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Application of response surface method (RSM) and central composite design (CCD) for optimization of cassava yield

Abass I. Taiwo[1,*], Saheed A. Agboluaje[2], and Waliu A. Lamidi[1]

[1]Department of Mathematical Sciences, Olabisi Onabanjo University, Ago Iwoye, Nigeria.
[2]Department of Statistics, The Polytechnic Ibadan, Ibadan, Nigeria.

Abstract

The decline of agricultural output which has made Nigeria turn from a major agriculture-based exporter to an importing country has prompted us to investigate the effects of Nitrogen, Phosphorus and Potassium (N.P.K) fertilizer on the yield of cassava planted on non-fertile land using the Response Surface Methodology (RSM). A three-factor Central Composite Design (CCD) was applied to determine the effects of the fertilizers on the yield of cassava. The polynomial regression model was developed and validated prior to optimization studies. It was found that the optimum production conditions for the cassava yield were 63.95 kg/ha of nitrogen, 154.35 kg/ha of phosphorus and 45.56 kg/ha of potassium. The 3D response surface plot derived from the Mathematical models was applied to determine the optimal conditions. Under the conditions, the maximum cassava yield was 29.90kg/ha. The Coefficient of determination (R^2) and adjusted R^2 values were 0.9240 and 0.8556 respectively. This showed that the experimental values are in good agreement with the predicted values based on the analysis of variance result. This study proved that Response Surface Methodology can be used effectively to optimize the yield of cassava, and the Central Composite Design is efficient, simple, economical and time-saving which can be adopted for optimizing crop yields.

Keywords: Central composite design, response surface methodology, cassava yield
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1. Introduction

The decline in agricultural production has made Nigeria turn from a major producer of stable foods and cash crops to an importing nation that is dependent on importation for stable food supply [1]. The decline can be attributed to among other factors like planting on over-used land, inadequate fund, non-availability of modern farming tools, machinery and lack of information. These challenges have persistently militated against the growth of agricultural production in Nigeria and even it has led to a rural to urban movement of rural workforce in order to seek for unavailable white-collar jobs [2]. One of the most planted and common agricultural produce is Cassava (*Manihot esculenta Crantz*) which is cultivated mainly in the tropic and sub-tropic regions of the world, over a wide range of environmental and soil conditions. It is very tolerant of drought and heat stress and produces well on marginal soils. It is an important dietary staple in many countries within the tropical regions of the world [3], where it provides food for more than 800 million people [4]. As a subsistence crop, cassava is the third most important carbohydrate food source in the tropics after rice and maize, providing more than 60% of the daily calorific needs of the populations in tropical Africa and Central America [5]. According to [6], cassava plays an important role in alleviating food problems, because it thrives and produces stable yields under conditions in which other crops fail. Cassava is a versatile crop and can be processed into a wide range of products such as starch, flour, tapioca, beverages and cassava chips for animal feed. Cassava is also gaining prominence as an important crop for the emerging biofuel industry and a potential carbohydrate source for ethanol production [7].

Despite the cultivation of Cassava by several farmers, the output is still low. Therefore, in order to boost it, [8] recommended that 60 kg N, 10-20 kg P_2O_5, and 50 kg K_2O ha^{-1} should be applied to the soil for an expected yield of 15 t/ha where all stems and leaves are returned to the soil. On the other hand, [9] emphasized that cassava requires fertilization especially nitrogen, phosphorus and potassium; and even more nitrogen than phosphorus. Also, [10] noted that cassava is known to respond to the application of organic

*Corresponding author; email:taiwo.abass@oouagoiwoye.edu.ng

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and inorganic fertilizer while several other types of research like [11 – 13] reported that the crop is responsive to fertilizer usage. But over-application of fertilizer may as well lead to unusually luxuriant vegetative growth at the expense of roots and tubers [14 – 15].

Having discussed this, there is need to attain an optimal production for cassava planted on over-used farmland in this research work, statistical approaches were used to model Cassava yield with respect to level of fertilizer application to varieties of cassava in order to attain cassava production efficiency. Response Surface Methodology (RSM) which is a combination of mathematical and statistical techniques was used. This approach has been used by several researchers to analyze agricultural experiments and these include [16 – 35] but an application to fertilizer application to cassava is not very common. In essence, this research involved the design of a statistical experiments using a central composite design (CCD), development of a mathematical model of the experimental data, representation of the direct and interactive effects of process parameters through two and three-dimensional plots and finding an optimal set of experimental parameters that produce a maximum value of response.

2. Materials and Methods

2.1. Factorial design

A factorial design was used in experiments involving several factors where it was necessary to investigate the joint effects of the factors on a response variable. In this research, Nitrogen, Phosphorus and Potassium fertilizers were used as predictor variables and cassava yield was considered as the dependent variable. Then, the coded values of the variables were determined by

$$X_i = (x_i - x_0)/x \tag{1}$$

where X_i is a coded variable of the i$^{\text{th}}$ variable, X_0 is the average value of the variable in high and low levels, x is (variable at the high level – variable at low level)/2 and X_i is an uncoded value of the i$^{\text{th}}$ test variable. The factorial point is defined as ±1 unit for each factor.

2.2. Response surface methodology

The Response Surface Methodology (RSM) is a collection of Mathematical and Statistical techniques which are useful for the modeling and analysis of problems in which a response variable of interest is influenced by several independent variables. In this research, Cassava yield was the response variable, and it was a function of Nitrogen, Phosphorus and Potassium. This is expressed as

$$y = f(x_1, x_2, x_3) + e \tag{2}$$

where x_1, x_2, x_3 are predictor variables, y is the response variable and e is the experimental error term. The error term e represents any measurement error on the yield, as well as other types of variations were not counted in the function.

In order to develop a proper approximation for f, a low-order polynomial in some small region was used to define a linear function of independent variables, then the approximating function was a first-order model. A first-order model with k independent variables is expressed as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + ... + \beta_k x_k \tag{3}$$

where y is the dependent variable, $\beta_i, i = 0, 1, ..., k$ is the regression coefficients that measure the expected change in the response y per unit change x_k when other predictor variables are held constant. If there is a curvature in the response surface, then a higher degree polynomial should be used.

2.3. Step in response surface methodology

When there is a curvature in the response surface, the first-order model is insufficient. Therefore, the second-order model is useful in approximating a portion of the true response surface with a curvature. The second-order model includes all the terms in the first-order model, and quadratic and cross product terms. It is represented as

$$y_i = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^k + \sum_{i=1}^{k} \sum_{j=1}^{i=1} \beta_{ij} x_i x_j \tag{4}$$

The second-order models illustrate quadratic surfaces such as minimum, maximum, ridge, and saddle. If there exists an optimum, then this point is called stationary point. The stationary point is the combination of design variables where the surface is at either a maximum or a minimum in all directions. If the stationary point is a maximum in some direction and minimum in another direction, then the stationary point is a saddle point

2.4. Designs for fitting the second-order model

The second-order model is fitted using central composite Design (CCD). It consists of a factorial point, central point, and axial points. CCD is developed through sequential experimentation. When the first-order model shows evidence of lack of fit, then axial points can be added to quadratic terms and with more center points to develop CCD. The number of center points m at the origin and the distance α of the axial runs from the design center are two parameters in the CCD design.

2.5. Parameter estimation in second order regression model

The second order model in equation (4) can be written in matrix notation as

$$y = \beta_0 + x'b + x'Bx \tag{5}$$

where

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix}, \; b = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix}$$

and

$$B = \begin{bmatrix} \beta_{11} & \beta_{11}/2 & \cdots & \beta_{1k}/2 \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2k}/2 \\ \vdots & \vdots & \cdots & \vdots \\ sym. & \cdots & \cdots & \beta_{ik} \end{bmatrix}$$

2.6. Testing for lack of fit for second-order model

In order to determine the lack of fit of the model, the hypothesis below is considered.

H_0: There is no lack of fit

H_1: There is lack of fit

using $\alpha = 0.05$ as the significance level.

Decision rule: Reject H_0, if the lack of fit p-value is less than the significance level (α) otherwise accept H_1. If the lack of fit attributable to curvature in the response function is not adequately modeled, then in such cases a polynomial of a higher degree must be used sure as third-order.

2.7. Location of the stationary point

Once a second order model is fit to the response but if not locating the stationary point enough, the next step is to locate the point of maximum or minimum response. The point for which the response $\hat{y}$ is optimized is the point at which the partial derivatives, $\frac{\delta\hat{y}}{\delta x_1}, \frac{\delta\hat{y}}{\delta x_2}, ..., \frac{\delta\hat{y}}{\delta x_k}$ are all equal to zero. This point is called the stationary point. The stationary point may be a point of maximum response, minimum response or a saddle point. The stationary point can be determined by firstly differentiating equation (5) with respect to x and this gives

$$\frac{\delta\hat{y}}{\delta x} = b + 2B = 0 \tag{6}$$

Thus, the stationary point is

$$x_s = -\frac{1}{2}B^{-1}b \tag{7}$$

The predicted response at the stationary point is

$$\hat{y} = \beta_0 + x_s'b + x_s'Bx_s$$

$$\hat{y} = \beta_0 + x_s'b + \left(-\frac{1}{2}b'B^{-1}\right)Bx_s$$

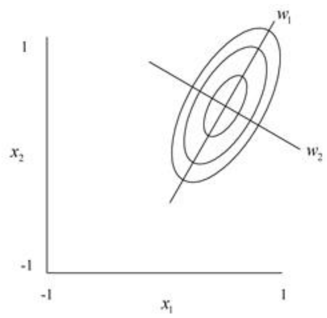

Figure 1: Canonical representation of the stationary points.

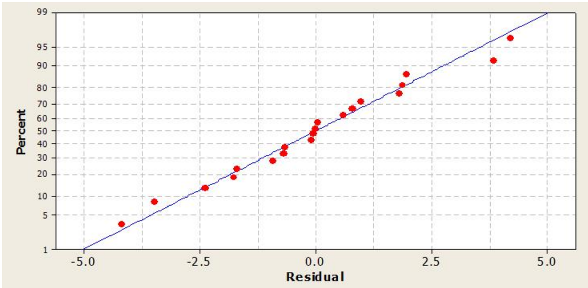

Figure 2: Residual normal probability plot for second order regression model.

$$\hat{y} = \beta_0 + \frac{1}{2}x_s b' \tag{8}$$

Once the stationary point is known, it is necessary to determine if it is a maximum, minimum or saddle point. This is done by transforming the model to a new coordinate system such that the origin lies at the stationary point and the axes are parallel to the principal axes of the fitted response surface. An example is given in Fig.1. The w-axes in Fig. 1 are the principal axes of the contour system and this can be expressed as

$$\hat{Y} = \hat{y}_s + \sum_{i=1}^{k} \lambda_i w_i^2 \tag{9}$$

where $\hat{y}_s$ is the estimated response at the stationary point and $\lambda_1, \lambda_2, ..., \lambda_k$ are the eigen values of B. The variables $w_1, w_2, ..., w_k$ are the transformed independent variables which are called canonical variables. If the λ_i's are all negative, then x_s is a point of maximum response. If the λ_i's are all positive then x_s is a point of minimum response and if the λ_i's have different signs, then x_s is a saddle point

3. Results and Discussion

The codes, ranges and levels of independent variables which are Nitrogen, Phosphorus and Potassium were given in Table 1. The data were collected from the International Institute of Tropical Agriculture, Ibadan (IITA). The data comprised of the response variable (cassava yield (kg)) and three factors

Table 1. Codes, ranges and levels of independent variables of nitrogen, phosphorus and potassium.

Symbols	Predictor Variable	Code levels		
		-1	**0**	**+1**
x_1	Nitrogen (Urea)	40 kg/ha	80 kg/ha	120 kg/ha
x_2	Phosphorus (P_2O_5)	115 kg/ha	172.5 kg/ha	230 kg/ha
x_3	Potassium (K_2O)	30 kg/ha	45 kg/ha	60 kg/ha

Table 2. Central composite design for coded and uncoded forms.

Runs	Coded Variables			Uncoded Variables			Response (Y)
	x_1	x_2	x_3	Nitrogen	Phosphorus	Potassium	
1	-1	-1	-1	40	115	30	21.49
2	+1	-1	-1	120	115	30	17.55
3	-1	+1	-1	40	230	30	21.15
4	+1	+1	-1	120	230	30	11.97
5	-1	-1	+1	40	115	60	19.97
6	+1	-1	+1	120	115	60	12.88
7	-1	+1	+1	40	230	60	24.95
8	+1	+1	+1	120	230	60	9.73
9	-1.682	0	0	12.7	172.5	45	22.70
10	1.682	0	0	147.3	172.5	45	5.25
11	0	-1.682	0	80	75.8	45	30.44
12	0	1.682	0	80	269.2	45	23.21
13	0	0	-1.682	80	172.5	19.8	12.42
14	0	0	1.682	80	172.5	70.2	16.99
15	0	0	0	80	172.5	45	25.25
16	0	0	0	80	172.5	45	24.54
17	0	0	0	80	172.5	45	27.81
18	0	0	0	80	172.5	45	29.32
19	0	0	0	80	172.5	45	32.93
20	0	0	0	80	172.5	45	32.58

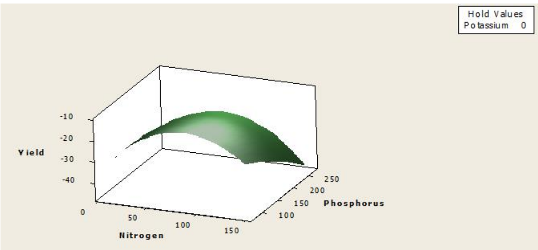

Figure 3: Surface plot for nitrogen and phosphorus on the yield of cassava.

each at two levels as follow: Nitrogen (40 kg/ha & 120 kg/ha), Phosphorus (115 kg/ha & 230 kg/ha) and Potassium (30 kg/ha & 60 kg/ha). The predictors variable (Nitrogen, Phosphorus and Potassium) were optimized by using 2^3 central composite design (CCD) with six axial points (α = 1.682) and six center points leading to a total of twenty experiments. From Table 2, the result of the central composite design values of α was given and for the three independent variables, the optimum value of α was 1.682 for both coded and uncoded forms of the design. Based on the CCD results, the fitted response surface first order regression model results in Table 3 showed that 28.21% (R^2 = 0.2821) of variation in the response variable could be accounted for by the independent variables (x_1, x_2 and x_3).

Moreover, using the results in Table 3, only Nitrogen fertilizer was statistically significant on the yield of cassava, the P-value was less than 0.05 (0.027 < 0.05). This implied that Nitrogen fertilizer was very critical in the production of cassava by farmers $Y = 21.1565-4.7432x_1-1.1898x_2+0.2238x_3$ with R^2 (Coefficient of Determination) = 28.21% or 0.2821. In order to determine the lack of fit for the first order regression, the hypothesis was set as

H_0: There is no lack of fit (insignificant)

H_1: There is lack of fit (significant)

α = 0.05.

Then, the lack of fit test was determined using the result of the Analysis of variance in Table 4 where the lack of fit P-value (0.036) < 0.05, therefore H_0 was rejected and this indicated the presence of curvature. In essence, the first-order model was not an appropriate approximation therefore, there was a need to construct a second-order regression model.

Table 3. Response surface first order regression analysis.

Term	Coefficient	SE Coefficient	T-Value	P-Value
Constant	21.1565	1.613	13.114	0.000
Nitrogen	-4.7432	1.952	-2.430	0.027
Phosphorus	-1.1898	1.952	-0.609	0.551
Potassium	0.2238	1.952	0.115	0.910

Table 4. Analysis of variance for response surface first order regression analysis.

Source	DF	SEQ SS	ADJ SS	ADJ MS	F	P-Value
Regression	3	327.27	327.270	109.090	2.10	0.141
Linear	3	327.27	327.270	109.090	2.10	0.141
Nitrogen	1	307.25	307.252	307.252	5.90	0.027
Phosphorus	1	19.33	19.334	19.334	0.37	0.551
Potassium	1	0.68	0.684	0.684	0.01	0.910
Residual Error	16	832.82	832.818	52.051		
Lack-of-Fit	11	769.49	769.495	69.954	5.52	0.036
Pure Error	5	63.32	63.323	12.665		
Total	19	1160.09				

The second order regression model (Polynomial regression modeling) was performed based on the responses of the corresponding coded values of the three different process variables. Table 5 was used to present the results obtained. The regression estimates, standard error of estimate, t-value and probability value associated with the estimate of linear, quadratic and interaction effects were presented. The result as well indicated that not all main effect had a significant effect on cassava yields. For instance, for an increase in x_1 by one unit, the yield of cassava would decrease by 4.7432 units. Indeed, for an increase in x_2 by one unit, the yield of cassava would decrease by 1.1898 units. Similarly, an increase in x_3 by one unit, the yield of cassava would increase by 0.2238 units. The results in Table 5 revealed as well that x_1, x_1x_1 and x_3x_3 were statistically significant on the yield of cassava with P-value that was less than 0.05 ($0.000 < 0.05, 0.000 < 0.05$ and $0.000 < 0.05$ respectively). This implied that x_1 and x_3 were very critical in the production of cassava by cassava farmers. In addition, the value coefficient of determination was 92.40% ($R^2 = 0.9240$) and this implied that 92.40% of the variation in the response variable could be accounted for by the variables (x_1, x_2 and x_3).

$$\begin{aligned} Y = 28.7519 &- 4.7432x_1 - 1.1898x_2 + 0.2238x_3 \\ &- 5.3081x_1^2 - 0.7650x_2^2 - 5.0500x_3^2 - 1.6712x_1x_2 \\ &- 1.1488x_1x_3 + 0.9688x_2x_3 \end{aligned}$$

with R^2 (Coefficient of Determination) = 92.40%

In order to determine the lack of fit for the second order regression, the hypothesis was set as

H_0: There is no lack of fit (insignificant)

H_1: There is lack of fit (significant)

$\alpha = 0.05$.

Then, the lack of fit test was determined using the result of the analysis of variance in Table 6 where the lack of fit P-value (0.836) > 0.05, therefore H_0 was accepted and this implied that the second order regression model was adequate for the response surface. The model was as well appropriate based on the values of R^2 (Coefficient of Determination) at 92.40% and $\bar{R}^2$ (Adjusted R^2) at 85.56% respectively. This implied that 92.40% of variations in the response variable was explained and the model had a good fit. The Normal Probability plot in Fig. 2 from the residual in the second order regression model showed neither response transformation was required nor there was an apparent problem with normality, therefore, the residual was normally distributed. This was also used to verify that the model was stable and suitable.

Since the response surface has been approximated by the second-order model, then it was important to determine the required level of the three factors that can guarantee the maximum yield of cassava without incurring an extra cost of input. A three-dimensional (3D) surface plot was constructed to investigate the interactive effect of the two factors on the yield within the experimental ranges. The 3D surface plots in Fig. 3 to Fig. 5 revealed the interaction between the response variables and the independent variables. Fig. 3 denoted the surface plot of the cassava yield as a function of Nitrogen and Phosphorus at Potassium of 0 kg/Ha and Nitrogen and Phosphorus were revealed to have a direct effect on the yield of cassava up to a certain level, then yield of cassava decreased with an increase of Nitrogen and Phosphorus. An increase of Nitrogen and Phosphorus, up to a maximum of 63.95 kg/Ha and 154.35 kg/Ha respectively could give a maximum cassava yield of 29.90 kg/ha.

The surface plot of the cassava yield as a function

Table 5. Response surface second order regression analysis.

Term	Coefficient	SE Coefficient	T-Value	P-Value
Constant	28.7519	1.2110	23.741	0.000
Nitrogen	-4.7432	0.8035	-5.903	0.000
Phosphorus	-1.1898	0.8035	-1.481	0.169
Potassium	0.2238	0.8035	0.278	0.786
Nitrogen*Nitrogen	-5.3081	0.7822	-6.786	0.000
Phosphorus*Phosphorus	-0.7650	0.7822	-0.978	0.351
Potassium*Potassium	-5.0500	0.7822	-6.456	0.000
Nitrogen*Phosphorus	-1.6712	1.0498	-1.592	0.142
Nitrogen*Potassium	-1.1488	1.0498	-1.094	0.300
Phosphorus*Potassium	0.9688	1.0498	0.923	0.378

Table 6. Analysis of variance for response surface first order regression analysis.

Source	DF	SEQ SS	ADJ SS	ADJ MS	F	P-Value
Regression	9	1071.92	1071.92	119.102	13.51	0.000
Linear	3	327.27	327.27	109.090	12.37	0.001
Nitrogen	1	307.25	307.25	307.252	34.85	0.000
Phosphorus	1	19.33	19.33	19.334	2.19	0.169
Potassium	1	0.68	0.68	0.684	0.08	0.786
Square	3	704.24	704.24	234.746	26.62	0.000
Nitrogen*Nitrogen	1	335.70	406.06	406.058	46.05	0.000
Phosphorus*Phosphorus	1	1.01	8.43	8.433	0.96	0.351
Potassium*Potassium	1	367.53	367.53	367.531	41.68	0.000
Interaction	3	40.41	40.41	13.470	1.53	0.267
Nitrogen*Phosphorus	1	22.34	22.34	22.345	2.53	0.142
Nitrogen*Potassium	1	10.56	10.56	10.557	1.20	0.300
Phosphorus*Potassium	1	7.51	7.51	7.508	0.85	0.378
Residual Error	10	88.17	88.17	8.817		
Lack-of-Fit	5	24.85	24.85	4.969	0.39	0.836
Pure Error	5	63.32	63.32	12.665		
Total	19	1160.09				

Table 6. Analysis of variance for response surface first order regression analysis.

Variables	Descriptions	Optimal Values
x_1	Nitrogen	63.95
x_2	Phosphorus	154.35
x_3	Potassium	45.56
Y	Yield	29.90

of Nitrogen and Potassium at Phosphorus of 0 kg/ha was displayed in Fig. 4. Nitrogen and Potassium were revealed to have a direct effect on the yield of cassava up to a certain level, then the yield of cassava decreased with an increase of Nitrogen and Potassium. An increase of Nitrogen and Potassium up to a maximum level of 63.95 kg/ha and 45.56 kg/ha respectively could give a maximum cassava yield of 29.90 kg/ha. Fig. 5 is the surface plot of the cassava yield as a function of Phosphorus and Potassium at Nitrogen of 0 kg/ha. This showed that Phosphorus and Potassium had a direct effect on the yield of cassava up to a certain level, then the yield of cassava decreased with an increase of Phosphorus and Potassium. An increase of Phosphorus and Potassium, up to a maximum of 154.35 kg/ha and 45.56 kg/ha respectively could give a maximum cassava yield of 29.90 kg/ha.

In order to determine the optimal settings, a canonical analysis was performed by obtaining the stationary point

$$b = \begin{bmatrix} -4.7432 \\ -1.1898 \\ 0.2238 \end{bmatrix}$$

$$B = \begin{bmatrix} -5.3081 & -0.8356 & -0.5744 \\ -0.8356 & -0.7650 & 0.4844 \\ -0.5744 & 0.4844 & -5.0500 \end{bmatrix}$$

and

$$B_0 = 28.7519$$

The computed stationary point is;

$$x_s = \begin{bmatrix} -0.4011 \\ -0.3157 \\ 0.0375 \end{bmatrix}$$

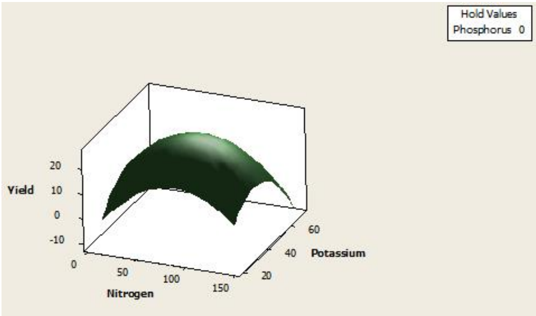

Figure 4: Surface plot for nitrogen and potassium on the yield of cassava.

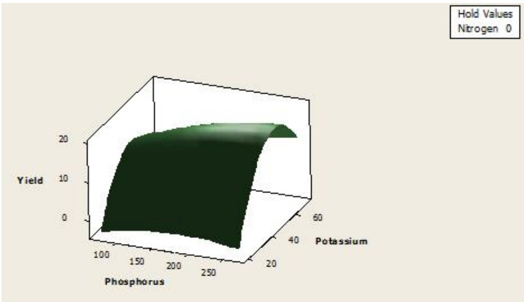

Figure 5: Surface plot for phosphorus and potassium on the yield of cassava.

and the predicted response at the stationary point is $\hat{y} = 29.90$. The eigen values of the matrix B obtained are

$$\lambda_1 = -0.5414, \lambda_2 = -4.7859, \lambda_3 = -5.7958$$

Then, the Canonical form is

$$\hat{y} = 29.90 - 0.5414w_1^2 - 4.7859w_2^2 - 5.7958w_3^2$$

Since all the eigen values were negative, the stationary point was a point of the estimated maximum yield of cassava and in order to optimize independent variables (nitrogen, phosphorus and potassium), the first partial derivatives of the regression model were equated to zero according to x_1, x_2 and x_3 respectively. Thereafter, the stationary points were substituted in equation (1) to obtain the optimal values given in Table 7. This result implied that the highest yield of cassava was 29.90 kg/plot when 63.95 kg/ha of Nitrogen, 154.35 kg/Ha phosphorus and 45.56 kg/ha of potassium (K_2O) were applied to a Cassava farm.

4. Conclusions

The research work was used to determine the optimal operating conditions for cassava production on an over-used farmland that required fertilizer application. The methods used were Central Composite Design and Response Surface Methodology. A three factors central composite design (CCD) was applied and the dependent variable was cassava yield while the independent variables were Nitrogen (x_1), Phosphorus (x_2) and Potassium (x_3) fertilizers. The first order regression model showed a significant lack of fit and this made its inappropriate. A second-order regression model considered exhibited no lack of fit after the ANOVA test while the values of R^2 and $\bar{R}^2$ showed that higher level of variations in the response variable was explained and the model had a good fit. The normal probability plot was used to validate the model since the residual was normally distributed. The two-factor interactions were revealed with 3D response surface plots while the canonical form was obtained. The stationary point was the maximum point since the eigenvalues are all negative. The optimal value indicated that the highest yield of cassava was 29.90 kg/plot when 63.95 kg/ha of Nitrogen, 154.35 kg/ha phosphorus and 45.56 kg/ha of potassium (K_2O) were applied to an over-used land where cassava was planted. In essence, this research work has been used to show that central composite design and response surface methodology can efficiently be applied for modeling crops optimal yield.

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