OPTIMIZATION OF GROUNDNUTS *(Archis hypogeal*) YIELD THROUGH RESPONSE SURFACE METHODOLOGY

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A Thesis Submitted to the Graduate Schools in Partial Fulfillment of the Requirements for the Award of the Degree of Masters of Science in Applied Statistics of Chuka University

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DECLARATION AND RECOMMENDATION

Declaration

This thesis is my original work and has not been presented for award of Degree in any other university

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Recommendation

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

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DEDICATION

I dedicate this work to my family for their constant support, love, and encouragement throughout my academic journey. Your belief in my ability to succeed has been my greatest motivation, and I am deeply grateful for everything you have done to help me achieve this milestone.

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ABSTRACT

The country current agronomic practices are not sufficient to satisfy the future global food demand. Maximizing crop yield potential is a strategy that can boost agricultural production, resulting in higher income and improved food security. Groundnuts or peanuts is an important legume nut known for its diverse uses including oil production and direct human consumption as food. Being a legume, peanut plant is of great importance for human beings. Despite its importances groundnut production has been faced by various constrains which include poor soil fertility, small land sizes and the inappropriate agricultural techniques. This study investigates the use of CCD and RSM in formulation of optimal use of rabbit, poultry and sheep manure for maximum groundnuts yield. The objective of this study was to optimize groundnuts (*Archis hypogeal*) yield through response surface methodology with the specific objective was **t**o determine the effect of organic manure on groundnuts yield, determining a functional relationship between the groundnut yield and the organic manure that can be used to predict the response value and to obtain the optimal levels of the organic manure that produces a maximum groundnut yield. The study was conducted at the Chuka University Teaching and Training Farm, Kairani. The experimental design was developed using Central Composite Design (CCD), with 20 experimental runs derived from 2^3 full factorial designs with six axial points and six center points. The CCD was used to develop the independent input components corresponding to the coded factor levels as well as fitting an appropriate second-order regression model. Data collected included number of pods per plant, the number of seeds per plant and the weight of groundnuts seeds. Response Surface Methodology techniques was adopted for data analysis in R-statistical software and R studio programing language. The study found that that there was a positive response of poultry and the sheep manure ($p < 0.05$) and the quadratic term of sheep manure was significant to the weight of groundnuts. It was concluded that application of poultry and sheep manure would improve the yields of groundnuts in the study area. The study recommended application of 13.6097 t ha-1, 10.582 t ha-1 and 11.0814 t ha-1 poultry manure, rabbit manure and sheep manure respectively. These are the optimum levels that would lead to maximum weight of groundnut without an extra cost of input thus contributing to increased income for farmers. This study concludes that poultry, rabbit and sheep manure had a significant effect on the yield of groundnuts. This study recommended that farmers should adopt model in order to reduce reliance on chemical fertilizers hence improving soil health, and contribute to environmental sustainability.

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ABBREVIATIONS AND ACRONYMS

AFA	Agricultural and Food Authority
ANOVA	Analysis of Variance
CCA	Canonical Correlation Analysis
CCC	Circumscribed Central Composite
CCD	Central Composite Design
CCF	Face-Centered Composite
CCI	Inscribed Central Composite
NPK	Nitrogen, Phosphorus and Potassium
RCBD	Randomized Complete Block
RSM	Response Surface Methodology

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Response Surface Methodology is a statistical mathematical strategy employed to optimize and comprehend the relationship between a dependent variable and independent variables (Breig *et al.,* 2021). It is commonly used in experimental design and process optimization across diverse domains including industrial, clinical, social, biological science, engineering, and agricultural sciences. Response Surface Methodology (RSM) was first presented by Box and Wilson (1951) who were driven by the need to conduct experiments effectively by selecting appropriate designs and identifying operational conditions among controllable variables that gives the optimal responses (Myers *et al*., 2016).

Groundnut ***(****Archis hypogeal*), also known as peanut is a species in the legume family Fabaceae that originated from South America (Krishnamurthy *et al.,* 2007). It is an important food and cash crop in Kenya, contributing to the country's agricultural sector and economy with a yield of 2.5 tones per hectare. However, groundnut production in Kenya has been declining, with farmers achieving only about 50% of the expected yield. For the past seven years, the Agriculture and Food Authority's (AFA) Nuts and Oil Crops Directorate statistical report shows that the groundnut production has been a decreasing in production (Nyandiala *et al*., 2023). In 2019/2020 Agriculture and Food Authority's reported there was a decrease for example 216 Mt in Homa Bay and 30 Mt in Kisumu. Yield loss is attributed to inadequate agricultural practices, such as improper soil management, lack of crop rotation, or insufficient pest control measures, has led to decreased yields over time (Nyandiala *et al*., 2023).

Groundnuts are widely cultivated for their edible seeds, which are rich in protein, oil, and other essential nutrients (Toomer, 2017). As a tropical plant, it needs a long, warm growing season in order to grow to an elevation of 1160 meters above sea level (Snapp *et al*., 2019). The ideal growing conditions for it include plenty of sunshine, reasonably mild temperatures, and evenly distributed rainfall of at least 50 mm during the growing season. The crop is primarily grown for domestic consumption but also serves as a source of income through exportation.

Groundnut thrives in warm temperatures. The ideal temperature range for their growth is between 20^0c and 30^0c with well-distributed rainfall. However, they are also tolerant of drought conditions making them suitable for rain-fed and irrigated cultivation. The crop grows well in a well-drained sandy loam or sandy soil (Kadiyala *et al.,* 2021). The preferred soil by this crop is slightly acidic to neutral soil PH ideally within the range of 6.0 to 7.0.

In Kenya; groundnuts are cultivated in various regions with suitable agro-climatic conditions. The crop is grown in both small-scale, subsistence farming and larger commercial farming. Some of the key regions that commonly grow groundnuts in Kenya include Nyanza, the Rift Valley, the Western, and portions of the Central and Eastern provinces (Khagul, 2023). Two main varieties of groundnuts that are mainly grown in Kenya are the bunch type (red Valencia) and the runner type. Bunch type is a highly marketable variety that is usually small and tastier. It takes 60-75 days for this variety to mature. Whereas the runner type is primarily grown for commercial purposes, this is the larger variety that is preferred because of its yield. It matures in between 90- 100 days. Other varieties of groundnuts encompass Red Oriata, Manipinta, Makulu Red, Bukene, Homa Bay, Texas Peanut, and Atika (Desmae *et al*., 2017).

Groundnuts are incredibly nutrient-dense and abundant in nutrients like protein, fiber, fats, vitamin E, and minerals like magnesium, phosphorus, potassium, and antioxidants (Hammons *et al*., 2016). This crop has tremendous advantages as it contributes to a well-balanced diet and offers a valuable source of energy, making it in high demand by many people. Moreover, it takes a short period for it to mature as compared to other crops hence increasing the market surplus and generating a higher profit improving farmer's economic well-being (Hammons *et al*., 2016).

However, obtaining high yields can be difficult due to several factors, such as nutritional deficits in the soil. Adding organic fertilizers to groundnut fields would improve soil fertility and supply the nutrients needed for vigorous plant growth and high yields (Singh *et al.,* 2020). Also establishing the optimal application rate of organic manure through the use of response surface methodology is necessary for maximum groundnut production in Kenya.

Poultry manure is an effective organic fertilizer derived from the droppings of chickens. It is abundant in nutrients, including potassium, phosphorus, and nitrogen, all of which are essential to plant growth. (Rasool *et al.,* 2023). When properly composted and applied, poultry manure can improve soil structure, fertility, and overall health. However, its high nitrogen content can lead to ammonia emissions and nutrient runoff if not managed correctly. Therefore, proper handling and composting techniques are essential to maximize its benefits while minimizing environmental impacts (Aina *et al*., 2019).

Rabbit manure is a nutrient-rich organic fertilizer that provides essential plant nutrients such as nitrogen (N), phosphorus (P), and potassium (K). These nutrients are of importance for the growth and development of plants (Shaji *et al.,* 2021). A balanced nutrient content of rabbit manure can contribute to improved plant vigor, increased flowering, and enhanced yield parameters (Sheteiwy *et al.*, 2020). It boosts soil health by stimulating microbial activity and promoting nutrient cycling. Additionally, the presence of organic matter also improves the soil's capacity to retain water, thereby mitigating the risk of water stress and fostering the overall health and productivity of plants. Rabbit manure can be used in various ways, including as a top dressing for garden beds, a component of compost or compost tea, or incorporated directly into the soil before planting. It is suitable for both outdoor and indoor gardening applications (Sheteiwy *et al.*, 2020).

Sheep manure is a valuable organic fertilizer and soil amendment derived from the waste produced by sheep. It is rich in nutrients and organic matter, making it beneficial for enhancing soil fertility and promoting plant growth (Lal *et al.,* 2020). Sheep manure contains essential nutrients such as nitrogen (N), phosphorus (P), and potassium (K), as well as micronutrients like calcium, magnesium, and sulfur. These nutrients are crucial for plant growth and development. Sheep manure can help balance soil pH levels. While it tends to be slightly alkaline, its use can help amend both acidic and alkaline soils, creating a more suitable environment for plant growth (Lal *et al.,* 2020). It can be incorporated into the soil before planting during soil preparation, also it can be applied as a top dressing around established plants or directly onto the surface between rows of crops.

The aim of Response Surface Methodology (RSM) is to formulate a mathematical model that effectively depicts the relationship between groundnut yield and independent variables (rabbits, poultry, and sheep). There are several types of mathematical models that can be used in RSM applications, including linear, quadratic, and higher-order polynomial models (Myers *et al.*, 2016). The choice of the model depends on the complexity of the association between the response variable and the independent variables.

When the response function exhibits minimal curvature, it is expected that the first-order model would suffice for approximating the response surface, especially within a relatively narrow range of the independent variable's space (Myers *et al.*, 2016). In cases where the system displays curvature, higher-order polynomial models become necessary to capture the more complex relationships between the response variable and the independent variables (Jankovic *et al.*, 2021). However, as the order of the polynomial increases, the model in plant growth becomes more complex and may require more data to accurately estimate the coefficients.

In most cases the true response surface curvature is typically strong enough that the first-order model is insufficient, even when the interaction term is added (Myers *et al.*, 2016). In these cases, a second-order model is needed. An approximate response such as yield, where we would anticipate operating close to a maximum point on the surface, might give rise to such a response surface (Khuri *et al.*, 2010).

An example of the second-order response surface model can be expressed as;

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 + \varepsilon \quad (3)$$

where y represents the plant growth,

β_0 the intercept term representing the average plant growth when effect of both water and warmth is zero

β_1, β_2 are the regression coefficients representing the linear effect of warmth and water

β_{11}, β_{22} Coefficients represent the quadratic effects of warmth and water

β_{12} The coefficient representing the interaction effect between warmth and water.

The central composite design is an experimental tool that enables efficient exploration of the response surface methodology, which represents the relationship between input factors and the output response (Khuri *et al*., 2018). The CCD typically starts with a factorial design, which involves varying each factor at two or more levels. This allows for the assessment of main effects and interactions among factors. Center points are added to the design to provide replicates at the center of the experimental region. These points are used to estimate the pure error and provide a baseline for assessing curvature in the response surface. In addition to the factorial and center points, CCD includes axial points, also known as star points. These points are located at a distance from the center in each factor direction and allow for the exploration of the curvature of the response surface away from the center (Khuri *et al.*, 2018).

The central idea behind CCD is to design an experiment that includes three types of experimental points: factorial points, axial points, and center points (Goia *et al.*, 2021). This design enables researchers to systematically vary input factors and observe their effects on crop yield while minimizing the number of experimental runs needed. The quadratic and interaction terms included in CCD enable the assessment of nonlinear relationships between input factors and crop yield. CCD allows for the efficient exploration of the response surface by incorporating both factorial points and additional axial points. This is often considered in experiments aimed at optimizing the yield of a crop using Response Surface Methodology (RSM) (Goia *et al.*, 2021). By analyzing the experimental data obtained from these points, a response surface model can be developed to forecast and optimize groundnut yield in response to the application rate of organic manure.

The application of organic manure such as poultry, rabbit, and sheep manure in this study will help provide essential plant nutrients such as nitrogen (N), phosphorus (P), and potassium (K). These organic manures are rich in nutrients and organic matter, making it beneficial for enhancing soil fertility and promoting plant growth. The Central Composite Design (CCD) is used in optimizing the process and evaluating the relationship and the relative significance between the independent variables (Khuri *et al.*, 2018). This design enables researchers to systematically vary input factors and observe their effects on crop yield while minimizing the number of experimental runs needed. CCD allows for the efficient exploration of the response surface by incorporating both factorial points and additional axial points.

In a study by Olajide, (2014) the study seeks to Optimize Oil Yield from Groundnut Kernel (*Arachis hypogeae*) in a hydraulic press using response surface methodology**.** A five factor, five levels central composite design (CCD) was applied to determine the effects of five independent variables (moisture content, heating temperature, heating time, applied pressure and pressing time) on oil yield. Response surface analysis method was employed to optimize the parameters in the experiment. The results showed that all the variables significantly affected the oil yield at 95% confidence level. Optimum oil yield of 32.36 % was obtained when the moisture content, heating temperature, heating time, applied pressure and pressing time were 8.13%, 81.93ºC, 7.03 minutes, 15.77 Mpa and 6.69 minutes, respectively. The experimental values were very close to the predicted values and were not statistically different at $p<0.05$.

Incorporating organic manures like rabbit, poultry, and sheep manure in this study facilitates the provision of crucial plant nutrients such as nitrogen (N), phosphorus (P), and potassium (K). These organic sources are abundant in nutrients and organic matter, thus enhancing soil fertility and fostering plant growth (Singh *et al*., 2020). The utilization of Central Composite Design (CCD) serves to optimize the process and assess the relationship and relative importance among the independent variables. This design enables researchers to systematically vary input factors and observe their effects on crop yield while minimizing the number of experimental runs needed. By integrating both factorial and additional axial points, CCD efficiently explores the response surface, allowing for a comprehensive understanding of the experimental system.

1.2 Statement of the Problem

In Kenya, the demand for groundnut has increased due to its source of proteins to human beings and also being a source of income in some of the regions in the country. Despite the demand, Kenyan groundnut production has been declining with farmers achieving below the potential expected yield, partly meeting 20% of the necessary groundnut demand, yet the country has capacity to produce more. For the last seven years, the Agriculture and Food Authority's (AFA) Nuts and Oil Crops Directorate has consistently released annual statistical reports demonstrating groundnut yield reduction. However, maximizing groundnut yield can be challenging due to various factors like nutrient availability, pest management, and diverse growing conditions. Response Surface Methodology (RSM) has shown promise in optimizing crop yields, a gap exists in understanding how this technique can be applied to groundnut production, particularly considering the use of manure as a nutrient source. The primary goal of Response surface methodology is to establish a relationship between explanatory variables (such as rabbit, poultry, and sheep manures) and response variables (the number of pods per plant, number of seeds per plant, and weight of grains per plant) using a mathematical model. This study seeks to investigate the use of CCD and RSM in formulation of optimal use of rabbit, poultry and sheep manure for maximum yield of groundnuts.

1.3 Objective

1.3.1: General Objective

The broad objective of the study was to determine the optimal groundnut production using organic manure through response surface methodology.

1.3.2: Specific Objectives

i. To determine the effect of organic manure on groundnuts yield
ii. To determine a functional relationship between the groundnut yield and the organic manure that can be used to predict the response value
iii. To obtain the optimal levels of the organic manure that produces a maximum groundnut yield

1.4 Research Hypotheses

H_{01}: There is no statistically significant effect of organic manure on groundnuts yield

H_{02}: There is no functional relationship between the groundnut yield and the organic manure that can be used to predict the response value

H_{03}: There is no significant optimal level of the organic manure that produces a maximum groundnut yield

1.5: Significance of the Study

The employment of scientific models, and response surface methodology, offers a promising avenue for maximizing crop yield while concurrently reducing input costs for small-scale farmers. This approach not only enhances agricultural efficiency but also alleviates financial burdens on farmers, thereby improving their economic sustainability. Importantly, the study underscores the potential of increased food crop production to uplift the livelihoods of smallholder farmers in Kenya, highlighting the substantial economic benefits that stem from advancements in agricultural science and practice. The study anticipates filling a knowledge gap and enriching existing literature on response surface methodology (RSM). By employing RSM to optimize crop yield, the research aims to offer valuable insights into agricultural practices. These findings hold relevance beyond the current study, serving as a resource for scholars and academicians interested in conducting research in this field.

This study provides policymakers with valuable information to make informed decisions and design effective policies. It helps them understand problems, evaluate solutions, and predict outcomes. This study will also aid in efficient resource allocation, monitoring policy effectiveness, and enhancing public accountability. Overall, research plays a crucial role in improving policy making by providing evidence-based insights and solutions to complex challenges. By utilizing RSM and CCD, the study will identify the optimal combination of factors such as manure application rates to maximize groundnuts yield. This information can help farmers in Kenya adopt more efficient and effective agricultural practices, leading to increased productivity and income.

The economic pillar of Kenya Vision 2030, which seeks to develop the country into a contemporary, globally competitive middle-income nation by 2030, has selected the agriculture sector as one of its primary industries. Because of this, the study's conclusions will be important to those involved in the creation and execution of public and private policies. The results of this investigation will be presented at a conference.

1.6 Scope of the Study

The experiment will be carried out at Chuka University Training and Teaching Farm, Kairini where groundnuts will be planted using different rates of sheep and rabbit manure. The study will employ a central composite design (CCD).

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

Groundnut (Archis hypogeal) production spans several centuries and is inextricably related to agricultural methods, trade, and culinary traditions around the world. Groundnuts are believed to have originated in South America, particularly in regions now part of Brazil and Peru, where indigenous peoples cultivated them as early as 3,500 years ago (Hammons *et al*., 2016). Spanish and Portuguese explorers introduced groundnuts to Europe in the 16th century, and from there, they spread to Africa, Asia, and other parts of the world during the Columbian Exchange. Groundnuts gained popularity due to their high nutritional value, adaptability to various climates, and versatility in culinary applications. In the 19th and 20th centuries, groundnut cultivation expanded significantly, particularly in regions with suitable climates such as sub-Saharan Africa, India, China, and the United States (Hammons *et al*., 2016). Today, groundnuts are a vital crop for millions of smallholder farmers and a key component of global food security, with production continuing to evolve through advances in agricultural technology, breeding programs, and sustainable farming practices.

In 2020, global peanut production reached 47 million tons, with China contributing the largest share. China alone produced 18.3 million tons, nearly half of the world's total output (Navaratnarajah *et al*., 2023). Alongside China, other significant peanut-producing nations include India and Argentina. Though being the largest producer in the world there has been a consistent increase in demand of peanuts and peanut oils in the country thus becoming a small importer of groundnuts. In 2021, Argentina emerged as the top exporter of groundnuts globally, shipping approximately $958.9 million worth of products. In Africa, Nigeria holds the position of the leading producer of groundnuts with 4.5 million metric tones, while in Kenya the western region has long been the major growing areas for groundnuts.

Groundnuts thrive in warm climates with temperatures ranging between 20°C to 30°C (68°F to 86°F) throughout the growing season. They are sensitive to frost and require a frost-free period of at least 4 months. Additionally, groundnuts need ample sunlight for proper growth and development. Groundnuts grow best in well-drained soils, particularly sandy loam or sandy clay loam, with a preferred pH level between 5.8 and 6.5. (Kadiyala *et al.,* 2021) The soil should be deep, loose, and friable to allow for good root development and penetration. Compacted or waterlogged soils should be avoided as they can hinder root growth and lead to poor aeration.

There are several varieties of groundnuts, each with different characteristics suited to various growing conditions and end uses. Varieties may differ in size, shape, shell color, and oil content. Breeding programs continually develop new varieties with improved yield, and other desirable traits (Singh *et al*., 2020). They are usually ready for harvesting within 100 to 150 days after planting, depending on the variety and growing conditions. Harvesting involves uprooting the entire plant or digging up the underground pods. After harvesting, the plants are left to dry in the field or cured to facilitate easier removal of the pods from the plants. Once harvested, groundnuts undergo processing to separate the pods from the plants and remove any remaining debris (Desmae *et al*., 2017). This may involve threshing, cleaning, and drying the pods. The dried pods are then shelled to extract the kernels, which can be consumed raw or roasted, or processed into various products such as peanut butter, oil, flour, and snacks.

2.1.1 Effect of Rabbit Manure on Crop Growth and Yield

Rabbit manure is a valuable organic fertilizer that can improve soil fertility and enhance plant growth. It is rich in essential nutrients such as nitrogen, phosphorus, and potassium, as well as organic matter, which can benefit soil structure and water retention (Sheteiwy *et al.,* .2020. Empirical studies have provided evidence supporting the use of rabbit manure as a valuable organic fertilizer in agriculture and horticulture. Rabbit manure offers numerous benefits, including improved soil fertility, enhanced plant growth, increased crop yields, and environmental sustainability (Sheteiwy *et al.,* 2020). Further research is needed to optimize the application of rabbit manure and explore its potential in diverse agricultural systems.

In (Abdelhalem,2022), study the impact of furrow irrigation techniques, rabbit waste rates, and potassium fertilizer levels on potato yield was examined. The experiment followed a split-plot design with three replications. Potassium sulfate was administered to the sub-subplots, rabbit manure to the subplots, and furrow irrigation was assigned to the main plots. Results indicated significant effects on potato tuber yields as well as the nitrogen (N), phosphorus (P), and potassium (K) content. In both the initial and subsequent seasons, the highest yields recorded were 37.87 and 38.35 t/ha, respectively.

Udayana *et al., (*2020) estimated the effects of rabbit compose and NPK on the growth of zucchini (*Cucurbita pepo*) using a factorial randomized blocked design. The results showed that the interaction between the NPK and rabbit composition had no significant effect on all the variables. The highest fresh fruit weight was obtained at the rabbit manure compared with treatments that had not composed an increase of 16.09 %.

2.1.2 Effect of Poultry Manure on Crops Growth and Yield

Poultry manure is an organic fertilizer derived from the droppings of chickens or turkeys. It is abundant in nitrogen, phosphorus, and potassium essential nutrients (Ashworth *et al*., 2020). In order to boost plant development, crop yields, and improve soil fertility, poultry manure is frequently utilized in agriculture. By boosting nutrient availability and adding organic matter, its application improves agricultural soils' long-term health and productivity. Beneficial bacteria found in poultry manure help promote the diversity and activity of soil microbiota. Poultry manure is generally appreciated for its potential to improve agricultural output in a sustainable manner while fostering soil health and environmental responsibility (Ashworth *et al*., 2020).

According to (Rasool *et al*., 2023) who investigate on the effect of different rates of poultry manure on the soil chemical properties, growth, and yield of maize. This study was conducted to determine the effect of various treatments of poultry manure on the morphological, physiological, and yield attributes of two maize varieties, Pearl and MMRI. The results showed a significantly improved of maize varieties with application of poultry manure. It is also showed that poultry manure is an eco-friendly and economical for maize growers of arid and semi-arid. Poultry manure could be useful to ameliorate the adverse effects of salinity stress on all parameters, particularly the grain yield.

According to (Oke *et al*.,2020), who conducted a study to assess the effect of poultry manure levels on the growth and yield of cucumber (*Cucumis Sativus* Linn*)*, a randomized complete block design (RCBD) was employed. The experiment comprised two treatments and a control, each replicated five times, resulting in fifteen treatments in total. Significant differences were observed in growth and yield parameters between the two treatments. Results indicated that cucumber plants treated with 15g of poultry manure exhibited the highest number of leaves (62.28), vine length (44.04 cm), vine diameter (4.86 cm), and number of branches (4.5). Consequently, this treatment yielded substantial fruit production, with an average of 18.1 cm/ha for fruit length, 4.5 cm/ha for fruit diameter, 4.8 for the number of fruits, 169.5 g/ha for average fruit weight, and 31.9 t/ha for yield. Notably, both leaf production and vine diameter significantly increased ($p<0.05$ and $p<0.1$, respectively). Interactions among other parameters were deemed non-significant, except for average fruit weight. The study recommends the application of poultry manure at 15 t/ha for commercial cucumber production, attributing to rapid growth and high yield.

In a study investigating the effects of chicken manure on cassava conducted by (Biratu *et al*., 2018), four treatment levels of chicken manure (0, 1.4, 2.8, 4.2 tons/ha) along with a single level of mineral NPK applied at 100N-22P-83K kg/ha were evaluated. The experiment was designed as a Randomized Complete Block Design (RCBD) with three replications, utilizing the improved cassava variety "Mweru". Results indicated that the treatments had a significant ($p < 0.05$) impact on various yield components of cassava, including fresh and dry root, leaf, stem, and total biomass. The application of 4.2 tons/ha of chicken manure resulted in the highest mean fresh root yield (27.66 tons/ha), dry root yield (9.55 tons/ha), total fresh biomass (53.68 tons/ha), and dry biomass (16.12 tons/ha). All treatments involving chicken manure exhibited positive marginal rates of return (MRRs), with the highest percentage (315%) observed for the application of 4.2 tons of manure per hectare. These findings suggest that the use of chicken manure represents a cost-effective approach to significantly enhance cassava yield and biomass production.

In a study investigating the impact of poultry manure and NPK fertilizer on soil physical properties and the growth yield of carrots (Agbede *et al*., 2017), a field experiment was conducted. The experiment involved the application of poultry manure and NPK fertilizer to assess their effects on soil physical properties, growth, and yield of carrot plants. Five treatments were evaluated, including a control (no fertilizer), 300 kg/ha of 15 N-15 P-15 K fertilizer, and three levels of poultry manure (10, 20, and 30 megagrams Mg/ha). Results indicated that all levels of poultry manure improved overall soil porosity and moisture content while reducing soil temperature and bulk density compared to the control and NPK fertilizer treatments. Furthermore, compared to the control, treatments with poultry manure and NPK fertilizer resulted in enhancements in plant height, leaf count, root diameter, root length, and fresh root yield. Specifically, carrot plants treated with 20 and 30 mg/ha of poultry manure exhibited higher growth and yield metrics. These treatments contributed to a substantial increase in fresh root production of carrots compared to the control, with poultry manure and NPK fertilizer treatments leading to improvements of 39.9%, 62.0%, 64.9%, and 37.3%, respectively. Overall, soil characteristics and carrot productivity were most improved by the 20 mg/ha poultry manure treatment.

2.1.3 Effect of Sheep Manure on Crops Growth and Yield

Sheep manure is another valuable organic fertilizer that has been the subject of empirical studies investigating its agricultural benefits. Empirical studies have consistently shown that the application of sheep manure improves soil structure, increases nutrient availability, and boosts crop yields while enhancing the quality of fruits, vegetables, and grains. Additionally, sheep manure contributes to weed suppression and pest control in agricultural fields, reducing the reliance on synthetic herbicides and pesticides (Lal *et al.*,2020). From an environmental perspective, sheep manure is considered a sustainable alternative to chemical fertilizers as it reduces nutrient runoff and leaching, minimizes environmental pollution, and promotes soil health and biodiversity.

Many studies have not taken into consideration the potential benefits of using sheep manure in enhancing crop yield and improving soil quality. Jia *et al.*, (2023) conducted research on the application of sheep manure fertilizer to mitigate soil acidification and enhance tea yield and quality. Different depths of sheep manure fertilizers were applied to assess their effects on soil acidification, tea yield, and quality over a five-year period from 2018 to 2022. The long-term application of sheep manure fertilizer led to improvements in soil pH and ammonium nitrogen content, increased root activity, and enhanced root nitrogen uptake capacity in tea plants, resulting in improved tea output and quality. The study findings indicated a significant reduction in soil acidification ($P<0.05$) in tea plantations due to the application of sheep manure fertilizer (Jia *et al.*, 2023).

Yang *et al*., (2021) conducted a study to examine the impact of combining sheep waste with chemical fertilizer on maize yield, quality, and the temporal distribution of soil inorganic nitrogen. The research employed a randomized block design comprising six treatments: T3 involved a mixture of 15% sheep manure with chemical fertilizer, T4 combined 30% sheep manure with chemical fertilizer, T5 incorporated 45% sheep manure along with chemical fertilizer, and T6 solely utilized sheep manure. Additionally, the experiment included a single application of chemical fertilizer in T2. For every treatment, the same amounts of potassium, phosphorus, and nitrogen are used. The outcome revealed that the T1 treatment yields the least, followed by the T6 treatment; however, the yield of sheep manure mixed with chemical fertilizer is significantly higher. Additionally, it demonstrated that a combination of chemical fertilizer and sheep manure could somewhat enhance the quality of maize kernels. The partial productivity of nitrogen fertilizer in the T3 and T5 treatments was 3.7% and 0.8% higher than in the T2 treatment, and the agronomic utilization rate was 10.9% and 1.6% higher than in the T2 treatment. T6 is significantly less effective than T2 therapy. It attests to the fact that applying chemical fertilizers along with sheep manure can raise the nitrogen fertilizer's partial productivity and agronomic utilization rate, which in turn can raise crop yields and farmers' income.

In a study conducted by (Abubaker *et al*.,2020) investigated the response of winter wheat to varying application rates of raw and digested sheep manures, both individually and in combination with urea. Six application rates, or 50, 150, 250, 350, 450, and 550 kg Tot N ha^{-1}, were employed in the study's pot experiment, with unfertilized soil serving as the control. The study assessed several growth variables, including plant height, plant tillering percentage, leaf area, ear length, biomass yields of ears, straw, and roots, total biomass, grain yield, weight of fifty seeds, and percentage of protein in the grain. According to this study, digested sheep dung does not stimulate wheat development and production as well as raw sheep dung does.

When it was combined with urea, the results improved, while the addition of urea did not significantly increase the value of raw manure, it did improve the performance of digested manure. According to this study, high rates of application of both raw and digested sheep manure, either on its own or in combination with urea, are required to produce high grain yields of good quality from the soil.

An experiment was designed by (Sajid Khan *et al*., 2017) to assess the impact of sheep manure (AT) and nitrogen fertilizer (urea) on the harvest index and dry matter partitioning of maize crops. Split-plot arrangements for RCBD were used in this experiment. The primary plots received the sheep manure, which was applied both before and during the sowing process. In the sub-plots, nitrogen fertilizer (N) was applied at three different rates: N1 = 0 kg/ha, N2 = 90 kg/ha, and N3 = 120 kg/ha. The application of 5 t/ha of sheep manure 15 days prior to sowing significantly enhanced pre-tasseling (stem and leaves), physiological maturity (stem, leaves, cobs, and grains), dry matter partitioning, and harvest index. Dry matter accumulation increased with treatment before tassels and at physiological maturity. The study recommends applying 5 tons of sheep manure per hectare 15 days before sowing, along with 120 kilograms of nitrogen per hectare, for achieving higher dry matter accumulation in maize crops.

2.2 Central Composite Design

A Box-Wilson Central Composite Design, often referred to as a "central composite design," encompasses an underlying factorial or fractional factorial design. Center points within this design are supplemented by a set of "star points that allow the estimation of curvature. (Myers *et al*., 2016). The application of a CCD in practice often involves sequential experimentation. That is, a 2^b design is utilized to create a first-order model. If this model shows a lack of fit, axial runs are subsequently introduced to enable the inclusion of quadratic terms into the model (Soltani, *et.al*, 2022).

Factorial points in a central composite design are one of the standard experimental points located at the corners of the experimental region. These points represent combinations of the highest and lowest levels of each factor. The factorial points consist of a 2^b factorial design $(\pm 1, \pm 1, \dots, \pm 1)$, Where b is the number of independent variables. The design can be replicated n_f times (Khuri *et al.,* 2018). These cube points help in estimating the main effects of each factor and can provide information about how changing one factor affects the response variable when all other factors are held constant. The star points are positioned at $2b$ units along the axis of each factor, located at a distance α from the center of the design [(±α, 0…0), (0, ±α, 0…, 0)]. Their selection adheres to orthogonality and rotatability criteria, involving one observation at each of the vectors $\pm \alpha e_i$, which can be replicated n_s times, where, e_i represents the i^{th}Euclidean unit vector, and $\alpha > 0$.The center points are designated as "0" points and can be replicated n_c times (Khuri *et al.,* 2018). Consequently, if n denotes the total number of experimental runs in the CCD, based on b design factors, we have:

$$n = 2^{b-p}\, n_f + 2bn_s + n_c$$

where;

n is the sample size

$2^{b-p}\, n_f$ is the factorial component of the design, replicated n_f times,

where b the number of factors varied and p is the number of factors subtracted from b.

$2bn_s$ is the axial component of the design replicated n_s times and

n_c is the number of times the Centre points.

There are three types of central composite design, circumscribed CCD, inscribed CCD, and face-centered CCD.

i. The circumscribed central composite design represents the original type of CCD, wherein the axial points are positioned at a distance α from the center points.
ii. In a Face-centered CCD, the axial points are situated at a distance of 1 from the center points, specifically when the design incorporates three experimental factors.
iii. Inscribed CCD is defined by axial points positioned at factors -1 and 1. Meanwhile, the factorial points are brought inward to the interior of the design

space and situated at a distance of $1/\alpha$ from the center points. (Khuri *et al*., 2018).

Table 1: The Central Composite Design Plans

Type of design	Description
Circumscribed central composite (CCC)	The star points lie beyond the initial experimental range (distance α). This setup necessitates five levels for each factor.
Central composite Face-centered (CCF)	With $\alpha = \pm 1$, the star points are located on the faces of the experimental domain. This design calls for three levels per factor.
Central composite Inscribed (CCI)	$\alpha = \pm 1$, this design is used when it is not possible to leave the experimental domain. The CCC design is then reduced to fit within this domain. This plan requires five levels per factor.

Source: Bouzid et al., (2014)

In response surface designs such as central composite designs and Box-Behnken second-order design should ideally be rotatable. This ensures that the curvature of the response surface is consistent across different orientations of the design space (Bhattacharya, 2021). This property is desirable because it allows for reliable estimation of model coefficients and predictions regardless of the direction in which the design is conducted. Rotatable designs provide more robust and efficient experimentation, as it ensures that the statistical properties of the model remain consistent and valid throughout the experimental region (Soltani *et.al.*, 2022). Therefore, when designing a second-order response surface experiment, it is beneficial to choose a rotatable design to achieve accurate and reliable results.

A design is considered orthogonal if it can offer independent information about the effects of different terms in the model (Myers *et al.*, 2016). To guarantee both orthogonality and rotatability of the design, a circumscribed composite design is often favored. This design ensures that any non-allowable operating conditions at two or more extremes of the design region are encompassed (Myers *et al.*, 2016). The design matrix for a CCD experiment with b independent variables is a matrix derived from the values corresponding to three types of experimental runs which is orthogonal and rotatable as shown in matrix R;

$$R = \begin{bmatrix} \pm 1_{1,1} & \pm 1_{1,2} & \cdots & \pm 1_{1,b} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha & 0 & \cdots & 0 \\ -\alpha & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \alpha \\ 0 & 0 & \cdots & -\alpha \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0_{n,1} & 0_{n,2} & \cdots & 0_{n,b} \end{bmatrix} \tag{17}$$

Box and Hunter (1957) asserted that a design of the aforementioned structure will be a rotatable design of order d if a response polynomial surface is fitted in such a way that the variance, $Var\hat{y}(x)$ is a function of x from the origin but not the direction, thus remaining constant at all points equidistant from the design center (Kasina *et al*., 2020). Achieving rotatability involves choosing an appropriate distance parameter α. For a full factorial design, α is typically set to $\propto = 2^{a/4}$, where ' a ' is the number of factors (Myers *et al*., 2016).

A Box-Behnken design is a type of response surface methodology (RSM) used to efficiently explore and optimize complex processes with multiple factors. It strikes a balance between full factorial and fractional factorial designs, requiring fewer experimental runs while still providing valuable insights (Ye *et al*., 2017). This design layout was created by Box and Behnken (1960). It includes a specific subset of the factorial combinations from the 3^k factorial design and offers three levels for each factor unlike central composite designs which can have up to five levels (Nikolett *et al*., 2023). Box and Draper (2007) as well as Myers and Montgomery (1995) developed the actual building of this design which can efficiently be used to estimate the model coefficients.

In this design, factors are studied at three levels (low, high, and mid) with the mid-level chosen as the midpoint between the low and high levels The experimental points are strategically arranged so that each factor is tested at the mid-level once and at the high and low levels twice, ensuring a thorough exploration of the response surface. (Nikolett *et al*., 2023). This design minimizes the number of experiments needed compared to full factorial designs, making it suitable for situations where conducting numerous experiments is impractical or costly.

The Box-Behnken design has no points at the vertices of the cubic region formed by the factors' upper and lower limits. This could be very useful when the points at the cube's corners indicate factor-level combinations that are prohibitively expensive or impossible to test due to physical process constraints. Also, unlike central composite designs, Box-Behnken designs never include runs where all factors are at their extreme setting. Some Box-Behnken designs are rotatable in some cases; however, this is not always the case (Ye *et al*., 2017).

In a study by (Muriithi, 2018) who applied Central Composite Design and response surface methodology in the formulation of optimal use of organic manure to obtain maximum growth and yield of watermelon using organic manure (poultry, goat, and cow manure). He found that poultry manure had a superior effect on the growth of the watermelon growth with a higher number of branches as compared to their counterparts possibly because higher rates of manure supplied nutrients required for vigorous growth. He also found that plants that received an adequate number of poultry and goat manure had a higher fruit weight. It showed that they were the most significant variables for the fruit weight of watermelon with the p values of goat being $p=0.00046$ and poultry $p=0.00052$.

Bahrim *et al*., (2017) utilized Central Composite Design and Response Surface Methodology to optimize the conditions for submerged cultivation of the *Fomes fomentarius* mushroom. They investigated the effects of dextrose concentration, yeast extract concentration, and cultivation duration on mushroom growth. The study found that the maximum yield of dry weight biomass reached 23.74 g/L after eleven days of submerged cultivation, with dextrose concentrations ranging from 0.8 to 7.5 g/L. This optimization was achieved through the application of Response Surface Methodology and Central Composite Design.

Using a randomized full block design, the impact of NPK fertilizers, chicken manure, and their mixtures on common beans revealed varied bean crop performance (Alhrout *et al*., 2016). Plant height, the average number of leaves per plant, the average number of pods per plant, grain yield per plant, and pod productivity per hectare were all taken into account in the study along with other yield and yield component factors. The treatment of both NPK and chicken manure considerably enhanced the production of common beans, according to the results; however, since chicken manure was less expensive than NPK hence chicken manure was recommended (Alhrout *et al*., 2016).

According to Dressaire, (2016), who demonstrated using CCD that convective airflows capable of delivering spores at centimeters per second were produced by the evaporative cooling of the air surrounding the pileus, that work revealed mushrooms' high-water requirements and showed how they can withstand and even benefit from crowding. It was evident that spores continuously flow out from thin gaps, even in the absence of external winds.

2.3 Response Surface Methodology

Response surface methodology (RSM) involves a set of mathematical and statistical methods utilized to establish a suitable functional connection between a response variable of interest, y, and a set of related control (or input) variables denoted as $x_1, x_2 \ldots x_b$ (Breig *et al*., 2021). Typically, this relationship is not explicitly known but can be estimated using a low-degree polynomial model structured as follows;

$$y = f'(x)\beta + \varepsilon \qquad (4).$$

where $x = (x_1, x_2, \ldots, x_b)', f(X)$ is a vector function of b elements comprising of quadratics and cross-products of powers of $(x_1, x_2, \ldots, x_b)$ up to a specified degree denoted by $d(\geq 1)$.

β Is a vector of n unknown constant coefficients

ε Is a random experimental error

The expectation of the response (y) is represented as;

$$E(y) = f'(x)\beta$$

Two important models that are commonly used by response surface methodology, including the first-order and the second-ordered model, these models are special cases for models (4). The first-order model is suitable when the researcher aims to approximate the genuine response surface within a limited area of the independent variable space, particularly in scenarios where the response function exhibits minimal curvature. (Montgomery, 2013). This model can be expressed as,

$$y = \beta_0 + \sum_{i=1}^{b} \beta_i x_i \varepsilon \quad (5)$$

The second-order model can be expressed as

$$y = \beta_o + \sum_{i=1}^{b} \beta_i x_i + \sum_{i=1}^{b} \beta_{ii} x_i^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \quad (6)$$

The purpose for response surface methodology includes

i. To establish a relationship between the response variable and the independent variables that can be used to predict the response value
ii. To determine the statistical significance of the factor variables $x_1, x_2 \dots x_b$
iii. To find the optimum setting of $x_1, x_2 \dots x_b$, that gives a maximum or minimum response over a certain region of interest.

To achieve its goal, a set of experiments is first conducted to measure the response y for a given settings of input variable. These configurations collectively form the response surface design, which can be depicted by a matrix **A** of order (**n**$\times$ $\boldsymbol{b}$) known as the design matrix.

where $x_{i,j}$denotes the i^{th} design setting of x_j for $i = 1,2 \dots n$; $j = 1,2 \dots b$

$$\boldsymbol{A} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1b} \\ x_{21} & x_{22} & \cdots & x_{2b} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nb} \end{bmatrix} \quad (7)$$

The rows in $\boldsymbol{A}$ are the design points in a b-dimensional Euclidean space. Letting y_v be the response value measured by applying i^{th} settings of x, that is,

$x_i = (x_{i1}, x_{i2}, \dots, x_{ib})'$ for $i = (1,2, \dots, n)$ and about equation (4) we get

$$y_v = f'(x)\beta + \varepsilon_i \quad i = 1,2, \dots, n \quad (8)$$

where ϵ_i is the error term at i^{th} experimental run. In matrix notation, the polynomial model (4) is expressed as

$$y = X\beta + \epsilon \tag{9}$$

where, $\boldsymbol{y} = (y_1, y_2, \dots, y_n)'$, X be a $(n \times b)$ matrix whose i^{th} row is $f'(X_u)$ and $\boldsymbol{\epsilon} = (\boldsymbol{\epsilon}_1, \boldsymbol{\epsilon}_2, \dots, \boldsymbol{\epsilon}_n)'$. The first column for the variable matrix $\boldsymbol{X}$ comprises ones 1_n (Khuri, 2010).

To estimate the model parameters β the least square method is used and the choice of β's should minimize the sum of square of error ϵ_i. The least-square estimator function is

$$e = \sum_{i=1}^{n} \epsilon_i{}^2$$

$$e = \sum_{i=1}^{n} \epsilon_i{}^2 = \epsilon'\epsilon = (y - X\beta)'(y - X\beta)$$

$e = y'y - \beta'X'y - y'X\beta + \beta'X'X\beta$; $\beta'X'y$ is a scalar matrix and its transpose

$(\beta'X'y)' = y'X\beta$ is the same scalar. Therefore,

$$e = y'y - 2\beta'X'y + \beta'X'X\beta \tag{10}$$

According to Montgomery (2004), the function e is minimized with respect to β and the resulting least square estimators $\hat{\beta}$ minimize equation (10) and must satisfy equation (11 which is the matrix form of the least square normal equation.

$$\left.\frac{\partial e}{\partial \beta}\right|_{\hat{\beta}} = -2X'y + 2X'X\,\hat{\beta} = 0$$

$$X'X\beta = X'y \tag{11}$$

The least squares estimator of β is given by equation (12).

$$\hat{\beta} = (X'X)^{-1}X'y \tag{12}$$

Given that ϵ has a mean of zero and a variance-covariance matrix given by $\sigma^2 1_n$, then variance-covariance matrix of $\hat{\beta}$ has the form given by the equation (13).

$$var(\hat{\beta}) = (X'X)^{-1}X'(\sigma^2 1_n)X(X'X)^{-1}$$

$$= \sigma^2 (X'X)^{-1} \tag{13}$$

The estimate $\hat{y}$ of the mean response at x_i is obtained by substituting β with $\hat{\beta}$ as in equation (14). This is the predicted response $\hat{y}(x_i)$ at the i^{th} design point.

$$\hat{y}(x_i) = f'(X_i)\hat{\beta}, i = 1,2, \dots, n \tag{14}$$

Generally, at any given point x, in the experimental region of interest, the expected response $\hat{y}(x)$ is,

$$E(\hat{y}(x)) = f'(X)\hat{\beta}, x \epsilon \text{ region of interest} \quad (15)$$

For $\hat{\beta}$ is an unbiased estimator of β, it implies $\hat{\boldsymbol{y}}(\boldsymbol{x})$ is an unbiased estimator of $f'(X)\beta$. From equation (15) the variance of $\hat{y}(x)$ assumes the form

$$var[\hat{y}(x)] = \sigma^2 f'(X)(X'X)^{-1}f(X) \quad (16)$$

In response surface proper choice of design is crucial since the quality of prediction, as measured by the size of the prediction variance, depends on the design matrix **A** (Khuri *et al.*, 2018). Moreover, the determination of these optimum response amounts to finding the optimal value of $\hat{y}(x)$ over the region of interest. It is therefore necessary that the prediction variance be as small as possible provided that equation (1) does not suffer from lack of fit. The region of interest (response surface) can be visualized graphically. The graph helps in seeing the shape of the response surface; hills, valleys, and ridge lines. Therefore, the function $y = f(x_1, x_2)$ can be plotted versus the levels of x_1, and , x_2 as shown in Figure 1, (Breig *et al.*, 2021)

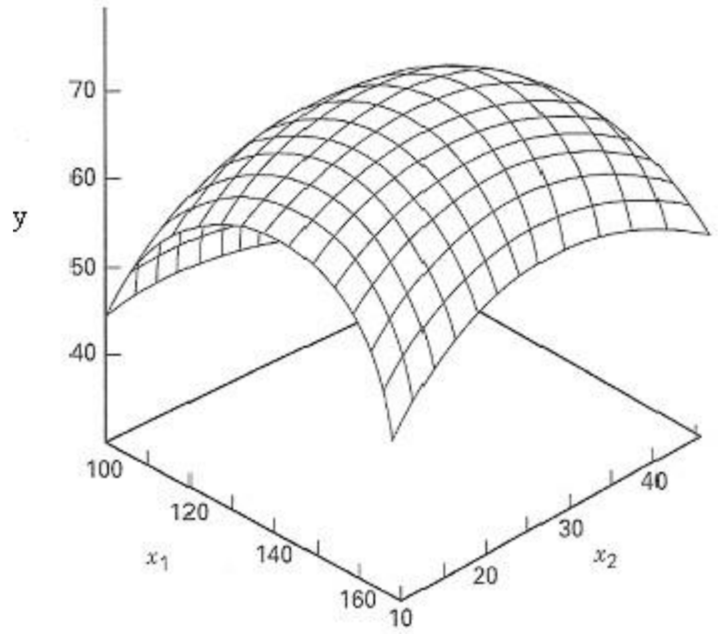

Figure 1: Response Surface Plot

A response surface plot is a three-dimensional graph illustrating the response surface from a single perspective. Representing the response on a two- dimensional graph makes it easier to visualize. Contour plots depict lines connecting pairs of x_1 and x_2

values that yield the same response value y. An example of contour plot as shown in Figure 2

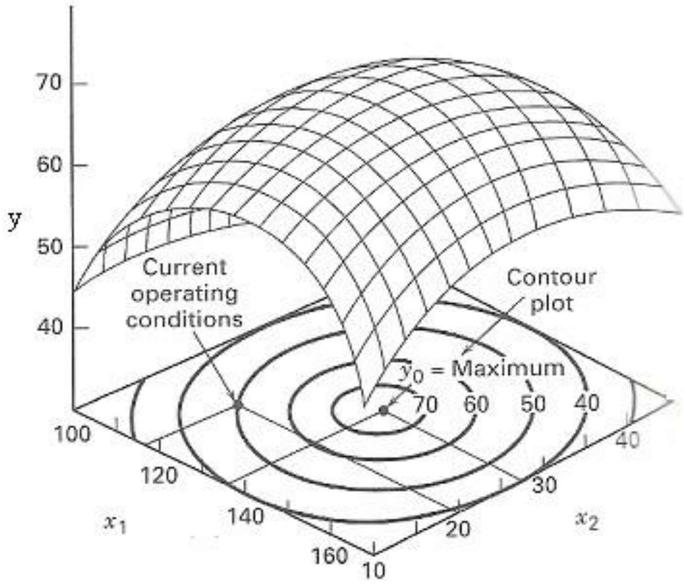

Figure 2: Contour Plots

To understand a response's surface, graphs are useful tools. Graphs, however, are hard or nearly impossible to use to show the response surface when there are more than two independent variables because they are beyond three dimensions. Response surface models are therefore crucial for analyzing the unknown function f (Breig *et al*., 2021).

2.3.1 Empirical Studies on Response Surface Methodology

Tüfekçi *et al.,* (2023) conducted a study whereby they employed response surface methods to optimize the process parameters of hybrid drying sweat potato. The drying time was the researched response, and the study took into account air temperatures, microwave power, and other independent parameters. Producing dried potatoes with a maximum rehydration ratio, water-holding capacity, and minimal bioactive content in the shortest amount of time was the primary criterion for optimizing the hybrid drying of sweet potatoes. A drying temperature of 54.36 °C and a microwave power of 101.97 W were found to be the optimum conditions.

In a study by (Muhammad *et al*., 2021) This study evaluated the influence of drum speed, moisture content, and feed rate on the performance indices of groundnut sheller using Ex-Dakar groundnut variety. Response surface methodology was used to study the influence of input variables and optimize the processing conditions. The developed second-order polynomial model adequately described the performance responses, including output capacity, shelling and cleaning efficiencies, and kernel damage. The input variables indicated significant influences on performance responses. The optimized processing variables for the responses were drum speed of 210 rpm, moisture content of 8%, and feed rate of 350 kg·h-1. The optimum responses obtained were output capacity of 302.52 kg·h-1, shelling efficiency of 97.61%, cleaning efficiency of 53.16%, and kernel damage of 4.04%. These performance responses were validated experimentally and were close to the observed results. d manufacturing to improve processes efficiently and effectively.

In the study by (Masai *et al*., 2020) also researched on the application of response surface methodology in complete block design. The study considered various yield and yield components i.e. average number of leaves per plant, average of pod number per plant, grain yield per plant, and pod productivity per hectare. The study found that poultry and goat manure were significant in the growth of the common beans while cow manure was insignificant. He also found that the number of pods had an effect on the organic manure applied, with poultry and goat manure showing a positive effect.

2.4 Optimization of Response Surface

To determine the levels of x_1, x_2, x_3 that optimizes the response, the point of optimum therefore becomes a set of x_1, x_2, x_3 for which the partial derivatives given in equation (17) are zero.

$$\frac{\partial \hat{y}}{\partial x_1} = \frac{\partial \hat{y}}{\partial x_2} = \frac{\partial \hat{y}}{\partial x_3} = 0 \qquad (17)$$

$$\hat{y} = \hat{\beta}_0 + \boldsymbol{X'd} + \boldsymbol{X'\beta X}$$

where $\boldsymbol{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ $\boldsymbol{d} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \end{bmatrix}$ $\boldsymbol{\beta} = \begin{bmatrix} \hat{\beta}_{11} & \hat{\beta}_{12} & \hat{\beta}_{13} \\ \hat{\beta}_{21} & \hat{\beta}_{22} & \hat{\beta}_{23} \\ \hat{\beta}_{31} & \hat{\beta}_{32} & \hat{\beta}_{33} \end{bmatrix}$ (18)

Differentiating $\hat{y}$ with respect to the elements of the vector X and setting it equal to zero, we have,

$$\frac{\partial \hat{y}}{\partial \boldsymbol{X}} = \boldsymbol{d} + 2\boldsymbol{\beta X} = 0 \quad (19)$$

This circumstance arises at the stationary point where the set of x_1, x_2, x_3 mathematical solution corresponds to the optimal values for the input variables that maximized the response. The mathematical solution for the set of x_1, x_2, x_3at the stationary point that produces the optimal values was deduced from equation (19), and it is represented as

For second-order model in matrix notation

Thus, the stationary point was given by;

$$x_s = -\frac{1}{2}\boldsymbol{\beta^{-1} d} \quad (20)$$

Thus, the yields of groundnut at the stationary point were therefore be predicted by

$$\hat{y} = \hat{\beta}_0 + \frac{1}{2}\boldsymbol{X^{-1} d} \quad (21)$$

Once the stationary point is established, this study evaluated whether it represents a maximum, minimum, or saddle point by analyzing the response surfaces and the corresponding contour plots.

CHAPTER THREE
METHODOLOGY

3.1 Study Site

The research was done at the Chuka University Teaching and Training Farm in Kairani, situated roughly 186 km away from Nairobi along the Nairobi-Meru highway, within Tharaka Nithi County in Meru South, Kenya. In this region, the prevalent soil type is Humic Nitisols (Jaetzold *et al.*, 1983). The soils are characterized by their depth, extensive weathering, and inherent fertility ranging from moderate to high, making them naturally fertile. The altitude is approximately 1560 meters above sea level. Its longitude is 37.6575° E, and its latitude is 0.3190° S. The region's yearly rainfall varies, with the western part receiving 2208 mm and the eastern part receiving 544 mm. With yearly average temperatures of about 19.5°C, the climate is warm. This area has the potential to develop into an agricultural area, with farming being defined by the growth of crops and the primarily small-scale keeping of cattle. The principal crops that are grown are vegetables, beans, bananas, coffee, maize, sunflowers, and groundnuts.

3.2: Establish the Effect of Organic Manure on Groundnuts Yield Parameters

3.2.1 Design of Experiment

The experiment was laid out in a central composite design with 20 experimental runs determined by 2^3 full factorial design with six axial points and six center points. 3 factors and 5 levels central composite design was applied in the groundnut's growth process. Poultry (x_1), rabbit (x_2) and Sheep (x_3) manure were the independent variables that were used in this study to optimize the yield of groundnuts and its yield components.

The experiment was carried out in a Randomized complete Block Design (RCBD) with four replicates. Rates of poultry manure, rabbit manure and sheep manure in tons per hectare were as shown in Table 2. The manure was incorporated into the soil two weeks before planting.

3.2.2 Central Composite Design

Central Composite Design (CCD) was utilized because this design extends the Box-Behnken design by including additional points at the center of the design space and at the extremes. These additional points allow for the estimation of curvature in the response surface and provide more information for fitting a quadratic model. The center runs provide information regarding curvature, while additional axial points were incorporated to facilitate efficient estimation of quadratic terms in cases where significant curvature is observed.

When constructing the regression model, the test variables were transformed according to the formula given as.

$$X_i = \frac{x_i - x_o}{x} \quad (22)$$

where X_i is a coded variable of the i^{th} variable, x_o is an average of the variable in high and low level, x is half of the difference between the levels of the i^{th} variable and x_i is an encoded value of the i^{th} test variables.

The i^{th} actual variables X_i corresponding to the axial variable coded $\pm\alpha$ are obtained through the equation (23)

$$X_i|_{\pm\alpha} = \varphi_i \pm \alpha x \quad (23)$$

where φ_i is the current operating condition for the i^{th} variable and x being half of the difference between the levels of the i^{th} variable.

The experimental natural variables and their coded factors to be applied in this experiment are as in Table 2.

Table 2: Actual Variables and the Coded Factor Levels

Independent variable	Coded and natural factor levels				
	-1.682	-1	0	1	1.682
Poultry manure (x) tons/ha	1.908	6	12	18	22.092
Rabbit manure (x_2) tons/ha	1.908	6	12	18	22.092
Sheep manure (x_3) tons/ha	1.908	6	12	18	22.092

For this study the natural variables X_i corresponding to the axial variable coded $\pm\alpha$ therefore with reference to equation 19 it becomes:

$X_1|_{\pm\alpha} = 12 \pm 1.682(6)$, $X_2|_{\pm\alpha} = 12 \pm 1.682(6)$ and $X_3|_{\pm\alpha} = 12 \pm 1.682(6)$

The value of the parameter α for a given α in CCD represents the distance of the axial points from the center of the design, and its value influences the shape and properties of the experimental design. This parameter α can be obtained by the formula in table 3;

Table 3: The Value of the Parameter α for a Given CCD Design Plan

Design Characteristic	α
Rotatability	$\alpha = \sqrt[4]{N_f}$
Orthogonality	$\alpha = \sqrt{\frac{\sqrt{N_f + N} - N_f}{2}}$
Rotatability and Orthogonality	$\alpha = \sqrt[4]{N_f}$

where N_f is the number of experimental runs in the factorial portion

N is the total number of experimental runs

The value of the axial parameter α will now be obtained as,

$$\alpha = \sqrt[4]{N_f} = \sqrt[4]{(2^b)} = \sqrt[4]{(2^3)} = \pm 1.682 \quad (24)$$

So as to ensure consistent and stable variance this study employed central composite design which is both rotatable and orthogonal. A rotatable design in the context of response surface methodology is achieved when its precision remains the same at all points on a sphere centered at the origin (Myers *et al*., 2016). Rotating a rotatable design about the center, its variance on the response will remain the same. The study uses three factors (*b=3*) rabbit manure, poultry manure and sheep manure whose effect on the yield of groundnuts production measured as the response surface and 5 levels.

The application of a CCD in practice typically involves a step-by-step process of experimentation (Myers *et al*.,2016). That is, a 2^3 design is utilized fit a first-order model, which may exhibit a lack of fit. Subsequently, axial runs are introduced to enable the inclusion of quadratic terms into the model (Soltani *et al*., 2022). The full factorial CCD design for this study consisting of experimental runs, coded variable and actual values is shown in the Table 4

Table 4: Full Factorial Central Composite Design Matrix

	Coded Values			Weight Yield	Number 0f Pods	Number of Seeds
run	X_1	X_2	X_3	y_1	y_2	y_3
1	-1	1	-1	372	82	159
2	1	1	-1	406	96	180
3	-1	-1	1	360	77	158
4	1	-1	1	381	99	190
5	-1	0	-1.682	360	78	165
6	1	0	1.682	361	80	180
7	-1	-1	0	380	88	174
8	0	-1	0	384	89	180
9	-1.682	0	0	370	79	148
10	1.682	0	0	410	103	200
11	1	-1.682	0	389	96	190
12	0	1.682	0	378	80	165
13	0	1	0	393	93	184
14	0	1	0	405	98	185
15	0	0	0	399	94	186
16	0	0	0	400	97	190
17	0	0	-1	379	87	184
18	0	0	-1	378	81	180
19	0	0	1	381	92	178
20	0	0	1	370	80	175

3.3 Determine a Functional Relationship Between Groundnuts Yield and Organic Manure

3.3.1 Response Surface Methodology

Response Surface Methodology (RSM) is a set of statistical and mathematical tools used for modeling and analyzing problems where a response variable is influenced by several (three) factors, with the goal of optimizing this response. (Breig *et al.*, 2021). RSM simplifies the evaluation of the experimental controllable variables that may or otherwise have a significant effect on the yield of groundnuts production. 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 (yield of groundnuts, number of pods and number of seeds)
ii. Develop a Mathematical model of the second-order model with best fittings
iii. Evaluate the optimal set of experimental parameters, that produces a maximum value of yield of groundnuts

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

3.3.2 Fitting a Second Order Model

Central composite design (CCD) was applied in this study in determining an appropriate relationship between yields of groundnuts and organic manure applied poultry manure (x_1), rabbit manure (x_2) and sheep manure (x_3). A second order model given by equation (25) was successfully used for describing this relationship.

$$y_i = \beta_0 + \sum_i^3 \beta_i x_i + \sum_{i=1}^3 \beta_{ii} x_i^2 + \sum\sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \qquad (25)$$

where $i, j = 1,2,3; i \neq j$)

y_1 weight in grams per plant

y_2 number of pods per plant

y_3 number of seeds per plant

β_0 constant

β_i linear coefficient

β_{ii} coefficient of pure quadratic terms

β_{ij} interaction terms

In matrix form equation (21) take the form of equation (26)

$$y = \widehat{\beta_0} + X'd + X'\beta X + \epsilon \qquad (26)$$

where $y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{20} \end{bmatrix}$ $X = \begin{bmatrix} 1 & x_{1,1} & x_{1,2} & x_{1,3} \\ 1 & x_{2,1} & x_{2,2} & x_{2,3} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{20,1} & x_{20,2} & x_{20,3} \end{bmatrix}$ $\epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_{20} \end{bmatrix}$

d is a (3×1) vector of the first-order regression coefficients and β is a (3×3) symmetric matrix whose main diagonal elements are pure quadratic coefficients (β_{ii}) and whose off-diagonal elements are one-half the mixed quadratic coefficients (β_{ij}).

ε is the error term which is normally distributed with an expected value of zero and a variance of one.

The least square method was used in estimating the model parameters β and the choice of β's should minimize the sum of square of error ϵ_i.
The yield is the least square estimators, given by the

$$L = \sum_{i=1}^{20} \epsilon_i{}^2 \quad ; \; i = 1,2,\dots,20$$

$$L = \sum_{i=1}^{20} \epsilon_i{}^2 = \epsilon'\epsilon = (y - X\beta)'(y - X\beta)$$

$$L = y'y - 2\beta'X'y + \beta'X'X\beta \qquad (27)$$

L being a function is minimized with respect to β and the resulting least square estimators $\hat{\beta}$ minimize equation (27) satisfying equation (28).

$$\left.\frac{\partial L}{\partial \beta}\right|_{\hat{\beta}} = -2X'y + 2X'X\,\hat{\beta} = 0$$

$$X'X\beta = X'y \qquad (28)$$

Equation (28) is the Matrix form of the least square normal equations and the least squares estimator of β is given by equation (29).

$$\hat{\beta} = (X'X)^{-1}X'y \qquad (29)$$

The fitted regression model in matrix notation therefore becomes

$$\hat{y} = \hat{\beta}_0 + X'd + X'\beta X \qquad (30)$$

To estimate the variance σ^2, consider the sum of squares of the residuals, say

$SS_E = \sum_{i=1}^{20}(y_i - \hat{y}_i)^2$ where $i = 1,2,\dots,20$

$= \sum_{i=1}^{20} \epsilon_i{}^2$

; where $\epsilon_i = y_i - \hat{y}_i = residuals.$

$= \epsilon'\epsilon$

$= \left(y - X\hat{\beta}\right)'(y - X\hat{\beta})$; substituting for ϵ

$= y'y - 2\hat{\beta}'X'y + \hat{\beta}'X'X\hat{\beta}$

$= y'y - \hat{\beta}'X'y$; Since $X'X\hat{\beta} = X'y$ from equation (28)

$$SS_E = y'y - \hat{\beta}'X'y \tag{31}$$

Equation (31) is the residual sum of squares and has $n - p$ degrees of freedom. It can be shown that,

$$E(SS_E) = \sigma^2(n - p) \tag{32}$$

From this we get the unbiased estimator of σ^2 as in equation 33

$$\sigma^2 = \frac{E(SS_E)}{(n-p)} \tag{33}$$

3.3.3 Testing for the Significance of the Model Parameters

A significance test is a formal method for comparing collected data with a stated claim or hypothesis to evaluate its validity. To assess the significance of an individual regression coefficient β_j both the P-Value and the t-test were utilized. The t-test statistic follows a t-distribution and is expressed as:

$$t = \frac{\hat{\beta}_j}{s(\hat{\beta}_j)}$$

where $\hat{\beta}_j$ denotes the least square estimator of the parameter $\hat{\beta}_j$ (j= 1,2…b)

$s(\hat{\beta}_j)$ represents the estimated standard error of $\hat{\beta}_j$

The standard error of each parameter $\hat{\beta}_j$ is determined by taking the square root of the diagonal elements of the variance-covariance matrix $\hat{\beta}$, given by

$Cov(\hat{\beta}_j)= \sigma^2(X'X)^{-1}$

3.3.4 Checking the Adequacy of the Model

This research adopted the analysis of variance (ANOVA) to assess the suitability of the model for the experiment's response. The sum of squares and the F-statistic test were utilized to ascertain whether the model effectively captures the relationship between the independent variables (factors) and the response variable(s). Specifically, it can be used to compare the variance explained by the model to the residual variance. If the model explains a significant portion of the variance compared to the residuals, it indicates that the model adequately represents the inherent relationships in the data. In other words, if the p-value for the F-statistic F_0 is below the significance level of $\alpha = 5\%$, it implies that at least more than one coefficient differs, that is, model terms are significant.

Table 5: Analysis of Variance for the Fitted Model

Source of Variation	Sum of Squares (SS)	Degree of Freedom (df)	Mean Square (MS)	F statistics
Linear	$SS_{R\ linear}$	p_{linear}	MSR_{linear}	$\frac{MSR_{linear}}{MS_{PE}}$
Two-way interaction	$SS_{R\ interaction}$	$p_{interaction}$	$MSR_{interaction}$	$\frac{MSR_{interaction}}{MS_{PE}}$
Pure Quadratic	$SS_{R\ quadratic}$	$p_{quadratic}$	$MSR_{quadratic}$	$\frac{MSR_{quadratic}}{MS_{PE}}$
Lack of Fit	SS_{LOF}	$n - p_{total}$	MS_{LOF}	$\frac{MS_{LOF}}{MS_{PE}}$
Pure Error	SS_{PE}	$n - p_{total} - 1$	MS_{PE}	
Total	SS_T	$n - 1$		

where p is the number of parameters estimated in the model

n is the total number of experiments

If the p-value for the statistic F_0 is less than $\alpha = 5\%$ level of significance, it implies that at least more than one coefficient differs, that is, model terms are significant.

3.3.5 Model Validation

The models were validated using the coefficients of determination R^2 and the adjusted R^2. If $R^2$and adjusted R^2 differ greatly, there is a high likelihood of non-significant terms being present in the model. Large values of $R^2$and adjusted R^2 that are close to one show that the model can adequately explain the variations in the response surface and therefore the model can approximate the experimental data at the design points given. To determine if there is any statistically significant difference between the predicted and the experimental values the paired t-test would be carried out.

3.4: Determining the Optimal Values of Organic Manure for Maximum Yield of Groundnuts

3.4.1. Obtaining Optimal Values

To determine the levels of x_1, x_2, x_3 that optimizes the response, the point of optimum therefore becomes a set of x_1, x_2, x_3 for which the partial derivatives given in equation (34) are zero.

$$\frac{\partial \hat{y}}{\partial x_1} = \frac{\partial \hat{y}}{\partial x_2} = \frac{\partial \hat{y}}{\partial x_3} = 0 \qquad (34)$$

For second-order model in matrix notation

$$\hat{y} = \hat{\beta}_0 + \boldsymbol{X}'\boldsymbol{d} + \boldsymbol{X}'\boldsymbol{\beta}\boldsymbol{X}$$

$$\text{where } \boldsymbol{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \boldsymbol{d} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \end{bmatrix} \quad \boldsymbol{\beta} = \begin{bmatrix} \hat{\beta}_{11} & \hat{\beta}_{12} & \hat{\beta}_{13} \\ \hat{\beta}_{21} & \hat{\beta}_{22} & \hat{\beta}_{23} \\ \hat{\beta}_{31} & \hat{\beta}_{32} & \hat{\beta}_{33} \end{bmatrix} \qquad (35)$$

where $\boldsymbol{d}$ represents a vector of first-order regression coefficients with dimensions (3×1),

$\boldsymbol{\beta}$ represents a symmetric matrix with dimensions (3×3) where the diagonal elements are pure quadratic coefficients (β_{ii}) and whose off-diagonal elements are half of the mixed quadratic coefficients ($\beta_{ij}, i \neq j$). Differentiating $\hat{y}$ with respect to the elements of the vector X and setting it equal to zero, we have,

$$\frac{\partial \hat{y}}{\partial \boldsymbol{X}} = \boldsymbol{d} + 2\boldsymbol{\beta}\boldsymbol{X} = 0 \qquad (36)$$

Thus, the stationary point was given by;

$$x_s = -\frac{1}{2}\boldsymbol{\beta}^{-1}\boldsymbol{d} \qquad (37)$$

Thus, the yields of groundnut at the stationary point were therefore be predicted by

$$\hat{y} = \hat{\beta}_0 + \frac{1}{2}\boldsymbol{X^{-1}d} \tag{38}$$

Once the stationary point is established, this study evaluated whether it represents a maximum, minimum, or saddle point by analyzing the response surfaces and the corresponding contour plots.

3.4.2 Canonical Analysis

Canonical analysis, or canonical correlation analysis (CCA), is a method in multivariate statistics employed to examine the associations between two sets of variables. It identifies the linear combinations of variables from each set that optimize the correlation between them. (Kasina *et al*., 2020). Canonical analysis was employed to examine the relationships between independent variables (factors) and dependent variables (responses). Its objective is to ascertain the characteristics of the stationary point and the entire response surface.

The characterization of stationary points was by determined by the signs of the eigenvalues of $\hat{\beta}$, while the nature of the response surface was determined by evaluating the magnitude of these eigenvalues. Canonical analysis transforms the second-order model into:

$$\hat{y}=\hat{y}_s + \lambda_1 z_{1i}^2 + \lambda_2 z_{2i}^2 \tag{39}$$

where λ_i represents the eigenvalues or the characteristic roots of the matrix $\hat{\beta}$, $\hat{y}_s$ is the predicted response at the stationary point x_s while z variables are rotated axes and z are the values used to describe the fitted quadratic model. If all the λ values are positive it implies that the surface is a minimum otherwise the surface is a maximum when the values are negative. When some of the values of λ are positives and some are negative we characterize the surface a saddle point. If some λ values are closed to zero, then the surface has one or more ridges. The response surface exhibits its steepest slope in the direction of (z_i) that corresponds to the largest absolute eigenvalues. (Kasina *et al*., 2020). In many dimensions, canonical analysis plays a crucial role in determining systems of maxima and minima. It is especially useful in identifying complex ridge systems, for which direct geometric representation is not possible.

3.5 Ethical Considerations

The research obtained clearance from the Chuka University Ethics Committee and get a license from the National Commission of Science, Technology and Innovation (NACOSTI) to ensure that the research meet all requirements before data collection. This study observed all principles of ethics to ensure the accuracy of the data and avoiding of plagiarism. The data was collected and analysis were done as per the stated procedures.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Effect of Organic Manure on Groundnut Yield

Box and whisker plots are an effective method for visually assessing the effect of organic manure on groundnut yield, as they reveal the distribution and variability of yields across different treatments. It compares the medians, interquartile ranges (IQRs), and spotting any outliers, these plots help to highlight differences between plots treated with organic manure and those without. This allows for a clear comparison of central tendencies and spread within the data.

4.1.1 Effect of Poultry Manure on Weight of Groundnuts Seed

The weight of groundnuts generally increased with application of higher levels of poultry manure (Figure 3). The highest weights are observed at the extreme coded levels of 1.682, suggesting that higher levels of poultry manure might lead to higher yields. There is greater variability in the weight responses at moderate levels (e.g., at a coded level of 1), but weights are consistently higher at the highest level. The plot suggests a positive relationship between poultry manure and groundnuts weight, with the potential for higher yields at higher poultry manure levels through with some variability in the weight at moderate levels. It is worth noting that increasing the levels of poultry manure from -1.682 to 1.682 are reflected in increasing medians of weights. Thus, it implies that the amount of poultry manure correlates positively with their mass; hence more manure will cause increased weights.

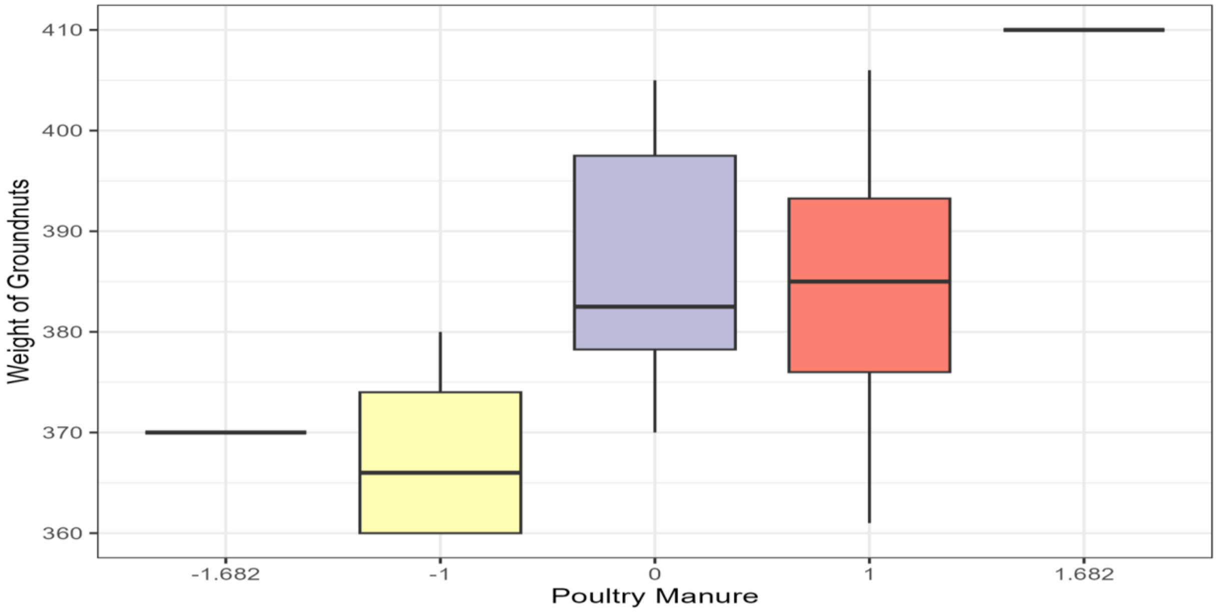

Figure 3: Box and Whisker Plots Showing the Effect of Different Rates of Poultry Groundnuts Weight

4.1.2 Effect of Poultry Manure on Groundnuts Number of Pods

Figure 4 shows the number of pods of groundnuts as influenced by different levels of poultry manure. The spread of the data within each manure level varies. For the lowest manure level (-1.682), the spread is very narrow, while for others, the spread is broader, especially around the 0 and 1 levels. The graph shows a positive correlation between the amount of poultry manure and the number of pods, up to a point. As the poultry manure increases from -1.682 to 1.682, the number of pods increases, suggesting that higher amounts of poultry manure generally result in more pods.

There is one outlier at the 1 level, suggesting that one plant produced significantly fewer pods than the others in this group. The consistent whiskers at the extreme levels (-1.682 and 1.682) indicate stable pod production with no extreme deviations. However, the effect seems to stabilize at higher levels, indicating there may be an optimal level. Further increase in manure levels do not significantly boost the number of pods.

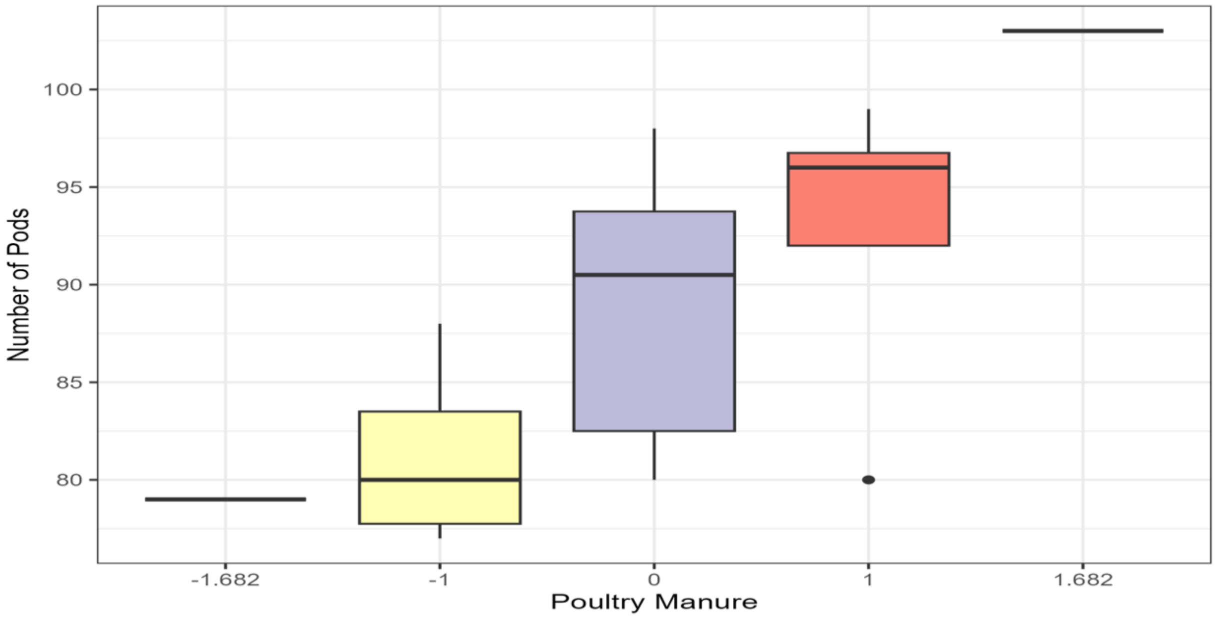

Figure 4: Box and Whisker Plots Showing the Effects of Different Rates of Poultry Manure on Groundnut Number of Pods

4.1.3 Effect of Poultry Manure on Number of Groundnuts Seeds

The effect of poultry manure on seed production, as illustrated by the boxplot in Figure 5 shows a clear increase in the median number of seeds as manure levels rise from level -1 to 1. At the lowest level (-1.682), the seed count is high. The level -1 exhibits the lowest median seed count and the most considerable variability, with some very low values. As manure levels increase to 0 and 1, the seed count becomes more consistent, with the median rising significantly, especially at the 1 level, which shows the highest and most consistent seed counts. There is an outlier at the 0-manure level, indicating that one plant produced significantly fewer seeds than the rest, deviating from the main distribution. The whiskers at the extreme levels (-1.682 and 1.682) indicate consistent seed production with no outliers.

This plot suggests that increasing levels of poultry manure generally led to higher and more consistent seed production, especially at the highest level (1.682). The right-skewed distribution at the -1 level indicates variability, with some plants underperforming compared to others

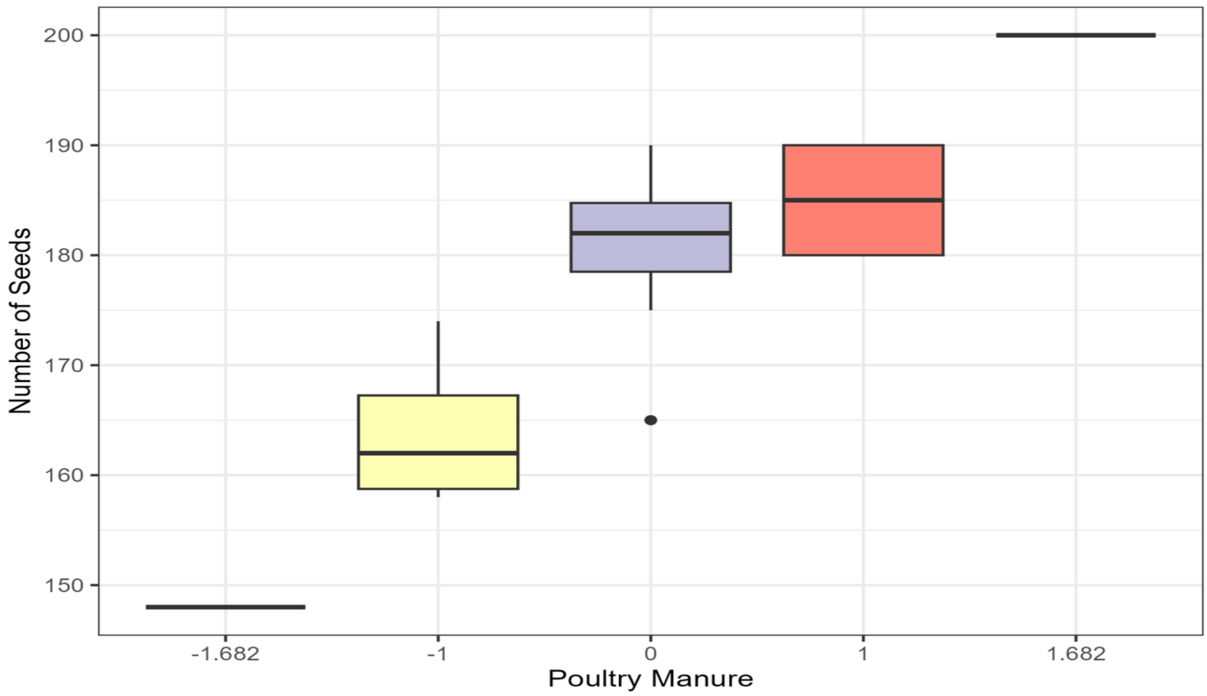

Figure 5: Box and Whisker Plots Showing the Effect of Different Rates of Application of Poultry Manure on Groundnut Number of Seeds

4.1.4 Effect of Rabbit Manure on Weight of Groundnuts

The effect of rabbit manure on groundnuts weight production, as illustrated by the boxplot in Figure 6 shows a significant impact on groundnut weight, with the effect varying depending on the level applied. At low levels of manure, groundnut weights are relatively low and stable, with slight positive skewness. As the manure level increases to a moderate amount, the distribution of groundnut weights becomes highly variable, indicating potential for higher weights but also an increased risk of lower weights.

At higher levels, the distribution shifts to a left skew, with consistently higher groundnut weights, and at the highest manure level, the weights stabilize with minimal variation, suggesting this level may be optimal for maximizing groundnut yield. The extreme observation at the -1 level of rabbit manure in the boxplot shows a notably lower groundnut weight compared to the other data points at this level. This outlier implies that, at this particular concentration of manure, the groundnut weight was unexpectedly low, possibly due to natural variation, a data collection error, or the impact of unaccounted-for factors. This observation is significant because it falls outside the expected range of the dataset.

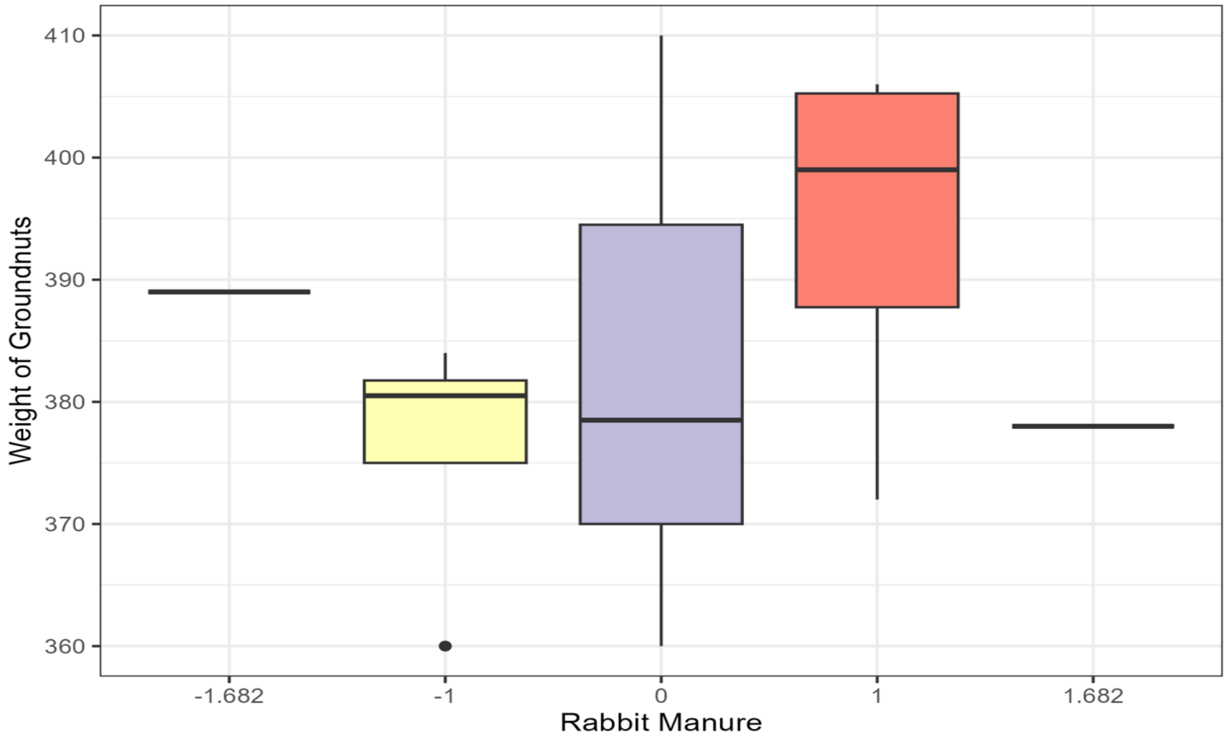

Figure 6: Box and Whisker Plots Showing the Effect of Different Rates of Rabbit Manure on Groundnut Weight

4.1.5 Effect of Rabbit Manure on Number of Groundnuts Pods

The Box and Whisker plot in Figure 7 illustrates the impact of rabbit manure on pod production, showing variability across different application levels. Pod counts generally increase as manure levels move from -1 to 1, though there is a noticeable decrease at the 0 level. The distributions at -1exhibit a left skew, a slight right skew at 0, and near symmetry at 1.

The interquartile range is widest at the 0 level, indicating greater variability. In general, rabbit manure appears to influence pod production, with an optimal level at 1, though the effect is not linear and may lead to inconsistent results depending on the manure level used. There are a few extreme observations at the -1 and 1 manure levels, represented by the dots outside the whiskers. These outliers indicate that a small number of plants produced either significantly fewer or more pods than the majority under these conditions. Specifically, at the -1 level, there is an outlier showing lower pod production, while at the 1 level, there is an outlier with slightly lower pod production compared to the main distribution.

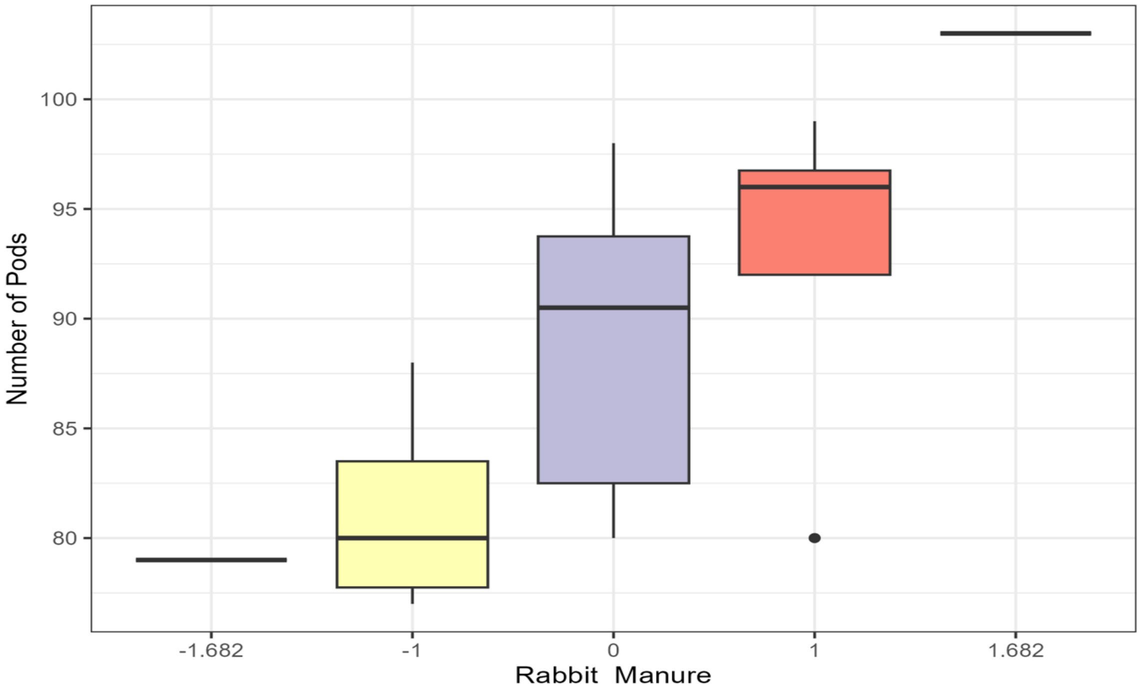

Figure 7: Box and Whisker Plots Showing the Effects of Different Rate of Application of Rabbit Manure on Groundnut Number of Pods

4.1.6 Effect of Rabbit Manure on Number of Groundnuts Seeds

The Box and Whisker plot in (Figure 8) illustrates the relationship between the number of seeds and the application of rabbit manure. As the application of rabbit manure increases from -1.682 to 0, the number of seeds also increases. The highest median number of seeds is observed at the 0 level of rabbit manure application. However, as the application of rabbit manure increases further from 0 to 1.682, the number of seeds starts to decline. There is some variability in the number of seeds at each level of rabbit manure application, especially at higher levels of application.

The boxplot shows extreme observations at the 0 and 1 levels of rabbit manure, where the number of seeds is significantly lower than the rest of the data points at those levels. These outliers suggest that at these specific concentrations of manure, there were instances of unusually low seed production, possibly due to natural variation, experimental errors, or unaccounted factors. The boxplot suggests that there is an optimal level of rabbit manure application for maximizing seed production, with both lower and higher levels leading to reduced seed yields.

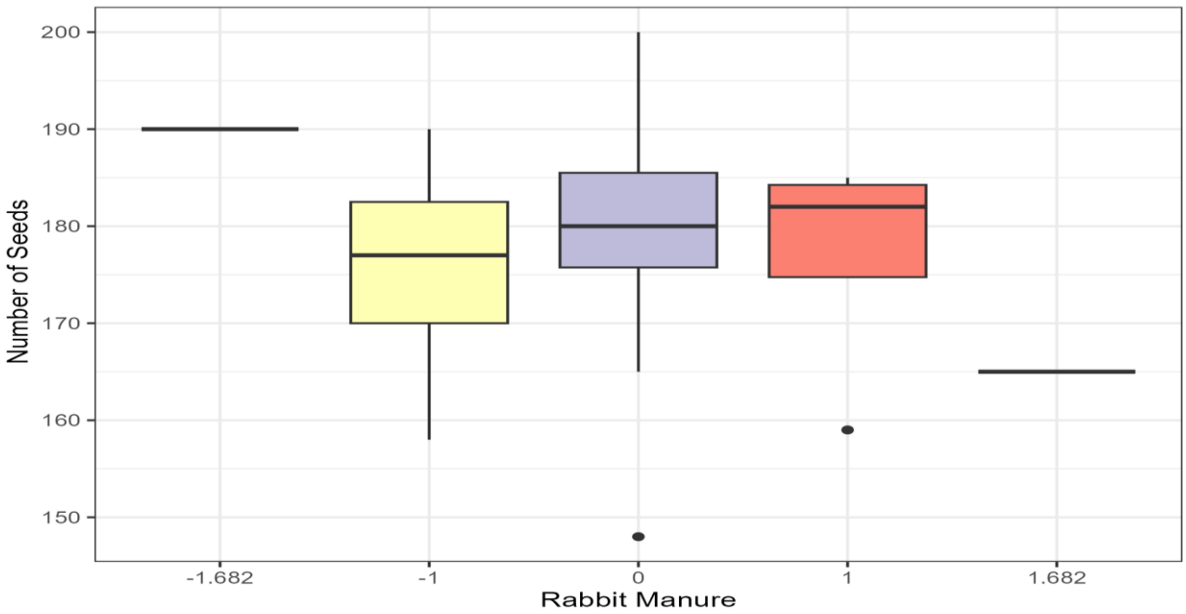

Figure 8: Box and Whisker Plots Showing the Effects of Rates of Rabbit Manure on Groundnut Number of Seeds

4.1.7 Effect of Sheep Manure on Weight of Groundnuts

The Box and Whisker plot in (Figure 9) illustrates the relationship between the weight of groundnut and the application of sheep manure. At both the extreme low (-1.682) and high (1.682) levels of sheep manure, the weight of groundnuts is more constrained, showing lower median values and less variation. As the level of sheep manure increases from -1.682 to 0, the weight of groundnuts improves, with the highest median weight occurring around level 0, indicating that moderate manure application yields the best results. However, as manure levels rise from 0 to 1, the median weight declines, suggesting diminishing returns.

The manure level of -1 exhibits some variability but results in slightly lower median weight compared to level 0. The boxplot reveals an extreme observation at the -1 level of sheep manure, where the weight of groundnuts is notably higher than the other data points at this level. This outlier suggests that at this specific manure concentration, there was an instance of unusually high groundnut weight, which could be due to natural variability, data collection errors, or external factors not accounted for in the experiment. This observation is significant as it lies outside the expected range of the dataset. Despite the presence of an outlier at level 0, this level remains the most favorable for achieving higher groundnut weight.

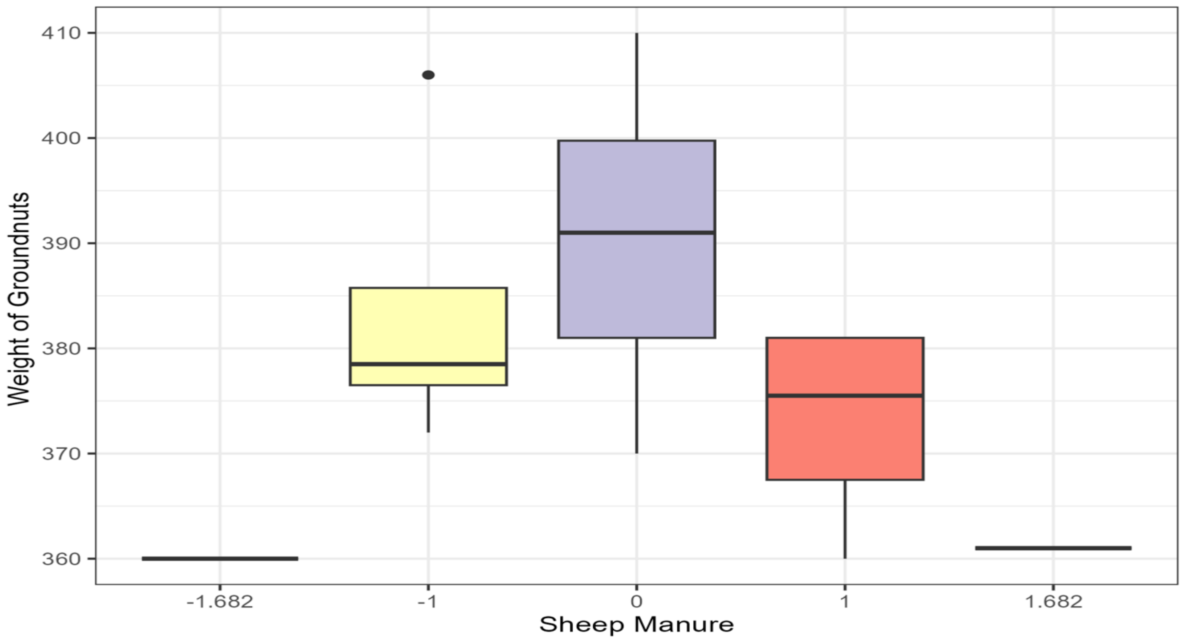

Figure 9: Box and Whisker Plots Showing the Effect of Different Rate of Application of Sheep Manure on the Weight of Groundnut

4.1.8 Effect of Sheep Manure on Groundnuts Number of Pods

The Box and Whisker plot in (Figure 10) illustrates the relationship between groundnut weight and the application of sheep manure. As the application of sheep manure increases from -1.682 to 0, the number of pods also increases, with the highest median number of pods observed at the 0 level of sheep manure application. However, when the application of sheep manure increases further from 0 to 1.682, the number of pods starts to decline. There is some variability in the number of pods at each level of sheep manure application, with a few outliers, especially at higher levels of application, leading to a positively skewed distribution. The boxplot suggests that there is an optimal level of sheep manure application for maximizing pod production, with both lower and higher levels resulting in reduced pod yields.

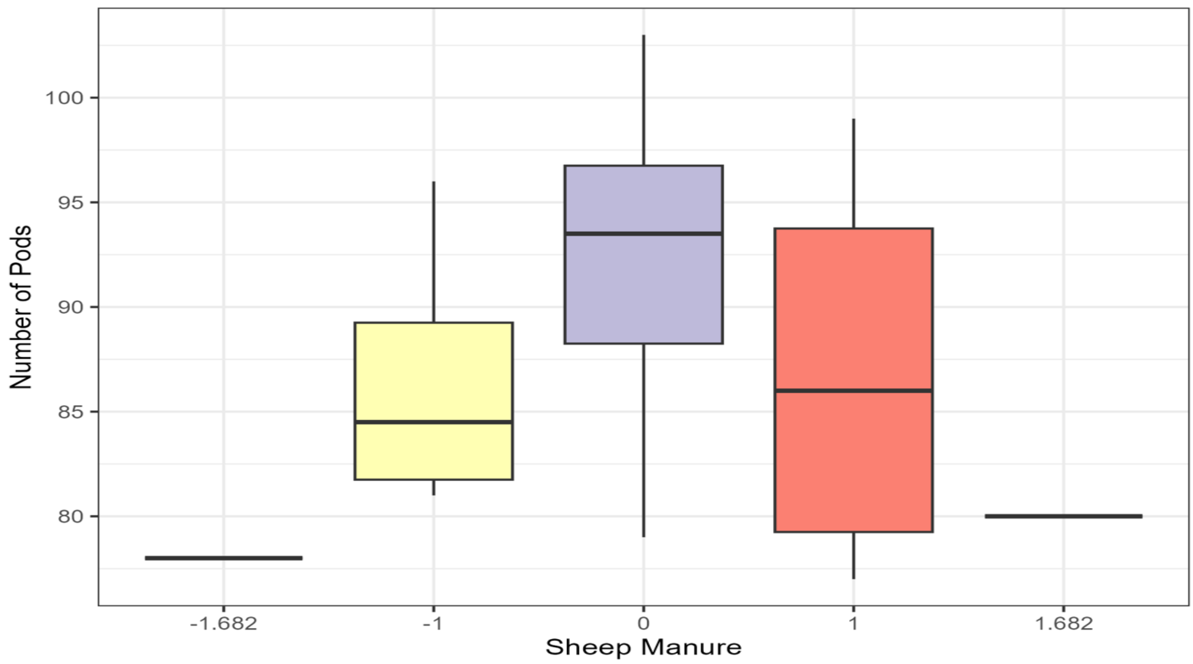

Figure 10: Box and Whisker Plots Showing the Effect of Different Rate of Application of Sheep Manure on Groundnut Number of Pods

4.1.9 Effect of Sheep Manure on Groundnuts Number of Seeds

The impact of sheep manure on seed count (Figure 11) reveals that moderate manure levels, particularly around 0, yield the highest seed counts with a balanced distribution. At extreme levels, both low (-1.682) and high (1.682), the seed count is more restricted, with lower median values and reduced variability. The distribution at level -1 exhibits slight negative skewness, while level 1 presents a more symmetrical distribution but with a decreased median seed count. It appears that moderate levels of sheep manure (around 0) encourage the highest seed count, whereas both very low and high levels lead to fewer seeds and more constrained distributions.

The boxplot indicates an outlier at the -1 level of sheep manure, where the number of seeds is significantly lower than the general trend, around 160 seeds. This suggests that at this particular level, at least one experimental run produced a much lower yield than expected. These could result from experimental error, natural variability, or sensitivity to the treatment.

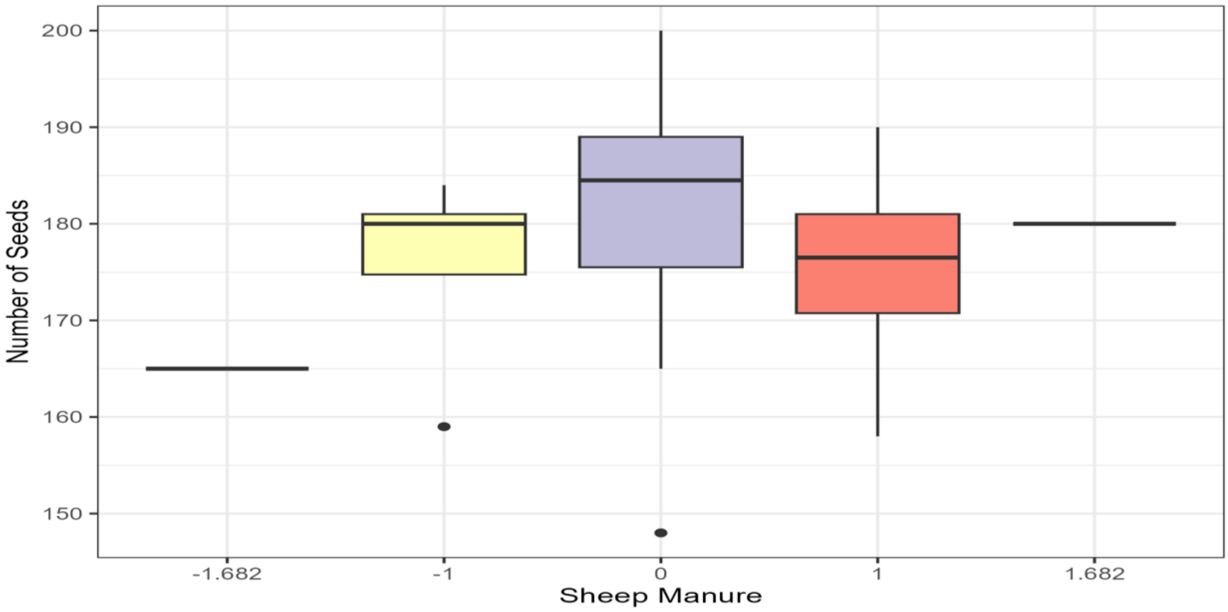

Figure 11: Box and Whisker Plots Showing the Effects of Different Application Rates of Sheep Manure on Groundnuts Number of Seeds

4.2 Establishing a Functional Relationship Between Groundnut Yield and Organic Manure

4.2.1 The Second Order Model for the Weight of Groundnuts Seeds Per Plot

This section presents the relationship between organic manure (poultry, rabbit and sheep manure) and response variables (weight of groundnuts) using second-order models.

4.2.1.1 Model Fitting

This study aimed to investigate how different types of organic manure affect the weight of groundnuts seeds**.** The study was guided by the following hypothesis,

Ho: There is no functional relationship of poultry, rabbit and sheep manure on weight of groundnuts seeds per plot

The data collected from the experiment were analyzed to create a mathematical model. A multiple regression analysis, using the least squares method, was fitted to develop a quadratic polynomial model for predicting the weight of groundnuts seeds. The relevant results are shown in Table 6.

The overall fit of the second-order RSM model is summarized by the adjusted R-squared, 0.762, accounts for the number of predictors in the model and provides a more accurate measure of model fit. In this case, 76.2% of the variance is explained after adjusting for the number of predictors. The difference between the R-squared and adjusted R-squared values suggests some degree of model complexity, but the overall fit remains strong.

The F-statistic of 7.757 which is less than the critical value of 3.020, indicates that the model is statistically significant. The P-value=0.002, which is well below the common significance level of 0.05. This strongly suggests that the overall model is statistically significant, meaning that at least one of the predictors is significantly associated with the response variable. This implies that the hypothesis suggesting no functional relationship between poultry, rabbit, and sheep manure on the weight of groundnuts seeds is not supported by the current study. Therefore, the proposed regression model is statistically significant in predicting the weight of groundnuts.

The model show that poultry and sheep manure were statistically significant at 5% significance level with a P-value 0.000<0.05 and 0.032<0.05 respectively. The model output shows that a unit increase in poultry manure leads to a corresponding increase of 12.600g in the weight of groundnuts seeds and a unit increase in sheep manure leads to a drop in 5.557g in the weight of groundnuts seeds. The model output also showed that the quadratic effect of sheep manure was significant P-value=< 0.002, this means that a unit increase in the quadratic effect on sheep manure would lead to a decrease in 14.587g of the weight of groundnuts seeds. In addition, the model output showed that the interaction effect of poultry and sheep manure, rabbit and poultry manure were all insignificant with P-values greater than 0.05. This result revealed that poultry manure had a higher effect on the weight of groundnuts seeds as compared to sheep manure.

Table 6: Second Order RSM Model for the Weight of Groundnut seeds on Organic Manure

Variables	Estimate	S. E	t-value	Pr(>|t|)
(Intercept)	395.261	3.474	113.788	0.000
x_1	12.600	2.272	5.545	0.000
x_2	1.953	2.287	0.854	0.413
x_3	-5.557	2.238	-2.483	0.032
x_1:x_2	4.071	4.191	0.971	0.354
x_1:x_3	3.005	4.832	0.622	0.548
x_2:x_3	-4.525	5.042	-0.898	0.391
x_1^2	-1.144	2.133	-0.536	0.603
x_2^2	-4.305	2.375	-1.813	0.100
x_3^2	-14.587	3.393	-4.299	0.002
Multiple R-squared	*0.875*			
Adjusted R-squared	*0*.762			
F-statistic	*7.757*			
DF	(9,10)			
p-value	0.002			

x_1 = Poultry manure: x_2= Rabbit manure: x_3 =Sheep manure

The output in Table 6 of the second order regression model was presented using the optimization model equation (36)

$$y_1 = 395.261 + 12.600x_1 + 1.953x_2 - 5.557x_3 + 4.070x_1x_2 + 3.005x_1x_3 - 4.525x_2x_3 - 1.144x_1^2 - 4.305x_2^2 - 14.587x_3^2$$
(40)

The findings of this study are in agreement with those of Oke *et al*. (2021), who found that poultry manure is the richest known animal manure in nutrient concentration, especially nitrogen, which enhances plant growth and the production of cucumber plants. In his study, he found that cucumber plants treated with 15g of poultry manure produced the highest number of leaves (62.28), vine length (44.04 cm), vine diameter (4.86 cm), and number of branches (4.5). Consequently, this treatment resulted in substantial fruit production, with averages of 18.1 cm/ha for fruit length, 4.5 cm/ha for fruit diameter, 4.8 for the number of fruits, 169.5 g/ha for average fruit weight, and 31.9 t/ha for yield. Notably, both leaf production and vine diameter significantly increased (p<0.05 and p<0.1, respectively).

4.2.1.2: Analysis of Variance for the Second Order Model for the Weight of Groundnuts Seeds

Analysis of variance was used to check the adequacy of the model in equation (36) for the response (weight of groundnuts seeds) in the experimentation as in (Table 7). The Table 7 outputs display first-order response surface, the response surface with Two-Way Interaction model (TWI), the pure quadratic terms and lack-of-fit test. The results showed that the First Order (P-value=0.002), Pure Quadratic terms (PQ) (p-value=0.010) and the Two-Way Interaction (P-value=0.013) were all significant since the P- values were less than 5%. The lack of fit test results is non-significant if (P > 0.05), we reject the null hypothesis, suggesting that there is no significant lack of fit, and the model is adequate. In this model the lack of fit was insignificant (P-value =0.238> 0.05), this indicates that the model could predict the response variable appropriately.

Table 7: Analysis of Variance for the Second Order Model for the Weight of Groundnuts Seed

Source of variation	Df	SS	MSS	F-value	Pr(>F)
FO (x_1,x_2 x_3)	3.000	1829.060	609.690	10.764	0.002
TWI (x_1,x_2 x_3)	3.000	1016.380	338.790	5.981	0.013
PQ (x_1,x_2 x_3)	3.000	1108.690	369.560	6.525	0.010
Residuals	10.000	566.420	56.640		
Lack of fit	6.000	432.920	72.150	2.162	0.238
Pure error	4.000	133.500	33.380		

4.2.1.3 Validation of the Model on the Weight of Groundnuts Seeds per Plant

The study sought to assess the precision of the model. For better comprehension and clarity, Figure 12 displays graphical representations comparing the predicted values from the model with the actual measured values for all responses.

The graph provided is a scatter plot showing the relationship between the actual values and the predicted values for the weight of groundnuts seeds. In theory, if a model could account for 100% of the variance if the predicted values would perfectly align with the observed values, placing all data points directly on the line of best fit. In this study, although the fitted and observed values are not exactly the same, they are quite close to the line of best fit. This suggests a relatively strong correlation between the fitted and observed values, as illustrated (Figure 12).

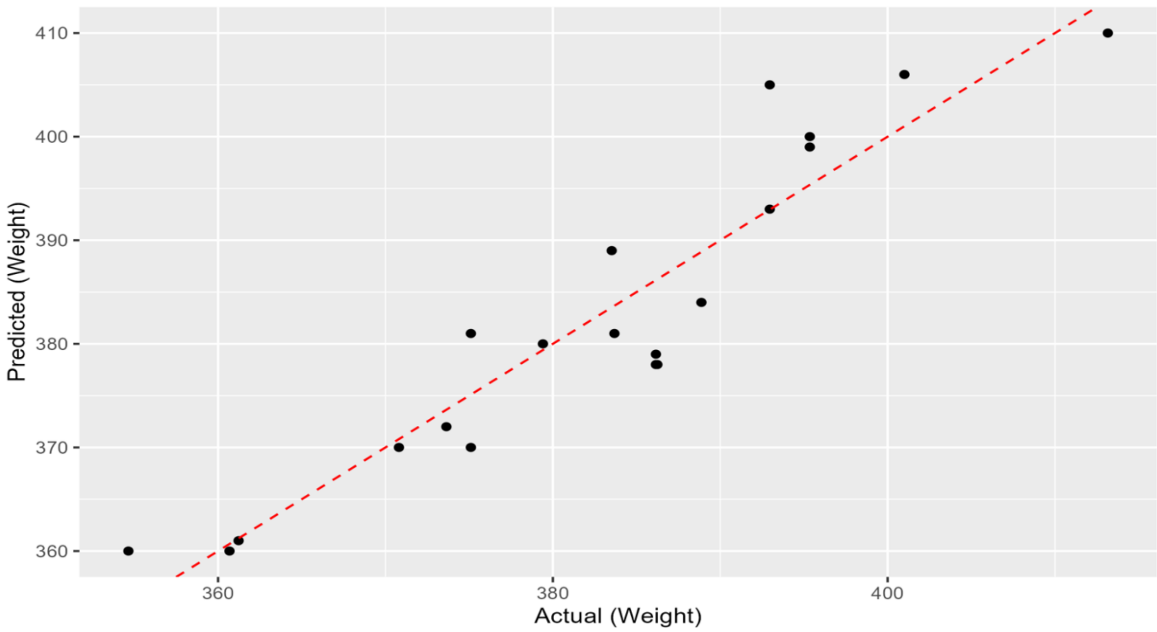

Figure 12: Predicted Values Versus Experimental Value of Weight of Groundnuts Seeds Per Plot

4.2.2 The Second Order Model for the Number of Pods Per Plant

This section presents the relationship between organic manure (poultry, rabbit and sheep manure) and response variables (number of pods per plant) using second-order models.

4.2.2.1 Model Fitting

The current study was based on the premise that organic manure influences the number of pods of per plant. The study was guided by the following hypothesis,

Ho: There is no functional relationship of poultry, rabbit and sheep manure on the number of pods per plant.

The overall fit of the second-order RSM model for the number of pods per plant is summarized by an R-squared value of 0.789 Indicating that approximately 78.9% of the variance in the response variable is explained by the predictors in the model. This suggests a reasonably good fit. The Adjusted R-squared accounts for the number of predictors in the model and provides a more accurate measure of model fit. At Adjusted R-squared of 0.582, it indicates that around 58.2% of the variance in the response variable is explained, adjusting for the number of predictors. The decrease from R-squared to Adjusted R-squared suggests that not all predictors may be contributing significantly to the model. These results revealed that the predicted response model was statistically significant since F-Value=3.939 which is less than the critical value of 3.020 and Pr(>F) =0.022 <0.05. This suggests that the hypothesis stating there is no functional relationship between poultry, rabbit, and sheep manure and the number of pods per plant is not supported by the current study. As a result, the proposed regression model is statistically significant in predicting the number of pods.

The model output from Table 8 showed that only poultry manure and the quadratic effect of the sheep manure were significant (P=0.001 and 0.007) which was less than 0.05. The regression coefficient estimates showed that for one unit change in poultry manure, the number of pods per plant would increase by a factor of 7.379, this implies that poultry manure had a higher effect on the number of pods per plant as compared to sheep manure and rabbit manure, since rabbit and sheep manure were both insignificant with the P values greater than 0.05, (P=0.421, 0.279) respectively.

In addition, the models output showed that the interaction effect of poultry, rabbit and sheep manure were all insignificant with the p- value greater than 0.05 implying that a unit increase in the interaction effect of rabbit, poultry and sheep manure would negatively affect the number of pods per plant. These results revealed that poultry manure is the most effective manure to the number of pods.

Table 8: Second Order RSM Model for the Number of Pods Per Plant

Variables	Estimate	S. E	t-value	Pr(>|t|)
(Intercept)	94.670	2.477	38.220	0.000
x_1	7.379	1.620	4.554	0.001
x_2	-1.369	1.631	-0.839	0.421
x_3	-1.826	1.596	-1.144	0.279
x_1:x_2	1.658	2.988	0.555	0.591
x_1:x_3	4.505	3.445	1.307	0.220
x_2:x_3	-5.607	3.595	-1.560	0.150
x_1^2	-0.925	1.521	-0.608	0.557
x_2^2	-2.606	1.693	-1.539	0.155
x_3^2	-8.246	2.420	-3.408	0.007
Multiple R-squared	0.789			
Adjusted R-squared	0.582			
F-statistic	3.939			
DF	(9,10)			
p-value	0.022			

x_1 = *Poultry manure:* x_2 = *Rabbit manure:* x_3 =*Sheep manure*
The predicted model for number of pods per plant in terms of coded factors is as shown in Equation (41)

$$y_2 = 94.670 + 7.379x_1 - 1.369\, x_2 - 1.827\, x_3 + 1.658x_1x_2 + 4.505x_1x_3 - 5.607x_2x_3 - 0.925x_1^2 - 2.607x_2^2 - 8.246x_3^2 \quad (41)$$

This was in line with a study by (Biratu *et al*., 2018), who found that application of 4.2 tones/ha of poultry manure resulting in the highest mean fresh root of 27.66 tones/hac. In a study to investigate the effect of poultry manure on yield component of cassava. The result was consistent to that of (Masai *et* al., 2020), who found that organic manure improved the common beans performance.

4.2.2.2: Analysis of Variance for the Second Order Model for the Number of Pods Per Plant

ANOVA was used to check the adequacy of the model in equation (41) for the response (number of pods) in the experimentation as shown in (Table 9). The results showed that the First Order (P=0.009) and the Pure Quadratic term (P=0.039) was significant since the p-values were less than 5% levels of significance, with Two-Way Interaction (P=0.417) was also insignificant. The lack of fit test results is non-significant if (P=0.05), we reject the null hypothesis, suggesting that there is no significant lack of fit, and the model is adequate. The lack of fit was insignificant P =0.475) then this model could predict the response variable appropriately.

Table 9: Analysis of Variance for the Second Order Model for the Number of Pods Per Plant

Source of variation	Df	SS	MSS	F- value	Pr(>F)
FO (x_1,x_2 x_3)	3.000	576.200	192.066	6.669	0.009
TWI (x_1,x_2 x_3)	3.000	89.740	29.912	1.039	0.417
PQ (x_1,x_2 x_3)	3.000	355.010	118.335	4.109	0.039
Residuals	10.000	288.010	28.801		
Lack of fit	6.000	181.010	30.168	1.128	0.475
Pure error	4.000	107.000	26.750		

4.2.2.3: Validation of the Model of Number of Pods Per Plant

The graphical representation of the predicted values using the model, along with the corresponding measured values of the response, is shown in (Figure 13). The line of best fit was plotted with the predicted values equated to the measured values, serving as a reference line. The measured values of each response are plotted, and their proximity to this reference line reflects the model's accuracy. The model is considered accurate when the measured values are close to the line of best fit. The comparison between the predicted and measured values showed a good correspondence, indicating that the empirical model derived from RSM effectively describes the relationship between the organic manure used and the number of pods per plant in the study area.

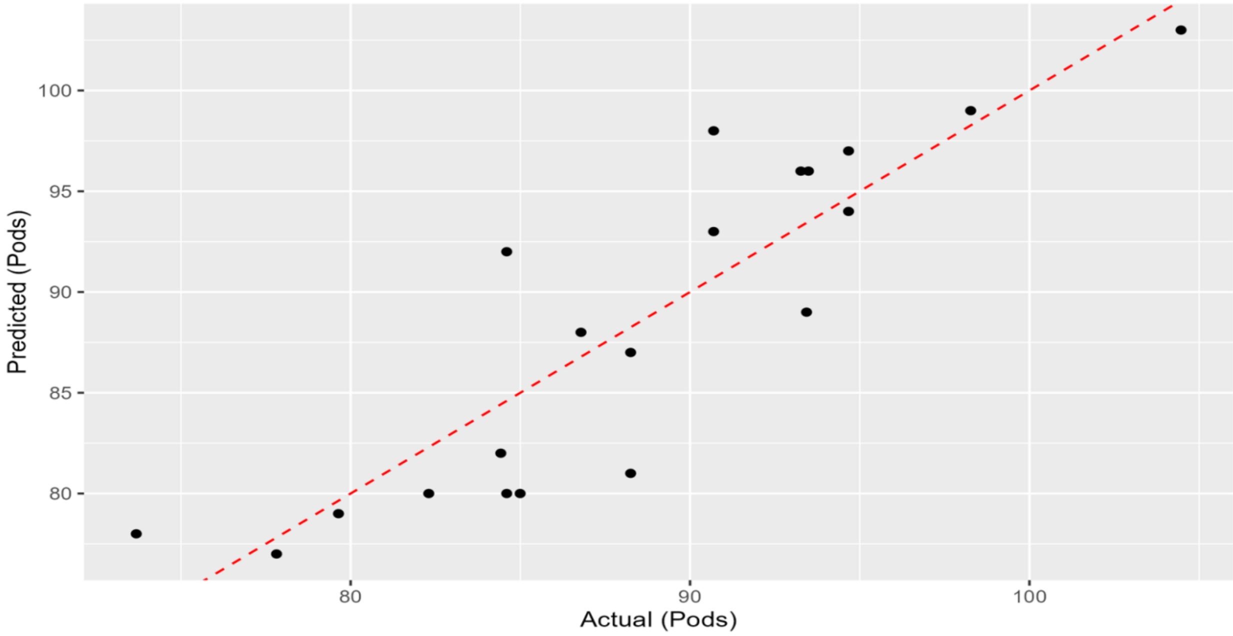

Figure 13: Predicted Values Versus the Experimental Value of Number Pods

4.3.3 Second Order Model for the Number of Seeds Per Plant

This section presents the relationship between organic manure (poultry, rabbit and sheep manure) and response variables (number of seeds) using second-order models.

4.3.3.1: Model Fitting

The current study was based on the premise that organic manure influences the number of seeds per plant. The study was guided by the following hypothesis,

Ho: There is no functional relationship of poultry, rabbit and sheep manure on number of seeds per plant.

The data collected from the experiment were analyzed to create a mathematical model. A multiple regression analysis, using the least squares method, was conducted to develop a quadratic polynomial model for predicting the number of seeds. The relevant results are shown in Table 10.

The R-squared value indicates the proportion of the variance in the dependent variable (number of seeds per plant) that is predictable from the independent variables (poultry, rabbit and sheep manure). The Adjusted R-squared of 0.887 is slightly lower than the Multiple R-squared, which is expected when more predictors are included. However, it still indicates that about 88.7% of the variance is explained by the model, which is very strong.

The small P-value 0.000 reinforces the model's significance, and the relatively high F-statistic 17.540 >3.021 indicates that the predictors collectively have a strong relationship with the number of seeds. This suggests that the model was robust and reliable for making predictions based on the data, thus rejecting the null hypothesis and concluding that there is a functional relationship of poultry, rabbit and sheep manure on number of seeds.

Table 10 showed the models output for the data that was collected and analyzed on the number of seeds. This output showed that only poultry manure, rabbit and sheep manure were all significant on the number of seeds with a p- value of 0.000,0.011,0.042 respectively which is less than 0.05. In addition, the regression coefficient showed that a unit increase in poultry manure would lead to an increase in the number of seeds by a factor of 14.214.

However, a unit change in rabbit manure, sheep manure would negatively impact on the number of seeds by a factor of 4.072 and 2.993 respectively. This could be attributed to the fact that poultry manure has the highest effect on the number of seeds as it contains more nutrients as compared to rabbit and sheep manure. Moreover, interaction effects were all insignificant while the quadratic terms were all significant with the p -values of poultry, rabbit and sheep manure ,0.005,0.013,0.003 respectively which is less than 0.05. The regression coefficients of the quadratic term showed that a unit increase in the quadratics of the manure would negatively affect the number of seeds of plant by a factor of 4.453, 4.121 and 7.590 respectively.

Table 10: Second Order RSM Model for the Number of Seeds Per Plant

Variables	Estimate	S. E	t -value	Pr(>|t|)
(Intercept)	187.595	1.995	94.020	0.000
x_1	14.214	1.305	10.890	0.000
x_2	-4.072	1.314	-3.100	0.011
x_3	-2.993	1.286	-2.328	0.042
x_1:x_2	2.924	2.407	1.215	0.252
x_1:x_3	6.123	2.775	2.206	0.052
x_2:x_3	-0.320	2.896	-0.110	0.914
x_1^2	-4.453	1.225	-3.635	0.005
x_2^2	-4.121	1.364	-3.021	0.013
x_3^2	-7.590	1.949	-3.894	0.003
Multiple R- squared	0.940			
Adjusted R-squared	0.887			
F-statistic	17.540			
DF	(9,10)			
p-value	0.000			

**** *x_1 = Poultry manure: x_2= Rabbit manure: x_3 =Sheep manure*

The predicted model for number of seeds of groundnuts in terms of coded factors is as shown in equation (42)

$$y_3 = 187.595 + 14.214x_1 - 4.072\,x_2 - 2.993 + 2.924x_1x_2 \\ +6.123x_1x_3 - 0.320\,x_2x_3 - 4.453x_1^2 - 4.121x_2^2 - 7.590x_3^2 \qquad (42)$$

The results were consistent with those of Muriithi (2018), who conducted a study on using response surface methodology to optimize multiple responses in watermelon cultivation with organic manure. The study revealed that the response surface for the second-order model showed that a moderate amount of cattle manure combined with a high amount of poultry manure boosts watermelon yields. This was attributed to the fact that poultry manure is known to be nutrient-rich, particularly in nitrogen, which promotes watermelon growth and production.

The results were also in agreement with research experiment which was conducted to determine the impact of NPK fertilizers, chicken manure, and their mixtures on common beans (Alhrout *et al*., 2016). It concluded that the treatment of both NPK and chicken manure significantly boosted common bean production. However, since chicken manure was more cost-effective compared to NPK fertilizer, it was recommended as the better option.

4.3.3.2 Analysis of Variance for the Second Order Model for the Number of Seeds

ANOVA was used to check the adequacy of the model in equation (38) for the response (number of seeds) in the experimentation as shown in (Table 11). The results showed that the First Order and the Pure Quadratic were significant (P=0.000, 0.004) which were less than 5%. with the Two-Way Interaction (P=0.0690) were insignificant. The lack of fit was statistically insignificant (P =0.065). The study, therefore, found no significant lack of fit in the model and concludes that the reduced model is adequate, satisfying the adequacy conditions in its non-linear form.

Table 11: Analysis of Variance for the Second Order Model for the Number of Seeds Per Plant

Source of Variation	Df	SS	MSS	F-value	Pr(>F)
FO (x_1,x_2 x_3)	3.000	2268.810	756.27	40.468	0.000
TWI (x_1,x_2 x_3)	3.000	181.440	60.48	3.236	0.069
PQ (x_1,x_2 x_3)	3.000	499.820	166.61	8.915	0.004
Residuals	10.000	186.880	18.69		
Lack of fit	6.000	165.880	27.65	5.266	0.065
Pure error	4.000	21.000	5.25		

4.2.6.2 Validation of the Model of Number of Seeds Per Plant

The graphical representation of the predicted values using the model, along with the corresponding measured values of number of seeds, is shown in (Figure 14). The model for predicting the number of seeds per plant were highly accurate and well-validated based on this graph. The strong positive correlation and close fit between the actual and predicted values indicate that the model was performing very well on the response variable.

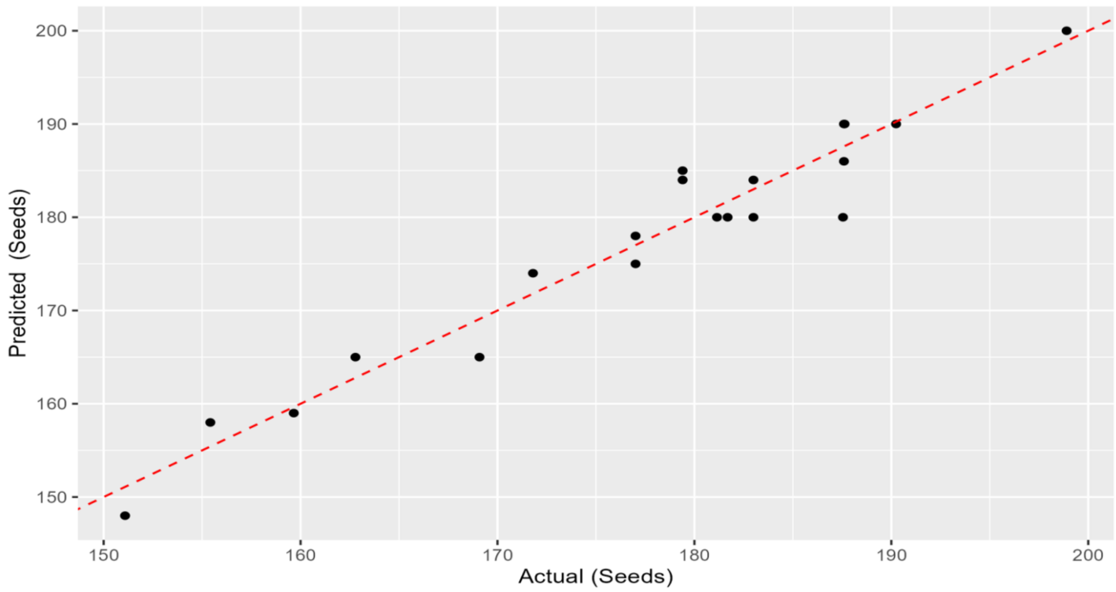

Figure 14: Predicted Values Versus the Experimental Value of Number of Seeds Per Plant

4.4: Optimization

4.4.1 Nature of Stationary Points

The stationary point of the response surface was computed using the R-statistical software and the output presented in (Table 12). One of the primary goals of Response Surface Methodology (RSM) is to identify the optimal settings for control variables that lead to the highest or lowest response within a specified region of interest. Achieving this requires a well-fitting model that accurately represents the mean response, as this model was used to determine the optimal values.

Table 12 indicates that the optimal manure application rates for achieving the maximum groundnut weight were 12.697 tons/ha for poultry manure, 10.582 tons/ha for rabbit manure, and 11.081 tons/ha for sheep manure, resulting in a yield of 396.188grams per plot, which is equivalent to 1.650 tons/ha. For the number of pods per plant, the optimal application rates were 12.290 tons/ha for poultry manure, 11.418 tons/ha for rabbit manure, and 10.980 tons/ha for sheep manure, resulting in a maximum of 396 pods per hectare. Additionally, applying 24.720 tons/ha of poultry manure, 13.980 tons/ha of rabbit manure, and 15.924 tons/ha of sheep manure resulted in a maximum yield of 833 seeds per hectare.

Table 12: Optimal Conditions for Optimum Groundnuts Yield

	coded points			Actual Manure			
Variables	X_1	X_2	X_3	Poultry	Rabbit	Sheep	Output
Weight	0.116	-0.236	-0.153	12.697	10.582	11.081	1.650 tons/ha
Number of pods	0.049	-0.097	-0.170	12.294	11.418	10.980	396 pods
Number of seeds	2.122	0.233	0.654	24.720	13.398	15.924	833 seeds

4.4.2: Canonical Analysis

Canonical correlation analysis was conducted to explore the relationship between the set of dependent variables (weight, number of pods, and number of seeds) and the independent variables. The canonical analysis yielded several canonical correlations, each representing the strength of the relationship between a pair of canonical variates from the dependent and independent variable sets.

With reference to the second-degree model earlier computed in (equation 31) which can be transformed into matrix form as;

$$\boldsymbol{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad , \quad = \begin{bmatrix} 12.600 \\ 1.953 \\ -5.557 \end{bmatrix}, \text{ and } \boldsymbol{\beta} = \begin{bmatrix} -1.144 & 2.035 & 1.504 \\ 2.035 & -4.305 & -2.264 \\ 1.503 & -2.264 & -14.587 \end{bmatrix}$$

for completing the second order model matrix notation in equation (31) was used. The eigenvalues and the eigenvectors output calculated using the R commands were

$$\lambda_1 = -0.138, \quad \lambda_2 = -4.579 \;, \lambda_3 = -15.319$$

$$v_1 = \begin{bmatrix} 0.904 \\ 0.427 \\ 0.027 \end{bmatrix} \; v_2 = \begin{bmatrix} 0.406 \\ -0.876 \\ 0.259 \end{bmatrix}, v_3 = \begin{bmatrix} -0.134 \\ -0.223 \\ -0.966 \end{bmatrix}$$

now $$p = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0.902 & 0.427 & 0.027 \\ 0.406 & -0.876 & 0.259 \\ 0.134 & -0.223 & -0.965 \end{bmatrix}$$

Therefore $$p^{-1} = \begin{bmatrix} 0.902 & 0.406 & 0.134 \\ 0.427 & -0.876 & -0.223 \\ 0.027 & 0.259 & -0.965 \end{bmatrix}$$

Then $pp'^{`} = pp^{-1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I$

Because $pp^{-1} = I$, because $z = p^{-1}x$,Therefore,

$\hat{y} = \hat{y}_s + x'\hat{\beta}$ x

Therefore, the p is orthogonal matrix since column and rows are orthogonal unit vector

Suppose $\lambda = \begin{bmatrix} -0.138 & 0 & 0 \\ 0 & -4.579 & 0 \\ 0 & 0 & -15.319 \end{bmatrix}$

(43)

Let $z = px = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} = \begin{bmatrix} -0.138 & 0 & 0 \\ 0 & -4.579 & 0 \\ 0 & 0 & -15.319 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$

(44)

$$\begin{bmatrix} -0.138 & 0 & 0 \\ 0 & -4.579 & 0 \\ 0 & 0 & -15.319 \end{bmatrix} \begin{bmatrix} 0.904x_1 & 0.406x_2 & 0.134x_3 \\ 0.427x_1 & -0.876x_2 & -0.223x_3 \\ 0.134x_1 & 0.259x_2 & -0.963x_3 \end{bmatrix}$$

Using equation 38 and 39 the following is obtained

$$z'\lambda z = \lambda_1 z_1^2 + \lambda_2 z_2^2 + \lambda_3 z_3^2$$

$$= 0.417x_1^2 - 4.813x_2^2 - 14.492x_3^2 + 1.130x_1x_2 + 2.395x_1x_3 + 2.927x_2x_3 = x'\beta x$$

Therefore, in canonical form, it can be expressed as,

$$y_1 = 395.261 - 0.417x_1^2 - 4.813x_2^2 - 14.492x_3^2$$

$$y_2 = 95.072 - 0.688x_1^2 - 2.609x_2^2 - 8.251x_3^2$$

$$y_3 = 201.220 - 3.827x_1^2 - 5.082x_2^2 - 7.251x_3^2$$

The sign of the all the eigen values were all negative indicating that the stationary points was at a point of maximum.

4.4.3: Response Surface and Contour Plots

Contour plots provide researchers with a graphical depiction of the response surface, facilitating an easier and more accurate description of the surface's form and identification of the optimum. The study used the R-Statistical program to generate the response surfaces and corresponding contour plots. Figures 15,16,17,18,19,20,21,22 and 23, illustrate the plots for different combinations of variables (rabbit manure, poultry manure, and sheep manure), along with the observed trends in the response (groundnuts seeds weight).

Figure 15 shows a response surface output of groundnut seed weight as a function of poultry manure and rabbit manure. The model output showed that poultry and rabbit manure had positive effect on groundnuts production. Increasing either poultry or rabbit manure generally leads to higher yields. This suggests a synergistic effect where both types of manure work together to improve the response variable, potentially due to enhanced nutrient availability.

The contour lines show that the highest response values were achieved with the highest levels of both manures. Indicating that combined application of both manures leads to significantly higher responses than applying either manure alone. The surface is not a flat planet thus indicating a non-linear and possibly synergistic effect. This is so because both poultry and rabbit manure are abundant in crucial plant nutrients including potassium, phosphorus, and nitrogen, all of which are essential to groundnuts growth. (Rasool *et al.*, 2023).

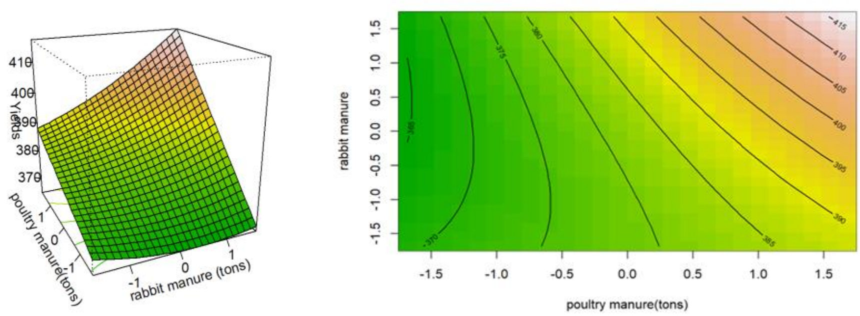

Figure 15: Groundnut Seeds Weight as a Function of Poultry and Rabbit Manure at Fixed Sheep Manure

Figure 16 shows a 3D surface plot of groundnuts seeds weight yield as a function of rabbit and sheep manure. It was noted that combined effect of sheep manure and rabbit factors on yields is synergistic on the groundnut's seeds weight yield. When both factors are at higher levels, the yields are maximized. The slope of the surface suggests that adding more manure beyond a certain point might not significantly increase yields.

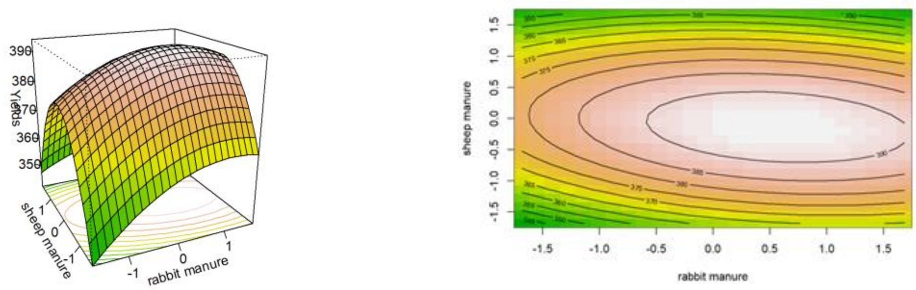

Figure 16: Groundnut Seeds Weight as a Function of Sheep Manure and Rabbit Manure at Fixed

The surface (Figure 17) is curved, indicating that the relationship between the two types of manure and the response variable is non-linear. This curvature suggests that the effects of manure application are not constant but change depending on the levels of each type of manure. The peak of the surface represents the combination of sheep and poultry manure that leads to the maximum response.

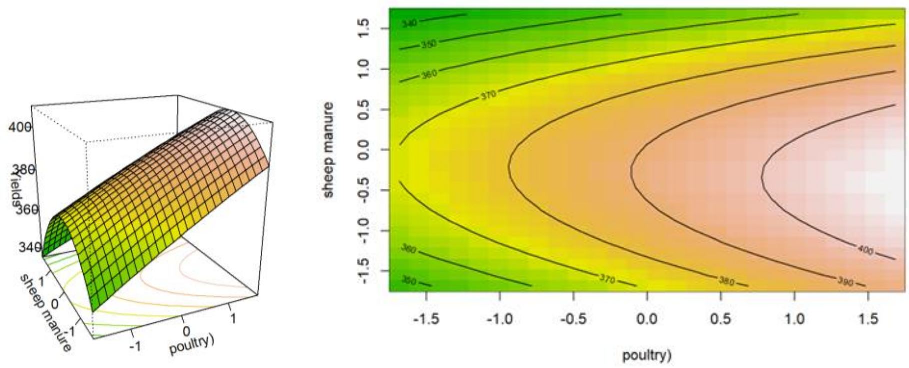

Figure 17: Groundnut Seeds Weight as a Function of Sheep Manure and Poultry Manure at Fixed Rabbit Manure

Figure 18 shows a 3D surface plot of groundnuts number of pods as a function of poultry manure and rabbit manure. This showed that as poultry manure increases the number of pods also increase significantly. Further increase levels of rabbit manure may reduce the yield. This revealed a strong positive correlation between poultry manure and groundnuts number of pods. Also, as rabbit manure increases tends to decrease the groundnuts number of seeds. This indicates a negative correlation between poultry manure and groundnuts number of seeds. The slope suggests that the negative impact of increasing rabbit manure on yield is somewhat mitigated when poultry manure is at lower levels, but the overall trend remains a decrease in yield as rabbit manure increases

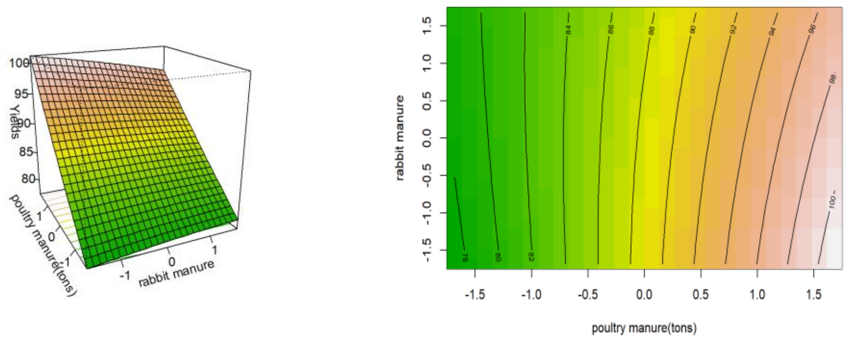

Figure 18: Groundnuts Number of Pods as a Function of Poultry Manure and Rabbit Manure

The graph (Figure 19) shows that the number of pods of groundnuts increases when both sheep was at low to moderate levels and rabbit manure was at low levels. However, as either sheep or rabbit manure levels increase beyond a certain point, the yield started to decline. The highest point on the surface (representing the maximum number of pods) is observed when sheep manure is at moderate levels and rabbit manure is at low levels. Conversely, number of pods decreases as rabbit manure increases, especially when combined with high levels of sheep manure**.**

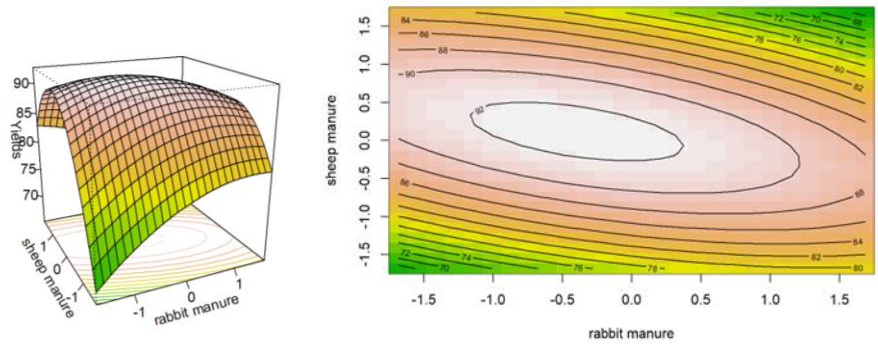

Figure 19: Groundnuts Number of Pods as a Function of Sheep Manure and Rabbit Manure at a Fixed Poultry Manure

The slope of the surface (Figure 20) indicate that both poultry and sheep manure had significant effect on the number of pods of groundnuts plants. the yield increases to a certain point, but further increase in the application of this manure can lead to a decrease in the number of pods. The peak of the surface represents the optimal combination of sheep and poultry manure for maximizing groundnuts number of pods within the studied range. In this case, it appears to be a relatively balanced mix of both manures.

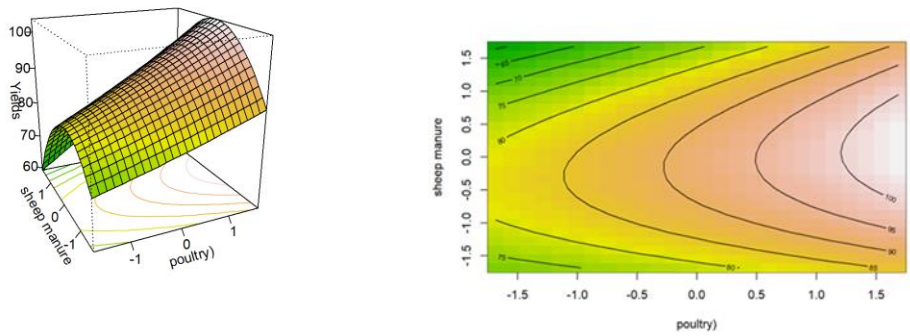

Figure 20: Groundnuts Number of Pods as a Function of Sheep Manure and Poultry Manure at a Fixed Rabbit Manure.

The surface plot (Figure 21) suggests that there was a positive relationship between the two types of manure and the number of groundnuts seeds, as the values generally increase with increasing levels of manure, peaking towards the center or slightly offset towards higher levels of rabbit manure. This indicates that a balanced or moderately high combination of both manures leads to higher response values in this specific study. The curvature of the plot, smooth and arching upwards, indicates that the response improves as the amount of manure increases, up to a certain point after which the response potentially could decreases. This could be used to optimize the levels of rabbit and poultry manure to maximize the response outcome, assuming other conditions remain constant.

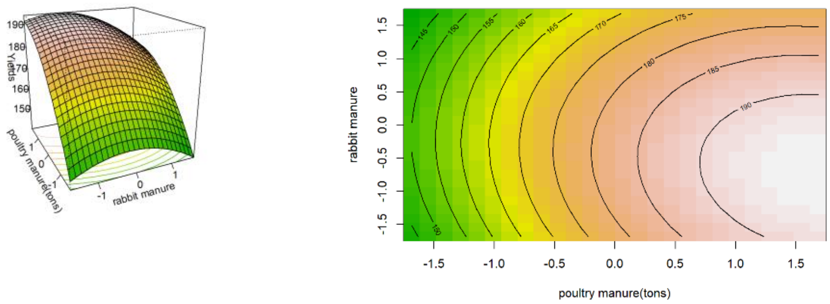

Figure 21: Groundnuts Number of Seeds as a Function of Rabbit Manure and Poultry Manure at a Fixed Sheep Manure.

Figure 22 illustrate a surface that arcs downwards, suggesting that there is an optimal range or combination of sheep and poultry manure that maximizes the number of seeds per plant, with the highest values concentrated towards the middle of the poultry manure axis (near zero). As poultry manure increases or decreases from this central point, the number of seeds per plant decreases, which could be interpreted as showing that too much or too little poultry manure, relative to sheep manure, reduces the effectiveness in terms of maximizing seed production.

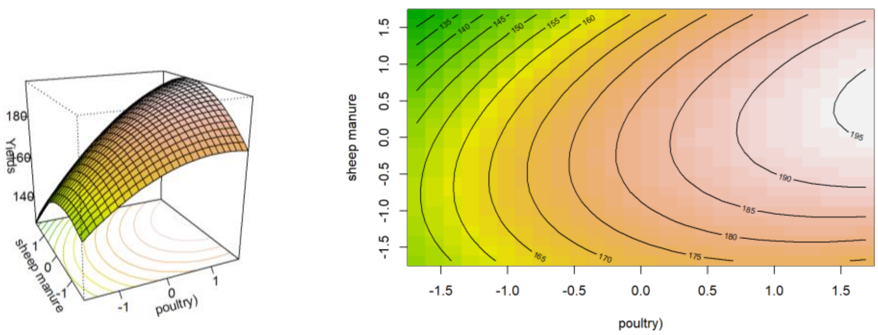

Figure 22: Groundnuts Number of Seeds as a Function of Sheep and Poultry Manure at a Fixed Rabbit Manure

The plot (Figure 23) shows a saddle-like surface, indicating an interaction between the two types of manure in influencing the response variable. This shape suggests that there are combinations of rabbit and sheep manure that led to higher and lower values of the response. The curvature of the surface suggests the interaction and optimal levels of sheep and rabbit manure to maximize the number of seeds of groundnuts. It appears that there was a peak in the center where the combination of these two types of manure might yield the highest response in the plotted variable.

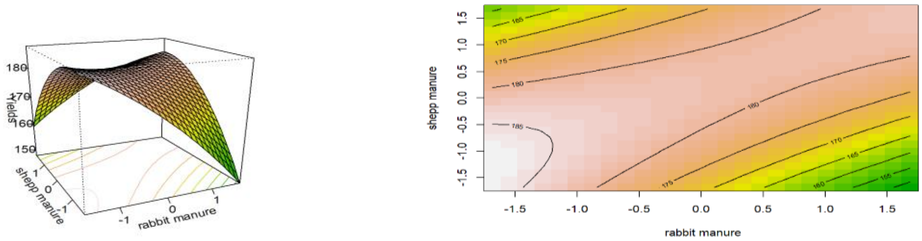

Figure 23: Groundnuts Number of Seeds as a Function of Rabbit Manure and Sheep Manure at a Fixed Poultry Manure

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Summary

This study aimed at optimizing the yield of groundnuts through response surface methodology using organic manure. This study employed a central composite design that was used to develop 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 groundnuts. The data for this research was collected from an experiment carried out at the Chuka University horticultural research and teaching Kairini farm. A response surface methodology was used to establish a relationship between explanatory variables (poultry manure, rabbit manure and sheep manure) and the response variable (weight of groundnuts, number of groundnuts pods, number of groundnuts seeds).

The first objective was to establish the effect of poultry, rabbit, and sheep manure on groundnut yield. The results revealed that optimal amounts of organic manure significantly influence groundnut weight, the number of pods, and number of seeds. Poultry manure had a positive effect across all parameters, yielding the highest results at the maximum application rate compared to rabbit and sheep manure. Rabbit manure showed an impact at moderate levels for weight and pod number, but the number of seeds decreased at higher application rates. Similarly, sheep manure exhibited optimal levels for weight and number of pods, with lower performance at extreme application rates. Therefore, the findings suggest that careful management of organic manure application is crucial for maximizing groundnut yield, with specific optimal levels varying by manure type and yield parameters.

The study's second objective was to determine a functional relationship between groundnut yield and the impact of organic manure on the growth and yield of the groundnuts. A second-order polynomial model was developed using the least squares method to predict groundnuts weight. This regression model was evaluated through analysis of variance to minimize residuals and it was found to be statistically significant, with an adjusted R-squared value of 0.762. The relatively high coefficient of determination suggests that the model effectively represents the relationship between the variables studied. It was noted that the main effects of poultry and sheep manure had a significant influence on groundnut weight at the 5% significance level in the study area. The study also found that F-statistic was statistically significant F=7.757, this indicates that the model is statistically significant. Additionally, the study determined that there was no significant lack of fit, concluding that the reduced model was adequate.

A second-order polynomial model for the number of pods in groundnuts indicated that the predicted response model was statistically significant, with a coefficient of determination (R-squared) value of 0.789. This suggests that 78.9% of the variation in the model was explained by the controlled variables, making the model suitable for representing the relationships among the studied variables. The study found that the application of poultry manure alone and the quadratic effect of sheep manure had statistically significant regression coefficients at the 5% significance level. Specifically, a one-unit increase in combined poultry manure would result in an increase of 7.379 pods, indicating that poultry manure is significantly more effective in increasing the number of pods compared to other combinations of manure. The study found that the model had an adjusted R-squared value of 0.887 on the prediction of number of seeds of groundnuts. This suggests that 88.7% of the variation in the model is accounted for by the factors considered in this study and the rest by other factors not considered in 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 and the quadratic effect are more influential on number of groundnuts seeds.

The third objective of this study was to identify the ideal optimal application rates of organic manure that would maximize groundnut yield. The optimal application rates of poultry manure, rabbit manure, and sheep manure to maximize the weight of groundnuts, the number of pods, and the number of seeds were identified from the stationary points of the response surface. For maximizing the weight of groundnuts 1.65 t/ha, the optimal amounts were 12.697 t/ha of poultry manure, 10.582 t/ha of rabbit manure, and 11.0814 t/ha of sheep manure. To achieve the maximum number of pods, the stationary points indicated 12.290 t/ha of poultry manure, 11.418 t/ha of rabbit manure, and 10.980 t/ha of sheep manure, resulting in 396 pods. Lastly, the maximum seed yield of 833 seeds was obtained by applying 24.720 t/ha of poultry manure, 13.980 t/ha of rabbit manure, and 15.924 t/ha of sheep manure.

5.2 Conclusion

The study found that different types of organic manure (poultry, rabbit, and sheep) significantly impact groundnut yield. Poultry manure consistently increased yield parameters, while rabbit and sheep manure showed an inconsistency on the yield parameters. The research highlights the importance of precise manure management for maximizing groundnut production. The second-order model developed showed that the models was valid. The model adequately explains at least 76.2% of the variations on the weight of groundnuts, 78.9% of the variation on the number of pods and 88.7% on the number of seeds to poultry manure, rabbit manure and sheep manure. The developed models accurately predict groundnut yield based on manure application. The optimal settings for poultry manure, rabbit manure and sheep manure that led to maximum groundnuts yield of 1.65 tons per hectare were 12.697 t/ha of poultry manure, 10.582 t/ha of rabbit manure, and 11.0814 t/ha of sheep manure.

5.3 Recommendations

Based on the findings the study made the following recommendations:

i. Investigate the conditions under which rabbit and sheep manure could be beneficial, as their effects were inconsistent. This may include factors like application rates, soil type, or environmental conditions.
ii. The validation of the second-order model and its ability to explain at least 76.2% of the variations in the groundnut's response to poultry manure, rabbit manure and sheep manure was a significant finding hence the study recommend that the model be applied by farmers in predicting the groundnuts response to poultry manure, rabbit manure and sheep manure.
iii. The study found that the main effects of poultry manure and sheep manure significantly influence groundnut yields. Farmers are encouraged to use poultry and sheep manure to boost groundnut production, which could lead to improved financial outcomes for small-scale farmers in the study area. The study recommends applying 12.697 t/ha of poultry manure, 10.582 t/ha of rabbit manure, and 11.0814 t/ha of sheep manure to maximize groundnut production in the area.

5.4 Suggestions for Further Research

The study made the following recommendations for further research:

i. Future research to refine and expand the model's applicability to other crops or environments to enhance its generalizability. Moreover, there is a need to assess the model's performance under varying conditions to ensure its robustness.

ii. In this dissertation, the classical Response Surface Methodology (RSM) using Central Composite Design (CCD) was employed for comparison. Future research could explore alternative methods, such as the Box-Behnken design and Plackett-Burman designs.

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APPENDICES

APPENDIX I: R Codes

```
# set a work directory
setwd("~/MSC2024")
## Step 1: Install and Load Necessary Packages
 ##Step 2: Load the CSV Data
library(rsm)
library(psych)
library(ggplot2)
Grd=read.csv ("C:/data set/Gdf.csv", header=TRUE)
Grd
 x1=poultry manure,
#x2 = rabbit manure, x3 = sheep manure#y1=weight in grams, y2 = number of pods ,
y3 = number of seeds## Explore and Preprocess the Data
data.frame(Grd)
library(ggplot2)
# Q-Q plot with ggplot2
ggplot(Grd, aes(sample = y1 )) + geom_qq() + geom_qq_line(color = "red") +
ggtitle("Q-Q Plot of y1") +
  xlab("Theoretical Quantiles") + ylab("Sample Quantiles")
boxplot(Grd$y2, main="Yield", sub=paste("Outliers: ", boxplot.stats(Grd$y2)$out))
# Scatter plot to identify outliers in relation to other variable
pairs(Grd)
# Establish Functional Relationship
# Fit a response surface model
#fitting a first order model
model_FO_y1<- rsm(y1~FO(x1,x2,x3), data = Grd)
summary(model_FO_y1)
#Establish Functional Relationship
library(ggplot2)
ggplot(Grd, aes(x = as.factor(x1), y = y1, fill = as.factor(x1))) +    geom_boxplot() +
  labs( x = "Poultry Manure", y = "Weight of Groundnuts") +
```

```
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()ggsave("figure1.png")
ggplot(Grd, aes(x = as.factor(x2), y = y1, fill = as.factor(x2))) +     geom_boxplot() +
labs( x = "Rabbit Manure", y = "Weight of Groundnuts") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
 ggsave("figure2.png")
ggplot(Grd, aes(x = as.factor(x3), y = y1, fill = as.factor(x3))) +   geom_boxplot() +
  labs(x = "Sheep Manure", y = "Weight of Groundnuts ") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
ggsave("figure3.png")
ggplot(Grd, aes(x = as.factor(x1), y = y2, fill = as.factor(x1))) +  geom_boxplot() +
  labs(x = "Poultry Manure", y = "Number of Pods") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
  ggsave("figiure4.png")
ggplot(Grd, aes(x = as.factor(x1), y = y2, fill = as.factor(x1))) +   geom_boxplot() +
  labs(x = "Rabbit  Manure", y = "Number of Pods") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
  ggsave("figiure5.png")
ggplot(Grd, aes(x = as.factor(x3), y = y2, fill = as.factor(x3))) +    geom_boxplot() +
  labs( x = "Sheep Manure", y = "Number of Pods") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
ggsave("figure6.png")
ggplot(Grd, aes(x = as.factor(x1), y = y3, fill = as.factor(x1))) +    geom_boxplot() +
  labs( x = "Poultry Manure", y = "Number of Seeds") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
ggsave("figure7.png")
```

```
ggplot(Grd, aes(x = as.factor(x2), y = y3, fill = as.factor(x2))) +    geom_boxplot() +
  labs( x = "Rabbit Manure", y = " Number of Seeds") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
ggsave("figure8.png")
ggplot(Grd, aes(x = as.factor(x3), y = y3, fill = as.factor(x3))) +    geom_boxplot() +
  labs( x = "Sheep Manure", y = "Number of Seeds") +
  scale_fill_brewer(palette = "Set3") +  # This adds a pleasant color palette
  theme_bw()
ggsave("figure9.png")
# Fit a response surface model
model_y1 <- rsm(y1 ~ SO(x1,x2,x3), data = Grd)
summary(model_y1)
model_y2 <- rsm(y2 ~ SO(x1,x2,x3), data = Grd)
summary(model_y2)
##Establish Optimal Levels of Organic Manure
# Find the stationary point of the response surface model
canonical_model1 <- canonical(model_y1)
canonical_model1
canonical_model2 <- canonical(model_y2)
canonical_model2
canonical_model3 <- canonical(model_y3)
canonical_model3
# Extract and print the stationary point
stationary_point1 <- canonical_model1$xs
print(stationary_point1)
stationary_point2 <- canonical_model2$xs
print(stationary_point2)
stationary_point3 <- canonical_model3$xs
print(stationary_point3)
#predicting the yield at the stationary point
 max<- data.frame(x1= 0.04906855  ,x2= -0.09685238 , x3=-0.16990644
```

```
)
predict(model_y2, max)
 # Assuming model_y1, model_y2, model_y3 are your fitted models and 'data' is your dataset
predicted_y1 <- predict(model_y1, newdata = Grd)
predicted_y2 <- predict(model_y2, newdata =Grd)
predicted_y3 <- predict(model_y3, newdata = Grd)
# Calculate residuals
residuals_y1 <- Grd$y1 - predicted_y1
residuals_y2 <- Grd$y2 - predicted_y2
residuals_y3 <-Grd$y3 - predicted_y3
library(ggplot2)
# Plot for y1
ggplot(Grd, aes(x = predicted_y1, y = y1)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, linetype = "dashed", color = "red") +
  labs(y = "Predicted (Weight)", x = "Actual (Weight)")
ggsave("figure20.png")
# Plot for y1
ggplot(Grd, aes(x = predicted_y2, y = y2)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, linetype = "dashed", color = "red") +
  labs(y = "Predicted (Pods)", x = "Actual (Pods)")
ggsave("figure21.png")
# Plot for y1
ggplot(Grd, aes(x = predicted_y3, y = y3)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, linetype = "dashed", color = "red") +
  labs(y = "Predicted  (Seeds)", x = "Actual (Seeds)")
ggsave("figure22.png")
##Plot the response surface
# Second Order plot for Y1 (groundnuts  Grain yields in grams per plot)
```

```
#contour/perspective plots on y1
#Optimal 1 with sheep manure kept constant for y1
plot<-lm(y1~ poly(x1,x2, degree=2), data=Grd)
contour(plot,~x1+x2, image= TRUE, xlabs=c("poultry manure(tons)","rabbit manure"))
persp(plot, x1~x2, col=terrain.colors(50), contours = "colors",
    zlab="Yields", xlab=c("poultry manure(tons)","rabbit manure (tons)"))
##optimal 1 with rabbit  manure kept constant on y1
plot1<-lm(y1~ poly(x1,x3, degree=2), data=Grd)
library(rsm)
contour(plot1,~x1+x3, image= TRUE, xlabs=c("poultry)","sheep manure"))
persp(plot1, ~x1+x3, col=terrain.colors(50), contours = "colors",
zlab="Yields",
xlab=c("poultry)","sheep manure"))
#optimal 1 with poultry manure kept constanton y1
#optimal 1 with poultry manure kept constant
library(rsm)
par(mfrow=c(1,1))
plot2<-lm(y1~ poly(x2,x3, degree=2), data=Grd)
contour(plot2,~x2+x3, image= TRUE, xlabs=c("rabbit manure","sheep manure"))
persp(plot2, ~x2+x3, col=terrain.colors(50), contours = "colors",
    zlab="Yields", xlab=c("rabbit manure","sheep manure"))
#Optimal 2 with sheep manure kept constant on y2
plot<-lm(y2~ poly(x1,x2, degree=2), data=Grd)
contour(plot,~x1+x2, image= TRUE, xlabs=c("poultry manure(tons)","rabbit manure"))
persp(plot, x1~x2, col=terrain.colors(50), contours = "colors",
    zlab="Yields", xlab=c("poultry manure(tons)","rabbit manure"))
#optimal 2 with  rabbit  manure kept constant on y2
#optimal 2 with rabbit  manure kept constant
plot1<-lm(y2~ poly(x1,x3, degree=2), data=Grd)
library(rsm)
```

```
contour(plot1,~x1+x3,  image= TRUE, xlabs=c("poultry)","sheep manure"))
persp(plot1, ~x1+x3, col=terrain.colors(50), contours = "colors",
    zlab="Yields",   xlab=c("poultry)","sheep manure"))
#optimal 2 with poultry manure kept constant on y2
#optimal 2 with poultry manure kept constant
library(rsm)
par(mfrow=c(1,1))
plot2<-lm(y2~ poly(x2,x3, degree=2), data=Grd)
contour(plot2,~x2+x3, image= TRUE,  xlabs=c("rabbit manure","sheep manure"))
persp(plot2, ~x2+x3, col=terrain.colors(50), contours = "colors",
    zlab="Yields", xlab=c("rabbit manure","sheep manure"))
#Optimal 3 with sheep manure kept constant on y3
plot<-lm(y3~ poly(x1,x2, degree=2), data=Grd)
contour(plot,~x1+x2,    image=    TRUE,    xlabs=c("poultry    manure(tons)","rabbit
manure"))
persp(plot, x1~x2, col=terrain.colors(50), contours = "colors",
    zlab="Yields",  xlab=c("poultry manure(tons)","rabbit manure"))
#optimal 3 with rabbit manure kept constant on y3
#optimal 3 with rabbit  manure kept constant
plot1<-lm(y3~ poly(x1,x3, degree=2), data=Grd)
library(rsm)
contour(plot1,~x1+x3,image= TRUE,  xlabs=c("poultry)","sheep manure"))
persp(plot1, ~x1+x3, col=terrain.colors(50), contours = "colors",
    zlab="Yields",  xlab=c("poultry)","sheep manure"))
#optimal 3 with poultry manure kept constant on y3
#optimal 3 with poultry manure kept constant
library(rsm)
par(mfrow=c(1,1))
plot2<-lm(y3~ poly(x2,x3, degree=2), data=Grd)
contour(plot2,~x2+x3, image= TRUE, xlabs=c(" rabbit manure","shepp manure"))
persp(plot2, ~x2+x3, col=terrain.colors(50), contours = "colors",
    zlab="Yields",  xlab=c("rabbit manure","shepp manure"))
```

```
#y1 the yield of groundnuts (weight in grams )

Gdc.p <-Grd

x.pred <- expand.grid(x1 = seq( min(Gdc.p$x1),  max(Gdc.p$x1), length=15),

  x2 = seq( min(Gdc.p$x1),   max(Gdc.p$x1), length=15),   x3 = seq( min(Gdc.p$x3),   max(Gdc.p$x3), length=3) )

x.pred$yp <- predict(model_y1,x.pred)

library(lattice)

#install.packages("pals")

library("pals")

lattice::wireframe(yp~x1*x2|x3,   data=x.pred,layout=c(3,1), zlab=list(label="y",cex=1.3,rot=90),   xlab=list(label=expression(x [1]),cex=1.3,rot=55),

          ylab=list(label=expression(x [2]),cex=1.3,rot=0),

          drape=TRUE,

          par.strip.text=list(cex=1.5),

          col.regions = pals::parula(100),

          strip=T,

          scales = list(arrows = FALSE,

                 x=c(cex=1.3),

                 y=c(cex=1.3),

                 z=c(cex=1.3))

          ,screen = list(z = 60, x = -55, y=0)

          )##y2 number of pods

Gdc.p.y2 <-Grd

x.pred <- expand.grid(x1 = seq( min(Gdc.p$x1),

                 max(Gdc.p$x1), length=15),

            x2 = seq( min(Gdc.p$x1),

                 max(Gdc.p$x1), length=15),

            x3  = seq( min(Gdc.p$x3),

                 max(Gdc.p$x3), length=3) )

x.pred$yp2 <- predict(model_y2,x.pred)

lattice::wireframe(yp2~x1*x2|x3, data=x.pred,layout=c(3,1),

          zlab=list(label="y",cex=1.3,rot=90),
```

```
            xlab=list(label=expression(x [1]),cex=1.3,rot=55),
            ylab=list(label=expression(x [2]),cex=1.3,rot=0),
            drape=TRUE,
            par.strip.text=list(cex=1.5),
            col.regions = pals::parula(100),
            strip=T,
            scales = list(arrows = FALSE,
                     x=c(cex=1.3),
                     y=c(cex=1.3),
                     z=c(cex=1.3))
            ,screen = list(z = 60, x = -55, y=0)
)
# number of seeds per plant
Gdc.p.y3 <-Grd
x.pred <- expand.grid(x1 = seq( min(Gdc.p.y3$x1),
                    max(Gdc.p.y3$x1), length=15),
              x2 = seq( min(Gdc.p.y3$x1),
                    max(Gdc.p.y3$x1), length=15),
              x3  = seq( min(Gdc.p.y3$x3),
                     max(Gdc.p.y3$x3), length=3) )
x.pred$yp3 <- predict(model_y3,x.pred)
lattice::wireframe(yp3~x1*x2|x3, data=x.pred,layout=c(3,1),
            zlab=list(label="y",cex=1.3,rot=90),
            xlab=list(label=expression(x [1]),cex=1.3,rot=55),
            ylab=list(label=expression(x [2]),cex=1.3,rot=0),
            drape=TRUE,
            par.strip.text=list(cex=1.5),
            col.regions = pals::parula(100),
            strip=T,
            scales = list(arrows = FALSE,
                     x=c(cex=1.3),
                     y=c(cex=1.3),
```

```
                    z=c(cex=1.3))
          ,screen = list(z = 60, x = -55, y=0)
)
model_fo <- lm(y2 ~ x1 + x2 + x3, data = Grd)
model_fo
# Fit a first-order model with two-way interactions
model_fo_twi <- lm(y2 ~ x1 + x2 + x3 + x1:x2 + x1:x3 + x2:x3, data = Grd)
model_fo_twi
# Fit a second-order model
model_so <- rsm(y2 ~ SO(x1, x2, x3), data =Grd)
model_so
# Calculate AIC values
aic_fo <- AIC(model_fo)
aic_fo_twi <- AIC(model_fo_twi)
aic_so <- AIC(model_so)
print(paste("AIC for First-Order Model:", aic_fo))
print(paste("AIC for First-Order with Two-Way Interactions Model:", aic_fo_twi))
print(paste("AIC for Second-Order Model:", aic_so))

# Compare models
aic_values <- c(aic_fo, aic_fo_twi, aic_so)
names(aic_values) <- c("First-Order", "First-Order with Two-Way Interactions", "Second-Order")
best_model <- names(which.min(aic_values))
# Print the best model
print(paste("The best model is:", best_model))
```

APPENDIX II: Project Pictures

F1: Overview of Groundnuts Crop 6 Days After Planting

F2: Overview of Groundnuts Crop After 50 Days

F3: Harvest Day of Groundnuts

F4: Drying Groundnut’s Pods and Seeds After Harvest

APPENDIX III: Chuka University Ethics Review Authorization

CHUKA UNIVERSITY

Knowledge is Wealth *(Sapientia divitia est)* Akili ni Mali

CHUKA UNIVERSITY INSTITUTIONAL ETHICS REVIEW COMMITTEE

Telephones: 020-2310512/18 **P. O. Box 109-60400, Chuka**
Direct Line: 0772894438 **Email: info@chuka.ac.ke,** **Website: www.chuka.ac.ke**

25th July, 2024

REF: CUIERC/ NACOSTI/600
TO: **Dennis Kiprotich**

RE: Optimization of Groundnuts (Archis hypogeal) Yield Through Response Surface
This is to inform you that *Chuka University IERC* has reviewed and approved your above research proposal. Your application approval number is *NACOSTI/NBC/AC-0812.* The approval period is 25th July, 2024 – 25th July, 2025.

This approval is subject to compliance with the following requirements;

i. Only approved documents including (informed consents, study instruments, MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by *Chuka University IERC.*
iii. Death and life threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to *Chuka University IERC* within 72 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to *Chuka University IERC* within 72 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days upon completion of the study to *Chuka University IERC.*

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://oris.nacosti.go.ke and also obtain other clearances needed.

Yours sincerely

Dr. Benjamin Kanga
SECRETARY

APPENDIX IV: NACOSTI Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION

Ref No: **223959**

Date of Issue: **08/August/2024**

RESEARCH LICENSE

This is to Certify that Mr. Dennis Kiprotich of Chuka University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Tharaka-Nithi on the topic: OPTIMIZATION OF GROUNDNUTS (Archis hypogeal) YIELD THROUGH RESPONSE SURFACE METHODOLOGY for the period ending: 08/August/2025.

License No: **NACOSTI/P/24/38582**

223959

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Director General
NATIONAL COMMISSION FOR
SCIENCE, TECHNOLOGY &
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