Application of Response Surface Analysis of Three Factors of Fertilizer Treatment Combination to Determine the Optimum Plant Height of Maize

Oladipupo Olayinka Olusegun[1*],
[1]Department of Mathematics & Statistics,
Redeemer's University,
Ede, Osun State,
Nigeria

Dare Julius Remi [2]
[2]Department of Mathematical Sciences,
Kings University,
Odeomu, Osun State,
Nigeria

Ayanlowo Emmanuel A[3]
[3]Department of Basic Sciences,
Babcock University,
llisan Remo, Ogun State,
Nigeria

Abstract:- This study evaluated how three different fertilizer treatment combinations affected plant height. For specific variables or characteristics that can be taken into account, the optimal plant height is calculated using the first and second-order models of the Responsive Surface Methodology. According to the study's p-value of 0.087 for lack of fit, the Ho cannot be entirely discounted. Thus, there is no proof that the response surface lacks curvature or is poorly fitted. The interaction between 100 kg/ha of poultry manure (P/M10), 50 kg/ha of organic minerals (O/M5), and 50 kg/ha of poultry manure (P/M5) is shown by the main effect plot, contour plot, and surface plot to be significant at the level of 0.05. Moreover, poultry manure at 50 kg/ha (P/M5), which spreads the longest, has the highest impact at 100 kg/ha (P/M10) and organic mineral at 50 kg/ha (O/M5). With the use of a Pareto chart, that serves as the reference line. The ideal values for the response variable for a specific location with the accompanying expected response plant height are 101.31 cm and a composite desirability of 0.996269 to achieve the ideal plant height. The findings of this study demonstrate the potential of response surface analysis as a tool for optimizing fertilizer treatment combinations for the growth of maize. By identifying the optimal combination of fertilizer treatments, farmers can maximize the yield and quality of their maize crops, while minimizing the cost and environmental impact of their fertilizer use.

Keywords: *Poultry Manure, Organic-Mineral Fertilizer, Maize, Box-Behnken Design, Reaction Surface Design, and Central Composite Design.*

I. INTRODUCTION

- *Technique for Response Surfaces*

Response surface analysis is a powerful statistical technique used to model and optimize the relationship between a response variable and multiple input variables or factors. It is widely used in agricultural research to optimize crop yield and quality. In recent years, response surface analysis has been applied to determine the optimum plant height of maize through fertilizer treatment combination.

Maize is an important staple crop that is widely cultivated for food and feed purposes. The height of maize plants is a critical factor that influences crop productivity and quality. The use of fertilizers is one of the most effective ways to improve plant height and crop yield. However, the optimal fertilizer treatment combination that can achieve the maximum plant height of maize is not always known.

To address this challenge, researchers have applied response surface analysis to model the relationship between plant height and three fertilizer treatment factors. This involves designing a set of experiments with different combinations of fertilizer treatments and measuring the resulting plant height. The data is then analyzed using response surface methodology to determine the optimal combination of fertilizer treatments that will maximize plant height.

This approach has been successfully applied in several studies to optimize the plant height of maize. For instance, a study conducted in China found that response surface analysis of three fertilizer factors (nitrogen, phosphorus, and potassium) could be used to determine the optimal combination for achieving the maximum plant height of maize. The study showed that the optimal fertilizer treatment combination was 282.85 kg/ha nitrogen, 73.14 kg/ha phosphorus, and 157.62 kg/ha potassium.

Several studies have applied RSA to determine the optimal fertilizer treatment combination for maize. For instance, in a study by Zhang et al. [1] (2021) applied RSM to optimize the combination of three fertilizer treatments (nitrogen, phosphorus, and potassium) for maize growth in a greenhouse experiment. The results showed that the optimum plant height was achieved at the nitrogen-phosphorus-potassium combination of 200-60-200 kg/ha, respectively.

Another study by Yang et al. [2] (2021) used RSA to optimize the fertilizer rate and placement to achieve the maximum plant height of maize. The study found that RSA effectively identified the optimal fertilizer treatment combination and significantly increased the plant height.

Oladipupo O. O. [3] adopted first-order and second-order techniques to determine the appropriate plant height at two variables and levels, it is widely employed the response surface technique respectively, of various places taken into account. The optimal process parameter settings that optimize the rate of material removal were found using a genetic algorithm developed by V. Panwar et al. [4]. K.B. Zabin et al. [5]. The author claims that seeds grown with enhanced phosphatase concentration and bathed in bacterial culture broth showed better growth in terms of plumule and radical length. B. Nitin et al [6]. Using the Responsive surface approach (RSM), bacterial isolates produce gibberellic acid (GAs), which is the subject of the study. It also examines the effects of GAs production on Cicer arietinum seed germination and growth promotion (Chickpea). [7] Mohsen B. et al. This study's goal was to assess and measure the effects of different vermicompost, phosphate rock, and sulfur to determine the ideal concentrations of each factor for an effective biofertilizer. It was demonstrated by P. Sunitha et al. [8] that RSM may be used to optimize the growth of Pennisetum, and that the CCD is effective, easy, affordable, time-saving, and can be adapted for optimizing crop yields.

In conclusion, RSA is a valuable statistical technique for optimizing fertilizer treatments to achieve maximum plant height and yield in maize production. The cited studies highlight the relevance of RSA in the optimization of fertilizer treatments to achieve maximum plant height, emphasizing its importance in the agriculture sector. Here, three alternative fertilizer treatment factors are examined, and the impacts of their combination are predicted, together with the effects of varying concentrations of organic-mineral and poultry manure. For instance, a function of poultry manure at 50kg, 100kg, and organic-mineral at 50kg will have an impact on the response variable if a plant height is "y."

$$y = f(x_1, x_2, x_3) + e. \text{ ------------------------------------- } (1)$$

When the explanatory variables x_1, x_2, and x_3 are functions of the response variable y, the error component, e, is considered to be normally distributed with a mean and variance of zero. Since the true response function f is frequently unknown in RSM problems, the experimenter usually begins with a first-order model in a small region. As a result, the experimenter must develop an appropriate estimate for f. A first-order technique, which has the following formula and uses three independent variables,

$$y = \beta o + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + e \text{ --------------------- } (2)$$

The response surface's curvature would result in a higher degree polynomial (i.e. second order model). The following three variables are listed as an approximation to a second-order model's function:

$$y = \beta o + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x^2_1 + \beta_{22} x^2_2 + \beta_{33} x^2_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 + e \text{ ---------------- } (3)$$

Most RSM issues make use of one, both, or a combination of the two models. The amounts of each element are unrelated to the levels of the other factors for each of the models. RSM can be completed by either locating the ideal response region, which is the purpose of RSM, or by having a response surface with well-defined topography (local maximum, minimum, and ridge lines).

RSM assumes that the level of each component must have an equal space interval and that the factor must be composed of numerical data.

The scope of this study is to evaluate the application of response surface analysis for determining the optimal plant height of maize using a combination of three fertilizer treatment factors. This study aims to provide insights into the potential of response surface methodology as a tool for optimizing maize growth and yield.

- *Objectives:*

The primary objectives of this study are to:

Determine the effects of three fertilizer treatment factors (e.g., type of fertilizer, application rate, and frequency of application) on maize plant height.

Develop a response surface model to describe the relationship between the three fertilizer treatment factors and maize plant height.

Use the response surface model to identify the optimal combination of fertilizer treatment factors that results in maximum maize plant height.

Validate the response surface model using experimental data and statistical analysis.

Provide recommendations for optimizing maize growth and yield based on the response surface model.

II. METHODOLOGY

This study will involve a series of experiments conducted in a controlled environment (e.g., greenhouse) using maize plants. The experiments will involve varying the three fertilizer treatment factors (e.g., type of fertilizer, application rate, and frequency of application) according to a design of experiments (DOE) approach. The response variable of interest will be maize plant height, which will be measured periodically throughout the growth cycle.

Data analysis will involve the use of response surface methodology to model the relationship between the three fertilizer treatment factors and maize plant height. This will involve fitting a second-order polynomial model to the experimental data and using statistical techniques to identify the optimal combination of fertilizer treatment factors that results in maximum maize plant height. The response surface model will be validated using statistical analysis.

➢ *Designed Experiments:*

Using well-planned experiments, an analysis can manipulate variables that are crucial for describing or interpreting the experiment's response variable(s). The traditional industrial, life sciences, and agricultural contexts, as well as several commercial sectors, including marketing and financial services, were all used in designed experiments.

If the indication indicates that we are outside of the optimum, we can use the "steepest ascent" strategy, which entails increasing the response until the increase ceases, to fit the model appropriately after the first-order model evaluation demonstrates a negligible lack of fit. To estimate the model's additional second terms, higher-order terms, such second-order terms, are introduced to the first-order model, and the design is enhanced with (2^k) axial runs. When a higher polynomial model fits better than the first-order model, which exhibits a lack of fit, we apply designs that can assist us in modeling curvature (i.e., the second-Order approach), causing surface curvature to exist. The first-order model's shortcomings are improved by the addition of higher-order (for example, second-order) terms. The resulting second-order model is higher is listed as follows:

$$y = \beta o + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_{21} + \beta_{22} x_{22} + \beta_{33} x_{23} + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 + e \text{ -------- } (4)$$

- *The Most two Popular Designs in this Class are:*

✓ Design firms Box- Behnken Design (BBD) and Central Composite Design (CCD)

✓ Box and Wilson (1951) proposed the Central Composite Design (CCD), which comprises of:

▪ A full 2^k factorial design, where point 'a' is designated,
▪ An axial or star point
▪ 'c' center points.

Thus in a CCD, f = a + nα + c.

Below is the structure (design matrix) for3- factor CCD with one center point

Table 1 The 3 Factors of Central Composite Design (CCD)

S/N		A_1	A_2	A_3
1	Factorial runs 2^3 = 8	-1	-1	-1
2		1	-1	-1
3		-1	1	-1
4		1	1	-1
5		-1	-1	1
6		1	-1	1
7		-1	1	1
8		1	1	1
9	Axial (star) point runs 2x3 = 6	-1.682	0	0
10		1.682	0	0
11		0	-1.682	0
12		0	1.682	0
13		0	0	-1.682
14		0	0	1.682
15	Center point	0	0	0

The Box-Behnken Design (BBD), first proposed by Box and Behnken, is an effective design for fitting second-order RSM by fusing balanced-incomplete block designs (BIBD) with two-level factorial designs. The treatment combinations in this design are located halfway between the factor space's center and its boundaries. The three central locations for the 3-factor BBD are shown in the table 2 below.

Table 2 Three Central Locations for the 3-factor BBD

Run Order	Standard Order	Factor C_1	Factor C_2	Factor C_3
6	1	-1	-1	0
13	2	1	1	0
11	3	-1	-1	0
5	4	1	1	0
10	5	-1	0	-1

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1	6	1	0	1
8	7	-1	0	-1
4	8	1	0	1
9	9	0	-1	-1
3	10	0	1	1
14	11	0	-1	-1
12	12	0	1	1
2	13	0	0	0
15	14	0	0	0
7	15	0	0	0

The figure 1 below represents the matrix design notation method which spelled out as

$$\hat{y} = \hat{\beta}_0 + x`\beta + x`Bx$$

First-order coefficient "β" is represented by a (k x 1) vector, while "B" is a (k x k) symmetric matrix with one-half mixed quadratic coefficients as its off-diagonal members and pure quadratic coefficients as its main diagonal elements, given as

$$X = \begin{bmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ . \\ X_k \end{bmatrix} \qquad b = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ . \\ . \\ . \\ . \\ \hat{\beta}_k \end{bmatrix} B = \begin{bmatrix} \hat{\beta}_{11}, & \hat{\beta}_{12}/2, . & . ., \hat{\beta}_{1k}/2 \\ & \hat{\beta}_{22}, , . & . ., \hat{\beta}_{2k}/2 \\ & . & \\ & . & \\ & . & \\ sym & & \hat{\beta}_{kk} \end{bmatrix}$$

Fig 1 Matrix Design Notation Method

III. METHODS

By carefully and methodically gathering, analyzing, and interpreting data that can be obtained, the research seeks to find a trustworthy solution to the issue at hand. Pure research aims to create or identify novel theories in a particular field that will be widely accepted. Because it enables the experimenter to assess Factorial design is the statistical method used for this study because it may be used to analyze the impacts of two or more elements.

Two-level (2^k) designs with factorials that are 2^3 designs. You can view the eight treatment combinations in the figure 2a below if there are three factors, F_1, F_2, and F_3. 2^3 factorial designs are this kind of design. The components' "low" and "high" levels are coded in an orthogonal manner, respectively, "+" and "-."

	Factors		
Run	F_1	F_2	F_3
1	-	-	-
2	+	-	-
3	-	+	-
4	+	+	-
5	-	-	+
6	+	-	+
7	-	+	+
8	+	+	+

Fig 2 (a) The 2^3 Factorial Designs

These treatment combinations can be expressed as follows, and the structure is also known as a "design matrix": (1), a, b, ab, c, ac, bc, and abc.

Let A_1 stand for F_1, A_2 for F_2, and A_3 for F_3. Thus, the various notations for these 2^3 designs are shown in figure 2b below:

Run	F_1	F_2	F_3	Labels	F_1	F_2	F_3
1	-	-	-	(I)	0	0	0
2	+	-	-	a	1	0	0
3	-	+	-	b	0	1	0
4	+	+	-	ab	1	1	0
5	-	-	+	c	0	0	1
6	+	-	+	ac	1	0	1
7	-	+	+	bc	0	1	1
8	+	+	+	abc	1	1	1

Fig 2 (b) The 2^3 Factorial Designs

This study uses a factorial design with three components. A: 50kg/ha (P/M5) of poultry manure, B: 100kg/ha (P/M10), and C: 50kg/ha (P/M5) of organic mineral (O.M5). Amongst the eight treatment combinations, there are seven (7) degrees of freedom in the 2^3 factorial design. The principal impact of each of the three (A, B, and C) has one (1) degree of freedom. Interactions with AB, AC, BC, and ABC each have one (1) degree of freedom, giving a total of four (4).

- *Methodology:*

Whether determining the best treatment combination or analyzing the response, Reaction Surface Techniques are designed to handle treatment fusions.

The function f's plot is shown (x_1, x_2) vs the P/M5 and O.M5 factors is presented in figure 3 below.

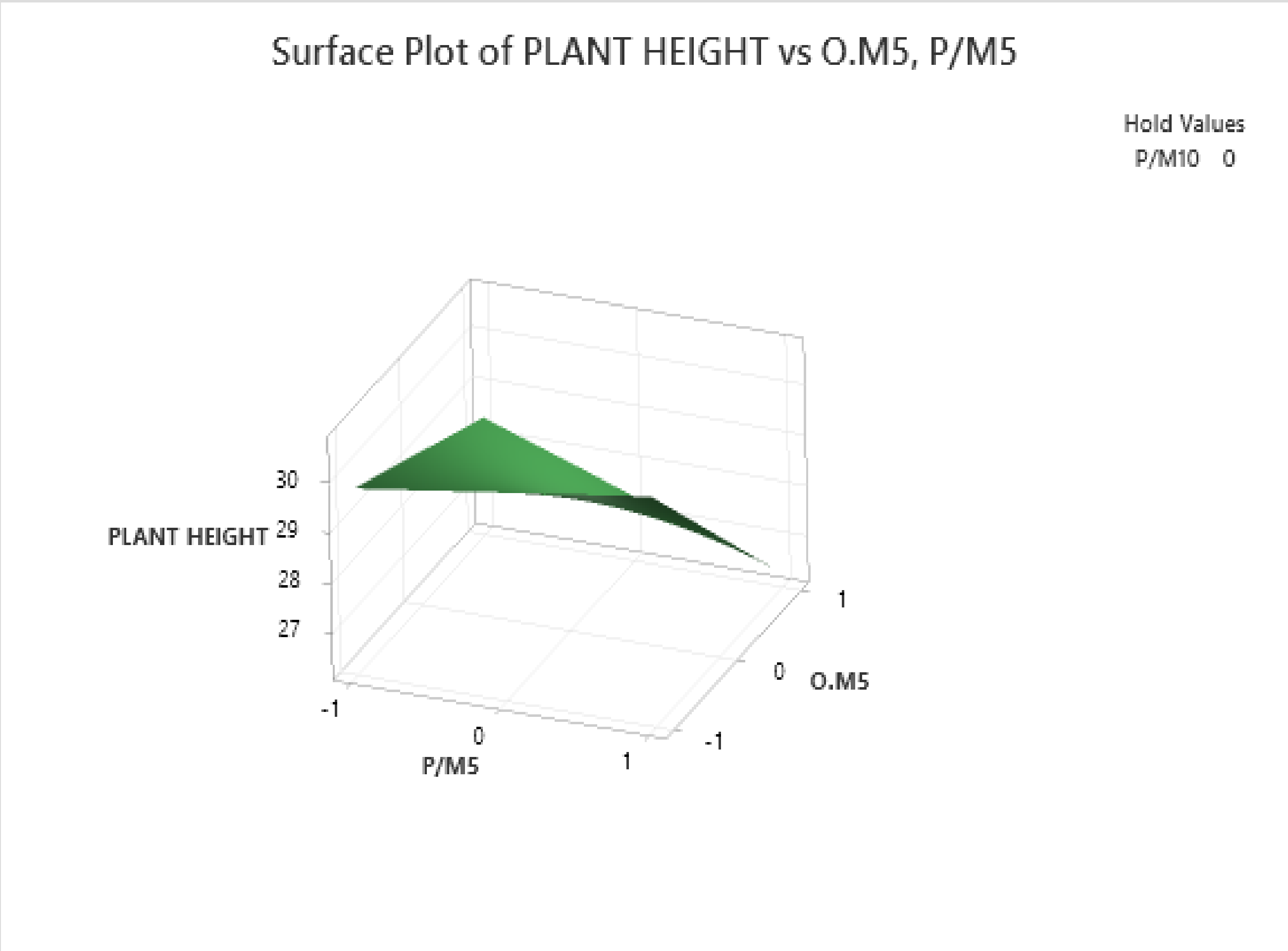

Fig 3 Surface Plot of Plant Height vs the P/M5, O.M5

A response surface plot, also known as a y-value (Plant Height) response, is produced from the figure 3 above by P/M and O.M. Moreover, a contour plot example is displayed in figure 4 below.

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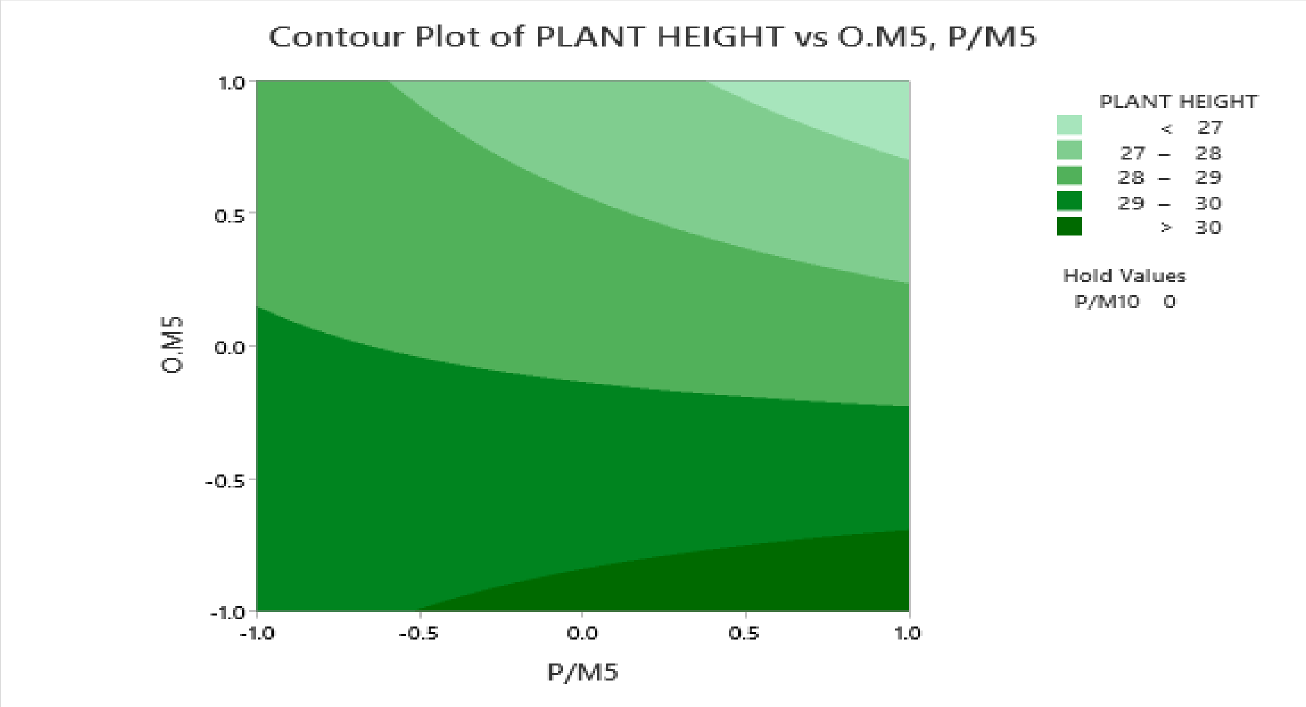

Fig 4 Contour Plot of Plant Height vs the P/M5, O.M5

The surface response can be understood using graphs, but when there are more than two independent variables, it becomes difficult or perhaps impossible to visualize the response surface.

- *The First-Order Model of RSM:*

The analysis of the first-order model of RSM involves several steps. First, a design of experiments (DOE) is created to generate data points for the response variables. Then, the data is fitted to the first-order model using regression analysis. The fit of the model is evaluated using various statistical tests such as the R-squared value and the analysis of variance (ANOVA).

Once the model has been fitted and validated, it can be used to identify the optimal settings for the input variables to achieve the desired response. This is typically done using optimization techniques such as the steepest ascent/descent method or the response surface methodology.

One advantage of the first-order model is its simplicity, which makes it easier to interpret and apply. However, it may not capture all the complex interactions between the input variables and may result in a less accurate prediction of the response variables compared to the full second-order model. Therefore, it is important to assess the adequacy of the first-order model before using it for optimization.

- *The Second-Order Model of Response Surface Methodology (RSM):*

The second-order model is a type of Response Surface Model (RSM) that is used to describe the relationship between a response variable and a set of input variables. In this model, the response is a quadratic function of the input variables, and it is represented by the following equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{11} X_{12} + \beta_{22} X_{22} + \beta_{12} X_1 X_2 + \varepsilon \quad \ldots\ldots\ldots\ldots (5)$$

where Y is the response variable, X_1 and X_2 are the input variables, β_0 is the intercept, β_1 and β_2 are the linear coefficients, β_{11} and β_{22} are the quadratic coefficients, β_{12} is the interaction coefficient, and ε is the error term.

The second-order model is used in RSM to optimize the response variable by determining the optimal combination of input variables. The model can be analyzed using various statistical techniques, such as regression analysis and analysis of variance (ANOVA), to estimate the coefficients and assess the significance of the model terms.

The second-order model can provide a more accurate representation of the relationship between the response and input variables compared to a first-order model, which only includes linear terms. However, it is important to note that the second-order model assumes a constant curvature for the response surface, which may not be accurate in all cases. Therefore, it is always recommended to validate the model assumptions and verify its accuracy through experimental data.

IV. RESULTS AND DISCUSSION

Response surface analysis is a powerful tool in optimizing the response of a system, and it can be applied to various fields such as agriculture. The application of response surface analysis on three factors of fertilizer treatment combination to determine the optimum plant height of maize is an excellent example of the effectiveness of this technique.

The study aimed to optimize the plant height (y) of maize by applying three factors of fertilizer treatment combination, which are the organic mineral at 50kg/ha, poultry manure at 100kg/ha, and poultry manure at 50kg/ha. The study used a Central Composite Design (CCD), which is a type of response surface design that requires fewer experiments than a full factorial design while still allowing for accurate predictions.

To find the area where the best reaction takes place, a method known as response surface analysis is used. The study also performed an analysis of variance (ANOVA) in table 4 to determine the significance of each factor and their interaction effects.

Table 3 Response Surface Regression: PLANT HEIGHT versus P/M5, P/M10, O.M5

Term	**Coef**	**SE Coef**	**T-Value**	**P-Value**	**VIF**
Constant	87.57	2.81	31.19	0.000	
P/M5	6.31	2.81	2.25	0.038	1.00
P/M10	0.66	2.81	0.24	0.816	1.00
O.M5	0.17	2.81	0.06	0.953	1.00
P/M5*P/M10	-2.79	2.81	-0.99	0.334	1.00
P/M5*O.M5	1.46	2.81	0.52	0.611	1.00
P/M10*O.M5	6.93	2.81	2.47	0.024	1.00

Model Summary

S	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
13.7555	42.28%	21.91%	0.00%

Table 4 Analysis of Variance

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
Model	6	2356.05	392.67	2.08	0.111
Linear	3	965.60	321.87	1.70	0.205
P/M5	1	954.32	954.32	5.04	0.038
P/M10	1	10.59	10.59	0.06	0.816
O.M5	1	0.69	0.69	0.00	0.953
2-Way Interaction	3	1390.45	463.48	2.45	0.099
P/M5*P/M10	1	186.71	186.71	0.99	0.334
P/M5*O.M5	1	50.87	50.87	0.27	0.611
P/M10*O.M5	1	1152.87	1152.87	6.09	0.024
Error	17	3216.63	189.21		
Lack-of-Fit	1	554.30	554.30	3.33	0.087
Pure Error	16	2662.33	166.40		
Total	23	5572.68			

We are unable to rule out the null hypothesis since the p-value for lack of fit (0.087) is higher than the level of significance. As a result, the response surface is not curved and no sign of a bad fit is present. The response of the variable and the result of the Plant height completed following the experiments' basic tenets are given along with the run's order using second-order surface response equations and computer software (the Minitab package). The uncoded value of the dependent variables can be used to express the equations: The equation for regression is as follows:

- *The Equation for Regression with Uncoded Units*

PLANT HEIGHT	=	87.57 + 6.31 P/M5 + 0.66 P/M10 + 0.17 O.M5 - 2.79 P/M5*P/M10 + 1.46 P/M5*O.M5 + 6.93 P/M10*O.M5

- *Diagnostics and Fits for Anomalous Observations*

Obs	**PLANT HEIGHT**	**Fit**	**Resid**	**Std Resid**	
1	50.30	79.07	-28.77	-2.49	R
22	94.50	69.59	24.91	2.15	R

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➢ *Pareto Chart:*

In Response Surface Methodology (RSM), a Pareto chart is a graphical tool used to identify the most significant factors affecting the response variable. The chart shows the relative importance of each factor by displaying their effect estimates and the corresponding confidence intervals.

The Pareto chart in RSM is created by arranging the effect estimates in descending order of their magnitudes. The effect estimates are represented by bars, and the confidence intervals are indicated by error bars. The chart also includes a line representing the critical value for the selected significance level, which is used to determine the significant factors.

The Pareto chart is an effective way to identify the significant factors and prioritize them for further analysis. It can also be used to identify potential interactions between factors, as any significant interaction effects will be reflected in the effect estimates of the individual factors.

To create a Pareto chart in RSM, the effect estimates and confidence intervals can be obtained using statistical software, such as Minitab or R. The effect estimates are calculated by fitting the response surface model to the experimental data, and the confidence intervals are calculated using standard statistical methods.

Overall, the Pareto chart is a useful tool in RSM for identifying the most significant factors affecting the response variable and prioritizing them for further analysis. It helps to focus resources and efforts on the most important factors, thereby improving the efficiency and effectiveness of the optimization process. Minitab uses a 0.05 threshold of significance to generate the reference line, and it shows which effects are significant on the chart. As a result, any impact below the reference line is not significant.

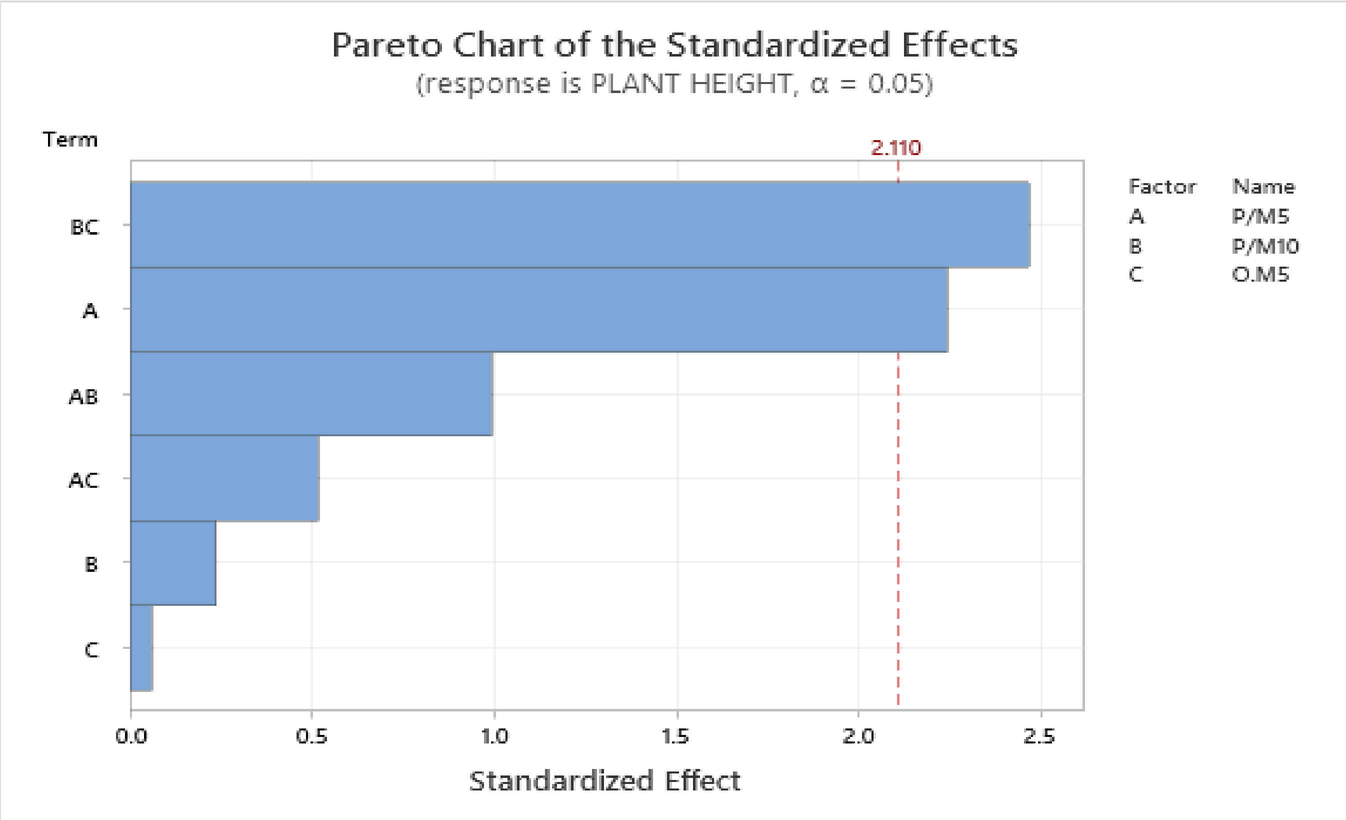

Fig 5 Pareto Chart of the Standardized Effect

According to the findings in figure 5 at a significance level of $\alpha = 0.05$, significant interactions exist between 100 kg per hectare (P/M10) of poultry manure, 50 kg per hectare (O.M5) of organic mineral and 50 kg per hectare (P/M5) of poultry manure. Consequently, we can also observe that the reference line, which is comprised of 50 kg/ha of organic minerals and 100 kg/ha of poultry manure (P/M10) (BC), has the highest effects. Because it extends the least, organic-mineral at 50kg/ha (O.M5) (C) is the smallest.

Residual plots are a graphical method used in response surface methodology (RSM) to evaluate the adequacy of the fitted model. A residual is the difference between the actual response and the predicted response, which is the value obtained from the model.

Residual plots are created by plotting the residuals against the predicted response or the experimental factor levels. If the model is adequate, the residuals should be randomly scattered around zero with no obvious pattern. However, if there is a pattern in the residuals, it indicates that the model may not fit the data adequately.

There are several types of residual plots used in RSM, including normal probability plots, histogram of residuals, and scatter plots of residuals. Normal probability plots are used to check the normality assumption of the residuals, while histograms of residuals provide an overall visual inspection of the residuals distribution. Scatter plots of residuals can be used to identify patterns in the residuals, such as a U-shaped curve, which suggests a lack of fit in the model.

In summary, residual plots are an essential tool for evaluating the adequacy of a response surface model. They provide a visual representation of the discrepancies between the observed data and the fitted model and can help identify potential issues with the model's fit to the data.

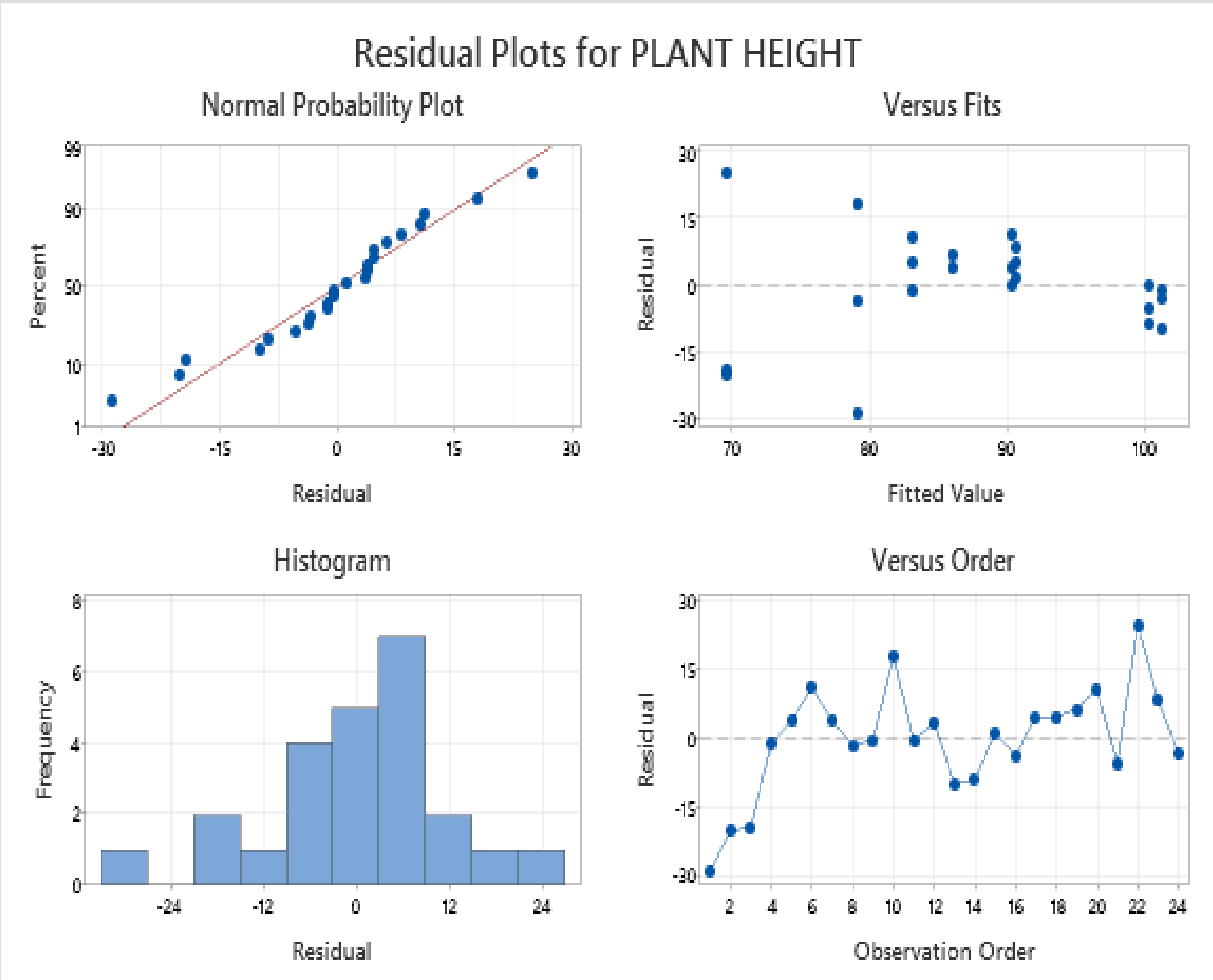

Fig 6 Residual Plots for Plant Height

The figure 6 represents the residual plots used to validate the model against the analysis's requisite assumptions and to assess the model's suitability. **Residuals versus fits plot;** this diagram is used to show how the residuals are distributed normally, randomly, and with a constant variance, with the points lying arbitrarily on either side of zero. The purpose of the **ordered plot vs. residuals** is to determine whether points' independence from one another complies with the residuals' assumption. Even though the plot's residuals should be randomly distributed around the center line, these patterns demonstrate that the residuals are dependent. The probability of the residuals having a normal distribution and plotting in a straight line is depicted by the normality probability plot. Because the study's residuals were normally distributed, all of the responses met the normality assumptions.

➢ *The main Effect Regression Coefficient Test:*

This is to determine whether the main effect regression coefficient hypotheses are required. The means of the response variable, plant height, are represented on the main effects plot for each level of a factor. The locations of the primary effects of plant height are depicted in the figure 7 below.

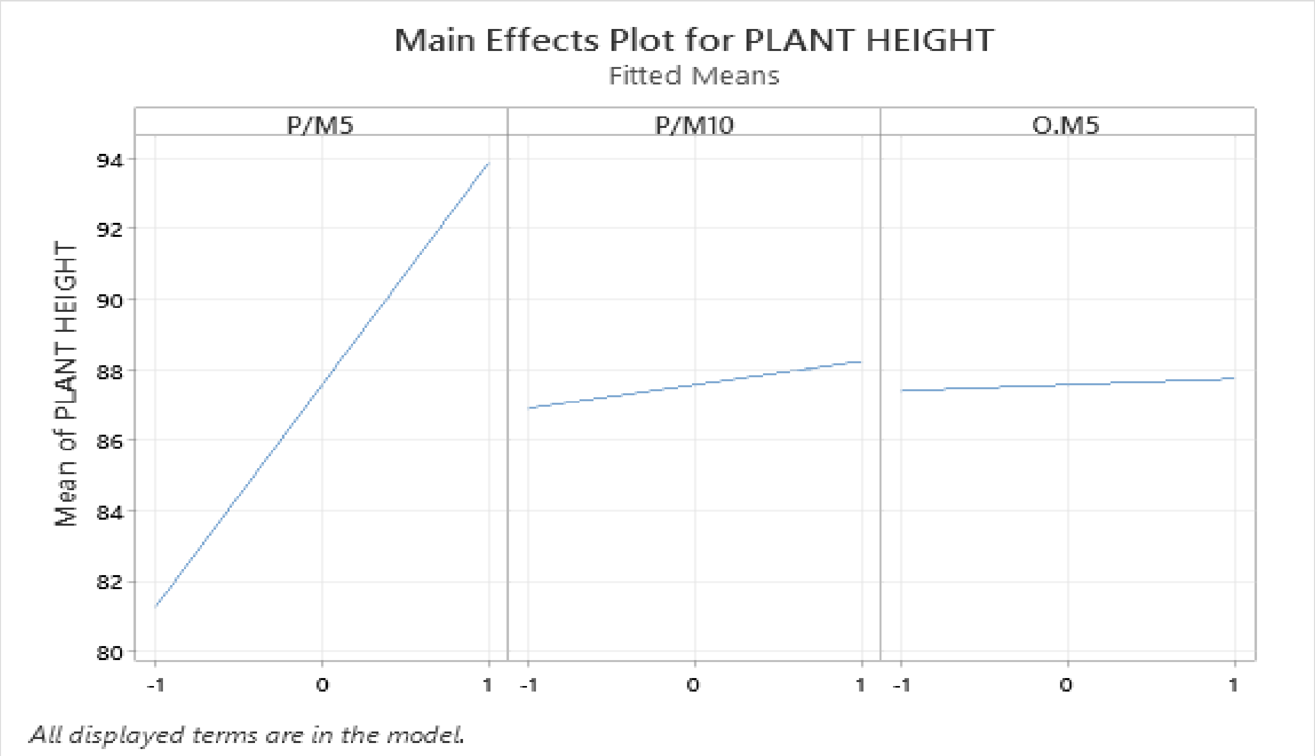

Fig 7 Main Effect Plot for Plant Height

The factors P/M10 and O.M5 show just a very modest rise in the data above, however, the factor P/M5 increases Plant height and seems to have a higher impact on the responses.

- *Visualization of the Response Surface's Contours*

This is used to represent the variable's response surface, which depicts how the response variable interacts with the two components simultaneously.

The contour plots of the two factors are related in the figure below.

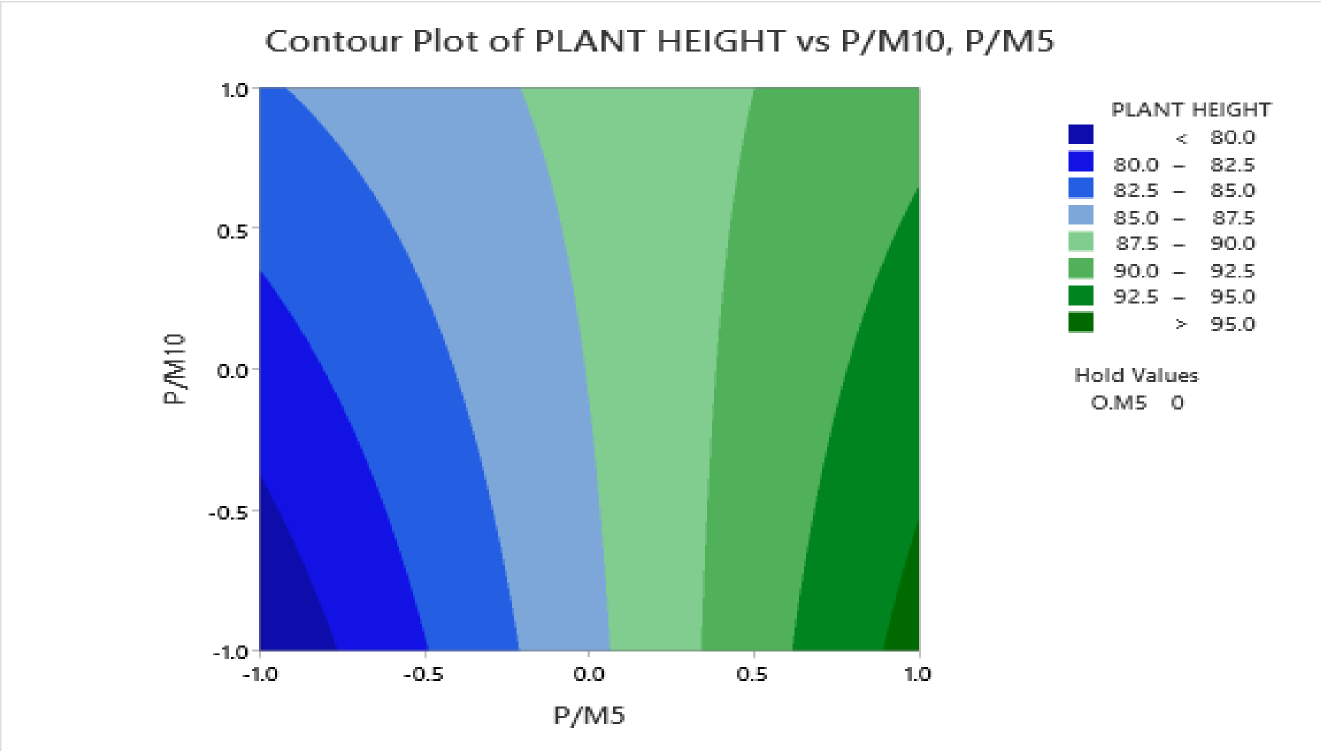

Fig 8 Contour Plot of Plant Height versus P/M10, P/M5

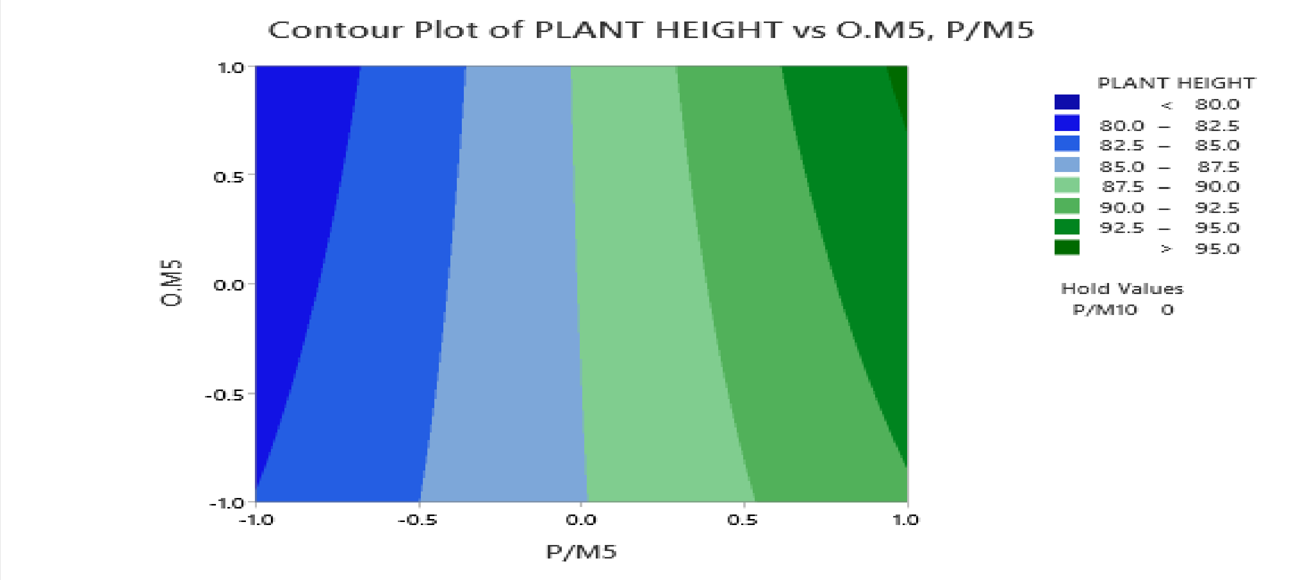

Fig 9 Contour Plot of Plant Height versus O.M5, P/M5

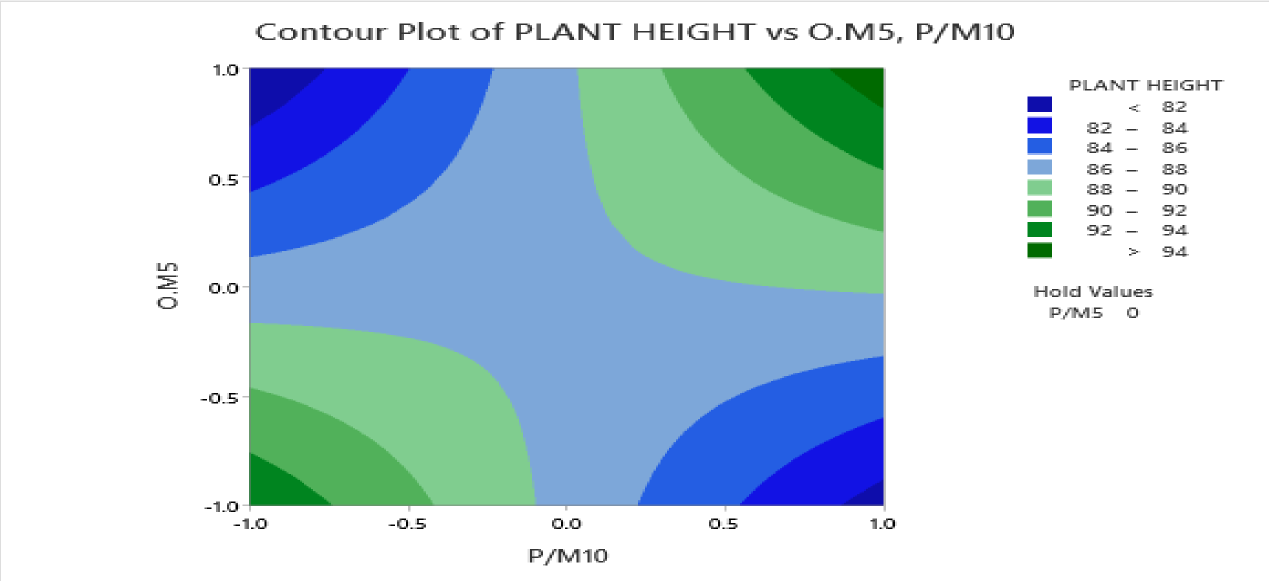

Fig 10 Contour Plot of Plant Height versus O.M5, P/M10

There are parallel straight lines that represent the response surfaces for plant height versus P/M10, P/M5, and plant height versus O.M5, P/M5 in this instance. Hence, the comprehensive analysis of the plots above is as follows:

Figure 8 represents the Plant height vs. P/M10, P/M5; this plot shows how the variables Poultry-manure at 50kg/ha and 100kg/ha are related to the Plant height while the other variable, Organic-mineral at 50kg/ha, is at a high level of 1.0. The darkest portion of the graph contains the highest response level, which is greater than 95.

Figure 9 shows the O.M.5, P/M5 vs. plant height; this graph displays the link between the plant height and the various variables, including poultry manure at 50 kg per ha, organic mineral at 50 kg per ha, and poultry manure at 100 kg per ha, which is at a high level 1.0. The graph's darkest region indicates the highest reaction level, which is larger than 95.

Also, figure 10 shows the Plant height versus O.M.5, P.M.10; this graph shows the relationship between two variables—poultry manure at 100 kg per ha and organic mineral at 50 kg per ha—and the height of the plants, while the third variable, poultry dung at 50 kg per ha, is at a high level 1.0. The darkest portion of the graph contains the greatest response level, which is more than 95.

- *An Examination of the Second-Order RSM:*

When the response surface technique is curved, the first-order method is ineffective. Genuine response surface with parabolic curvature is therefore approximated using a second-order method, which is commonly carried out by software programs, most notably Minitab. To describe the response surface, contour plots, response surface regression, and ANOVA for fitting the data to the second order are all used.

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The responsibilities performed by each element are highlighted in the graphs created for the combinations of the two factors, with one being the best level for plant height. The surface plot was drawn and fitted to the above response surface regression model in the figures 11, 12 and 13 below.

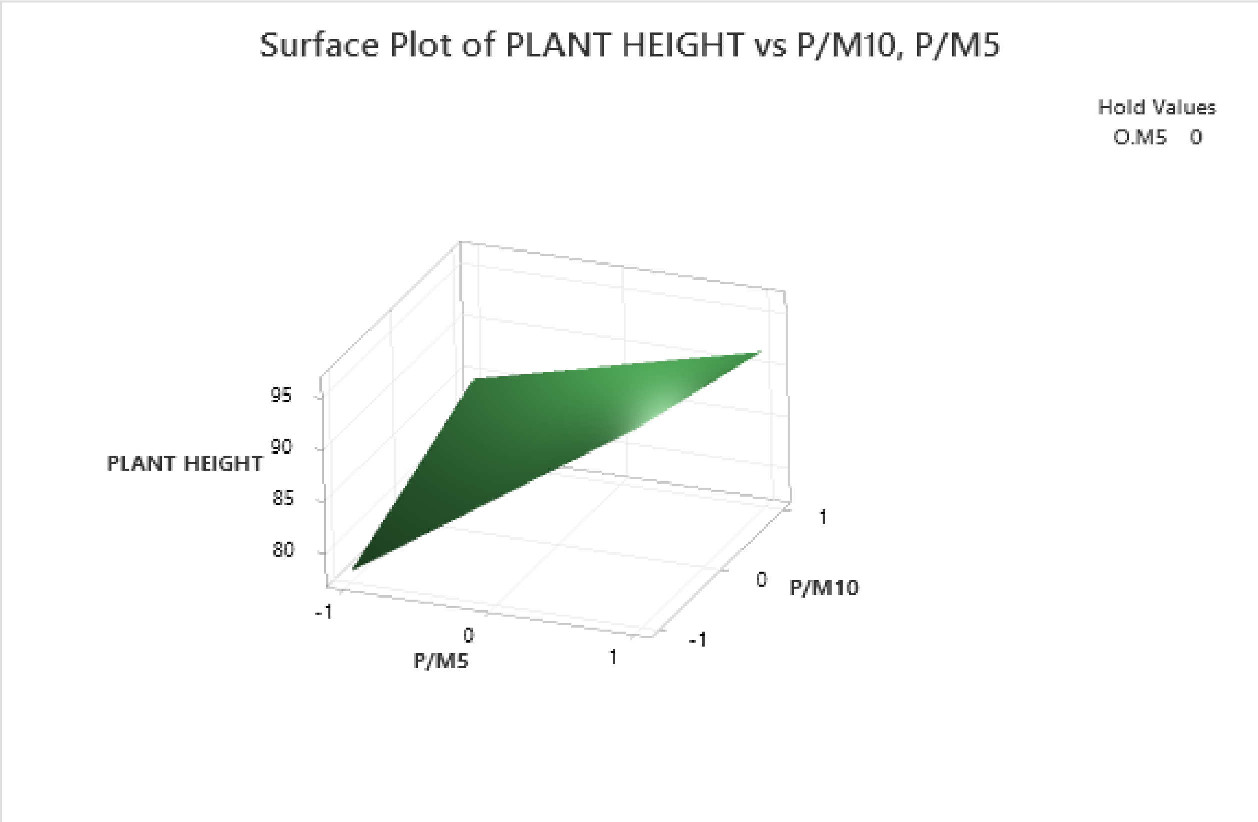

Fig 11 Surface Plot of Plant Height versus P/M10, P/M5

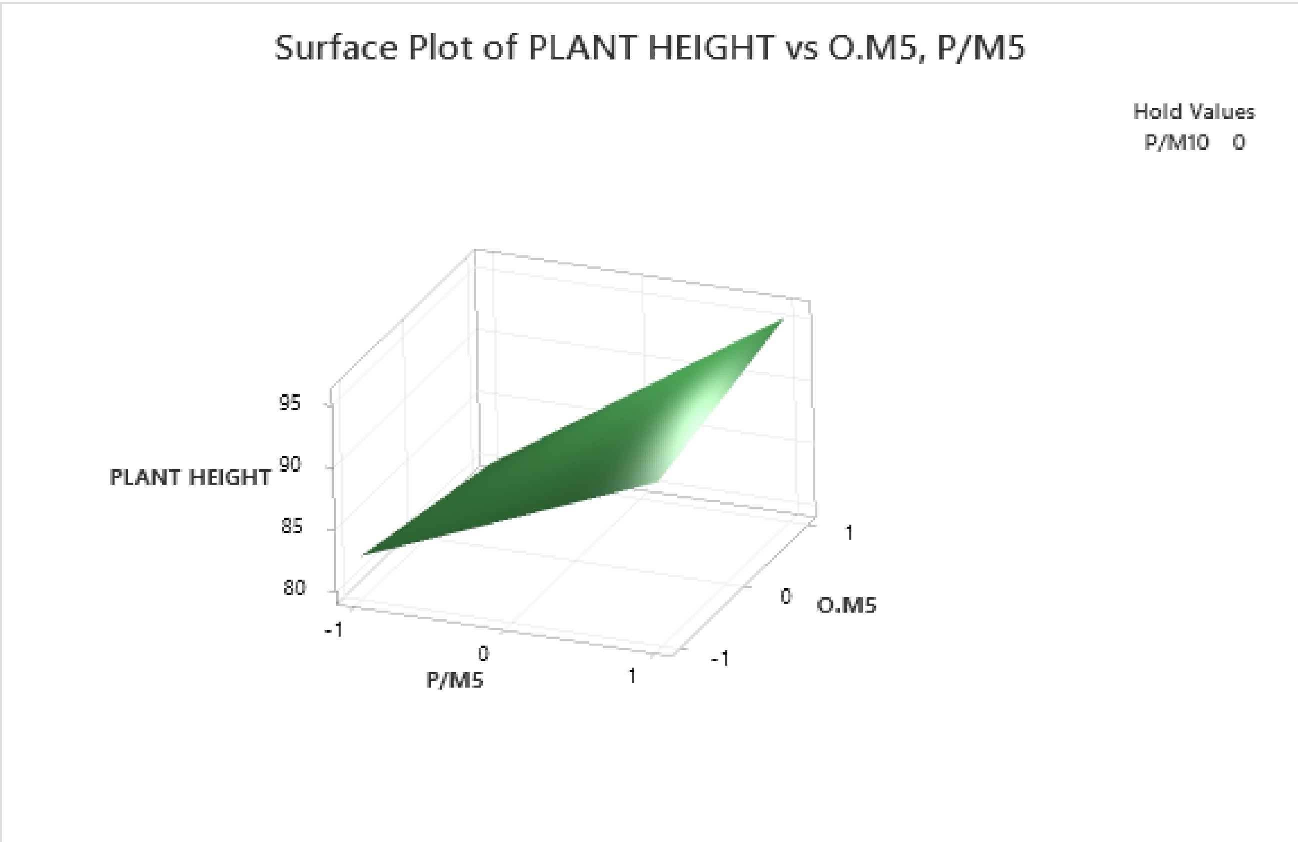

Fig 12 Surface Plot of Plant Height versus O.M5, P/M5

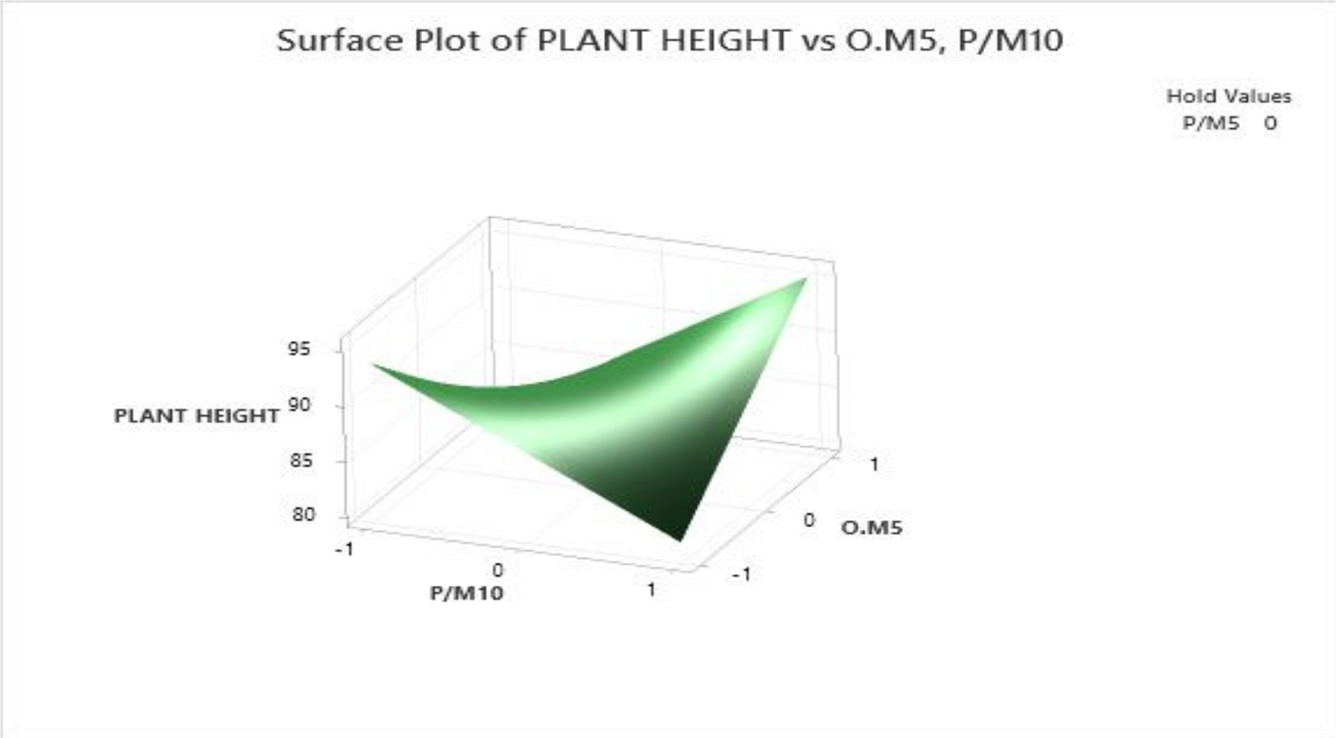

Fig 13 Surface Plot of Plant Height versus O.M5, P/M10

➢ *Plant Height Optimization for Responses:*

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
PLANT HEIGHT	Maximum	49.46	101.5		1	1

Solution

Solution	P/M5	P/M10	O.M5	Plant HeightFit	Composite Desirability
1	1	-1	-1	101.306	0.996269

➢ *Forecasting Several Responses*

Variable	Setting
P/M5	1
P/M10	-1
O.M5	-1

Response	Fit	SE Fit	95% CI	95% PI
PLANT HEIGHT	101.31	7.43	(85.63, 116.98)	(68.32, 134.29)

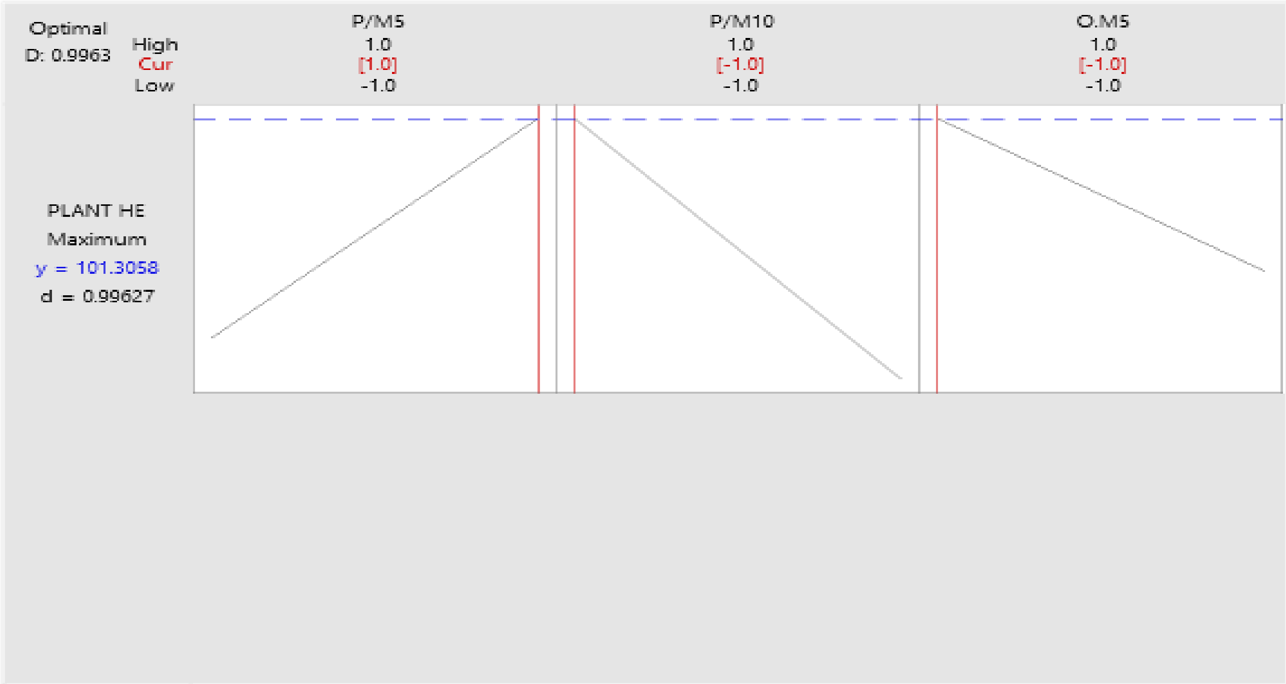

Fig 14 Plant Height Optimization for Responses

By using the computer program Minitab, it is possible to obtain response optimization at the optimal levels of anticipated value for poultry manure and organic minerals as shown in figure 14. The location's optimal values have a composite desirability of 0.996269 and an anticipated response plant height of 101.31 cm. The height at which the dot was placed represents the degree of composite attractiveness, and the value ranges from 0 to 1 depending on how closely the outputs resemble the target, or how matches the real values.

V. CONCLUSION

In conclusion, response surface analysis is a useful statistical tool that can be used to determine the optimum combination of fertilizer treatments for maximizing the plant height of maize. By analyzing the effects of three factors, such as type, amount, and frequency of fertilizer application, response surface analysis can provide insights into the relationships between these factors and plant height. Optimal level for plant height, which is nearly impossible to visualize on the surface, is the other element that is combined with the other two, and a surface plot is created for these combinations to highlight the roles performed by each factor. The ideal value has now been discovered because there isn't a discernible lack of fit at the point where the model is being applied.

According to a response surface analysis, response optimization was used to achieve the best levels of the predicted, studied factors, poultry manure, and organic minerals. The ideal values for the area provide the optimum plant height with a composite desirability of 0.996269 and a forecasted response plant height of 101.31 cm.

Through this analysis, it is possible to identify the optimal combination of fertilizer treatments that can result in the highest plant height of maize. This information can be used by farmers and agronomists to optimize their fertilizer application strategies and achieve higher crop yields. It enables farmers and researchers to identify the most effective and efficient combinations of fertilizer treatments to maximize maize growth and yield.

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