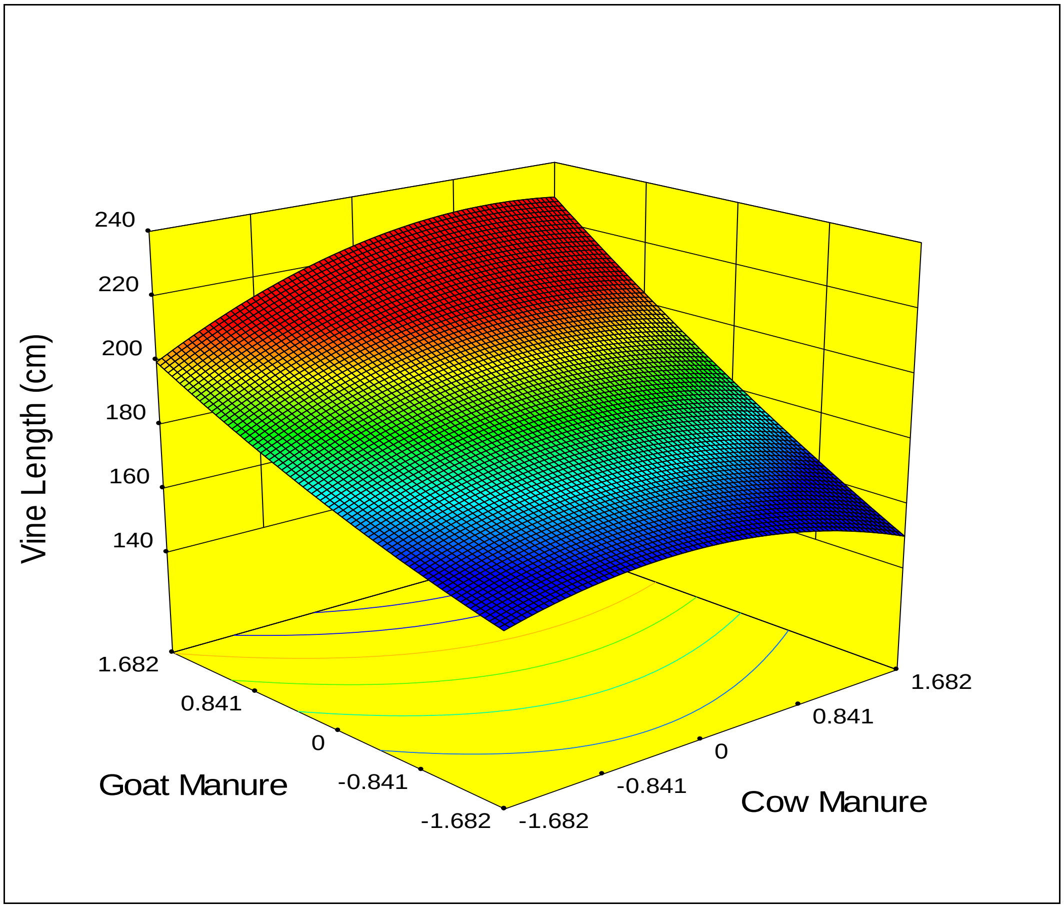

Figure 4.18: Vine Length as a Function of Goat and Cow Manure at fixed Poultry Manure of 17.55 ton/ha

Figure 4.18 denotes the surface plot of the vine length as a function of cow and goat manure at a constant 17.6 ton/Ha of poultry manure. The results showed that cow and goat manure have direct effect on the vine length but the same decreased with increasing cow manure and increase of goat manure.

4.4.4 Simultaneous Optimization of Multiple Responses using Desirability Function

Process optimization through the use of the desirability function, started with defining the specifications required for increased growth and production of watermelon. In this case, the data was analyzed separately to optimize the variable responses. Specifications (minimum, target and maximum) are related to the experimental data and they are presented in Table 4.14. In this case, the study sought target value to fruit weight, the number of branches and vine length of watermelon, search for maximum point because the higher value is better for the increased growth and production of watermelon.

Table 4.14: Specification for Increased Growth and Production of Watermelon

Response Variable	Minimum	Target/Average	Maximum
Fruit Weight (Kgs)	17.0	23.287	29.574
No. of Branches	4	8	12
Vine Length (cm)	165.4	223.743	282.09

The desirability (D) is the global index calculated from the combination of response of interest, processed through a geometric mean and this index is responsible for showing the best condition for optimization of all variable responses at the same time. To achieve a maximum possible value for desirability which reflects, in the best condition variable responses in relation to the attendance of their specification, the best settings (optimal values) using standardized variables of the factors are as shown in Table 4.15.

Table 4.15: Optimal Parameter-Setting

Symbols	Organic Manure	Optimal Values (coded)	Actual Optimal Values
X_1	Poultry Manure	1.52754	17.6377tons/Ha
X_2	Cow Manure	0.233256	11.1663tons/Ha
X_3	Goat Manure	1.61003	18.05015tons/Ha

The results in Table 4.16 show that the value of D, belongs to the range from 0 until 1 and is maximized when all the answers are approaching their specifications, because the nearest one in D, closer to the original answers will be their respective specifications limits. The great general point of the system is achieved by maximizing the geometric mean, calculated from the individual desirability functions (d_i) which in this case are the values for each of the variable responses as shown in Table 4.16.

Table 4.16: Desirability Function Values

Response Variable	Individual Desirability (d_i) Values	Global index (D)
Fruit Weight	1.0	
No. of Branches	1.0	**1.0**
Vine Length (cm)	1.0	

The values obtained for the compound desirability (D) and individual desirability (di) demonstrate that the process was well optimized, because these indices are equal to the condition great value of one (1.0). Thus under the best parameter setting all the responses were maximized as shown in Table 4.17.

Table 4.17: Simultaneous Optimization of Multiple Responses

	Responses	Maximum Value	
Y_1	Fruit Weight	23.295 Kgs/plant	93.73 tons/Ha
Y_2	Number of Branches	8.97122	9 Branches/Plant
Y_3	Vine Length (cm)	225.43	225.43 cm

The aim of the study was to optimize the multiple responses of watermelon to organic manure. It was revealed that, 17.64 tons/Ha of poultry manure, 11.2 tons/Ha of cow manure and 18.1 tons/Ha of goat manure were essential or required to simultaneously optimize the multiple responses of watermelon. These optimal conditions (requirement of organic manure) could attain a maximum of 93.73 tons/Ha of fruit weight of watermelon.

Also under the same conditions nine (9) branches per watermelon plant were achieved. Indeed, the length of about 225.4 cm was attained at the same optimal conditions.

An increase of poultry manure led to an increase in fruit weight, numbers of branches and vine length of watermelon plant as well as desirability compound D (Figure 4.19).

Noting the increase of cow manure factor, it is possible to perceive that there will be fall in the value of the response variables and increased desirability compound D. Also an increase of poultry manure led to an increase in fruit weight, numbers of branches and vine length of watermelon plant. Multiple response optimization using desirability functions has until now had its utilization limited to the chromatographic field, its related techniques, and to electrochemical methods (Candioti et al., 2014). However, its principles can be applied to the development of procedures using various analytical techniques, which demand a search for optimal conditions for a set of responses simultaneously.

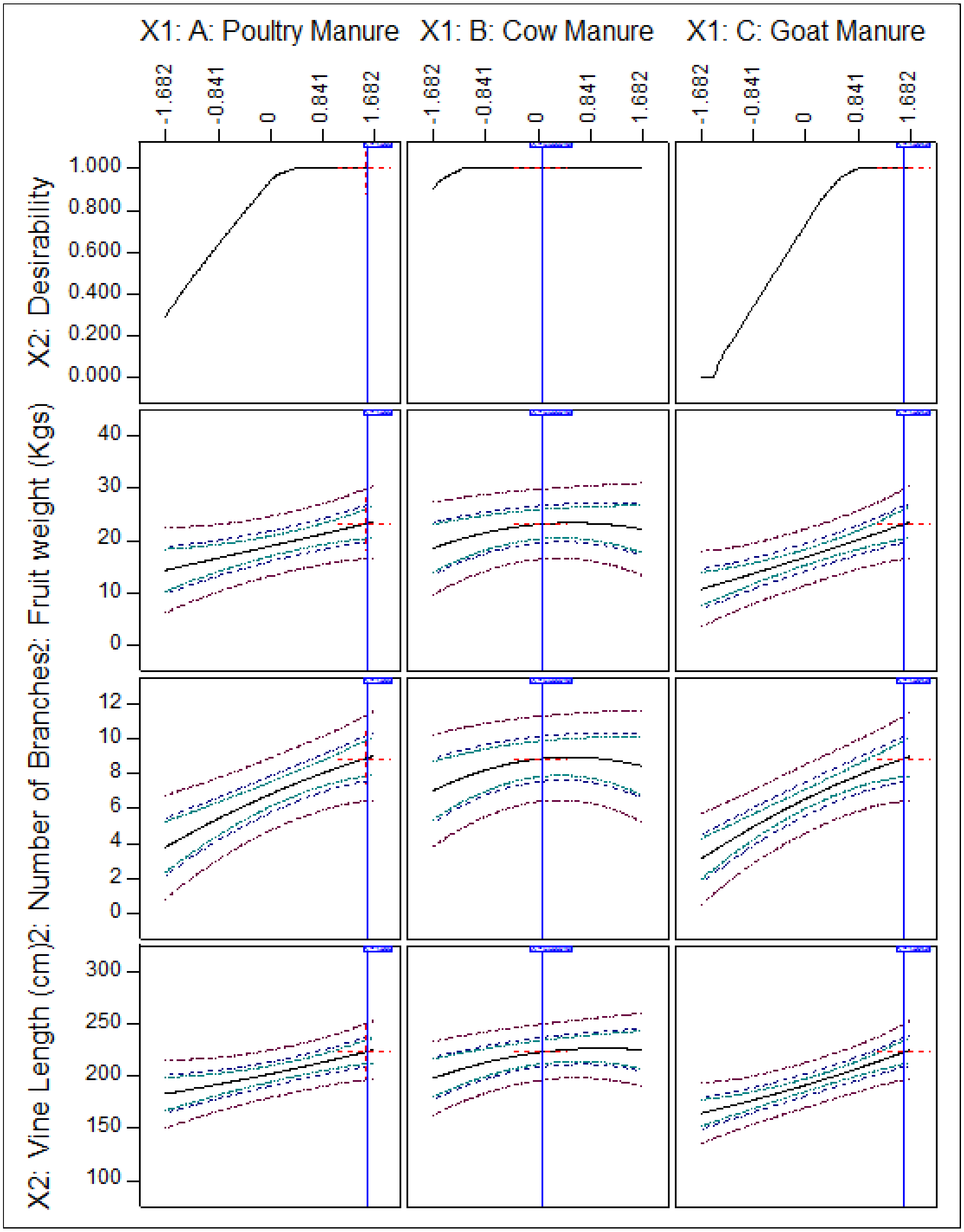

Figure 4.19: Desirability Function Applied in Multiple Responses

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary of major finding, conclusions, recommendations and areas for further study. The study aimed at optimizing the multiple responses of watermelon to organic manure using Central Composite Design and Response Surface Methodology. It was guided by the following specific objectives; to establish the effect of organic manure on growth and yield of watermelon using CCD, determine an appropriate second-order polynomial model that best fits the data as well as find an optimal setting on the control variables that produce maximum response values on watermelon crop

5.2 Summary of Major Findings

The first objective of the study was to establish the effect of organic manure on growth and yield of watermelon crop. It was found that goat manure and poultry manure were the most significant variables for fruit weight of watermelon, followed by their interaction poultry and goat manure, as well as cow manure and goat manure**.** However, interaction of poultry and cow manure had negative effect and was insignificant at 95% confidence level. Plant that received adequate amount of poultry or goat manure had higher fruit weight possibly because higher rate of manure not only improve the soil conditions for crop establishment, but also released adequate nutrient element for yield enhancement.

In addition, it was observed that poultry manure significantly influences the growth of watermelon plants, followed by goat manure, as well as interaction of cow and goat manure. Plants that received adequate poultry manure were superior with respect to higher number of branches of watermelon plant over their counterparts possibly because higher rates of manure supplied nutrients required for vigorous growth. Likewise, the study found that goat manure significantly influences growth of watermelon plant, followed by poultry manure as well as interaction of poultry and goat manure. Plant that received adequate amount of poultry or goat manure had higher vine length than other plants possibly because higher rate of manure improves nutrient availability which enhanced increased vine growth of watermelon plant.

The second objective of the study was to determine an appropriate second-order polynomial model that best fits the data. A second order polynomial model was obtained by employing a least squares technique for prediction of fruit weight of watermelon. This regression model was tested using analysis of variance for residuals minimization and revealed that the predicted response model was statistically significant with an adjusted R-squared value of 0.8591. The slightly high coefficient of determination indicates that the model was suitable to represent the relationship among the studied variables. It was observed that main effects are more influential on fruit weight of watermelon plant at 5% significant level. The study found that there was no significant lack of fit in the model and so the study concluded that the reduced model was adequate.

Certainly, a second order polynomial model was obtained by employing a least squares technique for prediction of number of branches of watermelon plant. The study revealed that the predicted response model was statistically significant. The coefficient of determination had a value of 0.9129. This implies that 91.3% variation in the model was accounted for by the controlled variables. Hence the model was suitable to represent the relationship among the studied variables. The study revealed that combined application of cow and goat manure had a statistically significant regression coefficient at 5% significance level. This implies that for one unit change in combined cow and goat manure growth of branches (in number) of watermelon plant would increase by a factor of 0.75. This shows that combined application of cow and goat manure is much more effective on growth (number) of branches of watermelon plant than any other combinations in the studied variables. It was observed that main effects were more influential on growth of watermelon plant (number of branches).

Similarly, a second order polynomial model was obtained by employing a least square technique for prediction of vine length of watermelon plant. The study found that the model had an adjusted R-squared value of 0.907. This suggests that 91% of the variation in the model is accounted for by the factors considered in the current study and the rest by other factors not considered by the study. The high coefficient of determination indicates that the model was suitable to represent the relationship among the studied variables. The study found that main effects are more influential on vine growth.

The last objective was to find optimal settings on the control variables that produce maximum response values on watermelon crop. The findings revealed that the process was well optimized, because the indices were very close or equal to the condition great value of one (1.0). In this study, the best solution was found to be 17.64 tons/Ha, 11.17 tons/Ha and 18.05 tons/Ha of poultry, goat and cow manure respectively that are required to achieve maximum response values as 93.73 tons/Ha of fruit weight, 9 branches/plant and 225.43 cm of vine length of watermelon plant.

5.3 Conclusions

The experiment was carried out at horticultural research and teaching farm of Chuka University, Kenya. This study was carried out to evaluate the effect of organic manure and their interaction in achieving the optimal values using CCD and RSM. Rate of each type of manure in tons per hectare were 1.6, 5, 10, 15 and 19.4. The parameters assessed to achieve the objective of the study were vine length, number of branches per plant and fruit weight of watermelon. The study found that main effect (where poultry, cow or goat manure were applied alone) were more influential on growth and yield of watermelon crop because higher rate of poultry or goat manure improved soil condition and nutrient availability.

Optimal conditions for yields of watermelon by the application of design of experiments using RSM were investigated. A quadratic model was suggested for the prediction of yield of watermelon crop. The multiple adjusted R-squared value was 0.859=85.9% thus indicating an acceptable fitting to the experimental data. The variance analysis of the model proved that the poultry manure and goat manure were significant factors. The results of the study estimated that the plants that received 17.13 tons/Ha of poultry manure, 13.3 tons/Ha of cow manure and 18.1 tons/Ha of goat manure were superior in the optimal parameter tested. At optimal conditions, the actual value of the fruit weight of watermelon was 93.15 tons/Ha, This translates to 37.26 tons per acre piece of land of watermelon fruit weight for a period of 75 -85 days after sowing. In addition, a peasant farmer can generate about 745,184 Kenya shillings within a period of 85 day in one acre piece of land at a low price of Kshs 20 per kilogram of watermelon fruit.

Optimal conditions for growth of watermelon plant by the application of design of experiments using RSM were investigated. A quadratic model was suggested for the prediction of number of branches of watermelon plant had an adjusted R-squared value of 0.913=91.3% thus indicating an acceptable fitting to the experimental data. The study found that the optimal value for each factor was 14.7 tons/Ha of poultry manure, 13.5 tons/Ha of cow manure and 17.8 tons/Ha of goat manure. At optimal conditions, the actual value of the growth of watermelon was eight (8) branches per plant within 56 days after sowing.

Optimal conditions for growth of watermelon by the application of design of experiments using RSM were investigated. A quadratic model suggested for the prediction of increased growth of watermelon plant. The adjusted R-squared value was 0.91=91% that indicating an acceptable fitting to the experimental data. The variance analysis of the model proved that the poultry manure and goat manure were significant factors. The optimal value for each factor was found to be; 17.6 tons/Ha of poultry manure, 13.5 tons/Ha of cow manure and 18.4 tons/Ha of goat manure. At optimal conditions, the actual value of the vine length of watermelon plant was 224 cm per pant within 56 day after sowing. It was concluded through experimental analyses that all factors (poultry, cow and goat manure) were influential in the process of increased growth and production of watermelon.

Finally, this study exemplified that the use of mathematical models for crop production based on statistics can be useful for predicting and understanding the effects of experimental factors. What must be noted here is that RSM does not explicate the mechanism of the studied crop production, but only ascertain the effects of variables on response and interactions between the variables. It can also be stated that it would be a scientific and economic approach to obtain the maximum amount of information in a short period of time and with the lowest number of experiments.

5.4 Recommendations

Based on the findings of the study, the following recommendations were made.

i. The study has established that main effect of poultry manure and goat manure influences the growth and yields of watermelon crop. Farmers should adopt application of poultry and goat manure to increase the yield of watermelon. This translates to improvement in financial performance of small scale farmers in the study area. The study recommends use of organic manure in order of 18.1 tons/Ha of goat manure, 17.13 tons/Ha of poultry manure and 13.3 tons/Ha cow manure to enhance production of watermelon in study area.

ii. In order to create much awareness of RSM on Agricultural settings the study recommends joint development by statisticians and Agriculturalists to reasonably model practical Agricultural research problems using CCD and RSM

iii. To achieve the aspiration in Kenya’s vision 2030, the ministry of agriculture, livestock and fisheries should have concerted effort to promote production of watermelon using organic manure which is locally available and accessible by farmers. This could improve the living standard of farmers since production of watermelon takes about 85 days to mature. This translates to some income after three months depending with the size of land used for production. The study found that farmers can generate about 700,000 Kenya shillings per acre piece of land in the study area. The recommendation of this study will be disseminated through conference presentation and publication of the thesis.

iv. The study found that all the three estimated models had some negative parameters which, of course, should be positive. This shows that taking into account any physical knowledge known about the response can be very beneficial when choosing an appropriate model. Therefore the study recommends use of inverse polynomial model in such a case.

v. The current study recommended the cost of organic manure to 15,000, 14,000 and 12,000 Kenya shillings per ton of poultry, goat and cow manure respectively.

5.5 Suggestions for Further Research

i. The study found that organic manure namely; poultry, cow and goat manure influenced the growth and production of watermelon in the study area. The study focused only on organic manure among all other sources of important nutrients for growth and crop production. Indeed, since the study considered only three factors, further research should consider more measurable factors such as rabbit manure and donkey manure that can affect growth and production of watermelon or any other crop.

ii. Further research may be commissioned with CCD, Box–Behnken and Doehlert design approach to plan the experiments for growth and yield of watermelon with an overall objective of optimizing the responses (such as number of fruits/plant and number of leaves per plant) of watermelon to organic manure (poultry manure, goat manure, rabbit manure and donkey manure)

REFERENCES

Aghdead, H.S., & Laith, A.M. (2014). Application of Response Surface Methodology for determine hole diameter model in EDM based microhole cutting process. *Al-Qadisiya Journal for Engineering Science*, 7(2), 137-147.

Allen, T. T., & Yu, L. (2002). Low-Cost Response Surface Methods from Simulation Optimization, *Qual. Reliab. Eng. Int*., 18(1), 5-17.

Atapour, M, & Kariminia, H. (2013). Optimization of Biodiesel Production from Iranian Bitter Almond Oil Using Statistical Approach. *Waste Biomass* Valor 4:467-474 *Retrieved on September 5, 2015 from (www.researchgate.net/publication)*

Bhatti, H.N., Hanif, M.A., Qasim, M. & Rehman, A. (2008). Biodiesel production from waste tallow. *Fule*, 87, 2961-2966.

Box, G.E.P., W.G. Hunter & Hunter, J.S. (1987). *Statistics for Experimenters:* An Introduction to Design, Data Analysis and Model Building, John Wiley, New York

Box, G. E. P., & Behnken, D. W. (1960). Simplex-Sum Designs: A Class of Second Order Rotatable Designs Derivable From Those of First Order. *Ann. Math. Statist*, 31 (4) 838--864. http://dx.doi:10.1214/aoms/1177705661.

Box, G.E.P. & Wilson, K.B. (1951). On the experimental attainment of optimum conditions, *J. R. Stat. Soc*. 13, 1–45.

Boyhan, G.E. S. M. Granberry & W. T. Kelley. (1999). Soils and Fertilizer management for water melon production. The University of Georgia College of Agricultural and Environmental Sciences and the U.S. Department of Agriculture Bulletin 996

Candioti, L. V., De, M. M., Zan, M. S., & Goicoechea, C. H. (2014). Experimental design and multiple response optimization. Using the desirability function in analytical methods development. Talanta, 124(1), 123-138. *Retrieved on October 9, 2015* (www.iosrjournals.org)

Chernoff, H. (1953) Locally Optimal Designs for Estimating Parameters. *The Annals of Mathematical Statistics*, 24, 586-602.

Chang, S. (1997). An algorithm to generate near D-optimal designs for multiple response surface models. *IIE Trans*, 29:1073–1081.

Charnes, A., Cooper W. W., & Rhodes, R. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444.

Cho, T-Y. (2010). Mixture-Process variable Design Experiments with Control and Noise variables within a Split-Plot Structure. A PhD Dissertation, Arizona State University

Dauda, S.N., Ajayi, F.A. & Ndor E. (2008). Growth and Yield of Watermelon (*Citrullus lanatus*) as Affected by Poultry Manure Application. *Journal of Agriculture & Social Sciences; 4,121–124*. http://www.fspublishers.org (accessed 2016 August 22).

Derringer, G. & Suish, R. (1980). Simultaneous Optimization of Several Response Variables, *Journal of Quality Technology*, 12, 214-219.

DIPA (2006). Handbook of Agriculture: facts and figures for farmers, students and all interested in farming. Directorate of Information and Publications of Agriculture. *Indian Council of Agricultural Research,* New Delhi, p. 435.

Edmondson, R.N. (1991), "Agricultural response surface experiments based on four-level factorial designs." *Biometrics*, 47, 1435–1448.

Enujeke, A, Canakci. M. (2010). Optimization of pretreatment reaction for methyl ester production from chicken fat, *Fuel* 89: 4035-4039.

Enujeke, E.C. (2013a). Effects of Poultry Manure on Growth and Yield of Improved Maize in Asaba Area of Delta State, Nigeria. *IOSR Journal of Agriculture and Veterinary Science.* 4, (5), 24-30. International Organization of Scientific Research, India.

Enujeke, E.C (2013b). Response of Watermelon to Five different rate of Poultry Manure, *IOSR-JAVS,* 5(2), 45-50 (www.iosrjournals.org)

Friedrich, P.(1993). *Optimal Design of Experiment.* Society for industrial and applied m athematics, John Wiley & Sons, Inc, New York, USA

Ghadge, S.V., & Raheman, H. (2006). Process optimization for biodiesel production from mahua *(Madhucaindica)* oil using response surface methodology. *Bio resource Technology*, 97, 379-384.

Hill, W J., & Hunter, W.G (1966). A Review of Response Surface Methodology: A Literature Survey, *Technometrics*, 8, (4), 571-590

IITA, (2013). Growing watermelon commercially in Nigeria- an illustrated guide. International Institute of Tropical Agriculture (IITA), 1-16.

Jarret, B., Bill, R., Tom, W. & Garry, A. (1996). *Cucurbits Germplasm Report*, Watermelon National Germplasm System, Agricultural Service, U.S.D.A, 29-66.

Jeong, G.T., Yang, H.S., & Park, D.H. (2009). Optimization of Transesterification of animal fat ester using Response Surface Methodology. *Bioresource Technology*, 100, 25-30.

John, L.W., Jamer, D.B. Samuel, L.T. & Warner, L.W. (2004). *Soil Fertility and Fertilizers: An Introduction to Nutrient Management, Pearson Education*, India 106–153.

Kadirgama. K., Abou-El-Hosseirr. K., Mohammad, A., B & Habeeb. H. (2007). Statistical model to determine surface roughness when milling hastelloy C-22HS, *Journal of Mechanical Science and Technology, 21,1651-1655.*

Khuri A.I., Cornell J.A. (1987), *Response Surfaces*. Marcel Dekker, New York

Khuri, A. & Siuli, M. (2010). Response Surface Methodology. *Sons Inc, Wileys Coup stat* 2, 128-149. *Retrieved October 1, 2015 (www.wiley.com/wire/compstas)*

Kiefer, J., & Wolfowitz, J. S. (1959). Optimum designs in regression problems. *Annals of Mathematical Statistics 30, 271–294.*

Leduc, S., Natarajan, K., Dotzauer, E., McCallum, I., & Obersteiner, M. (2009). Optimizing biodiesel production in India. *Appl. Energy* 86, 125–131

Leung, D.Y.C, & Guo, Y. (2006). Transesterification of neat and used flying oil: Optimization for biodiesel production, *Fuel Processing Technology* 87: 883-890.

Liu, Y., Yan, Y., Hu, F., Yao., A, Wang, Z. & Wei, F. (2010). Transesterification for Biodiesel Production Catalyzed by Combined Lipases: *Optimization and Kinetics*. AIChE J. 56, 1659–1665

Nam-Ky, N., John J. & Borkowskib, S. (2008). New 3-level response surface designs construc- ted from incomplete block designs, Journal of Statistical Planning and Inference 138, 294–305

Mangila, E., Tabiliran, F.P., Naguit., M.R.A & Malate, R (2007). Effects of Organic Fertilizer on the Yield of Watermelon, *Threshold* 2, 27-35.

Mansourpoor, M, & Shariati A. (2012). Optimization of Biodiesel Production from Sunflower Oil Using Response Surface Methodology. *Journal of Chemical Engineering and Process Technology* 3,141. *Retrieved October 1, 2015 from (http://dx.doi.org)*

Mapham, W.R. (1975), *Some Biometrical Aspects of Soil Calibration*. M.Sc. thesis,University of Natal, South Africa.

Mead, R. & Pike, D.J. (1975). A review of response surface methodology from a biometric viewpoint. *Biometrics* 31, 803–851.

Montgomery, D.C. (2013). *Design and analysis of experiments:* 8^{th} Edition, New York: John Wiley & Sons; 203

Montgomery, D.C. (2005). *Design and Analysis of Experiments: Response surface method and designs.* New Jersey: John Wiley and Sons, Inc.

Montgomery, D.C. (1997). *Design and Analysis of Experiments.5th Edition*, John Wiley and Sons, Inc New York

Muriithi, D. K. (2015). Application of Response Surface Methodology for Optimization of Potato Tuber Yield. *American Journal of Theoretical and Applied Statistics*. 4(4), 300-304. http:// dx.doi: 10.11648/j.ajtas.20150404.20

Myers, R. H., Montgomery, D. C., Vining, G. G., Borror, C. M. & Kowalski, S. M. (2004). "Response Surface Methodology: A Retrospective and Literature Survey*," J. Qual. Technol.,* 36, 5377.

Myers, R. H., Montgomery, D. C., Christine M, & Anderson C. (2009)."*Process and product Optimization Using Designed experiments"* 3rdEdition, John Wiley & Sons New Jersey

Myers, Raymond H., Khuri, Andre I. & Carter, Walter H., Jr. (1989). Response Surface Methodology: *Technometrics*, 31 (2): 137-153 http://www.jstor.org

Oehlert, G. W. (2000). *Design and analysis of experiments: Response surface design.* New York: W.H. Freeman and Company

Raheman, H. & Phadatare, A.G. (2004). Diesel engine emissions and performance from blends of Karanja methyl ester and diesel. *Biomass Bioenerg*. 27, 393–397

Sahu J., Chinmaya, P., & Mahapatra, S. S. (2013). A DEA Approach for Optimization of Multiple Responses in Electrical Discharge Machining of AISI D2 Steel. *Procedia Engineering*, 51(1), 585-591.

Salawu, I.S., Adeyemi, R.A. & Aremu, T.A. (2007). Modified inverse polynomial and ordinary polynomial as a response surface model: A case study of nitrogen, phosphate and potassium levels on the yield of maize, *International Journal of Pure Applied Sciences,* 1, 18-24.

Shadkam, E. & Mehdi, B. (2015). The Optimization of Bank Branches Efficiency by Means of Response Surface Method and Data Envelopment Analysis: A Case of Iran**.** *Journal of Asian Finance Economic and Business*, 2(2), 13-18

Shahin,G., Hamidi,A.A., Mohamed,H. & Ali, A.Z.(2009). Application of response surface methodology (RSM) to optimize coagulation–flocculation treatment of leachate using poly-aluminum chloride (PAC) and alum, *Journal of Hazardous Materials, 163,* 650–656, *Retrieved October 9, 2015 from (www.elsevier.com)*

Silva, F. G., Fernandi, L.C, & Anderea, L. (2011). Application of Response Surface Methodology for Optimization of Biodiesel Production by transesterification of soya bean oil with ethanol. *Journal of Fuel processing Technology*, 92, 407-413 *Retrieved October 5, 2015 from (www.elsevier.com)*

Tanarkorn, S., & Vittaya, P. (2013). Process Optimization of Crude Palm Oil Biodiesel Production by Response Surface Methodology, *European International Journal of Science and Technology,* 2(7), 49-56.

Tsai, C., Lee-Ing, T. & Chung-Ho, W. (2010). Optimization of Multiple Responses Using Data Envelopment Analysis and Response Surface Methodology, *Tamkang Journal of Science and Engineering*, 13 (2)

Vicente, G., Coteron, A., Martinez, M. & Aracil, J. (1998). Application of the factorial design of experiments and response surface methodology to optimize biodiesel production. *Ind. Crops Production*, 8, 29–35 *Retrieved on October 5, 2015 (www.ingenta.connet.com)*

Wilson, H. (1951). Approximation of Response variable using first degree polynomial *http://en.wikipedia.org/wiki/response_surface_methodology (accessed September 22, 2015).*

Wang, Y., Myers, R. H., Smith, E. P. & Ye, K. (2006). D-optimal designs for Poisson regression models in toxicological and medical studies. *Journal of Statistical Planning and Inference*, 136, 2831–2845

Wang, J. & Wan, W. (2009). Application of desirability function based on neural network for optimizing biohydrogen production process. *International journal of hydrogen energy*, Sidney, 34(1), 1253-1259

Wu, F. C. (2005). Optimization of correlated multiple quality characteristics using desirability function. *Quality engineering*, New York, 17,(1), 119-126.

Wikepedia encyclopedia (2015). Response surface Methodology, http://en.wikipedia.org/wiki/response_surface_methodology (accessed September 21, 2015).

APPENDICIES

APPENDIX I: Experimental Layout

1	**25.92**	7	**25.92**	14	**25.92**	**KEY** Measurement **Plot** $4M \times 3M = 12M^2$
2	**42**	8	**36**	15	**36**	**Land** 28M $\times 16M = 448M^2$
3	**30**	9	**48**	16	**42**	**Spacing** 3 seed/Stand 4 Stands /plot
4	**18**	10	**36**	17	**42**	
5	**30**	11	**48**	18	**54**	**Units** Kgs/plot
6	**36**	12	**36**	19	**30**	
	0	13	**36**	20	**48**	***Author*** *Dennis Muriithi.* ***Date*** *1/3/2016*

APPENDIX II: Manure Requirement

	Coded Values			Kgs/plot(12msqd)			
Runs	X_1	X_2	X_3	Poultry	Cow	Goat	TOTAL
1	-1.682	0	0	1.92	12	12	25.92
2	-1	1	1	6	18	18	42
3	-1	-1	1	6	6	18	30
4	-1	-1	-1	6	6	6	18
5	-1	1	-1	6	18	6	30
6	0	0	0	12	12	12	36
7	0	0	-1.682	12	12	1.92	25.92
8	0	0	0	12	12	12	36
9	0	1.682	0	12	24	12	48
10	0	0	0	12	12	12	36
11	0	0	1.682	12	12	24	48
12	0	0	0	12	12	12	36
13	0	0	0	12	12	12	36
14	0	-1.682	0	12	1.92	12	25.92
15	0	0	0	12	12	12	36
16	1	1	-1	18	18	6	42
17	1	-1	1	18	6	18	42
18	1	1	1	18	18	18	54
19	1	-1	-1	18	6	6	30
20	1.682	0	0	24	12	12	48
			TOTAL	241.92	241.92	241.92	725.76
Variable	**Description**		**-1.682**	**-1**	**0**	**1**	**1.682**
X_1	**Poultry Manure(tons/Ha)**		**1.6**	**5**	**10**	**15**	**19.4**
X_2	**Goat Manure(tons/Ha)**		**1.6**	**5**	**10**	**15**	**19.4**
X_3	**Cow Manure(tons/Ha)**		**1.6**	**5**	**10**	**15**	**19.4**

APPENDIX III: R-CODE

```
#Attach data into R
data1=read.table("C:\\den\\WATERMELON_DATA.txt",header=TRUE)
M<-cbind(x1,x2,x3,x1.2,x2.2,x3.2,x1x2,x1x3,x2x3,y1,y2,y3,y4,y5)
#Fit a second order model
mod2=lm(y2~x1+x2+x3+x1.2+x2.2+x3.2+x1x2+x1x3+x2x3)
mod21=lm(y2~x1+x2+x1.2+x2.2+x1x2)
mod22=lm(y2~x1+x3+x1.2+x3.2+x1x3)
mod23=lm(y2~x2+x3+x2.2+x3.2+x2x3)
mod3=lm(y3~x1+x2+x3+x1.2+x2.2+x3.2+x1x2+x1x3+x2x3)
mod31=lm(y3~x1+x2+x1.2+x2.2+x1x2)
mod32=lm(y3~x1+x3+x1.2+x3.2+x1x3)
mod33=lm(y3~x2+x3+x2.2+x3.2+x2x3)
mod5=lm(y5~x1+x2+x3+x1.2+x2.2+x3.2+x1x2+x1x3+x2x3)
mod51=lm(y5~x1+x2+x1.2+x2.2+x1x2)
mod52=lm(y5~x1+x3+x1.2+x3.2+x1x3)
mod53=lm(y5~x2+x3+x2.2+x3.2+x2x3)
summary(mod2)
anova(mod2)
summary(mod3)
anova(mod3)
summary(mod5)
anova(mod5)
##############################################MODEL I ##########################
A2<-matrix(data = c(-0.04141,-0.25,-3.9245e-17,-0.25,0.1357,-0.125,-3.9245e-17,-
0.125,0.04141), nrow = 3, ncol = 3,  byrow =TRUE)
C2<-matrix(data = c(-2.345e-02,-2.932e-01,4.163e-01), nrow = 3, ncol = 1,  byrow =T)
#Inverse of A2
INA2=solve(A2)
#Stationary points(Operating condition)
Xss2=((INA2%*%C2)/(-2))
#Transpose of vector Xss2
T2=t(Xss2)
#OPTIMAL VALUE at stationary point
Yss2=4.664+((T2%*%C2)/2)
#####ASSESSING THE NATURE OF STATIONARY POINTS
mod21=lm(y2~x1+x2+x1.2+x2.2+x1x2)
mod22=lm(y2~x1+x3+x1.2+x3.2+x1x3)
```

```
mod23=lm(y2~x2+x3+x2.2+x3.2+x2x3)
x1=seq(-1.68, 1.68, 0.1)
x2=seq(-1.68, 1.68, 0.1)
x3=seq(-1.68, 1.68, 0.1)
#FIGURE B1
model21 = function (a, b){4.63008-.02345*a-0.29315*b-0.03733*a^2+.13982*b^2-.50*a*b}
z21<-outer(x1,x2,model21)
W21<-contour(x1,x2,z21,xlab="Poultry manure in Kilograms",ylab="Cow manure in
Kilograms", main="CONTOUR PLOT")
persp (x1,x2,z21,theta=50,phi=12,col=2,ticktype="detailed",zlab="No. of Branches per
plant",xlab="Poultry manure in Kilograms",ylab="Cow manure in Kilograms")
#FIGURE B2
model22 = function (a, b){4.77471-.02345*a+0.41628*b-0.05475*a^2-.05475*b^2-.0*a*b}
z22<-outer(x1,x3,model22)
W22<-contour(x1,x3,z22,xlab="Poultry manure in Kilograms",ylab="Goat manure in
Kilograms", main="CONTOUR PLOT")
persp (x1,x3,z22,theta=50,phi=12,col=2,ticktype="detailed",zlab="No. of Branches per
plant",xlab="Poultry manure in Kilograms",ylab="Goat manure in Kilograms")
#FIGURE B3
model23 = function (a, b){4.63008-0.29315*a+0.41628*b+.13982*a^2-.03733*b^2-.250*a*b}
z23<-outer(x2,x3,model23)
W23<-contour(x2,x3,z23,xlab="Cow manure in Kilograms",ylab="Goat manure in Kilograms",
main="CONTOUR PLOT")
persp (x2,x3,z23,theta=50,phi=12,col=2,ticktype="detailed",zlab="No. of Branches per
plant",xlab="Cow manure in Kilograms",ylab="Goat manure in Kilograms")
##################################################MODEL II ##########
A3<-matrix(data = c(-0.3436,-6.5625,1.7125,-6.5625,6.2997,-3.75,1.7125,-3.75,2.544), nrow =
3, ncol = 3,  byrow =TRUE)
C3<-matrix(data = c(-2.8143,-11.3157,16.7964), nrow = 3, ncol = 1,  byrow =T)
#Inverse of A3
INA3=solve(A3)
#Stationary points(Operating condition)
Xss3=((INA3%*%C3)/(-2))
#Transpose of vector Xss3
T3=t(Xss3)
#OPTIMAL VALUE at stationary point
Yss3=200.0259+((T3%*%C3)/2)
#####ASSESSING THE NATURE OF STATIONARY POINTS#############
```

```
mod31=lm(y3~x1+x2+x1.2+x2.2+x1x2)
mod32=lm(y3~x1+x3+x1.2+x3.2+x1x3)
mod33=lm(y3~x2+x3+x2.2+x3.2+x2x3)
x1=seq(-1.68, 1.68, 0.1)
x2=seq(-1.68, 1.68, 0.1)
x3=seq(-1.68, 1.68, 0.1)
#FIGURE C1
model31 = function (a, b){202.1028-2.8143*a-11.3157*b-0.5937*a^2+6.0496*b^2-13.125*a*b}
z31<-outer(x1,x2,model31)
W31<-contour(x1,x2,z31,xlab="Poultry manure in Kilograms",ylab="Cow manure in
Kilograms", main="CONTOUR PLOT")
persp (x1,x2,z31,theta=50,phi=12,col=2,ticktype="detailed",zlab="Vine Length per
plant",xlab="Poultry manure in Kilograms",ylab="Cow manure in Kilograms")
#FIGURE C2
model32 = function (a, b){205.169-2.814*a+16.796*b-0.963*a^2+1.925*b^2+3.425*a*b}
z32<-outer(x1,x3,model32)
W32<-contour(x1,x3,z32,xlab="Poultry manure in Kilograms",ylab="Goat manure in
Kilograms", main="CONTOUR PLOT")
persp (x1,x3,z32,theta=50,phi=12,col=2,ticktype="detailed",zlab="Vine Length per
plant",xlab="Poultry manure in Kilograms",ylab="Goat manure in Kilograms")
#FIGURE C3
model33 = function (a, b){199.745-11.316*a+16.796*b+6.333*a^2+2.578*b^2-7.5*a*b}
z33<-outer(x2,x3,model23)
W33<-contour(x2,x3,z33,xlab="Cow manure in Kilograms",ylab="Goat manure in Kilograms",
main="CONTOUR PLOT")
persp (x2,x3,z33,theta=50,phi=12,col=2,ticktype="detailed",zlab="Vine Length per
plant",xlab="Cow manure in Kilograms",ylab="Goat manure in Kilograms")
################################################## MODEL III ################
A5<-matrix(data = c(-0.5524,-0.5,1.8125,-.5,0.6877,-.625,1.8125,-.625,-0.2867), nrow = 3, ncol
= 3,  byrow =TRUE)
C5<-matrix(data = c(0.3811,-2.3833,1.8322), nrow = 3, ncol = 1,  byrow =T)
#Inverse of A5
INA5=solve(A5)
#Stationary points(Operating condition)
Xss5=((INA5%*%C5)/(-2))
#Transpose of vector Xss5
T5=t(Xss5)
#OPTIMAL VALUE at stationary point
```

```
Yss5=9.4283+((T5%*%C5)/2)
#####ASSESSING THE NATURE OF STATIONARY POINTS###############
mod51=lm(y5~x1+x2+x1.2+x2.2+x1x2)
mod52=lm(y5~x1+x3+x1.2+x3.2+x1x3)
mod53=lm(y5~x2+x3+x2.2+x3.2+x2x3)
x1=seq(-1.68, 1.68, 0.1)
x2=seq(-1.68, 1.68, 0.1)
x3=seq(-1.68, 1.68, 0.1)
#FIGURE D1
model51 = function (a, b){9.1942+0.3811*a-2.3833*b-0.5242*a^2+.7159*b^2-1*a*b}
z51<-outer(x1,x2,model51)
W51<-contour(x1,x2,z51,xlab="Poultry manure in Kilograms",ylab="Cow manure in
Kilograms", main="CONTOUR PLOT")
persp (x1,x2,z51,theta=50,phi=12,col=2,ticktype="detailed",zlab="Yields in Kgs per
plant",xlab="Poultry manure in Kilograms",ylab="Cow manure in Kilograms")
#FIGURE D2
model52 = function (a, b){9.9897+0.3811*a+1.8322*b-0.62*a^2-0.3543*b^2+3.625*a*b}
z52<-outer(x1,x3,model52)
W52<-contour(x1,x3,z52,xlab="Poultry manure in Kilograms",ylab="Goat manure in
Kilograms", main="CONTOUR PLOT")
persp (x1,x3,z52,theta=50,phi=12,col=2,ticktype="detailed",zlab="Yields in Kgs per
plant",xlab="Poultry manure in Kilograms",ylab="Goat manure in Kilograms")
#FIGURE D3
model53 = function (a, b){8.9773-2.3833*a+1.8322*b+0.742*a^2-0.2324*b^2-1.25*a*b}
z53<-outer(x2,x3,model53)
W53<-contour(x2,x3,z53,xlab="Cow manure in Kilograms",ylab="Goat manure in Kilograms",
main="CONTOUR PLOT")
persp (x2,x3,z53,theta=50,phi=12,col=2,ticktype="detailed",zlab="Yields in Kgs per
plant",xlab="Cow manure in Kilograms",ylab="Goat manure in Kilograms")
```

APPENDIX IV: Project Pictures

F1: Demarcation and planting work in progress

F2: Weighing of Organic Manure in the presence of the second supervisor

F3: Overview of watermelon after 6 weeks

F4: Overview of watermelon in the plots after 8 weeks

F5: Overview of watermelon in the plots after 10 weeks

F6: Overview of watermelon in the plots after 70 days

F7: Overview of watermelon in the plots on harvest day (85days)

F8: Principal investigator weighing watermelon on harvest day

F9: Bunch of Harvested watermelon

F10: Watermelon Fruit

APPENDIX V: Publications

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Application of Central Composite Design Based Response Surface Methodology in Parameter Optimization of Watermelon Fruit Weight Using Organic Manure

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Abstract: Response Surface Methodology (RSM) is a critical technology in developing new processes, optimizing their performance and improving the design. In Kenya, watermelon cultivation is gradually gaining ground. It is a crop with huge economic importance to man as well as highly nutritious, sweet and thirst- quenching. In order to increase crop production, there is need to increase soil nutrient content with organic manure such as poultry, cow or other animal wastes. At present, there are no recommended standards with respect to rate of poultry manure, cow manure and goat manure for enhancement of yield of watermelon in Kenya. The main objective of the study was to develop an approach for better understanding of the relationship between variables and response for optimum operating settings for maximum yield of watermelon crop using Central Composite Design and Response Surface Methodology. Response Surface Model evolved for response shown the effect of each input parameter and its interaction with other parameters, depicting the trend of response. Verification of the Fitness of the model using ANOVA technique shows that the model can be used with confidence level of 0.95, for watermelon production. Further validation of the model done with the additional experimental data collected demonstrates that the model have high reliability for adoption within the chosen range of parameters. The optimal value for each factor was found as 17.13tons/Ha of poultry manure, 13.3tons/Ha of cow manure and 18.1tons/Ha of goat manure. At optimal conditions, the actual value of the fruit weight of watermelon was 93.148tons/Ha. This translates to 37.3tons per acre piece of land of watermelon fruit weight for a period of 75-85 days after sowing. In addition, a peasant farmer can generate about 745,184 Kenya shillings within a period of 75 day in one acre piece of land at a low price of Kshs 20 per kilogram of watermelon fruit. RSM has resulted in saving of considerable amount of time and money hence recommended in similar study.

Keywords: Central Composite Design, Response Surface Methodology, Model, Optimization, Watermelon, Fruit Weight, Organic Manure

1. Introduction

Watermelon *(Citrullus lanatus thumb)* is a member of the cucurbitaceous family. According to Jarret [6], it originated from the Kalahari and Sahara deserts in Africa. In Kenya, the crop is mainly grown in lower and dry Semi-arid areas of the Country, namely Nyanza, Central, Eastern, Coast and Rift valley regions. Watermelon is a crop with huge economic importance to man as well as highly nutritious, sweet and thirst quenching Mangila [8]. It is mostly used to make a variety of salads, juice and food flavor. It is a cash crop for farmers due to its high returns on investment. Watermelon contains Vitamin C and A in a form of disease-fighting beta-carotene. In spite of the increasing relevance of watermelon in Kenya, yields across the country are decreasing and not

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The Optimization of Multiple Responses of Watermelon to Organic Manure Using Response Surface Methodology

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APPENDIX VI: Soil Analysis

Soil Analysis
Basic Soil Analysis

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Customer:	Chuka University	**Crop:**	Maize	**Date Received:**	18-Apr-16
Address:	P.O. BOX 109-60400Chuka	**Crop Stage:**		**Analysis Date:**	27-Apr-16
Farm Name:	Dennis Muriithi	**Comments:**		**Report Date:**	28-Apr-16
Contact Person:	Muriithi Dennis	**Condition:**	Dry	**Sample ID:**	CC143SA0003

Field: Soil Sample Top Soil

To maintain the correct history ensure that the next sample sent from this Field is labelled: Soil Sample

History (Last 3 analysis)

Parameter	Unit	Result	Guide Low	Guide High	Low	Optimum	High	Symbol	Current	Method
pH (H2O)		**6.54**	5.80	7.00				pH	6.54	Potentiometric
Phosphorus	ppm	**5.34**	40.0	100				P	5.34	Spectroscopy
Potassium	ppm	**586**	120					K	586	Spectroscopy
Calcium	ppm	**1730**	1740	2170				Ca	1730	Spectroscopy
Magnesium	ppm	**302**	174	278				Mg	302	Spectroscopy
*Sodium	ppm	**26.6**		< 167				Na	26.6	Spectroscopy
*Organic Matter	%	**5.54**	2.50	8.00				OM	5.54	Colorimetric
*Nitrogen	%	**0.23**	0.20	0.50				N	0.23	Colorimetric
*C.E.C	meq/100g	**14.5**	15.0	30.0				C.E.C	14.5	Calculated
***PERCENTAGES AND RATIOS**										
Calcium %	%	**59.7**	60	75				Ca%	59.7	
Magnesium %	%	**17.4**	10	16				Mg%	17.4	
Potassium %	%	**10.4**	2	10				K%	10.4	
Sodium % (ESP)	%	**0.80**	0	5				Na%	0.80	
Other Bases %	%	**4.86**	3	10				OB%	4.86	
Hydrogen %	%	**6.90**	10	15				H%	6.90	
Total	%	**100.00**								
Ca:Mg Ratio	%	**3.44**	4	7				Ca:Mg	3.44	

COMMENTS #
>Very Low Phosphorus in this Top Soil>Low Calcium in this Top Soil>High Magnesium in this Top Soil>Low C.E.C in this Top Soil>Low Calcium % in this soil.>High Magnesium % in this soil.>High Potassium % in this soil.>Low Hydrogen % in this soil.>Low Ca:Mg Ratio in this soil.

Gakobo Jo *Lab Manager*	*Cordingley Jeremy* *Managing Director*	*Approval Date:* *26/05/2016*

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RECOMMENDATIONS REPORT

SOIL FERTILITY CORRECTION AND CROP FERTILIZER PROGRAMS

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ISO17025 Accredited

Customer:	Chuka University	Crop:	Maize	Date Received:	18-Apr-16
Address:	P.O. BOX 109-60400Chuka	Crop Stage:		Analysis Date:	27-Apr-16
Farm Name:	Dennis Muriithi	Comments:		Report Date:	28-Apr-16
Contact Person:	Muriithi Dennis	Condition:	Dry	Sample ID:	CC143SA0003

Crop	Maize Find Maize Seed Suppliers	Yield Target	7 t/Ha

SOIL FERTILITY CORRECTION & FERTILIZER PROGRAM

PROBLEM	SOLUTION /INPUT	RATE		COMMENTS	STAGE (Input Type)
		Kg/Ha	Kg/Acre		
	ROCK PHOSPHATE Find Rock Phosphate Suppliers	410	165	Apply before planting to build up soil P levels. This can be split over 2 years depending on budget.	PREPLANTING (Soil Correction)
Balanced fertilization required.	Di- Ammonium Phosphate (DAP) Find DAP Suppliers	190	75	Apply below seed at planting.	PLANTING (Fertilizers)
Nitrogen fertilization required.	Urea Find Urea Suppliers	130	55	Apply at 5/6 leaf stage	TOP DRESS (Fertilizers)

ADDITIONAL RECOMMENDATIONS

> Apply high P MKP foliar feed at 6 leaf stage to boost root growth.

NEED HELP UNDERSTANDING THIS REPORT? Visit our Help Desk

NEED TO FIND FARM INPUTS? Search our Farm Inputs Directory

"Disclaimer: These fertilizer recommendations are only valid for the sample presented, specific crop type, yield target and estimated fertilizer recovery. However, please also note that the recommendations provide indicative rates only and should be validated at farm level through fertilizer trials. Whilst we have taken all reasonable care to ensure that our recommendations are accurate, we have not taken into account other factors that could greatly reduce crop nutrient uptake including but not limited to soil moisture, root diseases, nematodes, water logging, compaction, acidity, fertilizer placement and other management factors. Therefore, we accept no liability for any loss or damage arising directly or indirectly from the use of the fertilisers and under no circumstances whatsoever shall we be liable for any special, incidental or consequential damages which may arise therefrom. This document cannot be reproduced except in full, without prior written approval of the company."

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APPENDIX VII: Manure Compost Analysis

Manure Compost Analysis Report

Complete Compost/Manure Analysis

CROPNUTS
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Customer:	Chuka University	Fertilizer:	Manure	Date Received:	18-Apr-16
Address:	P.O. BOX 109-60400Chuka	Crop Stage:		Analysis Date:	27-Apr-16
Farm Name:	Dennis Muriithi	Comments:		Report Date:	28-Apr-16
Contact Person:	Muriithi Dennis	Condition:	Dry Organic Material	Sample ID:	CC143CM0004

Field: Poultry Manure

History (Last 3 analysis)

Parameter	Unit	Result	Guide Low	Guide High	Low	Optimum	High	Symbol	Current				Method
pH		7.99	6.00	8.50				pH	7.99				Potentiometric
EC (Salts)	mS/cm	7.94	0.75	1.20				EC(S)	7.94				Potentiometric
Dry matter	%	90.4						DM	90.4				Gravimetric
Carbon	%	41.5	15.0	60.0				C	41.5				Ignition
Nitrogen	%	2.08	0.80	1.50				N	2.08				Colorimetric
Phosphorus	%	1.45	0.20	0.75				P	1.45				Spectroscopy
Potassium	%	2.04	0.40	2.00				K	2.04				Spectroscopy
Calcium	%	3.04	0.60	1.50				Ca	3.04				Spectroscopy
Magnesium	%	1.01	0.20	0.80				Mg	1.01				Spectroscopy
Sulphur	%	0.45	0.20	0.50				S	0.45				Spectroscopy
Manganese	ppm	764	200	800				Mn	764				Spectroscopy
Iron	ppm	1920						Fe	1920				Spectroscopy
Zinc	ppm	581	40.0	300				Zn	581				Spectroscopy
Copper	ppm	93.3	8.00	400				Cu	93.3				Spectroscopy
Boron	ppm	36.9	20.0	140				B	36.9				Spectroscopy
Sodium	ppm	2300		< 3000				Na	2300				Spectroscopy
C/N ratio		20.0	10.0	20.0				C:N	20.0				Calculated

COMMENTS #

High levels of magnesium may inhibit uptake of other elements. > High calcium levels may induce magnesium and potassium deficiencies. > High levels of phosphates may inhibit the uptake of other elements. > Excess N can burn seedling roots, reduce immunity to pests, and shorten produce shelf life.

NUTRIENT CONTRIBUTION PER TON

N	P	K	Ca	S	Mg
kg/Ha	kg/Ha	kg/Ha	kg/Ha	kg/Ha	kg/Ha
5.64	3.93	5.53	8.24	1.22	2.74

NOTES:
Nutrient Contribution & Fertilizer Deductions

These figures estimate the quantity of nutrients supplied per 1000 kg (1 ton) of this manure/compost applied each hectare of land. The calculation takes into account the material dry matter %, the nutrient content % result above, and an estimated nutrient release of 30% to the first crop.

Gakobo Jo *Lab Manager*	*Cordingley Jeremy* *Managing Director*	*Approval Date: 26/05/2016*

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Manure Compost Analysis Report

Complete Compost/Manure Analysis

CROPNUTS Laboratory Services ISO17025 Accredited

Customer:	Chuka University	**Fertilizer:**	Manure	**Date Received:**	18-Apr-16
Address:	P.O. BOX 109-60400Chuka	**Crop Stage:**		**Analysis Date:**	27-Apr-16
Farm Name:	Dennis Muriithi	**Comments:**		**Report Date:**	28-Apr-16
Contact Person:	Muriithi Dennis	**Condition:**	Dry Organic Material	**Sample ID:**	CC143CM0002

Field: Cow Manure

History (Last 3 analysis)

Parameter	Unit	Result	Guide Low	Guide High	Low	Optimum	High	Symbol	Current	Method
pH		9.00	6.00	8.50				pH	9.00	Potentiometric
EC (Salts)	mS/cm	10.8	0.75	1.20				EC(S)	10.8	Potentiometric
Dry matter	%	92.8						DM	92.8	Gravimetric
Carbon	%	33.2	13.0	60.0				C	33.2	Ignition
Nitrogen	%	1.66	0.80	1.50				N	1.66	Combustion
Phosphorus	%	0.32	0.20	0.75				P	0.32	Spectroscopy
Potassium	%	2.04	0.40	2.00				K	2.04	Spectroscopy
Calcium	%	2.15	0.60	1.50				Ca	2.15	Spectroscopy
Magnesium	%	0.58	0.20	0.80				Mg	0.58	Spectroscopy
Sulphur	%	0.25	0.20	0.50				S	0.25	Spectroscopy
Manganese	ppm	379	200	800				Mn	379	Spectroscopy
Iron	ppm	15500						Fe	15500	Spectroscopy
Zinc	ppm	89.9	40.0	300				Zn	89.9	Spectroscopy
Copper	ppm	36.0	8.00	400				Cu	36.0	Spectroscopy
Boron	ppm	60.8	20.0	140				B	60.8	Spectroscopy
Sodium	ppm	165		< 3000				Na	165	Spectroscopy
C/N ratio		20.0	10.0	20.0				C:N	20.0	Calculated

COMMENTS

High calcium levels may induce magnesium and potassium deficiencies. > Excess N can burn seedling roots, reduce immunity to pests, and shorten produce shelf life. > High pH promote microbial activity, but may limit P, iron, manganese, copper, and zinc availability

NUTRIENT CONTRIBUTION PER TON

N	P	K	Ca	S	Mg
kg/Ha	kg/Ha	kg/Ha	kg/Ha	kg/Ha	kg/Ha
4.62	0.89	5.68	5.99	0.7	1.61

NOTES:

Nutrient Contribution & Fertilizer Deductions

These figures estimate the quantity of nutrients supplied per 1000 kg (1 ton) of this manure/compost applied each hectare of land. The calculation takes into account the material dry matter %, the nutrient content % result above, and an estimated nutrient release of 30% to the first crop.

Gakobo Jo *Lab Manager*	*Cordingley Jeremy* *Managing Director*	*Approval Date: 26/05/2016*

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Manure Compost Analysis Report

Complete Compost/Manure Analysis

CROPNUTS Laboratory Services ISO17025 Accredited

Customer:	Chuka University	**Fertilizer:**	Manure	**Date Received:**	18-Apr-16
Address:	P.O. BOX 109-60400Chuka	**Crop Stage:**		**Analysis Date:**	27-Apr-16
Farm Name:	Dennis Muriithi	**Comments:**		**Report Date:**	28-Apr-16
Contact Person:	Muriithi Dennis	**Condition:**	Dry Organic Material	**Sample ID:**	CC143CM0003

Field: Goat Manure

History (Last 3 analysis)

Parameter	Unit	Result	Guide Low	Guide High	Low	Optimum	High	Symbol	Current			Method
pH		**8.49**	6.00	8.50				pH	8.49			Potentiometric
EC (Salts)	mS/cm	**11.0**	0.75	1.20				EC(S)	11.0			Potentiometric
Dry matter	%	**92.5**						DM	92.5			Gravimetric
Carbon	%	**34.8**	13.0	60.0				C	34.8			Ignition
Nitrogen	%	**1.89**	0.80	1.50				N	1.89			Colorimetric
Phosphorus	%	**0.24**	0.20	0.75				P	0.24			Spectroscopy
Potassium	%	**1.35**	0.40	2.00				K	1.35			Spectroscopy
Calcium	%	**2.61**	0.60	1.50				Ca	2.61			Spectroscopy
Magnesium	%	**0.57**	0.20	0.80				Mg	0.57			Spectroscopy
Sulphur	%	**0.27**	0.20	0.50				S	0.27			Spectroscopy
Manganese	ppm	**475**	200	800				Mn	475			Spectroscopy
Iron	ppm	**15400**						Fe	15400			Spectroscopy
Zinc	ppm	**73.3**	40.0	300				Zn	73.3			Spectroscopy
Copper	ppm	**38.7**	8.00	400				Cu	38.7			Spectroscopy
Boron	ppm	**74.3**	20.0	140				B	74.3			Spectroscopy
Sodium	ppm	**264**		< 3000				Na	264			Spectroscopy
C/N ratio		**18.4**	10.0	20.0				C:N	18.4			Calculated

COMMENTS

High calcium levels may induce magnesium and potassium deficiencies. > Excess N can burn seedling roots, reduce immunity to pests, and shorten produce shelf life.

NUTRIENT CONTRIBUTION PER TON

N	P	K	Ca	S	Mg
kg/Ha	**kg/Ha**	**kg/Ha**	**kg/Ha**	**kg/Ha**	**kg/Ha**
5.24	0.67	3.75	7.24	0.75	1.58

NOTES:

Nutrient Contribution & Fertilizer Deductions

These figures estimate the quantity of nutrients supplied per 1000 kg (1 ton) of this manure/compost applied each hectare of land. The calculation takes into account the material dry matter %, the nutrient content % result above, and an estimated nutrient release of 30% to the first crop.

Gakobo Jo *Lab Manager*	*Cordingley Jeremy* *Managing Director*	*Approval Date: 26/05/2016*

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