

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

Abstract

Groundnut production faces several constraints, including poor soil fertility, small land sizes, and inappropriate agricultural techniques. The study aimed to optimize groundnut (*Archis hypogea*) yield using response surface methodology (RSM). It explored the use of CCD and RSM to determine the optimal application of rabbit, poultry, and sheep manure for maximum yield, a method not previously applied in groundnut production. 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. Data was collected on the weight of the groundnuts yield harvested in each experimental plot measured by use of a weighing scale. Response Surface Methodology techniques was adopted for data analysis in R-statistical software and R studio programming language. The study findings indicated that organic manures had a significant effect ($P < 0.05$) on the yield of groundnuts crop. The study revealed that application of 13.6097 t ha⁻¹, 10.582 t ha⁻¹ and 11.0814 t ha⁻¹ of poultry, rabbit and sheep manure respectively are the optimum levels that would lead to maximum weight of groundnuts in the study area. The finding of this study could have an economic benefit to farmers in the study area which aligns with broader national goals of poverty reduction, rural development, and economic growth. This study recommended that farmers should adopt organic farming practices to reduce reliance on chemical fertilizers, improve soil health, and contribute to environmental sustainability.

Keywords: Central Composite Design; Parameters; Optimize; Yield; Organic Manure; Groundnuts

1. Introduction

The optimization of agricultural practices is essential for improving crop yields and ensuring food security, especially in regions where farming is a primary source of livelihood [15]. Response Surface Methodology (RSM) is a widely recognized statistical approach that has been effectively utilized across various fields, including agriculture, to optimize processes and understand the complex relationships between multiple variables.

Groundnut is a legume species in the family Fabaceae that first originated from South Korea [13]. In Kenya groundnut crops are mainly grown in warm, tropical and subtropical climate areas include Nyanza, the Rift Valley, the Western, and portions of the Central and Eastern provinces [12]. Groundnut is a vital food and cash crop in Kenya which contributes significantly to the agricultural sector and the economy of Kenya. Despite its importance, groundnut production in Kenya has been declining, with farmers achieving only about 50% of the expected yield.

The drop in produce has been linked to a variety of issues, including ineffective farming practices, poor soil management, and insufficient pest control [12].

One of the most effective ways to improve soil fertility is to apply organic manure, such as poultry, rabbit, and sheep manure, which is commonly available and affordable. Despite the fact that organic manures are cheap and readily available in the country, application of organic manure in groundnuts crop has not been optimized for increased groundnut growth and yield [11]. Improving the groundnuts yield is a critical goal for the Kenya agriculture since the crop is of nutritional value and economic benefit.

Response Surface Methodology is a statistical mathematical strategy employed to optimize and comprehend the relationship between a dependent variable and independent variables [2]. Response Surface Methodology (RSM) was first presented by Box and Wilson (1951) [1], it has since become a cornerstone in experimental design, particularly in exploring how different factors influence a response variable. For instance, the plant growth (y) can be as a function of warmth (x_1) and water (x_2). The plant can grow under any combinations of treatments warmth (x_1) and water (x_2) which varies continuously. In this case the relationship can be expressed as,

$$y = f(x_1, x_2) + \varepsilon \quad (1)$$

where x_1 represents warmth factor

x_2 represent water factor

y represents response variable (plant growth).

ε experimental error term.

Error terms denote measurement errors in the response and other kinds of deviations that the function does not account for. This statistical error is considered to have a normal distribution with a mean of zero and a variance of one.

The aim of Response Surface Methodology (RSM) is to formulate a mathematical model that effectively depicts the relationship between dependent variables and independent variables. There are several types of mathematical models that can be used in RSM applications, including linear, quadratic, and higher-order polynomial models [10]. 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 [10]. Thus, the model is expressed as follows

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \quad (2)$$

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 [4]. However, as the order

of the polynomial increases, the model 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 [10]. In these cases, a second-order model is needed. This model can be expressed as follows,

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_{11}x_1^2 + \beta_{22}x_2^2 + \beta_{12}x_1x_2 + \varepsilon \quad (3)$$

For effective approximation of an empirical model, it is critical to adopt an appropriate experimental design for data collection. This data was used to develop an empirical model that connects the process response to numerous influencing factors. The empirical model's parameters are estimated using the least square methods. Application of RSM, particularly through the Central Composite Design (CCD), offers a promising solution. CCD allows for the systematic exploration of the effects of multiple factors on crop yield, providing a robust framework for identifying optimal conditions for maximum productivity [6]. Organic manures such as poultry, rabbit, and sheep manure have been recognized by other studies for their potential to enhance soil fertility and support plant growth. However, determining the optimal application rates of these manures remains a key challenge.

This study aims to utilize RSM and CCD in determining the optimal application rates that would optimize groundnut yield by establishing the effects of poultry, rabbit and sheep manure on the weight yield of groundnuts and to develop a mathematical model that accurately represents the relationship between weight of groundnut yield and manure application.

2. Materials and Methods

2.1 Study Site

This research was conducted at Chuka University Teaching and Training Farm in Kairini, Tharaka Nithi County, Kenya, approximately 186 km from Nairobi. The area features Humic Nitisol soils, known for their depth, extensive weathering, and moderate to high fertility. Situated at an altitude of 1,560 meters above sea level (37.6575° E, 0.3190° S), the region experiences an average annual temperature of 19.5°C and variable rainfall, ranging from 544 mm to 2,208 mm. The area is suitable for agriculture, with small-scale farming of crops such as vegetables, beans, bananas, coffee, maize, sunflowers, and groundnuts, along with livestock keeping.

2.2 Design of Experiment

The experiment used a central composite design consisting of 20 experimental runs that were determined by the 2³ full factorial designs with six axial points and six center points. A 3 factor and 5 levels central composite design was applied in the groundnut's growth process. Poultry manure (x_1), rabbit manure (x_2) and Sheep manure (x_3) was the independent variables used in this study to optimize the yield of groundnuts.

Table 1: Three Factors at Five Level Estimated Values

Independent variable	Coded and natural factor levels				
	-1.682	-1	0	1	1.682
Poultry manure (x_1) 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

Table 2. Full Factorial Central Composite Design Matrix and Experimental Results.

run	Coded Values			Weight Yield	Number of Pods	Number of Seeds
	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

2.3 Data Source

The data for this study was from an experiment that was carried out at Chuka university teaching and training farm, Kairani. The weight of the groundnut's seeds was then measured using the digital weighing balance machine.

2.4 Data Analysis

The data obtained from the weight of groundnuts seeds was then analyzed using the response surface methodology in R studio software and R programming language.

2.4.1 Model Fitting

Central composite design (CCD) was applied to determine an appropriate relationship between groundnuts yields and organic manure applied: poultry manure (x_1), rabbit manure (x_2) and sheep manure (x_3). A second order model representing the groundnuts weight yield expressed as

$$y_1 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 + \epsilon \quad (4)$$

where $i < j$, y_1 weight in grams per plot, β_0 constant, β_i linear coefficient β_{ii} coefficient of pure quadratic terms, β_{ij} interaction terms x_1 was poultry manure, x_2 was rabbit manure, x_3 was sheep manure and ϵ the error term. In matrix form equation it takes the form of equation (5)

$$y = \hat{\beta}_0 + X'd + X'\beta X + \epsilon \quad (5)$$

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 . In matrix form equation (3) take the form of equation $y = \hat{\beta}_0 + X'd + X'\beta X + \epsilon$. The least squares method was used to estimate the model parameters β by minimizing the sum of squared errors given as,

$L = y'y - 2\beta'X'y + \beta'X'X\beta$, differentiating L with respect to β gives equation 6

$$\frac{\partial L}{\partial \beta} \Big|_{\hat{\beta}} = -2X'y + 2X'X\hat{\beta} = 0 \quad (6)$$

$$X'X\hat{\beta} = X'y \quad (7)$$

Solving the least squares estimator of β is given by equation (8).

$$\hat{\beta} = (X'X)^{-1}X'y \quad (8)$$

The fitted regression model in matrix notation therefore becomes

$$\hat{y} = \hat{\beta}_0 + X'd + X'\hat{\beta}X \quad (9)$$

2.4.2 Optimization

To determine the levels of x_1, x_2, x_3 that optimizes the response, partial derivatives for the response against the levels and equating all to zero is given in equation (10).

$$\frac{\partial \hat{y}}{\partial x_1} = \frac{\partial \hat{y}}{\partial x_2} = \frac{\partial \hat{y}}{\partial x_3} = 0 \quad (10)$$

For second-order model in matrix notation is expressed as

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

$$\mathbf{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}, \mathbf{d} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix}, \boldsymbol{\beta} = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix}$$

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

$$\frac{\partial \hat{y}}{\partial \mathbf{X}} = \mathbf{d} + 2\boldsymbol{\beta}\mathbf{X} = 0 \quad (11)$$

Thus, the stationary point was given by;

$$x_s = -\frac{1}{2}\boldsymbol{\beta}^{-1}\mathbf{d} \quad (12)$$

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

$$\hat{y} = \hat{\beta}_0 + \frac{1}{2}\mathbf{X}^{-1}\mathbf{d} \quad (13)$$

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

2.5: Canonical Analysis

Canonical analysis examines the relationship between the factors and the response. It also ascertains characteristics of stationary points and the entire response surface [5]. The sign of the eigenvalues of β gives the characterization of the stationary points while the magnitude of the eigenvalues determines the nature of the response surface. canonical analysis can be transforms the second order model into

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

3.0 Results and Discussion

3.1 Preliminary Analysis

To test the normality of the data which is very important since most of the statistical tests and models assume the normal distribution of the data. Skewness and kurtosis were used to assess the normality of this data on the groundnuts weight yield [3]. The results according to **Table 3** showed that the groundnuts weight yield was normally distributed since the range of skewness and kurtosis was in between the range of ± 3 and ± 2 , respectively [11]

Table 3: preliminary analysis

Mean	Standard Deviation	Median	Skewness	Kurtosis	Maximum	Minimum
382.800	15.140	380.500	0.200	-1.150	360.000	410.000

3.2 Effect of Organic Manure on Groundnut weight Yield

In this study one of the objectives was to determine the effects of organic manure used in the weight yield of groundnuts. This was established by plotting the Box and whiskers plots as shown in Figure 1,2 and 3 for the poultry, rabbit and sheep manure.

The result in Figure 1,2 and 3 demonstrates that application of the three manures had a different effect at different levels, poultry manure however showed a relatively consistent increased in the weight yield of groundnuts and a less variation at higher levels. In the effect of sheep manure, it demonstrated a more variability across different levels while sheep manure showed a significant increase at the medium levels but at the extreme ends the yield display was lower. This was in agreement with other studies which showed that poultry manure is an organic manure with a high level of nutrients [11]. (Okeat *et al.*, 2020) found that poultry manure was the most significant on growth and yield of cucumber plant [14].

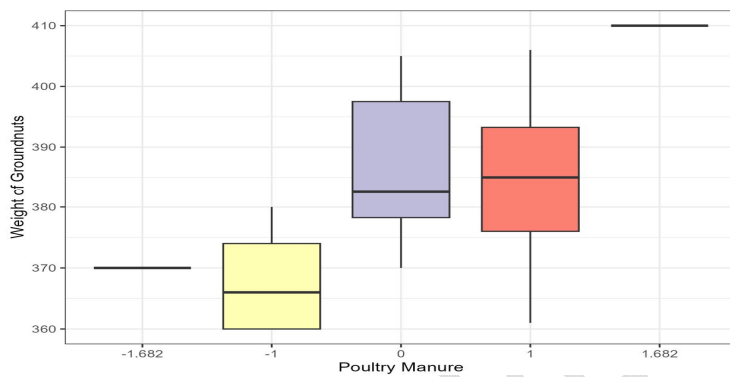


Figure 1: Box and Whisker Plots Showing the Effect of Different Rates of Poultry Manure on Groundnuts Weight

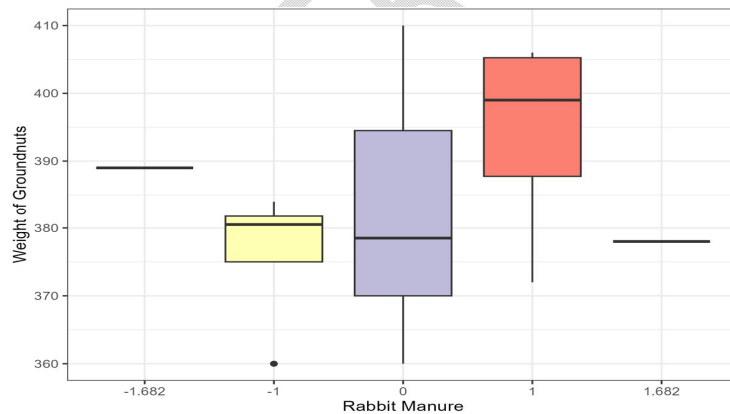


Figure 2: Box and Whisker Plots Showing the Effect of Different Rates of Rabbit Manure on Groundnut Weight

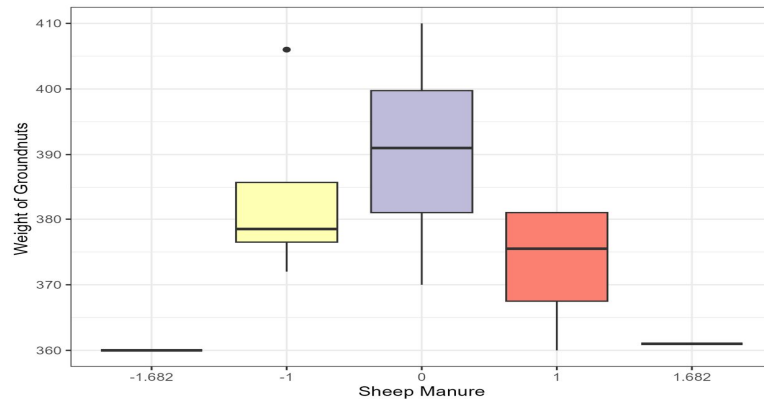


Figure 3: Box and Whisker Plots Showing the Effect of Different Rate of Application of Sheep Manure on the Weight of Groundnut

3.3: Fitting a Second Order Model for the Weight of Groundnuts Seeds

The second order model was fitted on the groundnut's seeds weight yield as in Table 4. The model was significant with a P-value of $0.02 < 0.05$ with a Multiple R-squared of 0.87, implying that the model could explain 87% of the variance of the weight of groundnuts is explained by the independent variables included in the model. 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 second order model also revealed that poultry and sheep manure was significant P-value < 0.05 in explaining the weight yield of groundnuts seeds. While the rabbit manure and all the interaction terms were all insignificant P-value > 0.05 in explaining the model on the groundnuts weight yield. However, the quadratic term for the sheep manure was significant P-value < 0.05 in explaining the weigh yield of groundnuts

The model output shows that for unit increase in poultry manure corresponds to an increase of 12.600g in the weight of groundnuts and a unit increase in sheep manure significantly led to a decrease in 5.557g in the weight of groundnuts. The quadratic effect of sheep manure was significant (P-value $= < 0.002$), implying that for 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 interaction effect of poultry and sheep manure, rabbit and poultry manure were all insignificant with P-values greater than 0.05. This result indicated that poultry manure had a greater impact on the weight of groundnuts compared to sheep manure.

Table 4: Second Order RSM Model for the Weight of Groundnut 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 (Table 4) of the second order regression model was presented using the optimization model equation (36)

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

Where y_1 is the weight of groundnuts seeds $x_1 =$ Poultry manure: $x_2 =$ Rabbit manure: $x_3 =$ Sheep manure

The adequacy of the model for the response (weight of groundnuts) in the experiment was evaluated using analysis of variance [14] as in (Table 5). The model 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%. 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 5: ANOVA 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		

3.4: Validation of the model

The study sought to assess the precision of the model. For better comprehension and clarity, Figure 4 displays graphical representations comparing the predicted values from the model with the actual measured values for all responses.

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 in Figure 4. 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 [9].

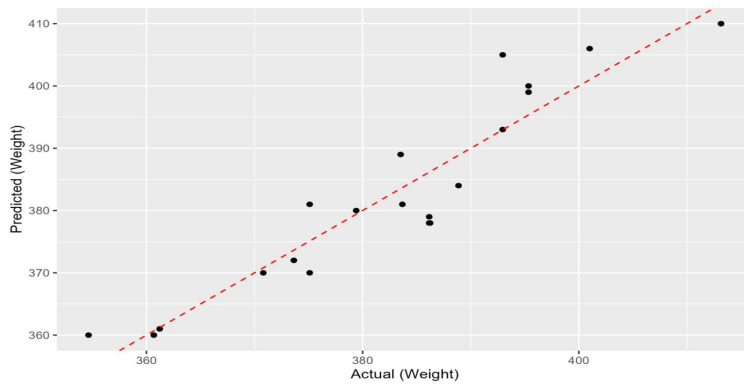


Figure 4: Predicted Values Versus Experimental Value of Groundnuts Seeds Weight

3.5: Optimization

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 6 indicates that the optimal manure application rates for achieving the maximum groundnut weight yield 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.

Table 6: Optimal Conditions for Optimum Groundnuts Yield.

Variables	coded points			Actual Manure			Output
	X_1	X_2	X_3	Poultry	Rabbit	Sheep	
Groundnuts Weight yield	0.116	-0.236	-0.153	12.697	10.582	11.081	1.650 tons/ha

The canonical analysis of the model was the performed to explore the relationship between the dependent and the independent variables. The Table 7 below shows that the eigen values of the model were all negative this revealed that the stationary points were all of the maximum response points.

In canonical form the second order model of the weight of groundnuts seeds is transformed into

$$y_1 = 395.261 - 0.417 z_1^2 - 4.813 z_2^2 - 14.492 z_3^2$$

Table 7: Eigenvalues for the weight of groundnuts seeds

Model	Eigenvalues		
Weight	-0.138	-4.579	-15.319

3.6: Response Surface and Contour Plots

Response surface and contour plots are very important in a study of a response surface methodology, especially visualizing the second order model. The Figure 5,6 and 7 gives a 3D plot for various combination of poultry, rabbit and sheep manure that illustrates the variation in the response (weight yield of groundnuts)

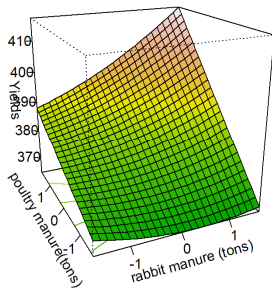
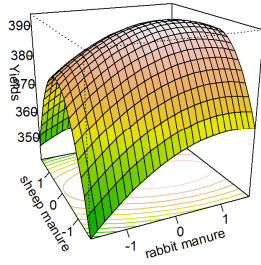


Figure 5: Groundnut Seeds Weight as a Function of Poultry and Rabbit Manure at Fixed Sheep Manure. The model output showed that poultry and rabbit manure had positive effect on weight of groundnuts yield. The plot indicates that increasing poultry manure tends to result in higher yield of groundnuts. The gradient for the rabbit manure appears to be less steep as compared to that for poultry, this implies that rabbit manure is less significant as compared to poultry manure. This is in agreement with previous studies which have shown that poultry manure is rich of nutrient especially nitrogen which enhance growth and yield of groundnuts [8]



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Figure 6: Groundnut Seeds Weight as a Function of Sheep Manure and Rabbit Manure at Fixed Poultry Manure. The surface of this response shows a slight curvature with a peak. This implies that combined application of both rabbit and sheep manure contribute to the weight yield of groundnuts. Groundnut weight increases with an increase in both rabbit and sheep manure to a point, beyond which it tends to decline slightly indicating that moderate application of both manures is more beneficial.

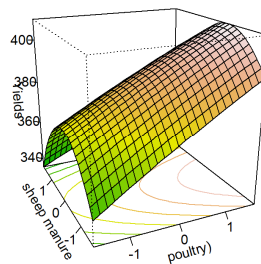


Figure 7: Groundnut Seeds Weight as a Function of Sheep Manure and Poultry Manure at Fixed Rabbit Manure. The Figure 7 show that increasing the application of both poultry and sheep manure results to the maximum response (groundnuts weight yield).

4.0 Conclusion and Recommendation

Groundnuts yield in Kenya has been declining in the recent years. However, measures and mitigation should be put in place to address this challenge since groundnuts production is beneficial and important to the country economy. In using central composite design and response surface methodology in this study, it has shown that poultry and sheep manure was more significant on groundnuts weight yield. The model was valid with a p-value being less than 0.05. This model adequately explained at least 76.2% of the variation on the weight of groundnuts yield. The optimal levels for poultry, rabbit and sheep manure used that to a maximum weight yield of 1.65 t/ha of groundnuts were 12.697t/ha, 10.582t/ha and 11.814 tr/ha respectively. In conclusion application of response surface methodology

help in optimizing the yield of groundnut weight yield and ultimately reducing the recent decline of groundnuts yield. From the results, farmers in the area are encouraged to adopt this model in predicting the groundnuts response.

Disclaimer (Artificial intelligence)

We hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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