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Response Surface Methodology for Optimization and Modeling of Cassava Yield

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ABSTRACT

This study utilized Response Surface Methodology (RSM) to optimize cassava yield by analyzing the effects of four key factors: planting date, fertilizer application, cassava variety, and harvest date. Data were collected from the International Institute of Tropical Agriculture (IITA) using a Central Composite Design (CCD), which assessed the impact of these variables at different levels. The findings revealed that planting date, fertilizer, and harvest date significantly influenced cassava yield, with fertilizer application and harvest date showing the most substantial effects. Specifically, the regression model showed that a unit increase in planting date, fertilizer, cassava variety, and harvest date contributed to increases of 0.88, 1.698, 0.034, and 4.554 in cassava yield, respectively. The model analysis showed that harvest date had a greater influence on yield than other factors, suggesting its critical role in optimizing cassava production. Furthermore, the study demonstrated the effectiveness of RSM in analyzing agricultural data, optimizing experimental design, and reducing both costs and time. Based on the findings of this study, it is recommended that cassava farmers prioritize the optimization of planting and harvest dates, alongside appropriate fertilizer application, to maximize yield and improve farming practices and greater food security.

Keywords: Cassava yield, Response Surface Methodology, fertilizer application, planting date, harvest date.

INTRODUCTION

Cassava (Manihot esculenta Crantz) one of the major staple foods globally is a perennial woody shrub with edible root. It originated from tropical America and was first introduced into Africa in the Congo basin by the Portuguese around 1558. It is an important staple food crop for millions of people in the tropical areas of Africa, Asia and Latin America (Rao and Hahn, 1984), it is also considered to be second most source of carbohydrate after maize (Haggblade *et al*.. 2012; Falade and Akingbala, 2010). It is rich in carbohydrates, calcium, vitamins B and C, and essential minerals; it plays a crucial role in global food security and rural livelihoods. It is a staple food whose roots are processed into garri, fufu, chips and other fermented products while the leaves equally serve as very nutritional foliage for domestic animals. It also serves as a very vital industrial raw material in the form of starch, chips, pallets, unfermented flours, etc. Nigeria is currently the largest producer of cassava in the world with an annual output of over 45 million tons of tubers roots (Anga, 2008).

However, achieving optimal cassava yield remains a significant challenge due to various factors affecting productivity, including soil fertility, pests and diseases, agronomic practices and climate variability. According to Bello (2014**)**, response surface methodology (RSM) is an effective statistical tool for modeling cassava yield. Taiwo *et al*. (2019**)** used the Central Composite Design (CCD) model of the RSM to optimize cassava yield by assessing the impact of Nitrogen, Phosphorus, and Potassium (NPK) fertilizer and found that optimal cassava yield was achieved at 63.95 kg/ha of nitrogen, 154.35 kg/ha of phosphorus, and 45.56 kg/ha of potassium. Klang *et al*. (2020) used response surface methodology to optimize the energy density of flour-based gruels made from sweet cassava. Krishnakumar *et al.* (2019) utilized RSM to develop a mathematical model for predicting the properties of cassava starch. Akinoso and Abiodun (2019) applied RSM to optimize crude protein extraction from sweet cassava. Sulaiman *et al*. (2021) conducted process optimization for ultrasound-assisted starch production from cassava tubers using response surface methodology.

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Research Design

The study utilized response surface methodology (RSM) to analyze and optimize cassava yield based on four key factors: planting date, fertilizer application, cassava variety, and harvest date. Data were collected from the International Institute of Tropical Agriculture (IITA), with a central composite design (CCD) applied to assess the effects of these factors at different levels. The data included cross-sectional information on planting dates (April, June, August), fertilizer application (no fertilizer, applied), cassava varieties (TME 419, TMS 30542), and harvest dates (9, 11, 13 months after planting) in south west Nigeria. The coverage start date for the data was April 2017 while the coverage end date was September 2018.

This study employed an experimental research design, specifically utilizing the central composite design within response surface methodology.

The design was chosen because it enables the evaluation of multiple treatments and their effectiveness on a dependent variable, which in this case is cassava yield. This study examined four independent variables: planting date, fertilizer application, cassava variety, and harvest date, each at different levels. Response surface regression, analysis of variance, Pareto charts, and surface plots were used to optimize the predictor variables and assessed their impact on cassava yield. Analysis of variance was applied to test the statistical significance of each factor while Pareto charts was used to visualize the magnitude and impact of different treatment effects.

Response Surface Regression

Response surface design is a statistical approach used for optimizing processes in experimental research where multiple independent variables influence a dependent variable. In this study, the response surface design is based on the central composite design, which is widely used for developing second-order response models with a minimal number of experimental runs. The central composite design consists of three main components: factorial points, axial (or star) points, and center points. The factorial points represent the main experimental runs at high and low levels of each factor, the axial points extend the design space by exploring the effects of variables beyond the factorial levels while the center points help estimate experimental error and improve model accuracy. The response surface methodology further enables visualization through contour and surface plots, illustrating how different factor levels influence cassava yield. The use of response surface design ensures efficiency in experimentation, reducing the number of trials needed while maximizing the accuracy of results.

Traditionally, the regression coefficients of the response model are computed by means of the multiple linear regression (MLR) method in order to minimize the sum of squares of the residuals. Thus, the least-squares estimations of the regression coefficients can be calculated using the matrix equation:

$$\hat{b} = \left(X^T X\right)^{-1} X^T Y \qquad \ldots\ldots\ldots 1$$

where b = vector of regression coefficients, X = matrix of independent variable levels, Y = vector of experimental runs.

In general, the response model of second-order is written as:

$$Y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} {x_i}^2 + \sum_{i<j}^{n} b_{ij} x_i x_j + \xi \qquad \ldots\ldots\ldots\ldots\ldots\ldots 2$$

where Y denotes the response of the process, xi refers to the coded levels of the factors (independent or control variables), b_0, b_i, b_{ii}, and b_{ij} are the regression coefficients, and ξ is the statistical error.

Hence, the response model of this study is specifically expressed as thus:

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$$Yi = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_{11} X_{12} + \beta_{22} X_{22} + \beta_{33} X_{32} + \beta_{44} X_{42} + \beta_1\beta_2 X_1 X_2 + + \beta_1\beta_3 X_1 X_3 + \beta_1\beta_4 X_1 X_4 + \beta_2\beta_3 X_2 X_3 + \beta_2\beta_4 X_2 X_4 + \beta_3\beta_4 X_3 X_4 + e_j \quad \ldots.3$$

Where Y_i= Cassava yield, X_1 = Planting date, X_2 = Fertilizer, X_3 = Cassava variety, X_4 = Harvest date, β_1, β_2, β_3, β_4 = linear coefficients, β_{11}, β_{22}, β_{33}, β_{44} = quadratic term coefficients, $\beta_1\beta_2$, $\beta_1\beta_3$, $\beta_1\beta_4, \beta_3\beta_4, \beta_2\beta_4$, $\beta_2\beta_3$, $\beta_3\beta_4$ = cross product coefficients

Analysis of Variance

Analysis of Variance (ANOVA) is used to assess whether the relationship between the response variable and each predictor variable in the model is statistically significant. It evaluates the extent to which variations in the independent variables influence the dependent variable by comparing the variation within groups to the variation between groups. The test relies on the computation of the p-value for each term in the model, which is then compared to a predetermined significance level (α). In this study, a significance level of 0.05 is used. ANOVA also helps determine the goodness of fit of the model by analyzing the F-statistic, which measures the overall significance of the regression equation.

Pareto Chart

A Pareto chart is used to compare the relative magnitude and statistical significance of the main effects, squared effects, and interaction effects in a response surface model. It helps identify which factors have the greatest impact on the response variable by visually displaying the standardized effects in descending order. The chart is particularly useful in determining which variables should be prioritized for optimization. If the model includes an error term, the Pareto chart displays the absolute values of the standardized effects, allowing for a clear comparison of the effect sizes. This tool is valuable for assessing the contribution of each factor and its interactions.

RESULTS AND DISCUSSION

Table 1: Response Surface Regression Result

Variables	Coefficient	Standard error	T-stat	Prob.
Constant	13.855	0.577	24.00	0.000
Planting_date	0.880	0.316	2.78	0.006
Fertilizer	1.698	0.258	6.58	0.000
Cassava_variety	0.034	0.258	0.13	0.895
Harvest_date	4.554	0.316	14.40	0.000
Planting_date*Planting_date	-1.035	0.548	-1.89	0.060
Harvest_date*Harvest_date	-1.125	0.548	-2.05	0.041
Planting_date*Fertilizer	-0.603	0.316	-1.91	0.058
Planting_date*Cassava_variety	-0.166	0.316	-0.52	0.600
Planting_date*Harvest_date	0.645	0.387	1.67	0.097
Fertilizer*Cassava_variety	0.377	0.258	1.46	0.146
Fertilizer*Harvest_date	0.597	0.316	1.89	0.060
Cassava_variety*Harvest_date	0.386	0.316	1.22	0.224

Table 1 showed the regression estimates of the response surface model in terms of coefficients, standard error, t-statistics and probability. The result showed that all the linear coefficients show positive and significant effects except cassava variety at p=0.895. Results from the quadratic coefficients of second order polynomial showed equal number of positive and negative coefficients with no significant probability except for the quadratic term of Harvest date at p=0.041.

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Table 2: ANOVA Result

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	12	4032.17	336.01	23.34	0.000
Linear	**4**	**3720.36**	**930.09**	**64.60**	**0.000**
Planting_date	1	111.41	111.41	7.74	0.006
Fertilizer	1	622.44	622.44	43.23	0.000
Cassava_variety	1	0.25	0.25	0.02	0.895
Harvest_date	1	2986.26	2986.26	207.42	0.000
Quadratic	**2**	**112.16**	**56.08**	**3.90**	**0.022**
Planting date* Planting date	1	51.39	51.39	3.57	0.060
Harvest date*Harvest date	1	60.77	60.77	4.22	0.041
2-Way Interaction	**6**	**199.66**	**33.28**	**2.31**	**0.035**
Planting date*Fertilizer	1	52.32	52.32	3.63	0.058
Plantingdate*Cassava variety	1	3.97	3.97	0.28	0.600
Planting date*Harvest date	1	39.99	39.99	2.78	0.097
Fertilizer*Cassava variety	1	30.64	30.64	2.13	0.146
Fertilizer*Harvest date	1	51.34	51.34	3.57	0.060
Cassava variety*Harvest date	1	21.41	21.41	1.49	0.224

The statistical significance was checked using the result of analysis of variance in Table 2. The overall model p-value (0.0000) showed that the full quadratic model of the independent variables (planting date, fertilizer, and harvest date) significantly affect the response variable (cassava fresh root yield). The linear terms except cassava variety were also significant; for the quadratic terms, harvest date was significant while planting date was not. All the interaction terms were not significant.

Surface Plot of Response and Interaction of Factors

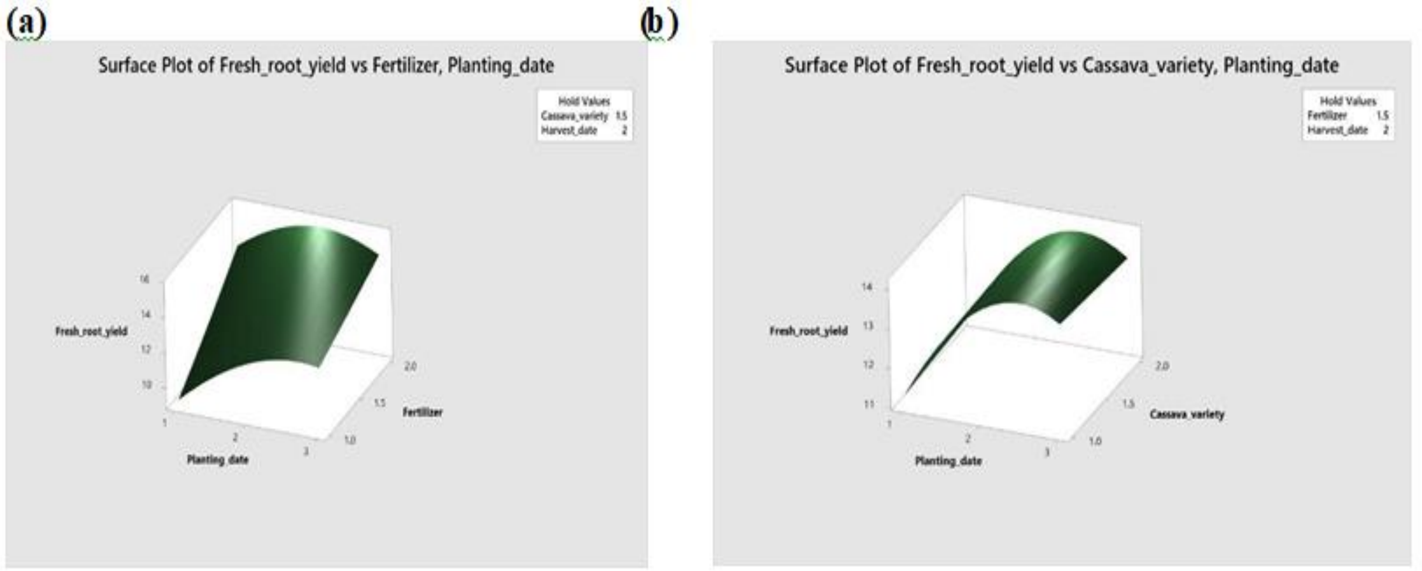

Figure 1: Effect of (a) fertilizer and planting date (b) Cassava variety and planting date

Figure 1a showed the interaction of fertilizer and planting size and their effect on the variability of the response of cassava fresh root yield. Result indicated that when cassava fresh root yield is at maximum, the level of fertilizer and planting date is low, but when the cassava fresh root yield is at minimum, the level of fertilizer and planting date is high. On the other hand, Figure 1b revealed interaction of cassava varieties and planting size and their effect on the variability of the response of cassava fresh root yield which showed that there is inverse relationship between cassava fresh root yield (response) and the planting date and cassava varieties (predictors).

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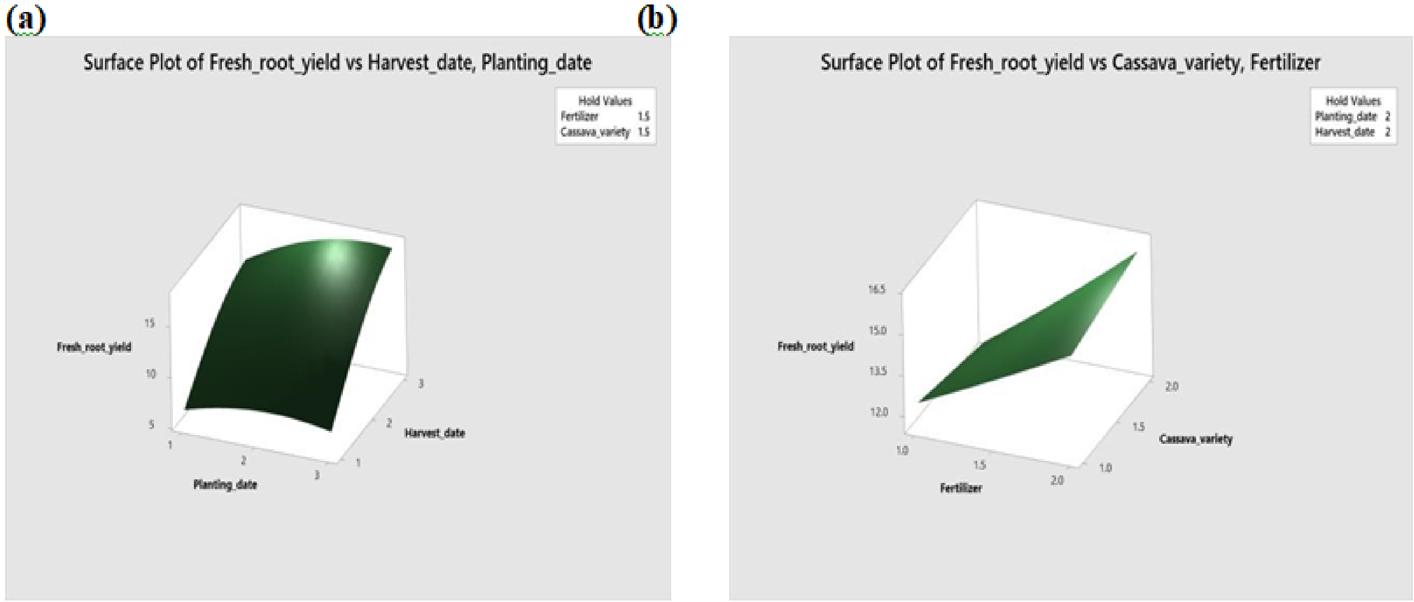

Figure2: Effect of (a) harvest date and planting date (b) cassava variety and fertilizer

Figure 2a revealed the interaction of harvest date and planting date and their effect on the variability of the response of cassava fresh root yield. Result indicated that when cassava fresh root yield is at maximum, the harvest date and planting date is high and vice versa. On the other hand, Figure 2b (response of cassava yield to the interaction of cassava variety and fertilizer) showed that cassava fresh root yield is at maximum, the cassava varieties and fertilizer is high and when the cassava fresh root yield is at minimum, the cassava varieties and fertilizer is low.

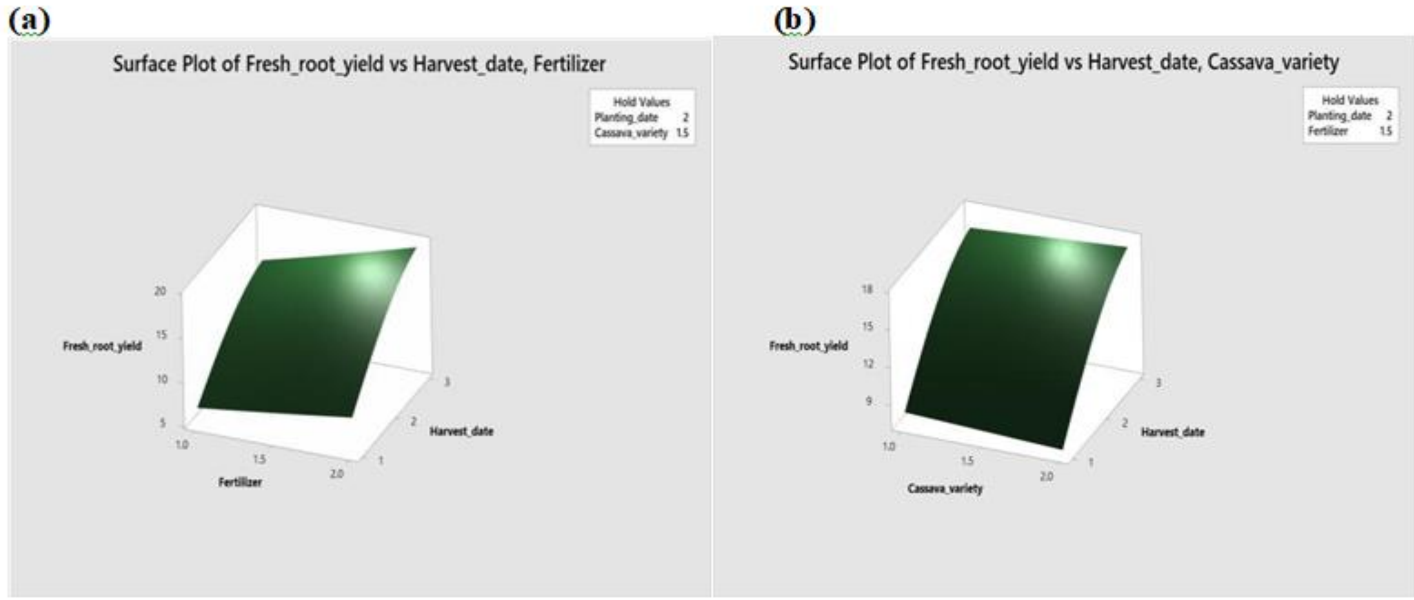

Figure 3: Effect of (a) harvest date and fertilizer (b) harvest date and cassava variety

Figure 3a revealed the interaction of harvest date and fertilizer and their effect on the variability of the response of cassava fresh root yield. Result indicated that when cassava fresh root yield is at maximum, the harvest date and fertilizer is high, and when the cassava fresh root yield is at minimum, the harvest date and fertilizer is low. On the other hand, Figure 3b showed the interaction of harvest date and cassava variety and its effect on the variability of the response of cassava fresh root yield which showed that when cassava fresh root yield is at maximum, the harvest date and cassava variety is high, and when the cassava fresh root yield is at minimum, the harvest date and cassava variety is low.

Pareto Chart

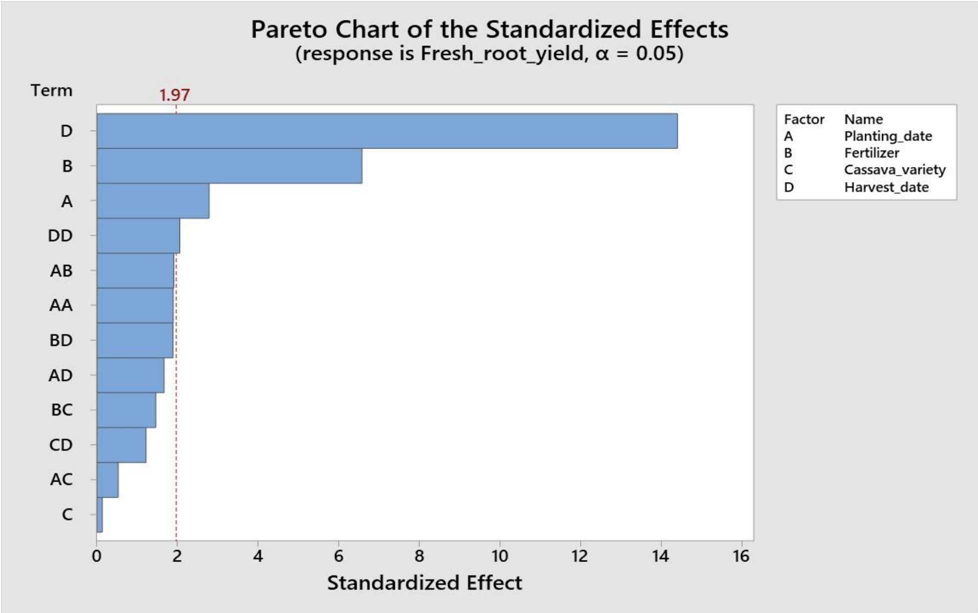

Figure 4: Pareto Chart of the Standardized Effects of Cassava Fresh Root Yield Factors

Result of Pareto Chart in Figure 4 based on the bar chart and the indicated minimum significance value of 1.97 at 0.05 probability level showed that only D, B, A, DD which represents harvest date, planting date, fertilizer, and square of harvest date respectively are the significant factors that contribute to the cassava fresh root yield. The result also revealed that among the four components, harvest date contribute more to cassava yield, followed by fertilizer, then planting date, and lastly, square of harvest date.

DISCUSSION OF FINDINGS

The study demonstrated that fertilizer has a significant and positive impact on cassava yield. It suggests that farmers can enhance cassava productivity by increasing both the quantity and quality of fertilizer applied to the farm. This highlights the importance of incorporating fertilizer into cassava farming practices for those seeking to improve productivity. The findings align with the work of Ogaraku and Madu (2021), Salako *et al.* (2019), Ghosh *et al.* (2019), and Hu *et al.* (2018).

The results further indicated that all factors such as planting date, fertilizer, cassava variety, and harvest date—positively influence cassava yield, suggesting that considering these variables is essential for maximizing productivity. However, the study found that only planting date, fertilizer, and harvest date are significant factors for optimizing cassava yield, with harvest date being the most influential, followed by fertilizer and planting date. These findings are consistent with previous studies by Salako *et al.* (2019), Ghosh *et al.* (2019), Hu *et al.* (2018), Akinyemi *et al.* (2017), Fasina *et al.* (2016), and Rodriguez-Burruezo *et al.* (2011). Finally, the study revealed that the interactions between the factors did not significantly affect yield optimization, suggesting that the relationships between the variables are minimal when focusing on ways to maximize cassava yield. This result contradicts the conclusions of studies like Salako *et al.* (2019), Fasina *et al.* (2016), Rodriguez-Burruezo *et al.* (2011), Ghosh *et al.* (2019), and Hu *et al.* (2018).

CONCLUSION

This study demonstrates the efficacy of Response Surface Methodology (RSM) in optimizing cassava yield through the analysis of key variables such as planting date, fertilizer application, cassava variety, and harvest date. The results indicated that planting date, fertilizer application, and harvest date significantly impacted cassava yield, with fertilizer and harvest date being the most influential factors. The regression model revealed that fertilizer and harvest date had a strong positive effect on yield, with coefficients of 1.698 and 4.554, respectively. In contrast, cassava variety had a minimal effect on yield. The study emphasizes the importance of optimizing these key variables to enhance cassava production, providing valuable insights for agricultural practices aimed at increasing yield efficiency. Additionally, the application of RSM reduces the need for extensive experimentation, thus saving time and resources in agricultural optimization studies.

REFERENCES

1. Akinoso, R., & Abiodun, O. (2019). Response surface methodology for optimizing crude protein extraction from sweet cassava. Journal of Food Engineering, 247, 58-65.
2. Anga, M. (2008). Cassava production and utilization in Nigeria: Challenges and opportunities. African Journal of Agricultural Research, 3(7), 482-488.
3. Bello, O. (2014). Response surface methodology for modeling cassava yield. Agricultural Systems, 130, 56-62.
4. Falade, K. O., & Akingbala, J. O. (2010). Cassava utilization in the African food system. Food Research International, 43(1), 1-7.
5. Fasina, O. O., Akinoso, R., & Oloruntoba, E. O. (2016). Optimization of cassava flour production: A response surface methodology approach. Journal of Food Science and Technology, 53(3), 1234-1241.
6. Ghosh, A., Mondal, R., & Ghosh, D. (2019). Effect of fertilizer application on cassava yield: A review. Agricultural Science Research Journal, 9(6), 143-150.
7. Haggblade, S., Gibbs, B., & Hossain, M. (2012). Cassava in the tropical food system. Food Security, 4(1), 61-71.
8. Hu, J., Zhang, Y., & Li, H. (2018). Fertilizer application and its impact on cassava yield and soil properties. Soil Science and Plant Nutrition, 64(1), 86-92.
9. Klang, T., Lim, H., & Lee, S. (2020). Optimizing the energy density of flour-based gruels made from sweet cassava using response surface methodology. Food Science and Technology, 44(5), 1218-1225.
10. Krishnakumar, K., Vaidyanathan, R., & Ramaswamy, S. (2019). Optimization of cassava starch properties using response surface methodology. Starch/Stärke, 71(1-2), 56-64.
11. Ogaraku, O. O., & Madu, F. O. (2021). Effect of fertilizer on cassava productivity in Nigeria: A review. Agriculture and Food Security, 10(1), 1-9.
12. Rao, A. N., & Hahn, S. K. (1984). Cassava breeding in tropical Africa. Euphytica, 33(1), 229-234.
13. Rodriguez-Burruezo, A., Moreno, D. A., & Ferreres, F. (2011). Cassava root tuber processing: From food to functional food. Trends in Food Science & Technology, 22(7), 306-313.
14. Salako, F. K., Ajibola, O. S., & Akinola, O. A. (2019). Impact of agronomic factors on cassava yield in tropical regions. African Journal of Agricultural Research, 14(17), 854-863.
15. Sulaiman, S. O., Olaleye, O. A., & Oladele, F. A. (2021). Process optimization of ultrasound- assisted starch production from cassava using response surface methodology. Food Chemistry, 337, 127-135.
16. Taiwo, A. T., Omidiji, O. B., & Babajide, J. A. (2019). Optimization of cassava yield using response surface methodology. Agricultural Engineering International: CIGR Journal, 21(2), 139-148.